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Pedestrian Behavior

Models, Data Collection and Applications

PEDESTRIAN BEHAVIOR: MODELS, DATA COLLECTION AND APPLICATIONS

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PEDESTRIAN BEHAVIOR: MODELS, DATA COLLECTION AND APPLICATIONS

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INVESTOR IN PEOPLE

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Introduction

Compared to the car and public transport, pedestrian movement has received considerably less attention in the transportation and urban planning literature. Yet, an understanding of pedestrian decision-making and movement is critical in a variety of application domains. The viability of stores in inner city areas largely depends on pedestrian flows. Especially those stores that cannot attract customers in their own right depend on pedestrian movement patterns. In addition to such feasibility and impact assessments, an understanding of pedestrian movement is important for planning and designing public spaces. The dimensions of public space influence pedestrian movement and in turn have an important impact on the general atmosphere in pedestrianized areas. In addition to public space, pedestrian movement patterns are critical in large buildings such as train stations, airports, stadiums and theatres not only in terms of the capacity of such buildings, but also with respect to such issues as safety, evacuation and navigation.

Although some attempts of modeling and simulating pedestrian movement have been around for decades, this field of research recently received a clear boost in attention in a variety of disciplines, not only in the disciplines, traditionally concerned with pedestrians such as urban planning, transportation and urban design, but also in computer science and applied physics. In the latter case, pedestrian movement is often viewed as an interesting case to show properties of complexity theory and multi-agent models such as aggregate patterns emerging from simple principles applied to microscopic agents.

The aim of this book is to document these new developments in research and modeling approaches. To that effect, leading scholars representing different new modeling approaches and fields of application were invited to write a chapter about the analysis and modeling of pedestrian movement patterns. Most of these chapters relate to contributions in modeling pedestrian choice behavior and movement. Innovative work related to different modeling approaches is included in this book. Other chapters are more focused on applications. They serve to illustrate how models of pedestrian behavior and movement patterns can be applied to a variety of important policy and design issues. Any empirical model of pedestrian behavior requires data. Over the years, different data collection methods have been used. Originally, data on pedestrian and movement depended largely on counts and survey. More recently, modern technology such as video, experiments and GPS

tracking has supplemented the portfolio of different data collection methods. The various chapters illustrate the different data collection methods that are applied in this field of research.

Normally, an introductory chapter like this starts with a brief summary of lines of development in the topic area of interest. In this case, however, this is not done because the contribution by *Bierlaire and Robin* is doing an excellent job in this regard. This chapter illustrates that cellular automata (CA) models constitute an important and viable approach to modeling pedestrian movement. *Schadschneider and Seyfried* discusses the principles underlying this approach and provides a framework for extremely efficient simulations even of very large systems. Various CA models and results derived from this framework are presented. The main focus is on the so-called floor-field CA model, in which the interactions are based on a kind of virtual chemotaxis, similar to the communication used by ants. This is especially useful for modeling pedestrian crowding.

CA models have found a strong competitor in multi-agent systems. *Bandini, Manzoni, and Vizzari* presents several computer simulations of multi-agent technology in simulating crowding. In particular, their chapter presents modeling and software tools provided by the so-called Situated Cellular Agent (SCA), an approach based on Multi-Agent Systems principles whose roots are on CA. Examples in which SCA formal tools have been exploited to represent relevant crowds' features and dynamics are presented.

The next chapter, by *Dijkstra, Timmermans, and de Vries*, is also about a multi-agent system, but in this case the focus is on impulse and non-impulse shopping. Their AMANDA model is quite general in scope, but still some parts need elaboration. In addition to outlining the general model system, the chapter focuses on some estimation results of the submodels on impulse and non-impulse buying behavior.

Compared to the CA models and some other multi-agent models, the richness of the behavioral underpinnings of their model is a distinctive feature. In that sense, different concepts of behavior have been used in the literature. Beyond pedestrian movement, random utility theory has been a dominant approach in transportation research and spatial choice behavior. This theory assumes that when choosing between discrete choice alternatives (destinations, routes, etc.) individuals choose the alternative that maximizes their utility. *Borgers, Kemperman, and Timmermans* demonstrate how this approach can be used in modeling pedestrian movement in shopping street segments, including entering shops. The model assumes a detailed network of links to represent the structure of street segments and entrances to the shops. The choice of a destination is modeled by means of a discrete choice model, including variables such as type-specific supply of shops, distances and tendency to visit a shop. After choosing a destination, the route to that destination is modeled using a similar type of model.

Zachariadis, Amos, and Kohn also report new developments, based on utility-maximizing behavior. They propose a dynamic pedestrian routing and traffic assignment approach that is based on route choices that are neither constrained by grid-based discretizations of space nor follow a user-defined network. Pedestrian

movement choices are defined heuristically and utility feedback is used to evaluate alternative options. Route choices are based on the experienced utility of preceding pedestrians as realized by Legion Studio's micro-navigation module.

Behaviorally, the principle of utility-maximization implies that pedestrians take into account all attributes that are relevant to their decision, use these attributes in a continuous manner and discriminate between choice options also with much precision. Because these assumptions may not be very realistic for pedestrian behavior, *Zhu and Timmermans* explore modeling pedestrian choice behavior using principles of bounded rationality. Their model acknowledges that pedestrian may only use a subset of attributes and use thresholds to identify satisfactory outcomes. An interesting unique feature of their model is that heterogeneous decision styles and rule are part of a single model.

The temporal dimension is most of this work does not play a role at all or an implied role. *Zhang* develops a model of time use and expenditures of pedestrians in city centers. A new resource allocation model is developed to describe how pedestrians allocate their available time and expenditure budgets to various activities using a utility-maximizing framework. Pedestrian's utility is defined as a multi-linear function, composed of time- and expenditure-specific utilities and inter-activity interactions. By maximizing the pedestrian's utility, conditional on available time and expenditure budgets, time use and expenditure functions for all the activities are derived as a nonlinear simultaneous-equation model system.

Data collection and parameters estimated of many models of pedestrian movement represent challenges in their own right. *Hoogendoorn and Daamen* provide a valuable generic approach to the calibration of especially microscopic pedestrian models using pedestrian trajectory data as the prime data source. The method allows for statistical analysis of the parameter estimates, including their cross-correlations. Moreover, as a further extension of the method, the inclusion of prior information on the parameters of the model, their distribution, and their cross-relations is proposed.

The remaining chapters, although some are also interesting from a modeling or data collection perspective, offer a good overview of the kind of applications for these models. The chapter by *Klüpfel* offers examples of evacuation and emergencies studies that benefit from models of crowd dynamics. His chapter also discusses the BDI framework (Beliefs, Desires, Intentions) that is often used in multi-agent modeling and discusses various issues including panic that should be incorporated into models of crowd dynamics for application to evacuation and emergency.

The next chapter, written by *Lämmel, Klüpfel, and Nagel* is also about emergency. In this case however, the MATSim multi-agent simulation system is applied to simulate the possible effects of a tsunami wave for the city of Padang, with approximately 1,000,000 inhabitants. The MATSim framework was originally developed for large-scale transport simulations, but this chapter shows the rich potential of this system. The paper also shows that large-scale applications of multi-agent models are now within reach.

The relevance of these approaches to shopping behavior is also illustrated in the next chapters. *Kurose, Deguchi, and Zhao* examines several temporal and spatial

heuristics to simulate pedestrian shopping behavior. They compare pedestrian behavior in the central shopping areas of Fukuoka (Japan), Busan (Korea), and Tianjin (China). Findings indicate that pedestrian behavior dependsnot only on pedestrian characteristics such as age and occupation, but also on street characteristics. Pedestrians in the central shopping areas of Busan and Fukuoka, where many shops are distributed in a rectangular shape make more trips than those in Tianjin, where shops are concentrated along a line. Compared with Fukuoka, pedestrians in the central shopping area of Busan, which has shorter links and a more densely distributed pattern of shops and vendors, make more return trips.

The influence of the environment at different environmental scales on pedestrian itineraries is nicely articulated in the next chapter by *Zacharias*, based on both theoretical considerations and empirical results from various studies. He assumes that decision points are decided *a priori* or are inserted into the itinerary as new information or events modify the set of opportunities available. The transport and land use structure of the larger environment plays a role at the urban scale. At the finer scale of blocks and streets, different physicalist descriptions of the walking network layout relate significantly to local choices, as do sensory inputs and the social meanings.

The application of models of pedestrian movement to support design (layout and capacity) decision is nicely illustrated by *Wang, Ma, and Zhu*, who applied a multinomial logit model to simulate pedestrian behavior of visitors in the Expo 2010, Shanghai. Influential factors, such as the distance and neighborhood between the visitor and the exhibition hall, features and the size of the hall, whether it is along the river and at the same bank as the visitor, and the number of visits the visitor accumulated, are used to explain the visitor choice behavior. The potential problem of an unbalanced distribution of visits and pedestrian flows is identified.

The final chapter by *Bauer* et al. is not only of interest for the case studies but also especially because they discuss the latest technology in collecting data on pedestrians' spatial movement at the very local level as an alternative to survey methods. The chapter reviews existing technologies for collecting such disaggregated information of pedestrian movement, with examples of infrared laser scanners and image analyses.

Together these chapters convincingly report the rapid recent progress in the analysis and modeling of pedestrian behavior and the wide range of problems to which these models can be applied. Hopefully, this book will stimulate innovative future work in this field.

Harry Timmermans
Eindhoven

Chapter 1

Pedestrians Choices

Michel Bierlaire and Thomas Robin

Abstract

We approach pedestrian modeling from a choice perspective. We first identify the list of choices that pedestrians are facing, and identify how each of them has been addressed in the literature. Then, we consider how the framework of discrete choice models may be considered in each case. Our objective is to trigger new ideas and new tracks of research in this particularly challenging field.

1.1. Introduction

Among the various modes of transportation, walking is probably the most natural but also the most complicated to apprehend from an analyst viewpoint. Contrary to most other travel modes, it is not associated with a vehicle and the underlying infrastructure is highly heterogeneous (sidewalks, crossings, buildings, shopping malls, squares, etc.). Understanding and predicting the evolution of pedestrians in these various environments is important in many aspects. The first application that comes to mind is the planning of building evacuation in case of emergency, or city evacuation in case of a disaster. Another important application is the description of congestion caused by heavy flows of pedestrians and their conflicting movements. Indeed, it must be accounted for the efficient design of new facilities (such as public buildings, train stations, airports, or intersections of urban streets) and the daily operations of these facilities. Focusing on individual behavior in sparse conditions is also important. Among others, travel guidance and information systems aim at helping the pedestrian in implementing her journey, surveillance systems are interested in detecting abnormal behavior, advertisers are interested in evaluating

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the global exposure of their announcements, movie and video games makers are interested in generating realistic synthetic behavior.

The flourishing scientific literature, as well as the increasing availability of commercial tools, are evidences of the growing importance of this field, but also of its multidisciplinary nature. Indeed, models inspired by physics, artificial intelligence, computer vision, econometrics, biology, and traffic flow theory have been proposed.

In this chapter, we consider the models capturing the behavior of individual pedestrians, described in terms of choices. Choice models have been successfully applied to forecast behavior in many instances of travel demand analysis for the past 40 years. Therefore, they immediately come to mind for pedestrian behavior. In Section 1.2, we identify the types of choices that a pedestrian is confronted to, and describe how each of them has been addressed in the literature. Section 1.3 summarizes the discrete choice framework and its underlying assumptions, and emphasizes how discrete choice models could be or have been used in this context.

1.2. Choices of Pedestrians

The concept of choice is present in many dimensions of the pedestrian behavior. Although most of these choice dimensions are highly interrelated in reality, and usually considered jointly in the literature, it is more convenient to analyze each of them separately. Let us consider a single individual at a given location at a given point in time.

1.2.1. Activity Choice

The first decision to be made is about what to do next. The choice of the next activity will indeed trigger the travel. This type of choice is not necessarily related to pedestrians, as it is relevant to any travel mode. Among the vast literature, we refer the reader to Jones, Koppelman, and Orfueil (1990), Morey, Shaw, and Rowe (1991), Axhausen and Gärling (1992), Ettema and Timmermans (1997), Kitamura and Fujii (1998), Bhat and Singh (2000), Bowman and Ben-Akiva (2001), Bhat and Koppelman (2004) and Abdelghany, Mahmassani, and Chiu (2001).

Few authors analyze the activity choice in the specific case of pedestrians. Hoogendoorn and Bovy (2004) distinguish between the choice of an *activity pattern*, performed at a so-called "strategic" level, from *activity scheduling*, performed at a "tactical" level, and assume that pedestrians make a simultaneous path-choice and activity area choice decision. Handy (1996) analyzes the impact of the urban form on the choices of the pedestrians in Austin to test if appropriate urban design can discourage automobile dependence. Borgers and Timmermans (1986) consider impulse stops, where the choice of the activity is not planned, but triggered by stimuli in the pedestrian's environment.

1.2.2. Destination Choice

The choice of the destination is related to the choice of the location of the chosen activity. Again, such a choice is not specific to pedestrians, and has been widely analyzed in the literature (Fotheringham, 1986; Fesenmaier, 1988; Woodside & Lysonki, 1989; Furuichi & Koppelman, 1994; Timmermans, 1996; Dellaert, Arentze, Bierlaire, Borgers, & Timmermans, 1998; Oppermann, 1999; Scarpa & Thiene, 2005; Bigano, Hamilton, & Tol, 2006 and many others).

With respect to pedestrians, Borgers and Timmermans (1986) develop a destination choice model as part of a system of models to predict the total demand for retail facilities within inner-city shopping areas. Timmermans, der Hagen, and Borgers (1992) provide a review of models existing in 1992 and of a few applications to urban and transportation planning in The Netherlands. Zhu and Timmermans (2005) focus on shopping decision processes, using bio-inspired heuristics to mimic the decision process. Eash (1999) has developed models for nonmotorized destination choice and vehicle versus nonmotorized mode choice, with application to the Chicago Area.

1.2.3. Mode Choice

Two types of mode choice are considered in the literature on pedestrian travel. First, the usual transportation mode choice analysis, where walking is one of the alternatives. For instance, Bhat (2000) presents a mode choice model in the Bay Area for work travel. Ewing, Schroeer, and Greene (2007) analyze travel decision of students going to school. Cervero and Radisch (1996) investigate the effects of New Urbanism design principles on both nonwork and commuting travel by comparing modal splits between two distinctly different neighborhoods in the San Francisco Bay Area. Rodriguez and Joo (2004) illustrate the link between mode choice and environmental attributes for commuters to the University of North Carolina in Chapel Hill.

The second type of mode choice focuses on the choice among stairways, escalators, or elevators while walking. Several models have been proposed in order to quantify the impact of such elements on the pedestrian behavior. Hamada et al. (2008) are interested in the configuration of a high building, in terms of optimization of floor plan, and elevator configuration. Cheung and Lam (1998) report on the behavior of pedestrians in choosing between escalators and stairways in Hong Kong Mass Transit Railway (MTR) stations during peak hours. Kinsey et al. (2008) propose an escalator model designed for circulation and evacuation analysis, involving microscopic person–person interactions. Toshiaki, Naoki, Masaru, and Minoru (2000) compare the choice between the stairs and the escalator for healthy and disabled people. Note that the analysis of this type of choice is of increasing interest for health applications in general, and overweight and obesity issues in particular (Eves, Webb, & Mutrie, 2006).

1.2.4. Route Choice

The choice of the itinerary (or route) is a critical dimension of the pedestrian behavior.

Kurose, Borgers, and Timmermans (2001) analyze the impact of the attractiveness of a street to the route choice in a shopping context. In the same spirit, Borst, Miedema, de Vries, Graham, and van Dongen (2008) describe the relationships between the perceived attractiveness of streets and the (physical) street characteristics. Seneviratne and Morrall (1985) report a study done by the University of Calgary to evaluate the factors affecting the choice of route. They emphasize the importance of distance, while the level of congestion, safety, or visual attractions appear to be secondary. Tsukaguchi and Matsuda (2002) combine the street environment, the characteristics of pedestrians, and the spatial relationship between the current location and the destination to analyze route choice behavior. Daamen, Bovy, Hoogendoorn, and de Reijt (2005) have collected route choice data in two Dutch train stations by following passengers from their origins to their destinations through the facility, and estimated route choice models. Hoogendoorn and Bovy (2004) combine route choice, activity area choice, and activity scheduling using dynamic programming. Okada and Asami (2007) incorporate utility at nodes in a pedestrian flow model, and derive route choice probability using an aggregate logit model. Millonig and Schechtner (2005) propose a route choice model in the context of pedestrian navigation services.

1.2.5. Walking Behavior: The Choice of the Next Step

The choice of the next step relates to the orientation of the walk, as well as the speed. Muramatsu, Irie, and Nagatani (1999) and Kessel, Klüpfel, Wahle, and Schreckenberg (2002) propose a so-called "driven" random walk model, where the probability of the next step depends on the number of occupied cells. Cellular automata models are built on a fixed spatial discretization (Blue & Adler, 2001; Burstedde, Klauck, Schadschneider, & Zittartz, 2001; Schadschneider, 2002; Dijkstra, Jessurum, & Timmermans, 2002a; Weifeng, Lizhong, & Weicheng, 2003; Schadschneider, Kirchner, & Nishinari, 2002; Yang, Fang, Huang, & Deng, 2002) where transition rates capture the dynamics of the pedestrians. Hoogendoorn, Bovy, and Daamen (2002) assume that pedestrians follow given trajectories, and can choose among many of them. Therefore, the next step behavior is driven by the current trajectory. Helbing and Molnár (1995) introduce the concept of social forces to describe the motion of pedestrians. Antonini, Bierlaire, and Weber (2006) adopt a discrete choice framework for the next step where a dynamic and pedestrian specific spatial discretization is used.

1.2.6. Walking Behavior: The Choice of the Speed

The choice of the speed is captured in different ways depending on the modeling framework. Statistical analysis on real data have been used to derive speed profiles.

Knoblauch, Pietrucha, and Nitzburg (2007) focus on crosswalks in urban areas, while Young (2007) collect data in airport terminal corridors. Tarawneh (2001) integrates the effect of age and gender in the analysis. In the context of flow models, the fundamental relationship among speed, flow, and densities is the main modeling element (Lam & Cheung, 2000; AlGadhi, Mahmassani, & Herman, 2002; Hughes, 2002; Lam, Morrall, & Ho, 1995; Virkler & Elayadath, 1994). Sugiyama, Nakayama, and Hasebe (2002) derive physic models, extending car-following models to pedestrians. At a more disaggregate level, Ishaque and Noland (2008) model the pedestrian street crossing movements and speed choice at a microscale. Antonini et al.(2006) combine the choice of the speed with the choice of the direction using a dynamic spatial discretization.

1.2.7. Interactions

The interactions among pedestrians play a key role in the analysis of their behavior.

First, group behavior, where individual decisions are influenced by the other members of a group (Goldstone & Janssen, 2005), has been analyzed by several authors. James (1953) and Coleman (1962) analyze the size of the groups, Goldstone, Jones, and Roberts (2006) focus on group formation, Was (2008) differentiates active and passive pedestrian behavior within familiar groups, Miyazaki et al. (2003) performed a series of experiments to investigate the behavior of groups of pedestrians and a wheelchair user. Yersin, Maïm, Morini, and Thalmann (2008) consider group behavior in real-time crowd motion planning.

Second, the complex self-organization of crowds (Helbing, Keltsch, & Molnár, 1998; Helbing, Molnár, Farkas, & Bolay, 2001; Hoogendoorn & Daamen, 2005; Goldstone & Roberts, 2006), where leader–follower and collision avoidance behavior generate specific patterns have been analyzed extensively. In particular, the spontaneous formation of lanes has been emphasized (Helbing & Molnár, 1995; Blue & Adler, 1999; Burstedde et al., 2001; Dzubiella, Hoffmann, & Löwen, 2002). Collision avoidance and leader–follower behavior have been specifically analyzed and modeled in various contexts (Loscos, Marchal, & Meyer, 2003; Daamen & Hoogendoorn, 2003b; Sakuma, Mukai, & Kuriyama, 2005; Pelechano & Badler, 2006; Robin, Antonini, Bierlaire, & Cruz, 2009).

The interactions with the environment are also important. Daamen, Bovy, and Hoogendoorn (2002) account for the entire picture of the scene in their models. Nagel (2002) includes walking in traffic simulations. Helbing et al. (1998) propose the "active walker" model that takes into account pedestrian motion and orientation and the concomitant feedbacks with the surrounding environment. Dijkstra, Jessurum, and Timmermans (2002b) use a multi-agent model to derive several performance indicators of building environments, which are related to user reaction to design decisions. Guo and Ferreira (2008) illustrate how the quality of pedestrian environments along transit egress paths affects transfers inside a transit system, and

how the impedance of transferring affects egress walking path choices. Zacharias (2001) is interested in assumptions about how pedestrians respond to characteristics of the environment as they formulate and enact their walking itineraries.

Finally, the interactions between pedestrians and drivers are relevant as a major safety issue (Himanen & Kulmala, 1988; Tidwell & Doyle, 1995).

1.2.8. Pedestrian Data

We conclude this section by describing various types of data that are collected to analyze pedestrian behavior.

Questionnaires and "manually" collected data have been used in many studies, to obtain behavioral data (Sisiopiku & Akin, 2003) or counts (Cunningham & Cullen, 1993). But data collection using technology is more and more common in various research communities interested in pedestrian behavior.

Pedometers have been used mostly in the context of health research programs. Whitt, DuBose, Ainsworth, and Tudor-Locke (2004) combine pedometer and physical activity reports to analyze walking patterns. Bassett, Cureton, and Ainsworth (2000) report that subjects underestimated their daily walking distance in a survey compared to the pedometer record. Bennett et al. (2007) use pedometers to analyze the relation between walking and the perception of safety.

Location-based services provided namely by cell phones generate relevant data. Sohn et al. (2006) use GSM traces for mobility detection, Ratti, Pulselli, Williams, and Frenchman (2006) analyze the potential of cell phones location-based services to the urban planning community, and Li (2006) uses location-based services to analyze pedestrian wayfinding behavior. Millonig and Gartner (2009) combine qualitative–interpretative and quantitative–statistical data leading to the determination of a typology of lifestyle-based pedestrian mobility styles.

The next obvious important data collection system is the global positioning system (GPS). For instance, Liao, Patterson, Fox, and Kautz (2007) use GPS data to calibrate activity and location choice models, as well as Ashbrook and Starner (2003) who also consider collaborative scenarios. Patterson, Liao, Fox, and Kautz (2003) derives the current transportation mode and the most likely route of a traveler from GPS data. Shoval and Isaacson (2006) review the use of satellite navigation systems and land-based navigation systems for gathering data on pedestrian spatial behavior. Flamm and Kaufmann (2007) propose a survey design combining GPS-based person tracking and qualitative interviews to understand behavioral changes occurring during life course transitions.

There is also an increasing interest in exploiting video sequences of pedestrians within urban or building areas. In this context, two types of data are considered: counts and trajectories. Pedestrian head counts are useful to calibrate flow models whereas pedestrian trajectories are used for the estimation of disaggregate models.

Several computer vision algorithms have been designed for counting pedestrians. Sexton, Zhang, Redpath, and Greaves (1995) propose an image processing counting

algorithm in unconstrained areas. Zhang and Sexton (1997) combine a model-specified directional filter with a matching process to count pedestrians against a dynamic background. Chen (2003) proposes an automatic bidirectional pedestrians counting method through gates.

With respect to pedestrian trajectories, Teknomo, Takeyama, and Inamura (2000) collect data on a real pedestrian crossing road in Sendai, Japan. Daamen and Hoogendoorn (2003b), Daamen and Hoogendoorn (2003a), and Daamen (2004) provide videos of experimental pedestrian trajectories of volunteer pedestrians performing walking tasks in controlled configurations. Several parameters are considered such as free speed, direction, density, and bottlenecks. Trajectories are extracted from video sequences, by using computer vision algorithms. Teknomo (2002) and Hoogendoorn, Daamen, and Bovy (2003) developed specific pedestrian tracking methods, Sullivan, Richards, Smith, Masoud, and Papanikolopoulos (1995) use active deformable models for the same purpose. Masoud and Papanikolopoulos (1997) and Denzler and Niemann (1997) present real-time systems to track pedestrians in video sequences. Antonini et al. (2006) propose a framework combining state-of-the-art detection and tracking methodologies with behavioral models.

1.3. Discrete Choice Models

Discrete choice models (McFadden, 1981; Ben-Akiva & Lerman, 1985; Train, 2003) have been widely applied in the context of travel decisions (Ben-Akiva & Bierlaire, 1999). Disaggregate in nature, these models are based on random utility theory. We consider a decision-maker n who is performing a choice among a set C_n of J_n alternatives. It is assumed that n associates a utility U_{in} to each alternative i within C_n, and selects the alternative corresponding to the highest utility. The utility is modeled as a random variable to account for uncertainty due to various issues, including unobserved variables and measurement errors. The utility is decomposed into a deterministic part V_{in} and an error term ε_{in}, so that

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

and the probability that individual n is selecting alternative i is

$$P_n(i|C_n) = Pr\,(U_{in} \geq U_{jn}\,\forall j \in C_n) \tag{2}$$

Operational models are derived from explicit specifications of V_{in} and distributional assumptions about ε_{in}.

The specification of V_{in} includes the selection of the explanatory variables, that is the attributes of i relevant to n, as well as the socioeconomic characteristics of n. A functional form used to compute the utility from these variables must also be assumed. The distributional assumptions determine the complexity of the model. The most widely used model is the *logit model*, which assumes that the ε_{in} are independent across both i and n, and identically distributed with an extreme value distribution,

leading to a simple and tractable formulation. The more complex models such as the nested logit (Ben-Akiva, 1973; Williams, 1977; Daly & Zachary, 1978), the multivariate extreme value (McFadden, 1978), the probit model (Thurstone, 1994), or the mixture of logit models (McFadden & Train, 2000) are designed to relax these assumptions that may be unrealistic in some contexts.

In the following sections, we review how discrete choice models have been or could be applied to model the various choices described in Section 1.2, focusing on the features specific to pedestrians. Most of the time, we raise issues instead of providing solutions. The objective is to stimulate new ideas and new potential models.

1.3.1. Activity Choice

Traditional travel demand analysis focus on the schedule of activities, where the choice of activity patterns is modeled (Bowman & Ben-Akiva, 2001). Due to the combinatorial nature of the choice set, operational models focus on scheduling the most important activities, such as *stay home*, *work*, *school*, and *shopping*. The analysis of pedestrian movements requires a more detailed analysis of activities, where the set of considered activities must be refined, and the choice of the next activity to be performed by a pedestrian at any point in time is relevant. For instance, on her way back home from work, a pedestrian may choose between rushing to catch the train, or having a coffee and taking the next train. Clearly, this decision will have significant impacts on her walking behavior, and may therefore be important to model. Impulse stops are another typical example, where the choice of the next activity is triggered by various stimuli in the environment. This is particularly relevant for shopping (Borgers & Timmermans, 1986) and tourism (Stewart & Vogt, 1997) activities, where individuals can easily be diverted from their original plans.

Several challenges are associated with the derivation of a choice model for the next activity. As discussed above, the characterization of the choice set is highly context-dependent, and the list of activities that may be potentially considered is not always available to the analyst. Moreover, walking may be a potential activity as such.

With respect to the explanatory variables, the location of an activity plays an important role. Consequently, it is natural to combine the activity choice model with the destination choice model, as discussed below. Variables describing the design of existing stimuli (e.g., type and size of an advertisement) are also important. Variables capturing the importance of activity providers can also be considered. Borgers and Timmermans (1986) use the retail turnover, the average per capita expenditure, and the turnover to floor space ratio of a category of stops to explain impulse stops. Contextual variables, such as the time of day (Dellaert, Borgers, & Timmermans, 1995) and the weather conditions may also play an important role. Finally, several relevant socioeconomic characteristics should be considered, such as gender (Jansen-Verbeke, 1987), age, or type of household (Krizek, 2006).

Due to the context-specific nature of pedestrian activity choice models, no general recommendation can be made for the distributional assumptions of the error terms, although it is likely that a simple logit model may not be appropriate for many instances due to unobserved attributes shared by several alternatives.

1.3.2. Destination Choice

Influenced by traditional practice in travel demand analysis, several models are derived from origin–destination matrices (Nagel & Barrett, 1997; Antonini et al., 2006), where the set of potential origins and destinations is predefined, and flows between origins and destinations are estimated. In a disaggregate context, the choice of the destination can be modeled conditional to a given activity, or as a joint choice of an activity and a destination. In both cases, the choice set is typically large and difficult to characterize. The size of the choice set depends on the application. For example, in a building, the number of possible exits is usually not huge. But in a shopping mall or a city center, the number of possible destinations or intermediate stops, can be extremely large. It is good practice to sample alternatives out of the full choice set to derive operational models. If a logit or a multivariate extreme value model is used, efficient estimators using samples of alternatives are available (Manski & Lerman, 1977; Bierlaire, Bolduc, & McFadden, 2008).

In addition to the variables describing the attractiveness of a destination, it is particularly important to also account for distance. Moreover, the impact of distance on the choice usually interacts with socioeconomic characteristics of the pedestrian, such as age, sex, possible disabilities, etc. Also, the number of other activities that may potentially be performed at a destination will influence the choice, as illustrated by the attractiveness of commercial centers or leisure parks.

The error structure of destination choice models can be complex. First, if we are considering the joint choice of an activity and a destination, we are dealing with a multidimensional choice set where alternatives are correlated by construction. If nested logit models have been historically used to handle part of the correlation in multidimensional choice sets (Ben-Akiva & Lerman, 1985, Chapter 10), mixture of logit models provide a more accurate representation of the correlation (Bhat, 1998), although at the cost of higher complexity. Second, destination choice includes a spatial dimension, and the associated spatial correlation should be accounted for in the model (Fotheringham, 1986). A typical example for pedestrians is when two doors are close to each other, or give access to the same room or the same street. Bhat and Guo (2004) suggest to account for the correlation among neighboring destinations, and use a cross-nested logit (CNL) to capture it.

We conclude this section by noting that, in some circumstances, it may happen that no destination is explicitly chosen by a pedestrian. It is typical when walking is the activity as such, or in shopping and touristic activities. In these cases, an itinerary is chosen without a known target, trying to maximize the chances to reach attractive places along the way (Borst et al., 2008). This type of behavior is clearly difficult to formalize, and is closely linked with the route choice behavior.

1.3.3. Mode Choice

Mode choice models are probably the most traditional discrete choice models. As discussed above, two types of mode decision can be considered. There is not much to discuss about the standard mode choice where walking is one of the alternatives.

With respect to the use of mechanized devices such as elevators, escalators, we first note that it is intrinsically related to route choice behavior (Daamen, Bovy, & Hoogendoorn, 2005). Focusing on the mode choice, the choice is typically small, as less than a handful of alternatives are in general available to change levels. With respect to explanatory variables, Cheung and Lam (1998) include expected delays in congested situations, Nicoll (2006) includes the visibility of stairs, the "imageability" (Lynch, 1960), that is quality in a physical object which gives it a high probability of evoking a strong image in any given observer (typically, the type of stairs, the type of elevator, etc.), the intelligibility of the environment, characterized for instance by the number of turns to reach the stairs, the setting appeal, that is the value of the view when using the stairs or the elevators. Comfort and safety variables can also be envisaged. Foster and Hillsdon (2004) consider the possible impact of health campaigns stimulating the use of stairs, but they did not find significant evidence of their impact in their studies.

The structure of the error term for these models should be similar to traditional mode choice models, where the logit model is usually appropriate.

1.3.4. Route Choice

Route choice models are traditionally based on a network structure (Bovy & Stern, 1990; Ramming, 2001; Frejinger, 2008). In the pedestrian context, there is no physical network infrastructure associated with the movements of the individuals (Hoogendoorn & Bovy, 2004). Within a discrete choice framework, two approaches can be considered.

A first possibility is to design a virtual network structure. The nodes would correspond to the key decision points (doors, intersections of corridors, crossways, stairs, elevators, etc.), and the links would connect adjacent nodes. Note that such a network would typically be denser than a road network, as a great deal of nodes may be necessary in the presence of large spaces. Also, it must not be assumed that the pedestrians will exactly follow the link of this virtual network, and the associated walking model must be designed accordingly. Network-free model estimation, as proposed by Bierlaire and Frejinger (2008), is then necessary. When the virtual network is defined, the usual complexities of route choice models must be addressed, including the very large size of the choice sets (Frejinger, 2007) and the high structural correlation among the paths (Frejinger & Bierlaire, 2007).

Another possibility would consist in assuming a more myopic behavior of the pedestrians, where they would choose the next intermediary point on their way to the

destination. The set of possible intermediary points can be constructed similarly to the nodes of the virtual network mentioned above, but may also be dynamically updated as the pedestrian moves and discovers her environment.

Compared to a network-based approach, the choice set contains the list of potential intermediary stops, which has no combinatorial dimension. The variables describing each of them should reflect not only the location of the place itself, but also all the elements that will be met on the way to it. This is where a combinatorial dimension may increase the complexity of the model. However, this can be controlled by excluding from the choice set the alternatives which are quite distant from the current location, so that the number of elements in between is bounded. The choice set can then be updated dynamically as the pedestrian moves.

Inspired by the walking model proposed by Antonini et al. (2006), and by suggestions from Fosgerau to address the complexity of traditional route choice models, this modeling scheme has several advantages. Structurally less complex than network-based approaches, it may also be appropriate as a basis to derive models capturing phenomenon such as impulse stops.

The spatial dimension of this choice would suggest an error structure based on mixtures of logit models, with error components explicitly capturing the correlation. If the size of the choice set is too large, multivariate extreme value models may be more appropriate, where the operational representation proposed by Daly and Bierlaire (2006) should be considered, together with sampling of alternatives (Bierlaire et al., 2008).

1.3.5. Walking Behavior: The Choice of the Next Step

The choice of the next step is central in the pedestrian modeling. It represents the instantaneous decision, and implies a lot of factors. In this context, Antonini et al. (2006) propose a discrete choice model where the pedestrian visual space is discretized in a set of possible next steps, corresponding to the choice set. It is dynamic, evolving with the individual's current speed and direction. The choice set is multidimensional, combining three acceleration patterns (deceleration to 0.75 times the current speed, same speed, and acceleration to 1.25 times the current speed) with 11 possible directions. While the discretization of directions is relatively straightforward and natural, the discretization based on acceleration patterns can be done in several ways, as discussed in the next subsection.

The choice set could be adapted to the environment. For example on a straight and large sidewalk, the number of considered direction could be decreased, if pedestrians are unlikely to make significant changes of direction. It could also be adapted to pedestrian characteristics, such as age, sex, height, visual angle, trip purpose, or group membership. Crassini, Brown, and Bowman (1988) performed visual experiments comparing young and elderly people and quantitatively measured the perceptions differences.

The utility function associated with a given alternative, that is, with a given combination of location and acceleration, must capture various behavioral patterns. Speed and interaction patterns are discussed in the following subsections. Two orientation patterns must also be considered. The first captures the propensity of pedestrians to keep their current direction, following a smooth and regular path. This is consistent with the findings of Turner (2001) who provides angular analysis of walking environments such as buildings. The second captures the attraction of the destination, consistently with Helbing, Farkas, Molnár, and Vicsek (2002) who state that pedestrians want to reach as fast as possible their destinations in non crowed situations. Therefore, alternatives allowing the pedestrian to move closer to the destination should have a higher utility. Antonini et al. (2006) and Robin et al. (2009) include the angle between the direction d_i associated with a given alternative i and the current direction to capture the first pattern. They also include the angle between d_i and the direction toward the destination for the second pattern, as well as the distance between the position of the next step and the destination.

The multidimensional nature of the choice set induces structural correlation among the alternatives, which suggests the use of a cross-nested logit (CNL) model (Bierlaire, 2006) or an error component model (Walker, Ben-Akiva, & Bolduc, 2007). Moreover, the typical panel nature of the data, where the same individual is observed over time, suggests the presence of unobserved heterogeneity which should be modeled using an error component distributed across the population and not across the observations (Train, 2003, Section 6.7).

1.3.6. Walking Behavior: The Choice of the Speed

Speed modeling can be considered in two ways. We described above how it can be integrated in the ''next step'' model. A second approach consists in considering the choice of the speed independently from other walking decisions. In both cases, there are typically two ways of defining the choice set. It can be a list of possible absolute speeds, ranging from 0 to the maximum possible speed that can be achieved by a pedestrian, discretized in some appropriate way. Although they do not use a discrete choice framework, Blue and Adler (1998) adopt a similar approach in a cellular automata context. Wakim, Capperon, and Oksman (2004) consider ''standing still,'' ''walking,'' ''jogging,'' and ''running'' in a Markov chain process. It can also be a list of possible modifications relative to the current speed. These modifications can be defined in absolute terms (e.g., $+0.1$ m/s) or in relative terms (e.g., $\times 1.10$). The former model is more natural, but must integrate mechanisms avoiding unrealistic variations in speed.

Many variables may explain the speed behavior and can be included in the model specification. The first set of variables is directly inspired from macroscopic flow theory, where the relationships between flow, density and speed of pedestrians are characterized. Therefore, current density, flow, or combination of the two should

be integrated as explanatory variables. Kessel et al. (2002) propose a microscopic model based on the fundamental relation between walking speed and crowd density. Seyfried, Steffen, Klingsch, and Boltes (2005) analyze experimentally the microscopic causes of the velocity decrease in the presence of medium or high densities, such as frequency of passing maneuvers and internal crowd frictions. Also, pedestrians' characteristics, such as age, height, sex, trip purpose influence the velocity. For instance, Coffin and Morrall (1995) analyze the speed behavior of elderly people on crosswalks in order to improve such infrastructure in occidental aging societies.

The pedestrian environment is of course predominant in the speed choice process. An arriving train, a traffic light turning to red while in the middle of the crosswalk, or the presence of a slow group of people are events that trigger change of speeds.

Among the possible speeds that a pedestrian may select, the zero speed has a different nature and must be treated separately. The variables explaining the choice of a zero speed may be different from the variables explaining another speed regime. For instance, the presence of an impassable obstacle, the sudden perception of a danger, or the occurrence of various external stimuli (traffic light, advertisements, etc.) may cause a pedestrian to stop.

It is important also that the speed model is able to manage restarts after stops. For instance, if the choice set is defined based on relative modifications of the current speed (e.g., + 10%), it is obviously not appropriate to model the restart. Also, if an impassable obstacle fills in the visual field of a pedestrian, the restart cannot occur before the direction is updated, clearing the visual field.

Finally, the speed may be influenced by the various interactions discussed below (group behavior, leader–follower, collision avoidance).

Depending on the nature of the choice set, the type of correlation between the error terms may vary, but it is seldom the case that independence can be safely assumed. Indeed, among the possible speed changes, the error terms of all alternatives corresponding to an acceleration are likely to be correlated, as well as the error terms of all alternatives corresponding to a deceleration. If the choice set contains a list of absolute speeds, two consecutive values are likely to be perceived more similar than two different values. In this case, models similar to departure time choice model (such as the Ordered GEV model by Small, 1987, which is a special instance of a CNL) are appropriate. Clearly, more complex MEV models, as well as error component models are relevant here as well.

1.3.7. Interactions: Group Behavior

Group behavior relates to the adjustment of individual behavior to comply to groupwise behavioral patterns. It can be motivated by behavioral affinities (fast people passing slower individuals in a dense crowd), social links among individuals, such as friends or relatives or simply fortuitous spatial proximity.

Assuming that the groups are clearly and unambiguously identified (which is by itself a challenge, as groups can split or merge dynamically), there are two ways of modeling this behavior. First, the decision-maker can be considered as the group itself, and its various moving decisions are modeled as a joined choice accounting for the larger physical space occupied by the group. It is similar to the concept of "packets" used in traffic simulation (Ben-Akiva, Koutsopoulos, & Mukundan, 1994; Cornelis & Toint, 1998). Second, the group characteristics, such as size, type or speed, can be considered as exogenous to the model describing the choices of a specific member of the group. Clearly, the two models can be merged in a two stages framework, where the group behavior is modeled at the higher level, and the individual behavior is modeled conditional to the group's.

Note that in addition to the moving behavior, the decision for a given individual to belong to a group can also be modeled in a discrete choice framework, where behavioral, social, and spatial similarities are typical explanatory variables.

1.3.8. Interactions: Leader–Follower

A leader–follower model captures the propensity of an individual to adjust (consciously or unconsciously) her speed and direction to another individual in order to make her way through a crowd. A similar type of behavior can be modeled in an emergency context, where trained employees may serve as leaders in an evacuation procedure (Pelechano & Badler, 2006).

Two types of choices can be modeled. First, the choice of a leader (or the decision not to follow anybody) is influenced by the characteristics of the surrounding crowd (density, speed, etc.) as well as the behavior of the potential leaders. Pedestrians in the visual field, and with behavior close to the desired target, particularly in terms of desired speed and direction, are more likely to be considered. In the literature, the deterministic choice of the nearest potential leader has been proposed by Blue and Adler (1999) and Robin et al. (2009), suggesting that the distance would be an important explanatory variable in a discrete choice model.

The second type of choice is the reaction to the leader's behavior. Robin et al. (2009) suggest an impact of the leader on the choice of the speed and the direction. Other choices, such as route or even destination can also potentially be affected by the leader's behavior.

The estimation of such models is complicated because the choice itself is not really observed, and can only be guessed by the analyst. It should be modeled as a latent construct.

Note that a great deal of insights can be derived from driving behavior models (Toledo, Koutsopoulos, & Ben-Akiva, 2007) where car-following (Chandler, Herman, & Monroll, 1958) and lane changing (Ahmed, Ben-Akiva, Koutsopoulos, & Mishalani, 1996) models play a key role.

1.3.9. Interactions: Collision Avoidance

Instead of being attracted by another individual, and positively influenced, a pedestrian in a collision avoidance context is repelled and negatively influenced by somebody else.

While the impacts themselves on the speed and direction are clearly different, the process of identifying the individual to avoid can be modeled with a discrete choice framework, in a way similar to the selection of the follower described above. As before, the identification of a potentially colliding individual is influenced by the characteristics of the surrounding crowd (density, speed, etc.) as well as the behavior of that person. Pedestrians in the visual field with speed and direction suggesting a possible collision are more likely to be considered in the choice set. Robin et al. (2009) select the "candidate" such that the angle of the two directions is the closest to π, suggesting that the angle would be an important explanatory variable in a discrete choice model. Also, the distance and the speed are important variables, as they characterize the imminence of the collision.

1.3.10. Interactions: Other Scene Elements

During the walking process, individuals have to interact with various elements of the scene, such as cars (on crossing road), sidewalk environment, or even isolated obstacles. Again, we distinguish between what elements influence the behavior, and how.

On crossing roads, pedestrians interact with cars. Himanen and Kulmala (1988) propose a discrete choice framework to model interactions between drivers and pedestrians on crossing roads without traffic lights. Pedestrian could pass or stop, and drivers brake or weave. The explanatory variables of their model are the number of pedestrians simultaneously crossing, the city size, the vehicle speed, and the vehicle size.

The crossing road modeling can be extended and adapted to the interaction between pedestrians and potentially dangerous elements of the scene, such as parking exits, or streetcar lines. Still, the pedestrian chooses between passing, stopping, or getting around (not always available). The choice is influenced by the pedestrian characteristics, such as determination, or by the level of danger (characterized, for instance, by the vehicle speed). Evans and Norman (1998) report a study on the pedestrians road crossing intentions based on the theory of planned behavior. Questionnaires with several crossing manners and scenarios were proposed to respondents. The perceived control of the situation appears to be crucial in the decision-making process.

Corners are present at crossings, either implying corridors or sidewalks. Those immobile scene elements can increase the likelihood of pedestrian collisions, due to lack of visibility. Different options can be combined by the pedestrian to anticipate such collisions, such as move away from the wall to improve the visual perception, or

decelerate (or even stop) at the crossing to check if there is any potential collider. Many factors influence these decisions such as the pedestrian prior experience and characteristics (age, gender, etc.), crowd density, crossing geometry such as angle between corridors or visibility.

Visual advertisements such as posters, screens, or shop windows are designed to attract pedestrians' attention. The walker can choose to stop in order to improve her knowledge of the displayed elements, to slow down to glance at it, or to ignore it and continue walking. Attraction must be included in the next step choice model and speed choice model, in order to account for the walking changes due to the advertisement. The stop decision should be considered independently. In addition to the pedestrian's socioeconomic characteristics, her current activity and destination, as well as her prior experience with the elements on display influence the choice. The visual attributes of the poster are also crucial. For example, Kerr, Eves, and Carroll (2001) perform several experiments in stations and shopping centers, to test the influence of health promotion posters on the pedestrian choice between stairs and escalators. They show that posters size and message have a high influence on the individual perception. In addition, other attributes of the visual form, such as color, or location should also be considered.

Doors are common in public spaces. A standard transparent door is an obstacle that produces only sporadic speed decrease in free-flow conditions. In the presence of high densities, notion of priorities have to be considered. If a dense crowd tries to pass through the door in one direction, and a single pedestrian tries in the other direction, the latter has a tendency to let pass the crowd. Several meanings of "let pass" can be considered. Indeed the pedestrian can anticipate the interaction by decreasing her speed, or modify her trajectory and speed, or even stop at the door. This decision can be modeled in a discrete choice framework. Crowd density, door characteristics, such as dimension and type, and pedestrian characteristics influence the choice (Daamen, Hoogendoorn, & van Wijngaarden, forthcoming).

Sidewalks are full of little elements such as benches, trees, garbage cans, or streetlights. They could possibly be modeled as static pedestrians, so that the interactions issues described before are applicable. But they can also be considered independently, because of their specificities, such as associated danger. Pedestrians have several possibilities to avoid collisions with those elements: go around by the left, or by the right, stop, or turn back. The crowd density is crucial to deal with this decision, as well as pedestrian characteristics.

1.4. Conclusion

Pedestrian behavior is a complex and important phenomenon. Capturing and forecasting it requires advanced modeling and simulation tools. We have tried here to analyze various behavioral dimensions in terms of choice. Not only this is a standard approach in travel demand analysis, but the availability of operational

models, such as discrete choice models, justifies to investigate the behavior from the choice viewpoint.

We conclude from this discussion that, if indeed many behavioral dimensions of pedestrian can be considered as choices (as detailed in Section 1.2), deriving operational models for these choices can be quite complex. The most important reason is that most of these choices are performed at the same time, and a decomposition into a sequence of choices is often not appropriate. The ''four-step'' approach adopted in travel demand analysis, where travel behavior is decomposed into location choice, destination choice, mode choice, and route choice, cannot be applied for pedestrian without major adjustments. Consequently, the complexity of the corresponding models may preclude their use in real applications. A second reason is the short lifetime of some of the choices, as decisions associated with the destination, the route, or even with the activity itself are subject to frequent changes. Consequently, the dynamic of the choices must be accounted for. A third major issue is the availability of appropriate data. Although recent developments in GPS data collection and video image analysis have allowed for the modeling of some complex behavioral dimensions, the detailed observation of pedestrian behavior is still a very complex issue.

In summary, we believe that investigating pedestrian behavior in terms of choice behavior is an exciting field of research, with many open issues and a high potential. We hope that this document will stimulate research in this direction.

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References

Abdelghany, A. F., Mahmassani, H. S., & Chiu, Y. (2001). Spatial microassignment of travel demand with activity trip chains. *Transportation Research Record: Journal of the Transportation Research Board*, *1777*, 36–46.

Ahmed, K., Ben-Akiva, M., Koutsopoulos, H., & Mishalani, R. (1996). Models of freeway lane changing and gap acceptance behavior. In: J.-B. Lesort (Ed.), *Proceedings of the 13th International Symposium on the Theory of Traffic Flow and Transportation* (pp. 501–515). Oxford: Pergamon Press.

AlGadhi, S. A. H., Mahmassani, H., & Herman, R. (2002). A speed-concentration relation for bi-directional crowd movements. In: M. Schreckenberg & S. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 3–20). Berlin: Springer.

Antonini, G., Bierlaire, M., & Weber, M. (2006). Discrete choice models of pedestrian walking behavior. *Transportation Research Part B: Methodological*, *40*(8), 667–687.

Antonini, G., Venegas, S., Bierlaire, M., & Thiran, J.-P. (2006). Behavioral priors for detection and tracking of pedestrians in video sequences. *International Journal of Computer Vision*, *69*(2), 159–180.

Ashbrook, D., & Starner, T. (2003). Using GPS to learn significant locations and predict movement across multiple users. *Personal and Ubiquitous Computing*, *7*(5), 275–286.

Axhausen, K., & Gärling, T. (1992). Activity-based approaches to travel analysis: Conceptual frameworks, models, and research problems. *Transport Reviews*, *12*(4), 323–341.

Bassett, D. R. J., Cureton, A. L., & Ainsworth, B. E. (2000). Measurement of daily walking distance-questionnaire versus pedometer. *Medicine and Science in Sports and Exercise*, *32*(5), 1018–1023.

Ben-Akiva, M. E. (1973). *Structure of passenger travel demand models*. Ph.D. thesis, Department of Civil Engineering, MIT, Cambridge, MA.

Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short-term travel decisions. In: R. Hall (Ed.), *Handbook of transportation science, operations research and management science* (pp. 5–34). Netherlands: Kluwer.

Ben-Akiva, M., Koutsopoulos, H. N., & Mukundan, A. (1994). A dynamic traffic model system for ATMS/ATIS operations. *Journal of Intelligent Transportation Systems*, *2*(1), 1–19.

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: Theory and application to travel demand*. Cambridge, MA: MIT Press.

Bennett, G. G., McNeill, L. H., Wolin, K. Y., Duncan, D. T., Puleo, E., & Em-mons, K. M. (2007/10/1). Safe to walk? Neighborhood safety and physical activity among public housing residents. *PLoS Medicine*, *4*(10), e306.

Bhat, C. R. (1998). Accommodating flexible substitution patterns in multidimensional choice modeling: Formulation and application to travel mode and departure time choice. *Transportation Research Part B: Methodological*, *32*(7), 455–466.

Bhat, C. (2000). Incorporating observed and unobserved heterogeneity in urban work travel mode choice modeling. *Transportation Science*, *34*(2), 228–238.

Bhat, C. R., & Guo, J. (2004). A mixed spatially correlated logit model: Formulation and application to residential choice modeling. *Transportation Research Part B: Methodological*, *38*(2), 147–168.

Bhat, C., & Koppelman, F. (2004). A retrospective and prospective survey of time-use research. *Transportation*, *26*(2), 119–139.

Bhat, C., & Singh, S. (2000). A comprehensive daily activity-travel generation model system for workers. *Transportation Research Part A: Policy and Practice*, *1*, 1–22.

Bierlaire, M. (2006). A theoretical analysis of the cross-nested logit model. *Annals of Operations Research*, *144*(1), 287–300.

Bierlaire, M., Bolduc, D., & McFadden, D. (2008). The estimation of generalized extreme value models from choice-based samples. *Transportation Research Part B: Methodological*, *42*(4), 381–394.

Bierlaire, M., & Frejinger, E. (2008). Route choice modeling with network-free data. *Transportation Research Part C: Emerging Technologies*, *16*(2), 187–198.

Bigano, A., Hamilton, J., & Tol, R. (2006). The impact of climate on holiday destination choice. *Climatic Change*, *76*(3–4), 389–406.

Blue, V. J., & Adler, J. L. (1998). Emergent fundamental pedestrian flows from cellular automata microsimulation. *Transportation Research Record: Journal of the Transportation Research Board*, *1644*, 29–36.

Blue, V., & Adler, J. (1999). Cellular automata microsimulation of bidirectional pedestrian flows. *Transportation Research Record: Journal of the Transportation Research Board*, *1678*, 135–141.

Blue, V. J., & Adler, J. L. (2001). Cellular automata microsimulation for modeling bi-directional pedestrian walkways. *Transportation Research Part B*, *35*(3), 293–312.

Borgers, A., & Timmermans, H. (1986). A model of pedestrian route choice and demand for retail facilities within inner-city shopping areas. *Geographical analysis*, *18*(2), 115–128.

Borst, H. C., Miedema, H. M., de Vries, S. I., Graham, J. M., & van Dongen, J. E. (2008). Relationships between street characteristics and perceived attractiveness for walking reported by elderly people. *Journal of Environmental Psychology*, *28*(4), 353–361. URL: http://www.sciencedirect.com/science/article/B6WJ8-4RY6WWF2/2/2b6674ce3f87791d5d48052506ff125d

Bovy, P. H. L., & Stern, E. (1990). *Route choice: Way finding in transport networks: Studies in Operational Regional Science* (Vol. 9). Dordrecht, NL: Kluwer Academic Publishers.

Bowman, J., & Ben-Akiva, M. (2001). Activity-based disaggregate travel demand model system with activity schedules. *Transportation Research Part A: Policy and Practice*, *35*(1), 1–28.

Burstedde, C., Klauck, K., Schadschneider, A., & Zittartz, J. (2001). Simulation of pedestrian dynamics using a two-dimensional cellular automaton. *Physica A: Statistical Mechanics and its Applications*, *295*, 507–525.

Cervero, R., & Radisch, C. (1996). Travel choices in pedestrian versus automobile oriented neighborhoods. *Transport Policy*, *3*(3), 127–141.

Chandler, R. E., Herman, R., & Monroll, E. W. (1958). Traffic dynamics: Studies in car following. *Operations Research*, *6*(2), 165–184.

Chen, T.-H. (2003). An automatic bi-directional passing-people counting method based on color image processing. *IEEE 37th Annual 2003 International Carnahan Conference on Security Technology* (pp. 200–207).

Cheung, C., & Lam, W. (1998). Pedestrian route choices between escalator and stairway in MTR stations. *Journal of Transportation Engineering*, *124*(3), 277–285.

Coffin, A., & Morrall, J. (1995). Walking speeds of elderly pedestrians at crosswalks. *Transportation Research Record*, *1487*, 63–67.

Coleman, J. (1962). Comment on Harrison White, "chance models of systems of casual groups". *Sociometry*, *25*(2), 172–176.

Cornelis, E., & Toint, P. (1998). PACSIM: A new dynamic behavioural model for multimodal traffic assignment. In: M. Labbe, G. Laporte, K. Tanczos, & P. Toint (Eds), *Operations research and decision aid methodologies in traffic and transportation management*, *Vol. 166 of NATO ASI Series*, *Series F: Computer and Systems Sciences*, Springer Verlag (pp. 28–45).

Crassini, B., Brown, B., & Bowman, K. (1988). Age-related changes in contrast sensitivity in central and peripheral retina. *Perception*, *17*(3), 315–332.

Cunningham, P., & Cullen, D. (1993). Pedestrian flow data collection and analysis. *Proceeding of the Institution of Civil Engineers. Transport*, *100*, 59–69.

Daamen, W. (2004). *Modelling passenger flows in public transport facilities*. Ph.D. thesis, Delft University of Technology, The Netherlands.

Daamen, W., Bovy, P., & Hoogendoorn, S. (2002). Modelling pedestrians in transfer stations. In: M. Schreckenberg & S. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 59–73). Berlin: Springer.

Daamen, W., Bovy, P., & Hoogendoorn, S. (2005). Influence of changes in level on passenger route choice in railway stations. *Transportation Research Record: Journal of the Transportation Research Board*, *1930*, 12–20.

Daamen, W., Bovy, P., Hoogendoorn, S., & de Reijt, A. V. (2005). Passenger route choice concerning level changes in railway stations. In: *Transportation research board annual meeting 2005* (pp. 1–18). Washington DC: National Academy Press.

Daamen, W., & Hoogendoorn, S. P. (2003a). Controlled experiments to derive walking behaviour. *European Journal of Transport and Infrastructure Research*, *3*(1), 39–59.

Daamen, W., & Hoogendoorn, S. P. (2003b). Experimental research of pedestrian walking behavior. *Transportation Research Record*, *1828*, 20–30.

Daamen, W., Hoogendoorn, S. P., & van Wijngaarden, H. (forthcoming). Results from a laboratory experiment involving pedestrians and a revolving door. *Proceedings of Pedestrians and Evacuation Dynamics 2008*.

Daly, A., & Bierlaire, M. (2006). A general and operational representation of generalised extreme value models. *Transportation Research Part B: Methodological*, *40*(4), 285–305.

Daly, A. J., & Zachary, S. (1978). Improved multiple choice. In: D. A. Hensher & M. Q. Dalvi (Eds), *Determinants of travel demand*. Sussex: Saxon House.

Dellaert, B. G., Arentze, T. A., Bierlaire, M., Borgers, A. W., & Timmermans, H. J. (1998). Investigating consumers' tendency to combine multiple shopping purposes and destinations. *Journal of Marketing Research*, *35*(2), 177–188.

Dellaert, B., Borgers, A., & Timmermans, H. (1995). A day in the city: Using conjoint choice experiments to model urban tourists' choice of activity packages. *Tourism Management*, *16*(5), 347–353.

Denzler, J., & Niemann, H. (1997). Real-time pedestrian tracking in natural scenes. In: *Computer analysis of images and patterns* (Vol. 1296, pp. 42–49). Lecture Notes in Computer Science. Berlin: Springer.

Dijkstra, J., Jessurum, J., & Timmermans, H. (2002a). A multi-agent automata model of pedestrian movement. In: S. Netherlands (Ed.), *Pedestrian and evacuation dynamics 2002* (pp. 173–179).

Dijkstra, J., Jessurum, J., & Timmermans, H. (2002b). A multi-agent automata model of pedestrian movement. In: M. Schreckenberg & S. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 173–179). Berlin: Springer.

Dzubiella, J., Hoffmann, G. P., & Löwen, H. (2002). Lane formation in colloidal mixtures driven by an external field. *Physical Review E*, *65*(2), 021402.

Eash, R. (1999). Destination and mode choice models for nonmotorized travel. *Transportation Research Record: Journal of the Transportation Research Board*, *1674*, 1–8.

Ettema, D., & Timmermans, H. (1997). *Activity-based approaches to travel analysis*. Bingley, UK: Emerald Group Publishing Limited.

Evans, D., & Norman, P. (1998). Understanding pedestrians' road crossing decisions: An application of the theory of planned behaviour. *Health Education Research*, *13*(4), 481–489.

Eves, F. F., Webb, O. J., & Mutrie, N. (2006). A workplace intervention to promote stair climbing: Greater effects in the overweight. *Obesity*, *14*(12), 2210–2216.

Ewing, R., Schroeer, W., & Greene, W. (2007). School location and student travel analysis of factors affecting mode choice. *Transportation Research Board of the National Academies*, *1895*, 55–63.

Fesenmaier, D. (1988). Integrating activity patterns into destination choice models. *Journal of Leisure Research*, *20*(3), 175–191.

Flamm, M., & Kaufmann, V. (2007). Combining person based GPS tracking and prompted recall interviews for a comprehensive investigation of travel behaviour adaptation processes during life course transitions. Paper presented at the 11th World Conference on Transportation Research, Berkeley, CA.

Foster, C., & Hillsdon, M. (2004). Changing the environment to promote health-enhancing physical activity. *Journal of Sports Sciences*, *22*, 755–769.

Fotheringham, A. (1986). Modelling hierarchical destination choice. *Environment and Planning A*, *18*(3), 401–418.

Frejinger, E. (2007). Random sampling of alternatives in a route choice context. *Proceedings of the European Transport Conference*, Leiden, The Netherlands.

Frejinger, E. (2008). *Route choice analysis*. Ph.D. thesis, EPFL, Lausanne. URL: http://library.epfl.ch/theses/?nr=4009

Frejinger, E., & Bierlaire, M. (2007). Capturing correlation with subnetworks in route choice models. *Transportation Research Part B: Methodological*, *41*(3), 363–378.

Furuichi, M., & Koppelman, F. (1994). An analysis of air travelers' departure airport and destination choice behavior. *Transportation Research Part A: Policy and Practice*, *28*(3), 187–195.

Goldstone, R. L., & Janssen, M. A. (2005). Computational models of collective behavior. *Trends in Cognitive Sciences*, *9*(9), 424–430.

Goldstone, R., Jones, A., & Roberts, M. E. (2006). Group path formation. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, *36*, 611–620.

Goldstone, R. L., & Roberts, M. E. (2006). Self-organized trail systems in groups of humans. *Complexity*, *11*(6), 43–50.

Guo, Z., & Ferreira, J. (2008). Pedestrian environments, transit path choice, and transfer penalties: Understanding land-use impacts on transit travel. *Environment and Planning B: Planning and Design*, *35*, 461–479.

Hamada, T., Hagiwara, T., Teramoto, T., Morishita, S., Umetsu, M., & Ohgama, M. (2008). A three-dimensional pedestrian-flow simulation for high-rising buildings. In: H. Umeo, S. Morishita, K. Nishinari, T. Komatsuzaki, & S. Bandini (Eds), *Cellular Automata: 8th International Conference on Cellular Automata for Research and Industry, ACRI 2008, Yokohama, Japan, September 23–26, 2008. Proceedings, Vol. 5191 of Lecture Notes in Computer Science*, Springer (pp. 417–424).

Handy, S. L. (1996). Urban form and pedestrian choices: Study of Austin neighborhoods. *Transportation Research Record: Journal of the Transportation Research Board*, 135–144.

Helbing, D., Farkas, I., Molnár, P., & Vicsek, T. (2002). Simulation of pedestrian crowds in normal and evacuation simulations. In: M. Schreckenberg & S. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 21–58). Berlin: Springer.

Helbing, D., Keltsch, J., & Molnár, P. (1998). Modelling the evolution of human trail systems. *Nature*, *388*, 47–50.

Helbing, D., & Molnár, P. (1995). Social force model for pedestrian dynamics. *Physical Review E*, *51*(5), 4282–4286.

Helbing, D., Molńar, P., Farkas, I. J., & Bolay, K. (2001). Self-organizing pedestrian movement. *Environment and Planning B: Planning and Design*, *28*(3), 361–383.

Himanen, V., & Kulmala, R. (1988). An application of logit models in analysing the behaviour of pedestrians and car drivers on pedestrian crossings. *Accident Analysis and Preventions*, *20*(3), 187–197.

Hoogendoorn, S., & Bovy, P. (2004). Pedestrian route-choice and activity scheduling theory and models. *Transportation Research Part B*, *38*, 169–190.

Hoogendoorn, S., Bovy, P., & Daamen, W. (2002). Microscopic pedestrian wayfinding and dynamics modelling. In: M. Schreckenberg & S. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 123–155). Berlin: Springer.

Hoogendoorn, S. P., & Daamen, W. (2005). Pedestrian behaviour at bottlenecks. *Transportation Science*, *39*(2), 147–159.

Hoogendoorn, S., Daamen, W., & Bovy, P. (2003). Extracting microscopic pedestrian characteristics from video data: Results from experimental research into pedestrian walking behavior. 82th Annual Meeting of the Transportation Research Board, Washington, DC (pp. 20–30).

Hughes, R. (2002). A continuum theory for the flow of pedestrians. *Transportation Research Part B*, *36*, 507–535.

Ishaque, M., & Noland, R. (2008). Behavioural issues in pedestrian speed choice and street crossing behaviour: A review. *Transport Reviews*, *28*, 61–85.

James, J. (1953). The distribution of free-forming small group size. *American Sociological Review*, *18*(5), 569–570.

Jansen-Verbeke, M. (1987). Women, shopping and leisure. *Leisure Studies*, *6*(1), 71–86.

Jones, P., Koppelman, F., & Orfueil, J. (1990). Activity analysis: State-of-the-art and future direction. In: P. Jones (Ed.), *Developments in dynamic and activity-based approaches to travel analysis* (pp. 34–55). Avebury: Oxford Studies in Transport.

Kerr, J., Eves, F. F., & Carroll, D. (2001). The influence of poster prompts on stair use: The effects of setting, poster size and content. *British Journal of Health Psychology*, *6*(4), 397–405.

Kessel, A., Klüpfel, H., Wahle, J., & Schreckenberg, M. (2002). Microscopic simulation of pedestrian crowd motion. In: M. Schreckenberg & S. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 193–200). Berlin: Springer.

Kinsey, M., Galea, E., Lawrence, P., Blackshields, D., Hulse, L., Day, R., & Sharp, G. (2008). Modelling pedestrian escalator behaviour. *Proceedings of the 4th Pedestrian and Evacuation Dynamics (PED) Conference*, Springer, Berlin.

Kitamura, R., & Fujii, S. (1998). Two computational process models of activity-travel behavior. In: T. Garling, T. Laitila & K. Westin (Eds), *Theoretical foundations of travel choice modeling* (pp. 251–279). Amsterdam: Elsevier.

Knoblauch, R., Pietrucha, M., & Nitzburg, M. (2007). Field studies of pedestrian walking speed and start-up time. *Transportation Research Record: Journal of the Transportation Research Board*, *1538*, 27–38.

Krizek, K. (2006). Lifestyles, residential location decisions, and pedestrian and transit activity. *Transportation Research Record. Journal of the Transportation Research Board*, *1981*, 171–178.

Kurose, S., Borgers, A. W. J., & Timmermans, H. J. P. (2001). Classifying pedestrian shopping behaviour according to implied heuristic choice rules. *Environment and Planning B: Planning and Design*, *28*, 405–418.

Lam, W., & Cheung, C. (2000). Pedestrian speed/flow relationships for walking facilities in Hong Kong. *Journal of Transportation Engineering*, *126*(4), 343–349.

Lam, W., Morrall, J., & Ho, H. (1995). Pedestrian flow characteristics in Hong Kong. *Transportation Research Record*, *1487*, 56–62.

Li, C. (2006). User preferences, information transactions and location-based services: A study of urban pedestrian way finding. *Computers, Environment and Urban Systems*, *30*(6), 726–740. URL: http://www.sciencedirect.com/science/article/B6V9K-4K1x5B21/2/13d1ff1e7243dcbfef2eb41e52ad9aea

Liao, L., Patterson, D. J., Fox, D., & Kautz, H. (2007). Learning and inferring transportation routines. *Artificial Intelligence*, *171*(5–6), 311–331.

Loscos, C, Marchal, D., & Meyer, A. (2003). Intuitive crowd behavior in dense urban environments using local laws. *Theory and Practice of Computer Graphics, 2003. Proceedings* (pp. 122–129).

Lynch, K. (1960). *The image of the city*. Cambridge, MA: The MIT Press.

Manski, C., & Lerman, S. (1977). The estimation of choice probabilities from choice-based samples. *Econometrica*, *45*(8), 1977–1988.

Masoud, O., & Papanikolopoulos, N. (1997). Robust pedestrian tracking using a model-based approach. *Intelligent Transportation System, 1997. ITSC '97, IEEE Conference on* (pp. 338–343).

McFadden, D. (1978). Modelling the choice of residential location. In: A. Karlquist, et al. (Eds), *Spatial interaction theory and residential location* (pp. 75–96). Amsterdam: North-Holland.

McFadden, D. (1981). Econometric models of probabilistic choice. In: C. Manski & D. McFadden (Eds), *Structural analysis of discrete data with econometric applications* (pp. 198–269). Cambridge, MA: MIT Press.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, *15*(5), 447–470.

Millonig, A., & Gartner, G. (2009). Ways of walking — Developing a pedestrian typology for personalised mobile information systems. *Location based services and telecartography II* (pp. 79–94). URL: http://dx.doi.org/10.1007/978-3-540-87393-86

Millonig, A., & Schechtner, K. (2005). Decision loads and route qualities for pedestrians-key requirements for the design of pedestrian navigation services. In: N. Waldau, P. Gatterman, H. Knoflacher & M. Schreckenberg (Eds), *Pedestrian and evacuation dynamics* (pp. 109–118). Berlin: Springer.

Miyazaki, K., Matsukura, H., Katuhara, M., Yoshida, K., Ota, S., Kiriya, N., & Miyata, O. (2003). Behaviors of pedestrian group overtaking wheelchair users. *Proceedings of Pedestrian and Evacuation Dynamics*. UK: CMS Press Publications.

Morey, E., Shaw, W., & Rowe, R. (1991). A discrete-choice model of recreational participation, site choice, and activity valuation when complete trip data are not available. *Journal of Environmental Economics and Management*, *20*(2), 181–201.

Muramatsu, M., Irie, T., & Nagatani, T. (1999). Jamming transition in pedestrian counter flow. *Physica A: Statistical and Theoretical Physics*, *267*(3–4), 487–498.

Nagel, K. (2002). Multi-modal traffic in transims. In: M. Schreckenberg & S. D. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 161–172). Berlin: Springer.

Nagel, K., & Barrett, C. L. (1997). Using microsimulation feedback for trip adaptation for realistic traffic in Dallas. *International Journal of Modern Physics C*, *8*(3), 505–525.

Nicoll, G. (2006). *Taking the stairs: Environmental features that predict stair use in 3 to 4 story academic workplace buildings*. Ph.D. thesis, Georgia Institute of Technology.

Okada, E., & Asami, Y. (2007). A pedestrian route choice model to evaluate alternative plans for regeneration of Galata region. *ARI Bulletin of the Istanbul Technical University*, *55*, 11–32.

Oppermann, M. (1999). Predicting destination choice — A discussion of destination loyalty. *Journal of Vacation Marketing*, *5*(1), 51–65.

Patterson, D. J., Liao, L., Fox, D., & Kautz, H. (2003). Inferring high-level behavior from low-level sensors. In: S. B. Heidelberg (Ed.), *UbiComp 2003: Ubiquitous Computing* (Vol. 2864, pp. 73–89).

Pelechano, N., & Badler, N. I. (2006). Modeling crowd and trained leader behavior during building evacuation. *IEEE Computer Graphics and Applications*, *26*(6), 80–86.

Ramming, M. S. (2001). *Network knowledge and route choice*. Ph.D. thesis, Massachusetts Institute of Technology.

Ratti, C., Pulselli, R. M., Williams, S., & Frenchman, D. (2006). Mobile landscapes: Using location data from cell phones for urban analysis. *Environment and Planning B: Planning and Design*, *33*(5), 727–748. URL: http://ideas.repec.org/a/pio/envirb/v33y2006i5p727-748.html

Robin, T., Antonini, G., Bierlaire, M., & Cruz, J. (2009). Specification, estimation and validation of a pedestrian walking behavior model. *Transportation Research Part B: Methodological*, *43*(1), 36–56.

Rodriguez, D., & Joo, J. (2004). The relationship between non-motorized mode choice and the local physical environment. *Transportation Research Part D: Transport and Environment*, *9*(2), 151–173.

Sakuma, T., Mukai, T., & Kuriyama, S. (2005). Psychological model for animating crowded pedestrians. *Computer Animation and Virtual Worlds*, *16*(34), 343–351.

Scarpa, R., & Thiene, M. (2005). Destination choice models for rock climbing in the north eastern Alps: A latent-class approach based on intensity of preferences. *Land Economics*, *81*(3), 426–444.

Schadschneider, A. (2002). Cellular automaton approach to pedestrian dynamics – Theory. In: M. Schreckenberg & S. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 75–86). Berlin: Springer.

Schadschneider, A., Kirchner, A., & Nishinari, K. (2002). CA approach to collective phenomena in pedestrian dynamics. In: S. Bandini, B. Chopard & M. Tomassini (Eds), *Cellular Automata: 5th International Conference on Cellular Automata for Research and Industry, ACRI 2002, Geneva, Switzerland, October 9–11, 2002, Proceedings, Vol. 2493 of Lecture Notes in Computer Science*, Springer (pp. 239–248).

Seneviratne, P., & Morrall, J. (1985). Analysis of factors affecting the choice of route of pedestrians. *Transportation Planning and Technology*, *10*(2), 147–159.

Sexton, G., Zhang, X., Redpath, G., & Greaves, D. (1995). Advances in automated pedestrian counting. *Security and Detection, 1995, European Convention on* (pp. 106–110).

Seyfried, A., Steffen, B., Klingsch, W., & Boltes, M. (2005). The fundamental diagram of pedestrian movement revisited. *Journal of Statistical Mechanics: Theory and Experiment*, *10*, P10002. URL: http://stacks.iop.org/1742-5468/2005/P10002.

Shoval, N., & Isaacson, M. (2006). Application of tracking technologies to the study of pedestrian spatial behavior. *The Professional Geographer*, *58*(2), 172–183.

Sisiopiku, V. P., & Akin, D. (2003). Pedestrian behaviors at and perceptions towards various pedestrian facilities: An examination based on observation and survey data. *Transportation Research Part F: Traffic Psychology and Behaviour*, *6*(4), 249–274. URL: http://www.sciencedirect.com/science/article/B6VN8-49NVN741/2/32b390573aa53a54d69d96016b5fcd3d

Small, K. (1987). A discrete choice model for ordered alternatives. *Econometrica: Journal of the Econometric Society*, *55*(2), 409–424.

Sohn, T., Varshavsky, A., LaMarca, A., Chen, M., Choudhury, T., Smith, I., Consolvo, S., Hightower, J., Griswold, W., & de Lara, E. (2006). Mobility detection using everyday gsm traces. In: S. B. Heidelberg (Ed.), *UbiComp 2006: Ubiquitous Computing* (pp. 212–224).

Stewart, S. I., & Vogt, C. A. (1997). Multi-destination trip patterns. *Annals of Tourism Research*, *24*(2), 458–461.

Sugiyama, Y., Nakayama, A., & Hasebe, K. (2002). 2-dimensional optimal velocity models for granular flow and pedestrian dynamics. In: M. Schreckenberg & S. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 155–160). Berlin: Springer.

Sullivan, M., Richards, C., Smith, C, Masoud, O., & Papanikolopoulos, N. (1995). Pedestrian tracking from a stationary camera using active deformable models. *Intelligent Vehicles '95 Symposium. Proceedings of the* (pp. 90–95).

Tarawneh, M. (2001). Evaluation of pedestrian speed in Jordan with investigation of some contributing factors. *Journal of Safety Research*, *32*(2), 229–236.

Teknomo, K. (2002). *Microscopic pedestrian flow characteristics: Development of an image processing data collection and simulation model*. Ph.D. thesis, Tohoku University, Japan, Sendai.

Teknomo, K., Takeyama, Y., & Inamura, H. (2000). Review on microscopic pedestrian simulation model. *Proceedings of the Japan Society of Civil Engineering Conference*, Morioka, Japan.

Thurstone, L. (1994). A law of comparative judgment. *Psychological Review*, *101*(2), 266–270.

Tidwell, J. E., & Doyle, D. P. (1995). Driver and pedestrian comprehension of pedestrian low and traffic control devices. *Transportation Research Record*, *1502*, 119–128.

Timmermans, H. (1996). A stated choice model of sequential mode and destination choice behavior for shopping trips. *Environment and Planning A*, *28*, 173–184.

Timmermans, H., der Hagen, X. V., & Borgers, A. (1992). Transportation systems, retail environments and pedestrian trip chaining behaviour: Modelling issues and applications. *Transportation Research Part B: Methodological*, *26B*(1), 45–59.

Toledo, T., Koutsopoulos, H. N., & Ben-Akiva, M. (2007). Integrated driving behavior modeling. *Transportation Research Part C: Emerging Technologies*, *15*(2), 96–112.

Toshiaki, K., Naoki, K., Masaru, K., & Minoru, Y. (2000). A study on walking route choice between stairs and escalator considering disabled people. *Papers on City Planning*, *35*, 583–588.

Train, K. (2003). *Discrete choice methods with simulation*. Berkeley, CA: Cambridge University Press.

Tsukaguchi, H., & Matsuda, K. (2002). Analysis on pedestrian route choice behaviour. *Proceedings of JSCE (Japan Society of Civil Engineers)*, *709*, 117–126.

Turner, A. (2001). Angular analysis. *Proceedings of the 3rd International Symposium on Space Syntax*, Georgia Institute of Technology, Atlanta (pp. 30.1–30.11).

Virkler, M., & Elayadath, S. (1994). Pedestrian speed–flow–density relationships. *Transportation Research Record*, *1438*, 51–58.

Wakim, C, Capperon, S., & Oksman, J. (2004). A Markovian model of pedestrian behavior. *Systems, Man and Cybernetics, 2004 IEEE International Conference on* (Vol. 4, pp. 4028–4033).

Walker, J. L., Ben-Akiva, M., & Bolduc, D. (2007). Identification of parameters in normal error component logit-mixture (NECLM) models. *Journal of Applied Econometrics*, *22*(6), 1095–1125.

Was, J. (2008). Multi-agent frame of social distances model. In: H. Umeo, S. Morishita, K. Nishinari, T. Komatsuzaki, & S. Bandini (Eds), *Cellular Automata: 8th International Conference on Cellular Automata for Research and Industry, ACRI 2008, Yokohama, Japan, September 23–26, 2008. Proceedings*, *Vol. 5191 of Lecture Notes in Computer Science*, Springer (pp. 567–570).

Weifeng, F., Lizhong, Y., & Weicheng, F. (2003). Simulation of bi-direction pedestrian movement using a cellular automata model. *Physica A: Statistical Mechanics and its Applications*, *321*(3–4), 633–640.

Whitt, M. C., DuBose, K. D., Ainsworth, B. E., & Tudor-Locke, C. (2004). Walking patterns in a sample of African American, native American, and Caucasian women: The cross-cultural activity participation study. *Health Education & Behavior*, *31*(4), 45S–65S.

Williams, H. (1977). On the formation of travel demand models and economic measures of user benefit. *Environment and Planning A*, *9*(3), 285–344.

Woodside, A., & Lysonki, S. (1989). A general model of traveler destination choice. *Journal of Travel Research*, *27*(4), 8–14.

Yang, L., Fang, W., Huang, R., & Deng, Z. (2002). Occupant evacuation model based on cellular automata in fire. *Chinese Science Bulletin*, *47*(17), 1484–1488.

Yersin, B., Mäım, J., Morini, F., & Thalmann, D. (2008). Real-time crowd motion planning: Scalable avoidance and group behavior. *The Visual Computer*, *24*(10), 859–870.

Young, S. (2007). Evaluation of pedestrian walking speeds in airport terminals. *Transportation Research Record: Journal of the Transportation Research Board*, *1674*, 20–26.

Zacharias, J. (2001). Pedestrian behavior and perception in urban walking environments. *Journal of Planning Literature*, *16*, 3–18.

Zhang, X., & Sexton, G. (1997). Automatic human head location for pedestrian counting. *Image Processing and Its Applications, 1997, Sixth International Conference on* (Vol. 2, pp. 535–540).

Zhu, W., & Timmermans, H. (2005). Exploring pedestrian shopping decision processes and application of gene expression programming. In: N. Waldau, P. Gatterman, H. Knofiacher & M. Schreckenberg (Eds), *Pedestrian and evacuation dynamics* (pp. 145–154). Berlin: Springer.

Chapter 2

Empirical Results for Pedestrian Dynamics and their Implications for Cellular Automata Models

Andreas Schadschneider and Armin Seyfried

Abstract

A large number of models for pedestrian dynamics have been developed over the years. However, so far not much attention has been paid to their quantitative validation. Usually the focus is on the reproduction of empirically observed collective phenomena, as lane formation in counterflow. This can give an indication for the realism of the model, but practical applications, for example, in safety analysis, require *quantitative* predictions. In this chapter, we discuss the current experimental situation, especially for the fundamental diagram which is the most important quantity needed for calibration. In addition we consider the implications for the modeling based on cellular automata. As specific example the floor field model is introduced. Apart from the properties of its fundamental diagram we discuss the implications of an egress experiment for the relevance of conflicts and friction effects.

2.1. Introduction

In recent years a large number of models for the simulation of pedestrian dynamics has been proposed, some of them being quite successful in providing a realistic description of a variety of different situation. In contrast, the empirical situation is much less satisfactory. Not much experimental data are available and if they are, they are often unreliable. This is reflected in the fact that the data are sometimes even contradictory (see e.g., Schadschneider et al., 2009), even for the simplest scenarios. This might be one of the reasons why so far not many models have been tested quantitatively by

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comparing with empirical data. Instead the reproduction of collective phenomena like lane formation, oscillations at bottlenecks, or pattern formation at intersections has been used as a criterion to judge the realism of the models.

Therefore there have been only a few attempts to calibrate and validate models of pedestrian dynamics properly. The application of models in the area of safety planning is somewhat limited or has to be taken with a grain of salt. A first important step to improve the current state of affairs would be to obtain reliable empirical data. This is an essential first step and would form the basis for validation and calibration. Only then one can make even quantitative predictions based on computer simulations.

Perhaps the most important characteristic of pedestrian dynamics is the fundamental diagram, i.e., the relation between pedestrian flow and its density. It is of obvious importance for the dimensioning of pedestrian facilities. Furthermore it is associated with many self-organization phenomena, like the formation of lanes or the occurrence of jams. However, even for this basic quantity the current situation is largely confusing (see Section 2.2).

In most models, pedestrians are considered to be autonomous mobile agents, hopping particles in a cellular automaton or self-driven particles in continuous space. These model classes form the basis for sophisticated multi-agent simulations. It is worth mentioning that in physics usually "multi-agent model" is taken as a synonym for "microscopic model." Usually one takes into account that a model should be (a) as realistic as possible and (b) flexible enough for different realistic applications. Point (b) is generically realized by multi-agent approaches that provide an environment to include the infrastructure, visualization, etc. In this spirit we will focus here on point (a), the realism of the modeling approach. This is intimately related to the qualitative and quantitative comparison with empirical data.

In Section 2.2 we compare existing various experimental data and specifications from the literature and discuss the observed discrepancies. The focus is on the fundamental diagram and the flow through a bottleneck.

In Section 2.3 we will review the basic modeling approaches focusing on cellular automata (CA) models. We present the floor field model, discuss the characteristics of this approach and discuss quantitative results obtained from computer simulations, especially for the fundamental diagram. By introducing the concept of "friction" the model is able to reproduce results from a large-scale evacuation experiment.

2.2. Empirical Results and Validation

2.2.1. Principles of Validation

Before any model is used in applications, especially in sensitive areas like safety analysis, it should be properly validated and calibrated (if reliable quantitative results are needed). But which principles should be used in the validation procedure? So far it appears that there is no consensus on this point and that everybody comes up with his/her own criteria. Often these appear to be somewhat biased by the performance

of the own favorite models and one tends to prefer methods where the own model fairs better.

Regarding validation, one could distinguish between "qualitative" versus "quantitative" and "macroscopic" versus "microscopic" validation procedures. Qualitative means that certain collective phenomena like lane formation or the formation of jams are reproduced qualitatively. Quantitative validation in contrast would test whether in case of lane formation the quantitative relation between velocity and density or in case of jam formation the value of the jam density is reproduced correctly. Regarding quantitative validation, one could distinguish between "macroscopic" and "microscopic" observables used for the procedure. Macroscopic means that the observable considered is a mean value over time or space. Microscopic validation in contrast would test more individual properties like individual velocities and their distribution at a certain density or properties of single trajectories, like the curvature.

For quantitative macroscopic validation it is important to note that system sizes as well as measuring methods have to be the same for comparison of experimental data with simulation results. Experimental data of pedestrian flow are often connected with inhomogeneities in space and time, finite size effects and nonequilibrium conditions.

Ideally the validation procedure should guarantee that the model works in very general settings, not just in the scenarios tested. How to achieve this is not obvious. For pedestrian dynamics one should try to formulate a number of tests a model should pass. We suggest, as part of these tests, to consider macroscopic trajectories, like the formation of lanes in counterflow and in narrow bottlenecks. Furthermore, qualitative aspects of the fundamental diagrams for strictly one-dimensional motion and at bottlenecks should be reproduced.

The fundamental diagram is the most important characteristic of pedestrian dynamics. Besides its importance for the dimensioning of pedestrian facilities it is associated with every qualitative self-organization phenomenon, like the formation of lanes or the occurrence of jams. However, specifications of various experimental studies, guidelines, and handbooks display substantial differences in maximal flow values and the corresponding density as well as the density where the flow vanishes due to overcrowding. Different explanations for these discrepancies have been proposed, ranging from differences between uni- and multidirectional flow and cultural or population effects to psychological factors given by the incentive for the movement. Also the behavior at bottlenecks is far from being understood, for example, why the flow can be significantly larger than the maximum of the fundamental diagram.

A validation of models with fundamental diagrams for (quasi-) one-dimensional motion only is certainly not sufficient. Pedestrian dynamics is complex due to its two-dimensional nature. However, it is believed that the behavior in one-dimensional scenarios can reflect the most relevant aspects of the significant interactions. Nevertheless this should be verified later, for example, by measuring fundamental diagrams for genuine two-dimensional motions.

This program makes sense only if sufficient reliable empirical data are available. Unfortunately this is not the case and the empirical understanding of pedestrian dynamics is far from satisfactory.

2.2.2. Fundamental Diagram

The most basic quantities to characterize the collective properties pedestrian (or, more generally, "particle") motion are the density ρ and flow J (or specific flow per unit width $J_s = J/b$). The relation between these quantities is usually called *fundamental diagram*, which already indicates its importance. Due to the hydrodynamic relation $J = \rho v b$, where v is the average velocity, three equivalent forms are used: $J_s(\rho)$, $v(\rho)$, and $v(J_s)$.

In applications the fundamental diagram is a basic input for most engineering methods developed for the design and dimensioning of pedestrian facilities (Predtechenskii & Milinskii, 1978; Fruin, 1971; Nelson & Mowrer, 2002). In the following we will consider only planar facilities like sidewalks, corridors, or halls. Other facilities like floors, stairs, or ramps are less well studied and the shape of the diagrams can differ from the planar case.

In Figure 2.1 fundamental diagrams that are frequently used in planning guidelines are shown. For comparison, results from two selected empirical studies are also included to demonstrate the variance of the data. Natural quantities that can be used to characterize empirical fundamental diagrams are

- the maximum of the function or capacity $J_{s,\max}$;
- the density ρ_c where the maximum flow is reached;
- the density ρ_0 where the velocity approaches zero due to overcrowding.

As seen in Figure 2.1 the specifications and measurements even for these most basic characteristics disagree considerably:

- $1.2\ (\mathrm{ms})^{-1} < J_{s,\max} < 1.8\ (\mathrm{ms})^{-1}$,
- $1.75\,\mathrm{m}^{-2} < \rho_c < 7\,\mathrm{m}^{-2}$,
- $3.8\,\mathrm{m}^{-1} < \rho_0 < 10\,\mathrm{m}^{-1}$.

Several explanations for these deviations have been suggested, for example

- cultural and population differences (Helbing, Johansson, & Al-Abideen, 2007),
- differences between uni- and multidirectional flow (Navin & Wheeler, 1969; Pushkarev & Zupan, 1975),
- short-ranged fluctuations (Pushkarev & Zupan, 1975),
- influence of psychological factors given by the incentive of the movement (Predtechenskii & Milinskii, 1978) or the type of traffic (commuters, shoppers) (Oeding, 1963).

However, currently no consensus about the relevance of these factors has been reached. For example, it is not even clear whether there is a difference between fundamental diagrams obtained from uni- and multidirectional flows. Weidmann (1993) neglects these differences and Fruin (1971) argues that the flows in these situations differ only slightly. However, this disagrees with results of Navin and Wheeler (1969) who found a reduction of the flow in dependence of directional imbalances.

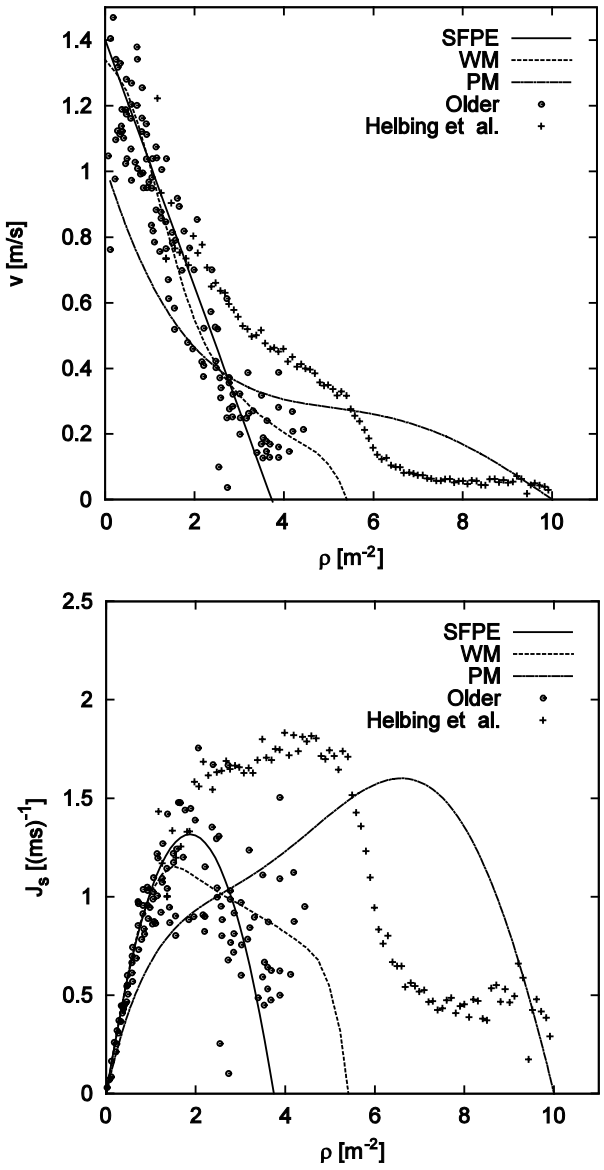


Figure 2.1: Fundamental diagrams for pedestrian movement in planar facilities. Lines refer to specifications in planning guidelines PM: Predtechenskii and Milinskii (1978), SFPE: Nelson and Mowrer (2002), and WM: Weidmann (1993). Data points are obtained from experimental measurements Older (1968) and Helbing et al. (2007).

This brief discussion clearly shows that up to now there is no consensus even on the basic characteristics of the fundamental diagram or its precise form. Even the origin of the observed discrepancies is still discussed controversially.

Another aspect which plays a role when comparing data from different sources is the fact that in the majority of cases error margins or even fluctuations are not shown. Furthermore, as it is well-known from vehicular traffic, different measurement methods can lead to deviations for the resulting relations (Leutzbach, 1988; Kerner, 2004). This is exemplified in Figure 2.2.

The deviations of the results obtained by the two methods depend on the fact that the velocity distributions measured at a certain location and averaged over time do not necessarily conform with velocity distributions measured at a certain point of time averaged over space. This is an important point for a quantitative macroscopic validation procedure comparing experimental data with simulation results.

We have recently performed a set of experiments with up to 250 persons under well-controlled laboratory conditions. Great emphasis was given to the method of data recording by video technique and careful preparation of the

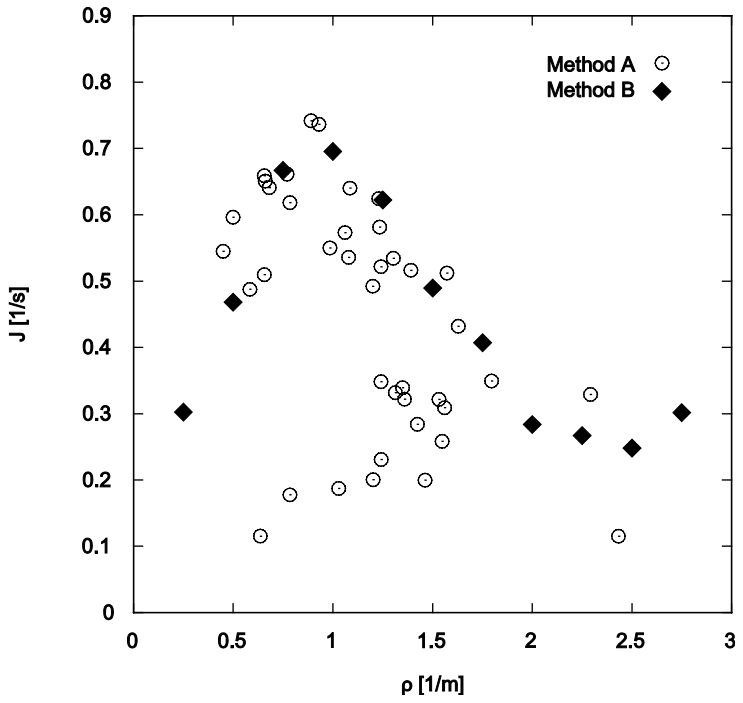


Figure 2.2: Fundamental diagram of single-file movement determined by different measurement methods. Method A: Direct measurement of the flow and velocity at a cross-section. The density is calculated via $\rho = \langle J \rangle_{\Delta t} / \langle v \rangle_{\Delta t}$. Method B: Measurement of the density and velocity at a certain time point averaged over space. The flow is given by $J = \rho \langle v \rangle_{\Delta x}$.

experimental setups. A more general discussion of the experimental setups, the definition of the objectives and some preliminary results are presented in Seyfried et al. (2009a).

2.2.3. Flow at Bottlenecks

In applications, one of the most important questions is how the capacity of a bottleneck increases with increasing width. Studies of this dependence can be traced back to the beginning of the last century (Dieckmann, 1911; Fischer, 1933) and are still discussed controversially. Intuitively, a stepwise increase of capacity with the width appears to be natural, especially in the case of lane formation. If these lanes are independent, i.e., pedestrians in one lane are not influenced by those in others, the capacity can only increase when an additional lane can be formed.

In contrast, the study (Seyfried et al., 2009b) found that the lane distance increases continuously as illustrated in Figure 2.3. Moreover this continuous increase leads to a very weak dependence of the density and velocity inside the bottleneck on its width.

To find a conclusive judgment whether the capacity grows continuously with the width the results of different laboratory experiments (Seyfried et al., 2009b; Müller, 1981; Muir, Bottomley, & Marrison, 1996; Nagai, Fukamachi, & Nagatani, 2006; Kretz, Grünebohm, & Schreckenberg, 2006) are compared in Seyfried et al. (2009b), see Figure 2.4. The data by (Muir et al., 1996) from airplane evacuations seem to support the stepwise increase of the flow with the width. They show constant flow values for $b > 0.6\,\mathrm{m}$. But the independence of the flow over the large range from $b = 0.6\,\mathrm{m}$ to $b = 1.8\,\mathrm{m}$ indicates that in this special setup the flow is not restricted by

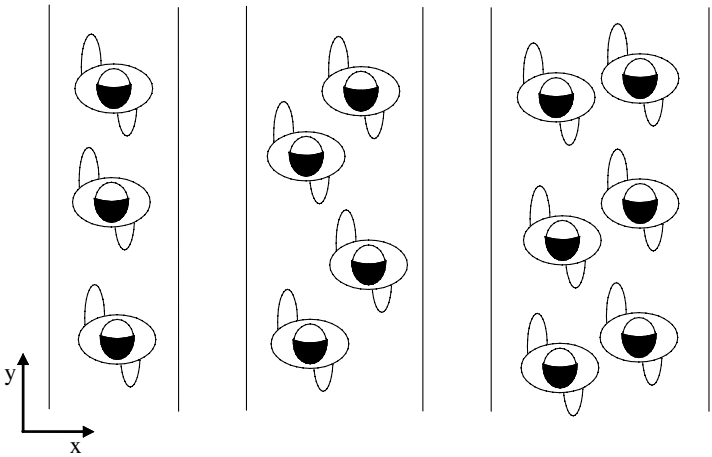


Figure 2.3: Zipper effect with continuously increasing lane distances: The distance in the walking direction decreases with increasing lateral distance. Density and velocities are the same in all cases, but the flow increases continuously with the width of the section.

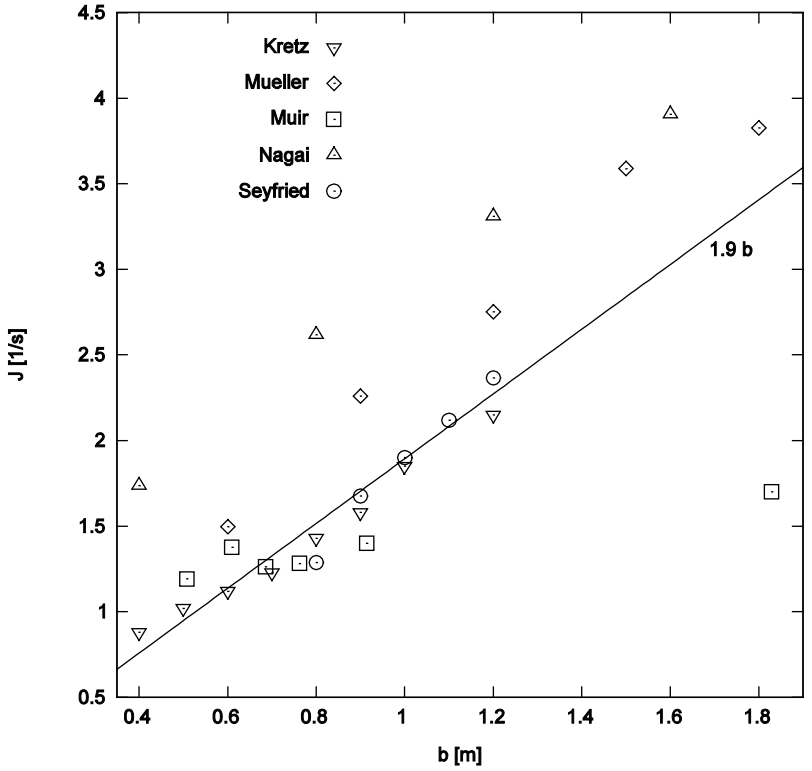


Figure 2.4: Influence of the bottleneck width on the flow. Experimental data (Seyfried et al., 2009a; Müller, 1981; Muir et al., 1996; Nagai et al., 2006; Kretz et al., 2006) for different bottleneck types and initial conditions. All data are taken under laboratory conditions where the test persons are advised to move normally.

the bottleneck width. Thus all collected data for flow measurements in Figure 2.4 are compatible with a continuous and almost linear increase with the bottleneck width for $b > 0.6\,\mathrm{m}$.

Surprisingly the data in Figure 2.4 differ considerably in the values of the bottleneck capacity. In particular the flow values of Nagai et al. (2006) and (Müller, 1981) are much higher than the maxima of empirical fundamental diagrams. It appears that the exact geometry of the bottleneck is of only minor influence on the flow while a high initial density in front of the bottleneck can increase the resulting flow values. This leads to the interesting question how the bottleneck flow is connected to the fundamental diagram. General results from nonequilibrium physics show that boundary conditions only select between the states of the undisturbed system instead of creating completely different ones (Popkov & Schütz, 1999). Therefore, it is surprising that the measured maximal flow at bottlenecks can exceed the maximum of the empirical fundamental diagram. These questions are related to the common jamming criterion. Generally it is assumed that a jam occurs if the

incoming flow exceeds the capacity of the bottleneck. In this case one expects the flow through the bottleneck to continue with the capacity (or lower values). The data presented in Winkens, Rupprecht, Seyfried, and Klingsch, (2009) show a more complicated picture. While the density in front of the bottleneck amounts to $\rho \approx 5.0(\pm 1)\,\mathrm{m}^{-2}$, the density inside the bottleneck tunes around $\rho \approx 1.8\,\mathrm{m}^{-2}$.

2.3. Models for Pedestrian Dynamics

2.3.1. Model Classes

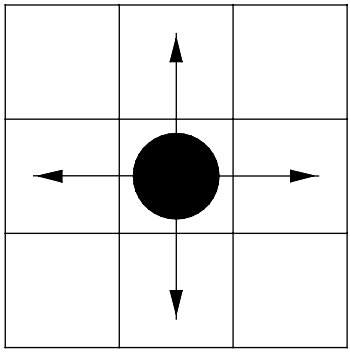
A large variety of models for pedestrian dynamics has been proposed, ranging from macroscopic approaches based on analogies with hydrodynamics to rather sophisticated multi-agent models (Bandini, Manzoni, & Vizzari, 2004; Kukla, Willis, & Kerridge, 2003) taking into account, for example, details of the decision-making processes of the individuals (for a review, see e.g., Schadschneider et al., 2009).

There are several ways of classifying the different modeling approaches:

- microscopic versus macroscopic description,
- discrete versus continuous variables (space, time, state),
- deterministic versus stochastic dynamics,
- rule-based versus force-based interactions,
- high versus low fidelity description.

Molecular dynamics based models are microscopic approaches where the agents are represented as self-driven objects moving in a continuous space. One example is the Social Force Model (Helbing & Molnar, 1995; Helbing, Farkas, & Vicsek, 2000). Interactions are given by (generically deterministic) repulsive forces with remote action, but this does not adequately take into account all relevant features. Modifications are necessary, for example, to account for the empirically observed velocity–density relation (Seyfried, Steffen, & Lippert, 2006; Seyfried, Steffen, Klingsch, & Boltes, 2005), especially the increasing step size at high walking speeds and other observations (Lakoba, Kaup, & Finkelstein, 2005).

Cellular automata, for example, (Fukui & Ishibashi 1999; Muramatsu, Irie, & Nagatani, 1999; Klüpfel, Meyer-König, Wahle, & Schreckenberg, 2000; Blue & Adler, 2000; Burstedde, Klauck, Schadschneider, & Zittartz, 2001) are discrete in space, time, and state variable. Usually the space discretization is determined by the space requirement of a person in a dense crowd ($\approx 40 \times 40\,\mathrm{cm}^2$). A timestep is then identified with the reaction time of a pedestrian and is this of the order of a few tenths of a second. CA models have become quite popular recently, probably because they allow for an intuitive definition of the dynamics in terms of simple rules. These are usually stochastic and specified by transition probabilities p_{ij} to one of the neighboring cells (i, j) (Figure 2.5). The transition probabilities for a specific particle are determined by the position of other particles in its vicinity. More realistic models like the floor field model also take into account further influences, for example, the infrastructure.



0	$p_{-1,0}$	0
$p_{0,-1}$	$p_{0,0}$	$p_{0,1}$
0	$p_{1,0}$	0

Figure 2.5: Definition of the transition probabilities p_{ij} for a von Neumann neighborhood.

2.3.2. Floor Field Model

The floor field model (Burstedde et al., 2001; Kirchner & Schadschneider, 2002; Kirchner, Nishinari, & Schadschneider, 2003b) is perhaps the most flexible CA approach as it incorporates the three relevant factors that determine the motion of a pedestrian in a unified way. These factors are:

- the desired direction of motion, for example, to find the shortest connection;
- interactions with other pedestrians; and
- interactions with the infrastructure (walls, doors, etc.).

This is achieved by taking inspiration from the motion of ants which is based on process of *chemotaxis* (Hölldobler & Wilson, 1990; Chowdhury, Nishinari, & Schadschneider, 2005), a chemical form of communication. Introducing a kind of *virtual chemotaxis* allows to translate effects of longer-ranged interactions into purely local ones. Ants deposit so-called pheromones to mark their paths. A similar mechanism is used in the floor field model to take into account the mutual interactions of pedestrians and those with the infrastructure. The virtual pheromones generate *floor fields*, which enhance transition probability in the direction of stronger fields.

However, the main factor for the determination of the transition probabilities is the preferred walking direction and speed. This information is encoded in the so-called *matrix of preference* M_{ij}. Its matrix elements are directly related to observable quantities, namely the average velocity and its fluctuations (Burstedde et al., 2001).

These basic probabilities are modified by two discrete *floor fields*, D and S. The field strengths D_{ij} and S_{ij} at site (i, j) modify the transition probabilities in such a way that a movement in the direction of higher fields is preferred. The *dynamic floor field* D represents a virtual trace left by moving pedestrians. Similar to the process of chemotaxis, this trace has its own dynamics, namely diffusion and decay, which lead to the broadening and dilution of the trace with time. The *static floor field* S, also called potential in other models, does not change in time and reflects the

infrastructure. In the case of the evacuation processes, the static floor field describes the shortest distance to an exit door. The field value increases in the direction of the exit such that it is largest for door cells. An explicit construction of S can be found in (Kirchner & Schadschneider, 2002; Nishinari, Kirchner, Namazi, & Schadschneider, 2004).

The full transition probability to cell a neighboring cell (i, j) is then given by

$$p_{ij} = NM_{ij}e^{k_S S_{ij}}e^{k_D D_{ij}}(1 - n_{ij}) \tag{2.1}$$

The occupation number n_{ij} is 0 for an empty and 1 for an occupied cell where the occupation number of the cell currently occupied by the considered particle is taken to be 0. The factor N ensures the normalization $\sum_{(i,j)} p_{ij} = 1$ of the probabilities. k_S and $k_D \in [0, \infty]$ are sensitivity parameters that control the relative influence of the fields D and S. They have a simple interpretation. The coupling k_D to the dynamic floor field controls the tendency to follow in the footsteps of others, which is often called *herding*. In the absence of a matrix of preference, k_S determines the effective velocity of a single agent in the direction of its destination.

The floor field model is one of the most sophisticated approaches for the description of pedestrian dynamics. Several simpler CA models have been proposed (Schadschneider et al., 2009) which do not include floor fields. Their transition probabilities p_{ij} are constant and depend only on the current local configuration in the neighborhood of a particle. However, these models are not able to reproduce the details of the empirically observed behavior.

2.3.3. Fundamental Diagram of the Floor Field Model

The fundamental diagram incorporates information about the relevance of mutual interactions of the agents at finite densities. Here, due to hindrance effects, their velocity will be reduced compared to the free walking speed.

Typically fundamental diagrams are obtained empirically and theoretically for quasi-one-dimensional motion, for example, along a corridor. Lateral motion is possible, but will mainly occur to avoid collisions. Since the motion in this situation consists basically of weakly coupled one-dimensional lanes, where only a few lane changes occur, it is not surprising that the fundamental diagrams are very similar to that of the strictly one-dimensional variant of the model. The latter exhibits the symmetry $J(\rho) = J(\rho_{\max})$ where $\rho_{\max}$ is the density where the flow vanishes (often normalized to $\rho_{\max} = 1$). Thus the function $J(\rho)$ is almost symmetric around the density $\rho_{\max}/2$ with deviations coming from lane changes induced by collision avoidance or fluctuations. A typical fundamental diagram obtained for the basic version of the floor field model (corresponding to $v_{\max} = 1$) is shown in Figure 2.6.

The comparison with the empirical results of Section 2.2 shows that the observed asymmetry of the fundamental diagram is not reproduced correctly. The origin of this discrepancy is the restriction to models with nearest-neighbor interactions, which do not capture essential features like the dynamic space requirement of the agents which depends on their velocity (and thus density).

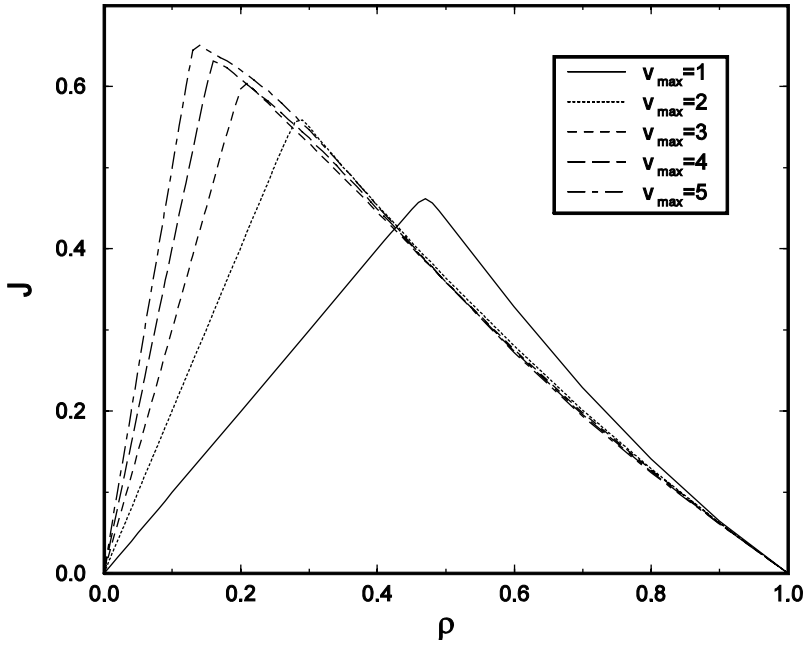


Figure 2.6: Fundamental diagrams of the floor field model for $v_{\max} = 1, \ldots, 5$. The maximum of the flow is shifted toward smaller densities for increasing $v_{\max}$.

Modifications of the floor field model (Kirchner, Klüpfel, Nishinari, Schadschneider, & Schreckenberg, 2004; Kretz & Schreckenberg, 2007) take this effect into account. Here motion is not restricted to nearest-neighbor cells. This is equivalent to a motion at different instantaneous velocities $v = 0, 1, \ldots, v_{\max}$ where v is the number of cells an agent moves. Then $v_{\max} = 1$ corresponds to the case where motion is allowed only to nearest neighbors. Note that different extensions of this type are possible, depending on how one treats crossing trajectories of different agents (Kirchner et al., 2004). But in all cases, the fundamental diagrams become more realistic since the maximum of the flow is shifted toward smaller densities with increasing $v_{\max}$ (Figure 2.6), in accordance with the empirical observations.

Another modification that appears to be necessary to reproduce empirical observations concerns the size of the cells. The cell size generically chosen corresponds to the space requirement of a single agent, i.e., $40 \times 40\,\text{cm}$. Since an agent occupies exactly one cell this does not allow to model overlapping lanes like those occurring in the zipper effect (see Section 2.2). This indicates that the cell size used in simulations should be smaller, so that for example, an agent occupies 2×2 cells (Kirchner et al., 2004).

2.3.4. *Conflicts and Friction*

Usually, CA and multi-agent models are based on discrete time dynamics, which is realized in computer simulations through a synchronous (parallel) updating scheme.

This is important for many applications since it implies the existence of a well-defined timescale that can be used for calibration and thus allows, for example, for quantitative predictions. This update scheme leads to inherent problems if at the same time an exclusion principle has to be satisfied, i.e., if a site can not be occupied by more than one particle at the same time. Such restriction is natural for any particle-hopping model related to transport or traffic problems, for example, intracellular transport, highway traffic, and pedestrian dynamics (Chowdhury et al., 2005; Chowdhury, Santen, & Schadschneider, 2000).

In this case *conflicts* occur where two or more particles try to move to the same destination cell within the same timestep (Figure 2.7). Since multiple occupations are not allowed, a procedure to resolve these conflicts has to be defined (Burstedde et al., 2001). Conflicts might appear to be undesirable effects that reduce the efficiency of execution of simulations and should therefore be avoided by choosing a different update scheme. However, it turns out that they are important for a correct description of crowd dynamics (Kirchner et al., 2003b), especially in clogging situations near bottlenecks. In real life this often leads to dangerous situations and injuries during evacuations. Although conflicts are local phenomena they can have a strong influence on global quantities like evacuation times. In the following we will show how the inclusion of conflicts improves the realism of the model dynamics.

In real life, conflict situations often lead to a moment of hesitation where the involved agents hesitate before trying to resolve the conflict. This reduces on average the effective velocities of all involved particles. This is taken into account in a modification of the floor field model by introducing a probability μ at which movement of *all* particles involved in the conflict is denied, i.e., all pedestrians remain at their site (see Figure 2.7). This means that with probability $1-\mu$ one of the individuals moves to the desired cell. This effect is called *friction* and μ *friction parameter* since it has similar consequences as contact friction, for example, in granular materials. It does not reduce the velocity of a freely moving particle and effects only show up in local interactions.

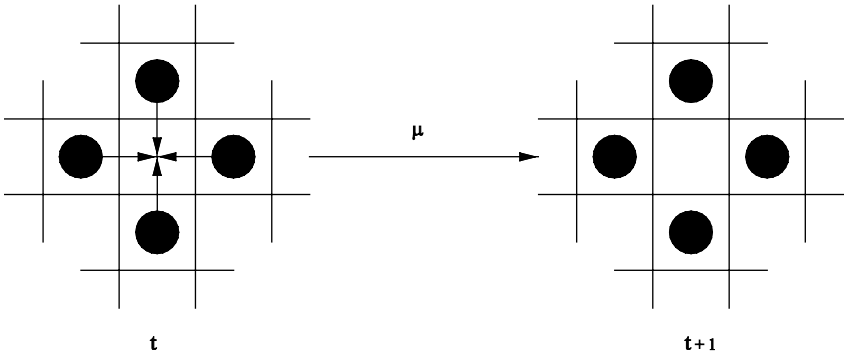


Figure 2.7: In a conflict several particles try to move to the same destination cell at the same time. The friction parameter μ determines the probability that such a conflict is not resolved and no particle will move.

Friction has a substantial influence on the dynamics in large density situations. For example, it leads to a faster-is-slower effect (Helbing, Farkas, Molnar, & Vicsek, 2002; Helbing et al., 2000) where an increase of the free velocity of the pedestrians does not lead to reduced evacuation times in the presence of friction (Kirchner et al., 2003b). This can be understood since for larger velocities even for relatively low densities jams will form at the exit. In such a situation many conflicts occur and thus large friction has a strong influence on the evacuation time (Figure 2.8). Another characteristic effect that is caused by friction is the bursty behavior of the outflow.

Another empirical result which shows the relevance of friction effects for the modeling of pedestrian dynamics comes from the study of evacuation times from airplanes as function of the exit width and the motivation level of passengers (Muir et al., 1996). It is found for narrow exits non-competitive (cooperative) passenger behavior leads to faster egress whereas for wider exits competitive behavior is advantageous (Figure 2.9).

These findings can be reproduced by the floor field model if friction effects are included (Kirchner, Klüpfel, Nishinari, Schadschneider, & Schreckenberg, 2003b). Competitive behavior is then described by a large walking speed (controlled by the parameter k_S) and large friction effects due to strong hindrance in conflict situations. Cooperation on the other hand corresponds to small speed and friction.

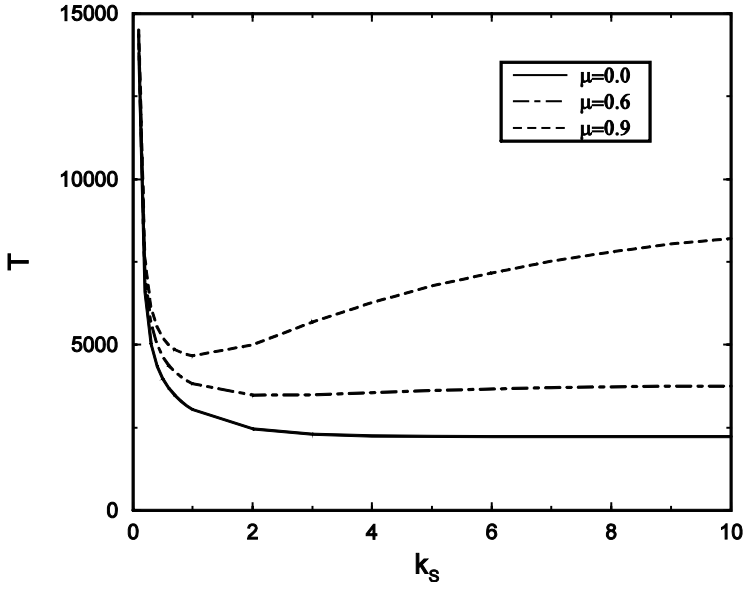


Figure 2.8: Evacuation time as function of the walking speed (controlled by the parameter k_S) for different friction strengths μ. For $\mu = 0.9$ a faster-is-slower effect is observed, i.e., the minimal evacuation time is not found for the largest walking speed (corresponding to $k_S \to \infty$).

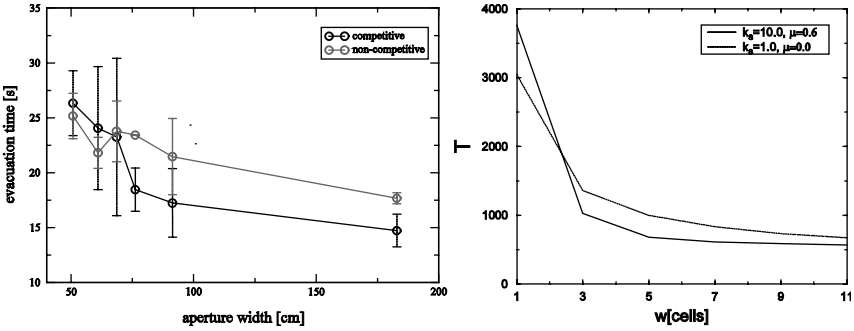


Figure 2.9: Left: Empirical egress time as function of the door width for competitive and non-competitive behavior (from Muir et al., 1996). Right: Simulation results based on the floor field model including friction effects.

2.4. Conclusions

We have discussed several aspects of the validation of models for pedestrian and crowd dynamics. A major problem is the lack of reliable and reproducible empirical data where even for the most essential quantities like the capacity there is currently no consensus. This is very unsatisfactory and a serious obstacle in the validation and calibration of the models which is of extreme importance for most applications, especially in the area of safety analysis.

Furthermore we have discussed various modeling approaches, focusing on a special cellular automaton model, the floor field model. It is not only relatively simple and intuitive, but also flexible enough to allow for calibration once the empirical situation has improved. One example is the fundamental diagram, which indicates that an extension beyond nearest-neighbor interactions is necessary. We have also discussed the relevance of conflicts and frictions effects as indicated also by experiments. These effects can easily be incorporated in CA approaches like the floor field model, which shows the flexibility of this model class.

Acknowledgment

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References

Bandini, S., Manzoni, S., & Vizzari, C. (2004). Situated cellular agents: A model to simulate crowding dynamics. *IEICE — Transactions on Information and Systems*, *E87-D*(3), 669–676.

Blue, V. J., & Adler, J. L. (2000). Cellular automata microsimulation of bi-directional pedestrian flows. *Journal of Transportation Research Board*, *1678*, 135–141.

Burstedde, C., Klauck, K., Schadschneider, A., & Zittartz, J. (2001). Simulation of pedestrian dynamics using a two-dimensional cellular automaton. *Physica A*, *295*, 507–525.

Chowdhury, D., Nishinari, K., & Schadschneider, A. (2005). Physics of transport and traffic phenomena in biology: From molecular motors and cells to organisms. *Physics of Life Review*, *2*, 318–352.

Chowdhury, D., Santen, L., & Schadschneider, A. (2000). Statistical physics of vehicular traffic and some related systems. *Physics Reports*, *329*, 199–329.

Dieckmann, D. (1911). *Die Feuersicherheit in Theatern*. München: Jung.

Fischer, H. (1933). *Über die Leistungsfähigkeit von Türen, Gängen und Treppen bei ruhigem, dichtem Verkehr*. Dissertation, Technische Hochschule Dresden.

Fruin, J. J. (1971). *Pedestrian planning and design*. New York: Metropolitan Association of Urban Designers and Environmental Planners.

Fukui, M., & Ishibashi, Y. (1999). Self-organized phase transitions in cellular automaton models for pedestrians. *Journal of the Physical Society of Japan*, *68*, 2861–2863.

Helbing, D., Farkas, I., & Vicsek, T. (2000). Simulating dynamical features of escape panic. *Nature*, *407*, 487–490.

Helbing, D., Farkas, I., Molnar, I., & Vicsek, T. (2002). Simulation of pedestrian crowds in normal and evacuation situations. In: M. Schreckenberg & S. D. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 21–58). Berlin: Springer.

Helbing, D., Johansson, A., & Al-Abideen, H. Z. (2007). The dynamics of crowd disasters: An empirical study. *Physical Review E*, *75*, 046109.

Helbing, D., & Molnar, P. (1995). Social force model for pedestrian dynamics. *Physical Review E*, *51*, 4282–4286.

Hölldobler, B., & Wilson, E. O. (1990). *The Ants*. Cambridge: Belknap.

Kerner, B. S. (2004). *The physics of traffic*. Berlin: Springer.

Kirchner, A., Klüpfel, H., Nishinari, K., Schadschneider, A., & Schreckenberg, M. (2003b). Simulation of competitive egress behavior: Comparison with aircraft evacuation data. *Physica A*, *324*, 689–697.

Kirchner, A., Klüpfel, H., Nishinari, K., Schadschneider, A., & Schreckenberg, M. (2004). Discretization effects and the influence of walking speed in cellular automata models for pedestrian dynamics. *Journal of Statistical Mechanics*, paper 10011.

Kirchner, A., Nishinari, K., & Schadschneider, A. (2003a). Friction effects and clogging in a cellular automaton model for pedestrian dynamics. *Physical Review E*, *67*, 056122.

Kirchner, A., & Schadschneider, A. (2002). Simulation of evacuation processes using a bionics-inspired cellular automaton model for pedestrian dynamics. *Physica A*, *312*, 260–276.

Klüpfel, H., Meyer-König, T., Wahle, J., & Schreckenberg, M. (2000). Microscopic simulation of evacuation processes on passenger ships. In: S. Bandini & T. Worsch (Eds), *Theory and practical issues on cellular automata* (pp. 63–71). Berlin: Springer.

Kretz, T., Grünebohm, A., & Schreckenberg, M. (2006). Experimental study of pedestrian flow through a bottleneck. *Journal of Statistical Mechanics*, paper P10014.

Kretz, T., & Schreckenberg, M. (2007). Moore and more and symmetry. In: N. Waldau, P. Gattermann, H. Knoflacher & M. Schreckenberg (Eds), *Pedestrian and evacuation dynamics 2005* (pp. 317–328). Berlin: Springer.

Kukla, R. Willis, A., & Kerridge, J. (2003). Application of context-mediated behavior to a multi-agent pedestrian flow model (PEDFLOW). *Transportation Research Board*, 001128.

Lakoba, T. I., Kaup, D. J., & Finkelstein, N. M. (2005). Modifications of the Helbing-Molnar-Farkas-Vicsek social force model for pedestrian evolution. *Simulation*, *81*, 339–352.

Leutzbach, W. (1988). *Introduction to the Theory of traffic flow*. Berlin: Springer.

Muir, H. C., Bottomley, D. M., & Marrison, C. (1996). Effects of motivation and cabin configuration on emergency aircraft evacuation behavior and rates of egress. *International Journal of Aviation Psychology*, *6*(1), 57–77.

Müller, K. (1981). *Zur Gestaltung und Bemessung von Fluchtwegen für die Evakuierung von Personen aus Bauwerken auf der Grundlage von Modellversuchen*. Dissertation, Technische Hochschule Magdeburg.

Muramatsu, M., Irie, T., & Nagatani, T. (1999). Jamming transition in pedestrian counter flow. *Physica A*, *267*, 487–498.

Nagai, R., Fukamachi, M., & Nagatani, T. (2006). Evacuation of crawlers and walkers from corridor through an exit. *Physica A*, *367*, 449–460.

Navin, P. D., & Wheeler, R. J. (1969). Pedestrian flow characteristics. *Traffic Engineering*, *39*, 31–36.

Nelson, H. E., & Mowrer, F. W. (2002). Emergency movement. In: P. J. DiNenno (Ed.), *SFPE handbook of fire protection engineering* (p. 367). Quincy, MA: National Fire Protection Association.

Nishinari, K., Kirchner, A., Namazi, A., & Schadschneider, A. (2004). Extended floor field CA model for evacuation dynamics. *IEICE — Transactions on Information and Systems*, *E87-D*, 726–732.

Oeding, D. (1963). Verkehrsbelastung und Dimensionierung von Gehwegen und anderen Anlagen des Fußgängerverkehrs. Forschungsbericht 22, Technische Hochschule Braunschweig.

Older, S. J. (1968). Movement of pedestrians on footways in shopping streets. *Traffic Engineering and Control*, *10*, 160–163.

Popkov, V., & Schütz, G. M. (1999). Steady-state selection in driven diffusive systems with open boundaries. *Europhysics Letters*, *48*, 257.

Predtechenskii, V. M., & Milinskii, A. I. (1978). *Planning for foot traffic flow in buildings*. New Delhi: Amerind Publishing.

Pushkarev, B., & Zupan, J. M. (1975). Capacity of walkways. *Transportation Research Record*, *538*, 1–15.

Schadschneider, A., Klingsch, W., Klüpfel, H., Kretz, T., Rogsch, C., & Seyfried, A. (2009). Evacuation dynamics: Empirical results, modeling and applications. In: R. A. Meyers (Ed.), *Encyclopedia of complexity and system science* (p. 3142). New York: Springer.

Seyfried, A., Boltes, M., Kähler, J., Klingsch, W., Rupprecht, T., Schadschneider, A., Steffen, B., & Winkens, A. (2009a). Enhanced empirical data for the fundamental diagram and the flow through bottlenecks. In: *Pedestrian and evacuation dynamics 2008*. Berlin: Springer.

Seyfried, A., Rupprecht, T., Passon, O., Steffen, B., Klingsch, W., & Boltes, M. (2009b). New insights into pedestrian flow through bottlenecks. *Transportation Science*, *43*(3), 395–406.

Seyfried, A., Steffen, B., Klingsch, W., & Boltes, M. (2005). The fundamental diagram of pedestrian movement revisited. *Journal of Statistical Mechanics*, paper P10002.

Seyfried, A., Steffen, B., & Lippert, T. (2006). Basics of modelling the pedestrian flow. *Physica A*, *368*, 232–238.

Weidmann, U. (1993). Transporttechnik der Fußgänger, Schriftenreihe des IVT Nr. 90, ETH Zürich.

Winkens, A., Rupprecht, T., Seyfried, A., & Klingsch, W. (2009). Empirical study of pedestrians' characteristics at bottlenecks. In: *Pedestrian and evacuation dynamics 2008*. Berlin: Springer.

Chapter 3

Modeling, Simulating, and Visualizing Crowd Dynamics with Computational Tools Based on Situated Cellular Agents

Stefania Bandini, Sara Manzoni and Giuseppe Vizzari

Abstract

Situated Cellular Agent (SCA) is a modeling and computational tool based on multi-agent systems principles whose roots are on cellular automata. In this chapter, after an introduction of main objectives and motivations of SCA approach within the research context on pedestrians and crowds dynamics, we describe some modeling examples in which SCA formal tools have been exploited to represent relevant crowd features and dynamics. The chapter ends with an overview of current and future developments on the modeling tools and on the software environment we adopt to support the design and execution of SCA-based models.

3.1. Introduction

Situated Cellular Agents (SCA, Bandini, Federici, & Vizzari, 2007b) is a modeling and computational tool based on multi-agent systems (MAS, Ferber, 1999) and cellular automata (CA, Wolfram, 1986) principles. SCA has been initially proposed within MAS research context as general-purpose tool for the modeling and simulation of system dynamics when the latter is influenced by spatial features and characterized by heterogeneity (Bandini, Manzoni, & Simone, 2002a). SCA, in fact, integrates MAS advantages in modeling heterogeneous systems (Bandini, Manzoni, & Simone, 2002c) and CA ones in the study of complex spatial dynamics

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(Bandini, Manzoni, & Simone, 2002b). Later, SCA formal framework and execution environment have been specialized to provide scholars and researchers in crowds and pedestrians dynamics with expressively rich and computationally efficient tools. Social psychology studies on crowds' behavior and the design and management of public spaces and events are both application contexts that SCA research aims at contributing to. Potentially complex dynamics, that can emerge as effect of physical, social, and emotional interactions between crowd members, can in fact be effectively studied according to SCA formal and computational tools.

Several modeling and computational approaches have been proposed to tackle the complexity of *crowding phenomena*, that is, phenomena that can emerge from the dynamic interaction of groups of moving entities (i.e., persons, in the case of human crowds) that share a limited space. Computational models for pedestrian dynamics can be classified into three main classes: models based on MAS, based on CA and many-particle models. The latter class involves models, like Social Force Model (Helbing, Farkas, Molnár, & Vicsek, 2002), where the dynamics of spatial features is studied through spatial occupancy of individuals, represented as moving particles subjected to forces. Peculiarity of CA-based models (Schadschneider, 2002a, 2002b) is the explicit representation of the modeled environment as a regular grid of cells whose state includes information about presence and direction of individuals, of environmental obstacles, and relevant objects. According to CA approach, several research groups have worldwide developed models to reproduce both specific phenomena (e.g., lane formation as the spontaneous formation of pedestrian lanes with the same direction, Blue & Adler, 2001), or specific scenarios (e.g., evacuation dynamics from public spaces like classrooms (Klupfel, 2003), metro stations (Morishita & Shiraishi, 2006)).

According to MAS approach (Toyama, Bazzan, & da Silva, 2006) pedestrians are instead explicitly represented as autonomous entities, with the ability to perceive information from the environment and to interact with each other. Recently MAS approach to pedestrians and crowds modeling has been largely encouraged and proposed, due to MAS ability to represent a potentially heterogeneous system of agents in a partially known environment (Axtell & Axtell, 2000). Among MAS-based approaches, SCA approach represents crowds as systems of situated agents that are able to move on structured spatial environments and that can interact locally and at-a-distance through the emission and perception of signals (Bandini et al., 2007b). The basic idea of SCA modeling approach is that the movement of pedestrians can be generated by means of attraction and repulsion effects to environmental stimuli (i.e., fields according to SCA terminology) that can be emitted by given points of the environment, and perceived or simply ignored by different types of pedestrians according to their internal states and behaviors. Pedestrians themselves are able to emit fields and thus, in turn, they can generate attraction/repulsion effects on other crowd members.

In the remaining sections of the chapter, after an introduction to SCA formal modeling tools, we overview a set of experiments we performed to model relevant dynamics in pedestrian systems according to SCA. First examples concern SCA-based computational models of traditionally studied scenarios in pedestrian dynamics (i.e., room evacuation, lane formation in corridor-like spatial environments).

Then, we overview a SCA-based model of an egress scenario from a lecture hall (in which agent visual perception ability is explicitly included), a SCA-based model of crowd aggregation phenomenon in *open crowds* as described in Canetti (1984), and a SCA-based specification of *affectons* (a formal framework proposed in Adamatzky, 2005 to study crowds' dynamics emerging from emotional interaction). The paper ends with an overview of ongoing works and future directions in SCA research project.

3.2. Situated Cellular Agents for Crowds and Pedestrian Dynamics

As previously introduced, SCA approach models human crowds as system of autonomous, situated agents that act and interact in a spatially structured environment (Bandini et al., 2007b). Three main methodological steps have to be followed to apply SCA-based modeling approach: abstract description of the spatial environment; representation of relevant environmental elements; and specification of agent behavioral models. A SCA space can represent a discrete abstraction of a physical environment, in which a site refers to pedestrian space occupancy. Relevant spots of the environment representing points of interest, reference points, or constraints (e.g., gateways, doorways) are situated and their interaction ability is defined (i.e., presence field specification). The behavior of SCA agents can be specified as purely reactive but also deliberative architectures granting situated agents with the ability to elaborate action plans and to perform decision-making behaviors are possible. Basic SCA reactive agents can change either their internal state or their position on the structured environment, as effect of the perception of environmental signals and local interaction with neighbors. Agent autonomy is preserved by an action-selection mechanism that characterizes each agent, and heterogeneous MAS can be represented through the specification of agents with several behavioral abilities (a formal language and its execution environment is provided by a dedicated software platform, Bandini, Manzoni, & Vizzari, 2006)). Interaction between agents can occur either locally, causing the synchronous change of state of a set of adjacent agents, and at-a-distance, when a signal emitted by an agent propagates throughout the spatial structure of the environment and is perceived by other situated agents. Heterogeneous perception abilities can be specified for SCA agents. Figure 3.1 shows a sample application where rooms, gateways, and potential point of interests within the map of a museum building are represented. Museum visitors, represented by SCA agents, are provided with abstract representation of the environment (potentially partial) and are able to build visiting plans, in terms of partially ordered set of sites where points of interest are situated.

According to SCA formal framework, the spatial abstraction in which the simulated entities are situated (i.e., *Space*) is an undirected graph of *sites* (i.e., $p \in P$), where graph nodes represent available space locations for pedestrians and graph edges define the adjacency relations among them (and agents' suitable movement directions). Each $p \in P$ is defined by $\langle a_p, F_p, P_p \rangle$, where $a_p \in A \cup \{\perp\}$ is the agent situated in p, $F_p \subset F$ the set of fields active in p, and $P_p \subset P$ the set of sites adjacent to p.

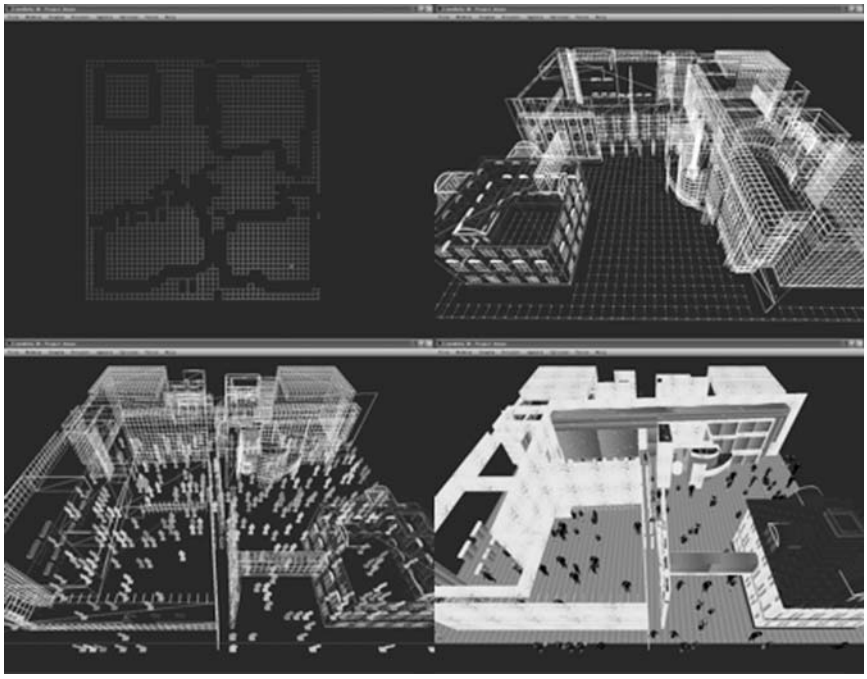


Figure 3.1: A sample application of SCA modeling approach: the map of a museum building is represented as a grid. Rooms and gateways represent potential points of interests for every visitor situated in the building. Visitors, represented by SCA agents, are provided with abstract representation of the environment (potentially partial) and are able to build visiting plans, in terms of partially ordered set of sites where objects of interest are situated.

Pedestrians and relevant elements of their environment that may interact with them and influence their movement (i.e., *active elements of the environment*) are represented by different types of SCA agents. Agent type is a specification of agent state, perceptive capabilities, and behavior. In fact an agent *type* $\tau = \langle \sum_\tau, \text{Perception}_\tau, \text{Action}_\tau \rangle$ is defined by:

- $\sum_\tau$: set of states that agents of type τ can assume.
- Perception_τ: $\sum_\tau \rightarrow W_F \times W_F$: function that associates each agent state to a pair (i.e., *receptiveness coefficient and sensitivity threshold*) for each field in *F*.
- Action_τ: agent behavioral specification in terms of L × MASS language (Bandini et al., 2006). In the following some examples of its syntax will be given.

SCA approach does not specify a standard way to define agents' behavioral model. The execution environment for SCA-based models has been designed in order to be incrementally extended to several execution strategies and agent internal

architectures. In our experiments we adopted a synchronous-parallel method for the system execution (i.e., at each time step each agent perceives its local environment and selects the action to be performed according to a priority list). Basic SCA agent architecture is composed by three functional modules (i.e., *perception*, *deliberation*, and *action*) that define agent actual behavior and two knowledge containers (i.e., *agent knowledge base — AKB and agent action set — AAS*). AKB is the internal representation of agent state and of its local perceptions (e.g., set of fields active in its site, set of empty sites in its surrounding), while the set *AAS* contains actions that define agent abilities. AAS is defined according to the agent type and cannot change during agent execution, while AKB updating can be the effect of agent actions or of a change in the agent environment perceived by the agent (e.g., an adjacent site becomes vacant, a new field reaches the agent site, or the agent moves to another site). Deliberation module implements the agent conflict resolution strategy between multiple actions that can be potentially executed (i.e., agent decision strategy). In our experiments we implemented purely reactive (i.e., random action-selection) or goal-driven architectures (i.e., action-selection strategy as a function of agent AKB) according to specific experiments requirements.

Agent behavior can be specified using a language that defines the following primitives:

- *emit*(s,f,p) causes the agent to start the diffusion of field f on p, on which it is situated;
- *react*(s,a_{p1},a_{p2},…,a_{pn},s') specifies a coordinated change of state with other adjacent agents. In order to preserve agents' autonomy, a compatible primitive must be included in the behavioral specification of all the involved agents; moreover when this coordination process takes place, every involved agent may dynamically decide to effectively agree to perform this operation;
- *transport*(p,f,p') causes agent movement from site p to site p' (that must be adjacent and vacant) as effect of the perception of signal f; other conditions can be specified to describe agent selection strategy when multiple directions are available;
- *trigger*(s,f,s') causes the agent to change its internal state from s to s' as effect of the perception of signal f. As for *transport*( ) additional conditions can be specified to rule agent state change.

Agent behavioral model of situated agents can be realized (as in the most of the examples presented in this chapter) by a utility function associating agent's states to a set of weights determining the attractiveness of each potential direction. Transport( ) action represents the main element of this agents' behavioral specification. More complex behavioral models endow agents with an abstract (potentially partial) representation of the environment they are situated in, and of means to explore it in order to build a plan toward their goals (i.e., destination node in the spatial structure).

Each SCA agent is thus provided with a set of sensors that allow its interaction with the environment and other agents. At the same time, agents can constitute the source of given fields acting within a SCA space (e.g., noise emitted by a talking

agent). Formally, a field type t is defined by $\langle W_t, \text{Diffusion}_t, \text{Compare}_t, \text{Compose}_t \rangle$ where W_t denotes the set of values that fields of type t can assume; Diffusion_t: $P \times W_f \times P \rightarrow W_t$ is the diffusion function of the field computing the value of a field on a given space site taking into account in which site (P is the set of sites that constitutes the space) and with which value it has been generated. It must be noted that fields diffuse along the spatial structure of the environment, and more precisely a field diffuses from a source site to the ones that can be reached through arcs as long as its intensity is not voided by the diffusion function. Compose_t: $(W_t)^+ \rightarrow W_t$ expresses how fields of the same type are combined (for instance, in order to obtain the unique value of field type t at a site), and Compare_t: $W_t \times W_t \rightarrow \{\text{True, False}\}$ is the function that compares values of the same field type. This function is used in order to verify whether an agent can perceive a field value by comparing it with the sensitivity threshold after it has been modulated by the receptiveness coefficient.

3.3. Experiments in Crowds and Pedestrian Dynamics

Interesting dynamics have been observed in pedestrian dynamics within systems of agents that interact to share a limited spatial environment in situations like the evacuation of a room and the walking through corridor-like spaces. For instance, freezing by heating phenomenon is a global slowdown of the system due to the high density rate of pedestrians through a narrow passage, while lane formation is the spontaneous formation of regular pedestrian flows with opposite walking directions. In the following sections we describe a SCA-based models of well-studied interaction situations in crowds observed by social psychology empirical studies and reproduced by other computational models in pedestrian dynamics research context (Schreckenberg & Sharma, 2002). Then, an indoor university scenario shows how agent visual perception can be included into SCA models of egress situations preserving original computational efficiency of the approach. A SCA-based specification of *affectons* (a formal framework proposed to study complex crowds' dynamics emerging from emotional interactions (Adamatzky, 2005), and a SCA-based model of *aggregation phenomenon in open crowds* as described in Canetti (1984) are then reported in order to exemplify how the proposed approach can be adopted to experiment multi-disciplinary theories on crowds behavior and dynamics.

3.3.1. Freezing by Heating Scenario

Freezing by heating is a phenomenon that occurs in situations of high density of pedestrians and it consists in an extreme slowing down of the flow of pedestrians that can end in a complete stall situation (Helbing et al., 2002; Klupfel, 2003). The immobility of pedestrians (i.e., *freezing*) is caused by the will (i.e., *heating*) of all the pedestrians to move toward a given destination (i.e., exit door in evacuation situations). The attempt of each pedestrian to move is the cause of their mutual

hampering. Social Force model was first proposed to reproduce the stall situation by the pressure exerted by individuals that globally determines pedestrian system impossibility to move (Helbing et al., 2002).

The application of SCA to study freezing by heating is given by a regular grid to represent the room structure (with a given number of exits and any internal obstacle or structure) and a set of situated agents that try to exit it (i.e., evacuees). Figure 3.2 shows some screenshots of the developed experiments where the scenario is given by a grid of 31×51 sites (a regular non oriented graph with Moore neighborhood), a single exit and no internal room obstacles. Room internal structure can be added, for instance to study the influence of room furniture on evacuation performances. Each site of the regular grid represents a square area of 45 cm (i.e., mean space occupied by a still person, according to experimental works presented in the literature, Schadschneider, 2002a, 2002b). *Exit doors* are represented by sites locally connected to a number of adjacent sites corresponding to maximum door capacity. Door agents (situated at door site to model its behavior) emit presence fields that attract pedestrian agents according to their distance and perception abilities. This model allowed the simulation of evacuation situations of heterogeneous systems in which contemporaneously agents are present that behave only according to local knowledge (i.e., purely reactive) and agents that know the direction toward the exit doors and are endowed with higher level decision-making abilities. Each evacuee is represented by an agent that locally behaves according to its state and to the intensity of the exit field it perceives (in case of multiple adjacent sites with the same intensity value, the evacuee chooses its next destination site according to its behavioral specification (e.g., randomly in the simplest case). When the agent reaches the exit, it exits the simulation.

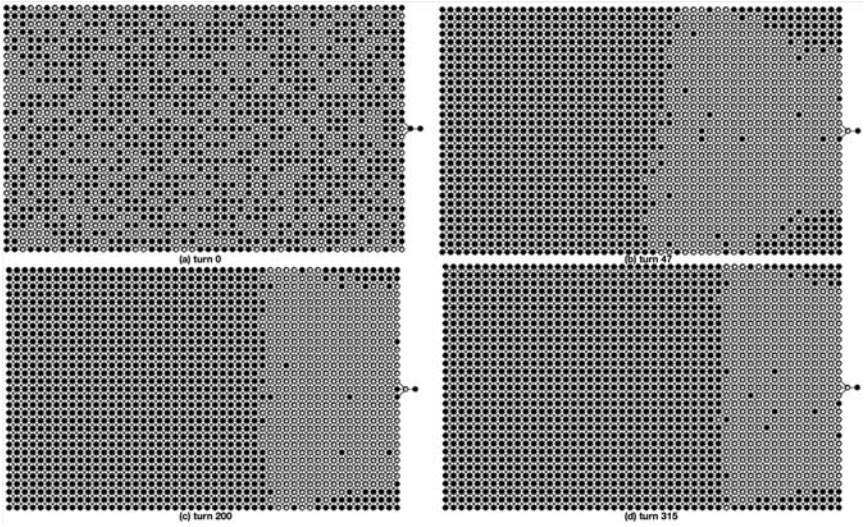


Figure 3.2: Four screenshots of the evacuation scenario showing the movement of simple reactive agents situated in a room toward the exit door in the right-hand side.

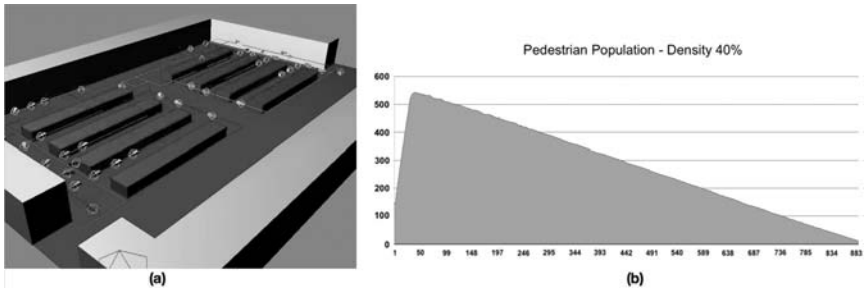


Figure 3.3: A screenshot of the 3D visualization of the model execution, and a diagram with mean number of still pedestrians at each simulation step for pedestrian population density of 40%. Freezing by heating phenomenon can be observed at about step 50 and the last agent leaves the room at step 913.

Figure 3.3 shows a screenshot of the 3D visualization of the model execution and the mean number of still pedestrians per simulation step measured on 10 experiments on a population density of 40%. The simulation campaign has been performed for population densities of 20, 40, and 60%, respectively 310, 620, and 930 agents distributed on 1550 sites. For each density value we performed 10 experiments in which the number of still pedestrians (agents that are not able to move) is measured at each simulation step. Freezing by heating phenomenon can be observed around step 50. The last agent, in average, leaves the room at step 913 for density 40%. Interested readers can find more details on experiments on freezing by heating phenomenon in Bandini, Federici, Manzoni, and Vizzari (2007a).

3.3.2. Lane Formation Scenario

Lane formation refers to the self-organization of pedestrians into separate flows (Blue & Adler, 2001). It has been empirically observed in scenarios like streets or corridor-like passages that are walkable in both directions. A common interpretation of this phenomenon is that when density is high, pedestrians start to move with more difficultly due to limited shared space. Pedestrian lanes form as the result of local behaviors and interactions to solve conflicts.

As in the previous experimentation, the simulation scenario consists of a regular grid of sites representing available locations for pedestrians, and two types of agents: pedestrians and exits. Both types of agents emit a presence field, and pedestrians are attracted by exits according to their individual goals (i.e., one of the two exits). Population density is maintained constant by reinserting into the simulation pedestrians that exit at any corridor side. Figure 3.4 shows two screenshots of experiments performed to observe the spontaneous formation of lanes through a 2D graphical interface (black sites are not occupied by any agent, other colors can visualize agent features like their walking direction as in this case).

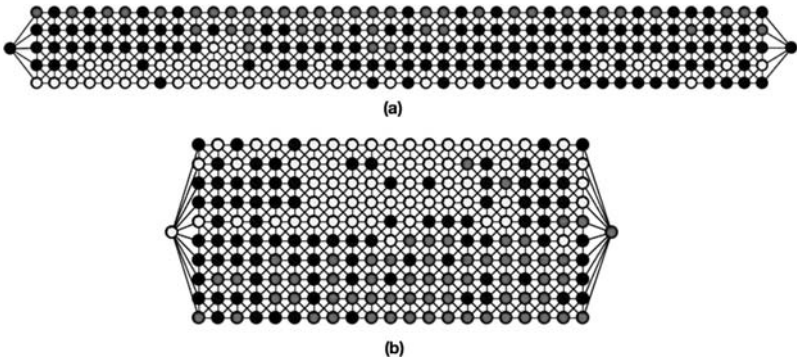


Figure 3.4: Two screenshots of the lane formation scenario. Black nodes of the graph indicate vacant sites (not occupied by any agent), while other colors graphically represent agent directions (i.e., left or right).

We studied and implemented several behavioral models for pedestrians in this scenario. Informally speaking, each pedestrian at each simulation step perceives its local environment (i.e., presence fields of other pedestrians and of active elements of the environment, e.g., exits). When possible, pedestrians move toward a vacant adjacent site with highest value of exit presence field. Otherwise, they remain still for at most a given number of steps, and then look for any adjacent vacant site. Each agent emits a presence field that is perceived as repulsive by other pedestrians. Anyway, presence fields of agents that move toward the same direction are interpreted as less repulsive than those emitted by agents that move in the opposite one. Finally, a conflict resolution strategy has been introduced to solve deadlock situations by agent coordination (i.e., more than one agent has chosen the same destination site). To this aim basic SCA agent actions have been extended to describe coordinated behavior involving set of agents.

Mean speed of pedestrians in relation to population density is shown in Figure 3.5, where we reported with dotted lines the results of reference works in pedestrian dynamics literature (Blue & Adler, 2001; Still, 2000). Simulations have been performed with densities from 10 to 90%. Curves of simulations based on SCA are between the two reference curves with some minor variations in relationship to different simulation settings. At higher densities the curves reach values more close to reference curve, also in terms of speed values of pedestrians.

3.3.3. Indoor University Scenario

This scenario refers to situations where a highly structured environment, like a building with working places potentially densely populated by visitors that hardly know its spatial structure. In this scenario we considered uniform conditions during working days, we do not refer to emergency evacuations, and we focus here on the dynamics during normal egress from a lecture room.

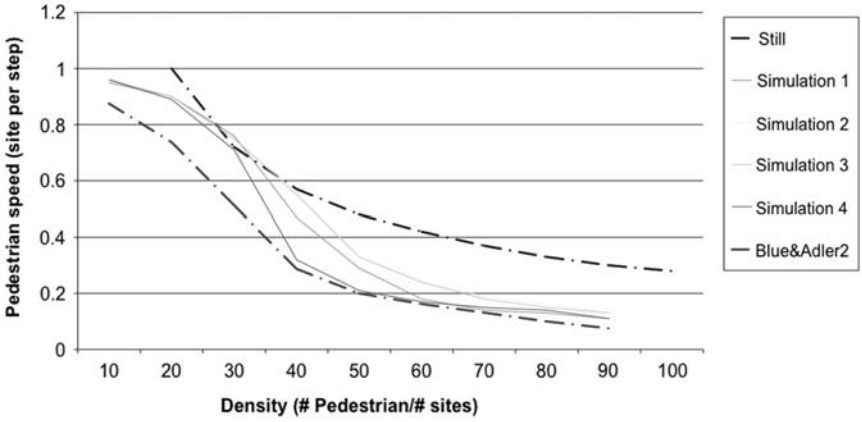


Figure 3.5: The mean speed of pedestrians in relation to population density. Dotted lines refer to reference results from the literature.

The developed SCA-based model defines two graphs of sites to model the spatial structure (i.e., *Movement Graph* and *Visibility Graph*, see Figures 3.6a and b respectively). Movement Graph represents the physical space in which pedestrians move on a discrete structure according to a simple behavioral model in which agents move toward exit door (the perception of an evacuation signal is the trigger condition for this agent behavior). Visibility Graph is defined by the same set of sites as Movement Graph but edges between graph nodes represent quite realistically linear distance in continuous space on which, for instance, it is defined the diffusion function of fields representing sounds or visual communications provided to room occupants. Basic behavioral specification for agents modeling visitors concerns obstacle avoidance, collaborative interactions at congestions, and the ability to perceive signals representing communication (Figure 3.7 shows the source code of evacuees' behavioral model that extends class Person provided by SCA software development tools).

3.3.4. Affective SCA

Affectons are finite-automata proposed to study the dynamics of emotional interactions in random environments and developed according to CA and other unconventional computing approaches (Adamatzky, 2005). CA-based specification of affectons is given as a mono-dimensional emotional automaton that takes states from a set of basic emotions (e.g., (H)appiness, (A)nger, (C)onfusion, and (S)adness, An(X)iety) and updates its state depending on its current state and states of its

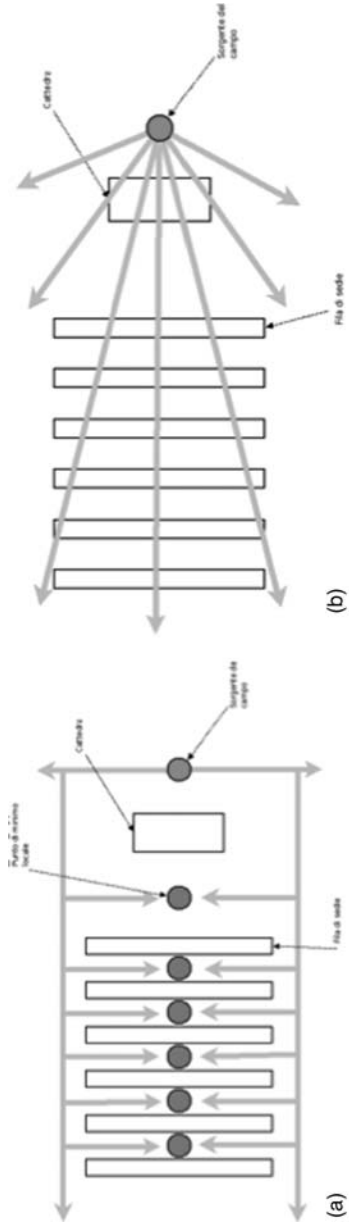


Figure 3.6: (a) Movement space; (b) Perception Space.

```
package mmass.test.evacuation;
import java.awt.*;
import mmass.platform.site.*;
import mmass.platform.agent.*;
public class Persona extends ScaWSightAgent {
     private boolean towardExit = false;

   public Person(String name, Site site, Color color, int intensity) {
     super(name, site, color, intensity);   }

   public void action() {
     Site nextSite;
     //If exit is reached, exit simulation
     if (this.agentReached("Exit"))
          this.nowDie = true;
     //If Danger is perceived and already not decided to Exit ...
     if (towardExit == false && getField("Danger") != null) {
          //...move one step away from Danger...
          nextSite = getMinRandomAdjReachable("Danger");
          //...if next site is towards Exit
          if (getField("Exit") != null &&
getMaxList(getAdjsReachable(),"Exit").contains(nextSite)) {
               //...go towards Exit.
               towardExit = true;
          }   //Move to next site
          tryToMove(nextSite);
     }     //...otherwise if Exit is perceived
     else if (getField("Exit") != null) {
          //...find next site towards Exit...
          nextSite = getMaxRandomAdjReachable("Uscita");
          //...if next site is towards Danger
          if (getField("Danger") != null &&
getMaxList(getAdjsReachable(),"Danger").contains(nextSite)) {
               //...stop moving towards Exit and move away
               towardExit = false;
          }     //Move to next site.
          tryToMove(nextSite);
     }   } }
```

Figure 3.7: Source code of evacuees' behavioral model. Agents move toward exit doors, can perceive evacuation signal (''Danger''). Obstacle avoidance and collaborative interactions at congestions are not specified since already implemented by Person class that is extended here.

neighbors (which is also a state — emotions). Table below shows the state-transition function of HAS affecton.

State	Neighbors	New state
H	A	A
H	A	F
A		H
F		H

Thanks to SCA roots on CA, the formal specification of affectons was easily obtained defining a SCA agent type (i.e., *Affective SCA*) as follows:

$$\text{Affective} = \langle \sum\nolimits_{\text{Aff}}, \text{Action}_{\text{Aff}} \rangle$$

where $\sum_{\text{Aff}} \subseteq \{H, A, C, S, X\}$ defines the set of emotional states that affective agents can assume and, $\text{Action}_{\text{Aff}}$ is the set of behavioral rules that defines agent's emotional response to the perception of emotional states of neighboring agents. $\text{Perception}_{\text{Aff}}$ function has not been defined here, since only local interactions have to be considered. We described state-transition functions to describe affecton dynamics as a set of coordinated action (i.e., *reaction*()) between adjacent SCA agents of type *Affective*. The effect of a reaction among a set of neighboring SCA agents is their synchronous change of state. Several sets of *reaction*() rules have been experimented. In the following we report the formal specification of HAF affecton as behavioral SCA actions.

$$\begin{aligned}
\text{action} &= \text{react}_x(H, y, A)\\
\text{condit} &= p_y \in \text{adjacent}(a_x), s_y = A, s_x = H\\
\text{effect} &= \text{state}_x\text{change}(A)\\
\text{action} &= \text{react}_x(H, y, F)\\
\text{condit} &= p_y \in \text{adjacent}(a_x), s_y = A, s_x = H\\
\text{effect} &= \text{state}_x\text{change}(F)\\
\text{action} &= \text{react}_x(A, y, H)\\
\text{condit} &= p_y \in \text{adjacent}(a_x), s_x = A\\
\text{effect} &= \text{state}_x\text{change}(H)\\
\text{action} &= \text{react}_x(F, y, H)\\
\text{condit} &= p_y \in \text{adjacent}(a_x), s_x = F\\
\text{effect} &= \text{state}_x\text{change}(F, H)
\end{aligned}$$

3.3.5. Aggregation in Open Crowds

According to Canetti (1984), *open crowds* are characterized by the spontaneous will of growing in an open space, avoiding or overcoming any physical constraints. Aggregation phenomenon of open crowds starts from an aggregative psychological impulse called the *discharge*. Discharge can occur spontaneously in people and it is able to overcome natural social repulsive behavior that characterizes each human beings (i.e., *fear to be touched*). Elias Canetti's studies can be inserted in the tradition of social studies that considers the crowd as an entity dominated by uniform moods and feelings. The results of his 40-years' studies on psychological and anthropological aspects of crowds are today a reference work within crowd dynamics

literature. Elias Canetti phenomenological description and classification of crowds was adopted as theoretical framework to develop a SCA-based computational model of the aggregation process in open crowds (i.e., crowds without physical and psychological constraints). To this aim, we defined a set A of pedestrian agents (i.e., $\forall a \in A, a = \langle s, p, \textbf{ped} \rangle$ where $\textbf{ped} = \langle \Sigma_{\text{ped}}, \text{Perception}_{\text{ped}}, \text{Action}_{\text{ped}} \rangle$ and $\Sigma_{\text{ped}} = \{\text{normal, dipole, excited}\}$. Agent behavior is defined as the reactive response to external signal perceived by agents that can assume states: normal, dipole, and excited (). Figure 3.8 overviews the behavioral specification of **ped** agents actions set (i.e., $\text{Action}_{\text{ped}}$) according to SCA behavioral specification language.

As introduced above, SCA fields are signals that can be emitted and perceived by agents and allow at-a-distance indirect interactions between agents. In this experiment we modeled three different types of external signals that can influence agents: $F = \{F_{\text{rep}}, F_{\text{dis}}, F_{\text{att}}\}$.

- F_{rep} (**repulsive** field): **ped** agents in **normal** state emit a repulsive field and move within the space avoiding sites with higher values of other **repulsive** fields (*fear to be touched* principle characterizing human behavior according to Canetti, 1984).
- F_{rep} (**discharge** field): when a **ped** agent is reached by a **discharge** field, it changes its internal state into **aggregated**.
- F_{att} (**attractive** field): **ped** agents in **aggregated** state follow **attractive** fields and emit themselves **attractive** field.

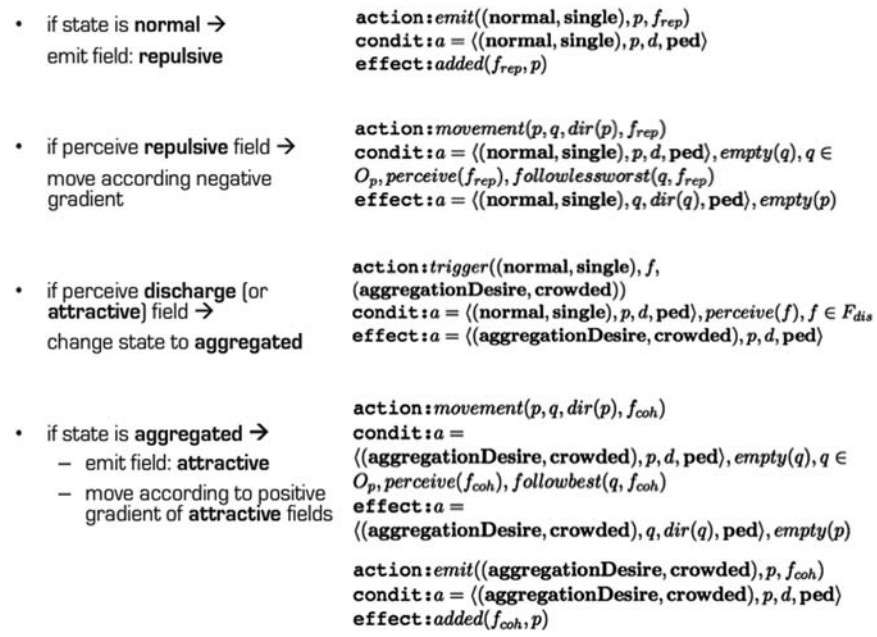


Figure 3.8: Specification of agent behavioral model for type **ped** according to SCA language.

We assumed additive property for external signals, therefore fields compose each other by summing up their values (the *attraction power of a crowd* is thus represented as the resultant of all the fields emitted by crowd components). Let f_g^p indicate the unique value of a given field type F_g at a site p,

$$f_g^p = \sum_{i=1}^{|F_g|} f_i^p$$

If p_0 is the site in which field $f_g \in F_g$ was emitted and $f_g^{p_0}$ indicates its emission intensity value in p_0, the diffusion function of the field is defined as follow:

$$\forall p \in P,\ \text{Diffusion}_g(p_0, f_g^{p_0}, p) = \begin{cases} \dfrac{f_g^{p_0}}{1 + \text{dist}(p_0, p)^6} & f_g^p > \text{thr} \\ 0 & \text{otherwise} \end{cases}$$

where *thr* is a threshold value set-up to filter lower values of fields that cannot be physically perceived by agents. This function describes a cusp-shaped diffusion for field values with the maximum value in the emission site and a uniform decreasing gradient of the field value according to $1/\text{dist}(p_0, p)^6$. The latter has been set to $1/r^6$ (as for London van der Waals forces), since we modeled behaviors and interactions modes of members of an open crowd as molecular meso-structures described by the London van der Waals interactions. This paradigm describes the aggregation of matter through the behavior of single molecules and the laws that govern the establishing of bonds between molecular meso-structures. It includes the model of a behavioral change of molecules that can be easily adapted to our aims. Molecules, normally neutral, ignore each other (i.e., *repulsive behavior*). The movement of electrons can occasionally transform molecules in a dipole for a very short time. If another molecule moves near a transient dipole, it is induced to become a dipole too. The bond established between the two dipoles is described by the London van der Waals forces, and can be extended to other proximal molecules by electrical induction *aggregative behavior*. Molecules avoid each other (*fear to be touched* principle); sometimes they can have an aggregation desire (*spontaneous possible discharge genesis*), and if there are other molecules sufficiently close (London van der Waals interaction is very short and decreases rapidly in the space with a factor equal to $1/r^6$) the aggregation desire can be transmitted to neighbors and generate a phenomenon similar to Canetti's uniform discharge on the crowd.

In a SCA-based model, each pedestrian has been represented as an agent that ignores other agents in normal state, while when it is in aggregated state, as effect of a discharge field perception, it can influence proximal agents with an aggregation desire. Since the London van der Waals forces are very short forces, and the SCA-based model imposes a spatial discrete representation, agents can influence only neighboring agents (i.e., situated in neighboring sites). If an agent is proximal to an agent in a dipole state it becomes aggregated, and it begins establishing bonds with close agents inducing the state aggregated. In this way agents start to aggregate to each other.

3.4. Concluding Remarks and Future Works

We presented SCA, a formal and computational framework for the specification of complex systems characterized by a set of autonomous entities interacting in an environment whose spatial structure represents a key factor in their behaviors (i.e., actions and interactions). The main advantage of SCA approach is to provide rich modeling and computational tools for the representation, simulation, and analysis of complex systems at individual scale. Moreover, SCA can represent potentially heterogeneous systems of agents that are spatially situated into an environment that qualifies their perceptions, interactions, and action abilities. In this chapter, we presented some examples in pedestrian and crowds dynamics research contexts in order to verify SCA ability to represent systems where self-organizing phenomena and common dynamics characterizing crowding situations.

Future works of SCA research is highly interdisciplinary and it concerns the design and development of:

- *computational models* based on individual-based approaches (i.e., CA and MAS) to represent complex systems, to study their behaviors and dynamics as potentially emerging from interactions. In order to enrich SCA modeling tool, we are currently studying an extension of SCA in which situated agents are endowed with a more complex model of perceptive, emotional, and behavioral models. We claim that these improvements will allow SCA model to be fruitfully adopted to study situations where emotions and their diffusion play a central role in the dynamics of the crowd. Moreover, such tools could potentially be useful to support social sciences in the study of relationships between emotions, perceptions, and behavior of human agents.
- *2D and 3D visualization tools t*o support the study and management of crowding situations in open and closed environments. The design of different kinds of environmental structures, at different detail levels, from corridors or emergency exits of a building to the whole transportation system on urban or regional scale, may benefit visualization functionalities. An innovative trend in supporting building and urban designers in their activities is represented by virtual environments in which alternative architectural designs can be visualized and compared by involved actors, in a collaborative decision scheme (Dijkstra, Van Leeuwen, & Timmermans, 2003; Batty & Hudson-Smith, 2005). This kind of approach could be improved by the possibility to include into the virtual environments also an envisioning of pedestrian dynamics, that has deep implications on the design of effective pedestrian facilities (Willis, Gjersoe, Havard, Kerridge, & Kukla, 2004; Vizzari, Pizzi, & SoaresCorrêada Silva, 2008).
- *methodologies and architectures for data acquisition, validation, verification and analysis on crowds* exploiting available and emerging technologies for sensing, localization, and interpretation.

References

Adamatzky, A. (2005). *Dynamics of crowd-minds*: *Patterns Of irrationality in emotions, beliefs and actions*. World Scientific Series on Nonlinear Science (Vol. 54).

Axtell, R., & Axtell, R. L. (2000). *Why agents? On the varied motivations for agent computing in the social sciences*. Working Paper no. 17, Center on Social and Economic Dynamics, Brookings Institution (p. 17).

Bandini, S., Federici, M. L., Manzoni, S., & Vizzari, G. (2007a). Pedestrian and crowd dynamics simulation: Testing SCA on paradigmatic cases of emerging coordination in negative interaction conditions. In: V. E. Malyshkin (Ed.), *PaCT, LNCS* (Vol. 4671), Springer-Verlag, Berlin.

Bandini, S., Federici, M. L., & Vizzari, G. (2007b). Situated cellular agents approach to crowd modeling and simulation. *Cybernetics and Systems*, *38*(7), 729–753, Taylor & Francis.

Bandini, S., Manzoni, S., & Simone, C. (2002a). Heterogeneous agents situated in heterogeneous spaces. *Applied Artificial Intelligence*, *16*(9–10), 831–852.

Bandini, S., Manzoni, S., & Simone, C. (2002b). Enhancing cellular spaces by multilayered multi agent situated systems. *Cellular Automata, LNCS* (Vol. 2493), Springer-Verlag, Berlin.

Bandini, S., Manzoni, S., & Simone, C. (2002c). Heterogeneous agents situated in heterogeneous spaces. *Applied Artificial Intelligence*, *16*(9–10), 831–852.

Bandini, S., Manzoni, S., & Vizzari, G. (2006). Towards a platform for MMASS-based simulations: Focusing on field diffusion. *Applied Artificial Intelligence*, *20*(4–5), 327–351, Taylor & Francis.

Batty, M., & Hudson-Smith, A. (2005). Urban simulacra: From real to virtual cities, back and beyond. *Architectural Design*, *75*(6), 42–47.

Blue, V. J., & Adler, J. (2001). Cellular automata microsimulation for modeling bidirectional pedestrian walkways. *Transportation Research Part B*, *35*, 293–312.

Canetti, E. (1984). *Crowds and power*. New York: The Noonday Press/Farrar, Straus and Giroux.

Dijkstra, J., Van Leeuwen, J., & Timmermans, H. J. P. (2003). Evaluating design alternatives using conjoint experiments in virtual reality. *Environment and Planning B*, *30*(3), 357–367.

Ferber, J. (1999). *Multi-agent systems*. Reading, MA: Addison-Wesley.

Helbing, D., Farkas, I., Molnár, P., & Vicsek, T. (2002). *Simulation of pedestrian crowds in normal and evacuation situations* (pp. 21–58). Berlin: Springer.

Klupfel, H. (2003). *A cellular automaton model for crowd movement and egress simulation*. Ph.D. thesis, Universität Duisburg-Essen, available at: http://www.ub.uni-duisburg.de/ETD-db/theses/available/duett-08012003-092540/

Morishita, S., & Shiraishi, T. (2006). Evaluation of billboards based on pedestrian flow in the concourse of the station. In: S. E. Yacoubi, B. Chopard & S. Bandini (Eds), *Cellular automata, LNCS* (Vol. 4173), Berlin: Springer.

Schadschneider, A. (2002a). *Cellular automaton approach to pedestrian dynamics — Theory* (pp. 75–86). Berlin: Springer.

Schadschneider, A. (2002b). *Cellular automaton approach to pedestrian dynamics — Applications* (pp. 87–98). Berlin: Springer.

Schreckenberg, M., & Sharma, S. (2002). *Pedestrian and evacuation dynamics*. Berlin: Springer Verlag.

Still, G. K. (2000). *Crowd dynamics*. Ph.D. thesis, University of Warwick, Warwick, available at: http://www.crowddynamics.com/

Toyama, M. C., Bazzan, A. L. C., & da Silva, R. (2006). An agent-based simulation of pedestrian dynamics: from lane formation to auditorium evacuation. In: H. Nakashima, M. P. Wellman, G. Weiss & P. Stone (Eds), 5th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2006), May 8–12, ACM 2006, ISBN: 1-59593-303-4, Hakodate, Japan (pp. 108–110).

Vizzari, G., Pizzi, G., & SoaresCorrêada Silva, F. (2008). A framework for execution and 3D visualization of situated cellular agent based crowd simulations. In: R. L. Wainwright & H. Haddad (Eds), *Proceedings of the 2008 ACM Symposium on Applied Computing (SAC)*, March 16–20, ACM 2008, ISBN: 978-1-59593-753-7, Fortaleza, Ceara, Brazil (pp. 18–22).

Willis, A., Gjersoe, N., Havard, C., Kerridge, J., & Kukla, R. (2004). Human movement behaviour in urban spaces: Implications for the design and modelling of effective pedestrian environments. *Environment and Planning B*, *31*(6), 805–828.

Wolfram, S. (1986). *Theory and applications of cellular automata*. Singapore: World Scientific Press.

Chapter 4

Modeling Impulse and Non-Impulse Store Choice Processes in a Multi-Agent Simulation of Pedestrian Activity in Shopping Environments

Jan Dijkstra, Harry Timmermans and Bauke de Vries

Abstract

This chapter presents a multi-agent approach for modeling impulse and non-impulse store choice processes of pedestrian activity in shopping environments. The pedestrian simulation context will be discussed as well as the behavioral principles underlying the store choice processes. For these behavioral principles equations are formulated. Parameters for these formulated equations will be shown and discussed. The model can be used when designers or planners need to analyze the functioning of networks, involving store choice processes of pedestrian activity, to assess their design or planning decisions.

4.1. Introduction and Motivation

Nowadays, great importance has been attached to models of pedestrian movement and pedestrian flows because the prediction of such behavior is of great public interest. Therefore, modeling behavioral aspects of pedestrians is also an important research topic. Several models of pedestrian movement have been developed since the 1990s. Worth mentioning are the success of cellular automata models in various disciplines, including transportation (e.g., Blue & Adler, 1999, 2000, 2001; Kukla, Kerridge, Willis, & Hine, 2001; Schelhorn, O'Sullivan, Hacklay, & Thurstain-Goodwin, 1999). Another type of pedestrian model is derived in analogy of fluid dynamics and particle systems but also shows ideas originating from the theory of

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self-organization. Helbing and Molnar (1997) have studied pedestrian crowds as a self-organizing phenomenon and self-organizing pedestrian movement (Helbing, Molnar, Farkas, & Bolay, 2001). Hazardous situations, such as evacuation and escape situations are of public interest and many models are concerned with such situations (e.g., Helbing, Farkas, & Viscek, 2000; Hoogendoorn, Bovy, & Daamen, 2001; Meyer-König, Klüpfel, & Schreckenberg, 2001). More recently, pedestrian following models (e.g., Hoogendoorn & Daamen, 2002; Teknomo, 2002), pedestrian dynamics (Bierlaire, Antonini, & Weber, 2003), walking behavior models (e.g., Daamen & Hoogendoorn, 2003; Daamen, 2004; Robin, Antonini, Bierlaire, & Cruz, 2009) as well as pedestrian behavior models (e.g., Borgers & Timmermans, 2004, 2005; Kitazawa & Batty, 2004; Masuda & Arai, 2005; Roland & Sterling, 2005; Shao & Terzopoulos, 2007; Zachariadis, 2005) have been suggested.

Some of these models involve an agent-based approach, which reflects the increasing interest in multi-agent models, not only for simulating pedestrians but also for other topics, such as models of cities populated with agents that represent individual citizens and reflect their migratory movements (Benenson, 1998). Pedestrian movement patterns probably offer more of a challenge in the sense that pedestrian movement is more chaotic and exhibits more variability. The challenge of cellular automata and multi-agent modeling therefore is to find the set of rules that would validly generate seemingly chaotic emerging patterns in pedestrian movement. One way of introducing this greater variability and complexity is to introduce agents in the simulated environment.

The main goal of studies within this context was to develop guidelines for urban planning and design. A number of simulation models have been proposed, for example, models for destination and route choice (Borgers & Timmermans, 1986a, 1986b). Although none of these first-generation simulation models used the agent-based approach, these models are of interest for conceptualizing particular aspects of pedestrian behavior. Dijkstra, Jessurun, and Timmermans (2002) set out to develop AMANDA, which stands for a multi-agent model for network decision analysis, to simulate pedestrian dynamic destination and route choice, and scheduling behavior, using a multi-agent approach. In this approach, it was not so much the actual detailed movement itself, but rather the outcomes of such movements in terms of destination and route choice that were the focus of the modeling process. It is assumed that individuals made decisions regarding their activity agenda, destination, and route choice when moving over a pedestrian network, such as for example the streets in a city center. The model can be used when planners need to analyze the functioning of such networks to assess the likely implications of their design or planning decisions. The basis of the model system is formed by a model, which simulates pedestrian movement across space, represented by a series of cells (Dijkstra, Timmermans, & Jessurun, 2001; Dijkstra & Timmermans, 2001). The pedestrians are represented in terms of autonomous agents. These agents have their own activity agenda, their cognition of the environment, their beliefs and their heuristics and scripts to organize their activities within a particular environment in time and space. Therefore, AMANDA differs from most other models of pedestrian behavior, which have focused primarily on movement rules, lane forming, and

crowd dynamics. The simulation of movement patterns is embedded in a more comprehensive model of activity-travel behavior.

The domain of the multi-agent based modeling approach is pedestrian behavior in a shopping environment and the choice mechanisms that are involved, including where to stop, in what order, and which route to take. It shows some similarity with other models. For example, Kitazawa, Tanaka, and Shibasaki (2003) develop a framework using multi-agent-based modeling for investigating pedestrian movement with fine-scale considerations. They analyzed the migration behavior of shoppers in a shopping center to suggest a generic model of such behavior. Models about pedestrians' shop-around behavior have also been subject of research (Yoshida & Kandea, 2007; Ali & Moulin, 2006). The work by Zhu and Timmermans (2008) offers an alternative theoretical approach, focusing on principles of bounded rationality.

AMANDA is based on a very general framework that does not only account for activity agendas, their implementation in time and space, generation of impulse behavior and the dynamics of belief updating and activity rescheduling. However, not all these aspects have been operationalized in specific models yet, and moreover not all components have been empirically tested. In that sense, AMANDA is best viewed as a research agenda, articulating various aspects and facets that can be elaborated over time, however, within an integrated framework. The aim of this chapter is to discuss the scope and some behavioral principles that underlie this model system. These behavioral principles are related to the perception of the environment, the concept of activation levels and the choice of store. The resulting decisions influence the actual movement patterns. Although movement principles about desired and actual speed are also significant, these principles will be left out of consideration in this chapter. The chapter will also discuss some estimation results of the proposed behavioral principles. The purpose of this approach is to utilize these behavioral principles for simulating pedestrian activity in shopping environments. The next section will describe the pedestrian simulation context and indicate that part of the simulation context which is the subject of discussion in this chapter.

4.2. Pedestrian Simulation Context

Figure 4.1 shows the activity diagram of the simulation setup that finally will be realized for pedestrian simulation in a shopping context. It shows that the simulation includes successively the start of the simulation process; creation of an initial situation; start of the simulation run; executing simulation steps; and finishing the simulation run. The simulation setup involves the creation of agents in the environment. Elements of the multi-agent simulation are:

- Pedestrian agents;
- Network: encloses built environment and urban space. Point of departure is a street network and stores; and
- Interaction between pedestrian agents and environment.

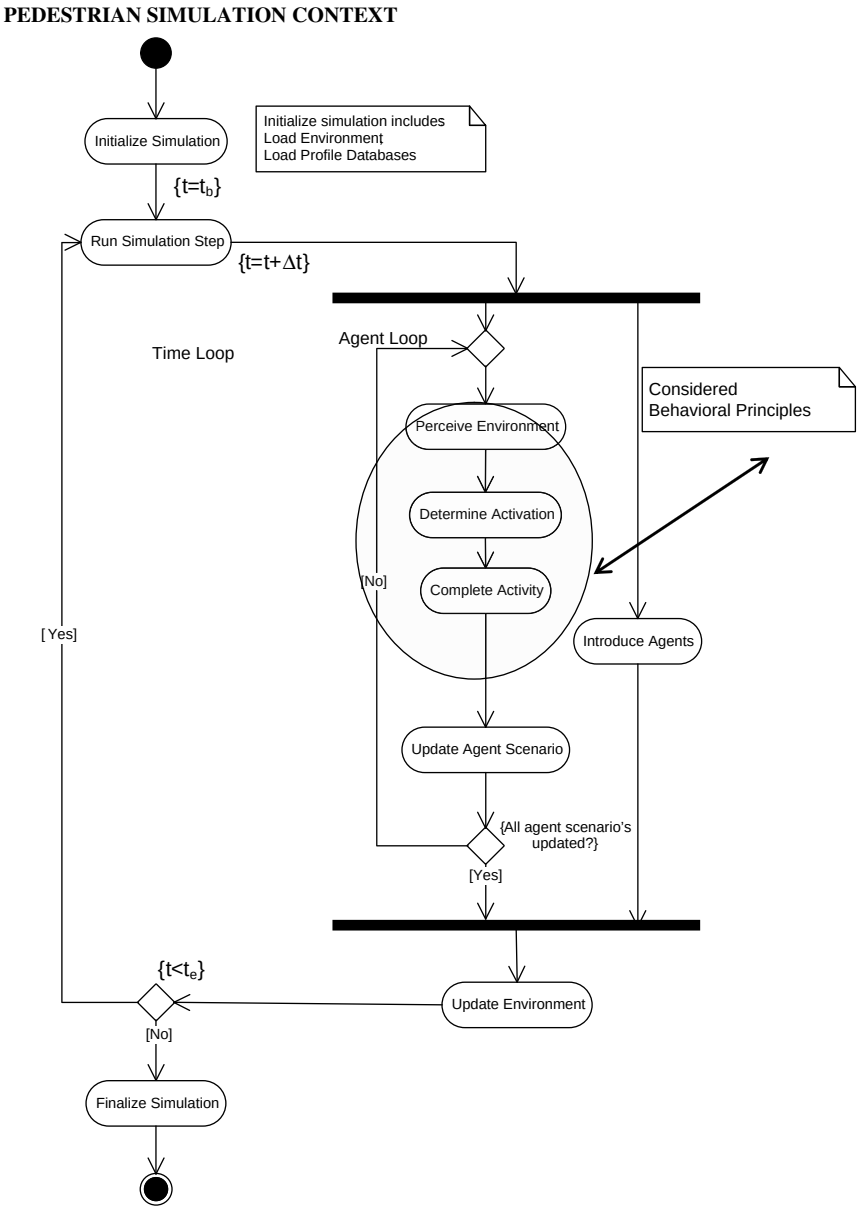


Figure 4.1: Activity diagram of the simulation setup.

Each pedestrian agent receives a pedestrian scenario for its stay in the simulation run, it includes:

- Pedestrian profile, involving personal characteristics like gender, age, and travel party, and attitudes like motivational state and familiarity with the environment.
- Pedestrian movement, involving desired/typical speed, actual speed, and position.
- Pedestrian status, involving status about moving, shopping or pause, and if the pedestrian is engaged at that moment.
- Activity agenda, involving time budget, and the activities, each activity includes activity number, priority, store name, store category, familiarity with store, duration, planned visits.
- Consideration set, involving list of store categories, and/or list of stores.
- Trip characteristics, involving start time and planned route.

Note that this initialization is not trivial and requires a considerable amount of research if a generalized model is to be developed. The discussion of these is beyond the scope of this chapter. In the remainder, we assume that the agenda, list of planned stores visits and the route are known/simulated in previous steps.

The elements of the network are stores and streets:

- A store has a store profile involving a store number, store name, store category, and position.
- A street has street characteristics involving proportion left–right in the street, and network movement, which includes tendency to keep right, tendency of increasing speed at inner lanes, and if distance to destination increases then choose a lane with faster movement.

The interaction between pedestrian agents and the environment is controlled by three key behavioral principles: perception, activation, and completing an activity. This part is subject of discussion in this chapter.

4.3. Conceptual Framework

To model pedestrian movement in a shopping environment, a multi-agent system is the starting-point. This multi-agent system is a collection of agents representing pedestrians, each with their own schedules of activities. These agents interact with this shopping environment. They perceive their environment; make their decisions and will be activated or not to visit stores in their environment. Success in visited stores determines whether an activity is completed or not. First, definitions and notations will be clarified in a generic way. After that, the behavioral principles will be explained.

4.3.1. Definitions and Notation

Consider a shopping mall or shopping environment with shopping pedestrians. This environment consists of streets, which can be represented by a network consisting of N nodes and L links, and a set of establishments, consisting of J stores, restaurants, etc. A subset of E of these N nodes represents the entry/departure points of the system. Let us assume that pedestrians can be presented by a multi-agent system with I agents. Each agent i is supposed to carry out a set of activities A_i. That is, agents are supposed to purchase a set of goods, become involved in window-shopping, and possibly conduct some other, related activities such as having lunch, going to a movie, etc. Let ${}_vA_i^{t=0}(\tau)$ represent the *activity agenda* that agent i wishes to implement at the start of her v-th visit to the shopping center at time τ. Note that three time representations are used here. Subscript v is a count of the number of visits to the center. The superscript t is the time during the visit, while τ represents clock time, for example, in days. It is assumed that the activity agenda is time-dependent to allow for changes in the agenda during the trip. The need to actually realize the various planned activities may differ, partly in relation to the nature of the trip. If the reason for the trip is primarily leisure-oriented, the goals and activity agenda may be relatively fuzzy. In contrast, if the trip is initiated because of some urgent goal, the need to realize the activity that serves this goal would be high. Thus, it is assumed that the activities differ in *priority*. Let w_{ia}^t denote agent i's priority of activity a at time t. If all activities are equally important and all can be conducted at a particular time, $w_{ia}^t = 1/n \; \forall a \in {}_vA_i^t(\tau)$, $n =$ number of activities. In contrast, if the agent would give the highest priority to activity a, $w_{ia}^t = 1$, and $w_{ia'}^t = 0 \; \forall a' \neq a \in {}_vA_i^t(\tau)$. Thus, the set of priorities allows one to partially schedule the activities included in the agenda. Let ${}_v\tilde{A}_i^t(\tau)$ be the set of partially scheduled activities of agent i at time t of visit v on day τ. It is assumed that an activity agenda may change during a trip for a number of reasons. First, successfully completed activities can be dropped from the agenda. Second, pedestrians may decide due to time pressure not to pursue a particular activity any longer. Third, the completion of an activity may induce other activities. For example, the purchase of a dress may induce an agent to buy matching shoes. Finally, the exposure to advertising and windows displays may result in unplanned, impulse behavior.

Agents derive a certain utility for conducting activities. It is assumed that this utility is represented by a logistic function of duration of the activity. This function has a maximum ${}_vU_{ia}^{\max_t}(\tau)$ and a minimum ${}_vU_{ia}^{\min x_t}(\tau)$. The more negative the constant in the logistic equation, the longer it requires for an agent to reach his point of maximum returns. Similarly, the slope of the logistic function determines the increase in marginal utility.

The set of activities should be completed within particular time constraints, set by personal and institutional constraints, such as the opening hours of the shopping center. Let ${}_vT_i^B(\tau)$ and ${}_vT_i^E(\tau)$ $({}_vT_i^B(\tau) < {}_vT_i^E(\tau))$ denote respectively the earliest possible start and latest possible end time for agent i during visit v on day τ and let ${}_vT_j^B(\tau)$ and ${}_vT_j^E(\tau)$ $({}_vT_j^E(\tau) > {}_vT_j^E(\tau))$ denote store opening and closing hours of store j at visit v on day τ. Then, an agent's time window for conducting an activity at store j

is defined by $[\max({}_vT_i^B(\tau), {}_vT_j^B(\tau)); \min({}_vT_i^E(\tau), {}_vT_j^E(\tau))]$. Let us assume that the time required to complete activity a (time spent in the store) by agent i during visit v on day τ is equal to ${}_v\Delta_{ia}(\tau)$. If ${}_vT_{ia}^m(\tau)$ denotes the amount of time spent for moving by agent i on the v-th visit on day τ to the shopping center to complete activity a, the total stay in the shopping center for agent i after completing the set ${}_vA_i^{\otimes}(\tau)$ of activities during the v-th visit on day τ is equal to:

$$ {}_vD_i^{\otimes}(\tau) = \sum_{a \in {}_vA_i^{\otimes}(\tau)} ({}_v\Delta_{ia}(\tau) + {}_vT_{ia}^m(\tau)) \tag{4.1} $$

It is assumed that the completion of an activity is a key *decision point*, where agents will adjust, if necessary their activity agenda and anticipated time allocation to the activities not yet completed. Another decision point is every node of the network where agents may decide to take another route, changing the *anticipated duration* of the overall visit in the shopping center. The total duration of the visit at node n for agent i at visit v on day τ, having completed the set of ${}_vA_i^{\otimes}(\tau)$ activities is equal to:

$$ {}_vD_i^n(\tau) = \sum_{a \in {}_vA_i^{\otimes}(\tau)} ({}_v\Delta_{ia}(\tau) + {}_vT_{ia}^m(\tau)) + {}_vT_{in}^m(\tau) \tag{4.2} $$

where ${}_vT_{in}^m(\tau)$ is the time to move to node n during the v-th visit on day τ by agent i having completed the set ${}_vA_i^{\otimes}$ of activities. The remaining *time budget* at these decision points then equals respectively:

$$ {}_vB_i^{\otimes}(\tau) = {}_vT_i(\tau) - {}_vD_i^{\otimes}(\tau) \tag{4.3} $$

and

$$ {}_vB_i^n(\tau) = {}_vT_i(\tau) - {}_vD_i^n(\tau) \tag{4.4} $$

The anticipated time to complete the remaining activities in the activity agenda at time t during visit v on day τ by agent i is given by:

$$ {}_v\widehat{D}_i^t(\tau) = \sum_{a \in {}_vA_i^t(\tau)} ({}_v\widehat{\Delta}_{ia}(\tau) + {}_v\widehat{T}_{ia}^m(\tau)) + {}_v\widehat{T}_{j^{\otimes}n_d}^m(\tau) - (t - {}_vT_{ij^{\otimes}t}^m(\tau)) \tag{4.5} $$

where, ${}_v\widehat{T}_{j^{\otimes}n_d}^m(\tau)$ is the anticipated time to move from the store $j^{\otimes}$ expected to be visited last during the trip and the departure node n_d; ${}_vT_{ij^{\otimes}t}^m(\tau)$ is the time used for movement after visiting the last store before time t.

The above set of equations represents the time constraints operating on pedestrian's choices. Agents can perform the activities in a set of J stores or establishments. Over time, agents build and update beliefs about these stores. It is assumed that that these beliefs are a function of the degree to which the beliefs of the store, driven by their actual attributes, match the agent's ideals, as indicated by the

following functions:

$$ {}_{v}\Theta_{ij}^{t}(\tau) = \prod_{k \in K} \left[\left(1 - \frac{|{}_{v}x_{ijk}^{t}(\tau) - {}_{v}\tilde{x}_{ik}^{t}(\tau)|}{{}_{v}r_{k}^{t}(\tau)} \right)^{{}_{v}\gamma_{jk}^{t}} \right] \prod_{k \in K} [(1 - {}_{v}\Lambda_{jk}^{t}(\tau))^{{}_{v}\gamma_{jk}^{t}}] \tag{4.6} $$

$$ {}_{v}x_{ijk}^{t}(\tau) = {}_{v}f_{i}^{t}(\tau)({}_{v}X_{jk}^{t}(\tau)) \quad \forall v, t, i, j, k, \tau \tag{4.7} $$

${}_{v}\Theta_{ij}^{t}(\tau)$ is the attractiveness of store j to agent i at time t of visit v on day τ, K the set of continuous attributes, describing the stores, ${}_{v}x_{ijk}^{t}(\tau)$ the perceived value of attribute k by agent i of store j at time t of visit v on day τ, ${}_{v}\tilde{x}_{ik}^{t}(\tau)$ the ideal value of attribute k for agent i at time t of visit v on day τ ($\min_{k} {}_{v}x_{jk}^{t}(\tau) \leq {}_{v}\tilde{x}_{ik}^{t}(\tau) \leq \max_{k} {}_{v}x_{jk}^{t}(\tau)$), ${}_{v}X_{jk}^{t}(\tau)$ the actual value of attribute k of store j at time t of visit v on day τ, ${}_{v}\Lambda_{jk}^{t}(\tau) = \alpha_{c,c'}^{k}(\tau), \alpha_{c,c'}^{k}(\tau) \geq 0 \quad \forall k, c, c' \wedge \sum_{c'} \alpha_{c,c'}^{k} = 1 \forall k, c, {}_{v}\gamma_{jk}^{t}$ parameters to be estimated of attribute k of store j at time of visit v.

Note that we assumed a multiplicative function. It implies that if the matching function on a single attribute is zero, the pedestrian will not choose that store, regardless of the value of the remaining attributes of that store.

It is assumed that agents have a *cognitive filter*, $0 \leq {}_{v}\zeta_{i}^{t}(\tau) \leq 1$, that may vary over time to define time-dependent consideration sets. In particular, it is assumed that:

$$ p(j \in \overleftrightarrow{C}_{i}^{t}(\tau)) = 1, \quad \text{if } \prod_{k \in K} \left[\left(1 - \frac{|{}_{v}x_{ijk}^{t}(\tau) - {}_{v}\tilde{x}_{ik}^{t}(\tau)|}{{}_{v}r_{k}^{t}(\tau)} \right) \right] \prod_{k \in K} [(1 - {}_{v}\Lambda_{jk}^{t}(\tau))^{{}_{v}\gamma_{jk}^{t}}] \geq {}_{v}\zeta_{i}^{t}(\tau) $$
$$ 0, \text{otherwise} \tag{4.8} $$

where, $p(j \in \overleftrightarrow{C}_{i}^{t}(\tau))$ is the probability that store j belongs to consideration set $\overleftrightarrow{C}_{i}^{t}(\tau)$ of agent i at time t of visit v on day τ.

Note that these cognitive filters allow one to limit the consideration set. Filters may be a function of the motivational state or urgency. For example, if urgency is high, a high filter would be expected, implying that the focus of attention of pedestrians will be only a small consideration set.

In the discussed definitions and notations, time representations were used for a particular visit on a particular day at a certain time. Although this is very useful for a general model of pedestrian behavior, the implication is that the model becomes very complex. Although time-varying behavior and dynamics are still on our research agenda, to reduce this complexity and focus on what we have actually done to date, in the remainder of this chapter the time dimension will be ignored in the discussion of behavioral principles. It means that notation, for instance, F_i which represents the perceptual field of agent i is a simplification of ${}_{v}F_{i}^{t}(\tau)$ that

denotes the perceptual field of agent i during the v-th visit on day τ to the shopping center at time t.

4.3.2. Behavioral Principles

In order to implement the activity agenda, the agents need to successfully visit a set of stores and move over the network. It is assumed that the agents' behavior is driven by a series of decision heuristics. Agents need to decide which stores to choose, in what order, and which route to take, subject to time and institutional constraints. It is assumed that agents are in different motivational states. They may at every point during the trip have general interests in conducting particular activities, without having decided on the specific store or establishment to visit, but they may also be in a more goal-directed motivational state in which case they have already decided which store to visit. Assume that information about motivational state and route choice is known.

When moving over the network, it is assumed that agents' decisions to visit a store depend on perceptual fields. Let F_i denotes the perceptual field of agent i. *Perceptual fields* may vary according to the agent's *awareness threshold*, which in turn may depend on his motivational state, age, travel party, eye-sight, and the like, and the *signaling intensity* of the store, which is a function of distance, appealing architecture, and whether or not the view is interrupted by other agents. Thus, when a pedestrian is in a goal-directed state and knows which store to visit, the awareness threshold will reduce when the agent is approaching this store. In particular, it is assumed that the probability that a store will be included in the perceptual field of an agent is given by the following equation:

$$p_{j\in F_i|A_i} = \frac{\exp(\vartheta_j.\varphi_{j|a} - w_{ia}.\theta_i)}{1 + \exp(\vartheta_j.\varphi_{j|a} - w_{ia}.\theta_i)} \tag{4.9}$$

where, ϑ_j is the signaling intensity of store j, θ_i the awareness threshold of agent i, $\varphi_{j|a} = 1$, if activity a can be conducted at store j; 0 otherwise, w_{ia} the priority of activity a for agent i.

Note that if the signaling intensity is much lower than the awareness, the probability that a store will be included in an agent's perceptual field is close to zero. On the other hand, if the signaling intensity is much higher than the awareness threshold, the probability of a store to be included in an agent's perceptual field approaches unity. The probability is 50% if the signaling intensity is equal to the awareness threshold. Figure 4.2 illustrates this behavior. Where the signaling intensity may be considered relatively constant, it may be adjusted by the purpose of the visit. Thus, it is assumed that the probability of the same store to be noticed is higher if it is instrumental in achieving the planned agenda. Similarly, the priority is assumed to have some influence.

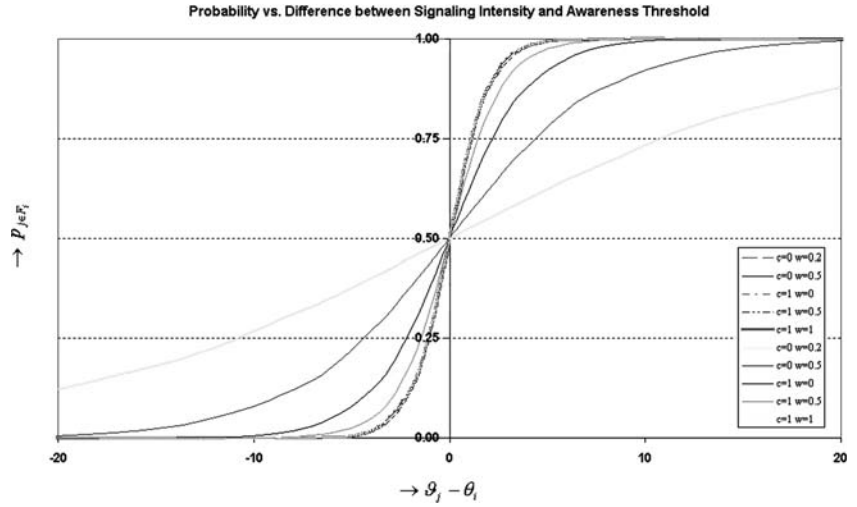


Figure 4.2: $p_{j\in F_i|A_i}$ versus $(\vartheta_j - \theta_i)$ at different $w_{ia}(w)$ and $\varphi_{j|a}(c)$.

The awareness threshold is assumed to be a function of the motivational state of the agent and the ability of the agent, represented by a set of personal characteristics. In equation:

$$\theta_i = \frac{\exp(\beta_0 + \beta_1 M_i + \sum_{k>1} \beta_k Y_{ik})}{1 + \exp(\beta_0 + \beta_1 M_i + \sum_{k>1} \beta_k Y_{ik})} \tag{4.10}$$

where, M_i is the motivational state of agent i, Y_{ik} characteristic k of agent i, β's are parameters to be estimated.

The inclusion of the motivational state variable is included to differentiate between window shopping and more goal-directed behavior. Parameter β_1 should be negative and approach $-\infty$ to ensure a lower awareness threshold when an agent is in a goal-directed state ($M_i = 1$).

Similarly, signaling intensity is defined as:

$$\vartheta_j = \frac{\exp\{\gamma_0 + \rho_{ij}[\gamma_1 d_{ij} + \gamma_2 R_{ij}] + (1 - \rho_{ij})[\gamma_3 d_{ij}]\}}{1 + \exp\{\gamma_0 + \rho_{ij}[\gamma_1 d_{ij} + \gamma_2 R_{ij}] + (1 - \rho_{ij})[\gamma_3 d_{ij}]\}} \tag{4.11}$$

where, $\rho_{ij} = 1$, if store j is located in front of agent i at time t for agent i; 0 otherwise, d_{ij} is the distance between agent i and store j, R_{ij} indicates whether the view between agent i and store j is interrupted, γ's are parameters to be estimated, $\gamma_1, \gamma_2, \gamma_3 (\gamma_3 < \gamma_2) < 0$.

Parameter γ_3 should approximate $-\infty$ to ensure that the signaling intensity goes to $-\infty$ if the view is interrupted ($R_{ij} = 1$). Parameter ρ_{ij} is introduced to differentiate

between the situation that a store is in front of an agent or behind the agent. In the latter case, a store might still be included in a perceptual field, due to memory recall. However, it is unlikely that the effect of distance on signaling intensity is symmetric between these two situations. The assumption that $\gamma_3 < \gamma_2$ indicates that the signally intensity is higher at the same distance if the store is in front of an agent.

When stores are signaled and become included in an agent's perceptual field, the agent has to decide whether or not to act and visit the store. The *activation* Γ_{ij} of an agent i is defined as:

$$\Gamma_{ij} = \upsilon_{ij}(1 - E_i) + (1 - \upsilon_{ij})\left\{(1 - E_i)\eta_{ij}.\delta_j.\overset{\leftrightarrow}{C}_{ij} \cdot \prod_{k \in K}\left(1 - \frac{|x_{ijk} - \tilde{x}_{ik}|}{r_k}\right)^{\gamma_{jk}}\right\} \qquad (4.12)$$

where, Γ_{ij} represents the activation of agent i toward store j, $0 \leq \upsilon_{ij} \leq 1$ is the tendency of impulse behavior in store j by agent i, E_i indicates whether or not agent i is engaged, $0 \leq \eta_{ij} \leq 1$ is the familiarity of store j to agent i, $\delta_j = 1$, if store j is suited to conduct one of the activities $a \in A_i$; 0 otherwise, $C_{ij}^{\leftrightarrow}$ indicates whether store j belongs to the consideration set of agent i, K is the set of continuous attributes, describing the stores, x_{ijk} is the perceived value of attribute k for agent i of store j, $\tilde{x}_{ik}$ is the ideal value of attribute k for agent i, $(\min_k x_{jk} \leq \tilde{x}_{ik} \leq \max_k x_{jk})$, $\Lambda_{jk} = \alpha^k_{c,c'}, \alpha^k_{c,c'} \geq 0 \quad \forall k, c, c' \wedge \sum_{c'} \alpha^k_{c,c'} = 1 \quad \forall k, c.$

Let us examine this equation. First, the structure of the equations indicates we assume there is some probability of impulse behavior and the complementary probability of non-impulse behavior. Impulse behavior is assumed a constant, unless an agent is engaged and fixed on a particular store, in which case the probability of non-impulse behavior drops to zero. Although triggers for engaged behavior should still be defined, one can for instance assume that pedestrians will become engaged in conducting a particular activity if there are only high priority activities left on the agenda and if the remaining time budget is limited. Several variables are introduced to influence the probability of activation for non-impulse behavior. If an agent is not familiar with a store, $\eta_{ij} = 0$, the activation of the agent toward this store will also be equal to zero. Similarly, activation will be equal to zero if the store is not suited to conduct any of the activities that are still scheduled to be completed at that time of the visit. On the other hand, if the agent is familiar with the store and if that store is suited, the activation level will be a function to what degree the store matches the agent's ideal. If it perfectly matches the ideal store, which will be the case in a specific goal-seeking mode, then activation will be equal to unity. If the store is extremely different from the agents' ideal store for conducting the specific activity, activation will approximate zero.

Figures 4.3–4.5 show the influence of impulsive behavior and the familiarity on the activation at different attractiveness levels. It shows that with a decreasing attractiveness level the importance of impulsive behavior increases, or with increasing attractiveness level the significance of the familiarity level increases.

Activation level is a probabilistic variable. This means that Monte Carlo simulation is applied to simulate the state of this variable. If the outcome of the

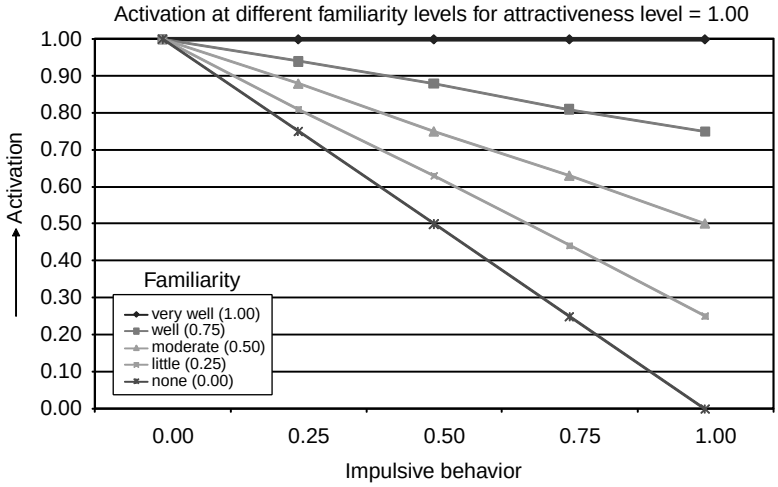


Figure 4.3: Influence of impulsive behavior and familiarity at attractiveness level 1.00.

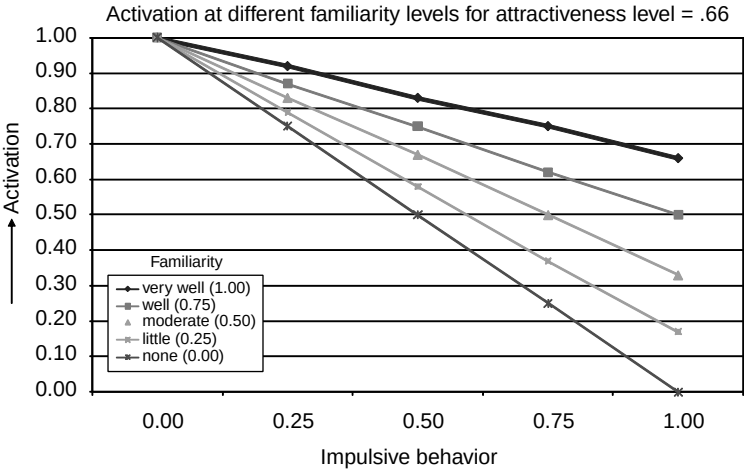


Figure 4.4: Influence of impulsive behavior and familiarity at attractiveness level .66.

simulation indicates that the agent is activated, it is decided that the agent is engaged ($E_i = 1$). As shown in the above equation, it is assumed that agents cannot be activated for another store, if they are already engaged. This principle can be amplified by raising the agent's awareness threshold.

If an agent becomes activated, it will gradually move to the store. The simulation then decides on the duration of window-shopping, if any, the probability and duration of an actual visit to the store, the probability of successfully completing the activity at the store, and the amount of money spent. It is assumed that the probability of a successful completion is a function of availability and predictability

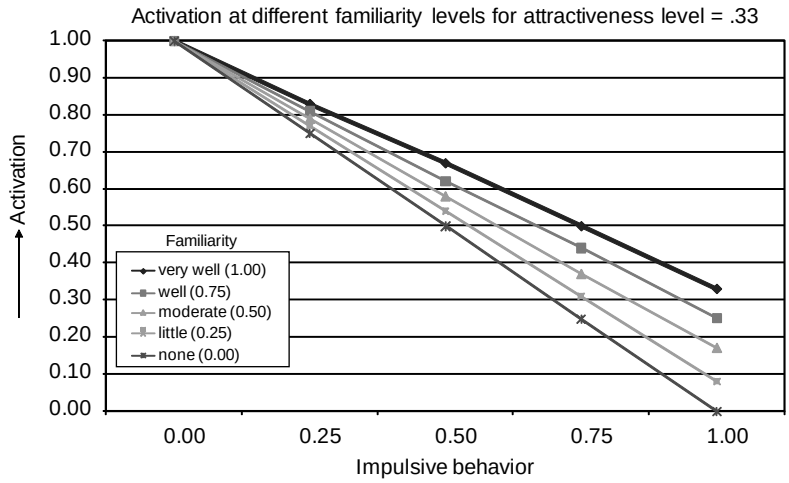


Figure 4.5: Influence of impulsive behavior and familiarity at attractiveness level .33.

of the product, the urgency of completing the activity, the familiarity of the store to the agent, the duration of the visit, and the attractiveness of the store. In particular,

$$p_{iaj} = \frac{\exp(\beta_{i1}X_{1aj} + \beta_{i2}X_{2aj} + \beta_{i3}u_{ia} + \beta_{i4}\eta_{ij} + \beta_{i5}\Delta_{ij} + \beta_{i6}\Theta_{iaj})}{1 + \exp(\beta_{i1}X_{1aj} + \beta_{i2}X_{2aj} + \beta_{i3}u_{ia} + \beta_{i4}\eta_{ij} + \beta_{i5}\Delta_{ij} + \beta_{i6}\Theta_{iaj})} \tag{4.13}$$

where, p_{iaj} is the probability that agent i will buy product a (compete activity a) at store j, X_{1aj} the available assortment of product a in store j, X_{2aj} the predictability of product a in store j, u_{ia} the urgency that agent i will buy product a (compete activity a) at store j, η_{ij} the familiarity of store j to agent i, Δ_{ij} the duration of the visit of store j by agent i, Θ_{iaj} the attractiveness of store j for agent i for conducting activity a, β's are parameters to be estimated.

After the activity is completed, the remaining activities are rescheduled and the simulation continues. Details of rescheduling are beyond the scope of this chapter.

4.4. Estimation Results and Discussions

When data are available, the parameters of the formulated equations can be estimated. In principles various approaches can be applied. At this stage of development, we decided to estimate probabilistic models, focusing on the statistical relationships between the identified variables. Estimating the equations for individual stores would be prohibitive, and therefore to generalize, the decision was made to classify stores, and estimate the models using this classification. In particular, the following types of stores were distinguished: clothing stores, shoe stores, health and body stores, department stores, and other specific stores (e.g., jewelry shop).

To define agents' motivational states, the categorization goal-directed, leisure shopping, and no specific intention was made for their visit. Data on motivation were derived from survey data. A distance categorization (<50, 50–100, 100–150, >150 m) is used to differentiate the distance between agent i and store j.

In this section, the estimation of parameters of the formulated equations representing the behavioral principles will be discussed one by one.

4.4.1. Perceptual Field

In Eq. (4.9), the dichotomous response variable is the probability of a store being spotted. The explanatory variables are store category, and the motivation for visiting the city center. Dummy coding was used to represent these variables. The category "other" was used here as a reference, both for motivational state (no specific intention) and store category (specific shops). As expressed by Eq. (4.11) the signaling intensity of a store is assumed to depend on distance. The parameters of the perceptual field model were therefore estimated specifically for each distance class. The following distance categories were used: <50, 50–100, 100–150, and >150 m. As mentioned before, a store might still be included in a perceptual field when an agent has passed that store. It is assumed that the effect of distance on signaling intensity is asymmetric between the situation that a store is in front of a pedestrian or behind the pedestrian. Separate models were therefore estimated for the perception of stores in the walking direction and in the opposite direction. Tables 4.1 and 4.2 present the estimated parameters of the variables.

Table 4.1 shows some interesting patterns. The model estimated for the walking direction shows that at a distance of more than 150 m, the probability of spotting a store is relatively small. Because of that, store categories do not seem to have a

Table 4.1: Estimated parameters (walking direction).

	Distance category							
	<50		**50–100**		**100 – 150**		**>150**	
	B	**Sig.**	***B***	**Sig.**	***B***	**Sig.**	***B***	**Sig.**
Store category								
Clothes	.346	.057	.944	.000	−.804	.022	−.135	.713
Shoes	−1.057	.000	.878	.001	−1.315	.001	−1.098	.024
Health and body	−1.488	.000	−.880	.015	−1.800	.000	−1.513	.007
Department store	−1.168	.000	1.075	.000	1.139	.000	−.224	.551
Motivational state								
Goal oriented	−.162	.387	−.586	.004	−.823	.001	−.938	.006
Leisure shopping	.124	.498	−.322	.102	−1.021	.000	−.934	.005
Constant	−.415	.027	−1.759	.000	−1.421	.000	−1.925	.000

Table 4.2: Estimated parameters (opposite direction).

	Distance category							
	<50		50–100		100–150		>150	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
Store category								
Clothes	.273	.269	.585	.033	−.146	.640	.410	.104
Shoes	−.692	.014	−.235	.445	−.634	.068	−.842	.006
Health and body	−.953	.001	−1.059	.005	−1.453	.001	−.523	.069
Department store	−2.38	.362	.708	.009	−.494	.141	−.571	.049
Motivational state								
Goal oriented	−.653	.048	.648	.160	.123	.791	.638	.164
Leisure shopping	−.660	.047	.612	.186	−.381	.427	.664	.150
Constant	−.374	.277	−2.134	.000	.476	.001	−1.765	.000

major effect. Only the estimated effect for health stores at this distance is significant, indicating that the probability of health stores being included in the perceptual field at this distance is even significantly smaller.

When distance becomes smaller, the probability of becoming included in a pedestrian's perceptual field is highest for department stores. This is also true for a distance between 50 and 100 m, but now the probability of inclusion in a perceptual field rapidly increases for clothing stores, followed by shoe stores. At very short distances of less than 50 m, the clothing stores stand out, suggesting that some of these stores catch the attention of pedestrians only at very short distances.

As for motivational state, the differences in estimated parameters between goal-oriented and leisure behavior are also interesting. At longer distances, there is no significant difference between these two motivational states, suggesting that pedestrian fields are dominated at this distance by distance only. The difference in parameters then increases with shorter distance, suggesting that the probability of a store being included in an agent's perceptual field is higher if the agent is involved in leisure shopping. Goal-oriented pedestrians seem more focused in their perception and less open to signals of stores they do not plan to visit.

Table 4.2 shows the results of the estimated parameters for the perception of stores that pedestrians have already passed (opposite direction). The pattern is less clear. First, the results suggest that the motivational state in general, and especially the difference between goal-oriented and leisure shopping does not have a significant effect on the recall of stores. Second, recall seems less with increasing distance. These results are consistent except for the 100–150 distance category. Third, recall seems higher for clothing stores and department stores, but again the overall pattern is rather erratic.

Table 4.3: Hosmer and Lemeshow test.

	Distance category							
	<50		50–100		100–150		>150	
	Walking direction	Opposite direction	Walking direction	Opposite direction	Walking direction	Opposite direction	Walking direction	Opposite direction.
Significance	.822	.941	.978	.635	.807	.189	.948	.865

To assess the goodness of fit of the estimated model, the Hoshmer and Lemeshow test was used. Table 4.3 presents the results, which suggests that the model performs quite well.

The results of this estimation provide face validity to the model in the sense that the signs of the estimated parameters are consistent and interpretable. For estimating the equation for the perceptual field, a simplification regarding the priority of activity a for agent i (w_{ia}) and conducting activity a at store j ($\varphi_{j|a}$) is implemented. Both are fixed at numerical value 1. Estimation results by estimating equations for the signaling intensity (4.10) and awareness threshold (4.11) provides low goodness of fit. Therefore, these equations are included in an overall equation; it is assumed that the probability that a store j will be included in the perceptual field of an agent i is given by the following equation:

$$p_{j\in F_i|A_i} = \frac{\exp(\beta_0 + \beta_1 d_{ij} + \beta_2 S_{ij} + \beta_3 C_j - \beta_4 M_i - \sum_{k>4} \beta_k Y_{ik})}{1 + \exp(\beta_0 + \beta_1 d_{ij} + \beta_2 S_{ij} + \beta_3 C_j - \beta_4 M_i - \sum_{k>4} \beta_k Y_{ik})} \tag{4.14}$$

where, d_{ij} is the distance between agent i and store j, S_{ij} appealing characteristic of store j, C_j store category of store j for differentiating stores, M_i the motivational state of agent i, Y_{i5} gender of agent i, Y_{i6} age category of agent i, Y_{i7} the companionship of agent i, Y_{i8} the familiarity with the city/shopping center of agent i, Y_{i9} the frequency of visit of the center of agent i, β_i's parameters to be estimated.

A parameter for "interrupted view" is ignored because of missing interrupted views during interviewing respondents for collecting data. Considering Tables 4.1 and 4.2 the distinction between "walking direction" (in advance) and "opposite direction" (behind) is remarkable. Therefore, no parameter about the store location "in advance" and "behind" is included in Eq. (4.14). From that, estimation results are provided for both directions.

A binary logit model was applied to estimate the parameters. Effect coding was used to represent the categorization of the explanatory variables. Table 4.4 shows the estimation results.

Table 4.4 shows that almost all parameters related to the spatial environment are significant and to a lesser extent this is also true for the motivation of an agent.

Table 4.4: Estimated parameters and McFadden's RhoSq. Goodness of Fit.

	In advance β	**Behind β**
Distance		
$< = 50$ m	1.034*	.292*
50–100 m	.469*	.115
100–150 m	−.380*	−.554*
150 m	−.1123	.147
Characteristics		
Information (advertisement, etc.)	−1.161*	.477*
Architecture (style)	.551*	−.359*
Shop window	−.341*	−.765*
Features (like color, light, etc.)	.951	.647
Store category		
Clothes	.749*	.817*
Shoes	−.587*	−.118
Health and body	−.883*	−.446*
Department store	.283*	−.323*
Specific	−.238	.070
Motive		
Goal oriented	−.167*	.202*
Leisure shopping	−.139*	−.029
No specific intention	.306	−.173
Gender		
Male	−.136*	−.122*
Female	.136	.122
Age		
<18	−.167	−.222
18–40	−.141*	.086
40–55	−.151	.158
>55	.459	−.022
Companionship		
Alone	.067	.048
+ 1	−.132	.211*
+ Kids	−.019	−.481*
>1	.084	.222
Familiarity		
Good	.155	−.363*
Moderate	−.188	.072
None	.033	.291

Table 4.4: (*Continued*)

	In advance β	Behind β
Visit		
Weekly	.275*	.433*
Monthly	.014	.422*
Now and then	−.261	−.057
Seldom	−.018	−.759
Constant	−1.287*	−1.801*
RhoSq.	.179	.05

*Significant at 0.05 level.

Personal characteristics seem to matter less. Notable is the result for "good" familiarity for the opposite walking direction, which indicates that recall of stores is more critical when stores have already been passed. The larger distance category "110–150 m" for the opposite walking direction is somewhat strange. It may be caused by the smaller number of observations in this category.

4.4.2. *Activation*

When stores are signaled and become included in an agent's perceptual field, the agent has to decide whether or not to visit the store. The *activation* Γ_{ij} of an agent i for visiting j was defined by Eq. (4.12). In this equation only the attributes *assortment*, *sphere*, *quality*, and *service* are included as descriptions of stores in the attractiveness of store j to agent i. Therefore, the activation of an agent is defined as:

$$\begin{aligned} \Gamma_{ij} &= \upsilon_{ij}(1 - E_i) + (1 - \upsilon_{ij})\{1 - E_i)\eta_{ij}.\delta_j.\overleftrightarrow{C}_{ij}.\Theta_{ij} \\ \Theta_{ij} &= \prod_{k \in K}\left[\left(1 - \frac{|x_{ijk} - \tilde{x}_{ik}|}{r_k}\right)^{\gamma_{jk}}\right] \end{aligned} \tag{4.15}$$

where, Θ_{ij} is the attractiveness of store j to agent i, x_{ijk} the expected value of attribute k for agent i of store j, $\tilde{x}_{ik}$ the ideal value of attribute k for agent i, with $r_k = 4$, $\tilde{x}_{ik} = 4$, and $(\min_k x_{jk} \leq \tilde{x}_{ik} \leq \max_k x_{jk})$, γ_{jk}'s are parameters to be estimated with $\gamma_{jk} \geq 0$.

The attractiveness function (Eq. (4.15)) is nonlinear. Therefore, constrained nonlinear regression was used to estimate the parameters of the attractiveness function. The response variable is the overall assessment of the attractiveness of the store. Explanatory variables are the set of attributes describing the store, namely *assortment*, *sphere*, *quality*, and *service*. Table 4.5 presents the estimation results.

Table 4.5: Estimated parameters.

	Store category				
	B				
	Clothes	**Shoes**	**Health and body**	**Department store**	**Specific**
Assortment	.456	.045	.170	.696	.000
Sphere	.054	.107	.000	.260	.191
Quality	.009	.628	.785	.000	.235
Service	.029	.100	.111	.052	.200

Examining this table, the prevailing influence of assortment for the clothes and department store categories is striking. This is convincing because a department store is the favorite place for all sort of things, and also clothing stores offer a wide selection. The prevailing influence of quality for the shoes and health and body categories is also striking. For the specific store category, the items are more uniform except assortment. In the latter, people are more goal-oriented and less interested in assortment but more in quality, service, and satisfying environment.

To evaluate the goodness of fit of the model, a pseudo RhoSq. was calculated and defined as:

$$R^2 = 1 - \frac{\text{Residual Sum of Squares}}{\text{Corrected Sum of Squares}} \tag{4.16}$$

The goodness of fit of the estimated model is fair for the store categories "Specific," "Clothes" and "Department Store" (respectively .068, .108, and .138) and reasonable for the store categories "Health and Body" and "Shoes" (respectively .227 and .253).

4.4.3. Completing an Activity

If an agent becomes activated, it will gradually move to the store. The model simulates the probability and duration of an actual visit to the store, and the probability of successfully completing the activity at the store. It is assumed that the probability of a successful completion of an activity is a function of the explanatory variables availability and predictability of product a in a store, the urgency that an agent will buy product a, the familiarity of the store to the agent, the duration of the visit, and the attractiveness of the store. Predictability concerns the belief of an agent to find a product the agent wants. The probability p_{iaj} that agent i will buy product a at a store j was defined by Eq. (4.13).

The dichotomous response variable is whether the concerning activity was successfully completed, which for these activities means whether a product has

been bought. Data collected about the response variable as well as the mentioned explanatory variables are used to determine the parameters of the equation. Dummy coding was used to represent these variables.

For each store category the model was estimated using binary logit model. Table 4.6 presents the estimated parameters of the variables.

This table shows some interesting patterns. The available assortment is a significant variable except for the specific stores. Duration is significant in case of clothing and less important for the other store categories. Familiarity of a store only plays a significant role in case of specific stores. This suggests that these stores are more unusual to visit and for visiting such a store some familiarity with that kind of stores seems necessary. Furthermore, the parameter values of store attraction suggest that the impact of store attraction is small. Maybe, this will be influenced by the overall perception of the store with regard to their appearance instead of closer

Table 6: Estimated parameters.

	Store category									
	Clothes		**Shoes**		**Department store**		**Health and body**		**Specific**	
	B	**Sig.**	***B***	**Sig.**	***B***	**Sig.**	***B***	**Sig.**	***B***	**Sig.**
Available assortment										
Good	2.481	.008	2.725	.030			1.106	.319	2.967	.003
Sufficient	1.376	**.138**	1.849	.124			.122	.920	2.885	.004
Available assortment										
Good					1.299	.013				
Product predictability										
Yes	.283	.539	.550	.414	.356	.556	1.524	.027	−1.585	.030
Product urgency										
Yes	1.158	.027	1.094	.071	.878	.078	.520	.420	1.226	.014
Familiar with store										
Good									1.195	.013
Duration of visit										
>15 min			.891	.283	1.154	.101	.449	.706	−.480	.469
5–15 min			.377	.610	.685	.218	.793	.305	−.808	.198
Duration of visit										
>15 min	1.831	.000								
Store attraction										
Good	−.143	.812	−.682	.361	.085	.888	−.477	.557	.191	.765
Reasonable	−.194	.741	.740	.270	.689	.300	−.535	.530	−.175	.775
Constant	−3.205	.003	−4.014	.002	−.521	.531	−.674	.554	−1.199	.221

Table 7: McFadden's RhoSq.

	Store category				
	Clothes	**Shoes**	**Department store**	**Health and body**	**Specific**
Significance	.198	.290	.455	.435	.287

examination of more detailed store characteristics. To assess the goodness of fit of the estimated model, McFadden's RhoSq. is used; Table 4.7 present the results.

The table shows that the results of McFaddens RhoSq. is reasonable up to good, so the conclusion can be made that the model fits the data quite well.

4.5. Conclusions and Future Research

In this chapter, behavioral principles regarding pedestrian dynamics that control the interaction with the environment were discussed. In a multi-agent approach for simulating pedestrian activity, it was assumed that agents represent pedestrians moving over a network. The network implies an environment, for instance a street network with establishments in the case of a shopping environment. It was assumed that these agents have their own activity agenda and their own beliefs about organizing their activities in this particular environment. The behavioral principles encompass the mechanism of perception, activation, and completing an activity.

The approach described here is novel in the combination of activity scheduling, destination and route choice, and microscopic movement. It is not the detailed movement itself, but rather the outcomes of such movement in terms of destination and route choice that is the purpose of the modeling process. Estimation results show that the outcomes are interpretable and that the goodness of fit is reasonable.

For simulating pedestrians in a shopping environment, the described behavioral principles together with movement rules will provide a picture of pedestrian movement. Yet, one must be aware that the described approach does not involve the identification of possible influential factors or prediction of possible destinations in a utility maximization process in order to develop econometrically more advanced models of pedestrian choice behavior. Still, this system approach has the power to evaluate the potential influence of a changing retail environment on pedestrian's shopping behavior. Therefore, for a manager or planner, this system approach results in a decision support tool for testing the effects of any design changes on pedestrian behavior before their implementation.

References

Ali, W., & Moulin, B. (2006). How artificial intelligent agents do shopping in a virtual mall: A 'believable' and 'usable' multiagent-based simulation of customers' shopping behaviour in

a mall. In: L. Lamontagne & M. Marchand (Eds), *Canadian AI, LNAI 4013* (pp. 73–85). Berlin: Springer-Verlag.

Benenson, I. (1998). Multi-agent simulations of residential dynamics in the city. *Computers, Environment and Urban Systems*, *22*(1), 25–42.

Bierlaire, M., Antonini, G., & Weber, M. (2003). Behavioral dynamics for pedestrians. In: K. Axhausen (Ed.), *Moving through nets: The physical and social dimensions of travel*. Amsterdam: Elsevier.

Blue, V. J., & Adler, J. L. (1999). Cellular automata microsimulation of bi-directional pedestrian flows. *Journal of the Transportation Research Board*, 135–141.

Blue, V. J., & Adler, J. L. (2000). Cellular automata model of emergent collective bi-directional pedestrian dynamics. In: M. Bedau, J. McCaskill, N. Packard & S. Rasmussen (Eds), *Artificial life VII* (pp. 437–445). Cambridge, MA: MIT Press.

Blue, V. J., & Adler, J. L. (2001). Flow capacities from cellular automata modeling of proportional splits of pedestrians by direction. In: M. Schreckenberg & S. D. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 115–122). Berlin, Heidelberg, New York: Springer-Verlag.

Borgers, A., & Timmermans, H. J. P. (1986a). A model of pedestrian route choice and demand for retail facilities within inner-city shopping areas. *Geographical Analysis*, *18*(2), 115–128.

Borgers, A., & Timmermans, H. J. P. (1986b). City centre entry points, store location patterns and pedestrian route choice behaviour: A micro-level simulation model. *Socio-Economic Planning Sciences*, *20*, 25–30.

Borgers, A. & Timmermans, H. J. P. (2004). Simulating pedestrian route choice behaviour in urban & retail environments. *Proceedings Walk 21*, Copenhagen, June 2004 (CD-rom).

Borgers, A. & Timmermans, H. J. P. (2005). Modeling pedestrian behaviour in downtown shopping areas. *9th Conference on Computers in Urban Planning & Urban Management Conference CUPUM '05*, London, June 2005.

Daamen, W. (2004). *Modelling passenger flows in public transport facilities*. Trail thesis series, Delft University Press, Delft.

Daamen, W., & Hoogendoorn, S. P. (2003). Controlled experiments to derive walking behaviour. *European Journal of Transport and Infrastructure Research*, *3*(1), 39–59.

Dijkstra, J., Jessurun, A. J., & Timmermans, H. J. P. (2002). Simulating pedestrian activity scheduling behaviour and movement patters using a multi-agent cellular automata model. *Proceedings of the Transportation Research Board Conference*, Washington, January 2002.

Dijkstra, J., & Timmermans, H. J. P. (2001). Towards a multi-agent model for visualizing simulated user behavior to support the assessment of design performance. *Automation in Construction*, *11*(2), 135–145.

Dijkstra, J., Timmermans, H. J. P., & Jessurun, A. J. (2001). A multi-agent cellular automata model of pedestrian movement. In: M. Schreckenberg & S. D. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 173–180). Berlin, Heidelberg, New York: Springer-Verlag.

Helbing, D., Farkas, I. J., & Viscek, T. (2000). Simulating dynamical features of escapic panic. *Nature*, *407*, 487–489.

Helbing, D., & Molnar, P. (1997). Self-organization phenomena in pedestrian crowds. In: F. Sweitzer (Ed.), *Self-organization of complex structures: From individual to collective dynamics* (pp. 569–577). London: Gordon and Beach.

Helbing, D., Molnar, P., Farkas, I. J., & Bolay, K. (2001). Self-organizing pedestrian movement. *Environment and Planning B*, *28*, 361–383.

Hoogendoorn, S. P., Bovy, P. H. L., & Daamen, W. (2001). Microscopic pedestrian wayfinding and dynamics modeling. In: M. Schreckenberg & S. D. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 123–154). Berlin: Springer.

Hoogendoorn, S. P. & Daamen, W. (2002). Extracting microscopic pedestrian characteristics from video data. *Proceedings of the Transportation Research Board Conference*, Washington, January 2002.

Kitazawa, K., & Batty, M. (2004). Pedestrian behaviour modelling — An application to retail movements using genetic algorithms. In: J. P. van Leeuwen & H. J. P. Timmermans (Eds), *Developments in design & decision support systems in architecture and urban planning*. Eindhoven: Eindhoven University of Technology.

Kitazawa, K., Tanaka, H., & Shibasaki, R. (2003). A study for agent-based modeling of migration behavior of shoppers. *8th Conference on Computers in Urban Planning & Urban Management Conference CUPUM '03*, Shendai, Japan, May 2003.

Kukla, R., Kerridge, J., Willis, A., & Hine, J. (2001). PEDFLOW: Development of an autonomous agent model of pedestrian flow. *Transportation Research Record*, *1774*, 11–17.

Masuda, H. & Arai, T. (2005). An agent-based model of evacuation in a subway station. *9th Conference on Computers in Urban Planning & Urban Management Conference CUPUM '05*, London, June 2005.

Meyer-König, T., Klüpfel, H., & Schreckenberg, M. (2001). Assessment and analysis of evacuation processes on passenger ships by microscopic simulation. In: M. Schreckenberg & S. D. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 297–302). Berlin: Springer.

Robin, Th., Antonini, G., Bierlaire, M., & Cruz, J. (2009). Specification, estimation and validation of a pedestrian walking behavior model. *Transportation Research Part B*, *43*, 36–56.

Teknomo, K. (2002). *Microscopic pedestrian flow characteristics: Development of an image processing data collection and simulation model*. Ph.D. thesis, Graduate School of Information Sciences, Tohoku, Japan.

Roland, N. & Sterling, L. (2005). Modelling pedestrian behaviour using the BDI architecture. *Proceedings of the 2005 IEEE/WIC/ACM International Conference on Intelligent Agent Technology (IAT'05)*, Compiègne, France, September 2005.

Schelhorn, T., O'Sullivan, D., Hacklay, M., & Thurstain-Goodwin, M. (1999). STREETS: An agent-based pedestrian model. *Computers in Urban Planning and Urban Management*, Venice, July 1999.

Shao, W., & Terzopoulos, D. (2007). Autonomous pedestrians. *Graphic Models*, *69*, 246–274.

Yoshida, T. & Kandea, T. (2007). An architecture and development framework for pedestrians' shop-around behavior model inside commercial district by using agent-based approach. *10th Conference on Computers in Urban Planning & Urban Management Conference CUPUM '07*, Iguassu, Brazil, July 2007 (CD-rom).

Zachariadis, V. (2005). Modelling pedestrian movement and choices from micro to urban scale: Issues, patterns and emergence. *9th Conference on Computers in Urban Planning & Urban Management Conference CUPUM '05*, London, June 2005.

Zhu, W., & Timmermans, H. J. P. (2008). Cut-off models for the 'go-home' decision of pedestrians in shopping streets. *Environment and Planning B: Planning and Design*, *35*(2), 248–260.

Chapter 5

Modeling Pedestrian Movement in Shopping Street Segments

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Abstract

The main purpose of this paper is to test a model that aims at modeling and simulating micro pedestrian behavior in shopping street segments, including entering shops. The model assumes a detailed network of links to represent the structure of street segments and entrances to the shops. The basic principle underlying the model is that a pedestrian chooses a destination when entering a shopping street segment. Destinations may be shops located along the segment or the exit points at the opposite side of the segment. The choice of a destination is modeled by means of a discrete choice model, including variables such as type-specific supply of shops, distances, and tendency to visit a shop. After choosing a destination, the route to that destination is modeled by a discrete choice model as well. However, route choice is modeled at the link level, not at the level of complete routes. A sequence of chosen links constitutes the route to the destination. Relevant variables included in this model are walking distance, and angles between links and the direction of the destination. If the destination is a shop, the destination choice model is applied again to select the next destination. This process is repeated until one of the exit points of the segment is chosen or the pedestrian stays in a shop.

The study area is the main shopping street of Antwerp (Belgium). During a one-week workshop in July 2004, students observed pedestrian movement in this shopping street. An inventory of physical characteristics of the shopping street was made and pedestrians were unobtrusively tracked through two separate segments of the shopping street (approximately 100 m of length each). In total, 335 pedestrians were tracked.

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The choice models were estimated using the tracked routes. Next, the models were used to simulate pedestrians' behavior by consecutively selecting destinations and links to these destinations. The models perform well. Observed and simulated routes were used to determine and compare observed and simulated link loadings. It can be concluded that by using observational data only, relevant models of pedestrian behavior can be developed.

5.1. Introduction

Over the last decades, we have seen two main streams of development in modeling pedestrian behavior in shopping areas. First, the models have become more complex by incorporating individual data regarding schedules of activities to be performed, the motivation of the shopper, the familiarity of the shopper with the shopping environment, etc. Consequently, a lot of data has to be collected by means of questionnaires or interviews (see e.g., Ali & Moulin, 2006). Second, high-tech equipment has become available to collect pedestrian movement data, for example, cameras, RFID, and GPS (e.g., Teknomo, 2002; Tanaka & Shibasaki, 2005; Shoval & Isaacson, 2006). These tools allow tracking pedestrians through a shopping area. However, this kind of data does not include information usually collected by on street interviews or questionnaires, and provides only data about shops visited, trajectory, and possibly some characteristics of the pedestrian that can be observed: gender, age-class, and group composition.

Thus although complex models of pedestrian behavior may take advantage of these technological developments to trace pedestrian movement, additional data will be required. Combining both techniques of data collection might be problematic. Inviting pedestrians to carry equipment to trace their path and participate in an interview after finishing shopping or fill out a questionnaire may affect their decision behavior during the shopping trip. Alternatively, tracing pedestrians by, for example, cameras and inviting them at the end of the trip to provide additional data might raise ethical questions. The purpose of this chapter is not to solve this problem, but to develop and test a model of pedestrian behavior in shopping street segments based on observational data only. By observational data, we mean the path through the shopping street (including entering shops), and some characteristics of the pedestrian such as gender, group composition, and (an estimate of) age.

This chapter is organized as follows. In Section 5.2, the literature relevant to modeling behavior of pedestrians in shopping areas will be briefly reviewed. In Sections 5.3 and 5.4, the collection of the data used in this study will be described and the results of descriptive analyses will be presented. Then, the models will be specified and estimation results will be discussed. This is followed by a description of the simulation results. Finally, the chapter is concluded by a discussion and recommendations for future research.

5.2. Literature

In this section, we will review a number of models that have been proposed to predict or simulate how individual (or small groups of) pedestrians move through shopping areas. Our main interest concerns how these models were conceptualized regarding visiting shops (or performing activities at specific locations) and how people move from one location to another location in the shopping area. First, we will consider models of shopping behavior in entire shopping areas (a shopping center or mall). Next, attention will be paid to some aspects of route choice.

To the authors' knowledge, the model proposed by Borgers and Timmermans (1986) was one of the first models to predict individual routes through a shopping area. They used observed shopping lists to predict shopping behavior. This shopping list consisted of (types of) products to be bought in the shopping area. It was assumed that at the start of the shopping trip (the entry point of the shopping area), the pedestrian would decide where to buy the first item on the list. All shops selling this type of product were considered possible destinations. The decision which shop would be visited was modeled by means of a gravity-type model including the size of the shops and the shortest distance to the shops as explanatory variables. Having visited the first destination, the second item on the shopping list was used to select the second destination, and so on. After finishing the list of products to be bought, the pedestrian was assumed to leave the shopping area where he or she entered the shopping area. The route choice to each destination was assumed to be dependent on the length of the route to the destination. A multinomial logit model was used to predict which route, out of the set of 50 shortest routes between origin and destination, would be chosen. Knowing that a significant proportion of the visited shops were not planned beforehand, a module was included to add unplanned shop visits on the route along the planned shop visits. This was done at the level of links in the network of shopping street segments.

The model proposed by Helbing (1992) is based on the assumption that pedestrians' behavior in a shopping area will be determined mainly by their demand. Pedestrian's destinations will be stores where the required commodities can be acquired. The probability to decide for a certain store as the next destination depends among others on the supply of the store and the distance to the store. The probability to decide for a certain route to the destination depends on distance. When arrived at the chosen destination, the pedestrian may buy a certain commodity. The purchase of a required commodity changes the remaining demand and calls for a decision about the next destination. A pedestrian will leave the shopping area when the demand is satisfied. When moving to a destination, pedestrians may be attracted by other persons or objects, for example, window-displays (Helbing & Molnár, 1995). Such attractions may lead to impulse stops.

According to the AMANDA model (Dijkstra & Timmermans, 1998; Dijkstra, Jessurun, & Timmermans, 2002; Dijkstra, Jessurun, de Vries, & Timmermans, 2006), each pedestrian is supposed to carry out a set of activities (buy something, having lunch, etc.) in the shopping environment. The shopping environment consists of a

network of streets (nodes and links) and establishments (shops, restaurants, etc.). In order to perform activities, pedestrians have to decide which stores to visit, in what order, and which route to take. The activity agenda is time dependent and the need to actually realize activities may differ. When completing an activity, the activity agenda will be updated. At nodes of the network, the pedestrian may decide to change route or to adjust the anticipated duration of visiting the shopping environment. When moving over the network, the exposure to advertising and window-displays may result in unplanned, impulse behavior.

The STREETS model (Schelhorn, O'Sullivan, Haklay, & Thurstain-Goodwin, 1999; Haklay, O'Sullivan, Thurstain-Goodwin, & Schelhorn, 2001) considers pedestrian activity to be the product of the configuration of the street network and the location of particular attractions (shops, offices, public buildings). In STREETS, modeling proceeds in two phases: (1) a ''pre-model'' which uses socioeconomic and other data about the wider metropolitan area to populate the urban center with a statistically valid population of pedestrians, and (2) an agent-based model to simulate the movement of this pedestrian population around the urban district under the influence of spatial configuration, predetermined activity schedules, and the distribution of land-uses. Each pedestrian enters the town center environment with a planned or intended sequence of waypoints along the route up to, and including, their intended destinations. Periodically, the possibility that a building which a pedestrian has seen will distract the pedestrian from the predefined plan is checked. Pedestrians with low fixation may possibly change their original plan.

Although primarily developed for public transport facilities like train stations, the model developed by Daamen (2004) could be used in shopping areas as well. A hierarchical decision structure is assumed. Given a list of ordered activities, the locations where to perform activities are determined at the moment the pedestrian enters the area. These locations will be chosen simultaneously. All possible combinations of activity locations are considered and the minimum cost (shortest travel time) combination will be chosen. A route is defined as a chain of nodes, beginning at the origin, passing, if needed, different activity locations and ending at the pedestrian's destination. Route choice is based on shortest walking time (including necessary waiting and service times). The choice set consists of all feasible routes from the actual node to the destination. At each node, the pedestrian chooses the link of the network with shortest travel time to the destination. The shortest paths may differ between two consecutive time instants, due to changes in density on the links. A more extended version of Daamen's model was developed by Hoogendoorn (2002). Pedestrian schedule their activities, the activity areas, and the paths (continuous in time and space) between the activity locations simultaneously to maximize the utility of their efforts (see also Hoogendoorn & Bovy, 2004).

Borgers and Timmermans (2005) proposed a model to simulate individual pedestrians through shopping areas without assuming some list of activities to be performed. The main assumption underlying their model is that a pedestrian navigates through the shopping area by first moving away from the entry point and later moving back to this point and leave the shopping area. At each link in the network, the pedestrian decides about the next link that can be chosen. This choice is

driven by the history of the route up to the current location of the pedestrian, the attraction of retail and other facilities available in the shopping area, characteristics of the links, and the distance from the current position to the exit point. This model does not simulate visiting shops (see also Kemperman, Borgers, & Timmermans, 2009).

Ali and Moulin (2006) developed a model to simulate shopping behavior in a mall. They generate a list of stores or kiosks to be visited by a pedestrian on the basis of his or her characteristics. During the shopping trip, the pedestrian makes decisions about the next store or kiosk to be visited. When moving to a chosen destination, the pedestrian may perceive another store or kiosk that is on the shopping list as well. Then he or she will move to this new destination and memorize its location. After completing the shopping list, the pedestrian may start exploring the shopping mall for unknown stores and kiosks (if there is time). A pedestrian may also explore the mall without a shopping list at all. In that case, the pedestrian follows his or her preferred path in the mall, based on habits and preferences. If, during the shopping trip, a pedestrian feels the need to eat or to go to the restroom, corresponding destinations will be visited.

The model by Zhu (2008) contains four mayor decisions: the go-home decision, direction choice, the rest decision, and shopping patronage. The go-home decision represents the decision to end the shopping trip. This is modeled by means of time variables. If the pedestrian decides not to go home, the pedestrian has to choose a direction to continue the shopping trip. The chosen direction determines the activity space of the pedestrian. Only shops in the activity space can be visited. Factors influencing this choice are retail attractiveness, whether the direction will be the same as the previous direction, and length of pedestrianized street in the chosen direction. The decision to take a rest depends on time variables. If the decision is not to rest, the pedestrian will look for a shop to visit. A sequential satisfying framework is adopted: the pedestrian judges stores one by one whether it is satisfactory based on attractiveness and uniqueness.

Many pedestrian route choice or movement models have been proposed. Most of these models try to describe how pedestrians move through a street segment or corridor at a very detailed level, taking interactions between pedestrians into account. For example, the model by Hoogendoorn and Bovy (2004) predicts routes as continuous trajectories in time and space and the PEDFLOW model by Kukla, Kerridge, Willis, and Hine (2001) and Kerridge, Hine, and Wigan (2001) uses a two-dimensional grid to represent the environment and pedestrian movement. However, modeling pedestrian movement at this microscopic level is out of the scope of this chapter. We will only summarize some findings that might be of interest in the case of modeling pedestrian movement at a less detailed level.

Helbing, Molnár, Farkas, and Bolay (2001) observed from video films that pedestrians show a strong aversion to taking detours. Pedestrians normally choose the fastest route to their destination. If alternative routes are of the same length, a pedestrian prefers the one where he or she can go straight ahead for as long as possible and change direction as late as possible, provided that other routes are not more attractive. Daamen (2004) and Hoogendoorn and Bovy (2004) summarize

distance, time, pleasantness, directness, crowdedness, number of crossings, pollution and noise levels, safety and shelter from poor weather conditions, and quality of the walking surface as relevant variables.

Of interest is the model specified by Antonini, Bierlaire, and Weber (2006). Their model focuses on micro behavior of pedestrians. They assume that the destination of a pedestrian is known. To predict the next step of a pedestrian, the space in front of a pedestrian (170°) is split up in 11 radial cones. The center cone is in line with the current walking direction of the pedestrian. One of the explanatory variables to predict an alternative cone will be chosen is defined as the angle between the center cone (the current walking direction) and the alternative cone. It is expected that pedestrians have a propensity to keep walking in the current direction. Another variable measures the angle between the direction of the destination and the direction of the alternative cone. This variable captures the propensity to walk in the direction of the destination. The model is extended by Robin, Antonini, Bierlaire, and Cruz (2009), who added (among other things) the distance to the destination as an explanatory variable.

5.3. Data Collection

During a one-week workshop in July 2004, six students collected data in the main shopping street of Antwerp, Belgium. The students made an inventory of the physical characteristics of the street and the buildings along the street, counted the number of pedestrians passing screen lines, and tracked pedestrians. The data regarding the tracking of pedestrians is used in this study. To track the pedestrians, the main shopping street, called "De Meir," was divided into seven segments. Two segments (see Figure 5.1) were selected to track the pedestrians. Although the number and functions may be different from those described by Ciolek (1978), zones can be distinguished in the shopping street segments (see Figure 5.2). First of all, there are walking zones along the shops. These zones can be used to walk from east to west and vice versa. Of course, these are also the zones for window-display and entering shops. In addition to the northern and southern zones, a zone in the center of the street provides another opportunity to walk from one side to the other side of the street segment. This zone also allows bicyclists. In between the center zone and the northern/southern zones, narrow intermediate zones provide space for street furniture, streetlamps, advertising columns, litterbins, and some trees. Also a number of small cubes is placed in the intermediate zones to separate the center zone from the zones along the shops. Still enough space is available to transfer walking zones via the intermediate zones.

The length of the two segments is approximately 120 and 100 m for segments A and B respectively. In segment A, 13 shops are located, mainly offering fashion products (10 × clothing, 1 × shoes, 2 × take away). In segment B, 14 shops offer a more divers supply (7 × clothing, 2 × shoes, 2 small department stores, 1 × books, 2 × electronics). Segments A and B are not connected to each other.

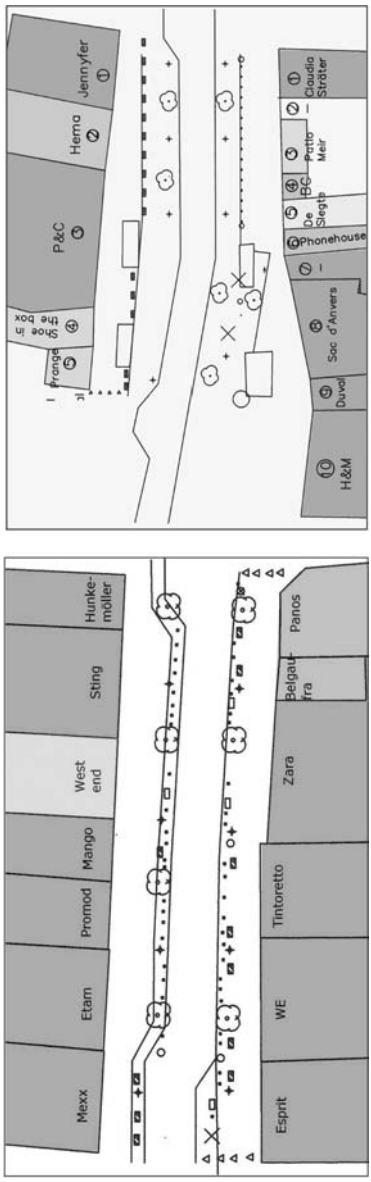


Figure 5.1: Selected segments of "De Meir," segment A (left) and segment B (right).

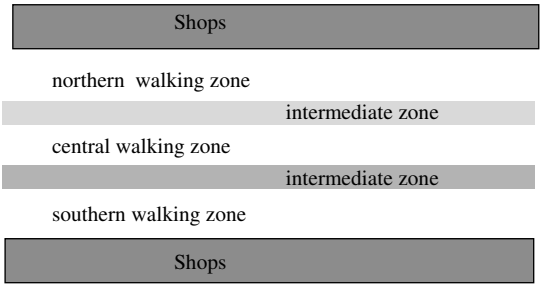


Figure 5.2: Structure of the street segment: walking zones and intermediate zones.

To observe the pedestrians, a student was assigned to each walking zone in both segments. Upon start of an observation period, each student had to randomly select a pedestrian (or group of pedestrians) entering the segment in his/her zone and trace the route and activities of the pedestrian. While tracking pedestrians, actions like walking, changing walking direction, transferring to another zone, window-shopping, entering a shop, making a conversation, sitting down, etc. were registered. The route of each pedestrian through the segment was drawn on a map. As it is virtually impossible to track the footprints of a pedestrian without technical equipment, the path of a pedestrian was registered at a semi-micro-level (say within a few meters accuracy), taking into consideration the main walking zones, and the location and direction of transferring into other zones or shops. Because the pedestrian density levels during observations were relatively low, effects of crowding may be assumed absent. Therefore, a somewhat less detailed registration of pedestrian movement may be justified. Tracking of a pedestrian ceased when the pedestrian reached one of the terminal points of the street segment. A new pedestrian to be tracked was randomly selected from the pedestrians entering the segment at this point. In case a pedestrian visited a shop for more than 5 min, the first person leaving the shop after 5 min was selected as the next person to be tracked. According to this observation scheme, the number of pedestrians entering and leaving each side of the segments and the number of pedestrians staying and starting in shops should roughly be balanced. Note that this observation scheme does not necessarily yield a representative set of routes through the segments.

Pedestrians were tracked on a Thursday during two time intervals: from 11.15 a.m. to 12.20 p.m. and from 13.45 p.m. to 15.55 p.m. Consequently, people strolling around in the shopping area during their lunch break were excluded from the observations. At the time of data collection, weather conditions were fine. In total, 335 pedestrians were tracked (178 pedestrians in segment A and 157 in segment B). Care was taken that pedestrians did not notice they were being observed. By taking strategic positions, the students were able to examine the entire segment. According to the observers, no pedestrians noticed being observed. Only a small number of pedestrians were lost while being observed.

Figure 5.3 shows some examples of tracked routes. Note that entering a shop and window-shopping were registered separately. However, in this analysis we treat both

as visiting a shop. Apart from moving through the segments and visiting shops, the other activities were hardly observed and will be paid no further attention to in this chapter.

Pedestrians' Characteristics

The number of pedestrians observed in both segments in the morning and afternoon period is displayed in Table 5.1. As the observation period in the afternoon lasted longer than in the morning, the number of pedestrians observed in the morning is considerable lower than in the afternoon. Surprisingly, however, in the morning the number of observations in segment B is somewhat higher than in segment A, while in the afternoon, this pattern is reversed. Altogether, according to a χ^2-test, the variables are independent at the 5% significance level. Also striking is that the number of males (or male groups) observed in segment B is much lower than in segment A, while the females (or female groups) and the mixed groups are evenly distributed across both segments (Table 5.2). However, these variables are independent as well.

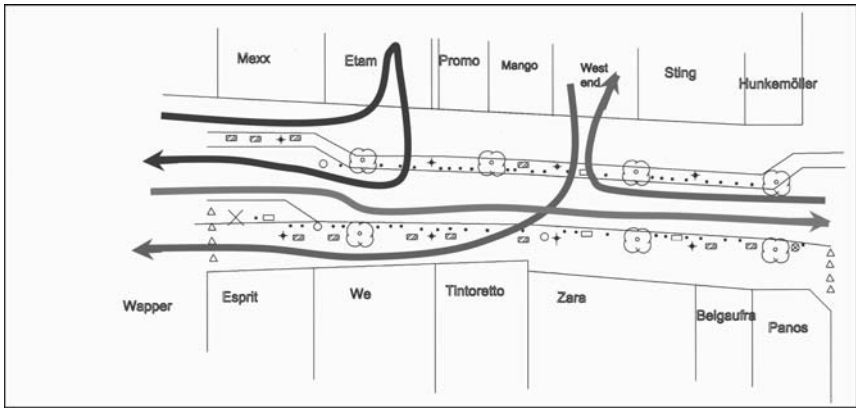


Figure 5.3: Some examples of tracked routes.

Table 5.1: Number of observations per segment and time of day[a].

	Morning	**Afternoon**	**Total**
Segment A	55	123	178
Segment B	61	96	157
Total	116	219	335

[a]Statistically independent.

Table 5.2: Number of observations per segment and type of group[a].

	Male(s) only	Female(s) only	Male(s) and female(s)	Total
Segment A	52	89	37	178
Segment B	31	87	39	157
Total	83	176	76	335

[a]Statistically independent.

Table 5.3: Gender and group composition.

	No.	%		No.
Male(s)	83	25	1 Male	63
			>1 Male	20
Female(s)	176	52	1 Female	86
			>1 Female	90
Male(s) and Female(s)	76	23	1 Male and 1 female	60
			Otherwise	16
Total	335	100		335

Approximately half of the observations concerns females or groups consisting of females (Table 5.3). A quarter of the observations concerns male groups and also a quarter concerns mixed groups. Most male groups consist just of one male. In case of the mixed groups, most consist of couples: one male and one female. Overall, individual females and females in small groups constitute the largest set of observed units. In addition to gender and group composition, the age-class of each tracked pedestrian was estimated. Three age-classes were used; however, by far most tracked pedestrians were estimated to be in the middle age class.

5.4. Descriptive Analyses

The observed routes were drawn on maps of the street segments. Often, a raster of cells is used to model pedestrian movement at a detailed level. Especially if the aim is to model pedestrian behavior at the micro level, a cell-based system might be very suitable to predict the position of each step of the pedestrian. Alternatively, polygon-based systems may be used as well. The purpose of this study, however, is not to model pedestrian movement at this level of detail, because observations were registered less precisely. Therefore, we superimposed a network of links on the map of each segment, taking into consideration the spatial structure of the segment, entries of shops, and position of street furniture and other objects. Entry- and exit

locations of each segment (termini) and shops were represented by links as well. Each observed route was represented by a sequence of connected links in the network.

As noted before, both exploring a shop windows and entering a shop are considered as "visiting a shop." On average, the ratio "window-shopping" and "entering a shop" is approximately 1:2. Furthermore, it should be noted that only occasionally a person entered a shop immediately after having observed the window of that shop. This was observed approximately once out of 10 times a shop was entered. In these cases, observing the window and entering the shop was considered as one shop visit.

A terminus is defined as an entry or exit of each walking zone. Of all tracked pedestrians, 64% entered and left the segment at a terminus (see Table 5.4). Only 4% of the routes start and end at a shop. There are differences between the two segments. Shops in segment A seem to attract fewer pedestrians than shops in segment B. This is confirmed by the mean number of shops visited by the pedestrians. Overall, the mean number of shops visited is 0.74 shops per tracked pedestrian. In segment A, the mean is less (0.65) than in segment B (0.83). This may be due to the types of shops available in the segments.

Table 5.5 provides information about the starting position and visiting shops. It shows that pedestrian entering the segments in the northern or southern walking zone, have a higher propensity to visit a shop compared to pedestrians starting in the center zone. Also the mean number of shops visited per pedestrian is higher for pedestrians starting in the northern or southern zone. The reason may be twofold: (1) pedestrians choosing the center segment may be less interested in shops at that

Table 5.4: Start and finish of observed routes (in %).

	Segment A ($N = 178$)		**Segment B ($N = 157$)**		**Both segments ($N = 335$)**	
Finish	**Terminus**	**Shop**	**Terminus**	**Shop**	**Terminus**	**Shop**
Start						
Terminus	69	15	57	21	64	18
Shop	12	4	19	3	15	4

Table 5.5: Visiting shops by starting position.

Starting position	***N***	**Shop visited (%)**		**Mean number of shops visited**
		No	**Yes**	
Terminus north	87	48	52	0.70
Terminus center	104	76	24	0.31
Terminus south	81	48	52	0.69
Shop	63	0	100	1.56
Overall	335	48	52	0.74

moment, they just want to traverse from one side to the other side of the segment; (2) pedestrians walking in the center zone are less attracted by the shops in the segment. By definition, pedestrians starting in a shop have visited at least one shop. However, only 25 of them (40%) visited another shop. The pedestrians starting in the center zone have to transfer to the northern or southern zone if they want to visit a shop. In contrast, the other pedestrians do not have to transfer walking zones to visit a shop. Considering the pedestrians starting in the northern or southern zone visiting a shop and the pedestrians starting in a shop and visiting another shop, only 24% of the 112 pedestrians changed walking zone. This means that most pedestrian visiting shops keep their zone while walking through the segment. A strategy may be to first walk through the entire shopping street along the shops on one side and walk back along the shops on the other side. Of course, we cannot verify this from our data.

Table 5.6 lists the typical routes that were observed. In total, 124 pedestrians move directly from a terminus to the opposite terminus without visiting a shop or changing zone (see pattern 1 and pattern 2 in Figure 5.4). So, 37% of the pedestrians just move straight through the segment. In addition, 27 pedestrians (8%) walk to the opposite

Table 5.6: Typical walking patterns.

Pattern	Description	No.	%
1	From N/S-terminus to opposite side (*no change of zone*)	67	20
2	From center-terminus to opposite side (*no change of zone*)	57	17
3	From shop to exit-terminus in same zone	32	10
4	From N/S-terminus to shop in same zone	28	8
5	From N/S-terminus to center-terminus on opposite side (or vv)	27	8
6	From N/S-terminus to opposite side via shop in same zone	21	6
7	From center-terminus to shop on north or south side	11	3

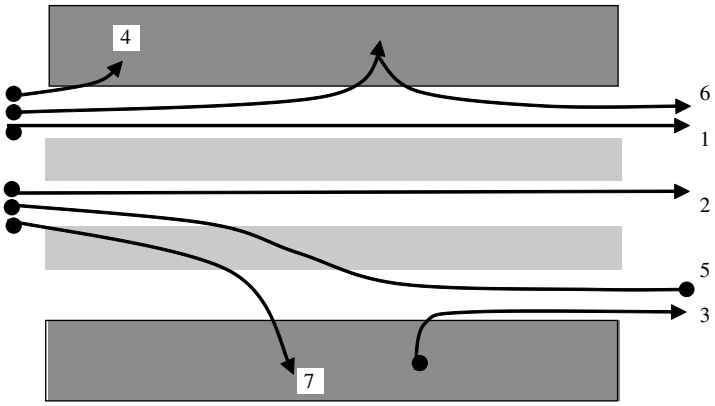


Figure 5.4: Typical routes.

side without visiting a shop, but changing from northern/southern zone to the center zone or vice versa (pattern 5). Patterns 3 and 4 represent simple routes from pedestrians leaving a shop walking to a terminus in the same zone or pedestrians entering the segment at a terminus and visiting a shop in the same zone. Note that these latter pedestrians stay in the shop for more than 5 min. The pedestrians walking according to pattern 6 also visit a shop, but do not stay there. Pattern 7 represents 11 routes starting from a center terminus and ending in a shop.

Note that routes presented in Table 5.6 and Figure 5.4 represent typical patterns; other origin and destination termini and shop positions may be applicable. These typical routes represent 72% of all observed routes. The remaining types of routes occur less than 10 times or are even unique. As shown, most pedestrians leave the segment at the opposite site, but after visiting a shop, pedestrians may decide to walk back to the side of the segment where they entered the segment. Note that returning to the entry side without visiting a shop rarely happens.

The number of shops visited by the pedestrians is 247, including the shops where tracking of a number of pedestrians started. As the supply mainly consists of shops selling cloths and shoes, 80% of all shops visits concern these fashion shops. About 14% of the visits concern department stores and the remaining 6% other shops. The mean number of shops visited depends on gender and group composition. It appeared that individual females or groups consisting solely of females visit on average 0.98 shops, while individual males or groups of males or mixed groups on average visit 0.47 shops. This difference is very significant. Differences within each of these two clusters (one person vs. more persons) did not appear to be significant. No significant differences could be found between the number of shops visited in the morning period versus the afternoon period.

Important conclusions that can be drawn from the descriptive analyses are: (1) many pedestrians use rather simple routes, resulting in a small number of frequently used types of routes, (2) transferring walking zones via the intermediate zones seems to be unusual, (3) shops are mainly visited in the zone where a pedestrian walks, (4) female pedestrians or groups of female pedestrians have a higher propensity to visit shops than male pedestrians or other group compositions, and (5) leaving a segment at the entry side without visiting a shop is very exceptional.

5.5. Model Specification and Estimation

From the literature review, it can be concluded that most models of pedestrian movement in shopping areas assume that each pedestrian uses a predefined schedule of activities to be conducted during the shopping trip. While walking to a destination (e.g., a shop), a pedestrian may be attracted by a shop or window-display. This may lead to impulse stops or adaptations to the schedule. However, as described before, we unobtrusively observed pedestrians in shopping street segments, implying that we have no information about schedules and whether shop visits were planned or unplanned. Furthermore, pedestrian movement was recorded by drawing the path

followed on a map, implying that modeling of pedestrian movement at a very detailed level is beyond the scope of this contribution.

5.5.1. Destination Choice

It is assumed that at each terminus or shop, a pedestrian decides about his/her destination. The set of destinations that can be chosen consists of all shops and termini in the street segment. However, if the starting position is a terminus, the termini on the starting side of the segment will be excluded from the set of destinations at the start of the trip through the segment. Similarly, if a pedestrian's route starts at a shop, this shop will be excluded from the choice set when choosing the first destination. In other cases when a pedestrian is in a shop, he or she may decide to stay longer than 5 min in that shop. In fact, staying longer than 5 min terminates the trip for this person (because tracking ceased when pedestrians stayed more than 5 min in a shop).

Thus, if the starting position is a terminus, the pedestrian is assumed to choose a destination from all shops in the segment and the termini on the other side of the segment. If the chosen destination is a terminus, the pedestrian will leave the segment at that terminus. If the chosen destination is a shop, the pedestrian will go to that shop, and then, the pedestrian has to choose between staying in that shop for more than 5 min (which ends the trip), or going to one of the other shops in the segment or going to one of the termini. After visiting a shop, also the termini at the starting side of the segment can be chosen. In that case, the pedestrian returns to the starting side of the segment.

If the starting position is a shop, the pedestrian chooses one of the other shops in the segment or one of the termini. Note that the termini on both sides can be chosen. If a terminus is chosen, the pedestrian will leave the segment there. If another shop is chosen, the pedestrian will go there and then has to choose between staying there or going to another shop or going to a terminus. Anyway, each shopping trip ends at a terminus or in a shop.

We assume pedestrians choose one alternative destination at a time. Therefore, discrete choice models are suitable models. The conventional multinomial logit model is used (see e.g., Ben-Akiva & Lerman, 1985). This model is defined as:

$$p_{ij} = \frac{\exp(V_{ij})}{\sum_{j'} \exp(V_{ij'})}$$

where p_{ij} is the probability that pedestrian i chooses alternative j from the set of alternatives that can be chosen; V_{ij} the structural utility of alternative j for pedestrian i.

To model destination choice behavior, the following variables may be of interest. Note that all termini and shops are represented by links of the network.

$Dist_{ld}$: The distance in meters from the current link l to destination d. The effect of distance is expected to be negative, but the effect of distance to shops may differ from

the effect to termini. Distances are calculated from the center of link l to the center of link d according to the shortest route between both links.

$Supply_{dt}$: The supply of shop d of type t. This variable may be used to explain the power of shops to attract pedestrians. Six types of shops have been distinguished (1: clothing, 2: shoes, 3: department store, 4: take away, 5: books, 6: electronics). Note that a shop belongs to only one type. $Supply_{dt}$ measures the shop's floor space (in m^2).

$Zone_{ld}$: Three zones can be distinguished in each street segment: a northern, center and southern zone. It is assumed that shops and termini in the current zone are preferred over shops and termini in other zones. If the origin link (l) and destination link (d) are located in the same zone (N–N, M–M, or S–S), the score of $Zone_{ld}$ is 1; if l and d are located in opposite zones (N–S, S–N), the score is equal to -1; in the case l and d are in adjacent zones (N–M, M–N, S–M, M–S), the score is 0.

$Visited_{ld}$: A shop may be less likely to be visited more than once. $Visited_{ld}$ is 1 if d is a shop which has been visited at one of the links traversed before the current link l, 0 otherwise.

$Passed_{ld}$: Shops that have been passed while walking through the street segment may be less attractive to the pedestrian than shops that not have been passed. This variable is 1 if d is a shop which has been passed on one of the links traversed before the current link l, 0 otherwise. The system keeps track of the east–west range that has been traversed. All shops located within this range will score 1.

$PassedClosely_{ld}$: In addition to $Passed_{ld}$, a shop may even be more unattractive to be visited if the pedestrian walked along (or visited) the shop before. $PassedClosely_{ld}$ is 1 if d is a shop which has been "closely" passed on one of the previous links, 0 otherwise. In fact, only if $Passed_{ld} = 1$ and d is equal or adjacent to one of the traversed links, $PassedClosely_{ld}$ is equal to 1.

$Nshops_l$: Is the number of shops that has been visited until the decision moment. Both the tendency to visit a shop or stay in a shop may be influenced by the number of shops visited before during the shopping trip.

$Term1_d$, $Term2_d$, and $Term3_d$: Termini are located east or west. If the pedestrian entered the segment at a terminus, it may be expected that the pedestrian prefers the termini on the other side of the segment. $Term1_d$ scores 1 if d is a terminus on the other side of the segment, 0 otherwise. However, after visiting a shop, a pedestrian may walk back to the side of the segment where he/she entered the segment. If the pedestrian started at a terminus and visited at least one shop, $Term2_d$ will be equal to 1 for the termini at the starting side of the segment, and 0 for the other termini. If the tracking of a pedestrian started when the pedestrian left a shop, there is no expectation about the termini the pedestrian may choose. In this case $Term3_d$ will score 1 for all termini.

$Gender_i$: Personal characteristics may affect pedestrian behavior. Based on the descriptive analyses, only gender in combination with group composition is taken into consideration. If pedestrian i is a female or member of a group of females, $Gender_i = 1$, otherwise, $Gender_i = -1$.

The utility of each destination is estimated by assuming a weighted summation of attribute scores. Choice alternatives are shops, termini and "stay-in-shop" if

applicable. Limdep (Greene, 2007) was used to estimate the destination choice model. Various model specifications were tested. The best model is described below. The estimated parameters are reported in Table 5.7.

$$\begin{aligned} V_{ild} = {} & \theta_0 + \theta_{\text{gender}}\text{Gender}_i + \alpha\text{Dist}_{ld} + \psi_{\text{shop}}\text{Zone}_{ld} \\ & + \beta_{\text{fashion}}\sqrt{\text{Supply}_{d,\text{fashion}}} + \beta_{\text{fashion}|PC}\sqrt{\text{Supply}_{d,\text{fashion}}} \times \text{PassedClosely}_{ld} \\ & + \beta_{\text{deptstore}}\sqrt{\text{Supply}_{d,\text{deptstore}}} + \beta_{\text{deptstore}|G}\sqrt{\text{Supply}_{d,\text{deptstore}}} \times \text{Gender}_i \\ & + \beta_{\text{other}}\text{Dummy}_{d,\text{other}} + \beta_{\text{other}|G}\text{Dummy}_{d,\text{other}} \times \text{Gender}_i; \text{if } d \text{ is a shop} \end{aligned}$$

$$V_{ild} = \tau\ \text{Gender}_i;\ \text{if } l = d \text{ is a shop}$$

$$\begin{aligned} V_{ild} = {} & \delta_1\text{Dist}_{ld} \times \text{Term}_{1d} + \delta_2\text{Dist}_{ld} \times \text{Term}_{2d} + \delta_3\text{Dist}_{ld} \times \text{Term}_{3d} \\ & + \psi_{\text{terminus}}\text{Zone}_{ld} + \omega\text{Wapper}; \text{if } d \text{ is a terminus} \end{aligned}$$

The overall utility of visiting a shop is negative ($\theta_0 = -2.54$), meaning that pedestrians have a low tendency to visit a shop. This corresponds to the findings of the descriptive analyses. However, this tendency represents the mean tendency of visiting a shop. If we take into consideration gender, the tendency increases to $(-2.54 + 0.75) = -1.79$ if the tracked pedestrian is a female or member of a group

Table 5.7: Parameters of destination choice model.

Parameter	**Variable**	**Value**	$P(\lvert Z\rvert > z)$
θ_0	Tendency to visit a shop	−2.5425	0.000
θ_{gender}	Tendency to visit a shop by *Gender*	0.7463	0.000
α	Distance to shop	−0.0186	0.000
ψ_{shop}	Shop by *Zone*	0.9950	0.000
β_{fashion}	$\sqrt{}$floor-space fashion shops	0.0174	0.000
$\beta_{\text{fashion}\|PC}$	$\sqrt{}$floor-space fashion shops by *PassedClosely*	−0.1397	0.057
$\beta_{\text{dept store}}$	$\sqrt{}$floor-space department store	0.0315	0.000
$\beta_{\text{dept store}\|G}$	$\sqrt{}$floor-space department store by *Gender*	−0.0180	0.024
β_{other}	Dummy 'other shop'	−0.6493	0.045
$\beta_{\text{other}\|G}$	Dummy "other shop" by *Gender*	−0.9017	0.003
τ	Gender-specific dummy 'stay in shop'	0.4432	0.023
δ_1	Distance to terminus by $Term_1$	−0.0193	0.000
δ_2	Distance to terminus by $Term_2$	−0.0824	0.000
δ_3	Distance to terminus by $Term_3$	−0.0339	0.000
ψ_{terminus}	Terminus by *Zone*	1.4862	0.000
ω	Wapper	−0.3992	0.125

LL(equal probabilities) = −1491.29; LL(estimated model) = −998.36; $\rho^2 = 0.331$

of females and the tendency decreases to even (-2.54–0.75) $= -3.29$ in the case of males or mixed groups. Nearby shops are preferred by pedestrians as indicated by a negative distance parameter. Although this distance effect is significant, it should be noted that the maximum distance to a shop is about 100 m, resulting in an effect of approximately -0.18. This is still much lower than the effect of the zone in which the pedestrian is located when choosing a destination. If, for example, the pedestrian is in the northern zone of the segment, shops located in the same zone have a much higher utility ($+1.0$) than shops located in the opposite (southern) zone (-1.0).

The relative small number of shops of types 2–5 appeared to hinder the estimation of type-specific supply-variables. Therefore, clothing and shoe shops were merged into *fashion* shops and all other shops (except department stores) were merged into *other* shops. In addition, due to a lack of variance in size of these other shops, floor space was replaced by a dummy. For the fashion shops and department stores, the square root of floor space appeared to perform better than floor space in m^2. Supply of fashion shops has a positive effect, however, this effect of a fashion shop decreases substantially if the pedestrian walked along or visited the shop. Department stores have a positive effect as well, but this effect should be differentiated for males and females. Females seem to appreciate department stores less than males. Other shops seem to be unattractive in general. However, for males, the effect is still positive ($-0.65 + 0.90 = 0.25$). Note that one of these shops sells mobile phones, which seems to be of interest for male pedestrians.

If a pedestrian chooses a shop as destination, the next decision to be made is which destination will be chosen next. However, as explained before, the pedestrian may decide to stay longer than 5 min in the shop. The utility of staying in a shop was expected to be dependent on variables like the type of shop, the size of the shop, and the number of shops visited before, Unfortunately, no significant effect were found. Only gender seemed to be of importance: females showed a higher tendency to stay in a shop ($+0.44$) than males or mixed groups (-0.44).

If a pedestrian entered the segment at a terminus, only the opposite termini can be chosen. In that case, the effect of distance to a terminus (-0.0193) is not very different from the effect of distance to a shop (-0.0186). However, if the pedestrian decides to visit a shop, the termini at the starting side of the segment may be chosen as a destination when leaving the shop. The effect of distance to these termini is equal to -0.0824, which is considerably more negative than the effect to the termini on the opposite side of the segment, meaning that there is a tendency to keep walking away from the starting side of the segment. If the tracking of a pedestrian started at a shop, we do not know where the pedestrian entered the segment. The pedestrian can choose any terminus. The estimated effect of distance is in between the previous distance effects, which might be expected. Just like in the case of shops, the effect of being in the same zone is much more important than the effect of distance. Now, if the pedestrian is for example in the northern zone, the termini in the northern zone are much more attractive ($+1.49$) than in the termini in the center zone (0.0) or in the southern zone (-1.49). Finally, a specific effect was found for the two adjacent termini in the southwest of segment A. The link heading southward is called "Wapper". Because two links in fact represent one exit point, the utility of both decreases by 0.4.

Overall, the destination choice model performs well. Estimated parameters are as expected and a ρ^2 of 0.33 can be considered as satisfactory.

5.5.2. Route Choice

If the origin and destination of a pedestrian is known, the route from the origin to the destination has to be predicted. To model route choice, an alternative to the conventional route choice models will be applied. In this study, we assume a link-to-link decision-making process. The pedestrian is located at the origin link. From this location, he or she will choose one of the adjacent links to proceed his/her way to the destination. If the next link has been chosen, the pedestrian moves to this link and the process is repeated until the pedestrian reaches a link that is adjacent to the destination link. It is assumed that from this link, the destination link will be chosen by definition. This sequence of links constitutes the route to the destination. It is assumed that when going from an origin to a destination, a pedestrian never makes a return-movement in a link. Only the links connected to the end-node of the current link can be chosen. This assumption is based on the observation that pedestrians almost never make return-movements. To predict which link will be chosen from the set of adjacent links, the multinomial logit model is used again.

Three variables are used to model link choice behavior. Two of them measure angles, as proposed by Antonini et al. (2006), while the third variable is related to distances.

$Angle_{la}$: Pedestrians may have a tendency to walk straightforward. This variable measures the angle (in degrees) between the current link l and the alternative link a under consideration, see Figure 5.5. If $Angle_{la}$ is equal to zero, the alternative link is perfectly in line with the current link. If the current and alternative links are at right angles to one another, $Angle_{la}$ increases to 90°.

$Angle_{a,ld}$: The ideal path to the destination link would be a straight line from the end-node of the current link l to the nearest node of the destination link d. The angle between this ideal line and the alternative link a is measured by $Angle_{a,ld}$ (see Figure 5.5). Again, it is assumed that a small angle is preferred over a large angle.

$Dist_{lad}$: Is the shortest distance from the current link l to the destination link d via the alternative link a.

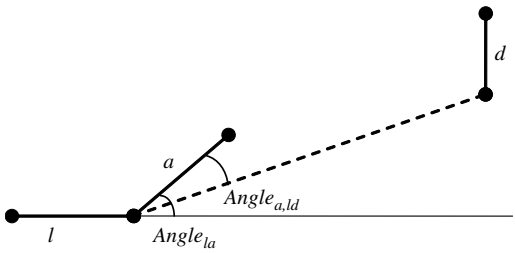


Figure 5.5: Definition of angles.

Table 5.8: Parameters of link choice model.

Parameter	Variable	Value	$P(\|Z\| > z)$
ψ_1	$\sqrt{\text{Angle between link } l \text{ and link } a}$	−0.2597	0.000
ψ_2	$\sqrt{\text{Angle between link } a \text{ and the ideal line } ld}$	−0.3452	0.000
λ	Distance via a to d	−0.1248	0.000
LL(equal probabilities) = −2700.45; LL(estimated model) = −388.44; $\rho^2 = 0.856$			

Other variables like safety, shelter from bad weather conditions, and crowding are assumed to be irrelevant or invariant across choice alternatives in this study. Again, Limdep is used to estimate the parameters of various MNL model specifications. The results of the best model are shown in Table 5.8. The utility of alternative link a to go from current link l to destination link d is defined as:

$$V_{lad} = \gamma_1 \sqrt{\text{Angle}_{la}} + \gamma_2 \sqrt{\text{Angle}_{a,ld}} + \lambda \text{Dist}_{lad}$$

The parameters for both angles are negative, as expected. The magnitude of the parameter for the angle of the alternative link with the ideal line between the current link and the destination link is larger than for the other angle, meaning that the former angle is more important. The distance-parameter is negative as well, also as expected. Combining these results, it can be concluded that pedestrians have a tendency to walk in straight lines as much as possible to their destination. Judging by the ρ^2-value, the model performs extremely well.

5.6. Simulation

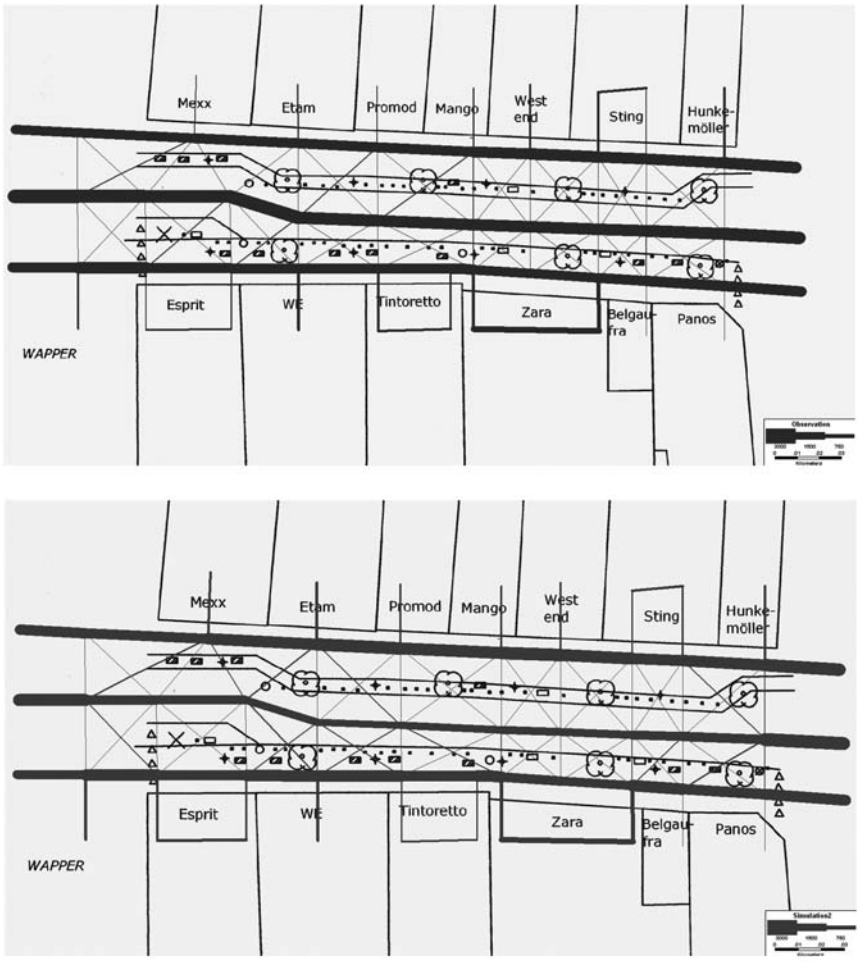
To test whether the estimated models are able to reproduce observed pedestrian movement in the two segments, the models are used to simulate routes for each tracked pedestrian. The simulation of a pedestrian starts at the link where tracking started. Thus, the first link of the simulated route is equal to the first link of the observed route. Given this starting position and the pedestrian's gender and group composition, the probability that a destination will be chosen from the set of shops and termini is calculated according to the destination choice model. Using Monte Carlo simulation, a specific destination is selected. That is, the probabilities for the alternative destinations are cumulated and a random number is drawn from a uniform distribution. The first alternative for which the cumulated probability is greater than or equal to the random number will be selected. If the selected destination is a terminus, the pedestrian will leave the segment at that destination. If the selected destination is a shop, the destination choice model is used again to select the next destination or the option to stay more than 5 min in the

current shop. If the selected alternative is to stay in the shop, simulation ceases at the current shop, otherwise the pedestrian will go to the next destination. As long as the pedestrian is simulated to choose a shop, the destination choice model is used to determine the next destination. Each time a destination is selected, the route of the pedestrian to the destination is simulated. A sequence of links is selected by using the link choice model. Just as in the case of estimating the link choice model, the pedestrian is assumed to select the destination when he or she has reached a link that is connected to the destination link. The simulation of a route for each pedestrian is repeated 50 times. Table 5.9 presents some summarizing statistics. Observed and simulated link loadings are shown in Figure 5.6.

Overall, the models seem to reproduce observed pedestrian movement very well. The mean absolute difference between observed and simulated link loading is only 3.5 pedestrians in segment A and 2 pedestrians in segment B. The correlation between observed and predicted link loadings is very high in both segments. The mean length of simulated routes differs only a few meters from the mean length of observed routes. Movement in east–west direction in the northern, center, and southern zone accounts for approximately three quarters of the total observed transitions from link to link. In the northern and southern zones, the share of simulated east–west transitions is reproduced by the simulations very well. However, in the case of the center zone, transitions are underpredicted, especially in segment A. Inspection of Figure 5.6 reveals that the number of simulated pedestrians in the

Table 5.9: Performance of simulation (50 runs per pedestrian).

	Segment A		**Segment B**	
Mean absolute difference between observed and simulated link loadings	3.5		2.0	
Correlation between observed and simulated link loadings	0.962		0.988	
	Observed	**Simulated**	**Observed**	**Simulated**
Mean length of routes	110	111	90	93
East–west transitions in northern zone (%)	21.8	22.8	22.2	22.5
East–west transitions in center zone (%)	29.7	19.8	20.8	18.6
East–west transitions in southern zone (%)	25.6	25.9	31.4	30.1
East–west transitions in N, C, S zone (%)	77.1	68.5	74.4	71.2
Number of visits to fashion shops	5550	6284	4350	4248
Number of visits to department stores			1750	1657
Number of visits to other shops	250	256	450	429



(a)

Figure 5.6: (a) Observed (top) and simulated (bottom) link loading segment A. (b) Observed (top) and simulated (bottom) link loading segment B.

center of the center zone of segment A is considerably less than the number of observed pedestrians.

As for visiting shops, shop visits in segment A are overpredicted and underpredicted in segment B. As described in the descriptive analyses, the number of shop visits per tracked pedestrian in segment A (0.65) is lower than that in segment B (0.83). The tendency (θ_0) to visit a shop was not differentiated across segments in the model. This may cause the observed over- and underprediction.

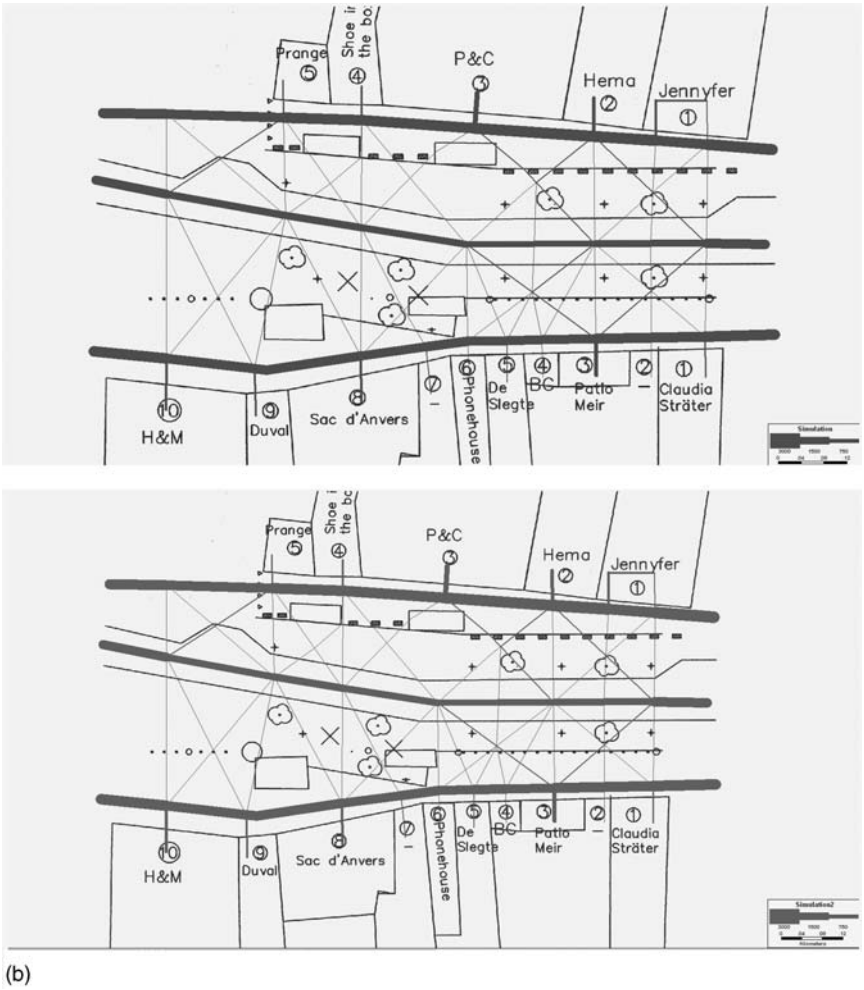


Figure 5.6: (Continued)

5.7. Conclusions

In this chapter, a model to simulate pedestrian behavior in two segments of Antwerp's most important shopping street was presented. Data was collected by unobtrusively observing pedestrians in shopping street segments. Locations of entering a segment, visiting shops (including window-shopping), and leaving the segment were registered. The path of each pedestrian was registered by means of a network of nodes and links that was superimposed on each segment, representing three east–west directed walking zones and the opportunities to transfer between the east–west zones and to enter the shops. The majority of pedestrians appeared to follow relatively simple paths, generally maintaining the east–west zone of entrance.

To simulate pedestrian behavior, two models were used, a destination choice model and a link choice model. It was assumed that when a pedestrian enters a segment, he or she chooses a destination. This may be one of the exit links on the opposite site of the segment, implying that the pedestrian will not visit a shop in the segment. In the case the pedestrian chooses a shop as destination, he or she has to choose a destination again, until he or she decides to choose an exit or stay in the shop. To each destination, a route was simulated by repeatedly choosing a link in the network. Both destination choice and link choice were modeled by means of a conventional multinomial logit model. Important variables in the destination choice model are related to distance to the destinations and supply of shops. Also, a parameter measuring the tendency to visit a shop was included. This parameter indicated a significant aversion to visiting a shop, although this aversion is significantly less for those shops located adjacent to the zone a pedestrian is walking. Differences between gender and group composition were found as well. Individual females or groups of females appeared to have a higher tendency to visit a shop in general and stay longer in shops. Individual males or mixed groups appeared to be more attracted by non fashion shops than the females or female groups. Only for fashion shops a decrease in attraction was found if the pedestrian had already passed along (or visited) the shop. This effect was not found for non fashion shops, probably because of the low number of non fashion shops in the street segments. The link choice model, using angles and distance as explanatory variables showed that pedestrians have a tendency to walk according to straight lines as much as possible to their destination. The models perform well, both in terms of face validity and ρ^2.

Although the models perform well, some shortcomings should be discussed. One shortcoming of the destination choice model is the absence of the pedestrians' history. Each pedestrian is observed during his or her movement through one segment only. Consequently, we do not know whether shops were visited before and if so which kinds of shops. If a pedestrian has visited shops in a previous segment of the shopping street, the probability that a shop will be visited while being observed may be affected, positively if the pedestrian is looking for a particular type of goods, or negatively if the pedestrian successfully acquired the product he or she was looking for. To prevent this problem, the full trip of each pedestrian through the shopping area should be observed. This would also create opportunities to investigate whether and how the overall tendency to visit a shop varies across segments.

The models presented in this chapter only simulate pedestrians' destination choices and path choices. Other activities that can be performed in pedestrianized shopping areas like sitting down on a bench or making a conversation are not taken into consideration because these activities were rarely observed. Tracking more pedestrians and maybe at other time periods could give better insight into this kind of activities. More in general, the models are based on pedestrians' behavior observed in two segments of one shopping street of one city during a particular day of the week under nice weather conditions. Pedestrians' behavior may be different in other shopping streets or street segments, in other cities, during other days, under other weather conditions, etc. It goes without saying that this research should be repeated under different conditions.

The main purpose of this contribution was to estimate and test a model of pedestrian behavior using observational data. Although data was "manually" observed in only two segments of a shopping street, we have successfully shown that modeling and simulating pedestrian behavior in shopping environments is possible without collecting (additional) data by means of interviews or questionnaires. Of course, additional data about activity schedules, motivations, and so on would be useful, but this study has shown that planning models can do without.

From a managerial point of view, it might be of interest that pedestrians have a higher propensity to visit a shop if they walk along a shop, implying that the pedestrians walking in the center east–west zones are less likely to visit a shop. Attracting more pedestrians to the zones along the shops thus might increase the number of pedestrians visiting a shop. Improving walking conditions in the zones along the shops might be a means to attract more pedestrians to these zones. Another means might be to stimulate pedestrians choosing the northern or southern entrance to the segment. As segments usually start at a traffic crossing, redesigning these crossing might be effective. However, it should be taken into consideration that at least part of the pedestrians walking in the shopping street (especially those walking in the center zone) may not be interested in shopping at all.

References

Ali, W., & Moulin, B. (2006). How artificial intelligent agents do shopping in a virtual mall: A 'believable' and 'usable' multiagent-based simulation of customers' shopping behavior in a mall. In: L. Lamontagne & M. Marchand (Eds), *Canadian AI 2006* (pp. 73–85). Berlin: Springer-Verlag.

Antonini, G., Bierlaire, M., & Weber, M. (2006). Discrete choice model of pedestrian walking behavior. *Transportation Research B*, *40*, 667–687.

Ben-Akiva, M., & Lerman, S. R. (1985). *Discrete choice analysis: Theory and application to travel demand*. Cambridge: The MIT Press.

Borgers, A. W. J., & Timmermans, H. J. P. (1986). City center entry points, store location patterns and pedestrian route choice behavior: A microlevel simulation model. *Socio-Economic Planning Sciences*, *20*, 25–31.

Borgers, A. W. J., & Timmermans, H. J. P. (2005). Modelling pedestrian behaviour in downtown shopping areas. Paper presented at the 10th International Conference on Computers in Urban Planning and Urban Management, London.

Ciolek, M. T. (1978). Spatial behavior in pedestrian areas. *Ekistics*, *268*, 120–122.

Daamen, W. (2004). *Modelling passenger flows in public transport facilities*. Delft: TRAIL Research School.

Dijkstra, J., Jessurun, A. J., de Vries, B., & Timmermans, H. J. P. (2006). Agent architecture for simulating pedestrians in the built environment. In: A. L. C. Bazzan, B. Chaib-draa, F. Kluegl, & S. Ossowski (Eds), *Fourth International Workshop on Agents in Traffic and Transportation [ATT 2006]* (pp. 8–16). New York, NY: ACM.

Dijkstra, J., Jessurun, A. J., & Timmermans, H. J. P. (2002). Simulating pedestrian activity scheduling behavior and movement patterns using a multi-agent cellular automata

model: The Amanda model system. *Proceedings of the Transportation Research Board Conference*, Washington.

Dijkstra, J., & Timmermans, H. J. P. (1998). A multi-agent systems approach for visualizing simulated behavior to support the assessment of design performance. In: M. N. Huhns & M. P. Singh (Eds), *Reading in agents* (pp. 217–224). San Francisco, CA: Morgan Kaufmann Publishers.

Greene, W. H. (2007). *Nlogit Version 4.0 Reference Guide*. Plainview, NY: Econometric Software, Inc.

Haklay, M., O'Sullivan, D., Thurstain-Goodwin, M., & Schelhorn, T. (2001). So go downtown: Simulating pedestrian movement in town centers. *Environment and Planning B*, *28*, 343–359.

Helbing, D. (1992). Models for pedestrian behavior. In: *Natural Structures* Part II (Vol. 230, pp. 93–98). Stuttgart: Sonderforschungsbereich.

Helbing, D., & Molnár, P. (1995). Social force model for pedestrian dynamics. *Physical Review E*, *51*, 4282–4286.

Helbing, D., Molnár, P., Farkas, I. J., & Bolay, K. (2001). Self-organizing pedestrian movement. *Environment and Planning B*, *28*, 361–383.

Hoogendoorn, S. (2002). Pedestrian travel behavior in walking areas by subjective utility optimization. *Proceedings of the Transportation Research Board Conference*, Washington

Hoogendoorn, S. P., & Bovy, P. H. L. (2004). Pedestrian route-choice and activity scheduling theory and models. *Transportation Research B*, *38*, 169–190.

Kemperman, A. D. A. M., Borgers, A. W. J., & Timmermans, H. J. P. (2009). Tourist shopping behavior in a historic downtown area. *Tourism Management*, *30*, 208–218.

Kerridge, J., Hine, J., & Wigan, M. (2001). Agent-based modeling of pedestrian movements: The questions that need to be asked and answered. *Environment and Planning B*, *28*, 327–341.

Kukla, R., Kerridge, J., Willis, A., & Hine, J. (2001). PEDFLOW: Development of an autonomous agent model of pedestrian flow. *Transportation Research Record*, *1774*, 11–17.

Robin, Th., Antonini, G., Bierlaire, M., & Cruz, J. (2009). Specification, estimation and validation of a pedestrian walking behavior model. *Transportation Research B*, *43*, 36–56.

Schelhorn, T., O'Sullivan, D., Haklay, M., & Thurstain-Goodwin, M. (1999). STREETS: An agent-based pedestrian model. In: P. Rizzi (Ed.), *Proceedings of the 6th International Conference on Computer in Urban Planning and Urban management on the Edge of the Millennium (CUPUM'99)*, Venice.

Shoval, N., & Isaacson, M. (2006). Application of tracking technologies in the study of pedestrian spatial behavior. *The Professional Geographer*, *58*, 172–183.

Tanaka, H., & Shibasaki, R. (2005). 3-D spatial behaviours or urban lives, a smart mobile mapping and visualizing system. Paper presented at the 10th International Conference on Computers in Urban Planning and Urban Management, London.

Teknomo, K. (2002). *Microscopic pedestrian flow characteristics: Development of an image processing data collection and simulation model*. Sendai: Graduate School of Information Sciences, Tohoku University.

Zhu, W. (2008). *Bounded rationality and spatio-temporal pedestrian shopping behavior*. Eindhoven: Eindhoven University of Technology.

Chapter 6

Simulating Pedestrian Route-Choice Behavior under Transient Traffic Conditions

Vassilis Zachariadis, James Amos and Brandon Kohn

Abstract

A dynamic pedestrian routing and traffic assignment approach is proposed. Unlike similar attempts in the past, our proposal is based on route choices that are neither constrained by grid-based discretizations of space, nor follow a user-defined network. Pedestrian movement choices are defined heuristically and utility feedback is used to evaluate alternative options. Route choices are based on the experienced utility of preceding pedestrians as realized by Legion Studio's micro-navigation module.

6.1. Introduction

Many well-established methods for route assignment through network-based transport systems, under steady conditions, are applied in simulating pedestrian route choice. However, real pedestrian systems are not necessarily constrained to a rigid network and are rarely subjected to fixed traffic conditions (stable in-flow to the model, etc.).

In this chapter, the theoretical foundations of traditional traffic assignment models are discussed along with the concepts of user-based equilibria and utility-maximizing behavior. The perception of cost (both estimated and experienced) in pedestrian movement is reviewed and an agent-based route-cost estimation model is proposed.

This chapter proposes a model that can efficiently simulate pedestrian routing choice behavior under transient conditions. The proposal is based on a method of

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decomposing complex configurations into simple spatial segments that can be used as components of a movement network along with a route evaluation mechanism that employs aggregations of agent feedback to simulate varying levels of experience.

The later part of the chapter discusses continuous space decision-making and proposes a spatial decomposition technique to limit the number of generated choice-sets and decision points. These choice-sets are further refined by incorporating behavioral criteria based on the behavioral characteristics of pedestrians.

Finally, the proposed method of movement network definition and the cost-estimation model are used together in proposed behavioral models of pedestrian route assignment under transient traffic conditions. These include models that aim to converge to steady-state-like flow patterns (useful when the transience is slow and gradual) and models that perform effectively under rapid and abrupt changes of traffic conditions.

6.2. Utility-Maximizing Behavioral Models

Utility maximization is a concept used widely as a framework for behavioral modeling. Its core assumption is that actors will form behavioral strategies that will, in time, maximize their perceived utility or minimize their perceived cost.

There are terminological clarifications that need to be made. Utility and cost need to be identifiable and quantifiable; in cases with many constituent factors, each factor needs to be quantifiable. Therefore, a modeling mechanism needs to be in place that associates observable metrics with utility or cost parameters.

The time period over which utility is calculated also needs to be defined. Short-term and long-term utility calculations may lead to very different behavioral strategies and emergent patterns. Actors need to be identifiable and relevant processes need to be taken into consideration.

Perception also needs to be treated carefully. There are two levels of uncertainty that need to be considered which are linked to perception of utility/cost:

- Modeling uncertainty related to behavioral assumptions; uncertainty about the factors (and their respective weights) that will form the function used to evaluate the utility of alternative options.
- Behavioral uncertainty related to the level of information that simulated pedestrians have access to during simulation (implies confidence in the cost estimation of each available option).

Utility maximization modeling frameworks can be suitable for both aggregate and individual-based approaches. Implementations typically involve discrete action spaces[1]

1. An action space is defined as the set of all available actions.

(Antonini, Bierlaire, & Weber, 2006; Zachariadis, 2005), although continuous action spaces can and are known to have been modeled (Hoogendoorn, 2002; Kagarlis, 2002).

Utility-based behavioral models display a series of characteristics that make them especially suited to modeling. Most importantly, such models can easily be extended through game theory to involve strategic interactions between agents (including risk management) and can be optimized.

6.3. Existing Approaches

Route-choice behavior and trip assignment modeling have been extensively researched over the last 30 years. The majority of proposed approaches rely on behavioral assumptions pertaining to utility maximization and their implementations apply to discrete state spaces[2] and a finite number of alternative routes.

6.3.1. Trip Assignment in Transport Networks

Traditionally, trip assignment focuses on tackling the combined route-choice-traffic-volume problem for discrete state spaces such as transport networks. In these cases optimum user-based equilibrium can be reached by solving a nonlinear programming problem subject to flow conservation constraints (Dafermos & Sparrow, 1969). Subject to constant in-flow demands during a simulation, equilibria that satisfy Wardrop's (1952) first principle of route choice exist and can be found using heuristic algorithms (Frank & Wolfe, 1956).

Given a fixed in-flow of demand, the outcomes of such processes are static flow maps that represent steady states. Different demand levels produce different maps and therefore it is possible to model study areas under different demand conditions (peak periods and off-peak periods, etc.). However, some of the underlying behavioral assumptions are rather restrictive. Network users (pedestrians in the case of pedestrian modeling) are assumed to have perfect knowledge of the movement network and to share a universal perception of the utility that each routing-option entails.

Arguably, the most important restriction of the methods employed to reach equilibrium is the fact that they are based on iterations that are not linked to physical time. Therefore, the process until equilibrium is reached has no physical meaning — nothing can be known from it about the transitional phases in-between equilibria — during which criticalities may be reached.

2. A state space is defined as the set of all possible states. Here, continuous state space means that pedestrians can move freely in continuous space while discrete state space means that they are restricted to only occupy discrete positions.

6.3.2. *Particularities of Pedestrian Route-Choice Behavior*

The modeling scales and formal movement regulations of conventional transport systems permit the generalization of observed movement using networks. Moreover, most of the formal transport networks are conventionally considered symmetric-cost networks, where the cost at each link is assumed to be dependent on the static and dynamic parameters of this and only this link. This is a reasonable assumption for most transport networks, where flow intersections are formal.

Abstracting pedestrian movement patterns to a movement network can prove extremely difficult due to the kinetic characteristics of pedestrians and the challenge they add to pedestrian modeling (the ability to turn and change speed rapidly, to walk on a variety of surfaces, etc.) (Inman, Ralston, & Todd, 1981).

However, the defining characteristic of pedestrian movement is arguably the total lack of explicit compulsory movement code and regulation. These characteristics account for very complex emerging patterns that prove extremely difficult to represent using planar graphs (networks). The level of detail required and the unregulated movements lead to extremely dense and complex networks. For such networks, the symmetric-cost assumption ceases to be valid. Under such circumstances, deducing the movement network by identifying corridors of movement (links) and flow intersections (nodes), i.e., movement patterns may prove inefficient or even unfeasible.

Furthermore, the complex configuration of walkable environments and the development of bi- and multi-directional pedestrian flows raise issues related to utility calculation and route evaluation. Unlike conventional transport networks, where the cost of traversing a network link can be computed analytically from the flow volume on this link and its width, the cost estimation in pedestrian flows is extremely difficult and depends on detailed geometry (street furniture, vegetation, etc.) and the emergent attributes of flows due to self-organization (Helbing, Molnár, Farkas, & Bolay, 2001).

6.3.3. *Simulating Pedestrian Trip Assignment*

Such complexities meant the focus of pedestrian simulation shifted either toward microsimulation approaches of agent interaction and collision avoidance that were not concerned with the effect of flow volumes on routing decisions (Helbing & Molnár, 1994; Blue & Adler, 1998), or toward activity scheduling and routing behavior models (Haklay, O'Sullivan, & Thurstain-Goodwin, 2001) that ignored infrastructure capacity and dynamic costs.

However, pedestrian simulation models are gradually paying increasing attention to emerging traffic patterns and their impact on routing decisions. Gipps (1986) was one of the first to consider volume delays in his *Simulation of Pedestrian Traffic in Buildings* (an approach based on a finite number of routes and discrete choice). More recently, Daamen (2004) proposed a network-based approach to determine

alternative routes in public transport facilities. In this implementation, link costs are estimated using densities and destination costs are calculated using shortest-path algorithms.[3]

Approaches based on user-defined routes or networks (finite number of options) assume that the anticipated flows and configurations are simple enough to be manually abstracted to networks. In other cases, instead of inferences based on movement patterns, movement choice networks can be approximated using grid cells or similar dense set points (meshes). Cell centroids are typically considered the nodes of an implicit movement network, which is inferred from proximity rather than pattern.

Such solutions, which result in an infinite number of paths, are usually generated by considering the routing problem within continuous space. Velocity is treated as the continuous action variable in continuous two-dimensional state space. It needs to be calculated in time–space by seeking to maximize the utility-to-destination function. The continuous problem is usually approached using Bellman's *principle of optimality* (1957), together with dynamic programming, to numerically calculate the velocities for any time and location.[4]

Hoogendoorn and Bovy (2004b) propose such a solution using dynamic programming[5] in the form of a backward recursion process. Starting from time t_D of terminal conditions, the model performs a backward value iteration algorithm in order to calculate optimal velocities for any state at any time t. Initially, the traffic-related costs are not considered. The process is repeated by feeding each new cycle with traffic-related costs based on the routing outcomes of the previous cycle and partially updating the flow distribution based on the new costs. The model (whose flow-diagram bears resemblance to aggregate route-choice models) concludes when the system reaches an acceptable point of convergence.[6]

Zachariadis (2005) and Castle (2007) offer simpler (suboptimal) solutions to the routing problem in continuous space. They do this by using regular grids and calculating utility-to-destination either by ignoring dynamic costs and focusing on static costs-to-destination or by directly assuming partial knowledge of the dynamic costs-to-destination.

In the latter case, the cost to a destination from any point in continuous space (a cell of the regular grid) is approximated by considering the current traffic conditions and solving the shortest-path problem, following proper adjustment of

3. The proposed approach bears close resemblance to network-based queuing models; for more details refer to Cruz & Smith (2007).

4. Restrictions in knowledge of costs may be considered by introducing uncertainty costs directly in the motion equation (Hoogendoorn & Bovy, 2004a).

5. The method is based on flow conservation (the *continuity equation*) and employs an iterative process that compromises route choice and traffic conditions.

6. This is characteristically reminiscent of the aggregate *method of successive averages* and the outcome can be viewed as a dynamic extension of the static equilibrium flow map.

maximum achievable speeds.[7] Limited knowledge of traffic conditions is simulated by reducing the impact of dynamic cost for parts of the grid-based graph that fall outside the visible area from the specific point.

Following references to optimality, it is important to clarify that the underlying modeling assumptions, especially different levels of assumed knowledge, dramatically alter the preferred approach. Non-regulated pedestrian route allocation is expected to be suboptimal (under transient conditions) and is expected to reach equilibrium satisfying Wardrop's first principle only in cases of constant or periodically regular in-flows developed over a long period. In other cases, approaches seeking to optimize routing decisions based on prevailing (rather than current) or unobservable traffic conditions need to ensure that assumed knowledge is justifiable and that uncertainty is considered.[8]

6.4. Restating the Problem

The routing problem can be restated, taking into account all relevant arguments, and to address any issues raised in the summary above. Routing problems under dynamic costs may be considered within a three-stage process:

1. Defining the options

   A set of alternative choices (countable or not) needs to exist. This leads the discussion to the quality and quantity of differentiation, i.e., the criteria that may be used to substantiate a potential trajectory as a unique choice. Handling space continuously appears to address the problem. However, the necessities of a numerical solution ultimately reintroduce discreteness (as evidenced by concepts such as grid resolution or mesh density). The potential number of trajectories may be infinite but they are evaluated using a spatial decomposition technique that implies discreteness.
2. Evaluating the options

   Following the definition of the relevant scope of action, and based on the behavioral assumptions, the utility of choices needs to be evaluated. Such evaluation requires a cost calculation mechanism to be established. Given the previous discussion on the difficulties of forming analytical cost functions (based on flow volumes) for pedestrians, the modeling implications of such mechanism remain to be defined.
3. Making the decisions

   After defining choice evaluation, the next step is to develop a selection process. Such a process may be stochastic or deterministic (depending on the modeling approach), and may be directly or indirectly related to route evaluation.

7. By employing empirically generated density–speed correlations.
8. Experience and a degree of extrapolation ability on prevailing conditions based on the current traffic state may be assumed but must be carefully applied to resemble acceptable cognitive processes.

The rest of this chapter proposes a routing model that adheres to this three-stage structure while addressing some of the challenging aspects of pedestrian route assignment in an innovative and behaviorally consistent way.

Section 6.5 proposes a route assignment model that offers a discrete but systematic approach to the definition of alternative routing options (the "choice-set"). This model is consistent with both the continuity of pedestrian walkable space and the behavioral characteristics of pedestrian routing strategies.

Section 6.6 discusses feedback-based approaches to route evaluation and lays out a set of methods that utilize the feedback of microscale movement[9] simulators (in particular Legion Studio's micro-simulator) to evaluate routing options while simulating varying levels of experience.

Section 6.7 discusses route selection processes that can effectively use feedback-based route evaluations to simulate route assignment under both constant and transient traffic conditions. Finally, an assignment process is proposed that successfully handles transient traffic conditions in real time[10] and converges toward user-based equilibrium during periods of constant in-flows.

The chapter finishes with a discussion about early results, some conclusions and plans for future steps.

6.5. Defining the Movement Network

In this chapter the debate on spatial representation approaches (network-based and grid-based) and their impact on the definition of route choices is resumed. Previously it was argued that the evaluation of alternative route choices implies the ability to describe them. Arguments were also made that the particular kinetic characteristics of pedestrian movement (especially acceleration characteristics) and, most importantly, the lack of pedestrian traffic regulation make the identification of *formal* pedestrian movement networks impossible. This difficulty introduces the subject of *informal* movement network definitions, which will be explored in this chapter.

The issue may be restated as the definition of the routing-relevant action space $[A(X)]$ of state space $X(t)$, i.e., the definition of the possible routing-related actions $[A]$ from point X of the accessible space[11] to destination D at time t. Cases of unrestricted pedestrian movement lead to the non-robust (and non-context-sensitive) conclusion that from a state point $X(t)$ there is an *infinite* and *uncountable* number of possible routes to destination D.

While the infinite — uncountable conclusion is valid, it usually produces extremely complicated modeling platforms. Continuous space can rarely be described

9. Microscopic movement focusing on step-by-step navigation, collision avoidance, and micro-scale crowd dynamics such as synchronization, lane formation, etc.

10. With no need for iterative circles.

11. Accessible space of point X is the area defined by all the points Y that can be reached from point X in any number of action-steps.

analytically. In most cases it needs to be approximated using numerically solvable methods that employ dense meshes or grid structures to discretize continuous space (Figure 6.1). Such approximations provide sensible numerical solutions for their continuous analogs, but must be considered non-robust, for they usually ignore the configuration of the accessible space and any (assumed) behavioral characteristics of pedestrian routing. However, they conveniently by-pass the routing choice-set problem, by implicitly considering a choice-set of state point $X(t)$ — within cell $C(X)$ — all the (*countable* but *infinite*) possible sequences of cells $\{C\}$ from $C(x)$ to $C(D)$.

The approximation of paths as sequences of points provides a manageable way of route-representation that allows path evaluation. Figure 6.2 illustrates this point

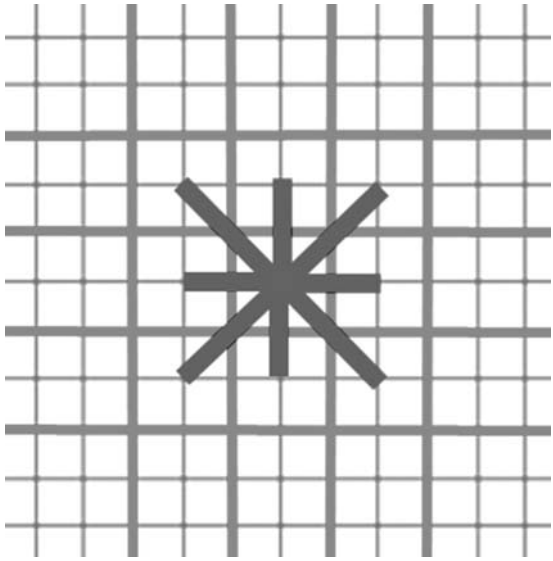


Figure 6.1: The Moore neighborhood of a cell-regular grid.

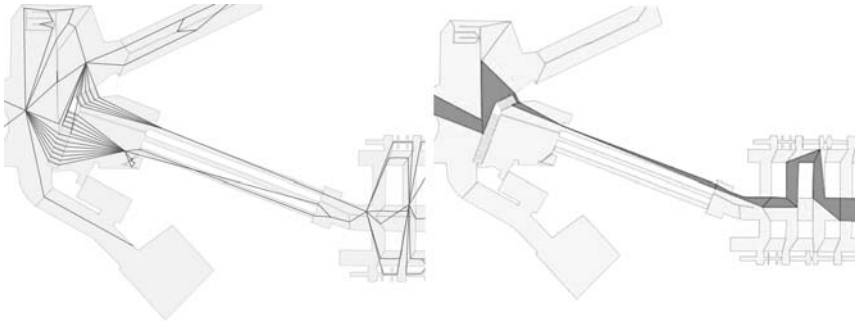


Figure 6.2: Spatial decomposition: decomposition graph (left) and cell sequence (right).

further; a complex walking environment is decomposed into a set of simple polygons. In the left image, the layout is represented as the proximity graph of the simple decomposition polygons (*decomposition graph*). Two nodes of the graph (polygons) can be linked only once (their intersection is a simple line-segment). Each sequence of nodes in the decomposition graph corresponds to only one ''movement corridor'' in real space (right image). Conversely, each alternative route option between two locations in the walking environment can be represented as a series of polygons (nodes) in the decomposition graph.

The rest of this chapter describes a behavior-aware and context-sensitive approach to the definition of routing choices. Under the proposed solution a route from point $X(t)$ to destination D may be considered distinctive if it can accommodate the development of distinct flow patterns for at least part of its length. This behavior-aware approach to route definition is based on two fundamental assumptions:

1. The abstract question of distinctiveness of a flow pattern should refer to a quantifiable configuration attribute.
2. Given the inherent macroscopic suggestion of flow, distinctive routes will imply identifiable clusters of similar trajectories assumed to contribute to the development of a distinctive flow pattern.

The second assumption relies on a specific interpretation of navigational cognition that proposes that during the decision process candidate routes are conceived as sets of simpler components (*spatial segments*) and not as unbounded trajectories in continuous space.

Meanwhile, for the purposes of the proposed method, the configuration attribute that will determine the distinctiveness of a route from $X(t)$ to D will be the proportion of the route that is different to comparable routes and the degree of difference.[12] This fundamental assumption provides a useful instrument for the restriction of alternative routes, which can be used for both conventional grid-based methods and the proposed method.

The second assumption permits the utilization of spatial decomposition[13] techniques that may generate simple components (*spatial segments*) that can subsequently be used to form distinct routes (Figure 6.3). Most of the existing spatial decomposition techniques abstract real space using a reference graph. The attributes of the links and nodes of the resulting graph have no physical meaning, which means the graph may be used for route definition but not for route evaluation.

The proposed approach uses a variation of spatial decomposition that captures all the behavioral characteristics of pedestrians, while referring directly to physical space. Employing the two fundamental assumptions under this decomposition framework leads to a robust and condensed set of alternative routes from $X(t)$ to D

12. That needs to be defined.
13. The term here refers to any method that is used to topologically describe space using a topological graph.

that can be directly evaluated and visualized. Routes should always lead to specific visible targets or to non-viewable parts of the accessible space. Parts of routes toward non-viewable parts of the accessible space are represented by the shortest path to these parts of the accessible space but correspond to clusters of *similar* paths to the respective space.

Alternative routes should be *self-consistent*. Therefore, parts of routes leading to non-viewable *spatial segments* should be followed by parts of routes that flow through the targeted non-viewable *spatial segment*. Looking at Figure 6.4, for all routes that contain point sequence $\{\ldots, Z, X, Y_n, \ldots\}$, Y_n must be within quadrant Q, where Q is defined by half-lines XX' and XZ' (extension of ZX). Clearly, for any

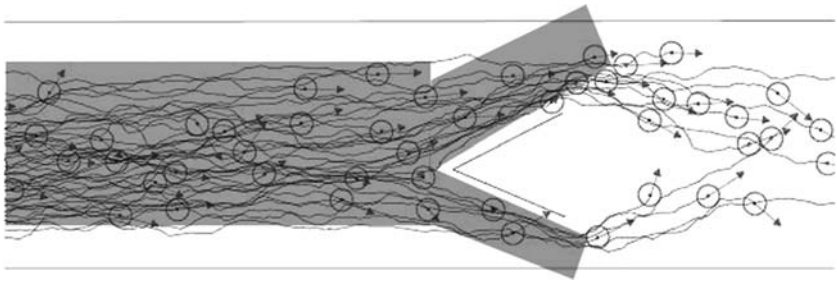


Figure 6.3: Spatial segments representing distinctive flow pattern development.

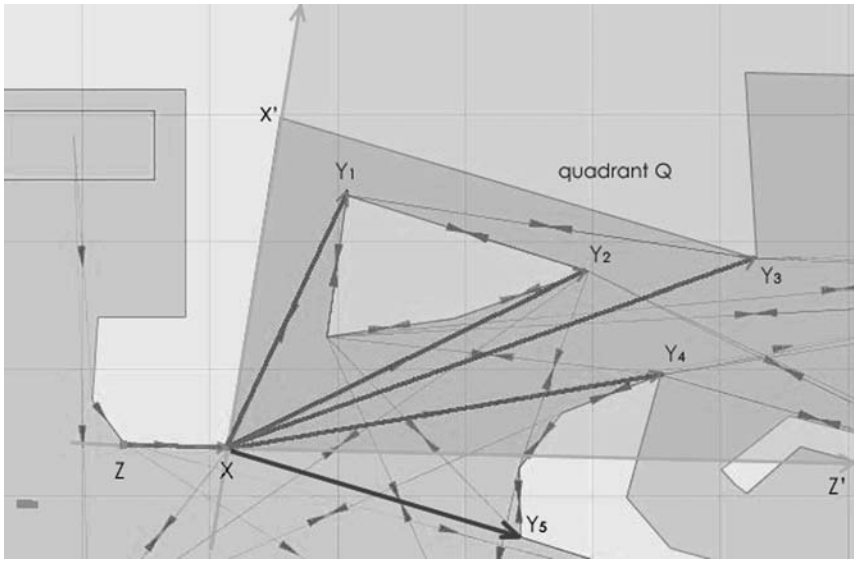


Figure 6.4: Forward-star (forward-star of a graph node is the set that contains all its valid successor nodes) the self-consistency of routes means that node Y_5 is not a valid alternative for routes that accommodate the previous, current sequence.

point Y_k (e.g., Y_5) outside Q, there will always exist a sequence of points $\{Z, W_1, W_1, \ldots, W_n, Y_k\}$ that conforms to the decomposition rules and will better represent the route cluster that corresponds to $\{Z, X, Y_k\}$.

6.6. Evaluating the Alternatives

This section has four parts. The first discusses costs experienced along realized trajectories. The next considers the physical meaning of feedback-based cost estimation. Part three proposes a method to model varying levels of experience and the final section discusses potential cost-forming factors.

6.6.1. The Experience Costs

Utility-based approaches link realized transitions between point $X(t)$ and destination D to specific utility values based on the cost experienced when moving from $X(t)$ to D and on the utility of destination D.

$$U(X(t)) = U(D) - C(X(t) \Rightarrow D) \tag{6.1}$$

$U(X(t))$ is the utility at point X for time t, $U(D)$ the utility at destination D, and $C(X(t) \Rightarrow D)$ the experienced movement cost from $X(t)$ to D. Assuming that destination D is fixed, the utility associated with a realized trajectory between $X(t)$ and D can be considered equal to the negative experienced transition cost without any loss of generality.

The previous point raises two issues. First, in order to estimate the expected utility of alternative routes, experienced transition costs need to be defined (and be potentially measurable). Second, a cost-estimation model must be developed.

Most routing methods employ a single process that uses a routing cost-estimation model based on observable metrics such as density, average speed, distance, etc. In contrast, the proposed approach implies that pedestrian routing behavior may be modeled on two levels. First, employing an internal experienced-cost model that quantifies the experienced conditions during transition between two points and second, an estimation model that uses the tracked average experienced-costs (among other metrics) to estimate costs related to candidate routes. Using the approach from the previous chapter, experienced costs are related to specific realized trajectories, while estimated costs refer to network components (implying clusters of potential trajectories).

The proposed structure implies that experienced costs need to be capable of being monitored and that experienced costs associated with a specific network segment will be fed back to contribute to the average experienced costs of the segment. This approach could offer certain advantages for pedestrian routing. Most traditional motor traffic models use functions of observable flow metrics (most notably flow

volume and/or critical density) to estimate the associated cost of a network link (volume delay functions). While in certain cases these functions provide accurate results, in the case of pedestrians they fail to capture critical parameters that determine transition costs. This is because:

- The volume delay of pedestrian network segments is affected by local geometry and configuration and is therefore hard to estimate in complex layouts.
- Pedestrian network segments accommodate at least bidirectional flows.
- Due to emergent self-organization (lane formation, drifting, synchronization, etc.) volume delays are extremely hard to estimate.
- The assumption of symmetric link costs is not acceptable, considering that distinct links potentially share walkable surfaces.

Therefore, the direct cost estimation of network links is considered to be particularly difficult. Alternatively, grid-based spatial representations may be used, and transition costs may be related to flow densities in each cell. While such approaches appear to solve some of the described difficulties, flow directions are still not taken into consideration and local geometry is not considered directly. Therefore, in many cost-estimation models, the costs of alternative routes are usually inaccurate and subsequent choices fail to reproduce realistic assignments.

Using average, "fed back," experienced costs may offer a solution to issues arising from using observable metrics for route-cost estimation. However, care is required on how it is associated with specific real processes. The remainder of the chapter discusses the physical meaning of feedback-based cost estimation for pedestrian routing choices.

6.6.2. The Physical Meaning of Feedback-Based Cost Estimation

The obvious advantage of feedback-based cost estimation is the accuracy of the approach. Instead of using cost estimation based on observable attributes related to a movement network component, the experienced transition costs of this component are used to formulate an average experienced cost:

$$C\exp\_\text{avg}\_k = C\exp\_\text{avg}\_k + n \times (C\exp\_\text{new}\_k - C\exp\_\text{avg}\_k) \qquad (6.2)$$

Cexp_avg_k is the average experienced cost of a specific network component k, Cexp_new_k a new fed-back-experienced cost, and n the individual weight of each new fed-back cost and signifies the impact of temporal circumstances on the volatility of the average cost.

Average cost Cexp_avg_k may be useful for identifying the estimated transition cost of network component k but is not informative about the estimated cost from a point $X(t)$ to destination D. In order to evaluate alternative routes from $X(t)$ to D, the estimated transition cost of each network component (let us temporarily assume it is equal to the average experienced cost Cexp_avg_k) could be used as the weight of the

component in the decomposition graph and calculate the shortest path from any point of the graph to the destination D. Alternatively, the scope of the feedback process could be broadened by feeding back cost-to-destination for each component (instead of feeding transition costs). Both approaches show strengths and weaknesses that will be further discussed.

By passing costs $C\text{exp\_avg\_}k$ to the decomposition graph, it is possible at any time to compute the minimum average experienced cost from $X(t)$ to D. Assuming that average experienced cost is a valid cost estimator, it is possible to use the minimum average experienced costs of each point of the immediate state space of $X(t)$ (i.e., each point of its forward star) to evaluate the routing options from $X(t)$ to D. Under such a structure, routing can be seen as a series of stochastic best-path choices. The physical meaning of such an approach is that all routes from $X(t)$ through forward-star component $Y(t')$ are evaluated using the same metric: the minimum estimated cost from $X(t)$ to D through $Y(t')$. This can be approximated as:

$$C\text{est\_}X\text{\_}Y\text{\_}D = C\exp\text{\_avg\_}k + \boldsymbol{Min}(C\exp\text{\_}Y(X)\text{\_}D) \tag{6.3}$$

where k is the component that links $X(t)$ and $Y(t')$ and $\boldsymbol{Min}(C\text{exp\_}Y(X)\text{\_}D)$ is the shortest (optimal) path to destination from $Y(t)$ to D. The reference of X in the calculation of the shortest path from $Y(t)$ to destination D signifies the self-consistency of the candidate route from X to D through Y. It is clear that for different previous points X a specific Y will provide different $\boldsymbol{Min}(C\text{exp\_}Y(X)\text{\_}D)$ based on the validity of its forward-star (as explained in the previous chapter).

It is evident that the proposed approximation leads to potentially suboptimal paths since at time t' $\boldsymbol{Min}(C\text{exp\_}Y\text{\_}D)$ will be different. Optimality could be reached if $\boldsymbol{Min}(C\text{exp\_}Y\text{\_}D)$ was calculated using backward value iteration from D at time t_terminal. The associated computational implications and the *a priori* need for feedback of experienced costs make this infeasible.[14]

Alternatively, utilizing feedback of experienced costs from a point $X(t)$ to destination D through forward-star point $Y(t')$ gives:

$$C\text{est\_}X\text{\_}Y\text{\_}D = C\exp\text{\_avg\_}X\text{\_}Y\text{\_}D \tag{6.4}$$

In this case the estimated cost-to-destination through $Y(t')$ is equal to the average fed back-experienced costs of all realized trajectories from X to D through Y.

14. Considering the impact of route choice on component transition costs, backward iteration would be insufficient. Route choices are related to costs and costs are based on the aggregate effect of route choices. To reach a stable system, the employment of an iterative process is needed — later in the chapter an alternative continuous process that resembles the iterative process is proposed.

This can be expressed as follows:

$$C\exp\_avg\_X\_Y\_D = C\exp\_avg\_X\_Y\_D + n \times (C\exp\_new\_X\_Y\_D - C\exp\_avg\_X\_Y\_D) \quad (6.5)$$

Here, Cexp_new_X_Y_D is the experienced cost of a realized trajectory from X to D through Y.[15] Cexp_avg_X_Y_D is therefore the real average cost from X to destination D through Y.

Both approaches require frequent cost feedback in order to preserve up to date link weights and costs-to-destination; this is achieved using a set of exploration rules that ensures a minimum frequency of visits.

The feedback process of experienced costs requires a cost monitoring mechanism and an operational-level movement model. In the proposed model, the routing navigational decisions are made at the operational level by the Legion Studio microscopic movement simulator (micro-simulator).

The micro-simulator (an agent-based, utility-maximizing pedestrian simulator) translates navigational decisions to intermediate targets and simulates microscopic pedestrian movement, collision avoidance and crowd dynamics, while monitoring experienced costs along the way. Therefore, the proposed model adopts a parallel microscopic/macroscopic approach in continuous time.

6.6.3. Modeling Varying Experience Levels Using Feedback

The methods described above use feedback to estimate the transition costs between points in continuous space. The proposed methods demand a micro-level pedestrian movement model to calculate and monitor the experienced costs that are being fed back. In the previous sections, the estimated cost-to-destination was assumed to be equal to the average experienced cost-to-destination. The behavioral assumption behind this statement is, however, both restrictive and unrealistic. This section looks at the potential behavioral implications and the physical meaning of the proposed feedback approach. It illustrates how average experienced costs can be used to model the route-choice behavior of pedestrians who possess varying levels of experience.

The use of average experienced-cost feedback to evaluate alternative routes from point $X(t)$ to destination D implies that pedestrians using this information to make routing decisions are either informed through an information-passing mechanism, or utilize past personal experienced costs. This section considers the implications of the latter statement. There are several cases where the realized costs of preceding users are fed back to succeeding users through information systems (ATIS, see Papageorgiou, 1990). However, the development of such systems for pedestrian traffic control is beyond the scope of this chapter.

15. The self-consistency demand is now implicitly satisfied as all realized trajectories will be valid.

According to Avineri and Prashker (2006), the sources of information used by travelers to make routing decisions are: historical experiences gained through the learning process of previous trips, current perceptions of the state of the accessible space, and external information from information systems. Past travel experience can be replicated by using the averages and the variations of experienced costs of preceding travelers. Hence the cost-estimation function for a path from a point $X(t)$ to destination D through $Y(t')$ in X's forward-star is given by:

$$Cest\_X\_Y\_D = Cest\_k + h \times \boldsymbol{Min}(Cest\_Y(X)\_D) \tag{6.6}$$

k is the component that links $X(t)$ and $Y(t')$, h a weighting factor, and $\boldsymbol{Min}(Cest\_Y(X)\_D)$ the estimated minimum cost from $Y(t')$ to destination D. $Cest\_k$ is the estimated cost for component k. Bearing in mind that, by default, paths from $Y(t')$ to D are at best partially visible from $X(t)$, it is assumed that the cost estimation of $\boldsymbol{Min}(Cest\_Y(X)\_D)$ is based solely on experience and the cost estimation of component k is based both on experience and observation of current state. Therefore Eq. (6.6) can be reformulated accordingly:

$$\begin{aligned} Cest\_X\_Y\_D = f(&Cest\_k\_\text{observation}, \; C\exp\_\text{avg}\_k) \\ &+ h \times g(\boldsymbol{Min}(C\exp\_Y(X)\_D)) \end{aligned} \tag{6.7}$$

The cost contribution of the visible portion of the path is a function of experience and observation while the cost contribution of the second portion of the path is a function of experience. In order to simulate varying levels of experience, function g is given by:

$$\begin{aligned} g(\boldsymbol{Min}(C\exp\_Y(X)\_D)) = b \times &\boldsymbol{Min}(C\exp\_Y(X)\_D) \\ &+ c \times \boldsymbol{Min}(C\text{static}\_Y(X)\_D) \end{aligned} \tag{6.8}$$

$\boldsymbol{Min}(C\text{static}\_Y(X)\_D)$ is the minimum static cost[16] from $Y(t')$ to D and b and c are weighting factors. High b values imply high levels of experience while high c values imply less experienced users.[17]

Using the Eq. (6.8), Eq. (6.7) can be approximated as a three-term function:

$$\begin{aligned} Cest\_X\_Y\_D = a \times Cest\_k\_\text{dynamic} + b \times &\boldsymbol{Min}(C\exp\_X\_Y\_D) \\ &+ c \times \boldsymbol{Min}(C\text{static}\_X\_Y\_D) \end{aligned} \tag{6.7}$$

16. Static costs are costs that do not change over time, regardless of the state of the network; i.e., distance related costs, walkability, and configurational costs, etc.

17. In all cases, users are assumed to have a "perfect" knowledge of the static costs associated with each choice.

where ***Min***(*C*exp_*X*_*Y*_*D*) and ***Min***(*C*static_*X*_*Y*_*D*) are respectively the minimum average experienced cost and minimum static cost from point $X(t)$ to destination D through Y, *C*est_*k*_dynamic is the traffic-delay related cost of component k and a, b, c are weighting factors that control the impact of experience on route evaluation:

- Low values of a and c combined with a high value of b imply considerably experienced users that seek to minimize the expected cost-to-destination.
- A low value for b and high values of a and c imply users with some static knowledge of the network.
- Low values for both b and c represent pedestrians with no or very restricted knowledge of the spatial configuration.[18]

Therefore, by varying the values of the weighting factors or by using specific distributions to define them, it is possible to generate populations that can efficiently simulate a diverse range of cases.

6.6.4. Cost-Forming Factors

Up to this point there has been no reference to specific cost factors. The adopted feedback approach allows the formation of both simple and complicated cost functions, as long as the relevant monitoring infrastructure exists.

It remains beyond the scope of this chapter to discuss the factors that determine the perceived transition costs. The relevant literature is vast and draws research from a broad field spanning from environmental psychology to economics and architecture. Basic cost-forming factors are introduced here.

Distance and time are usually considered the main factors of movement cost perception. Most transport models adopt generalized cost functions based on these two attributes (Lee & Machemehl, 2005). However, in the case of pedestrian movement, several studies have demonstrated the relative importance of several other evaluating criteria. Hill (1982) argues that route *directness* plays a considerable role on route evaluation, an idea that is implicitly shared by Hillier and Hanson (1984).

Moreover, Bovy and Stern (1990) discuss the importance of *pleasantness*, while Zacharias (2001; Stathopoulos, Wu, & Zacharias, 2004) presents experimental results focusing on the impact of activity, texture, typology, and configuration on route preference. Experienced densities — regardless of their effect of speed — also affect perceived costs due to experienced discomfort and acceleration/collision-avoidance maneuvering (Kagarlis, 2002; Schwartz, Wasserman, Robbins, 2002).

18. Note that different levels of space configuration knowledge and traffic-delay experience may correspond to different cost-estimation models for the *C*est_*k*_dynamic term. A characteristic example of this is the reverse effect that high flow volumes have on the cost calculation in cases of experienced users and in cases of users with no knowledge of the network (where high flow volumes are assumed to imply preference).

Additionally, uncertainty (Hoogendoorn & Bovy, 2004a) and risk (Appleyard & Lintell, 1972) may considerably affect route-cost perception.

6.7. Route Assignment under Stable and Transient Traffic Conditions

The definition and evaluation of routing choices allow the development of route selection strategies that may be directly or indirectly based on route costs. Direct consideration of the evaluation results leads to highly volatile traffic assignments where flow distributions follow the evaluation of current traffic conditions. A typical stochastic selection model will be based on Eq. (6.10).

$$P_{\text{direct, } i} = \frac{\exp(\text{beta} \cdot c_i)}{\sum_j \exp(\text{beta} \cdot c_j)} \tag{6.10}$$

$P_{\text{direct},i}$ is the direct probability of choosing routing option i, c_i the estimated cost associated with i, beta a rationality factor, and $j \in F$, where F includes all routing options from the current location.

The potential volatility of traffic assignment in systems that are directly based on route evaluation is related to infrastructural capacity and its effect on movement costs. In cases where cost-estimation functions are not associated with link capacity metrics[19] the impact of density on movement costs (and on subsequent direct probabilities $P_{\text{direct},i}$) is initially limited. However, when flow volumes reach critical levels the impact starts growing disproportionately (Seyfried, Steffen, Klingsch, & Boltes, 2005). Therefore, when infrastructural capacities lead to critical flow volumes, estimated costs based on fed back-experienced costs become extremely sensitive to changing conditions (which are shifting from saturation to free-flow conditions periodically). Furthermore, direct probabilities $P_{\text{direct},i}$ become very volatile and marginally out of sequence with their associated costs leading to further traffic condition changes.

The modeling implications of such volatile route assignment systems must be taken into account. The fact that pedestrians base their route choices on highly temporal route evaluations[20] implies that pedestrians make decisions based on information about parts of routes that are not observable. This assumed temporal knowledge of traffic conditions in arbitrarily volatile systems is not expected to accurately illustrate the cognitive capacities of pedestrians.

In order to address volatility issues, two methods of indirect route evaluation are introduced. The first one is influenced by research on ant colony optimization (ACO)

19. Such as average or minimum width of link, etc. — note that consideration of such link capacity metrics is arguably in discrepancy with the feedback-based approach.
20. Because of the volatility of traffic assignments.

(Dorigo, Di Caro, & Gambardella, 1999) and the second extends the existing direct costs framework by introducing information inertia.

6.7.1. The ACO-Based Assignment Model

A detailed review of ACO algorithms is beyond the scope of this chapter (readers are directed to Dorigo, Maniezzo, & Colorni, 1996). The proposed implementation is influenced by Di Caro and Dorigo (1998) and organized around a probability updating mechanism that indirectly considers local (observable) and global (system-wide) traffic conditions. Probabilities $p_{x\to y\to d}$ of route choices from a specific point x to a destination d through next node y are calculated using Eq. (6.11).

$$p_{x\to y\to d} = \frac{g_{x\to y\to d} + c \cdot l_{x\to y}}{1 + c} \tag{6.11}$$

$g_{x\to y\to d}$ is the probability of choosing y based solely on global costs, $l_{x\to y}$ the probability based only on local costs, and c a calibrating factor. $l_{x\to y}$ are calculated directly by evaluating the observable local costs of choices $x\to y$ at time t and using them with Eq. (6.10), while $g_{x\to y\to d}$ are updated every time a pedestrian W that traversed the node sequence $x\to y$ reaches destination d:

$$g_{x\to y\to d} = g_{x\to y\to d} + r \cdot (1 - g_{x\to y\to d}) \tag{6.12}$$

$$g_{x\to z\to d} = g_{x\to z\to d} - r \cdot g_{x\to z\to d}, \quad \forall z \in N,\ z \neq y \tag{6.13}$$

where N is the choice-set of x and r a performance evaluator of the cost of the path $x\to y\to d$ of pedestrian W compared to the average cost from x to d. The proposed trip assignment model is able to efficiently handle infrastructural capacity issues and leads to low volatility traffic assignment systems. There is further discussion on its performance in the next section.

6.7.2. The Information Inertia Approach

In order to address the destabilizing effects of capacity-related volatility, routing probabilities $P_{\text{routing},i}$ are introduced. Routing probabilities are calculated at time t by Eq. (6.14).

$$P_{\text{routing},i} = P_{\text{routing},i} + n \cdot (P_{\text{direct},i} - P_{\text{routing},i}) \tag{6.14}$$

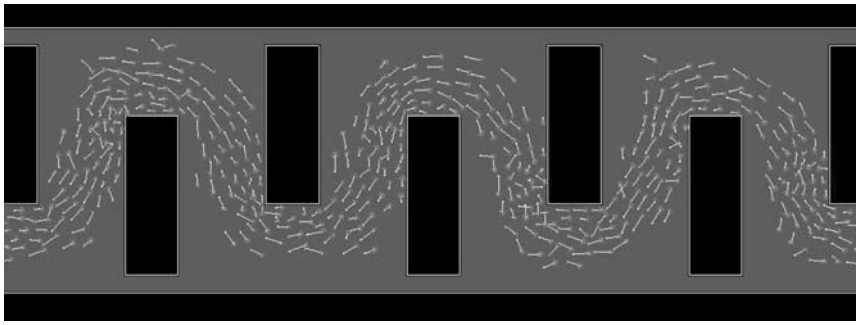


Figure 6.5: Suboptimal route assignment under the ACO-based assignment method with no exploration provisions.

Routing probabilities $P_{\text{direct},i}$ are calculated by Eq. (6.10) and n the *information inertia* factor, which can either be a user constant or related to cost dynamics.[21]

The fundamental concept of Eq. (6.14), namely the idea of lagged route assignment, is shared by most traditional traffic assignment methods (Frank–Wolfe method of successive averages, etc.) and is also used by Hoogendoorn and Bovy (2004b) for dynamic route assignment in continuous space. In contrast to previous implementations where the design is based on iteration to convergence, here Eq. (6.14) is used directly in real time.

The underlying assumptions comprise the gradual acquisition of information related to the state of a system through experience, and the ability of experienced users to conjecture prevailing unobservable conditions based on attainable information, meaning that experienced pedestrians use feedback information to simulate both experience and judgment.

The value of the information inertia factor controls the degrees of volatility and responsiveness in the assignment system and whether a user-defined equilibrium will be reached.

6.8. Early Results

Both trip assignment approaches have demonstrated the expected behavior under fixed and transient traffic conditions. Because both models base the evaluation of routing options on feedback information, it is important to facilitate exploration mechanisms that keep the system informed and updated without affecting the modeled route assignment. This is particularly true in the case of the ACO-based assignment model, which requires considerable exploration provisions to make sure that improbable distributions will not be reached (Figure 6.5).

21. The cost differentials ($d(\text{cost})/dt$) may be used to capture the traffic dynamics and refine the route assignment.



Figure 6.6: Route assignment under the information inertia model.

Each approach has advantages and disadvantages. Thus, preference will be case-specific and related to the required precision level, the fluctuation of the input and output flows, and the focus of the study. The information inertia model's updating process of routing probability distributions is based on more transparent mechanisms that hold behavioral meaning and its calibrating process appears more straightforward[22] (Figure 6.6).

Finally, the inertia model performs better in a wider range of traffic conditions and is able to model routing choices even under rapidly changing conditions, while the ACO-based model requires time to reach reasonable distributions after sudden flow changes.[23] Therefore, the recent focus of the writers' research agenda has been the information inertia model and the refinement of the inertia factor n.

6.9. Final Remarks

This chapter suggests a new approach to pedestrian route-choice simulation, which allows for the integration of micro-navigation movement modeling with macroscopic route-choice behavior modeling in real time. The proposal is based on a three-stage process: (i) network definition, (ii) route evaluation, and (iii) route assignment. A new method for representing continuous space, which is consistent with the behavioral characteristics of pedestrians and produces manageable movement networks, has been proposed. Available route choices are evaluated by a feedback-based evaluation system and route choices are simulated in ways that allow the system to respond efficiently under both steady and transient traffic conditions.

22. The calibration of the inertia factor n is simpler than this of the ACO-based performance evaluator r.
23. It should be noted that most known ACO implementations focus on suboptimal heuristic solutions to complex problems. While this is acceptable in the case of pedestrian route assignment, this suboptimality should not be contrary to basic behavioural assumptions and thus lead to unreasonable results.

The advantages of the approach are considerable. The two assignment methods that are presented in Section 6.7 are able to handle the dynamics of pedestrian systems under varying levels of in-flow demands. Under steady demands, both methods converge toward flow distributions that are consistent with Wardrop's first principle without requiring iterative equilibrium-seeking heuristics that are not attached to real time.

Moreover, the evaluation of available choices is based on feedback of experience costs and thus there is no requirement to formulate aggregate volume delay functions or associate estimated costs to macroscopic observable metrics. Finally, available choices are modeled through a link-based approach (rather than route-based) and, therefore, are restricted to manageable numbers.

The presented route assignment methods are based on behavioral assumptions related to observation and past experience. However, the impact of past experience on routing decisions is implicitly modeled through consideration of the fed-back-experienced costs. The effect of this approach on flow distributions during transitional phases (while Wardrop's first principle is not satisfied) and how well they represent reality is arguably one of the most interesting aspects of future research.

In particular, considerable effort will be targeted toward understanding the effect that lagged feedback-based costs (and the related out-of-synchronization effect) have on highly volatile flow distributions and toward further research on the role that the consideration of the dynamics of those costs can play in limiting this effect.

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References

Antonini, G., Bierlaire, M., & Weber, M. (2006). Discrete choice models of pedestrian walking behaviour. *Transportation Research Part B*, *40*, 667–687.

Appleyard, D., & Lintell, M. (1972). Environmental quality of city streets: The residents' viewpoint. *Journal of the American Institute of Planners*, *38*, 84–101.

Avineri, E., & Prashker, J. N. (2006). The impact of travel time information on travellers' learning under uncertainty. *Transportation*, *33*, 393–408.

Bellman, R. E. (1957). *Dynamic programming*. Princeton: Princeton University Press.

Blue, V. J., & Adler, J. L. (1998). Emergent fundamental pedestrian flows from cellular automata microsimulation. *Transportation Research Record* (1644), 29–36.

Bovy, P. H. L., & Stern, E. (1990). *Route choice: Wayfinding in transport networks*. Dordrecht: Kluwer Academic Publishers.

Castle, J. E. C. (2007). *Agent-based modelling of pedestrian evacuation — A study of Kings Cross Station*. Ph.D. thesis, UCL, University of London.

Cruz, F. R. B., & Smith, J. M. (2007). Approximate analysis of M/G/c/c state-dependent queuing networks. *Computers and Operations Research*, *34*(8), 2332–2344.

Daamen, W. (2004). *Modelling passenger flows in public transport facilities*. Ph.D. thesis, Delft University Press, Delft.

Dafermos, S. C., & Sparrow, F. T. (1969). The traffic assignment problem for a general network. *Journal of Research of the National Bureau of Standards*, *73B*, 91–118.

Di Caro, G., & Dorigo, M. (1998). AntNet: Distributed stigmergetic control for communications networks. *Journal of Artificial Intelligence Research*, *9*, 317–365.

Dorigo, M., Di Caro, G., & Gambardella, L. M. (1999). Ant algorithms for discrete optimization. *Artificial Life*, *5*(2), 137–172.

Dorigo, M., Maniezzo, V., & Colorni, A. (1996). The ant system: Optimization by a colony of cooperating agents. *IEEE Transactions on Systems, Man, and Cybernetics — Part B*, *26*(1), 29–41.

Frank, M., & Wolfe, P. (1956). An algorithm for quadratic programming. *Naval Research Logistics Quarterly*, *3*, 95–110.

Gipps, P. G. (1986). *Simulation of pedestrian traffic in buildings* (Vol. 35). Karlsruhe: Schriftenreihe des Instituts fuer Verkehrswesen, University of Karlsruhe.

Haklay, M., O'Sullivan, D., & Thurstain-Goodwin, M. (2001). So go downtown: Simulating pedestrian movement in town centres. *Environment and Planning B*, *28*, 343–359.

Helbing, D., & Molnár, P. (1994). Social Force Model for pedestrian dynamics. *Physical Review, E*, *50*, R5–R8.

Helbing, D., Molnár, P., Farkas, I. J., & Bolay, K. (2001). Self-organizing pedestrian movement. *Environment and Planning B*, *28*(3), 361–383.

Hill, M. R. (1982). *Spatial structure and decision-making of pedestrian route selection through an urban environment*. Ph.D. thesis, University Microfilms International.

Hillier, B., & Hanson, J. (1984). *The social logic of space*. Cambridge: Cambridge University Press.

Hoogendoorn, S. P. (2002). Pedestrian travel behaviour in walking areas by subjective utility optimization. Transportation Research Annual Meeting, Paper No. 02-2667, Washington.

Hoogendoorn, S. P., & Bovy, P. H. L. (2004a). Pedestrian route-choice and activity scheduling theory and models. *Transportation Research Part B: Methodological*, *38*(2), 169–190.

Hoogendoorn, S. P., & Bovy, P. H. L. (2004b). Dynamic user-optimal assignment in continuous time and space. *Transportation Research Part B: Methodological*, *38*(7), 571–592.

Inman, V. T., Ralston, H. J., & Todd, F. (1981). *Human walking*. Baltimore: Williams & Wilkins.

Kagarlis, M. A. (2002). Method of simulating movement of an autonomous entity through an environment. US Patent Application 20040059548.

Lee, C., & Machemehl, R. B. (2005). *Combined traffic signal control and traffic assignment: Algorithms, implementation and numerical results*. Research Report, University of Texas at Austin.

Papageorgiou, M. (1990). Dynamic modelling, assignment, and route guidance in traffic networks. *Transportation Research Part B: Methodological*, *24*(6), 471–495.

Schwartz, B., Wasserman, E. A., & Robbins, S. J. (2002). *Psychology of learning and behaviour* (5th ed.). New York, NY: W.W. Norton & Company.

Seyfried, A., Steffen, B., Klingsch, W., & Boltes, M. (2005). The fundamental diagram of pedestrian movement revisited. *Journal of Statistical Mechanics: Theory and Experiment*, *P10002*.

Stathopoulos, T., Wu, H., & Zacharias, J. (2004). Outdoor human comfort in an urban climate. *Building and Environment*, *39*, 297–305.

Wardrop, J. C. (1952). Some theoretical aspects of road traffic research. *Proceedings of the Institution of Civil Engineers, Part 2*, *9*, 325–378.

Zachariadis, V. (2005). *An agent-based approach to the simulation of pedestrian movement*. M.Phil. thesis, UCL, University of London.

Zacharias, J. (2001). Path choice and visual stimuli: Signs of human activity and architecture. *Journal of Environmental Psychology*, *21*(4), 341–352.

Chapter 7

Modeling and Simulating Pedestrian Shopping Behavior Based on Principles of Bounded Rationality

Wei Zhu and Harry Timmermans

Abstract

Modeling pedestrian behavior and decision making has dominantly relied on rational choice models, especially discrete choice models. These models, however, may not be appropriate for modeling the decision processes because they assume unrealistic cognitive and computational abilities of decision makers. Actually, people often use simplifying strategies or decision heuristics for complex decision problems in environments such as shopping streets. The theory of bounded rationality provides a more realistic basis for modeling these kinds of decision problems. Although models of bounded rationality have been studied for a long time, there are no applications in pedestrian research. Most research on bounded rationality has focused on the non-compensatory nature of the decision process or on the characteristics of strategy selection behavior, while other aspects such as factor selection, the coexistence of multiple strategies and integrated frameworks for these aspects have not received much attention yet. This paper therefore proposes such an integrated modeling framework which simultaneously deals with eliciting heterogeneous decision heuristics and the choice of decision heuristic. In addition, we propose an empirical framework for modeling pedestrian decisions including the go-home decision, direction choice decision, rest decision, and store patronage decision. The bounded rationality model is applied to these choice facets. For illustration, a dataset about pedestrian shopping behavior was collected in a shopping street in Shanghai, China. The model estimation results include pedestrians' preference structures and the probabilities of information search

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under different search sequences. Estimated parameters are reasonable, providing evidence of the validity of the proposed model. Results indicate that pedestrians tend to use simplified strategies for making satisficing decisions, and tend to search more information for comparative decisions. The predictive validity of the framework is tested using multi-agent simulation. The simulated aggregated spatio-temporal distributions of agent behavior are compared with observed pedestrian behavior. The results are satisfactory in general, however, with some under- and overestimation. Possible reasons are discussed.

7.1. Introduction

Almost all behavior can be understood as the result of choice decisions. For instance, pedestrians decide to leave or stay in the shopping center; decide to walk into a particular street rather than another; decide whether to visit a store; decide to buy something; etc. In the past, several different models of pedestrian behavior and movement have been developed. To the extent that these models are based on principles of choice behavior, most models of pedestrian choice behavior (and other types of activity choices) have been based on theories of rational choice. These theories suggest that individuals invariably take into account the set of factors influencing their choice behavior, attach some value judgment (utility, attitude, satisfaction) to each choice alternative, and choose the alternative that maximizes their value judgment. Most operational models use an additive function to represent the value judgment process, implying that a compensatory decision-making process is assumed in the sense that a low judgment on some factor may at least partially be compensated by higher judgments of one or more of the remaining factors influencing the decision. For example, in the context of pedestrian store or shopping center choice behavior, a pedestrian's utility of alternatives are commonly defined as the summation of weighted (evaluations of) physical factors like store floorspace, store type and variety, distance, traffic condition, and parking facility (e.g., Borgers & Timmermans, 1986; Saito & Ishibashi, 1992; Oppewal & Timmermans, 1997; Van der Waerden, Borgers, & Timmermans, 1998). Pedestrians are assumed to choose the store bringing them the highest utility. A potential limitation of these models is that they do not explicitly represent decision processes, such as information search and representation. Pedestrians are often assumed to have very good knowledge about the environment and the ability to take into account all relevant factors influencing the decisions. Choice outcomes are interpreted in terms of concepts of rational choice behavior.

In contrast to these models of rational choice behavior, models of bounded rationality assume that decisions are made on subsets of factors and do not necessarily result in optimal choices because people have limited cognitive and computational abilities (e.g., Simon, 1959). These models often adopt non-compensatory rules and decision heuristics to indicate that decisions may be made on an attribute-by-attribute

basis as opposed to a compensatory decision process (e.g., Tversky, 1972; Payne & Bettman, 1988; Gigerenzer, Todd, & ABC Research Group, 1999). A small number of examples of such models have appeared in the planning and transportation literature (e.g., Foerster, 1979; Recker & Golob, 1979; Timmermans, 1983; Young, 1984), but this work is not related to pedestrians. Thus, research on bounded rationality is relatively scarce in general, and we are not aware of any applications in pedestrian simulation. Nevertheless, given the complexity of pedestrian choice processes, it is of interest to explore the potential of formulating models of pedestrian choice behavior, based on the principle of bounded rationality.

The aim of this paper therefore is to give an overview of our attempts of developing a model of pedestrian choice behavior, based on the principle of bounded rationality, which incorporates not only choice outcomes, but also elements of the underlying choice processes. The objective is to suggest a model, which does not require more information than conventional discrete choice models, but is based on a richer set of behavioral assumptions.

The paper is organized as follows. Section 7.2 introduces the conceptual framework underlying the model. Section 7.3 discusses a dataset collected in a shopping street in China that serves to illustrate the model. Section 7.4 reports the results of the model estimation and validation, using multi-agent simulation. Section 7.5 concludes the paper.

7.2. Conceptual Framework

7.2.1. The Heterogeneous Heuristic Model

We proposed a new modeling approach, named the Heterogeneous Heuristic Model (HHM), which can estimate the coexistence of different decision strategies using a single model. Due to the page limitation, a detailed specification cannot be given in this paper. Readers are referred to Zhu and Timmermans (2008) and Zhu (2008). Only key concepts are introduced in the following.

7.2.1.1. Factor threshold Let $X = \{x_j | j = 1, ..., J\}$ represent the set of attributes or factors influencing the decision of interest. Based on the concept of bounded rationality, any decision or choice process can be understood as a problem-solving process in which an individual processes information to arrive at a decision that achieves a particular goal within some margin of accuracy. We assume that, rather than considering all factors and identifying nuances in factor values, individuals use factor thresholds as the basic mechanism for *filtering* and *representing* information. Let $\Delta_j = \{\delta_{j1} < \delta_{jn} < \delta_{jN} | n = 1, ..., N\}$ be a set of successively increasing activation thresholds for x_j, corresponding to stricter judgment standards. A factor is only considered when at least one of the thresholds is exceeded, $x_j \geq \delta_{jn}$. At the same time, the factor is represented in terms of a set of discrete states, $S_j = \{s_{j1} = x_j < \delta_{j1}, ..., s_{jn} = \delta_{jn-1} \leq x_j < \delta_{jn}, ..., s_{jN+1} = x_j \geq \delta_{jN}\}$.

7.2.1.2. Preference structure Each factor state is assigned by the individual a value, $W_j = \{w_{j1}, ..., w_{jn}, ..., w_{jN+1}\}$ corresponding to S_j, which can be understood as a part-worth utility. The overall value of the alternative is then formed by assuming that factor state values are linearly aggregated, $v_i = \sum_j \sum_n w_{jn} s_{jn}$. To make the decision, for example to reject or accept an alternative, an overall threshold, λ, is applied as the judgment standard. The alternative is accepted if $v_i \geq \lambda$, and rejected if $v_i < \lambda$. The complete factorial combination of the factor state values results in a set of overall value judgments, $\bar{V} = \{\bar{v}_1 < \bar{v}_k < \bar{v}_K | k = 1, 2, ..., K; K = \prod_j (N_j + 1)\}$. This set defines all possible overall values that result from the evaluation of an alternative. Checking these overall value judgments against the overall threshold λ results in a *preference structure* with some value judgments above the threshold and some below the threshold.

7.2.1.3. Heterogeneous heuristics We assume that decision heuristics are logical inferences from preference structures. Because preference structures may differ for different individuals or in different contexts in terms of the pattern of the sets of accepted and rejected values, the cognitive process model automatically generates heterogeneous heuristics. When λ is so high that no overall value judgment exceeds it, it represents the strategy of unconditional rejection. When λ is so small that only the overall value with the combination of the highest factor states exceeds it, it represents a conjunctive rule. At the other extreme, when λ is so low that all overall value judgments exceed it, it represents an unconditional acceptation strategy. A slightly strict λ with only the overall value judgment consisting of the lowest state values exceeding it will lead to a disjunctive rule. In-between, various other heuristics can be identified, including lexicographic rules.

7.2.1.4. Choice of heuristics We model any single decision as a two-stage process: choosing an appropriate preference structure and then applying this structure to the choice task. Because the preference structure actually applied by the decision maker is unknown to the researcher, the final probability of an alternative being satisfactory can be modeled as the expected result of choices aggregated from all possible choice outcomes under these latent preference structures, $p_i = \sum_{k=1}^{K+1} p_k p_{i|k}$, where $p_{i|k}$ is the probability that alternative i is satisfactory when preference structure k is applied. Assume that the probability of a preference structure being applied, p_k, is a multinomial logit distribution. The probability can then be specified as proportional to the expected value, u_k, of preference structure k, that is, $p_k = \exp(u_k) / \sum_{k'=1}^{K+1} \exp(u_{k'})$. Because using the heuristics implied by the same preference structure does not affect the decision outcome, p_k can also be formulated as the aggregation of the probabilities of the heuristics being chosen, that is$p_k = \sum_{h=1}^{J!} p_{kh} = \sum_{h=1}^{J!} \exp(u_{kh}) / \sum_{k'=1}^{K+1} \sum_{h'=1}^{J!} \exp(u_{k'h'})$, where u_{kh} is the expected value of heuristic h implied by preference structure k. It is assumed that this value is composed of expected mental effort (e_{kh}) inflicted when searching factors in a sequence, risk perception (r_k) as a representation of outcome diversity (by definition more outcome diversity implies less risk perception, and vice versa), and expected

outcome (o_k) as a priori preference for particular decision outcomes. It is assumed that $u_{kh} = \beta^e e_{kh} + \beta^r r_k + \beta^o o_k$, where the β's are parameters to be estimated.

7.2.2. Process Model of Pedestrian Behavior

Although pedestrian behavior in a shopping environment may seem complex, the components of underlying decisions are not necessarily complicated. In principle, if the mechanisms underlying each decision can be modeled accurately, the joint effect on pedestrian behavior will emerge. This idea is the key notion of many multi-agent systems.

Many agent-based pedestrian simulation systems have been developed (e.g., Haklay, O'Sullivan, & Thurstain-Goodwin, 2001; Dijkstra & Timmermans, 2002; Bandini, Federici, Manzoni, & Vizzari, 2006). However, none of these models are based on principles of bounded rationality. In the context of the present study, a dedicated multi-agent simulation system was built, based on NetLogo (see http://ccl.northwestern.edu/netlogo), an open-source multi-agent programmable modeling environment, to examine the validity of the estimated HHM model. This specific pedestrian simulation platform consists of the following four components: (1) Global variables are used to store global information that is accessible throughout the simulation process. Model parameters are stored as global variables that can be accessed by each agent. (2) Agents represent pedestrians who make decisions and move in space. Each agent is assigned a need which includes five intentions: going home, choosing direction, taking rest, patronizing store, and staying at the same place. Different needs are assigned at different stages to indicate to the agent which decision should be made next. Agents have their own location and orientation information in order to move on the grid space. An agent's activity history is also recorded for related decisions. (3) Grid space represents the physical environment (Figure 7.1). Each cell represents a 5×5 m area in the real environment and is assigned a particular type which includes six categories: (i) block, where agents cannot stand or move into, (ii) street, where agents can stand or move into, (iii) entry, where agents enter the shopping area and start the trip, (iv) waypoint, which may serve as general orientation guidance for agents and is usually set at street

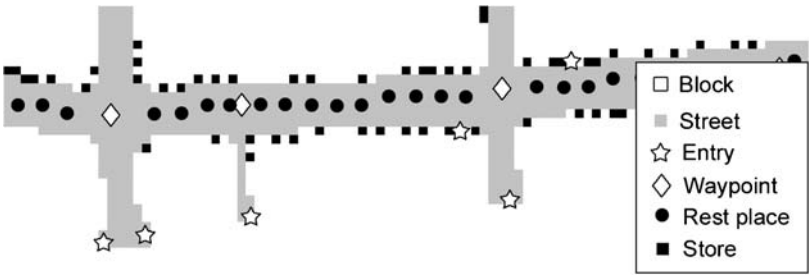


Figure 7.1: Illustration of the grid space.

intersections or locations where the street shape changes sharply, (v) rest place, where agents may take rests, and (vi) store, where agents shop. Except waypoint, which is virtual, the other types of cells all resemble the actual physical environment to be simulated. The physical properties of a place are stored in the variables of the cell representing this place, for example, the area of store floorspace and store type. Each cell also has some count variables to record the number and time of activities. These variables are very useful for studying aggregate behavior. (4) Interface provides a convenient mean for controlling the simulation processes and visualizing the real time situation of the simulated environment.

Figure 7.2 shows the flowchart of the multi-agent simulation of pedestrian shopping behavior. The simulation of each agent starts with entering the shopping area at one of the entries. After the entry, the first decision that the agent will make is the *direction choice decision*, based on the direction choice model, if there are alternative directions. The chosen direction defines the search space of the agent. The next need of the agent is to rest. This is simulated by first checking whether rest is already in the need stack. An agent's need stack is designed for storing unsatisfied needs, simulating the fact that pedestrians may postpone the pursuit of certain need if it cannot be satisfied under the current situation and give priority to another need. In this system, only two needs may enter the need stack. Shopping is the default need always in the stack. Rest is the other which may be in or out of the stack depending on related decisions and behaviors. The priorities of the two needs may alternate.

Obviously, for agents just entering the area, rest is not in the need stack. In that case, an agent will make the rest decision based on the *rest model*. A positive decision outcome will lead to the same behavior as that of agents who already have had rest in the need stack: they will find a place to rest. The search for a rest place is limited within the chosen direction. If an agent finds a rest place within the search range (which was set to 100 m), the agent will go to the nearest place to rest and the activity is removed from the need stack. When the agent reaches the rest place, the duration of the rest episode is predicted using the duration model. Then the agent stays in the rest place until the duration has been completed. After the rest, the agent decides whether or not to go home, based on the *go-home model*. A positive outcome will lead to the end of the shopping trip and the agent simply disappears from the environment. A negative outcome leads the agent back to the direction choice decision.

At the node of searching for a rest place, if no place is found within the search range, it is assumed that the agent will push the need for rest into the need stack and at the same time give priority to shopping. The agent will start searching for a store only if there are stores available in the chosen direction. Otherwise, the agent has to decide on a new direction. The procedure of searching for a store is similar as searching for a place to rest. The agent evaluates each store from the nearest one to the farthest one within the search range, based on the *store patronage model*. Once a satisfactory store is found, the agent will head for it. Upon reaching the target, the duration for the shopping activity is predicted using the shopping duration model and the agent will stay there for the predicted duration. After that, the go-home decision is prompted again. If no satisfactory store is found within the search range, the rest activity will receive priority if it is in the need stack. If further search in the

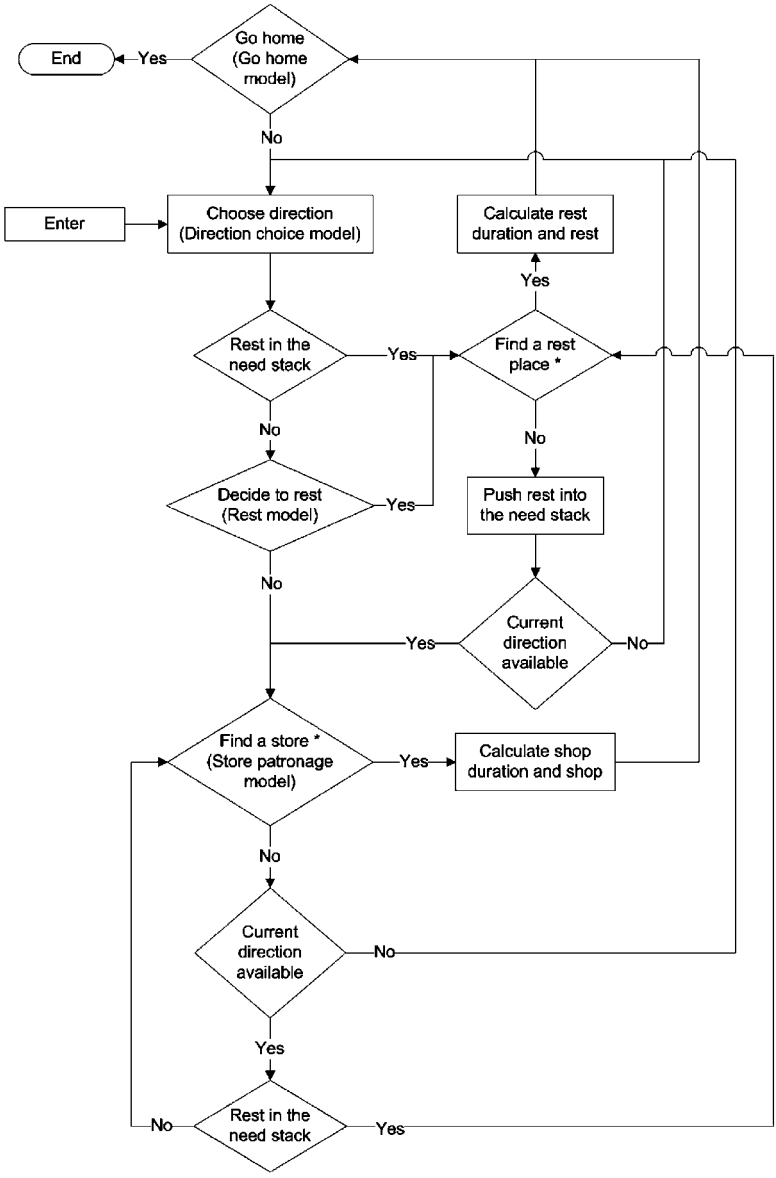


Figure 7.2: Flowchart of simulating pedestrian behavior. *Stores and rest places within 100 m search range are searched.

current direction is still possible, the agent will move about 100 m toward the nearest waypoint and starts to search for a place to rest at the new location if rest is in the need stack, or search for a store when a rest is not needed. In case search in that direction has been completed, a new direction choice is made.

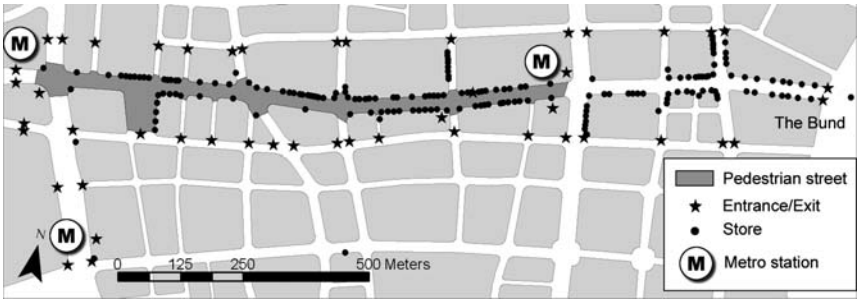


Figure 7.3: The survey area of East Nanjing Road.

7.3. Data

A dataset about pedestrian shopping diaries was collected on May 19 (Saturday) and 22 (Tuesday), 2007, in East Nanjing Road (ENR), the city center of Shanghai, China. The street is about 1600 m long, 1000 m of which is pedestrianized (Figure 7.3). People's Square, a multifunctional place for gathering, leisure, shopping, and museums, is located in the western end of the street. The eastern end locates The Bund, an internationally famous tourism site featuring buildings of the early 20th century. Many public transport stops are located near the Bund. There are two metro stations in the area, one near People's Square, and the other at the eastern end of the pedestrianized section, Mid Henan Road. Two very important metro lines, carrying a huge number of passengers everyday, run through these two stations. Stores are located along both sides of the street, which is largely shaped as a linear shopping space.

Twenty undergraduate students from Tongji University administrated the survey. Each day from 12:00 to 20:00, they randomly invited pedestrians in the street to complete a questionnaire. It took about 20 min for a respondent to answer the questions about their socio-demographics and shopping activities, such as which stores they visited, the sequence of their visits, what they bought and expenditure, and other activities that had been conducted up to the moment they were being interviewed. In total, 811 valid responses were obtained. Of these respondents, 55% were male and 45% were female; 51% were young people (16–29), 32% were middle-aged people (30–49), and 17% were old people (≥ 50); 29% came to the street for shopping purposes, 34% for tourism, 22% for leisure, and 15% for other purposes.

7.4. Model Estimation and Validation

7.4.1. Model Estimation

According to the process model of Figure 7.2, four decisions are critical for determining the behavioral chain of the pedestrian, go-home, direction choice, rest, and store patronage decision. We specify each of them based on HHM.

Pedestrians use the go-home decision to decide whether they should end the shopping trip and leave the street. We assume that it occurs after visiting a store or taking a rest. It is a binary rejection/acceptation decision and is specified as:

$$\sum_X \mathbf{W}^X \Psi(t^X \geq \mathbf{\Delta}^X) \geq \lambda \quad X = R, A \tag{7.1}$$

Two explanatory variables are used, relative time (t^R) and absolute time (t^A). Relative time represents a pedestrian's fulfillment of shopping purpose, the degree of fatigue, and boredom. Absolute time represents a pedestrian's predefined schedule for judging the end of the trip. $\mathbf{W}^X = [w_1^X, ..., w_j^X, ..., w_J^X]$ is a J-element row vector of factor state values, $\mathbf{\Delta}^X = [\delta_1^X, ..., \delta_j^X, ..., \delta_J^X]^{\mathrm{T}}$ a column vector of factor threshold values, and $\boldsymbol{\Psi}$ (ψ) an element-wise identity function being 1 for the true relationships ψ, being 0 for the false relationships. Eq. (7.1) means that if the overall value of going home, represented by the left term in the equation aggregated from the state values of the two time factors, is larger than the overall threshold λ, then the pedestrian will go home. Otherwise, he/she will keep shopping. To estimate the assumed multinomial logit distribution of λ, the utility of each decision heuristic was calculated. The estimations of $\mathbf{W}^X$ and $\mathbf{\Delta}^X$ provide the cognitive structure, from which the stopping conditions for each heuristic can be inferred. Then, the functions of mental effort, risk perception, and expected outcome can be derived and respective parameters $\boldsymbol{\beta}^e$, $\boldsymbol{\beta}^r$, and $\boldsymbol{\beta}^o$ are simultaneously estimated with $\mathbf{W}^X$ and $\mathbf{\Delta}^X$ using a maximum likelihood method.

The direction choice decision is a comparative decision which requires pedestrians to choose a walking direction among alternative directions. The framework of comparative choice under HHM was applied. It is assumed that a pedestrian, when comparing two directions, will choose the one which is better in value than the other, considering a certain discriminant threshold λ^R. When the threshold varies, with similar logic as satisficing decision, different non-compensatory heuristics can be deduced. If the value difference between the two directions is less than λ^R, random choice is assumed. The value function of each walking direction is defined as

$$v^Y = \mathbf{W}^x \Psi(x^Y \geq \mathbf{\Delta}^x) + w^d x^d + w^b x^b \qquad x = q, l \tag{7.2}$$

Four factors are considered relevant for evaluating a walking direction which, in this case, is defined as a relatively straight street with stores on both sides for more than 50 m: (i) the total retail floorspace in the direction (q) representing the attraction of retail activity; (ii) the length of pedestrianized street in the direction (l) representing the amenity of the walking environment; (iii) whether the direction is where the pedestrian just came from (d, a 0/1 variable, with 0 being the different direction and 1 being the same direction) representing people's unwillingness to make back-turns; and (iv) the location of landmark (b, a 0/1 variable, with 0 indicating there is no landmark and 1 indicating there is) representing its function as orientation guide. $\mathbf{W}^x$ and $\mathbf{\Delta}^x$ are vectors of state values and factor thresholds, similarly defined as in the go-home model; w^d and w^b are scalar state values for the two dummy variables.

Relative time and absolute time are also used for explaining the rest decision. Therefore, the model specification is the same as Eq. (7.1). If the equation is satisfied, the pedestrian decides to take a rest; if not, he/she continues to find a store.

The store patronage decision is framed as a sequential process. That is, we assume that pedestrians judge whether a store is satisfactory according to some descending sequence, determined by distances from the stores to the pedestrian's location. A pedestrian is assumed to choose the first store that is found satisfactory. Therefore, this decision also implies a binary judgment. The decision is assumed to be influenced by four factors: (i) the retail floorspace of a store (q) representing the attractiveness due to store size; (ii) the dominance of the store (m) defined as the proportion of store floorspace to the total floorspace of the stores within 100 m; (iii) store type (s) representing the retail sector of a store (18 types are identified and each store is assigned a type). Each store type is designated, through estimation, into an interest category. This set of categories reflects that pedestrians may cognize different types of stores into a limited number of interests, with $Z = \{z_1, ..., z_k, ..., z_K | K \leq 18\}$. Each category is assigned a value, β_k^z. The pedestrian will patronize the store, if he/she finds that,

$$\sum_x \mathbf{W}^x \Psi(x_i \geq \mathbf{\Delta}^x) + \sum_{k=1}^{K} \beta_k^z z_{ik} \geq \lambda \qquad x = q, m \tag{7.3}$$

The number of interest categories, K, is determined through model selection, similar to determining the numbers of thresholds for the other variables.

A hybrid estimation algorithm was developed to estimate the models. The algorithm consists of a genetic algorithm for global search, a taxi-cab algorithm for tunneling functionality when the genetic algorithm gets stuck, and a gradient-based algorithm to optimize the estimation locally. Consistent Akaike Information Criterion (CAIC) was used for model selection (e.g., Dayton & Lin, 1997). Table 7.1 shows the estimation results of the four models.

The go-home model turns out to have two thresholds for t^R and three thresholds for t^A. The pedestrians seem to have classified t^R into three states ($<$70 min, 70–240 min, $\geq$ 240 min) and t^A into four states ($<$14:30, 14:30–16:00, 16:00–20:00, $\geq$20:00). These segments are quite reasonable and conform with people's habit of using typical clock hours as decision references. The positive weights mean that as time goes by, the value of going home increases.

The direction choice model shows that only one threshold, 2005 m^2, is used for representing retail floorspace. The length of the pedestrianized section is classified into three states ($<$110 m, 110–341 m, $\geq$341 m). The positive w^b suggests that a landmark is useful as an orientation guide. The negative w^d is consistent with the hypothesis that people are unwilling to turn back.

In the rest model, t^R is represented by three states ($<$3 min, 3–179 min, $\geq$179 min). The first state reflects that some pedestrians rested just after they arrived, probably because they already felt tired from traveling or from conducting other activities. The second threshold is three hours after the start of the trip. t^A is also represented in terms of three states ($<$11:44, 11:44–19:50, $\geq$19:50). The first rest reference is near noon and

Table 7.1: Model estimation results.

Go-home		**Direction choice**		**Rest**	
Parameter	**Estimate**	**Parameter**	**Estimate**	**Parameter**	**Estimate**
$\delta_1^{R\,a}$	70 min	δ^q	2005 m^2	δ_1^R	3 min
δ_2^R	240 min	(w^q)	1.000*	δ_2^R	179 min
$(w_1^R)^b$	1.000*	δ_1^l	110 m	(w_1^R)	1.000*
w_2^R	0.766*	δ_2^l	341 m	w_2^R	0.347*
δ_1^A	14:30	w_1^l	7.452*	δ_1^A	11:44
δ_2^A	16:00	w_2^l	6.111*	δ_2^A	19:50
δ_3^A	20:00	w^b	0.787*	w_1^A	0.884*
w_1^A	0.822*	w^d	−6.936*	w_2^A	5.742*
w_2^A	0.710*	β^e	−3.437*	β^e	−3.377*
w_3^A	2.566*	β^r	7.652*	β^r	5.568*
β^e	−2.690*	β^o	4.116*	β^o	−2.229*
β^r	4.526*				
β^o	−1.026*				
N^{Cc}	808	N^C	2268	N^C	822
N^{Pd}	8	N^P	8	N^P	7
$LL0^e$	−560	$LL0$	−1,769	$LL0$	−570
LL^f	−396	LL	−1002	LL	−329
$CAIC$	853	$CAIC$	2074	$CAIC$	713
Store patronage					
δ_1^q	50 m^2	z_{Clth}	2	z_{Spor}	2
δ_2^q	420 m^2	z_{Dept}	3	z_{Toba}	1
δ_3^q	24,000 m^2	z_{Equi}	2	z_{Tour}	4
w_1^q	4.293*	z_{Fddr}	2	(z_{Oths})	1
w_2^q	4.775*	z_{Fdfa}	2	β_1^z	0.000
w_3^q	1.405*	z_{Fdfo}	1	β_2^z	1.000*
δ^m	0.999	z_{Fdre}	3	β_3^z	3.895*
w^m	9.370*	z_{Jewe}	1	β_4^z	9.770*
z_{Arts}	1	z_{Opti}	1	β^e	−2.893*
z_{Book}	2	z_{Phar}	1	β^r	6.450*
z_{Chil}	2	z_{Shoe}	1	β^o	−2.894*
N^C	47,111				
N^P	10				
$LL0$	−32,655				
LL	−7,012				
$CAIC$	14,141				

[a]Thresholds are not counted as free parameters as only their corresponding weights are potentially effective.
[b]Parameters in ( ) were set for the estimation. One value parameter is set to 1 because only the relative relationships between the values matter.
[c]Number of cases.
[d]Number of parameters.
[e]Log-likelihood of the null model.
[f]Optimal log-likelihood.
*Parameters are significant.

the other threshold is around 20:00, probably after dinner. Their values are all positive, meaning that the need for rest becomes higher as time elapses.

In the store patronage model, floorspace is classified into four states, ($<50\,m^2$, 50–420 m^2, 420–24,000 m^2, $\geq 24{,}000\,m^2$). The threshold for store dominance is near 1, suggesting that a detached store location can enhance the attractiveness of the store, probably because pedestrians can fully concentrate their attention on that store. However, since only one store satisfies this condition, this variable may also represent alternative-specific taste. As for store type, four interest categories were estimated, from the most interesting (4) to the least interesting (1). The most interesting category only includes tourism sites (i.e., The Bund). The second most interesting category includes department stores and food stores, mainly those selling local special food.

One advantage of HHM is that it estimates the probability of each heuristic being applied and the factor search sequence. Figure 7.4 shows the probabilities of preference structures for the four decisions. For example, the go-home model has three states for relative time and four states for absolute time, implying that the number of preference structures for this cognitive structure is 13 ($3 \times 4 + 1$). Every preference structure implies two heuristics, one from searching t^R and the other from searching t^A. The probabilities of these 26 heuristics were estimated. The larger the index for a preference structure (PS), the higher the overall threshold or the judgment standard. A general trend shared by Figure 7.4a–c (the three binary decisions) is the increasing probability as the standard becomes stricter, due to the negative β^o. It implies that simpler rules are preferred over more complex ones. However, the probabilities drop at some point (PS-10 in Figure 7.4a, PS-7 in Figure 7.4b, and PS-25 in Figure 7.4c), because the implied heuristics after these points are too risky (i.e., the decision outcome is very certain). The exception is that the probabilities of the last preference structure, implying unconditional rejection, are high because they cost almost no effort. In the go-home model, excluding the "no action" heuristics, the probability of searching t^A first is 62%, while the corresponding probability for t^R is 18%. In the rest model, t^A is also the dominant factor and searched first (at least for preference structures with relatively high standards) with a probability of 63% against a 10% probability for t^R. Store type is the most important factor in the store patronage model, which is consistent with the common sense that people go shopping primarily for satisficing their needs. The aggregated probabilities of first-to-search factors are: s — 41%, q — 17%, and m — 14%.

In contrast, Figure 7.4d shows that risk perception is the dominant force controlling the choice of heuristic in the direction choice model. It indicates that the distribution concentrates around PS-7. From this point, when preference structure becomes smaller, the probability drops. This suggests that pedestrians tend to avoid using extremely low discriminant thresholds. When preference structure becomes larger, the probability also drops due to the fact that fewer alternatives can be differentiated and random choices have to be made, giving pedestrians a feeling of loosing control. The exception is that the probability of PS-24 is high, even though pedestrians make random choices all the time without considering any information. The reason could be that this strategy is almost effortless. In general, pedestrians are risk averse and prefer information search in this particular decision problem.

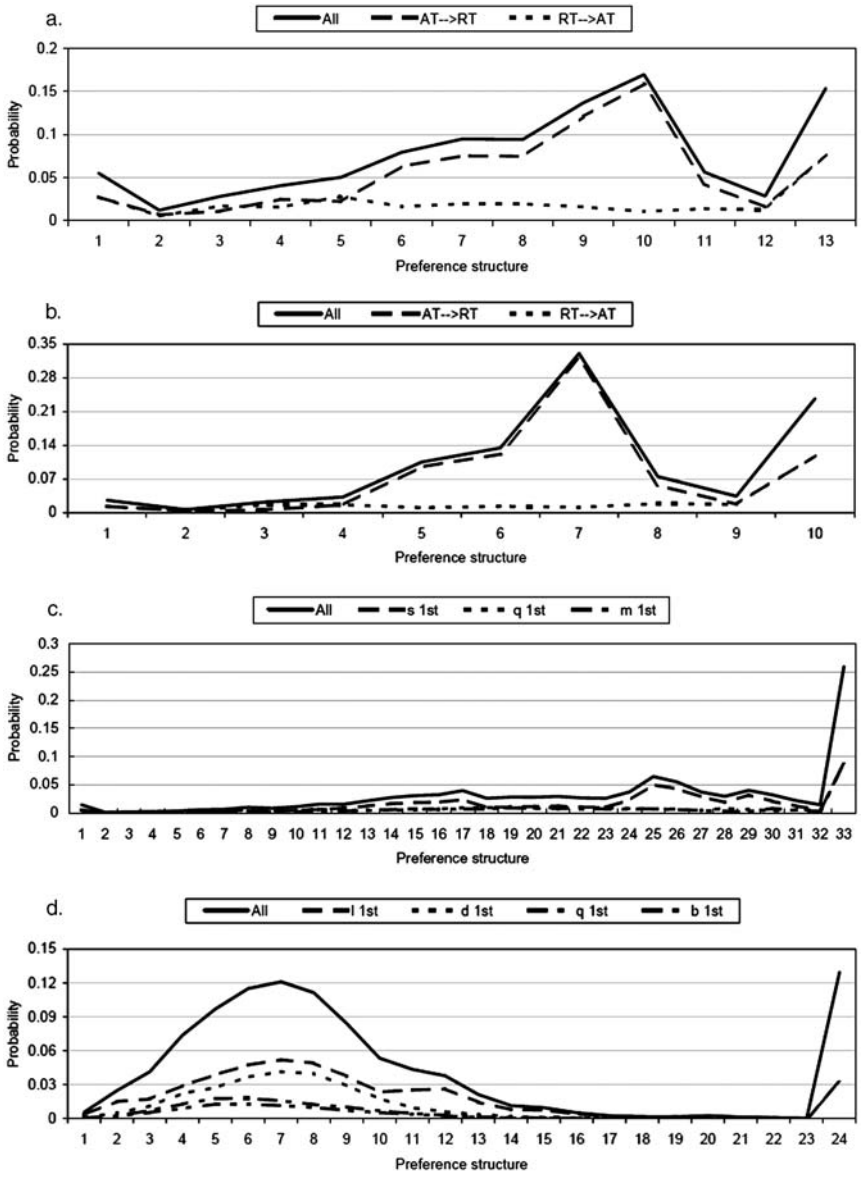


Figure 7.4: Probabilities of the preference structures. (a) Go-home decision; (b) rest decision; (c) store patronage decision; (d) direction choice decision.

Their way of decision making approaches rational mechanisms. Excluding PS-24, the aggregate probabilities of factors being searched first are, l — 41%, d — 26%, q — 12%, and b — 9%. Hence, the length of pedestrianized street and the previous direction are relatively important factors for the direction choice decision.

7.4.2. Multi-Agent Simulation

As these decisions were modeled separately and fitted to different subparts of the data, their joint ability to predict pedestrian behavior still needs to be tested. Twenty simulations were run according to the framework in Figure 7.2. Aggregate distributions of agent behavior were averaged over the simulations and compared with observed distributions of pedestrian behavior. In a single simulation, we took snapshots at 12 clock hours, 10:00–21:00, of the total number of agents.

Figure 7.5 shows the activity–time distributions. The simulated total number of agents fits the observations quite well. The distribution has a single peak at 15:00. Slight underestimates can be found before this time, mainly because the agent generation procedure, based on constant hourly generation rates, can not generate as many agents as in reality near the whole clock hours which were frequently reported

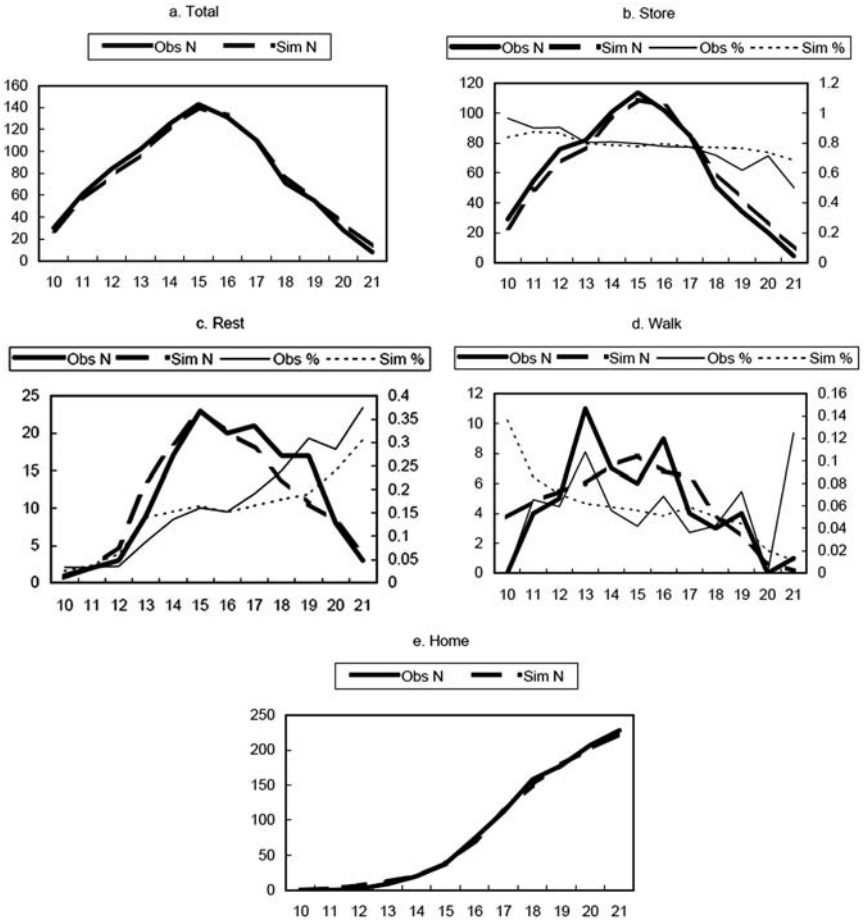


Figure 7.5: Distributions of agents by activity type over time.

by respondents as their arrival time. The mismatches become more apparent in the in-store distributions when the number of agents is less. Nevertheless, almost every turning point is well captured. The number of agents taking rests rise steeply from 12:00 to 15:00, and this is also well simulated. After 15:00, the simulated numbers drop too fast. The fit between the simulated and observed number of walking agents is poor, largely due to the small numbers. The two cumulative distributions of number of agents having gone home are very close. The ratio of in-store activities drops from about 90% in the beginning to about 60% in the end; the ratio of rest keeps rising from none to about 40%.

The map of ENR in 2007 was divided into 12 segments (Figure 7.6). The pedestrianized section was represented by segments 2–8. Some branch streets were also counted as segments if there was at least 50 m store front along either side of the street. The magnitude of the simulated number of agents in segments is right (Figure 7.7), although with more severe under- and overestimation. The fit in segments with very small numbers of pedestrians, such as segment 1, 3, 7, 9, and 11, is very poor, suggesting that the models may be invalid for at least for small numbers. It may reflect that branch streets are not competitive with the major street. The distributions in segments 2 and 4, the two segments closest to the western end, are reproduced relatively well. The numbers in the two segments in the middle (segments 5 and 6), are underestimated, mainly because the attractiveness of some famous stores in these segments are not well represented by the store patronage model. Thus, the probability of agents just walking through these segments becomes higher. In the non-pedestrianized section, as the numbers of pedestrians drop, the simulated numbers appear to be more erratic, with the numbers in segment 10 overestimated and those in segment 12 underestimated.

Figure 7.8a shows that the simulated number of visits in stores reflects the general trend, however, with some dispersion. This is not very surprising since the shopping environment in ENR is complicated and pedestrians are heterogeneous as ENR's strong regional fame attracts diverse consumer groups. Moreover, the inability of the store patronage model to consider more specific decision factors such as store reputation and retail strategy may also be responsible. The overall number of observed visits is 655, whereas 682 are simulated. The overestimation is 4.1%. In Figure 7.8b, most scatter points gather closer to the iso-value line except two points

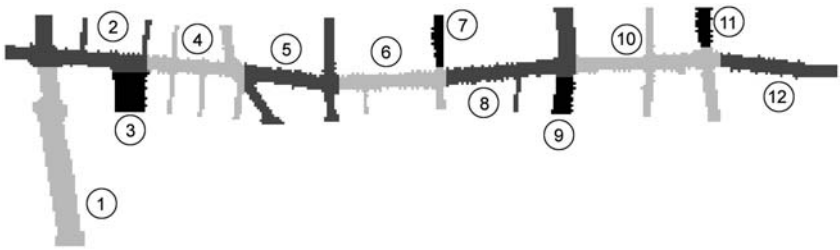


Figure 7.6: The segments of the street.

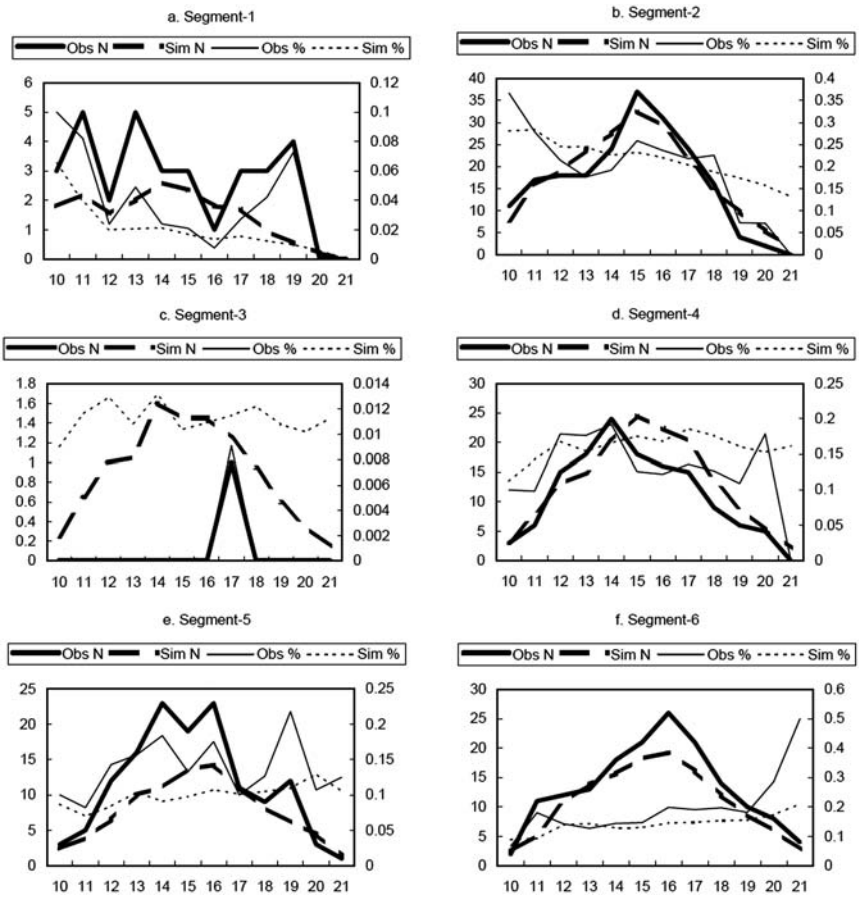


Figure 7.7: Distributions of agents in segments over time.

representing two large stores. The simulated overall in-store duration is 46,019 min, compared to the observed 44,084 min, an overestimation of 4.4%. The mean simulated duration is 67.5 min, which is very close to the observed 67.3 min.

7.5. Discussion and Conclusion

Shopping environments are probably one of the most complicated decision environments in the sense pedestrians in shopping streets are exposed to abundant information and need to make a series of choices. If this conjecture is accepted, the practice of using rational choice models to represent the actual decision process of pedestrians may be problematic as these models make unrealistic assumptions about the cognitive and computational abilities of people. Therefore, we contend that models of bounded rationality may be more appropriate for modeling pedestrians'

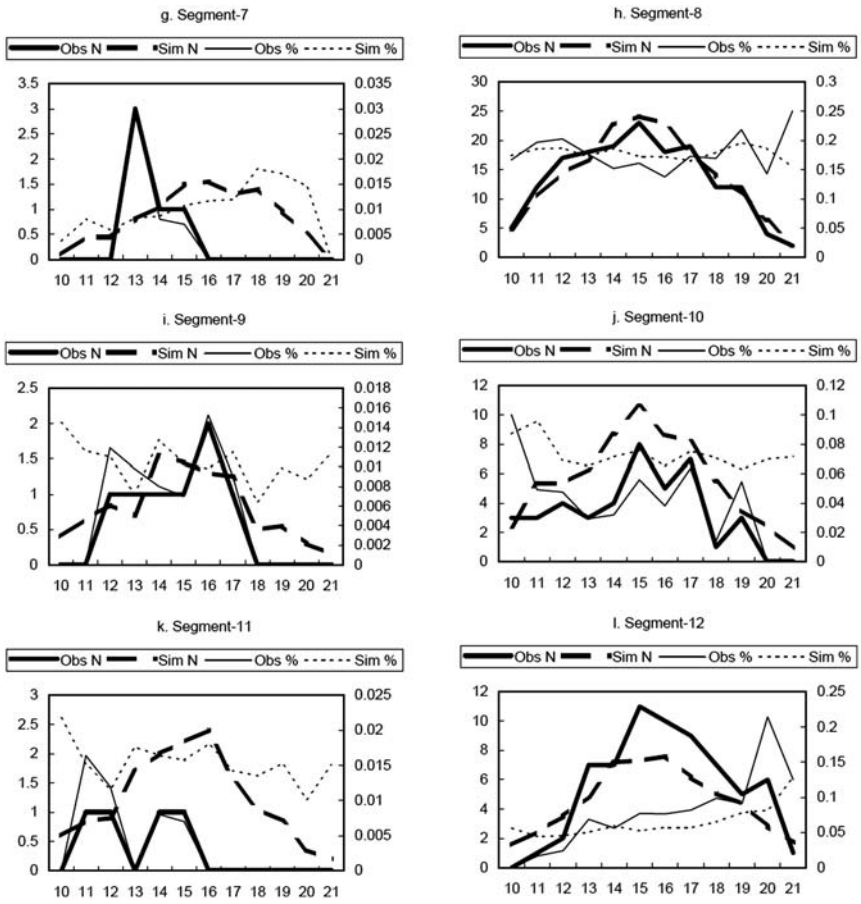


Figure 7.7: (Continued)

simplifying decision strategies. The new modeling approach, HHM, that we suggested in this paper has some unique properties. In particular, it deals simultaneously with elicitation of decision heuristics, selection of factors, choice of strategies, and the estimation of information search, while at the same time does not require more input data than conventional rational choice models. The results of the multi-agent validation support the promising potential of investigating the cognitive mechanisms and simplifying decision strategies involved in decision processes. Although the sub-models can and should be further improved, the results of the multi-agent simulation demonstrate generally satisfactory predictive validity of the set of HHM models. In particular, the activity–time distributions were predicted quite well, especially for the total number of agents, in-store activities, and the cumulative number of gone-home agents. The simulation results for rest behavior were only slightly worse. Walking behavior seems most difficult to predict accurately. However, we should also realize that some of the poor results may, at least partially,

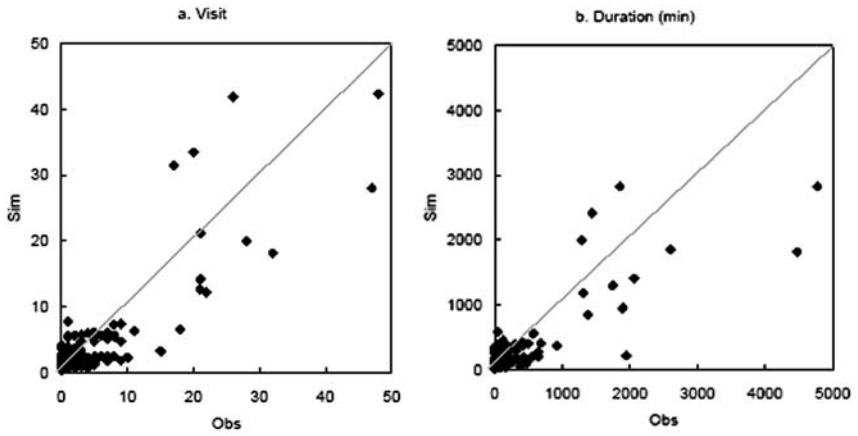


Figure 7.8: Visits and duration in stores.

be due to the large random fluctuations caused by the small number of observations. The test also showed regular changes over time in the ratios of activities to the total number of active agents, suggesting that pedestrians' shopping intentions decrease, while the need for rest increases with time. However, the changes were not as sharp as the observations, largely due to the averaging effects of the sub-models. In-store activity is the dominant activity throughout the whole shopping trip with an average of about 80%. The averaging effects of the store patronage and direction choice models caused more discrepancies in the comparisons of activity distributions in street segments, even though the general ratios between the activity numbers in segments were right. The simulations overestimated activities in stores along the non-pedestrianized sections and underestimated activities in stores along the pedestrianized sections. Again, distributions with a large number of activities were predicted better than distributions based on a smaller sample. The overall simulated number of visits and activity durations in individual stores, as well the average duration, were very close to observations.

The approach can be elaborated in different ways. First, context factors and socio-demographics can be easily incorporated into the model of strategy choice. For example, the effect of gender can be included in the relevant function such that the parameters for mental effort, risk perception, and expected outcome will reflect any gender-based taste variation. Second, although heterogeneous decision heuristics can be inferred from the cognitive structure, for the ease of operation, the current model still assumes that each respondent's cognitive structure is the same. A more realistic model would assume that people have different cognitive structures and therefore different repertoires of decision strategies. Third, incorporating interdependencies between decisions will enhance the realism of the framework. For example, the go-home decision may be influenced by the evaluation of walking directions and stores; people's judgment standard for store choice may be influenced by the estimation of time.

References

Bandini, S., Federici, M. L., Manzoni, S., & Vizzari, G. (2006). Towards a methodology for Situated Cellular Agent based crowd. *Lecture Notes in Computer Science*, *3963*, 203–220.

Borgers, A., & Timmermans, H. J. P. (1986). A model of pedestrian route choice and demand for retail facilities within inner-city shopping areas. *Geographical Analysis*, *18*(2), 115–128.

Dayton, C. M., & Lin, T. H. (1997). Model selection information criteria for non-nested latent class models. *Journal of Educational and Behavioural Statistics*, *22*(3), 249–264.

Dijkstra, J., & Timmermans, H. (2002). Towards a multi-agent model for visualizing simulated user behaviour to support the assessment of design performance. *Automation in Construction*, *11*(2), 135–145.

Foerster, J. F. (1979). Mode choice decision process models: A comparison of compensatory and non-compensatory structures. *Transportation Research A*, *13*, 17–28.

Gigerenzer, G., & Todd, P. M.ABC Research Group. (1999). *Simple heuristics that make us smart*. Oxford: Oxford University Press.

Haklay, M., O'Sullivan, D., & Thurstain-Goodwin, M. (2001). So go downtown: Simulating pedestrian movement in town centers. *Environment and Planning B*, *28*(3), 343–359.

Oppewal, H., & Timmermans, H. J. P. (1997). Modelling the effects of shopping centre size and store variety on consumer choice behaviour. *Environment and Planning A*, *29*(6), 1073–1090.

Payne, J. W., & Bettman, J. R. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *14*(3), 534–552.

Recker, W. W., & Golob, T. F. (1979). A non-compensatory model of transportation behaviour based on sequential consideration of attributes. *Transportation Research B*, *13*, 269–280.

Saito, S., & Ishibashi, K. (1992). A Markov chain model with covariates to forecast consumer's shopping trip chain within a central commercial district. Presented at Fourth World Congress of Regional Science Association International, Mallorca, Spain.

Simon, H. A. (1959). Theories of decision-making in economics and behavioural science. *The American Economic Review*, *49*(3), 253–283.

Timmermans, H. J. P. (1983). Non-compensatory decision rules and consumer spatial choice behaviour: A test of predictive ability. *The Professional Geographer*, *35*(4), 449–455.

Tversky, A. (1972). Elimination by aspects. *Psychological Review*, *79*(4), 281–299.

Van der Waerden, P., Borgers, A., & Timmermans, H. (1998). The impact of the parking situation in shopping centres on store choice behaviour. *GeoJournal*, *45*, 309–315.

Young, W. (1984). A non-tradeoff decision making model of residential location choice. *Transportation Research A*, *18*(1), 1–11.

Zhu, W. (2008). *Bounded rationality and spatio-temporal pedestrian shopping behavior*. Ph.D. thesis, Eindhoven University of Technology, Eindhoven, The Netherlands.

Zhu, W., & Timmermans, H. J. P. (2008). Bounded rationality cognitive process model of individual choice behavior incorporating heterogeneous choice heuristics, mental effort and risk attitude: Illustration to pedestrian go-home decisions. *Proceedings of 87th Annual Meeting of Transportation Research Board*, Washington DC, CD-ROM: No. 08-1169.

Chapter 8

A Model of Time Use and Expenditure of Pedestrians in City Centers

Junyi Zhang

Abstract

This paper deals with time use and expenditure of pedestrians in city centers. A new resource allocation model is developed to describe how pedestrians allocate their available time and expenditure budgets to various activities using a utility-maximizing framework. A pedestrian's utility derived from his/her consumption behavior is defined using a multi-linear function, which is further composed of time-specific and expenditure-specific utilities and interactivity interactions. The interactivity interactions consist of three parts: time-to-time, expenditure-to-expenditure, and time-to-expenditure interactions. By maximizing the pedestrian's utility, conditional on available time and expenditure budgets, time use and expenditure functions for all the activities are derived as a nonlinear simultaneous-equation model system. A function measuring pedestrian-specific value of activity time is also derived. Seemingly unrelated regression method is applied to estimate the model system. The limitation of this study is that spatial elements and activity participation are ignored. To estimate the model, weekend activity diary data were collected in the central area of Hiroshima City, Japan in November 2004. The validity of the model was empirically confirmed. Introducing interactivity interactions greatly improved model accuracy. It was found that existing models significantly underestimate the value of activity time. Many individual attributes were not sensitive to model structures. Employment status was an exceptional and in particular the proposed model revealed that its influence could account for more than 80% of the total utility. Influence of household income was extremely low.

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8.1. Introduction

The city center or central business district (CBD) is a symbolic place of a city. It is characterized by mixed urban functions (in Japan, mainly commercial and business functions), which significantly affect the city's attractiveness. After decades of distress and uncertainty, city centers are reclaiming their prominence as the focus of business, culture, and entertainment, and have the potential to stimulate local and regional economies (Paumier, 2004). In this sense, economic activities in the city center reflect the prosperity level of a city and as a result, an enormous amount of public and private investments is usually required to maintain and support the economic activities. Issues related to city centers can be roughly classified into two types: overconcentration and decline. Overconcentration is often observed in developing cities, such as Dhaka, Jakarta, Manila, and Shanghai. In Japan, and in many Western countries, decline has become a nationwide phenomenon, especially since the collapse of the bubble economy in the 1990s.

This paper deals with the CBD of a Japanese city, Hiroshima City, which is located in the south of Honshu, the largest island in Japan (Figure 8.1). It has about 1.2 million inhabitants. The city is rich in nature and is famous as an international peace and culture city, especially due to the Atomic Bomb Dome registered as a UNESCO world heritage for more than 10 years. The CBD of Hiroshima City has

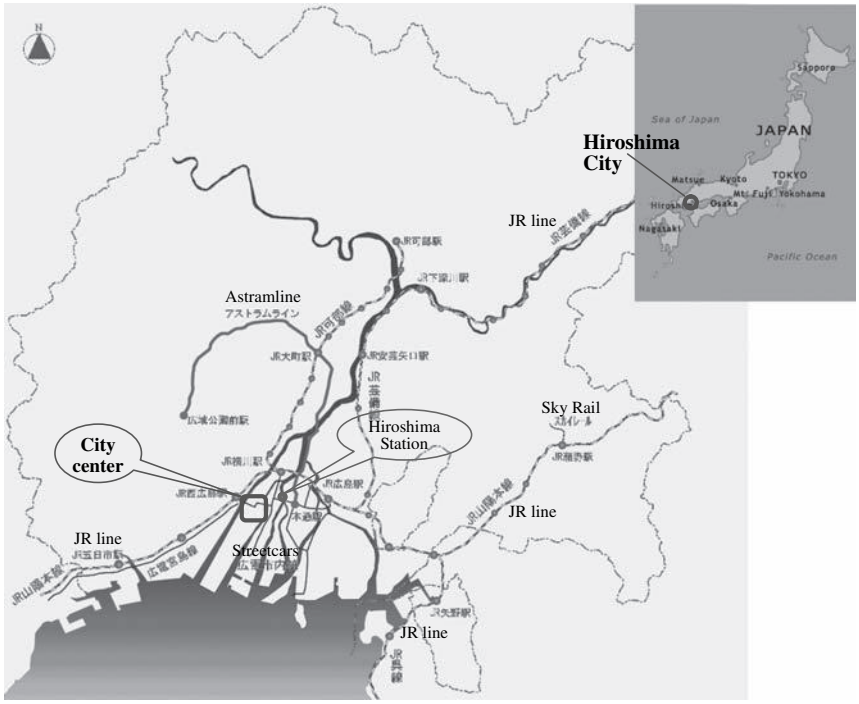


Figure 8.1: Hiroshima City, Japan.

been delineated as a square-sized area parallel to the grid street pattern and measures approximately 1 km^2 (Figure 8.2; see Saarloos, Fujiwara, & Zhang, 2007). From west to east, three main traffic roads (Jonan-dori Avenue, Aioi-dori Avenue, and Heiwa Odori Avenue) are crossing the area, where the first one and last one respectively run along the northern and southern borders. From north to south, two main roads (Rijo-dori Avenue and Chuo-dori Avenue) are running through the CBD. The center

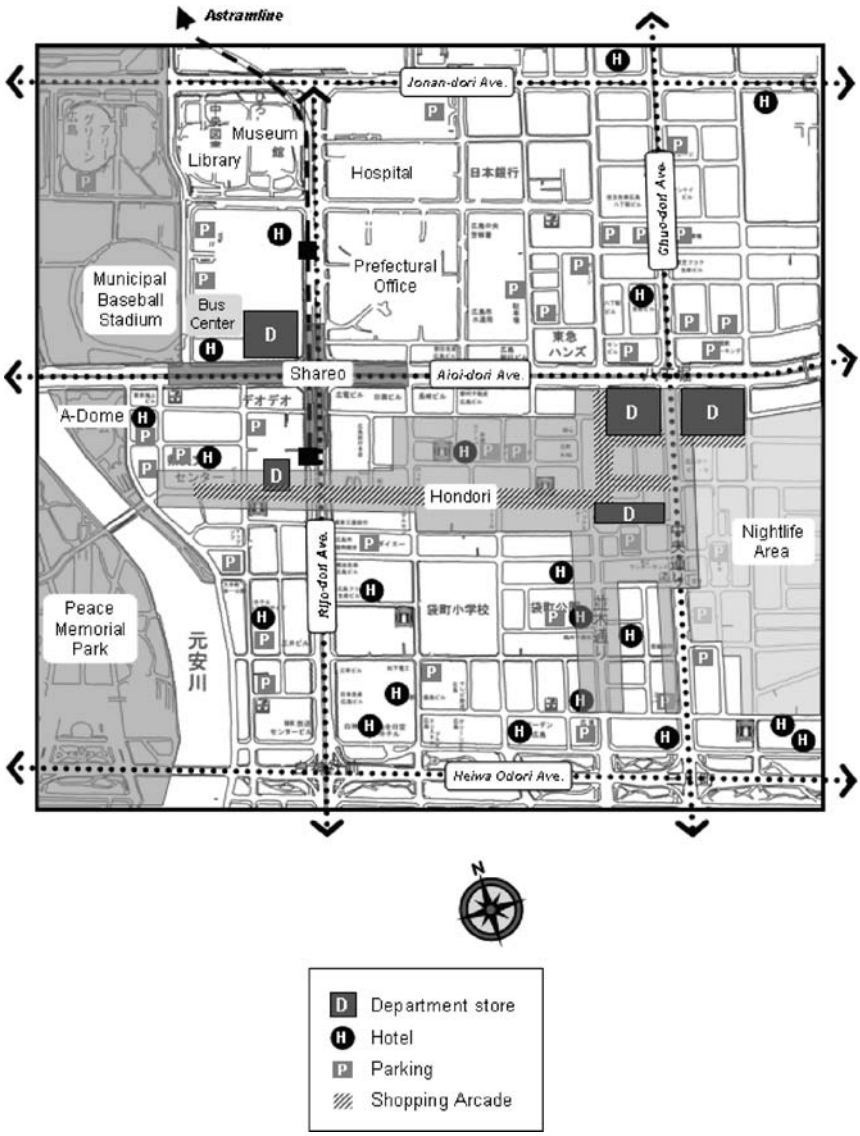


Figure 8.2: The CBD of Hiroshima City, Japan. *Source*: Saarloos et al. (2007).

of the area is formed by the east–west directed Hondori shopping arcade, which forms the artery of the main shopping area. It has three department stores located on the east end and another smaller one near the west end. Situated underneath the intersection of two main roads is the Shareo underground shopping mall. Another large department store is located adjacent to this mall. The area shows a considerable degree of functional zoning, as offices are mainly found in the northern part of the area, tourism and recreation (A-dome, Peace Memorial Park, riverside) in the western part, and nightlife and entertainment in the eastern part. Although present in every part of the area, most hotels are located in the southern part. Lines of public transport (buses and streetcars) run along the main roads, while a bus center is located near the Shareo mall. Situated in between Shareo and Hondori is the terminus of the Astramline, a rapid transit system operational since 1994 that connects the CBD with a long stretch of suburban areas in northern direction. A major railway station is the Japan Railway (JR) Hiroshima Station (Hiroshima), which is located north-east of the CBD and about 2.0 km far from the CBD.

In Japan, decline in urban cities has occurred as a result of the progressive decentralization of retail and leisure functions, which is further pushed by the rapid progress of motorization. One can observe increasingly more shopping facilities along major roads in the suburbs. This also applies to Hiroshima City. Even though several large-scale shopping centers were recently built within the city area, most of them are located in areas that are not convenient to users of transit systems. As a result, economic activities in the CBD are becoming less and less vigorous in the sense that total retail turnover has been decreasing year by year as well as the number of retail stores at the CBD (see Figure 8.3).

It seems that Japan has been experiencing what most of the advanced Western countries have experienced before (e.g., Lord, 1988; Thomas & Bromley, 2000).

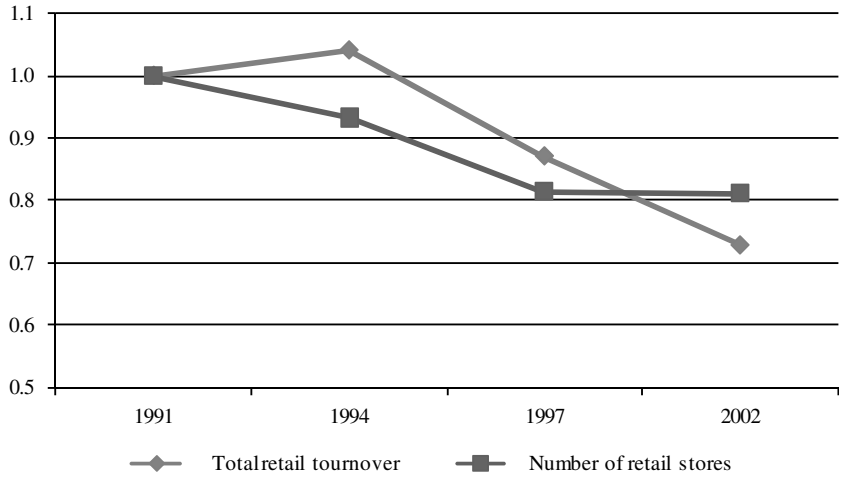


Figure 8.3: Trend of retail business indicators at the Hiroshima CBD. *Note*: the value in the year of 1991 is set to unity.

Therefore, it is becoming more and more important for policy makers in Japan to explore how to revitalize the economic activities in city centers. Needless to say, measures should be taken from various perspectives. One field of policy is related to pedestrian movement. It becomes important for urban planners to create pedestrian-friendly walking environments based on a better understanding of pedestrian behavior, especially shopping and recreational behavior.

Existing studies have examined many aspects of pedestrian behavior. Some of the studies focused on walking behavior itself (e.g., Antonini, Bierlaire, & Weber, 2006; Robin, Antonini, Bierlaire, & Cruz, 2009), while other studies examined a more broad set of pedestrian behavior such as destination and route choice behavior (e.g., Borgers & Timmermans, 1986a, 1986b; Dellaert, Arentze, Bierlaire, Borgers, & Timmermans, 1998; Hoogendoorn, Bovy, & Daamen, 2002), activity scheduling behavior (e.g., Hoogendoorn & Bovy, 2004), and neighborhood form and pedestrian life (e.g., Owens, 1993; Greenwald & Boarnet, 2001). Capturing pedestrian behavior is also important in architecture (Okazaki, 1979), urban planning (Jiang, 1999), land use (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003), marketing (Borgers & Timmermans, 1986a, 1986b), and traffic operations (Nagel, in progress).

Careful review of the literature suggests that little has been done with respect to pedestrian time use and expenditure. This chapter therefore attempts to explore such pedestrian behavior in city centers by developing a new model, which simultaneously represents time use and expenditure, conditional on available time and expenditure budgets.

The remaining part of this chapter is organized as follows. First, a brief literature review about pedestrian behavior is given. Second, the model developed in this study is explained. Third, the data is introduced. Fourth, model estimation and discussion are described. The study is concluded with a discussion of future research issues.

8.2. Literature Review

We only give a brief overview of pedestrian research in city centers. Such behavior can be roughly classified into the following categories (see Figure 8.4): choice of shopping destination (whether to visit city center or other place), trip frequency (how often to visit the city center), choice of travel mode, activity generation, time use and expenditure budgets, choice of shopping store, time use and expenditure at each store, and choice of walking route, etc.

Concerning the choice of shopping destination, methodologically most research is closely related to a concept of spatial choice behavior, discussed by Timmermans (1982). Applying an information integration approach, Timmermans (1982) found that introducing the influential attributes (i.e., number of shops, travel time, and time to find a parking place) in a multiplicative form is superior to other methods in describing the choices of 27 hypothetical shopping centers. Timmermans, Borgers, and van der Waerden (1991) argued that the mother logit model should be applied to represent consumer shopping destination choice in order to reflect substitution

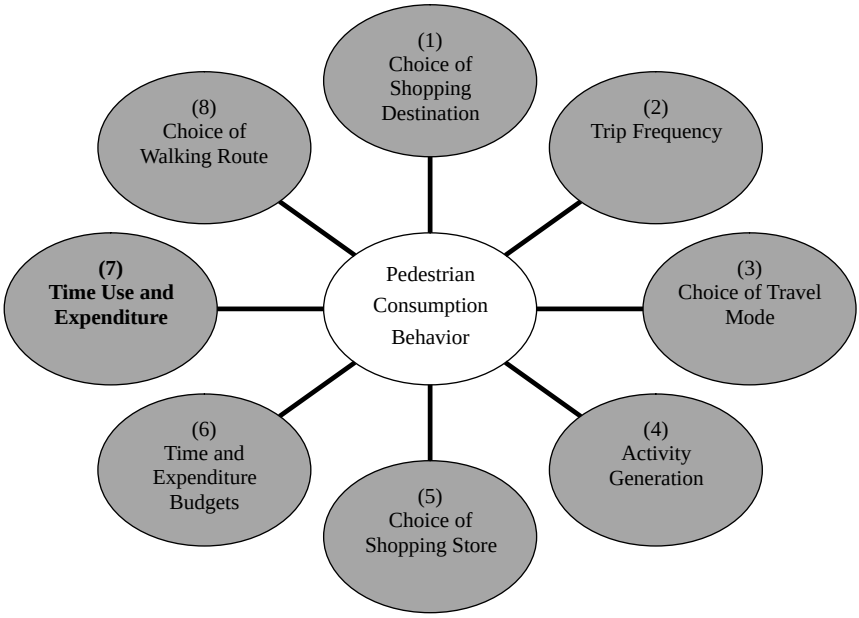


Figure 8.4: Dimensions of pedestrian consumption behavior.

effects (i.e., the utility of a destination is influenced by not only its own attributes, but also the attributes of other destinations). Oppewal and Timmermans (1999) applied a stated preference approach to examine the effects of various shopping center design/management attributes on consumers' evaluations of the public space appearance (or atmosphere) at shopping centers. Finn and Louviere (1996) demonstrated the strong impact that specific anchor stores and other physical characteristics of shopping centers have on consumers' images for shopping centers. To account for heterogeneity in shopping center choice behavior, Suarez, del Bosque, Rodriguez-Poo, and Moral (2004) applied a nested logit model and a random-effect model, using image, distance and first visit factor as explanatory variables. They observed that the opening of a new shopping center would not affect the other centers in the same way and those who spent more money at the centers were less sensitive to travel time. They further confirmed the existence of a segment of the market, which was less sensitive to travel time, although center image and the first visit factor had more impact on this segment.

As for trip frequency, Hu and Saleh (2005) examined the effects of road pricing on shopping trips in Edinburgh based on a logistic regression analysis and found a potential reduction in car trips to the city center. Schmöcker, Fonzone, Quddus, and Bell (2006) confirmed that after the introduction of the congestion charging scheme in London's central area in February 2003, a significant number of customers reduced their frequency of shopping primarily to avoid the £5 charge or issues such as the fear of fines or the payment procedure. Schmöcker, Fonzone, Quddus, and Bell (2008) explored travel mode choice of the elderly and disabled people for their

shopping trips in London, and found that it would be difficult to encourage a modal shift away from driving. There is a strong preference for car use among the elderly people when there is a car available in the household. It was also confirmed that the higher the bus stop density, the more the elderly and disabled people choose public transport systems. Hsiao (2009) measured consumers' value of time (VOT), focusing on a choice between physical store shopping and e-shopping, and found that the value of delivery time for a purchased book from an online bookstore is \$0.53 per day, which means that an online bookstore will have to lower a book's price by \$0.53 to attract a physical bookstore shopper if the delivery is delayed for one day.

Careful review suggests that activity generation in many ways is an overlooked or under researched area. Habib (2007) proposed a set of models to represent activity generation, which may be applicable to the analysis of shopping activity generation. Concerning the choice of shopping store, Bhat and Zhao (2002) proposed a mixed ordered logit model for the spatial analysis of shopping stop-making behavior and empirically confirmed the important effects of employment and household structure on stop-making behavior and accessibility to shopping opportunities influences the number of shopping stops made. On the other hand, shopping requires both time and money. Schwanen (2004) applied a hazard-based duration model to explore the determinants of shopping duration on workdays in the Netherlands and found that temporal constraints and activity/travel behavior surrounding the shopping episode affect its duration. However, it was found that the effects of expenditure budget constraints, commute distance, the presence and age of children were small for both men and women. Bhat (2007) developed a hazard-based duration model of shopping activity with a nonparametric baseline specification and nonparametric control for unobserved heterogeneity, and showed the important influence of the spouse's work characteristics and the travel mode to work used by the individual vis-a-vis the mode used by the individual's spouse. However, little research has been done to deal with shopping expenditure. Furthermore, the above-mentioned shopping duration refers to the total amount of time for one shopping trip. To explore policies that could stimulate economic activities in city centers, one also needs to know how a pedestrian simultaneously spends his/her time and money at different stores or on different activities (i.e., the time use and expenditure). However, there is no relevant research on this topic in the context of pedestrian behavior analysis.

Another important line of research is concerned with pedestrian shopping behavior. Borgers and Timmermans (1986a) proposed a time-varying Markov chain model for multistop and multipurpose trips, which consists of three submodels: destination choice, route choice, and choice of impulse stop. Borgers and Timmermans (1986b) presented a Monte Carlo simulation model to predict destination and route choice behavior of pedestrians within a city center, considering store location patterns. Hoogendoorn and Bovy (2004) presented a model of pedestrian walking route choice and activity scheduling behavior under uncertainty based on the concept of utility maximization. The proposed model covers activity scheduling, choice of activity area, and the path between activities. The utility reflects a trade-off between the utility of completing an activity and the cost of walking toward the activity areas. Different from the above modeling approach,

Antonini et al. (2006) developed a model predicting where the next step of a walking pedestrian will be at a given point in time by using a cross-nested logit model and a mixed nested logit model, which were further included in an agent-based pedestrian simulator. The data were collected from digital video sequences of actual pedestrians at an area nearby the entrance of a metro station. The model captures the tendency of individuals to avoid crowded spatial positions. Robin et al. (2009) improved Antonini et al.'s work by explicitly capturing leader–follower and collision–avoidance patterns and validated the model based on another experimental data set, not involving an estimation process. Gijsbrechts, Campo, and Nisol (2008) demonstrated, based on a multinomial logit model, that single-purpose multiple-store shopping is not only driven by opportunistic, promotion-based motivations, but may also result from a longer-term planning process based on stable store characteristics. This was done by considering (i) shopping benefits and costs, (ii) store choice and shopping pattern decisions, and (iii) overall and category-specific store features.

Finally, focusing on the value of shopping trips, Diep and Sweeney (2008) argued that product and store values contribute significantly to shopping trip value, and during a shopping trip, customers form value perceptions on the basis of their interaction with the products and various aspects of the store (e.g., location, staff, and environment). They identified the impact of product and store value on overall shopping trip value and investigated the interrelationship among their utilitarian and hedonic components. They further found that utilitarian store value and performance-related product values have significant effects on utilitarian shopping trip value, whereas hedonic shopping trip value is influenced most by hedonic store value and emotional product value.

8.3. Model Development

As reviewed at the previous section, there is little research dealing with time use and expenditure at different stores and/or on different activities. Therefore, this study attempts to fill this gap. Here, the modeling target is pedestrian time use and expenditure allocation behavior in city centers, considering available time and money. In other words, the modeling task is to represent how pedestrians allocate their limited time and expenditure budgets to various activities conducted in city centers. Therefore, other aspects of pedestrian behavior (e.g., visit frequency, travel mode choice, choices of destination facility and parking, and route choice) are beyond the scope of this study. Before moving to model development, it is necessary to clarify some conceptual issues.

8.3.1. Conceptual Issues

8.3.1.1. Relative importance of activity participation Following Maslow's hierarchy of needs, it is not difficult to understand that an activity is conducted to satisfy an

individual's certain dimension(s) of need(s), including physiological needs, safety, love and belonging, esteem, and self-actualization needs. Different needs require the individual to give different priorities to different activities. For example, if the individual feels very hungry, eating should be given the highest priority, compared with other activities. Such differentiated priorities could result in that the individual attaches different importance to different activities. Since such importance can be only determined by comparing different activities, the concept of such importance is completely relative, and consequently called relative importance in this study. Of course, need-orientation is not the only dominating source to generate relative importance. There are also other relevant sources, such as decision context, knowledge, experience, and time pressure. Decision context might include circumstantial context (e.g., weather condition and presence of decision partner), activity-specific context (e.g., complexity of decision and timing constraints), and decision maker context (e.g., age, gender, education level, character, and emotional mood). Knowledge about and experience of certain activity participation determines the familiarity level about an activity. Such familiarity might influence relative importance. The influence of time pressure on relative importance is straightforward. If a person has plenty of time, then he/she can decide to perform an activity at any time, and as a result, it might become unnecessary to differentiate different activities. Existence of time pressure means that an individual has not enough time to trade off all possible activities; instead, the individual has to pick up some activities and to give up the other activities.

8.3.1.2. Interactivity interaction In addition to the above-mentioned relative importance of activity, interactivity interaction might also affect the outcomes of activity decision-making processes. Since an individual has to perform various activities within the available time (e.g., 24 h), the individual has to decide how to make effective use of available time. The more time he/she spends on an activity, the less time he/she could spend on the other activities. Such interactivity interaction in the time dimension is called *time-to-time interaction* in this study. Similar interaction could also be observed with respect to expenditure, called *expenditure-to-expenditure interaction*, considering that expenditure is another scare resource. In addition, the longer stay at city center, the higher the possibility to purchase more goods and/or services. In this sense, *time-to-expenditure interaction* could also be observed.

8.3.2. Model Structure

To reflect the above-described decision-making mechanisms simultaneously, this study adopts the multi-linear utility function (e.g., Zhang, Timmermans, & Borgers, 2005) to define a pedestrian n's utility u_n, which is derived from various consumption activities. It is assumed that pedestrian n attempts to maximize his/her utility,

given his/her time and expenditure budgets. More specifically,

$$\begin{aligned}\text{Max} \quad u_n = & \sum_i (w_{ni}^t u_{ni}^t + w_{ni}^c u_{ni}^c) \\ & + \lambda_n^t \sum_i \sum_{i' \neq i} w_{ni}^t w_{ni'}^t u_{ni}^t u_{ni'}^t + \lambda_n^c \sum_i \sum_{i' \neq i} w_{ni}^c w_{ni'}^c u_{ni}^c u_{ni'}^c \\ & + \lambda_n^{tc} \sum_i w_{ni}^t w_{ni}^c u_{ni}^t u_{ni}^c \end{aligned} \tag{8.1}$$

$$s.t. \quad \sum_i t_{ni} = T_n, t_{ni} > 0 \tag{8.2}$$

$$\sum_i c_{ni} = C_n, c_{ni} > 0 \tag{8.3}$$

where, n, i: pedestrian and activity; u_n: utility that pedestrian n derives from various consumption activities; u_{ni}^t: utility that pedestrian n derives from consuming the time t_{ni} of activity i; u_{ni}^c: utility that pedestrian n derives from consuming the money c_{ni} of activity i; w_{ni}^t: weight that pedestrian n attaches to activity i when consuming the time t_{ni}; w_{ni}^c: weight that pedestrian n attaches to activity i when consuming the money c_{ni}; λ_n^t: parameter of interactivity interaction with respect to time consumption; λ_n^c: parameter of interactivity interaction with respect to expenditure; λ_n^{tc}: parameter of interactivity interaction with respect to time use and expenditure; t_{ni}: time that pedestrian n spends on activity i; c_{ni}: money that pedestrian n spends on activity i; T_n: available time budget of pedestrian n; and, C_n: available expenditure budget of pedestrian n.

Here, weight parameters w_{ni}^t and w_{ni}^c are used to represent the relative importance that individual n attaches to activity i. The rationality of introducing the concept of relative importance has been argued previously. Concerning interactivity interactions, three parameters are introduced, i.e., λ_n^t, λ_n^c, and λ_n^{tc}, to explain influences of time-to-time, expenditure-to-expenditure, and time-to-expenditure interactions on pedestrian time use and expenditure allocation behavior, respectively. These interaction terms are specified in the form of a product of a pair of activity utilities, as shown in the latter part of Eq. (8.1). Usually, it is realistic to assume that performing an activity generates a positive utility. Accordingly, a positive value of the interaction parameter means that interactivity interaction increases pedestrian utility. In contrast, a negative value indicates that the interaction induces competition among activities and consequently results in the occurrence of various conflicts.

Note that the modeling framework adopted here is similar to the traditional one (e.g., Becker, 1965; DeSerpa, 1971; Jara-Díaz, 2003), but this paper adopts a multi-linear utility function, instead of the widely used additive utility function, which ignores the influence of interactivity interactions. We will show later that ignoring the interactivity interactions would lead to a significantly biased estimation of VOT.

One can further see that income is not included in the expenditure constraint (Eq. (8.3)). Instead, in this study, total amount of money spent on various activities is selected as a proxy of the expenditure constraint.

The modeling framework shown in Eqs. (8.1)–(8.3) is based on the assumption that activity participation is pre-decided. It is important to represent such activity participation together with the consumption behavior, which is left as a future research issue. Since it is assumed here that the utility of time use or expenditure is positive, the adopted utility function should guarantee such characteristic. Meanwhile, it seems difficult to further assume that marginal utility gained from per unit increase in time use or expenditure also increases, considering that the pedestrian might feel tired/bored after staying a certain length of time in the city center, or might worry about the affordability or question about the worthiness of further purchase. In this sense, it seems reasonable to assume that marginal utility decreases with the increase of time or expenditure. To reflect this notion, a logarithm function seems appropriate. Since the logarithm function will become negative when its argument (here, t_{ni} or c_{ni}) is smaller than 1, of course, when t_{ni} or c_{ni} is equal to zero, the function will not be computable. To guarantee the computability of the logarithm function and the positivity of the utility function, Eqs. (8.4) and (8.5) are adopted.

$$u_{ni}^{t} = \rho_{ni}^{t} \ln(t_{ni} + 1) = \exp\left(\sum_{k} \beta_{k}^{t} x_{nik}^{t} + e_{ni}^{t}\right) \ln(t_{ni} + 1) \tag{8.4}$$

$$u_{ni}^{c} = \rho_{ni}^{c} \ln(c_{ni} + 1) = \exp\left(\sum_{k} \beta_{k}^{c} x_{nik}^{c} + e_{ni}^{c}\right) \ln(c_{ni} + 1) \tag{8.5}$$

where, x_{nik}^{t}: attribute k that affects the utility u_{ni}^{t} of consuming the time t_{ni}; β_{k}^{t}: parameter of attribute x_{nik}^{t}; x_{nik}^{c}: attribute k that affects the utility u_{ni}^{c} of consuming the money c_{ni}; β_{k}^{c}: parameter of attribute x_{nik}^{c}; e_{ni}^{t}: error term of u_{ni}^{t}; and e_{ni}^{c}: error term of u_{ni}^{c}.

Here, introducing x_{nik}^{t} and x_{nik}^{c} into the utility function reflects the fact that different pedestrians may have different (or heterogeneous) responses to time use and expenditure. The attributes x_{nik}^{t} and x_{nik}^{c} are observable and could include the pedestrian's personal attributes (e.g., age, gender, and occupation) and activity-specific attributes (e.g., facility type and location). An exponential function is used to guarantee the positive requirement for the sign of the utility function. Error terms e_{ni}^{t} and e_{ni}^{c} are introduced to reflect the influence of unobservable factors (e.g., psychological factors: character, motivation; omitted factors: impulse vs. planned shopping). Usually, an error term is introduced into the utility function as a linear combination with the deterministic term. However, for the sake of deriving an operational model, here, these two error terms are introduced as one argument of the exponential function. Furthermore, to simplify the expression, henceforth, it is assumed that t_{ni} refers to $t_{ni} + 1$ and c_{ni} to $c_{ni} + 1$, and Eqs. (8.4) and (8.5) are

rewritten as follows:

$$u_{ni}^{t} = \rho_{ni}^{t} \ln(t_{ni}) = \exp\left(\sum_{k} \beta_{k}^{t} x_{nik}^{t} + e_{ni}^{t}\right) \ln(t_{ni}) \tag{8.6}$$

$$u_{ni}^{c} = \rho_{ni}^{c} \ln(c_{ni}) = \exp\left(\sum_{k} \beta_{k}^{c} x_{nik}^{c} + e_{ni}^{c}\right) \ln(c_{ni}) \tag{8.7}$$

8.3.3. Deriving Time Use and Expenditure Functions

To derive time use and expenditure functions, the following Lagrange function is adopted.

$$L = u_{n} + \mu_{t}\left(T_{n} - \sum_{i} t_{ni}\right) + \mu_{c}\left(C_{n} - \sum_{i} c_{ni}\right) \tag{8.8}$$

First, the first derivatives with respect to time variable t_{ni} and expenditure variable c_{ni} are calculated.

$$\frac{\partial L}{\partial t_{ni}} = \frac{\partial u_{n}}{\partial t_{ni}} - \mu_{t} = 0 \tag{8.9}$$

$$\frac{\partial L}{\partial c_{ni}} = \frac{\partial u_{n}}{\partial c_{ni}} - \mu_{c} = 0 \tag{8.10}$$

The above two equations are further transformed below.

$$\begin{aligned} & w_{ni}^{t} \frac{\partial u_{ni}^{t}}{\partial t_{ni}} + \lambda_{n}^{t} \sum_{i' \neq i} w_{ni}^{t} w_{ni'}^{t} u_{ni'}^{t} \frac{\partial u_{ni}^{t}}{\partial t_{ni}} + \lambda_{n}^{tc} w_{ni}^{t} w_{ni}^{c} u_{ni}^{c} \frac{\partial u_{ni}^{t}}{\partial t_{ni}} = \mu_{t} \\ \Rightarrow \quad & \frac{w_{ni}^{t} \rho_{ni}^{t} \left(1 + \lambda_{n}^{t} \sum_{i' \neq i} w_{ni'}^{t} u_{ni'}^{t} + \lambda_{n}^{tc} w_{ni}^{c} u_{ni}^{c}\right)}{t_{ni}} = \mu_{t} \end{aligned} \tag{8.11}$$

$$\begin{aligned} & w_{ni}^{c} \frac{\partial u_{ni}^{c}}{\partial c_{ni}} + \lambda_{n}^{c} \sum_{i' \neq i} w_{ni}^{c} w_{ni'}^{c} u_{ni'}^{c} \frac{\partial u_{ni}^{c}}{\partial c_{ni}} + \lambda_{n}^{tc} w_{ni}^{t} w_{ni}^{c} u_{ni}^{t} \frac{\partial u_{ni}^{c}}{\partial c_{ni}} = \mu_{c} \\ \Rightarrow \quad & \frac{w_{ni}^{c} \rho_{ni}^{c} \left(1 + \lambda_{n}^{c} \sum_{i' \neq i} w_{ni'}^{c} u_{ni'}^{c} + \lambda_{n}^{tc} w_{ni}^{t} u_{ni}^{t}\right)}{c_{ni}} = \mu_{c} \end{aligned} \tag{8.12}$$

Substituting the above two equations into the constraint Eqs. (8.2) and (8.3) leads to the following time use and expenditure functions for activity i, respectively.

$$t_{ni} = \frac{\Psi^t_{ni}}{\sum_{i'} \Psi^t_{ni'}} T_n, \Psi^t_{ni} = w^t_{ni}\rho^t_{ni}\left(1 + \lambda^t_n \sum_{i' \neq i} w^t_{ni'}u^t_{ni'} + \lambda^{tc}_n w^c_{ni}u^c_{ni}\right) \tag{8.13}$$

$$c_{ni} = \frac{\Psi^c_{ni}}{\sum_{i'} \Psi^c_{ni'}} C_n, \Psi^c_{ni} = w^c_{ni}\rho^c_{ni}\left(1 + \lambda^c_n \sum_{i' \neq i} w^c_{ni'}u^c_{ni'} + \lambda^{tc}_n w^t_{ni}u^t_{ni}\right) \tag{8.14}$$

These functions will be used to represent pedestrian time use and expenditure behavior in this study. Assuming the number of activities performed is I, as a model system, there are $2 \times I$ functions in total. Hereafter, Eq. (8.13)1 is called the *time use* function and Eq. (8.14) the *expenditure* function.

Observing Eqs. (8.13) and (8.14), it is obvious that the time (expenditure) allocated to activity i is influenced by not only the information of activity i itself (both time- and expenditure-related information), but also the information about the time (expenditure) of other activities. Taking the ratio of a pair of time use (expenditure) functions for activities i and j (see Eqs. (8.15) and (8.16)), it is found that this ratio does not only include information about activities i and j, but also information about the other activities. This implies that the allocated time (expenditure) for an activity is affected by the available activities in the choice set. This attractive feature is due to the introduction of interactivity interaction. This is straightforward, if the interaction parameters λ^t_n, λ^c_n, and λ^{tc}_n are set at zero in the following equations.

$$\frac{t_{ni}}{t_{nj}} = \frac{w^t_{ni}\rho^t_{ni}\left(1 + \lambda^t_n \sum_{i' \neq i} w^t_{ni'}u^t_{ni'} + \lambda^{tc}_n w^c_{ni}u^c_{ni}\right)}{w^t_{nj}\rho^t_{nj}\left(1 + \lambda^t_n \sum_{i' \neq j} w^t_{ni'}u^t_{ni'} + \lambda^{tc}_n w^c_{nj}u^c_{nj}\right)} \tag{8.15}$$

$$\frac{c_{ni}}{c_{nj}} = \frac{w^c_{ni}\rho^c_{ni}\left(1 + \lambda^c_n \sum_{i' \neq i} w^c_{ni'}u^c_{ni'} + \lambda^{tc}_n w^t_{ni}u^t_{ni}\right)}{w^c_{nj}\rho^c_{nj}\left(1 + \lambda^c_n \sum_{i' \neq j} w^c_{ni'}u^c_{ni'} + \lambda^{tc}_n w^t_{nj}u^t_{nj}\right)} \tag{8.16}$$

8.3.4. Estimation Method

As shown above, the derived resource allocation model system consists of time use and expenditure functions for all activities under study. Since a time or expenditure

variable is included in the other time use or expenditure functions, it is logical to estimate these functions simultaneously. For the sake of model estimation, these functions are first log-transformed for time use and expenditure functions, respectively, by taking one of the activities (i_0) as a reference.

$$\ln\left(\frac{t_{ni}}{t_{ni_0}}\right) = \ln\left(w^t_{ni}\rho^t_{ni}(1+\lambda^t_n\sum_{i'\neq i}w^t_{ni'}u^t_{ni'}+\lambda^{tc}_n w^c_{ni}u^c_{ni})\right) - \ln\left(w^t_{ni_0}\rho^t_{ni_0}(1+\lambda^t_n\sum_{i'\neq i_0}w^t_{ni'}u^t_{ni'}+\lambda^{tc}_n w^c_{ni_0}u^c_{ni_0})\right) \tag{8.17}$$

$$\ln\left(\frac{c_{ni}}{c_{ni_0}}\right) = \ln\left(w^c_{ni}\rho^c_{ni}(1+\lambda^c_n\sum_{i'\neq i}w^c_{ni'}u^c_{ni'}+\lambda^{tc}_n w^t_{ni}u^t_{ni})\right) - \ln\left(w^c_{ni_0}\rho^c_{ni_0}(1+\lambda^c_n\sum_{i'\neq i_0}w^c_{ni'}u^c_{ni'}+\lambda^{tc}_n w^t_{ni_0}u^t_{ni_0})\right) \tag{8.18}$$

Since the above functions include ρ^t_{ni} and ρ^c_{ni}, which have an error term included in an exponential function respectively (see Eqs. (8.6) and (8.7)), the above equations can be further transformed as follows:

$$\begin{aligned}\ln\left(\frac{t_{ni}}{t_{ni_0}}\right) &= \ln\left(w^t_{ni}\tilde{\rho}^t_{ni}(1+\lambda^t_n\sum_{i'\neq i}w^t_{ni'}u^t_{ni'}+\lambda^{tc}_n w^c_{ni}u^c_{ni})\right)+e^t_{ni}\\ &\quad-\ln\left(w^t_{ni_0}\tilde{\rho}^t_{ni_0}(1+\lambda^t_n\sum_{i'\neq i_0}w^t_{ni'}u^t_{ni'}+\lambda^{tc}_n w^c_{ni_0}u^c_{ni_0})\right)-e^t_{ni_0}\\ &= \ln\left(w^t_{ni}\tilde{\rho}^t_{ni}(1+\lambda^t_n\sum_{i'\neq i}w^t_{ni'}u^t_{ni'}+\lambda^{tc}_n w^c_{ni}u^c_{ni})\right)\\ &\quad-\ln\left(w^t_{ni_0}\tilde{\rho}^t_{ni_0}(1+\lambda^t_n\sum_{i'\neq i_0}w^t_{ni'}u^t_{ni'}+\lambda^{tc}_n w^c_{ni_0}u^c_{ni_0})\right)+\varepsilon^t_{ni_0}\end{aligned} \tag{8.19}$$

$$\begin{aligned}\ln\left(\frac{c_{ni}}{c_{ni_0}}\right) &= \ln\left(w^c_{ni}\tilde{\rho}^c_{ni}(1+\lambda^c_n\sum_{i'\neq i}w^c_{ni'}u^c_{ni'}+\lambda^{tc}_n w^t_{ni}u^t_{ni})\right)+e^c_{ni}\\ &\quad-\ln\left(w^c_{ni_0}\tilde{\rho}^c_{ni_0}(1+\lambda^c_n\sum_{i'\neq i_0}w^c_{ni'}u^c_{ni'}+\lambda^{tc}_n w^t_{ni_0}u^t_{ni_0})\right)-e^c_{ni_0}\\ &= \ln\left(w^c_{ni}\tilde{\rho}^c_{ni}(1+\lambda^c_n\sum_{i'\neq i}w^c_{ni'}u^c_{ni'}+\lambda^{tc}_n w^t_{ni}u^t_{ni})\right)\\ &\quad-\ln\left(w^c_{ni_0}\tilde{\rho}^c_{ni_0}(1+\lambda^c_n\sum_{i'\neq i_0}w^c_{ni'}u^c_{ni'}+\lambda^{tc}_n w^t_{ni_0}u^t_{ni_0})\right)+\varepsilon^c_{ni_0}\end{aligned} \tag{8.20}$$

where,

$$\tilde{\rho}_{ni}^{t} = \exp\left(\sum_{k} \beta_{k}^{t} x_{nik}^{t}\right) \tag{8.21}$$

$$\tilde{\rho}_{ni}^{c} = \exp\left(\sum_{k} \beta_{k}^{c} x_{nik}^{c}\right) \tag{8.22}$$

$$\varepsilon_{ni}^{t} = e_{ni}^{t} - e_{ni_0}^{t} \tag{8.23}$$

$$\varepsilon_{ni}^{c} = e_{ni}^{c} - e_{ni_0}^{c} \tag{8.24}$$

Looking at the above transformation, one can see that the error terms are introduced into the exponential functions in Eqs. (8.6) and (8.7) for the sake of obtaining operational functions for estimation. It is obvious that the new error terms $\varepsilon_{ni}^{t}, \varepsilon_{ni}^{c}$ are correlated with each other. To accommodate such correlations, the seemingly unrelated regression (SUR) method is adopted. The software Time Series Processors (TSP) Version 5.0 is used to implement the SUR estimation. According to the TSP Reference Manual, SUR obtains SUR estimates of a set of nonlinear equations with cross-equation constraints imposed, but with a diagonal covariance matrix of the disturbances across equations (http://elsa.berkeley.edu/wp/tspref/sur.pdf). These parameter estimates are used to form a consistent estimate of the covariance matrix of the disturbances, which is then used as a weighting matrix when the model is reestimated to obtain new values of the parameters. These estimates are consistent and asymptotically normal, and, under some conditions, asymptotically more efficient than the single equation estimates.

8.3.5. Measuring Value of Time

It has been explained that in Eq. (8.1), the pedestrian utility function is defined as a function of both time use and expenditure. Using such a utility function, it is possible to calculate the VOT for activity i as follows:

$$\mathrm{VOT}_i = \frac{\partial u_n / \partial t_{ni}}{\partial u_n / \partial c_{ni}} \tag{8.25}$$

Substituting Eqs. (8.9) and (8.10) into the above equation, the VOT for activity i is obtained below.

$$\mathrm{VOT}_i = \frac{\mu_t}{\mu_c} \tag{8.26}$$

As seen above, even though it is attempted to calculate the VOT for each type of activity, but under the time use and expenditure constraints shown in

Eqs. (8.2) and (8.3), Eq. (8.26) reveals that the VOT does not change with the type of activity. In other words, as long as a pedestrian's time use and expenditure constraints are pre-given, no matter what kinds of utility functions are adopted with respect to time use and expenditure, the pedestrian's VOT is the same for any activity.

Since the first derivatives $\partial u_n/\partial t_{ni}, \partial u_n/\partial c_{ni}$ are equal to the Lagrange coefficients μ_t, μ_c, respectively, the two coefficients can be expressed as follows:

$$\mu_t = \frac{1}{I}\sum_i \frac{\Psi_{ni}^t}{t_{ni}}, \mu_c = \frac{1}{I}\sum_i \frac{\Psi_{ni}^c}{c_{ni}} \tag{8.27}$$

Excluding the error terms in the terms ρ_{ni}^t, ρ_{ni}^c, the common VOT for all the activities can be rewritten as follows:

$$\mathrm{VOT} = \frac{\sum_i \tilde{\Psi}_{ni}^t/t_{ni}}{\sum_i \tilde{\Psi}_{ni}^c/c_{ni}} \tag{8.28}$$

where,

$$\Psi_{ni}^t = w_{ni}^t \tilde{\rho}_{ni}^t \left(1 + \lambda_n^t \sum_{i' \neq i} w_{ni'}^t u_{ni'}^t + \lambda_n^{tc} w_{ni}^c u_{ni}^c\right) \tag{8.29}$$

$$\Psi_{ni}^c = w_{ni}^c \tilde{\rho}_{ni}^c \left(1 + \lambda_n^c \sum_{i' \neq i} w_{ni'}^c u_{ni'}^c + \lambda_n^{tc} w_{ni}^t u_{ni}^t\right) \tag{8.30}$$

It can be observed that the VOT is also influenced by the interactivity interaction. Ignoring such interaction will result in the misleading measurement of VOT, and consequently might lead to wrong policy decision. More importantly, since VOT is, in theory, completely dependent on the form of utility function, the biased specification of the utility function is undoubtedly problematic. The pedestrian utility function defined in Eq. (8.1) incorporates both the relative importance of the activity and the interactivity interactions, which have not properly represented in existing studies. The limitation, however, might be found in the definition of the utility function for each activity, in case that the other forms of functions would be more appropriate. This should be explored in the future.

8.4. Data

This study uses an activity diary data, which were collected from the pedestrians visiting the Hiroshima CBD during the weekend of November 13–14, 2004.

Questionnaires were handed out to pedestrians present in the CBD, mainly in and around Hondori shopping area (see Figure 8.2). They were invited to complete the questionnaire back home and return it by mail in a pre-stamped envelope. In total, 885 questionnaires were distributed on Saturday and 1000 on Sunday. Respondents were asked to report several personal and household characteristics (e.g., age, gender, and income) and to describe their visit to the CBD in terms of the transport mode(s) they used to come to the city center, the purpose of their visit, and the stops they made at stores in sequential order (including: type of store, whether stops were planned or not, the amount of time and money spent, and travel party). The respondents were also asked to draw the location of each stop and the route walked from the arrival point to the departure point on a map.

Valid sample size for this study is 494 persons, by excluding missing values in the data. Sample characteristics are summarized in Table 8.1, including individual and household attributes, visit behavior to the city center, and time use and expenditure in the city center. On the survey days, most of respondents visited the city center with the purposes of shopping (59.3%), followed by recreational, social, and dining activities (29.4%). Average time spent in the city center is 172 min, while the average amount of money spent is 15,715 Yen. In other words, respondents spent 5482 Yen/h on average. Hereafter, such value is named marginal value of time (MVOT). Note that MVOT is not necessarily equal to the widely accepted term "value of time VOT."

It is shown that females spent longer time (about 30 min) but less money (about 5000 Yen) than males. As a result, MVOT of males (7604 Yen/h) was 1.6 times higher than that of females (4711 Yen/h). Time use showed a decreasing relationship with age, whereas, in contrast, expenditure showed an increasing relationship with age. Respondents aged 20–29 spent almost the same amount of money as those over 50. MVOT clearly increased with age. The self-employed respondents spent the highest amount of money (22,075 Yen). Surprisingly, the unemployed and student respondents spent more than 19,000 Yen. In contrast, average expenditure of businesspersons was very close to the average amount of money of total samples. The self-employed and unemployed respondents showed the highest MVOT. On average, expenditure increased with household income level; in contrast, time use had a "U" shape relationship with household income level, where respondents with 6–12 million Yen of household income spent the shortest time at the city center. It is obvious that MVOT increased with household income. Furthermore, most of the respondents traveled to the city center by rail transit system (32.6% = street car 15.4% + Astramline (a new transit system with rubber tires) 7.3% + JR (Japan Railway) 9.9%), car (32.2%), and bus (23.5%), and visited together with other people (72.5%). Most of the respondents who usually visited the city center once or twice a week or a month (75.1% = 34.2% + 40.9%), and these visitors spent the highest amount of money (19,491 Yen), compared with the other visitors. MVOT of respondents visiting the city center with travel party was nearly twice higher than that of those without travel party. Car visitors showed the highest MVOT (10,416), which almost doubles the average MVOT (5482 Yen/h). MVOT of transit users ranged from 2625 to 4548 Yen/h, and it did not differ largely from MVOT of walkers (3762 Yen/h) and bikers (2760 Yen/h).

Table 8.1: Summary of the sample characteristics.

Item (unit)	Share (%)	Duration (min)	Expenditure (Yen)	Marginal expenditure (Yen/h)
Total value or average value	100	172	15,715	5482
Total sample size	494 persons			
Individual and household attributes				
Gender				
Female	70.2	180	14,141	4711
Male	29.8	153	19,432	7604
Age				
~19 years old	2.6	268	12,271	2750
20~29 years old	19.0	205	16,447	4805
30~39 years old	23.5	178	14,098	4739
40~49 years old	17.6	176	15,978	5435
50~59 years old	22.7	148	16,261	6579
Over 60 years old	14.6	133	16,822	7573
Occupation				
Businessperson	30.4	181	15,178	5033
Public servant	9.5	173	15,505	5384
Student	7.3	223	19,676	5289
Part-time worker	11.7	165	15,865	5755
Self-employed	6.9	151	22,075	8753
Agriculture, forest, and fishery	0.4	110	1866	1018
Unemployed	6.9	144	19,284	8018
Housewife	21.7	159	13,603	5136
Other	5.3	187	10,155	3253
Household income (Yen per year)				
Less than 3 million	22.1	179	15,122	5070
3~6 million	35.2	175	13,313	4572
6~9 million	23.7	164	13,407	4900
9~12 million	11.3	163	22,775	8366
Higher than 12 million	7.7	178	25,125	8449
Residential location				
Hiroshima City	69.4	163	15,024	5532
Other	30.6	193	17,285	5373
Usual visiting behavior to the central area of Hiroshima City				
Usual visit frequency to city center				
Almost everyday	8.7	163	9919	3656
Once or twice a week	34.2	174	14,807	5100

Table 8.1: (*Continued*)

Item (unit)	Share (%)	Duration (min)	Expenditure (Yen)	Marginal expenditure (Yen/h)
Once or twice a month	40.9	174	19,491	6708
Several times a year	15.0	163	11,377	4184
First time	1.2	218	9237	2538
Visiting behavior to the central area of Hiroshima City on the survey days				
Travel party				
Visit alone	27.5	155	9224	3578
Visit with other people	72.5	179	18,181	6102
Main travel mode				
Walk	5.5	135	8452	3762
Bicycle	5.5	201	9230	2760
Motorcycle	0.8	266	3173	715
Car	32.2	144	25,004	10,416
Bus	23.5	188	14,236	4548
Street car	15.4	171	11,102	3905
Astramline	7.3	173	7570	2625
JR (Japan Railway)	9.9	225	10,816	2881

8.5. Model Estimation and Discussion

8.5.1. Classification of Activities

In this study, activities were initially classified into nine categories: (1) cloth/accessory, (2) food, (3) book, CD, & DVD, (4) furniture, (5) grocery, (6) electronic product, (7) break/eating, (8) appreciation and gambling and so on, and (9) doing nothing. However, such detailed classifications resulted in many "zero" activities, consequently making the estimation of the derived model system difficult. To reduce the influence of "zero" activities, the above activities were further grouped into the following four major categories: (i) DGP: durable goods purchase (cloth/accessory (1), furniture (4), and electronic product (6)), (ii) MGP: maintenance goods purchase (food (2) and grocery (5)), (iii) BEA: break/eating (7), and (iv) OTP: other purchase (book, CD, & DVD (3), appreciation and gambling and so on (8), and doing nothing (9)). The time and money spent for each activity are summarized in Table 8.2. Here both gross mean and net mean are shown, where gross mean refers to the average value calculated using all the samples with and without purchase, and net mean indicates the average value calculated using only the samples with purchase. It is found that respondents spent the shortest time on MGP and the longest time on other purchase. Concerning expenditure, the amount of money spent on DGP showed the highest value and that on BEA the lowest value. The MVOT was also

Table 8.2: Time use and expenditure at city center by type of activity.

Consumption behavior	DGP (durable goods purchase)	MGP (maintenance goods purchase)	BEA (break/ eating)	OTP (other purchase)
Time spent (min)				
Gross mean[a]	39	19	42	72
Net mean[b]	297	217	296	393
Money spent (Yen)				
Gross mean[a]	9100	2140	1503	2972
Net mean[b]	15,136	4872	2517	6959
MVOT (Yen/h)				
Gross mean[a]	13,862	6848	2166	2465
Net mean[b]	3058	1347	510	1062

[a]Gross mean is the average value calculated using all the samples with and without purchase.
[b]Gross mean is the average value calculated using only the samples with purchase.

calculated with respect to both gross and net values. It is found that the observed MVOT showed the highest value of DGP, the lowest value of BEA, and similar values of MGP and OTP.

8.5.2. Explanatory Variables

To represent the observed heterogeneity in time use and expenditure utilities (Eqs. (8.6) and (8.7)), this study first introduced several individual and household attributes into the model, including gender, age, occupation, household income level, and number of members in travel party. Average travel time from home to the city center, and total walking distance were used to represent the influence of travel behavior on the time use and expenditure behavior. From the questionnaire, the only available activity-specific variables are the types of activities and visiting stores, which were also introduced. To enrich the activity-specific information, a composite variable Δ_n is first defined as a linear function of the above activity-generic variables (i.e., individual and household attributes, and travel behavior variables) (see Eq. (8.31)), and it is then used to define a time-specific variable Δ_{ni}^t and an expenditure-specific variable Δ_{ni}^c to explain the heterogeneous influence of these activity-generic attributes on the consumption behavior of different activities (Eqs. (8.32) and (8.33)).

$$\Delta_n = \sum\nolimits_k \gamma_k z_{nk} \tag{8.31}$$

$$\Delta_{ni}^t = \theta_{ni}^t \Delta_n \tag{8.32}$$

$$\Delta_{ni}^c = \theta_{ni}^c \Delta_n \tag{8.33}$$

where, z_{nk} indicates activity-generic attribute k and its parameter is represented as γ_k, and $\theta^t_{ni}, \theta^c_{ni}$ are the activity-specific parameters.

Note that for the purpose of model estimation $\theta^t_{ni}, \theta^c_{ni}$ will be set at zero for one activity and unity for another activity.

To evaluate the influence of each attribute on time use and expenditure with respect to each activity, four points are emphasized:

(1) $\theta^t_{ni}\gamma_k$ or $\theta^c_{ni}\gamma_k$: This composite parameter is used to evaluate marginal influence of each attribute (i.e., influence of each attribute per unit change) on time use or expenditure behavior.
(2) Sign of $\theta^t_{ni}\gamma_k$ or $\theta^c_{ni}\gamma_k$: It is used to evaluate how each attribute contributes to the change (i.e., positive or negative change) of time use or expenditure behavior.
(3) T-score of $\theta^t_{ni}, \theta^c_{ni}$, and γ_k: It is used to evaluate whether the influence of each attribute is statistically significant or not.
(4) Partial utility: It is defined as $\theta^t_{ni}\gamma_k x_{nk}$ or $\theta^c_{ni}\gamma_k x_{nk}$ and used to evaluate total magnitude of the influence of each attribute. The above marginal influence is used to evaluate the influence of each attribute per unit change, and can be also interpreted as the weight of each attribute in total utility. However, it cannot inform us how large of influence of each attribute is imposed on time use or expenditure behavior. To overcome such shortcoming of the marginal influence, the partial utility is introduced.

8.5.3. Model Estimation

The classification of activities into four major categories means we have a total of eight functions. To estimate these eight functions, they were first log-transformed into six new functions by taking BEA as a reference. Six types of models were estimated to examine the effectiveness of the proposed resource allocation model.

(1) Model-A: It is the full version of the proposed resource allocation.
(2) Model-B: All the interactivity interaction parameters, λ^t_n,λ^c_n. and λ^{tc}_n, are fixed at unity, but all the weight parameters (w^t_{ni},w^c_{ni}) and all other parameters included in the model system are estimated. Assuming interactivity interactions are equal to unity means that the model does not permit the existence of negative interaction. This model is used to examine how the introduction of interactivity interaction affects model estimation results.
(3) Model-C: All interactivity interaction parameters are fixed at unity and all the weight parameters are set to be equal (since there are four activities used, each weight parameter is set at 0.25 for each time use or expenditure function). This model is used to examine the influence of both interactivity interaction and the relative importance of each activity.
(4) Model-D: All weight parameters are set to be equal (i.e., 0.25) and the interactivity interaction parameters and all other parameters included in the model system are estimated. This model is used to examine the influence of relative importance of each activity.

(5) Model-E: All interactivity interaction terms are excluded from the model system, but all weight parameters are estimated together with all other parameters. This model is used to examine the influence of interactivity interaction.
(6) Model-F: All interactivity interaction terms are excluded from the model system, and all weight parameters are set to be equal (i.e., 0.25). The other parameters are estimated. This model is used to examine the influences of both interactivity interaction and relative importance of each activity.

Estimation results are shown in Table 8.3 (sample size was reduced to 481 persons by excluding missing values in data). Detailed discussions are given with respect to the following items: model accuracy, decision-making mechanisms, VOT, and influential factors, by comparing the six models.

8.5.3.1. Model accuracy The multiple correlation coefficient (MCC) is used as an indicator of model accuracy. Table 8.3 shows that Model-D has highest accuracy for each time use and expenditure function; except for the (log-transformed) time function for OTP, and that Model-C is the second-best model. Model-B only generates the higher values of MCC in the log-transformed time functions for DGP and MGP. In Model-E and Model-F, since the interactivity interaction parameters are excluded, the values of MCC decrease to extremely low levels (most of MCCs are smaller than 0.1), which is not acceptable at all. As a result, Model-E and Model-F perform the worst of all six models, implying that interactivity interactions cannot be ignored in representing pedestrian consumption behavior in city centers. Comparing Model-D with Model-A, it is found that these two models bear some comparison with each other in the sense that the three MCC values in Model-A are higher than those in Model-D, but the other three values in Model-A are lower than those in Model-D. In theory, Model-A is superior to Model-D. Such observed indifference might be observed because the estimated weight parameters are not so different from the assumed equal weight 0.25. In addition, it is observed that Model-A and Model-D, Model-B and Model-C, and Model-E and Model-F are not so different from each other in terms of their MCC values. This suggests that introducing interactivity interaction improves model accuracy more than introducing relative importance. Moreover, comparison of Model-B and Model-C with Model-A reveals that a wrongly specified interactivity interaction could significantly worsen the model accuracy (the MCC values in Model-B and Model-C are much lower than that in Model-A).

In order to judge whether the accuracy of the comparison model (Model-B ~ Model-F) is significantly different from that of Model-A, the following χ^2-statistic was calculated based on the converged log-likelihood values shown in Table 8.3, where Model-X refers to one of Model-B ~ Model-F. The χ^2-statistic has K degree of freedom, which is the difference in the number of attributes in Model-A from those in Model-X. If the calculated χ^2-value is larger than critical value, it can be judged that Model-A is superior to Model-X.

$$\chi^2 = -2\{\text{Log} - \text{likelihood(Model} - \text{X)} - \text{Log-likelihood(Model-A)}\} \tag{8.34}$$

Table 3: Estimation results of pedestrian time use and expenditure models.

Model	Model-A (full model)		Model-B (unity-interaction & unequal weight)		Model-C (unity-interaction & equal weight)	
Explanatory variable	**Estimated parameter**	***t*-score**	**Estimated parameter**	***t*-score**	**Estimated parameter**	***t*-score**
Weight parameter						
DGP	0.2356	9.18	0.0023[a]	2.10	0.25	–
MGP	0.2007[a]	10.05	0.0012[a]	2.16	0.25	–
OTP	0.1697[a]	5.08	0.9937[a]	367.60	0.25	–
BEA	0.3940[a]	13.21	0.0028[a]	2.16	0.25	–
Attributes for composite variable						
Total walking distance (m)	0.1661	3.72	−0.0846	−0.70	−0.0959	−2.39
Gender (male: 1; female: 0)	−0.1899	−1.30	−0.0497	−0.21	0.0310	0.83
Age	0.0212	0.63	−0.7253	−9.19	0.0001	0.02
Worker (yes: 1; no: 0)	0.9662	3.31	−0.9970	−3.05	−0.0725	−1.40
Housewife (yes: 1; no: 0)	0.7942	2.86	−0.6462	−1.69	−0.0035	−0.07
Student (yes: 1; no: 0)	0.9716	3.54	−1.7628	−4.65	−0.1351	−1.91
Income	−0.0483	−1.19	−0.2210	−2.53	−0.0049	−0.39
No. of members in travel party	−0.0095	−0.34	−0.3016	−3.54	−0.0122	−0.94
Travel time from home to city center	−0.0001	−0.14	−0.0041	−2.10	−0.0004	−1.13
Influence of composite variable on time allocation behavior						
DGP	0.0038	0.04	0.0147	0.23	3.2909	2.75
MGP	0.2098	2.33	0.0312	0.46	6.2054	2.78
OTP	1.0000	–	1.0000	–	1.0000	–
BEA (excluded)						

Table 3: (*Continued*)

Model	**Model-A (full model)**		**Model-B (unity-interaction & unequal weight)**		**Model-C (unity-interaction & equal weight)**	
Explanatory variable	**Estimated parameter**	***t*-score**	**Estimated parameter**	***t*-score**	**Estimated parameter**	***t*-score**
Influence of composite variable on expenditure behavior						
DGP	−0.0041	−0.05	−0.1329	−1.59	6.1606	2.64
MGP	0.3501	3.70	0.0954	1.20	12.3104	2.72
OTP	0.0092	0.04	1.4430	26.22	12.3834	2.75
BEA (excluded)						
Interaction term						
1. Time-to-time	−0.1267	−20.45	1.0000	–	1.0000	–
2. Expenditure-to-expenditure	-0.1267	−20.45	1.0000	–	1.0000	–
3. Time-to-expenditure	0.0313	4.86	1.0000	–	1.0000	–
Value of time (VOT: Yen/h)	9,227		5,310		6,084	
Multiple correlation coefficient (log-transformed function)						
Time: DGP	0.7048		0.4711		0.5671	
Time: MGP	0.8027		0.3736		0.3531	
Time: OTP	0.6048		0.2069		0.8297	
Expenditure: DGP	0.7429		0.2555		0.5299	
Expenditure: MGP	0.8418		0.1715		0.1760	
Expenditure: OTP	0.7351		0.1109		0.2467	
Converged log-likelihood	−2197.80		−2798.17		−2707.08	
χ^2 statistic (degree of freedom)	–		−1200.74 (3)		1018.56 (6)	
Sample size (persons)	481		481		481	

Model	Model-D (interaction & equal weight)		Model-E (no interaction & unequal weight)		Model-F (no interaction & equal weight)	
Explanatory variable	**Estimated parameter**	***t*-score**	**Estimated parameter**	***t*-score**	**Estimated parameter**	***t*-score**
Weight parameter						
DGP	0.25	–	0.2072	6.900	0.25	–
MGP	0.25	–	0.1912[b]	7.011	0.25	–
OTP	0.25	–	0.2969	4.872	0.25	–
BEA	0.25	–	0.3047	8.452	0.25	–
Attributes for composite variable						
Total walking distance (m)	0.2682	2.833	0.4050	3.459	0.3443	5.146
Gender (male: 1; female: 0)	0.1177	0.275	−0.1092	−0.912	−0.0965	−0.915
Age	−0.0784	−0.801	−0.0660	−1.949	−0.0358	−1.299
Worker (yes: 1; no: 0)	0.0013	0.003	0.5602	2.682	0.4498	3.170
Housewife (yes: 1; no: 0)	0.9072	1.521	0.4629	2.133	0.3069	1.881
Student (yes: 1; no: 0)	0.0008	0.001	0.7434	2.894	0.5644	3.501
Income	−0.0957	−0.668	−0.0154	−0.369	−0.0041	−0.111
No. of members in travel party	−0.0094	−0.072	−0.0481	−1.136	−0.0050	−0.136
Travel time from home to city center	−0.0082	−2.110	0.0006	0.626	0.0006	0.710
Influence of composite variable on time allocation behavior						
DGP	0.0003	0.003	0.3132	1.540	−0.0714	−0.500
MGP	0.0032	0.035	−0.4964	−1.643	−1.0210	−3.961
OTP	1.0000	–	1.0000	–	1.0000	–
BEA (excluded)						

Table 3: (*Continued*)

Model	Model-D (interaction & equal weight)		Model-E (no interaction & unequal weight)		Model-F (no interaction & equal weight)	
Explanatory variable	**Estimated parameter**	***t*-score**	**Estimated parameter**	***t*-score**	**Estimated parameter**	***t*-score**
Influence of composite variable on expenditure behavior						
DGP	−0.0018	−0.014	1.2851	2.928	0.9485	3.690
MGP	−0.0016	−0.012	−0.7210	−1.647	−1.2957	−3.091
OTP	−0.0012	−0.008	−1.1314	−1.661	−1.3224	−3.166
BEA (excluded)						
Interaction term						
1. Time-to-time	−0.1310	−20.344				
2. Expenditure-to-expenditure	−0.1310	−20.344				
3. Time-to-expenditure	0.0741	2.140				
Value of time (VOT: Yen/h)	12,766		5,058		5,122	
Multiple correlation coefficient (log-transformed function)						
Time: DGP	0.7667		0.0342		0.0114	
Time: MGP	0.7911		0.0758		0.1007	
Time: OTP	0.3727		0.1544		0.1176	
Expenditure: DGP	0.7582		0.0756		0.0539	
Expenditure: MGP	0.8279		0.0553		0.0829	
Expenditure: OTP	0.8024		0.0013		0.0230	
Converged log-likelihood	−2381.75		−2649.94		−2740.96	
χ^2 statistic (degree of freedom)	367.9 (3)		904.28 (3)		1086.32 (6)	
Sample size (persons)	481		481		481	

[a]Indicates that the weight parameter is significantly different from the equal weight 0.25 at 95% level.
[b]Indicates that the weight parameter is significantly different from the equal weight 0.25 at 95% or 90% level.

The converged log-likelihood value for Model-A is -2179.80, which is the largest of the six estimated models. The calculated χ^2 values are 1200.74 for Model-B, 1018.56 for Model-C, 367.90 for Model-D, 904.28 for Model-E, and 1086.32 for Model-F, respectively. It is obvious that all the calculated χ^2 values are larger than their critical values (7.81 and 11.34 at 95% and 99% significance levels when $K = 3$, and 12.59 and 16.81 at 95% and 99% levels when $K = 6$).

As a whole, it can be concluded that Model-A (the full version of the proposed resource allocation model) is the best model of pedestrian consumption behavior data in this case study. This implies that introducing interactivity interaction and relative importance of activity participation are important concepts to predict pedestrian time use and expenditure behavior.

8.5.3.2. Decision-making mechanisms Decision-making mechanisms related to the pedestrian consumption behavior are analyzed using the interactivity interaction and relative importance parameters. Interactivity interaction parameters are estimated in Model A and Model-D, and relative importance parameters are estimated in Model-A, Model-B, and Model-E, respectively. Originally, interactivity interaction parameters were defined differently for the time-to-time, expenditure-to-expenditure, and time-to-expenditure interactions. In this case study, however, Model-A with three different interaction parameters did not converge. As a result, the interaction parameters were assumed to be the same between the time-to-time and expenditure-to-expenditure interactions. For ease of model estimation, all the weight parameters (i.e., the relative importance parameters) were assumed to be the same for both time use and expenditure functions, i.e., they were only different across activities. And, the total utility in Model-A, which is decomposed into several sub-elements, was also analyzed to clarify the decision-making mechanisms.

All interactivity interaction parameters are statistically significant. Both Model-A and Model-D have negative estimated time-to-time and expenditure-to-expenditure interaction parameters, suggesting that when allocating available time and money to different activities, competition occurs between time-to-time consumptions and between expenditure-to-expenditure consumptions. On the other hand, the time-to-expenditure interaction parameter is estimated to be positive in both Model-A and Model-D, suggesting that a longer stay in the city center leads to higher expenditures. Considering that correlations between time and money spent on DGP, MGP, OTP, and BEA are 0.393, 0.165, 0.054, and 0.539, respectively, the positive time-to-expenditure interaction parameter are understandably realistic. In contrast, the time-to-time and expenditure-to-expenditure correlations range between -0.180 and -0.009 (one exception is that the expenditure-to-expenditure correlation between DGP and BEA is 0.007), supporting the observed negative interaction parameters for time-to-time and expenditure-to-expenditure interaction.

The relative importance parameters are all statistically significant different from zero and eight out of the 12 parameters are also significantly different from the assumed equal weight of 0.25. Model-A, the best model, suggests that shoppers attach the highest importance to BEA (0.3940) and low importance to OTP (0.2180). In contrast, compared with Model-A, Model-B extremely overestimates the highest

relative importance parameter (0.9937) and Model-E largely overestimates the relative importance parameter (0.2969) for OTP (0.1697 in Model-A).

Eq. (8.1) shows that a pedestrian's total utility is composed of the weighted utilities and three types of interaction terms. This means that how the pedestrian allocates his/her available time and money to various activities depends on how he/she attempts to trade off the preferences to each activity (i.e., the weighted utilities of the activities) and interactivity interactions. In this case study, since Model-A is the best model, discussions about utility function are given only with respect to Model-A. The obtained total utility and its compositions are shown in Figure 8.5. It is found that 74% of the total utility is accounted for by the additive part, while the remaining 26% comes from the three types of interactivity interactions. This does not imply that the influences of interactivity interactions are limited. Table 8.4 shows the activity-specific parameters for different models, which are calculated by multiplying the parameter of each attribute for composite variable and the parameter representing the composite variable on each activity (DGP, MGP, OTP, and BEA). Compared with the results of Model-A, 30 out of 54 parameters in Model-B have a different sign, 29 in Model-C, 22 in Model-D, 32 in Model-E, and 37 in Model-F. Model-D has the least number of different signs from Model-A. A change in sign is especially a serious issue from the perspective of policy decision-making. For example, most of the parameters for total walking distance within the city center have a positive value. This means that pedestrians derive more utility by walking around the city center, and as a result, improving the walking environment to induce pedestrians to walk longer could enhance pedestrian utility. In case that the sign of total walking distance parameter is wrongly estimated to be negative, the model would not support such policy.

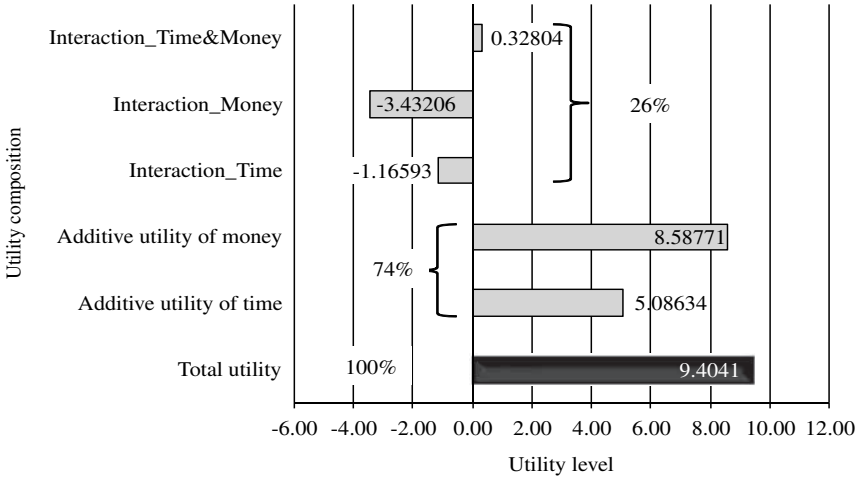


Figure 8.5: Utility composition in the proposed model (Model-A).

Table 8.4: Activity-specific parameters in different models.

	Model-A	Model-B	Model-C	Model-D	Model-E	Model-F
Time function for DGP						
Total walking distance (m)	6.28E-04	**−1.25E-03**	**−3.15E-01**	8.56E-05	1.27E-01	**−2.46E-02**
Gender (male: 1; female: 0)	−7.18E-04	−7.32E-04	**1.02E-01**	**3.75E-05**	−3.42E-02	**6.89E-03**
Age	8.00E-05	**−1.07E-02**	4.54E-04	**-2.50E-05**	**-2.07E-02**	2.55E-03
Worker (yes: 1; no: 0)	3.65E-03	**−1.47E-02**	**−2.38E-01**	4.16E-07	1.75E-01	**−3.21E-02**
Housewife (yes: 1; no: 0)	3.00E-03	**−9.52E-03**	**−1.15E-02**	2.89E-04	1.45E-01	**−2.19E-02**
Student (yes: 1; no: 0)	3.68E-03	**−2.60E-02**	**−4.45E-01**	2.49E-07	2.33E-01	**−4.03E-02**
Income	−1.83E-04	−3.26E-03	−1.62E-02	−3.05E-05	−4.82E-03	**2.96E-04**
No. of members in travel party	−3.61E-05	−4.45E-03	−4.03E-02	−2.99E-06	−1.51E-02	**3.54E-04**
Travel time from home to city center	−5.66E-07	−5.99E-05	−1.16E-03	−2.62E-06	**1.86E-04**	−4.24E-05
Time function for MGP						
Total walking distance (m)	3.48E-02	**−2.64E-03**	**−5.95E-01**	8.50E-04	**−2.01E-01**	**−3.52E-01**
Gender (male: 1; female: 0)	−3.98E-02	−1.55E-03	**1.92E-01**	**3.73E-04**	**5.42E-02**	**9.85E-02**
Age	4.44E-03	**−2.26E-02**	8.56E-04	**−2.49E-04**	3.27E-02	3.65E-02
Worker (yes: 1; no: 0)	2.03E-01	**−3.11E-02**	**−4.50E-01**	4.13E-06	**−2.78E-01**	**−4.59E-01**
Housewife (yes: 1; no: 0)	1.67E-01	**−2.02E-02**	**−2.16E-02**	2.88E-03	**−2.30E-01**	**−3.13E-01**
Student (yes: 1; no: 0)	2.04E-01	**−5.50E-02**	**−8.38E-01**	2.48E-06	**−3.69E-01**	**−5.76E-01**
Income	−1.01E-02	−6.90E-03	−3.06E-02	−3.03E-04	**7.64E-03**	**4.23E-03**
No. of members in travel party	−2.00E-03	−9.42E-03	−7.60E-02	−2.97E-05	**2.39E-02**	**5.06E-03**
Travel time from home to city center	−3.14E-05	−1.27E-04	−2.19E-03	−2.60E-05	−2.95E-04	−6.06E-04

Table 8.4: (*Continued*)

	Model-A	Model-B	Model-C	Model-D	Model-E	Model-F
Time function for OTP						
Total walking distance (m)	1.66E-01	**−8.46E-02**	**−9.59E-02**	2.68E-01	4.05E-01	3.44E-01
Gender (male: 1; female: 0)	−1.90E-01	−4.97E-02	**3.10E-02**	**1.18E-01**	−1.09E-01	−9.65E-02
Age	2.12E-02	**−7.25E-01**	1.38E-04	**−7.84E-02**	**−6.60E-02**	**−3.58E-02**
Worker (yes: 1; no: 0)	9.66E-01	**−9.97E-01**	**−7.25E-02**	1.30E-03	5.60E-01	4.50E-01
Housewife (yes: 1; no: 0)	7.94E-01	**−6.46E-01**	**−3.48E-03**	9.07E-01	4.63E-01	3.07E-01
Student (yes: 1; no: 0)	9.72E-01	**−1.76E + 00**	**−1.35E-01**	7.82E-04	7.43E-01	5.64E-01
Income	−4.83E-02	−2.21E-01	−4.93E-03	−9.57E-02	−1.54E-02	−4.14E-03
No. of members in travel party	−9.54E-03	−3.02E-01	−1.22E-02	−9.37E-03	−4.81E-02	−4.96E-03
Travel time from home to city center	−1.50E-04	−4.06E-03	−3.52E-04	−8.20E-03	**5.94E-04**	**5.94E-04**
Expenditure function for DGP						
Total walking distance (m)	−6.74E-04	**1.12E-02**	−5.91E-01	−4.88E-04	**5.20E-01**	**3.27E-01**
Gender (male: 1; female: 0)	7.70E-04	6.60E-03	1.91E-01	**−2.14E-04**	**−1.40E-01**	**−9.15E-02**
Age	−8.58E-05	**9.64E-02**	**8.49E-04**	**1.43E-04**	−8.48E-02	−3.39E-02
Worker (yes: 1; no: 0)	−3.92E-03	**1.32E-01**	−4.46E-01	−2.37E-06	**7.20E-01**	**4.27E-01**
Housewife (yes: 1; no: 0)	−3.22E-03	**8.59E-02**	−2.14E-02	−1.65E-03	**5.95E-01**	**2.91E-01**
Student (yes: 1; no: 0)	−3.94E-03	**2.34E-01**	−8.32E-01	−1.42E-06	**9.55E-01**	**5.35E-01**
Income	1.96E-04	2.94E-02	**−3.04E-02**	1.74E-04	**−1.98E-02**	**−3.93E-03**
No. of members in travel party	3.87E-05	4.01E-02	**−7.54E-02**	1.70E-05	**−6.19E-02**	**−4.70E-03**
Travel time from home to city center	6.07E-07	5.40E-04	**−2.17E-03**	1.49E-05	7.64E-04	5.63E-04
Expenditure function for MGP						
Total walking distance (m)	5.82E-02	**−8.07E-03**	**−1.18E + 00**	**−4.31E-04**	**−2.92E-01**	**−4.46E-01**
Gender (male: 1; female: 0)	−6.65E-02	−4.74E-03	**3.81E-01**	−1.89E-04	**7.87E-02**	**1.25E-01**
Age	7.41E-03	**−6.92E-02**	1.70E-03	1.26E-04	4.76E-02	4.63E-02
Worker (yes: 1; no: 0)	3.38E-01	**−9.52E-02**	**−8.92E-01**	**−2.09E-06**	**−4.04E-01**	**−5.83E-01**
Housewife (yes: 1; no: 0)	2.78E-01	**−6.17E-02**	**−4.28E-02**	**−1.46E-03**	**−3.34E-01**	**−3.98E-01**

Student (yes: 1; no: 0)	3.40E-01	**−1.68E-01**	**−1.66E + 00**	**−1.26E-06**	**−5.36E-01**	**−7.31E-01**
Income	−1.69E-02	−2.11E-02	−6.07E-02	**1.54E-04**	**1.11E-02**	**5.36E-03**
No. of members in travel party	−3.34E-03	−2.88E-02	−1.51E-01	**1.51E-05**	**3.47E-02**	**6.43E-03**
Travel time from home to city center	−5.24E-05	−3.88E-04	−4.34E-03	**1.32E-05**	−4.29E-04	−7.69E-04
Expenditure function for OTP						
Total walking distance (m)	1.54E-03	**−1.22E-01**	**−1.19E + 00**	**−3.27E-04**	**−4.58E-01**	**−4.55E-01**
Gender (male: 1; female: 0)	−1.76E-03	−7.17E-02	**3.83E-01**	−1.43E-04	**1.24E-01**	**1.28E-01**
Age	1.96E-04	**−1.05E + 00**	1.71E-03	9.56E-05	7.46E-02	4.73E-02
Worker (yes: 1; no: 0)	8.93E-03	**−1.44E + 00**	**−8.97E-01**	**−1.59E-06**	**−6.34E-01**	**−5.95E-01**
Housewife (yes: 1; no: 0)	7.34E-03	**−9.32E-01**	**−4.31E-02**	**−1.11E-03**	**−5.24E-01**	**−4.06E-01**
Student (yes: 1; no: 0)	8.98E-03	**−2.54E + 00**	**−1.67E + 00**	**−9.53E-07**	**−8.41E-01**	**−7.46E-01**
Income	−4.46E-04	−3.19E-01	−6.11E-02	**1.17E-04**	**1.74E-02**	**5.47E-03**
No. of members in travel party	−8.82E-05	−4.35E-01	−1.52E-01	**1.14E-05**	**5.45E-02**	**6.56E-03**
Travel time from home to city center	−1.38E-06	−5.86E-03	−4.36E-03	**1.00E-05**	−6.73E-04	−7.85E-04

Note: The values given in bold means either of the parameter of each attribute for composite variable or the parameter of the composite variable is significant at 95% or 90% level.

8.5.3.3. VOT The average values of time are illustrated in Figure 8.6. VOT is 9227 Yen/h, based on Model A, and 12,776 Yen/h, based on the second-best model, Model-B. The other four models estimate VOT ranging from 5058 to 6084 Yen/h.

Assuming that an individual earns 5 million Yen per year and works 8 h per day and 5 days per week, work time value can be calculated as 2404 Yen/h (= 5,000,000 Yen/(8 h/day × 5 days/week × 52 weeks/year)). Compared with such work hour value, the revealed pedestrian VOT is considerably higher. This suggests that work time value cannot be used to measure the pedestrian VOT. On the other hand, it seems that the calculated pedestrian VOTs in this case study are relatively high. It might be a promising research issue to examine how to justify VOT from empirical data.

8.5.3.4. Influential factors Table 8.4 shows the values of activity-specific parameters. The parameter means the influence of one unit change in each variable on decision outcome, and it can be also interpreted as marginal influence of each variable. To further make sure the influence magnitude for each variable, partial utility is calculated by multiplying the activity-specific parameter and average value of the variable. The results are displayed in Figures 8.7 and 8.8.

Table 8.4 confirms that AGE, SEX, PART (number of members in travel party), INCM (household income level), and TIME (travel time from home to city center) have a relatively stable marginal influence across the six models on the pedestrian time use and expenditure allocation decision. STDT (student dummy) is most unstable, followed by WKER (worker dummy) and WIFE. This implies that estimation of employment status is highly sensitive to the adopted model structures. DIST (total walking distance) parameter also strongly fluctuates across different models. As a general trend, most of the comparison models underestimate marginal influences of most of the variables. Such a trend is especially remarkable for both OTP time use and expenditure functions. One exception is that for DGP expenditure function, most of the comparison models overestimate the marginal influences.

Looking at Figure 8.7, Model-A indicates that employment status variables, i.e., worker, housewife, and student dummies, account for 25.1 ~ 30.7% of total utility, respectively, and 86.3% in total. Compared with Model-A, the second-best Model-D shows that the influence of employment status accounts for 60.2%, most of which

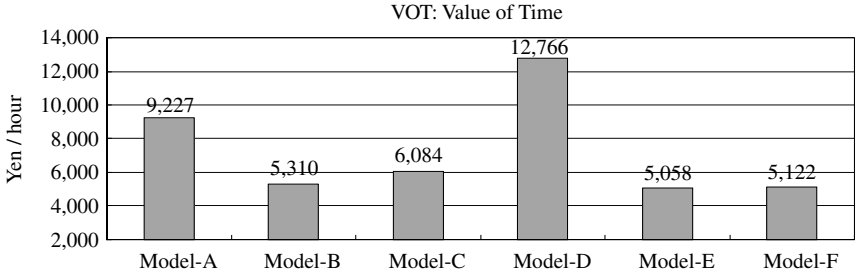


Figure 8.6: Value of pedestrian's activity time.

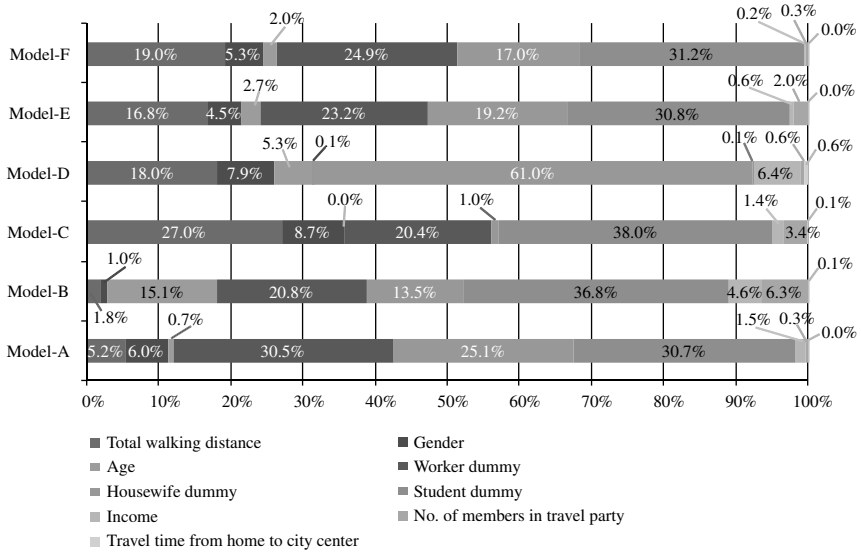
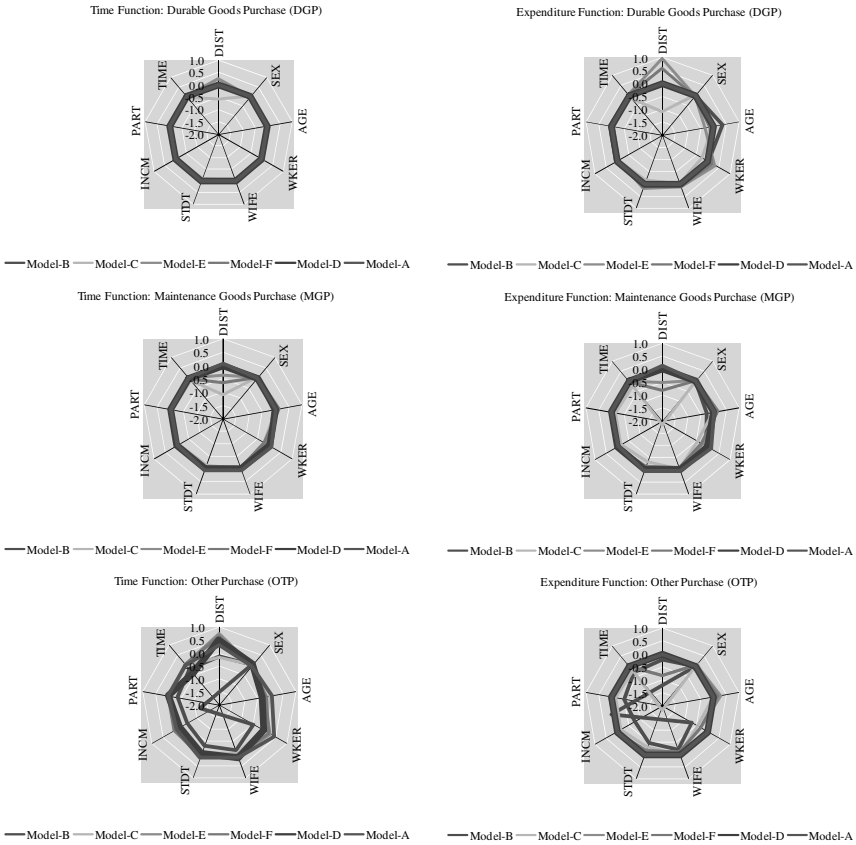


Figure 8.7: Shares of partial utilities in total utility for different models.

comes from the housewife dummy. In other words, Model-D extremely overestimates the influence of the housewife dummy (25.1% → 61.0%), but extremely underestimates the influences of student and worker dummies (30.5% → 0.1%; 30.7% → 0.1%). In contrast, the other models underestimate the influence of the worker dummy by 18∼33% (−18.4% = (24.9%–30.5%)/30.5%; −33.1% = (20.4%–30.5%)/30.5%), and overestimate the influence of the student dummy by 0.3∼23.8% (0.3% = (30.8%–30.7%)/30.7%; 23.8% = (38.0%–30.7%)/30.7%). Model-C∼Model-F overestimates the influence of total walking distance. Except for Model-B, the other models estimate a similar influence of gender. Influences of travel party size and travel time from home to city center are ignorable in most models. In addition, Figure 8.8 suggests that the actual values of partial utilities do not vary substantially, except for OTP functions. DIST estimates are sensitive to model structure. Influence of household income on pedestrian consumption behavior is extremely low, and this observation is consistent across all models.

8.6. Conclusions

Regeneration of central urban areas has attracted increasingly more attention in many local Japanese cities, aiming not only to revitalize economic activities, but also to mitigate environmental impacts due to the rapid progress of motorization and the resulting urban sprawl. Such a regeneration policy is also expected to play an important role in reshaping the sprawled urban structure into a compact structure. Since walk is usually one of the major travel modes used within city centers, given



Time function

DIST	Total walking distance (m)
SEX	Gender (Male: 1; Female: 0)
AGE	Age
WKER	Worker (Yes: 1; No: 0)
WIFE	Housewife (Yes: 1; No: 0)

Expenditure function

STDT	Student (Yes: 1; No: 0)
INCM	Income
PART	No. of members in travel party
TIME	Travel time from home to city center

Figure 8.8: Partial utility of each variable.

these policies, it becomes important to better understand pedestrian's consumption behavior.

Focusing on pedestrian's time use and expenditure behavior in city centers, this chapter has developed a new resource allocation model to describe pedestrian time use and expenditure, subject to time and expenditure constraints, using a utility-maximizing approach. It is assumed that pedestrians maximize their utility by taking into account the relative importance of different activities and inter-activity interactions. A pedestrian's utility is defined as a multi-linear function of time-specific, expenditure-specific utilities, and interactivity interactions. The interactivity interactions include three parts: time-to-time, expenditure-to-expenditure, and time-to-expenditure interactions. Utility maximization results in a

nonlinear simultaneous-equation model system, which is composed of time use and expenditure functions for different activities. Using the resulting model system, the pedestrian-specific value of activity time can be measured. In other words, the value of activity time is heterogeneous across pedestrians. SUR is used to simultaneously estimate the model system.

Using pedestrian weekend activity diary data collected in central area of Hiroshima City, Japan in November 2004, model estimation results confirmed the applicability of the proposed model system. Introducing interactivity interactions greatly improved model accuracy. Available time and expenditure constraints resulted in synergy effects between time use and expenditure, but they gave rise to competition between time-to-time consumption and between expenditure-to-expenditure consumption. It was further observed that ignoring relative importance of activity and/or interactivity interactions significantly underestimated the value of activity time. It was found that age, gender, size of travel party, household income, and travel time from home to city center had stable influences on pedestrian's consumption behavior across different model structures. In contrast, influence of employment status was more sensitive to the adopted model structures and the proposed model system revealed that it could account for more than 80% of the total utility. The total walking distance was also sensitive to model structures, but its influence on consumption behavior was much lower. Influence of household income was extremely low.

To better support policy decision on regeneration of central urban areas, it is noteworthy to further examine pedestrian behavior not only from the perspectives of time use and expenditure, but also in terms of store choice and activity participation, considering the spatial distribution of stores within city centers. In this sense, a comprehensive activity-based model system with both temporal and spatial interdependencies should be developed. In addition, a more general utility function for time use and expenditure should be applied to properly reflect pedestrian's preference, because the measured value of activity time depends on the form of utility function. Since the choice of access transport mode to the city center could influence pedestrian consumption behavior (e.g., car users have to pay parking fees, suggesting that at least duration might be influenced), such choice behavior should be integrated into the comprehensive model system as well as other aspects of pedestrian behavior. Considering the complexity of pedestrian behavior, it might also be a good idea to introduce the utility-maximizing modeling technique into a multi-agent simulation system. Needless to say, effects of various policy-related variables (e.g., pedestrian-exclusive mall, width of street, illegal parking on street, open space, short-distance transport system, and spatial layout of various stores) should also be evaluated.

References

Antonini, G., Bierlaire, M., & Weber, M. (2006). Discrete choice models of pedestrian walking behavior. *Transportation Research Part A*, *40*, 667–687.

Becker, G. (1965). A theory of the allocation of time. *The Economic Journal*, *75*, 493–517.

Bhat, C. (2007). A hazard-based duration model of shopping activity with nonparametric baseline specification and nonparametric control for unobserved heterogeneity. *Transportation Research Part B*, *30*, 189–207.

Bhat, C., & Zhao, H. (2002). The spatial analysis of activity stop generation. *Transportation Research Part B*, *36*, 557–575.

Borgers, A., & Timmermans, H. J. P. (1986a). A model of pedestrian route choice and demand for retail facilities within inner-city shopping areas. *Geographical Analysis*, *18*(2), 115–128.

Borgers, A., & Timmermans, H. J. P. (1986b). City centre entry points, store location patterns and pedestrian route choice behaviour: A microlevel simulation model. *Socio-Economic Planning Sciences*, *20*, 25–31.

Dellaert, B. G. C., Arentze, T. A., Bierlaire, M., Borgers, A. W., & Timmermans, H. J. P. (1998). Investigating consumers' tendency to combine multiple shopping purposes and destinations. *Journal of Marketing Research*, *35*(2), 177–188.

DeSerpa, A. C. (1971). A theory of the economics of time. *Economic Journal*, *81*(324), 828–846.

Diep, V. C. S., & Sweeney, J. C. (2008). Shopping trip value: Do stores and products matter? *Journal of Retailing and Consumer Services*, *15*, 399–409.

Finn, A., & Louviere, J. J. (1996). Shopping center image, consideration, and choice: Anchor store contribution. *Journal of Business Research*, *35*, 241–251.

Gijsbrechts, E., Campo, K., & Nisol, P. (2008). Beyond promotion-based store switching: Antecedents and patterns of systematic multiple-store shopping. *International Journal of Research in Marketing*, *25*, 5–21.

Greenwald, M. J., & Boarnet, M. G. (2001). Built environment as determinant of walking behavior: Analyzing nonwork pedestrian travel in Portland, Oregon. *Transportation Research Record*, *1780*, 33–41.

Habib, K. M. N. (2007). *Modelling activity generation processes*. Doctoral thesis, Department of Civil Engineering, University of Toronto.

Hoogendoorn, S., & Bovy, P. (2004). Pedestrian route-choice and activity scheduling theory and models. *Transportation Research Part B*, *38*, 169–190.

Hoogendoorn, S., Bovy, P., & Daamen, W. (2002). Microscopic pedestrian wayfinding and dynamics modelling. In: M. Schreckenberg & S. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 123–155). Berlin: Springer.

Hsiao, M. H. (2009). Shopping mode choice: Physical store shopping versus e-shopping. *Transportation Research Part E*, *45*, 86–95.

Hu, S., & Saleh, A. (2005). Impacts of congestion charging on shopping trips in Edinburgh. *Transport Policy*, *12*, 443–450.

Jara-Díaz, S. (2003). On the goods-activities technical relations in the time allocation theory. *Transportation*, *30*, 245–260.

Jiang, B. (1999). SimPed: Simulating pedestrian flows in a virtual urban environment. *Journal of Geographic Information and Decision Analysis*, *3*(1), 21–30.

Lord, J. D. (1988). Retail decentralisation and C.B.D. decline in American Cities, WP8802. Institute of Retail Studies, University of Stirling.

Nagel, K. (2005). Multi-agent transportation simulation. URL: http://www2.tu-berlin.de/fb10/ISS/FG4/publications/matsim-book/31jan05.pdf, accessed on January 6, 2009.

Okazaki, S. (1979). A study of simulation model for pedestrian movement in architectural space. Part 1: Pedestrian movement by the application of magnetic models. *Transactions of Architectural Institute of Japan*, *283*, 111–119.

Oppewal, H., & Timmermans, H. J. P. (1999). Modeling consumer perception of public space in shopping centers. *Environment and Behavior*, *31*(1), 45–65.

Owens, P. M. (1993). Neighborhood form and pedestrian life: Taking a closer look. *Landscape and Urban Planning*, *26*, 115–135.

Parker, D. C., Manson, S. M., Janssen, M. A., Hoffmann, M. J., & Deadman, P. (2003). Multi-agent systems for the simulation of land-use and land-cover change: A review. *Annals of the Association of American Geographers*, *93*, 316–340.

Paumier, C. (2004). *Creating a vibrant city center: Urban design and regeneration principles*. Washington D.C: The Urban Land Institute.

Robin, T., Antonini, G., Bierlaire, M., & Cruz, J. (2009). Specification, estimation and validation of a pedestrian walking behavior model. *Transportation Research Part B*, *43*, 36–56.

Saarloos, D., Fujiwara, A., & Zhang, J. (2007). The interaction between pedestrians and facilities in central business districts: An explorative case study. *Journal of the Eastern Asia Society for Transportation Studies*, *7*, 1870–1885.

Schmöcker, J. D., Fonzone, A., Quddus, M., & Bell, M. G. H. (2006). Changes in the frequency of shopping trips in response to a congestion charge. *Transport Policy*, *13*, 217–228.

Schmöcker, J. D., Fonzone, A., Quddus, M., & Bell, M. G. H. (2008). Mode choice of older and disabled people: A case study of shopping trips in London. *Journal of Transport Geography*, *16*, 257–267.

Schwanen, T. (2004). The determinants of shopping duration on workdays in The Netherlands. *Journal of Transport Geography*, *12*, 35–48.

Suarez, A., del Bosque, I. R., Rodriguez-Poo, J. M., & Moral, I. (2004). Accounting for heterogeneity in shopping centre choice models. *Journal of Retailing and Consumer Services*, *11*, 119–129.

Thomas, C. J., & Bromley, R. D. F. (2000). City-centre revitalisation: Problems of fragmentation and fear in the evening and night-time city. *Urban Studies*, *37*(8), 1403–1429.

Timmermans, H. J. P. (1982). Consumer choice of shopping centre: An information integration approach. *Regional Studies*, *16*, 171–182.

Timmermans, H. J. P., Borgers, A., & van der Waerden, P. (1991). Mother logit analysis of substitution effects in consumer shopping destination choice. *Journal of Business Research*, *23*, 311–323.

Zhang, J., Timmermans, H., & Borgers, A. (2005). A model of household task allocation and time use. *Transportation Research Part B*, *39*, 81–95.

Chapter 9

A Novel Calibration Approach of Microscopic Pedestrian Models

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Abstract

This contribution aims at providing a generic approach to the calibration of microscopic pedestrian models. In doing so, it proposes a new generic calibration methodology for microscopic pedestrian models using pedestrian trajectory data as the prime data source. The method allows for statistical analysis of the parameter estimates, including their cross-correlations. As a further extension of the method, the inclusion of prior information on the parameters of the model, their distribution, and their cross-relations is proposed. As a direct result, other data sources can be included in the model calibration, such as capacity observations.

The application results provide new insights into the behavior of individual pedestrians, inter-pedestrian differences, as well as the resulting pedestrian flow characteristics. By comparing different models of increasing complexity, it is investigated which of the model amendments are significant from a statistical point of view. It is shown that besides anisotropy, finite reaction times play an important role in correctly describing microscopic walking behavior.

The implications of these findings in the microscopic description of pedestrian flows are considered by studying the predicted flow operations at a narrow bottleneck. It turns out that the finite reaction times indeed have a significant effect on the pedestrian flow operations, and should hence be included in pedestrian models to ensure realistic predictions.

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9.1. Introduction

Estimating the parameters of microscopic pedestrian models is a complex task. This is in part caused by the relatively large number of parameters that can often not be observed directly, the lack of suitable data, as well as the lack of suitable calibration techniques. Calibration of microscopic pedestrian models is often performed by comparing aggregate model outcomes (flows, speeds, densities, etc.), predicted macroscopic relations (e.g., speed density curves), or emerging spatial-temporal patterns (dynamic lane formation, formation of diagonal strips in crossing flows — also referred to as *stripe formation* (Helbing, Buzna, Diel, Johansson, & Werner, 2005a)) with macroscopic empirical data or expert opinions. In doing so, it has been shown that a number of models are able to predict macroscopic flow conditions with reasonable accuracy (see, e.g., Hoogendoorn & Bovy, 2003; Helbing, Farkas, & Vicsek, 2000a, 2000b; Klüpfel, Schreckenberg, & Meyer-König, 2005).

There are many reasons why a macroscopic approach to microscopic model calibration will not always yield the correct results. For example, inter-pedestrian differences expressed by the variability in model parameters cannot be determined using macroscopic data. Furthermore, it is unclear if microscopic models are able to describe individual walking behavior accurately, or if they mainly provide a reasonable "average" macroscopic prediction. This being the case, there is no means to assess whether the behavioral assumptions underlying a microscopic model are valid or not. If the underlying assumptions are not valid, it is doubtful whether the microscopic model is sufficiently generic and able to predict pedestrian behavior in other situations than the model was calibrated for.

This main contribution of this chapter is the development of an estimation approach for calibrating microscopic models using pedestrian trajectory data collected via video or infrared sensors (Hoogendoorn & Daamen, 2005; Kerridge et al., 2005). An important property of the approach is that it provides insights into the statistical properties of the estimated parameters, such as standard errors and correlations. This allows application of all kinds of statistical tests, e.g., *t*-tests for parameters significance and likelihood-ratio (LR) tests to test which of two models performs better, while accounting for the number of parameters involved.

A continuous-time microscopic walker model including different aspects of walking that are deemed important is calibrated. It is emphasized that this is not a benchmarking study in the sense that a large range of microscopic pedestrian models are cross-compared. More specifically, we focus on (a simplified version of) the microscopic model Nomad (Hoogendoorn & Bovy, 2003), which is similar to the well-known social forces model (Helbing et al., 2000a, 2000b). An important contribution of the work presented in the chapter pertains to new insights into important processes in walking behavior, which are determined by cross-comparing the effects of different model extensions. That is, we determine which of the model parameters are important in predicting microscopic pedestrian behavior, as well as considering their statistical properties. In doing so, we will study two potentially important aspects of walking behavior, namely anisotropy and finite reaction times. Since we establish model parameters *for individual pedestrians*, we will show

inter-pedestrian differences in walking behavior. Finally, we discuss the implications of the findings for the emergent macroscopic properties of the pedestrian flow.

9.2. Considered Walker Models

This section presents the basic model and the amendments that are considered for further analysis. It is noted that many extensions to both the Nomad model and the social forces model have been proposed. For the purpose of this chapter, it is however not necessary to consider these. The approach can however be directly applied to other microscopic models, both continuous time and discrete time.

9.2.1. Basic Model

The basic model predicts the two-dimensional acceleration vector $\vec{a}_p(t)$ as follows:

$$\vec{a}_p(t) = \vec{f}_p(\vec{v}_p(t), \vec{r}_p - \vec{r}_q, ...) = \frac{\vec{v}_p^0 - \vec{v}_p(t)}{T_p} - A_p \sum_{q \in Q_p} \vec{u}_{pq}(t) e^{-((d_{pq}(t))/(R_p))} \tag{9.1}$$

In Eq. (9.1), the following variables are used: $\vec{r}_p(t)$, location of pedestrian p at time instant t; $\vec{v}_p(t)$, velocity of pedestrian p at time instant t; Q_{pq}, set of pedestrians q influencing p; $\vec{v}_p^0$, free velocity (free speed and desired direction) of pedestrian p; $d_{pq}(t)$, distance between centers of pedestrian p and pedestrian q; $\vec{u}_{pq}(t)$, unit vector pointing from pedestrian p to pedestrian q.

The basic model Eq. (9.1) has four pedestrian-specific parameters that are to be estimated: $V_p^0 = ||\vec{v}_p^0||$, free speed, describing the speed at which pedestrian p would walk when not influenced by any other pedestrian or obstacle; T_p, acceleration time, reflecting the time required to accelerate toward the free speed V_p^0; A_p, interaction constant or interaction strength, describing the extent in which pedestrian p is repelled by the other pedestrians q; R_p, interaction distance, reflecting the range at which interactions with pedestrians q will affect the behavior of pedestrian p.

Note that the desired walking direction $e_p^0 = \vec{v}_p^0 / V_p^0$ is determined by route choice and is assumed known.

9.2.2. Instantaneous Model Including Anisotropy

Anisotropy implies that pedestrians will only — or at least mainly — react to pedestrians in front of them. Eq. (9.1) has been amended to include anisotropy as follows:

$$\vec{a}_p(t) = \frac{\vec{v}_p^0 - \vec{v}_p(t)}{T_p} - A_p \sum_{q \in Q_p} \vec{u}_{pq}(t) e^{-((d^*_{pq}(t))/(R_p))} \tag{9.2}$$

with

$$d^*_{pq}(t) = \begin{cases} \sqrt{\left[\left(\vec{r}_q(t) - \vec{r}_p(t)\right) \cdot \vec{e}_p(t)\right]^2 + \eta_p^2 \left[\left(\vec{r}_q(t) - \vec{r}_p(t)\right) \cdot \vec{n}_p(t)\right]^2} & \text{if } q \text{ is in front of } p \\ \infty & \text{elsewhere} \end{cases} \tag{9.3}$$

where, $\vec{e}_p(t)$, unit vector pointing in the walking direction of pedestrian p; $\vec{n}_p(t)$, unit vector perpendicular to the walking direction of pedestrian p.

This implies *full anisotropy* in the sense that a pedestrian does not take notice of any pedestrian behind him or her.

9.2.3. Model Including Anisotropy and Finite Reaction Time

Unlike most car-following models, walker models generally do not include a finite reaction time. To determine if the reaction time can be neglected or not, we consider the following *retarded* or *delayed model*:

$$\vec{a}_p(t + \tau_p) = \frac{\vec{v}^0_p - \vec{v}_p(t)}{T_p} - A_p \sum_{q \in Q_p} \vec{u}_{pq}(t) e^{-((d^*_{pq}(t))/(R_p))} \tag{9.4}$$

where $\tau_p > 0$ is the pedestrian-specific reaction time (or rather, the *perception-response time*) to be estimated from the microscopic data. In this model, pedestrians are assumed to have a delayed response to the observations they make at time instant t.

9.3. Approach to Model Estimation

This section discusses the estimation of the unknown parameters for *general continuous-time microscopic pedestrian models*. The approach will be applied in the subsequent sections to estimate parameters *for individual pedestrians*. Besides cross-comparison of model performance, the parameter estimates provide new insights into walking behavior and inter-pedestrian differences in this behavior.

It is noted that few results on calibration of walker models have been reported. In related research fields, such as the identification of car-following models, the issue of model calibration and validation has received more attention. Also here, parameter identification remains one of the difficult tasks, primarily due to the fact that parameters are not only directly observable from common traffic data, but also because parameters are generally not transferable to other situations (different locations, periods of the day, etc.), real driving behavior is variable in time and space, etc. Without going into detail, let us recall two examples of automated approaches to model calibration.

Brockfeld et al. (2004) cross-compare different microscopic traffic flow models using data from car-following experiments. The error rates of the different models in comparison to the data varied between 9% and 24%, for validation between 12% and 30%. No single model appeared to be significantly better than the others (even the more complex ones). The authors argued that these errors could probably not be suppressed, irrespective of the model that is used, due to the different behavior of each driver (which is in line with the results that will be presented in this paper). In Schultz and Rilett (2004), a methodology is proposed to introduce and calibrate a parameter distribution using measures of central tendency and dispersion (i.e., mean and variance) to generate input parameters for car-following sensitivity factors in microscopic traffic simulation models. The approach is applied to the IH-10 in Houston, TX using the CORSIM model, and subsequently calibrated utilizing an automated genetic algorithm. In Hoogendoorn and Ossen (2005), we present a static as well as a dynamic method (Kalman filter) to determine and track the (changing) parameters describing car-following behavior. The static approach is strongly related to the approach described in the ensuing. Especially the approach described in Brockfeld et al. (2004) shows resemblance to the approach presented here, although that approach does not provide insight into the statistical properties of the parameter estimates and models.

9.3.1. Parameters to be Estimated

The parameters to be estimated are the free speed V_p^0, the acceleration time T_p, the interaction factor A_p, and the interaction distance R_p. The reaction time τ_p is determined by considering all plausible reaction time values — i.e., between 0.1 s and 0.8 s — and afterwards determining which value yields the best performance. For the anisotropy factor η_p, different values have been considered and cross-compared to test which yields good model performance, after which one fixed value was chosen.

9.3.2. Contents of the Sample Used for Parameter Estimation

The available observations are trajectories (the location $\vec{r}_p$ as a function of time instant $t_k = 0.1k$, for $k = 1,\ldots, n$, see Figure 9.1) of all pedestrians p. From these data, all relevant quantities can be derived either directly or by applying finite differences, such as velocities $\vec{v}_p(t_k)$, accelerations $\vec{a}_p(t_k)$, and distances between pedestrians.

9.3.3. Maximum-Likelihood Estimation

Most continuous-time microscopic walker models can be expressed in the following form:

$$\vec{a}_p(t+\tau_p) = \vec{f}_p(\vec{v}_p(t), \vec{r}_p(t) - \vec{r}_q(t), \ldots | \boldsymbol{\theta}_p) + \vec{\varepsilon}_p \tag{9.5}$$

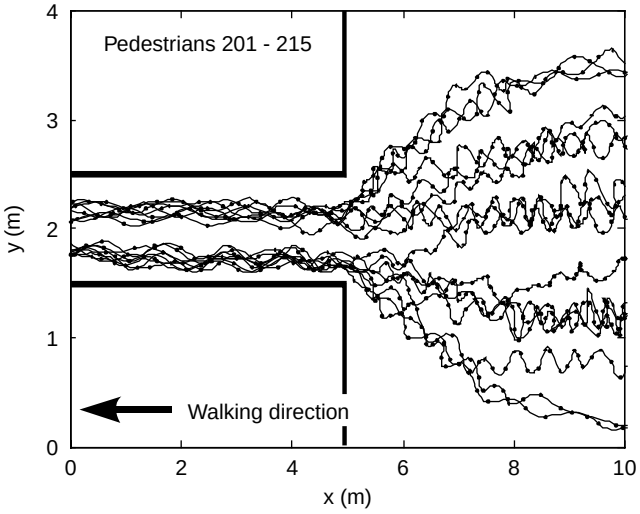


Figure 9.1: Example pedestrian trajectories for the narrow bottleneck.

The error vector $\vec{\varepsilon}_p$ is introduced to reflect modeling errors, similar to the error term used in multivariate linear regression. Note that the error vectors $\vec{\varepsilon}_p$ are generally *serially correlated* (i.e., $\vec{\varepsilon}_p(t)$ and $\vec{\varepsilon}_p(t-1)$ have a large positive correlation). We assume that the error term is normally distributed with mean zero and standard deviation σ_p (pedestrian specific).

Since we can determine all relevant variables (positions, distances, speeds, relative speeds) directly from available experimental data, we can use Eq. (9.5) to determine a *prediction for the retarded acceleration directly from the data*. The prediction $\vec{a}_p(t_k + \tau_p|\boldsymbol{\theta}_p)$ depends on the model parameters $\boldsymbol{\theta}_p$ to be estimated. It can be compared with the *observed* acceleration $\vec{a}_p^{\text{obs}}(t_k + \tau_p)$. Note that the difference between the prediction and the observation are assumed to follow the normal distribution with mean 0 and standard deviation σ_p.

The *likelihood* L_k of a single prediction step, say from time t_k to time t_{k+1}, is related directly to the probability density $f(\varepsilon)$ of the normal distribution:

$$L_k(\boldsymbol{\theta}_p, \sigma_p) = \frac{1}{\sigma_p\sqrt{2\pi}} e^{-((\vec{a}_p^{\text{obs}}(t_k+\tau_p) - \vec{a}_p(t_k+\tau_p))^2)/(2\sigma_p^2)} \text{ subject to}$$
$$\vec{a}_p(t_k + \tau_p|\boldsymbol{\theta}_p) = \vec{f}_p(\vec{v}_p^{\text{obs}}(t), \vec{r}_p^{\text{obs}}(t) - \vec{r}_p^{\text{obs}}(t), ...|\boldsymbol{\theta}_p) \tag{9.6}$$

Considering an entire sample of subsequent acceleration observations and neglecting correlation between subsequent samples (serial correlation) for now, the likelihood of the observation given the model parameters becomes:

$$L = L(\boldsymbol{\theta}_p, \sigma_p) = \prod_{k=1}^{n} \frac{1}{\sigma_p\sqrt{2\pi}} e^{-((\vec{a}_p^{\text{obs}}(t_k+\tau_p) - \vec{a}_p(t_k+\tau_p|\boldsymbol{\theta}_p))^2)/(2\sigma_p^2)} \tag{9.7}$$

where n denotes the number of time instants t_k for which an observation is available. Implying that the *log-likelihood* equals:

$$\tilde{L}(\boldsymbol{\theta}_p, \sigma_p) = -\frac{n}{2}\ln(2\pi\sigma_p^2) - \frac{1}{2\sigma_p^2}\sum_{k=1}^{n}(\vec{a}_p^{\,\text{obs}}(t_k + \tau_p) - \vec{a}_p(t_k + \tau_p|\boldsymbol{\theta}_p))^2 \tag{9.8}$$

Maximum-likelihood (ML) estimation involves finding the parameters that maximize the (log-) likelihood Eq. (9.8). A necessary condition for the optimum allows determination of the standard deviation:

$$\frac{\partial \tilde{L}}{\partial \sigma_p^2} = 0 \Rightarrow \hat{\sigma}_p^2 = \frac{1}{n}\sum_{k=1}^{n}(\vec{a}_p^{\,\text{obs}}(t_k + \tau) - \vec{a}_p(t_k + \tau_p|\boldsymbol{\theta}_p))^2 \tag{9.9}$$

From Eq. (9.9) we see that the ML estimate for the variance of the error term is given by the mean squared error (MSE) of the predictions and the observations. For the remaining parameters, the ML estimates can be determined by *numerical optimization*, i.e.,

$$\hat{\boldsymbol{\theta}}_p = \arg\max \tilde{L}(\boldsymbol{\theta}_p, \hat{\sigma}_p) \tag{9.10}$$

with

$$\tilde{L}(\boldsymbol{\theta}_p, \hat{\sigma}_p) = -\frac{n}{2}\ln\left(\frac{2\pi}{n}\sum_{k=1}^{n}(\vec{a}_p^{\,\text{obs}}(t_k + \tau) - \vec{a}_p(t_k + \tau_p|\boldsymbol{\theta}_p))^2\right) - \frac{n}{2} \tag{9.11}$$

This expression shows that maximization of the log-likelihood is equivalent to minimization of the MSE.

9.3.4. Covariance Estimates, Cramér–Rao Bounds, and Likelihood-Ratio Tests

To approximate the covariance matrix of the estimated parameters, we can use the so-called Cramér–Rao lower bound (Casella & Berger, 1990), stating that:

$$\text{var}(\hat{\boldsymbol{\theta}}_p) \geq -E(\nabla^2 \tilde{L}) \tag{9.12}$$

Since ML is asymptotically efficient, we can show that the asymptotic variance of the parameters is given by the right-hand side of Eq. (9.12) (see, Casella & Berger, 1990). In the remainder of this chapter, this approximation is used to determine an estimate for the covariance of the estimates.

The Cramér–Rao bound provides important insights into the statistical properties of the models by providing estimates for the model standard error and the statistical correlation between the parameter estimates. The standard errors can be used to determine whether the model parameters are not equal to zero in a statistical sense. The correlation matrix provides additional insight into the statistical properties of

the estimates, for instance by explaining large standard errors caused by large correlation between estimates.

In the remainder, we will use the so-called LR test to test whether one model is better than the other. To this end, we will use the *zero-acceleration model* as a reference model, i.e., $\vec{a}_p(t) = \vec{\varepsilon}_p$. For this model, we can determine the (null) log-likelihood:

$$\tilde{L}_0 = -\frac{n}{2}\ln\left(\frac{2\pi}{n}\sum_{k=1}^{n}\vec{a}_p^{\text{obs}}(t_k)^2\right) - \frac{n}{2} \tag{9.13}$$

The LR test involves testing the statistic:

$$2(\tilde{L}(\hat{\boldsymbol{\theta}}_p, \hat{\sigma}_p) - \tilde{L}_0) \tag{9.14}$$

which follows the χ^2 distribution with m degrees of freedom, where m denotes the number of parameters of the model. The LR test is passed with 95% confidence if:

$$2(\tilde{L}(\hat{\boldsymbol{\theta}}_p, \hat{\sigma}_p) - \tilde{L}_0) > \chi^2(0.95, m) \tag{9.15}$$

We emphasize that the log-likelihood test accounts for the number of parameters via the degrees of freedom, thereby enabling comparing simple and complex models.

9.3.5. *Inter-Pedestrian Parameter Correlation*

Besides the correlation in the parameter estimates determined via the Cramér–Rao bound, inter-pedestrians differences can be determined. In the ensuing, this is achieved by computing the mean, variance, and interpersonal correlation of the individual parameter estimates for different pedestrians. These statistics provide insight into the behavioral differences between pedestrians, and the inter-pedestrian correlation between the parameter estimates.

9.4. Approach Generalization

In this section, we present several generalizations of the approach that may be important for practical application purposes. In particular, the use of prior information on the parameter estimates as well as including other data sources can be important to ensure that the model parameters will also yield the desired macroscopic behavior. Furthermore, research on the calibration of car-following models has shown that the estimation results are sensitive to the variable that is compared to the observed data (acceleration, velocity, position). We will hence briefly describe how alternative prediction variables may be used in the proposed method.

9.4.1. Including Prior Information

Let us first consider including prior information into the estimation approach. To this end, let us assume that the parameters $\boldsymbol{\theta}_p$ to be estimated from the data are known to follow some joint distribution, which is described by the joint distribution function $g_p(\boldsymbol{\theta})$. Note that in principle, this joint distribution function can be pedestrian specific. In general however, it is more likely that we will have information about the pedestrian population, i.e., $g_p(\boldsymbol{\theta}) = g(\boldsymbol{\theta})$.

A very natural way to include the information in the estimation process is to include it directly in the likelihood function Eq. (9.7):

$$L^*(\boldsymbol{\theta}_p, \sigma_p) = \prod_{k=1}^{n} g_p(\boldsymbol{\theta}_p) \cdot \frac{1}{\sigma_p\sqrt{2\pi}} e^{-((\vec{a}_p^{obs}(t_k+\tau_p)-\vec{a}_p(t_k+\tau_p|\boldsymbol{\theta}_p))^2)/(2\sigma_p^2))} = (g_p(\boldsymbol{\theta}_p))^n \cdot L(\boldsymbol{\theta}_p, \sigma_p) \tag{9.16}$$

Eq. (9.16) yields the log-likelihood:

$$\tilde{L}^*(\boldsymbol{\theta}_p, \sigma_p) = n\ln(g_p(\boldsymbol{\theta}_p)) + \tilde{L}(\boldsymbol{\theta}_p, \sigma_p) \tag{9.17}$$

Again, we can show that Eq. (9.9) holds and the standard deviation estimate can be determined directly from the data.

We are now able to include all kinds of information about the parameters directly into the estimation process. For instance, if we know that the free speed V_p^0 is around $1.3\,\mathrm{m/s}^2$, we can include this knowledge by specifying the prior distribution function as follows:

$$g_p(..., V^0, ...) = \frac{1}{\sigma_{V^0}\sqrt{2\pi}} e^{-((V^0-1.3)^2)/(2\sigma_{V^0}^2)} \tag{9.18}$$

In Eq. (9.18), the standard deviation σ_{V^0} of the free speed prior information describes the level of uncertainty in the prior information. Also, this specification implies that we have *no prior information about the other parameters to be estimated.*

In Hoogendoorn and Bovy (2003) it is shown that for a single lane of pedestrians, the following fundamental relation between average inter-pedestrian spacing s and speed V^e can be established for the anisotropic model:

$$V^e(s|\boldsymbol{\theta}) = V^0 - TA\left(\frac{e^{-s/R}}{1-e^{-s/R}}\right) \tag{9.19}$$

Suppose that we have established a specific fundamental relation $V^e_{\mathrm{obs}}(s)$ (e.g., from literature or observed in data) and we want to ensure that the model reproduces this relation as closely as possible. We define the error between the observed

fundamental relation and the predicted fundamental relation as follows:

$$e_{FD}(\boldsymbol{\theta}) = \int (V^e_{\text{obs}}(s) - V^e(s|\boldsymbol{\theta}))^2 ds \tag{9.20}$$

To include this information in the estimation process, we define:

$$g_p(\theta) = \frac{1}{\sqrt{2\pi\sigma_{FD}}} \exp\left(-\frac{e_{FD}(\theta)^2}{2\sigma^2_{FD}}\right) \tag{9.21}$$

In Eq. (9.21), σ_{FD} again expresses the reliability of the prior information. In effect, including the prior information (Eq. (9.21)) into the estimation process will yield that the procedure aims to predict the pedestrian trajectories as closely as possible, while at the same time reproducing the observed fundamental diagram as closely as possible.

As a final remark, let us briefly discuss the role of the standard deviations σ_{V^0} and σ_{FD}. Considering the latter, looking at the log-likelihood Eq. (9.17), we find that:

$$\tilde{L}^*(\theta_p, \sigma_p) = -\frac{n}{2}\ln(2\pi\sigma^2_{FD}) - \frac{e_{FD}(\theta_p)}{2\sigma^2_{FD}} + \tilde{L}(\theta_p, \sigma_p) \tag{9.22}$$

This expression shows how the uncertainty parameter σ_{FD} affects the estimation: the larger the uncertainty, the less weight is put on the prior information and vice versa.

9.4.2. Joint Estimation Using Multiple Data Sources

The proposed approach to including prior information can also be generalized to include information from other data sources. These can include both microscopic data (e.g., headway distributions) and macroscopic data (e.g., flow and speed measurements, empirical fundamental diagrams, capacity estimates).

The inclusion of these kinds of data is straightforward, and entails defining function a mapping function $\mathbf{h}$ that maps the parameters $\boldsymbol{\theta}_p$ to the measured quantity, the so-called *measurement* equation. Let $\mathbf{y}$ denote the vector of available measurements. These measurements can be dynamic (i.e., $\mathbf{y}$ describes a time-series) or another set of measurements (e.g., a set of capacity estimates). Then, we assume that:

$$\mathbf{y} = \mathbf{h}(\theta) + \varepsilon \tag{9.23}$$

where ε is some zero-mean multivariate Gaussian variable. Using this expression, we can again determine the joint probability distribution function g and include the information in the (log-) likelihood.

Note that the measurement function $\mathbf{h}$ can take on many forms, either simple or complex. In fact, the measurement equation can be (an outcome of) a simulation run, in which for instance the capacity of a bottleneck has been estimated using the parameter set $\boldsymbol{\theta}_p$.

9.4.3. Alternative Prediction Variables

Let us finally briefly discuss another generalization. In Hoogendoorn and Ossen (2005), we propose using the location or the velocity as variables to be included in the likelihood function. This implies that the model needs to be discretized in order to compute the velocities and speeds from the acceleration expression. Furthermore, instead of predicting only one time-step ahead, Hoogendoorn and Ossen (2005) propose estimating multiple times ahead (or even the whole trajectory).

As these generalizations are straightforward adaptations of the work presented in Hoogendoorn and Ossen (2005), we will not discuss them in detail here.

9.5. Experimental Data Used for Model Calibration

Experimental research entails interfering with natural processes in order to obtain more insights into the causal relations between the independent process variables (stimuli) and the observed phenomena (responses). By performing experiments we can determine the causes and relations that determine the behavior of pedestrians. Apart from the methodological advantages, experiments allow observations of conditions that are not available or that are very difficult to observe in the outside world. The process variables are both the input and output variables that are deemed relevant. It is important that in an early phase of the research, a clear distinction is made between primary and secondary factors. In the end, pedestrian trajectories are determined from the video images. These trajectories are the most elementary and most valuable unit of analysis in traffic flow research, and provide all information required for analysis of both microscopic and macroscopic characteristics.

9.5.1. Overview of Experiments

In total, 10 different walking experiments have been performed. In each of these experiments, approximately 60–90 individuals have been involved. The participants were divided into eight groups, which were given separate walking tasks for each experiment (walk slowly, walk fast, etc.). The groups themselves were heterogeneous, and consisted of men and women of different ages. The group participants were indicated by the color of their caps (red or green). The red caps convey the ordinary behaving pedestrians, while the green caps were pedestrians that had to follow specific instructions (walk aggressively, walk slowly, etc.). The groups were not used to indicate the walking direction, as this could be determined from the video images straightaway. For a detailed discussion, we refer to Hoogendoorn and Daamen (2005) and Daamen and Hoogendoorn (2003).

9.5.2. Measurement Set-Up

The walking experiments were conducted in a large hallway. The ambient conditions were favorable. A digital camera was mounted at the ceiling of the hallway, at a height of 10 m, observing an area of approximately $14\,\text{m} \times 12\,\text{m}$. A wide lens was used enabling the camera to view the entire walking area. The digital camera has a resolution of 720×576 pixels. The distortions in the pedestrian trajectories caused by the slight pincushion effect and camera rotation were corrected for.

9.5.3. Description of Experiments

The data used for the estimates in this chapter stem from the narrow bottleneck experiment. For this experiment, the walking area had a length of 10 m and a width of 4 m. It is stressed that the experiments pertain to normal conditions: participants in the experiments were asked to walk as they would do in regular conditions. Walking behavior in safety-critical (emergencies) situations, or considering pedestrians being in a hurry to catch their train, may be very different.

This narrow bottleneck experiment is characterized by the presence of a bottleneck having a length of 5 m and a width of 1 m. The width is such that pedestrians inside the bottleneck are not able to pass each other. As the pedestrian demand increased, it exceeded the capacity of the bottleneck. From that time onward, congestion appeared just upstream of the bottleneck moving upstream toward the entry of the area. When the pedestrian demand decreased, congestion resolved in due time. An example of the trajectory data collected during the narrow bottleneck experiment is shown in Figure 9.1. Note that the figure clearly shows the swerving motion of the bodies of the pedestrians.

9.5.4. Approach to Data Extraction

Hoogendoorn, Daamen, and Bovy (2003) discuss an approach to extract individual pedestrian data from digital video footage. In the first phase of the pedestrian tracking process, different image processing operations, such as radiometric correction and correction for lens distortion are applied. Next, the pedestrians are detected by identifying the colored caps, which the pedestrians wore during the experiment. This detection occurs in a special zone where lighting conditions are optimal. Next, pedestrian tracking is achieved by application of a newly developed tracking technique. This is achieved by minimizing the so-called merit-function. After tracking has been achieved, a Kalman filter is applied to reduce the errors made during tracking. It turned out that the pedestrian trajectories have been determined with high accuracy.

9.5.5. Data Validity

Several arguments can be given that the data collected during the experiments reflect real-life walking behavior. For one, interviews with some of the participants showed that most of them tended to forget that they were participating in an experiment. For two, given the fact that walking itself is largely a subconscious process, differences between real-life behavior and the behavior observed in the experiments are likely to be relatively minor, except for possible shifts in parameter values caused by factors as hurry that is obviously not present in the experimental situation used (see, Daamen & Hoogendoorn, 2003 for details).

9.6. Estimation Results

To get a general impression of the model performance as well as a better understanding of the important behavioral processes underlying walking behavior, this section presents the results of cross-comparing the model predictions with the naïve zero-acceleration reference model. The parameters of the models have been estimated from the experimental data discussed in the preceding section. The performance of the models is cross-compared based on the overall relative increase in the log-likelihood compared to the null-log likelihood, and the percentage of models that passed the LR test.

Table 9.1 below shows an overview of the estimation results. The table clearly shows that the differences between model performances are considerable. Especially the difference between the instantaneous models and the retarded models is relatively large (improvement of the log-likelihood of 6.4% and 7.7% for the respective instantaneous models, compared to 19.7% in case of the retarded anisotropic model).

9.6.1. Basic Model

Let us first consider the basic model, without anisotropy and without a reaction delay (Eq. (9.1)). In this case, the model passed the LR test in 71% of all cases. For the remaining 29%, the basic model did show a higher log-likelihood than the null model (i.e., smaller RMSE), but the improvement was not large enough to pass the LR test.

Table 9.1: Overview of estimation results for selection of models.

Model type	% Improvement log-likelihood	% of models passing likelihood ratio test
Basic model	6.4	71
Anisotropic model	7.7	76
Retarded anisotropic model	19.7	83

Table 9.2 shows an overview of the statistics of the parameter estimates. The estimates are plausible in terms of their magnitude. The table shows that the inter-pedestrian differences are most prominently reflected by the differences in the acceleration times T_p and the interaction distance R_p, as can be concluded from the coefficient of correlation (CoV) values of 0.32 and 0.50, respectively. Furthermore, it turns out that the inter-pedestrian correlations between the parameter estimates are generally small, except for the positive correlation between free speed and interaction distance (0.49).

9.6.2. *Anisotropic Model*

As concluded before, the anisotropic model with instantaneous reaction outperforms the basic model, although the improvement is rather limited. The LR test shows that the model improves significantly with respect to the naïve zero-acceleration model in case of 76% of all pedestrians considered. Table 9.3 shows an overview of the parameter estimates for all individual estimates that passed the LR test, as well as the correlation between the individual estimates. The results show that especially the acceleration time T_p has a relatively large standard deviation

Table 9.2: Statistics of parameter estimates for non-anisotropic model.

Parameter	**Mean**	**Standard deviation**	**CoV**	**Correlation among personal parameter estimates**			
				V_p^0	T_p	A_p	R_p
V_p^0 (m/s)	1.34	0.21	0.16	1	−0.20	0.02	**0.49**
T_p (s)	1.09	0.35	**0.32**		1	0.10	−0.36
A_p (m/s^2)	11.96	0.23	0.02			1	−0.16
R_p (m)	0.16	0.08	**0.50**				1

Note: Values given in bold are significant values.

Table 9.3: Statistics of parameter estimates for anisotropic model.

Parameter	**Mean**	**Standard deviation**	**CoV**	**Correlation among personal parameter estimates**			
				V_p^0	T_p	A_p	R_p
V_p^0 (m/s)	1.32	0.22	0.17	1	−0.23	0.28	**0.62**
T_p (s)	0.96	0.24	**0.25**		1	**−0.54**	−0.32
A_p (m/s^2)	11.46	0.56	0.05			1	**0.46**
R_p (m)	0.33	0.09	**0.27**				1

Note: Values given in bold are significant values.

(judging from the CoV values), implying that the inter-pedestrian differences in acceleration times are large. This holds equally for the interaction distance R_p.

The correlation between the parameters reveals a considerable relation between the free speed and the interaction distance (positive correlation of 0.62), implying that on average, pedestrians having a large free speed V_p^0 have a large acceleration distance R_p. An interpretation of this (statistical) result might be that pedestrians with a high free speed have the tendency to better anticipate on pedestrians further away from them. However, the explanatory performance of the model is still limited, and care should be taken in interpreting the estimation results.

Other high correlations are found between the acceleration time T_p and the interaction factor A_p (negative correlation of 0.54), and between the interaction factor A_p and the interaction distance R_p (positive correlation of 0.46).

If we compare the estimates of the basic model with the estimates of the anisotropic model, we see that the estimates are similar, except for the interaction distance R_p. In the anisotropic model, the interaction distance R_p is on average twice as large as in the non-anisotropic model. Regarding the inter-pedestrian parameter differences, it turns out that the variability in the acceleration time T_p reduces substantially.

9.6.3. Retarded Anisotropic Model

The statistical analysis clearly reveals the importance of the finite reaction time in walking behavior modeling, as shown from the improvements of the model performances: besides the fact that 83% of the considered cases passes the LR test, we can also see that the log-likelihood improvement over the naïve zero-acceleration model of 19.7% is much higher than for the non-retarded models (6.4% and 7.7%, respectively).

Table 9.4 provides an overview of the average parameter values, their standard deviation and the inter-pedestrian correlation between the parameter estimates. The table shows that in particular the standard deviations — and thus the inter-pedestrian differences — of the acceleration times T_p and of the interaction distances are relatively large. Also note the medium inter-pedestrian differences in the reaction time (mean of 0.28 s and a standard deviation of 0.07 s).

Table 9.4: Statistics of parameter estimates for the retarded anisotropic model.

Parameter	**Mean**	**Standard deviation**	**CoV**	**Correlation among parameter estimates**				
				V_p^0	T_p	A_p	R_p	τ_p
V_p^0 (m/s)	1.34	0.23	0.17	1	0.23	0.39	**0.57**	−0.02
T_p (s)	0.74	0.23	**0.31**		1	−0.23	−0.06	0.44
A_p (m/s^2)	11.33	0.64	0.06			1	0.36	**−0.46**
R_p (m)	0.35	0.11	**0.31**				1	−0.17
τ_p (s)	0.28	0.07	0.25					1

Note: Values given in bold are significant values.

As for the instantaneous models, from Table 9.2 we again observe that the free speed V_p^0 and the interaction distance R_p are positively correlated (0.57). It also turns out that the reaction time τ_p and the interaction factor A_p are negatively correlated, implying that the reaction time and the interaction factor are to a certain extent mutually exclusive.

Let us finally note that the parameter estimates determined by applying the approach to data from other experiments are consistent (wide bottleneck, one-directional flow, bi-directional flow, etc.; see, Hoogendoorn & Daamen, 2005).

9.7. Consequences for Pedestrian Flow Modeling

The estimation results presented in the previous section show some interesting issues that may have important implications for microscopic pedestrian flow modeling. In particular, these findings relate to:

1. Inter-pedestrian differences as expressed by the variability in the parameter estimates.
2. Correlation between parameter estimates.
3. Importance of delays in the correct description of microscopic behavior.

Regarding the first point, the current models can in general be amended easily when sufficient insight has been gained into the distribution of the parameters for the pedestrian population to be simulated. The distribution that needs to be used will be dependent on among other things gender distribution, trip purpose, external conditions (such as weather), etc. The variability in pedestrian behavior will cause macroscopic properties of the pedestrian flow to become stochastic. This holds in particular for the bottleneck capacity and the jam-densities (and consequently the queue lengths). The extent in which this occurs is beyond the scope of this paper. The second issue is of particular interest when generating pedestrians in a microscopic model. When the behavioral parameters are generated, it is important to take into account the correlations during the parameter generation process.

With respect to the third point, considerable changes in the properties of the pedestrian flow dynamics are expected. A good example of the possible changes in the flow dynamics due to pedestrian heterogeneity is given by Helbing et al. (2005a) showing the impact of heterogeneity on dynamic lane formation. Other aspects that are likely to occur are instabilities in the flow, congestion probabilities, reduction in the queue discharge rate once congestion sets in, etc.

We have modified the Nomad model to include finite reaction times. We have applied the modified simulation model on a simple test-case example, namely a narrow bottleneck. The bottleneck has a width of 1.0 m. From experimental observations, we expect a bottleneck capacity of 1.6 P/s (see, Hoogendoorn & Daamen, 2005, for details). The pedestrian demand equals 1.8 P/s. The parameters used in the simulation correspond to the estimates determined in the previous sections. Nomad

can model physical contact and the resulting friction between pedestrians. This (and other) advanced feature(s) of Nomad were disabled for the sake of this study.

Pedestrians are generated at the right, and walk to the exit on the left. Figure 9.2 shows a snapshot of a Nomad simulation for this narrow bottleneck scenario. The figure shows the locations of the detectors that have been used to collect the synthetic data on which our analyses are based.

When comparing the instantaneous and the retarded models, several things become apparent. For one, the flow becomes more unstable, more erratic. Note that the considered flow operations are near oversaturation (volume to capacity nearly 1). From our (preliminary) simulation results, it turns out that *before congestion occurs*, the bottleneck capacity is higher than once congestion has set in. This phenomenon is quite common in car traffic, but is apparently also present in pedestrian flow operations. The reasons for this *capacity drop* is the fact that when congestion has set in, pedestrians are dispersed over part of the width of the walking area, i.e., they are not standing right in front of the bottleneck. When arriving at the bottleneck, they need to turn as well as to accelerate. This process is likely to be affected by the reaction time of the pedestrians: when the response to prevailing traffic conditions is retarded, both the turning and the acceleration will be delayed and hence capacity of the bottleneck is likely to decrease.

To quantify the expected shifts in the bottleneck capacity, let us compare the distribution of the queue discharge rate for three situations: the instantaneous model (no reaction time), and two retarded models with reaction times of 0.3 s and 0.6 s, respectively. Figure 9.3 shows the results of this comparison. Note that each data point in the figure corresponds to the outcomes of a 4 min simulation in which the oversaturated bottleneck was considered. The capacity estimate for this simulation is determined by considering the period in which congestion occurred and subsequently considering the queue discharge rate during this period.

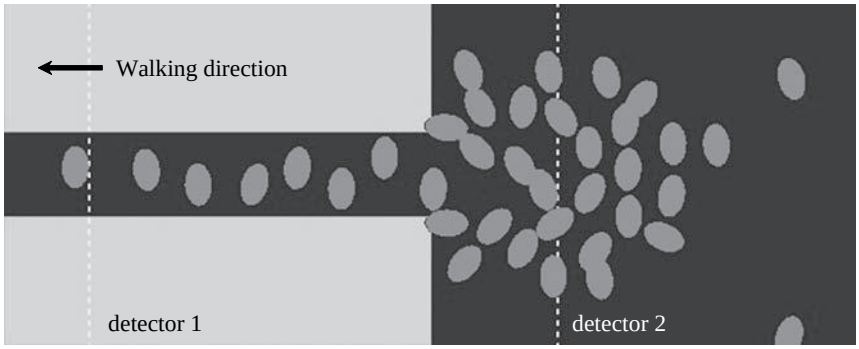


Figure 9.2: Snapshot of situation at the narrow bottleneck as determined by the adapted Nomad pedestrian simulation model. The figure shows the two detectors that have been used to compute the queue discharge rate. In the example shown, congestion is detected at detector 2. As a result, the flow observed at detector 1 is labeled as an observation of the queue discharge rate.

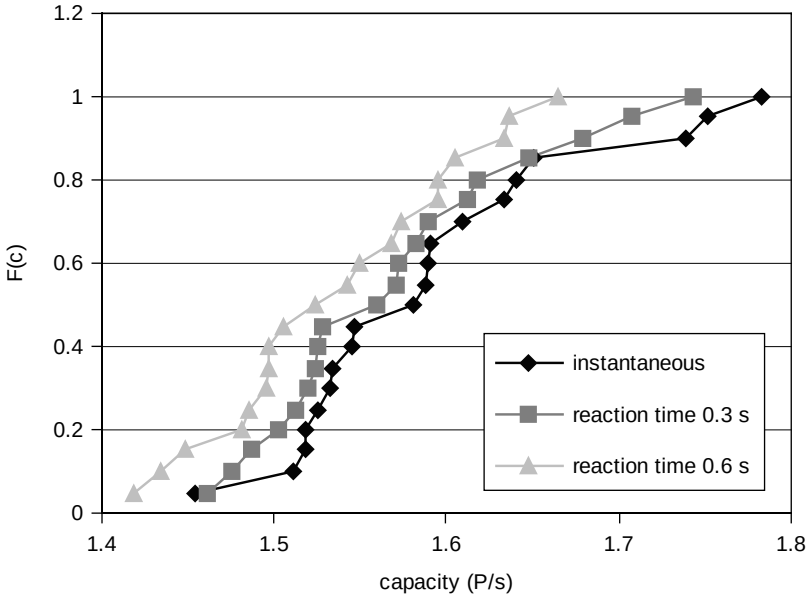


Figure 9.3: Distribution of the capacity (queue discharge rate) of a narrow bottleneck and the changes resulting from including the finite reaction time in the model.

Figure 9.3 clearly shows that the capacity of the bottleneck is not a constant value, but can best be described by a random variable. The figure also shows the changes caused by including the finite reaction time in the Nomad model in relation to the queue discharge rate. Although the change in the average capacity is statistically significant, it is small (only a few percent).

Figure 9.4 shows the distribution function of total congestion time (out of a simulation time of 240 s). In the figure, we see that the average congestion times for the retarded models are larger than for the instantaneous model.

We found that the predicted probability of congestion occurring is larger when using one of the retarded models than when using the instantaneous model. More precisely, the instantaneous model predicts congestion occurring in 54% of all simulations. For the retarded model with a reaction time of 0.3 s, congestion occurs more frequently, namely in 68% of all situations. For the reaction time of 0.6 s, this number is even higher, namely 74%.

9.8. Conclusion and Recommendations

In this chapter, a generic approach for calibration of microscopic models was put forward. Using trajectory data, the approach enables estimation of the

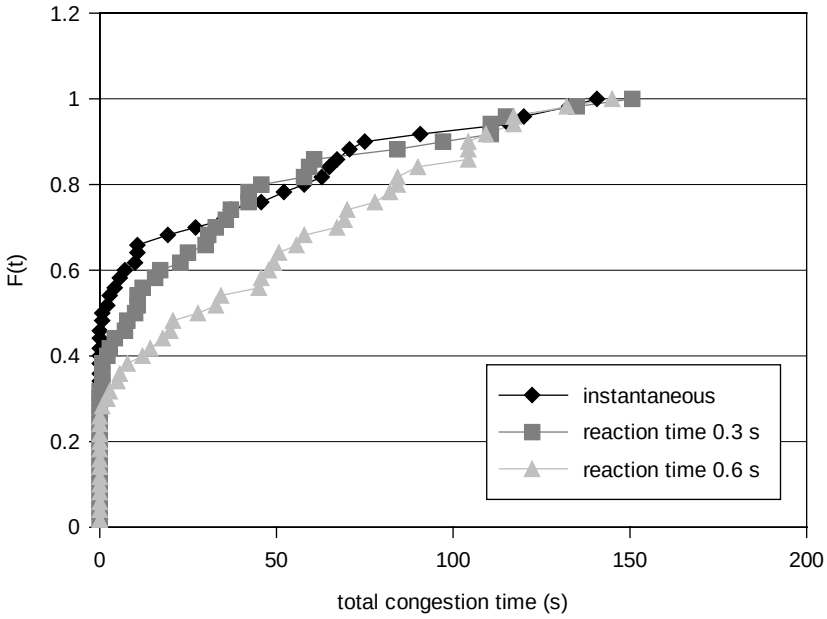


Figure 9.4: Distribution of total congestion time (out of 240 s).

pedestrian-specific parameters of different walker models. The approach provides insight into the statistical properties of the estimates, as well as the performance of the models to which the calibration approach is applied.

In the contribution we also put forward important generalizations of the approach, primarily focusing on including prior information in the estimation of the parameters. This is important when some of the parameters cannot be estimated from the available data, when the model needs to respect specific properties (e.g., correct capacity estimations) or if alternate data sources are available.

In applying the approach to data collected during walking experiments, inferences could be made regarding the behavioral processes that are to be included in the modeling to ensure a realistic description of walking. It turns out that besides anisotropy, finite reaction times play an important role in correctly describing microscopic walking behavior as is reflected by the considerable increase in model performance of the retarded models compared to the instantaneous model. Furthermore, the inter-pedestrian differences in walking behavior have been shown. Based on these findings, a small-scale study was performed regarding the changes in the dynamic properties of the pedestrian flow model. In particular, the changes in breakdown probabilities and the distribution of the queue discharge rate were considered. It was observed that including a reaction time has a significant effect on the pedestrian flow operations, in particular with respect to the congestion probabilities.

Future research will entail estimating parameters of more advanced models, as well as using empirically collected trajectory data. The latter will provide insight into the differences in behavior in experimental and real-life situations, as well as the

impact of factors such as walking purpose and environment on walking behavior. Furthermore, we will further study more thoroughly the macroscopic properties of microscopically calibrated pedestrian models, and compare these with field observations.

References

Brockfeld, E., Kühne, R. D., et al. (2004). *Calibration and validation of microscopic traffic flow models*. Transportation Research Board Annual Meeting Pre-Print, Washington, DC.

Casella, G., & Berger, R. L. (1990). *Statistical inference*. Belmont, CA: Duxbury Press.

Daamen, W., & Hoogendoorn, S. P. (2003). Controlled experiments to derive walking behaviour. *European Journal of Transport and Infrastructure Research*, *3*(1), 39–59.

Helbing, D., Farkas, I., & Vicsek, T. (2000a). Freezing by heating in a driven mesoscopic system. *Physical Review Letters*, *84*, 1240–1243.

Helbing, D., Farkas, I. J., & Vicsek, T. (2000b). Simulating dynamical features of escape panic. *Nature*, *4007*, 487–490.

Helbing, D., Buzna, L., Diel, V., Johansson, A., & Werner, T. (2005). Self-organized pedestrian crowd dynamics: Experiments, simulations, and design solutions. *Transportation Science*, *39*(1), 1–24.

Hoogendoorn, S. P., & Bovy, P. H. L. (2003). Simulation of pedestrian flows by optimal control and differential games. *Optimal Control Applications & Methods*, *24*, 153–172.

Hoogendoorn, S. P., Daamen, W., & Bovy, P. H. L. (2003). *Extracting microscopic pedestrian characteristics from video data*. Annual Meeting at the Transportation Research Board Pre-print CD-rom.

Hoogendoorn, S. P., & Daamen, W. (2005). Pedestrian behavior at bottleneck. *Transportation Science*, *39*(2), 147–159.

Hoogendoorn, S. P., & Ossen, S. (2005). Parameter estimation and analysis of car-following models. *Proceedings of the 16th International Symposium on Traffic and Transportation Theory*, Maryland.

Kerridge, J., Kukla, R., Willis, A., Armitage, A., Binnie, D., & Lei, L. (2005). A comparison of video and infrared based traffic of pedestrian movements. In: S. P. Hoogendoorn, S. Lüding, P. H. L. Bovy, M. Schreckenberg & D. E. Wolf (Eds), *Traffic and granular flow 2003* (pp. 383–392). Berlin Heidelberg: Springer-Verlag.

Klüpfel, H., Schreckenberg, M., & Meyer-König, T. (2005). Models for crowd movement and egress simulation. In: S. P. Hoogendoorn, S. Lüding, P. H. L. Bovy, M. Schreckenberg & D. E. Wolf (Eds), *Traffic and granular flow 2003* (pp. 357–372). Berlin Heidelberg: Springer-Verlag.

Schultz, G., & Rilett, L. (2004). *An analysis of the distribution and calibration of car-following sensitivity parameters in microscopic traffic simulation models*. Transportation Research Board Annual Meeting, Washington, DC, Transportation Research Board.

Chapter 10

Crowd Dynamics Phenomena, Methodology, and Simulation

Hubert Klüpfel

Abstract

This chapter deals with the modeling and simulation of pedestrian flow and evacuation processes, i.e., crow dynamics in emergency and nonemergency situations. This comprises three major areas (1) theory, (2) data, and (3) application. The terms used in this chapter conjecture a hierarchical structure (motivated by the terminology of mathematical logic), where models are derived from theories by interpretation and a simulation is derived from a model by implementation. Of course, theory, data, and application influence each other and neither can be investigated separately. Data collection requires an idea of what to collect (i.e., a theory) and later on interpretation. The application of a model is based on its implementation (simulation). Measurements contain assumptions about the observables. In the context of crowds, one of the questions is: Is the focus on trajectories or aggregated data? A model must be validated, the simulation verified. Validation (doing the right thing) is addressing the interpretation (of the theory) and verification (doing it right) addresses the implementation (of the model).

Data is used to calibrate models on the one hand and to test theories (by means of models and simulation results) on the other. In the case of crowd dynamics, there are, on all three levels (theory, data, and application), two major components of the system: population and geometry. And the major aim (from an engineering perspective) of the effort is of course to apply it for design and procedural improvements of crowd management in emergency (evacuations) and nonemergency (commuters, spectators, etc.) contexts.

The detailed structure of this chapter is as follows: (1) Theory (Models and Simulations); (2) Empirical Data: Literature Review (Population); (3) Design

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Elements (Geometry); (4) Models (Hydraulic and Individual); (5) Application (Simulation); (6) Summary (Conclusion and Outlook). The first section introduces the basic principles and terminology. The second section is devoted to a literature review of empirical data on crowd movement (i.e., mainly referring to the sub-system "population"). The geometry is addressed in detail in the third section "design elements." The two major model classes, namely hydraulic (macroscopic) and individual (microscopic) models will be described and compared in section four. The fifth section is dedicated to the application of crowd simulations in emergency (evacuation) and nonemergency scenarios. The chapter concludes with a summary (containing a list of major information resources), conclusion, and outlook.

10.1. Theories, Models, and Simulations

The connection between theory, model, and simulation is depicted in Figure 10.1. This connection will be discussed in more detail when the influences on crowd dynamics and the modeling criteria will be identified in the next paragraph.

10.1.1. A Theory for Crowd Dynamics

What would be a theory of crowd dynamics? When thinking about theories in other scientific disciplines, two prominent examples might come to mind: theory of special relativity (TSR) and the theory of evolution (TE). The former is based on the two postulates "all inertial systems are equivalent" and "the speed of light in vacuum is constant." The latter is based on the principles of "mutation" and "selection." In that sense, the arrows in Figure 10.1 can be read as "restrict" (downwards) or "must comply with" (upwards). Therefore, an elevator is no valid model for TSR; a platform and train with constant speed is a valid model.

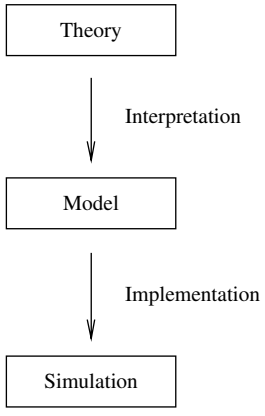


Figure 10.1: Theory, model, and interpretation.

Of course, the problem for crowd dynamics is the absence of comprehensive principles or postulates in the sense above. The first step would be to specify the meaning of crowd: "A group temporarily sharing the same place and focus" (cf. Figure 10.2).

In the terminology used in Figure 10.2, the subject of this chapter would be called "escape panics" or "gathering" (including commuters as "casual crowds"). The occurrence of "panics" or usefulness of the term itself shall not be discussed, here. Just note that the term itself is controversial (Clarke, 2002). The conclusion for the time being is that there is probably no "theory for crowd dynamics" like there is a "quantum field theory" or "quantum mechanics." Therefore, let us start with models.

10.1.2. Models for Crowd Dynamics

It might be interesting to look at the different models that have been developed for hydrogen to explain scattering experiments. Each model might be able to explain different aspects of crowd movement. A general framework for classifying models is shown in Figure 10.3.

The most important distinctions are probably the "discrete/continuous" and "microscopic/macroscopic" pairs. Additionally, the "estimation/first principles" can be further evaluated as shown in Figure 10.4.

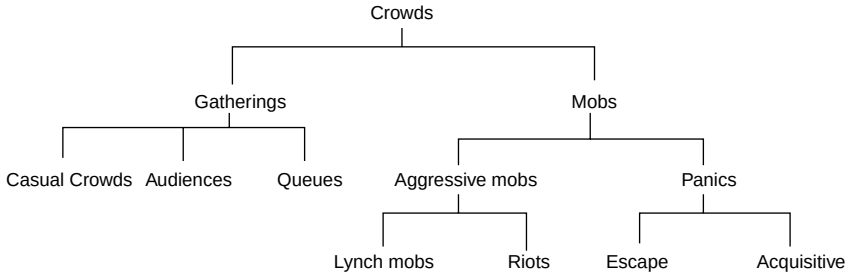


Figure 10.2: Classification of crowds (Forsyth, 1999).

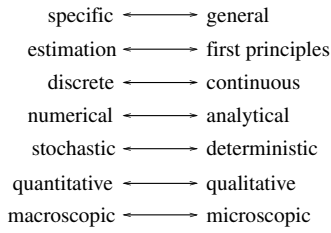


Figure 10.3: Modeling criteria.

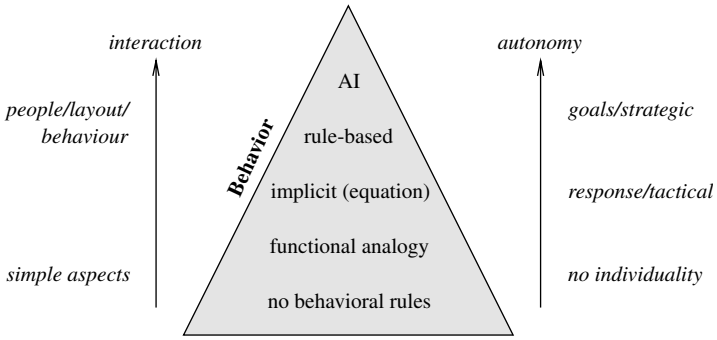


Figure 10.4: Autonomy and behavior modeling.

The term autonomy on the right axis connects the behavior modeling to a concept from computer science: multi agent simulation (MAS — which might also be read multi agent systems). Coming back to Figure 10.1, the term simulation is used in the sense of "model implementation," i.e., "system" might be the model. The term agent in MAS can be translated "autonomous entity," i.e., showing some sort of behavior that is "internally motivated." Finally, the term "multi" in MAS refers to the interaction (shown in the left vertical axis in Figure 10.4) between the agents. The interaction between an agent and its environment is already present in the (single) agent concept.

Usually, the internal motivation is represented on three different levels (BDI framework):

- Desires ("get out as fast as possible")
- Beliefs ("the best way is along the escape routes")
- Intentions ("I do not want to harm anyone")

In the context of egress from a building these levels might be the ones given in parentheses. These three motivational levels determine the decision-making process. Again, for the egress example this might be: "follow the exit signs, circumvent other people and obstacles; do not push"). Based on these assumptions (theory), a model can be formulated by defining a set of rules that applies for the agent's decision making and behavior. In MAS, usually, three different decision levels are distinguished:

- strategic
- tactical
- operational

The strategic level comprises "long-term goals," the tactical level a simple set of rules (that would be called conscious in humans), and the operational level the automatic responses ("subconscious" or mere physical like distance keeping or

slowing down upstairs or how to avoid collisions). All three BDI aspects can be connected to the decision levels (STO). In general, the D–S, B–T, and I–O connections are strongest.

In summary, MAS are (cf. Figure 10.3) general, estimate, numerical, quantitative, and microscopic. They can be both, "continuous" or "discrete" as well as "stochastic" or "deterministic," i.e., these two categories are indeterminate in MAS for crowd dynamics.

10.1.3. Calibration, Validation, Verification

As can be seen from Figure 10.5, model development is a creative process. Even though the calibration is often supposed to be at the beginning of model development, it is possible only after having formulated and implemented a model, i.e., after running a simulation (or performing a calculation) and evaluating simulation results.

Those simulation results are then compared to empirical data and the model parameters changed to get simulation results close to the empirical results (fitting). There are two important restrictions that apply to this process:

- the model parameters must be fewer than the data points
- the verification data must be different from the calibration data

Once these three steps have been carried out, the model is calibrated, verified, and validated. In the context of legal compliance of building or ship designs, validation is of course crucial, as stated above; the validation for models for the evacuation simulation of passenger ships is regulated in MSC.1/Circ. 1238.

10.1.3.1. Verification Verification is the check for the correct implementation, i.e., the mathematical part. It comprises the following four major activities:

- Analytical tests
- Numerical tests
- Sensitivity analysis
- Code checking

Of course, numerical tests are only applicable for numerical models.

Interpretation (Theory → Model)	↔	Validation (high level checking)
Implementation (Model → Simulation)	↔	Verification (low level checking)
Evaluation (Simulation → Results)	↔	Calibration (fitting)

Figure 10.5: Validation, verification, calibration.

10.1.3.2. Validation Validation is to check whether the model represents the part of the reality it is supposed to accurately enough. At this point it is helpful to keep in mind three major criteria for scientific results:

1. Valid
2. Objective
3. Reliable

The first has just been described. The second is the fact that different persons obtain the same results (under the same initial and boundary conditions), and the third requires the results to be repeatable. This might be considered common sense and trivial at first glance. It is not easily fulfilled in the context of pedestrian and crowd simulation, though.

10.1.3.3. Calibration Calibration is necessary for heuristic, phenomenological, or estimate models (cf. Figure 10.3). For first principle models, like the Navier–Stokes Equations for fluid dynamics, calibration is not part of the modeling process.

10.1.4. Models for Evacuation

Evacuation processes can be considered a special type of crowd dynamics. There are two special circumstances for evacuation: (1) the presence of hazards, (2) the absence of the strategic level of decision making. The second point requires some further consideration. In case of an evacuation process, people usually have a clear aim: getting to a safe place. Therefore, there is a clear desire. Of course, there might be tactical differences like either trying to get out through the main entrance/exit or follow the exit signs. They are considered not strategic, here.

10.1.4.1. Influences on the evacuation processes As already mentioned, apart from the absence of the strategic level, in an evacuation scenario, the presence of hazards is the second major difference to normal crowded situations. In Figure 10.6 the "population" in the center represents the crowd/population. The term population is

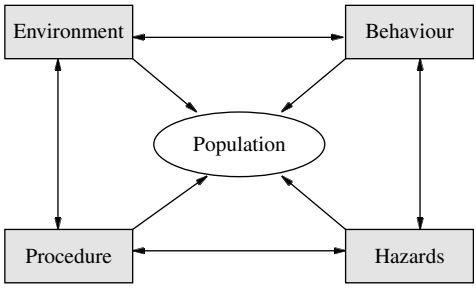


Figure 10.6: Influences on the evacuation process.

used here, since all the considerations also apply to smaller groups of people that usually are not considered a crowd.

The different influences shown by the rectangles are connected to the population via the tactical level of decision making. Hazards, which could be summarized under "environment" in the MAS framework and is shown here explicitly to stress the dynamical aspect, i.e., an environment changing with time. Similarly, the procedure is partially environmental, partially represented by the agents and the behavior represents the BDI or STO part of the agents, i.e., the decision making and action. Finally, the various interactions between the influences are depicted by the double-sided arrows.

Figure 10.7 shows different evacuation strategies. It is important to keep in mind that (especially but not only in complex environments) there are people who are forced to defend in place, i.e., cannot leave the potentially hazardous place on their own.

10.1.4.2. Evacuation exercises and emergencies In addition to the general sources for empirical data on crowd movement, there are two special sources for the evacuation case: evacuation exercises (announced or unannounced) and reports from actual incidents. The connection between these two with respect to stress level is depicted in Figure 10.8. One model for the analysis of evacuation processes are so-called simplified analyses. These range from prescriptive rules for the determination of escape route widths and lengths to flow calculations (macroscopic models). These

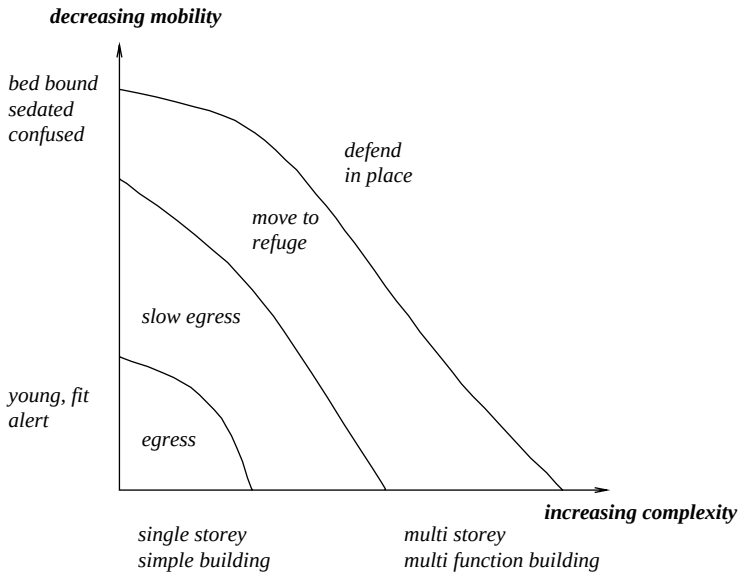


Figure 10.7: Different evacuation strategies depending on building layout and mobility.

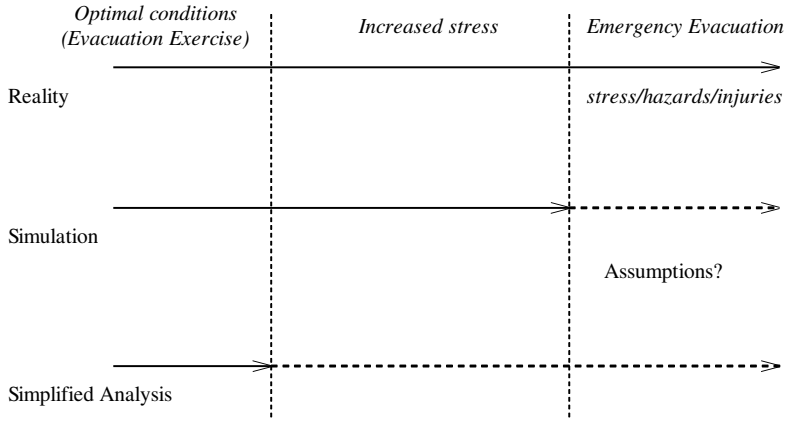


Figure 10.8: Exercise and emergency.

usually do not take into account behavioral aspects and can therefore not cover the increased stress level already present in some evacuation exercises (especially unannounced ones). It is questionable, however, if simulations (in this context used as a synonym for microscopic models or MAS, they may be deterministic or stochastic, discrete or continuous) can cover (e.g., predict) most aspects of an emergency evacuation, especially increased stress, hazards, and injuries (cf. Figure 10.8). A major part of the total evacuation time is pre-movement time (or response time), which usually is not predicted by simulations but is an input parameter. If this parameter is calibrated wrongly, the complete result is useless. This is of course a common observation.

Additionally, the increased stress present in an emergency evacuation is usually hard to extrapolate from the exercise situation. It might well be the case that it is a different realm and extrapolation is not allowed. Finally, in many disasters, there were quite specific influences like locked doors that could not be predicted by a simulation.

10.2. Empirical Data: Literature Review (Population)

For the investigation of pedestrian motion, there are three fundamental options:

- field surveys or observations,
- (evacuation) exercises, and
- experiments in a laboratory.

All these options have specific advantages and disadvantages. Observations are effortless with regard to preparation. They have the disadvantage, though, that the external influences (Figure 10.6) cannot be controlled. For experiments, the control

on the external influences is better. On the other hand, this might introduce external factors not present in a more realistic situation. And it is of course the first priority to avoid injuries. There are, in summary, practical, ethical, and financial constraints on experiments in the field of crowd dynamics. For examples on crowd experiments see Müller (1999) and Predtetschenskii and Milinskii (1978).

10.2.1. Individuals and Crowds

It has been briefly mentioned in the context of evacuation simulation in the previous section that some of the aspects of crowd dynamics are specific for crowds (like formation of lanes, oscillation at bottlenecks, to name just a few); others are not and are present in individual motion (like movement characteristics, influence of fire and smoke in an evacuation situation, etc.).

10.2.1.1. From a single person to a crowd What is the difference between a few persons and a crowd? There are several ways to draw the line. Starting with the definition "a crowd is group of people sharing the same place and the same focus" the next question pops up: How many people are necessary to form a crowd? At the end of the day, the definition will (and must) remain vague with respect to this question. Next to the definition given above, the best approach seems to be a phenomenological one: "a crowd is a group of people sharing the same space and focus and where typical crowd phenomena like lane formation or speed reduction due to high density are observed." For the sake of this contribution, this definition is sufficient.

10.2.1.2. The concept of "panic" Clarke (2002) writes: "pictures of mass panic and collective chaos are ubiquitous in Hollywood films, the mass media and the rhetoric of politicians. In contrast to those popular depictions, mass panics are rather rare. In a disaster, humans usually act quite civilized and cooperative." Panic is in the public perception something like mass hysteria. In line with Clarke, this "mass hysteria" concept of panic is considered useless. When talking about an incident with many pedestrians involved, the term crowd accident might be more appropriate.

10.2.1.3. Social influences and group formation An important aspect for crowd dynamics and evacuation processes is social behavior. In Figure 10.2 the classification of groups (Forsyth, 1999) was shown. As said above, characteristic for a group are size, commons space, and focus. The following two pictures show large crowds in situations at spare time activities (Figures 10.9 and 10.10).

The common focus in the previous two examples is music. Of course, there are many other activities, where there is a large group of people, sharing space and focus: commuting, all kind of audiences. The occurrence of crowds is a characteristic phenomenon of modern societies and cities.



Figure 10.9: Love parade in Berlin with high person densities (>4 per sqm) (http://www.backpacker.co.uk/images/loveparade/love.gif).



Figure 10.10: Realistic person densities in a dance club. They usually range, in contradiction to assumptions made in many building codes, between three and four persons per sqm (Forell, 2004).

10.2.1.4. Group size One major aspect of crowd dynamics (next to phenomena like lane formation, arching, and oscillation at bottlenecks) is the influence of group size and person density on the walking speed. The first one is conjectured to depend on the fact that a group's velocity is determined by the walking speed of the slowest group member. In Table 10.1, the results for groups up to the size of six members are summarized.

Table 10.1: Results for the walking speed of groups of different sizes.

Group size	**No. of groups**	**Mean speed**
1	95	1.38
2	149	1.28
3	59	1.24
4	17	1.24
5	10	1.22
6	2	1.10
Sum	332	1.30

The observation area was a flat pedestrian bridge of width 7 m. Video recordings were done from a bird's eye perspective and the group size and walking speed were determined by analyzing the videotape. The velocity was measured between two clearly visible wooden elements the bridge was composed of, which were 7 m apart. The time difference between the crossing of the first of those wooden planks by the last group member was evaluated and the velocity calculated ($v = \mathrm{d}s/\mathrm{d}t$), where $\mathrm{d}s = 7\,\mathrm{m}$.

A clear tendency is the decrease of the group's velocity with its size. The highest observed (average) speed was 1.38 m/s for single persons, the lowest 1.10 m/s for groups of size six (Figure 10.11).

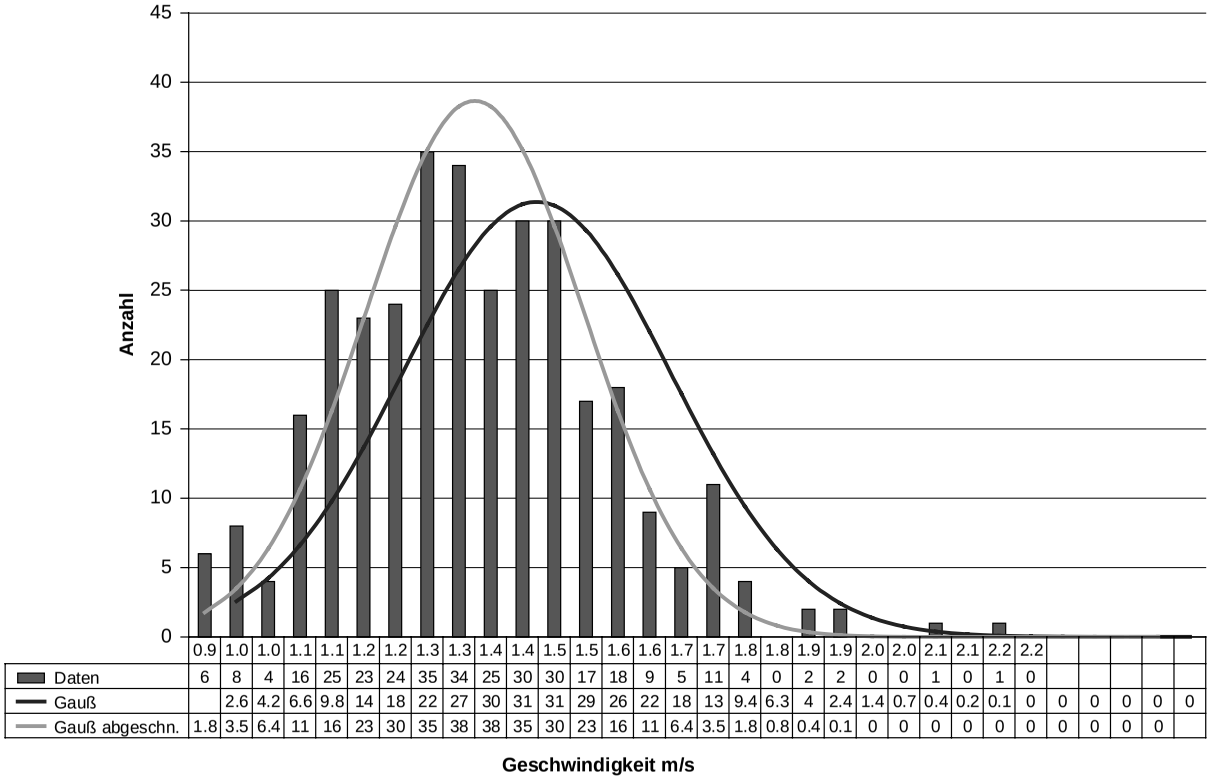
10.2.1.5. Audible exit signs Finally, and for the sake of completeness, a rather new development in marking exits shall be briefly mentioned. The basis of directional sound is to make exits not only visible but also audible. Such an exit marking by sounders is not a replacement for conventional exit signs but an addendum. It is especially useful in case of smoke (Figure 10.12).

The directional information is encoded by frequency, volume, and sound patterns. The length of consecutive tone and silence phases gets shorter as the sounder becomes closer to the exit from the building or the assembly point. The frequency of these sound/silence phases, on the other hand, gets higher.

10.2.1.6. Capacity of exit route elements The major elements, exit routes (i.e., the path from the initial position to the exit or assembly point) consist of:

- Doors
- Stairs
- Hallway

Usually, stairs are considered to have the lowest capacity, therefore being the bottleneck in the escape route system (Figure 10.13).



	0.9	1.0	1.0	1.1	1.1	1.2	1.2	1.3	1.3	1.4	1.4	1.5	1.5	1.6	1.6	1.7	1.7	1.8	1.8	1.9	1.9	2.0	2.0	2.1	2.1	2.2	2.2					
Daten	6	8	4	16	25	23	24	35	34	25	30	30	17	18	9	5	11	4	0	2	2	0	0	1	0	1	0					
Gauß		2.6	4.2	6.6	9.8	14	18	22	27	30	31	31	29	26	22	18	13	9.4	6.3	4	2.4	1.4	0.7	0.4	0.2	0.1	0	0	0	0	0	0
Gauß abgeschn.	1.8	3.5	6.4	11	16	23	30	35	38	38	35	30	23	16	11	6.4	3.5	1.8	0.8	0.4	0.1	0	0	0	0	0	0	0	0	0	0	

Figure 10.11: Distribution of walking speeds for groups of different size observed at the world exhibition Expo 2000 in Hannover, Germany.

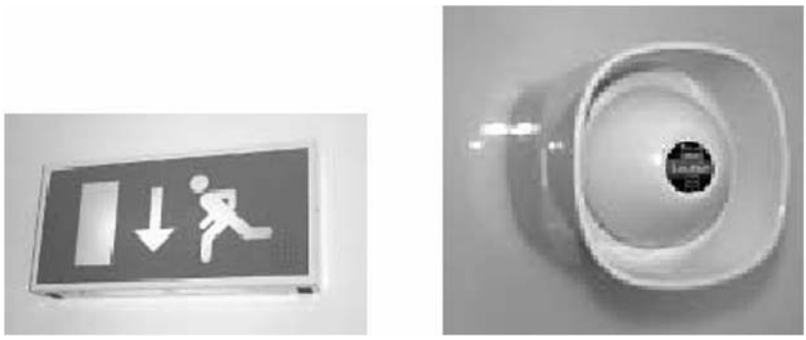


Figure 10.12: Directional sound.

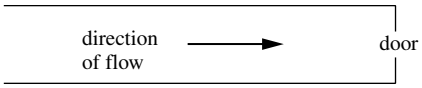


Figure 10.13: Simple escape route element.

A very rough estimate for the capacity is the following set of equations:

$$T = t_{\text{flow}} + t_{\text{walk}} \tag{10.1}$$

$$t_{\text{flow}} = w \cdot \frac{N}{j_{\text{specific}}(\rho)} \tag{10.2}$$

$$t_{\text{walk}} = \frac{l}{v(\rho)} \tag{10.3}$$

In this case $v(\rho)$ is the walking speed of the slowest individual, ρ the density, w the door width, and l the walking distance. With $v = 1\,\text{m/s}$, $j = 1\text{P/(ms)}$, $w = 1\,\text{m}$, the number of persons being $N = 100$, $l = 100\,\text{m}$, the overall time would be $T = 1\,\text{m} \times 100\text{P}/1\text{P/(ms)} + 100\,\text{m}/1\,\text{m/s} = 200\,\text{s}$. In our example, the overall time for this escape route element would be 200 s. For higher densities, the walking time increases.

10.2.1.7. Lifeboat capacity A recent concern that has been raised in the context of demographic change is the capacity of lifeboats for passenger ships. This is a prominent example for a more general concern in the context of design calculations: most of the formulas have been calibrated by data obtained 30 or more years ago. If a lifeboat is designed for 200 persons and the assumption is that the average mass is 75 kg and the shoulder width is 55 cm, then this might not hold for modern cruise

ships any more since the population characteristics are different from those calibration parameters.

10.2.2. Properties of Pedestrian Flow (Operational)

Having covered the more general aspects of pedestrian and crowd movement, i.e., the social and psychological influences, in the previous section, we will now turn to a more "physical" or statistical approach, i.e., focus on the physical movement of pedestrians and crowds.

10.2.2.1. Flow–density relationship (fundamental diagram) One major result of empirical investigations is the so-called fundamental diagram, i.e., the relationship between density and specific flow (or velocity). For flow models and simulations based on microscopic models it has got a different use. In flow models (e.g., Predtetschenskii & Milinskii, 1978; Mehl, 2003) it is the foundation of the calculations, i.e., an input parameter.

For simulations, it is used to calibrate the parameters on the one hand. On the other hand it is used for the validation of the simulation results, i.e., it is a simulation result itself (Figure 10.14).

10.2.2.2. Flow on stairs Finally, the vicinity influences the movement characteristics. Figure 10.15 shows the walking speed on stairs in a football stadium. A distinction between upstairs and downstairs was not made in this case.

For steeper stairs (upper curve: 30°, lower curve: 38°) a lower flow was observed. The density area covered is up to three persons per sqm. For that density range, the flow is increasing with the density. A higher density was not reached in the observation, which is probably due to safety precautions taken by the subjects, i.e., a higher density on stairs is perceived to be dangerous and therefore avoided.

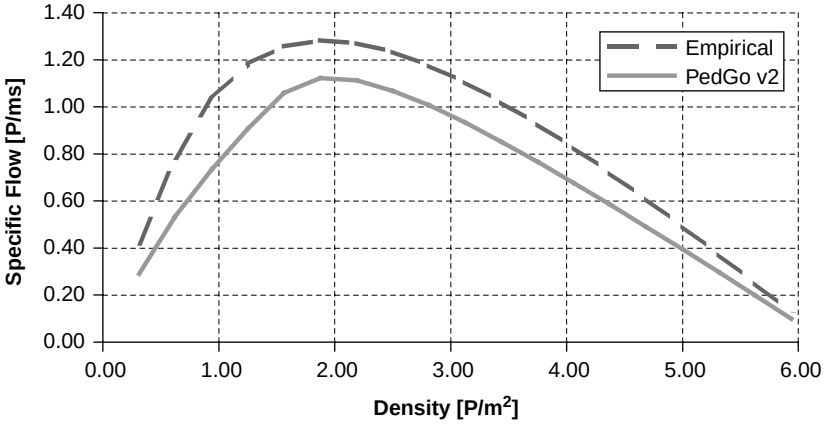


Figure 10.14: Fundamental diagram of pedestrian movement.

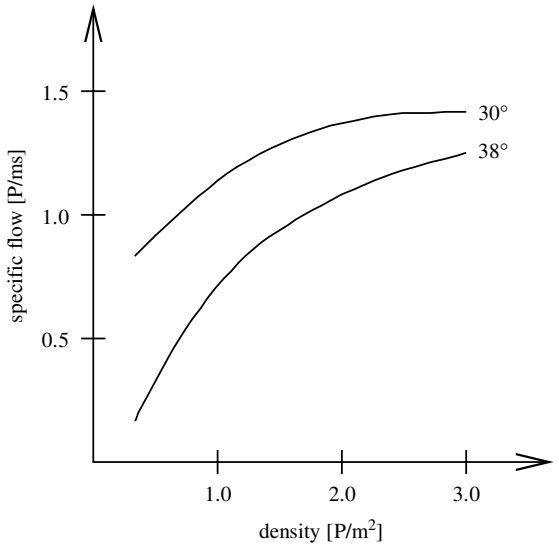


Figure 10.15: Specific flow on stairs (in a football stadium, Graat, Midden, & Bockholds, 1999).



Figure 10.16: Density fluctuations in a long hallway (simulation).

When using flow–density relations, a single or unique flow for a specific density is usually assumed. For the measurement of density as the number of persons per area, the measurement area has a considerable influence on the outcome. This is elaborated in more detail in the next section on density fluctuations.

10.2.2.3. Density fluctuations As can be seen from Figure 10.16, the density varies in, e.g., a hallway. Density fluctuations and density waves are well known in traffic flow for vehicular traffic.

Such inhomogeneous densities, density fluctuations, and density waves cannot easily be accounted for in flow models. In simulations based on spatially and temporarily discrete models, on the other hand, such influences can be represented.

10.2.2.4. Formation of lanes and oscillation at bottlenecks The formation of lanes can be observed in bidirectional pedestrian flow. Yamori has investigated bidirectional flow on pedestrian crossings in Japan and introduced a so-called band-index ranging from 0 to 1. The band-index gives the fraction of pedestrians walking in a lane. If there are no pedestrians opposing each other directly, the index is 1 (see Figure 10.17). In order to calculate the index, the image is divided into

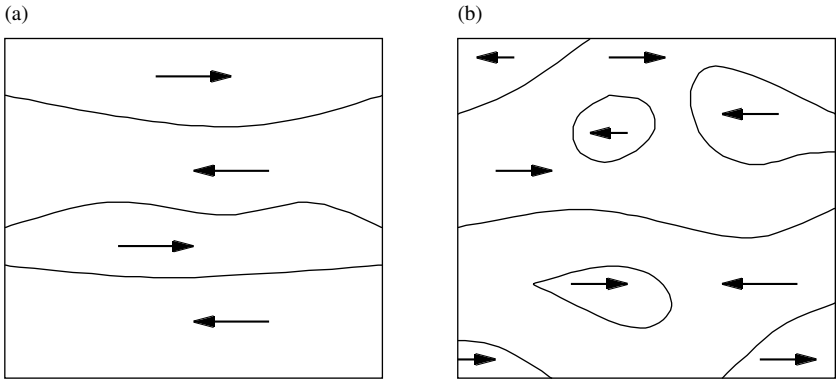


Figure 10.17: Formation of lanes in bidirectional flow (Yamori, 1998).

horizontal stripes. The area of the stripes where no change in the direction of movement occurs is divided by the overall area. Formation of lanes is of course a desirable phenomenon since it leads to a higher flow than a less organized situation. In the ideal case, for example, two lanes are formed leading to a flow for the bidirectional case as high as a one-directional flow. Formation of lanes is a self-organizing phenomenon and is interesting from that point of view too. We will not go into the psychological or details of perception and reaction necessary for such a self-organization phenomenon. It can, as all other phenomena in crowd dynamics, be investigated on different length scales, scales of details, and levels (physical or operational, tactical, and strategic).

Another phenomenon discussed in the literature is the formation of oscillations at bottlenecks (Helbing et al., 2002; Müller, 1999).

The oscillations at bottlenecks can have dangerous consequences: the flow in one direction can cease completely. Therefore, the people having to wait might get impatient and increase the pressure. Additionally, the oscillations lead to a less homogeneous flow. The phenomenon might be restricted to very narrow bottlenecks, though (at most two persons next to each other). In reality, this might be rarely the case — especially since it only occurs in bidirectional flow (Figure 10.18).

10.2.3. Tactical and Strategic Decisions

Up to now, we have covered mainly external influences on pedestrian movement or physical characteristics of movement (like walking speed, motion impairments, fitness, or the influence of geometry or density on pedestrian flow). This section will cover the internal aspects, i.e., the decision-making process. The strategic level covers desires, beliefs, and intentions; the tactical level is influenced by the beliefs and intentions and covers the actual movement behavior, i.e., the short-scale (concerning time and space) navigation.

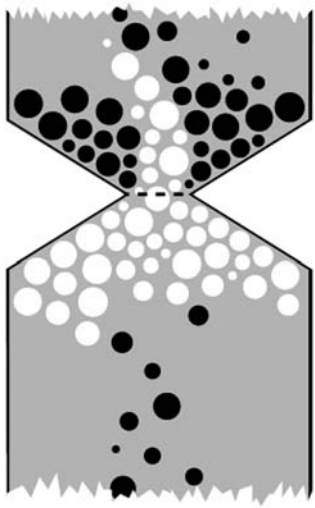


Figure 10.18: Oscillation at bottlenecks (Helbing et al., 2002; Müller, 1999).

10.2.3.1. Route choice Route choice is one of the most important aspects and decisions, in the evacuation scenario as well as in nonemergency activities like commuting or shopping. Figure 10.7 showed the connection between the movement ability or impairment and the geometric complexity of a building and the evacuation strategy. Similarly, the following list summarizes the motivations for and beliefs about route choice for an evacuation exercise in a supermarket:

1. Following the exit signs, public address system announcements, or staff (53%).
2. Taking the nearest exit (25%).
3. Get away from fire or smoke and escaping from immediate danger (12%).
4. Follow other persons (7%).
5. Going to the familiar exit (2%).
6. There was a window next to the exit. It was bright there (1%).
7. There was no crowding at the exit (1%).
8. Others.

These considerations influence the evacuation process. Therefore, the knowledge about the assumptions concerning the population is a prerequisite for the correct interpretation of simulation results.

10.2.3.2. Cooperation and competition One aspect that has been briefly mentioned in the context of ''panic,'' is social behavior. In order to use data on human behavior for the simulation of pedestrian flows and calculation of evacuation times, it must be observed objectively and be quantified. This comprises an operational description of concepts, e.g., the concept of ''panic.'' One type of behavior usually associated with ''panic'' is noncooperative and irrational behavior. Irrationality in this context is

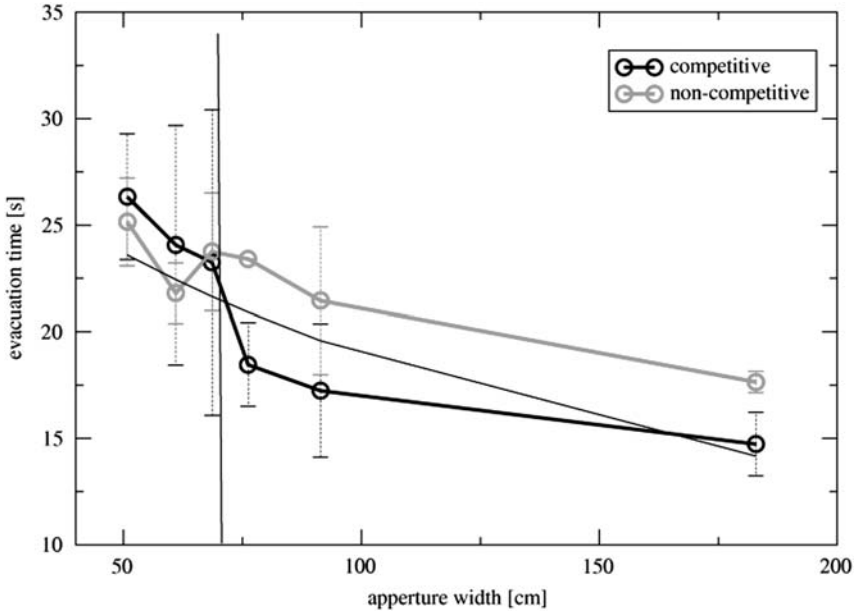


Figure 10.19: Difference between cooperative (black) and competitive (red) behavior in a mockup aircraft evacuation.

making decisions contrary to its own benefit and contrary to rather clear information pointing in the opposite direction. Usually, both are not the case. "Panic behavior" is used for extreme behavior motivated by immediate danger to one's health or even life. In such a case, running, making very fast decisions, and even jumping out of the window if threatened by great heat is a well-adapted decision.

Concerning the distinction between cooperative and competitive behavior, a well-established motivational clue is the use of a reward system (often money). The results of an experimental investigation in an aircraft mock-up are shown in Figure 10.19.

The empirical data is taken from Muir (1996). The figure shows the evacuation time versus the width of the aperture, for different aperture widths ranging from 50 to 180 cm were used.

10.2.3.3. Reaction times and wake-up times Proulx has investigated reaction times (pre-movement times) intensively. They can range from 5 to 30 min for an old-age population. Getting back to Eq. (10.1) above, the overall time for an evacuation is

$$T = t_{\text{detect}} + t_{\text{alarm}} + \max_i(T_i) \tag{10.4}$$

$$T_i = t_{\text{react},i} + t_{\text{move},i} \tag{10.5}$$

The parameter i denotes the individual in this case. Therefore, the overall evacuation time will not only depend strongly on the time for detection and raising

the alarm, but also on the individual reaction or pre-movement times. Of course, in this approach, the evacuation time is defined to be the time it takes all persons to escape.

10.2.4. Other Influences

10.2.4.1. Influence of alcohol The influence of alcohol on the level of aggressiveness has been shown in many scientific studies. In the context of crowd dynamics and crowd management, it is sort of obvious that dense crowds and an increased level of aggressiveness provide a very dangerous combination.

10.2.4.2. Mobility impairments Persons with mobility impairments often require separate access routes. In order to achieve a nondiscriminatory planning rationale and regime, there is still much to be done. Furthermore, in case of emergency, people with mobility impairments might need special assistance and be required to defend in place until the assistance arrives. This issue has been briefly addressed in Section 10.1.4.

10.2.5. Examples of Crowd Disasters

10.2.5.1. Heysel Stadium (Brussels) The Heysel Stadium Disaster occurred in 1985 during a football match between Liverpool FC and Juventus Turin. Detailed information on the sequence of events and the strategy of the security is available at www.wikipedia.org/Heysel_Disaster. This incident is often falsely denoted as "mass panic." However, it was rather an occurrence of hooliganism.

10.2.5.2. Acquisitive panics "Acquisitive Panics" are situations where the motivation driving the crowd is not "get away" or "get out" but "get there" or "get something."

A more detailed description based on accounts from the media can be found in Kretz (2003).

10.2.5.3. Baghdad A case of "panic" that was reported in Baghdad occurred because of rumors, there would be an attack by a suicide bomber. This was during a religious event, where many people gathered on a bridge and tried to get away from the location.

These few examples give a broad idea of what types of crowd accidents have happened in the past. A more detailed list including incidents at religious sites or events is available at www.crowddynamics.com.

10.3. Design Elements

In this section, some basic design elements for pedestrian facilities are investigated with relation to crowd dynamics and crowd management.

10.3.1. Some Fundamental Design Elements

One important aspect about pedestrian movement is its function as a connector between other modes of transport and the fact that the last-mile is usually always in one way or the other covered by walking. An exemption might be the case where parking is available right in front of the origin (e.g., ones own house) and the destination (e.g., the office or a shopping mall). In this case, walking is restricted to inside buildings and the parking lot. On the other hand, walking and pedestrian facilities are ubiquitous in public transport, on airports, in train stations, in subway-stations, in pedestrian zones, etc.

Similar to a trip consisting of a sequence of intermediate destinations, the pedestrian facilities used can be divided into basically seven categories:

- hallways
- ramps
- stairs
- doors
- conveyors
- escalators
- elevators
- others

Out of these elements (together with pedestrian bridges) all pedestrian facilities (that have been specifically been designed and built for this purpose) can be composed. In the following sections, each of these elements will be briefly addressed.

10.3.1.1. Hallways Hallways are in a sense the most basic elements. For the sake of simplicity, platforms are summarized under this category.

10.3.1.2. Ramps Ramps are similar to hallways but inclined.

10.3.1.3. Stairs Stairs are a very specific element. A relation between density and walking speed on stairs is shown in Figure 10.15. Additionally, the reduction of walking speed on stairs varies between 0.5 and 1.0 times the normal walking speed on flat terrain, according to various sources.

10.3.1.4. Doors Doors are mostly necessary design elements in pedestrian routes for purposes of fire protection. Sometimes, they are of course also necessary to control access.

10.3.1.5. Conveyors Conveyors are normally used in large facilities, especially airports. It has been regularly observed, though, that the speed increase due to conveyors is rather small (Fraport, private communication). This is due to the fact that conveyors have to be operated at a descent speed in order to make entering and exiting the conveyor a feasible task for everyone, especially movement impaired or less physically fit people.

10.3.1.6. Escalators Escalators can be portrayed as a combination of conveyors and stairs. The dangerous thing about escalators is the fact, that they increase the inflow to a certain level of a building or a specific area and furthermore provide a constant inflow. This inflow is not reduced by a density increase or crowding after the escalator. Therefore, in dense environments, escalators have either to be equipped with an automatic speed reduction or stop mechanism based on crowding observers or have to be operated or supervised manually.

10.3.1.7. Elevators Of course, elevators are a ubiquitous element of pedestrian transportation. The development that is interesting in our context is the use of elevators in emergency cases. There are already fire elevators in high-rise buildings. They must adhere to different regulatory requirements than "normal" elevators, though. Therefore, in order to use elevators as a means of evacuation, these requirements have to be applied accordingly.

10.3.1.8. Others There are a few other elements for escape paths, especially evacuation slides or chutes. These are used as a standard means of evacuation for aircraft, high-speed passenger craft (HSC), and many types of Ro-Ro passenger vessels (RoPax). For buildings, they are not yet used widely and cannot be used, to replace a required secondary escape route, since this would compromise the evacuation concept.

10.4. Flow Models and Individual Models

10.4.1. Methodology of Modeling

A basic approach for quantitative socio-psychological modeling is the field theory of Kurt Lewin. It describes human behavior as a function of person and environment:

$$B = F(P, U)$$

Most continuous models for crowd movement apply this approach to define a force field for the movement of pedestrians.

$$m_i \frac{d\vec{v}_i(t)}{dt} = \vec{f}_i(t) + \vec{\xi}_i$$

$$\vec{f}_i(t) = m_i \frac{v_i^0(t)\vec{e}_i^{\,0}(t) - \vec{v}_i(t)}{\tau_i} + \sum_{j(\neq i)} \left[\vec{f}_{ij}^{\,\mathrm{soc}}(t) + \vec{f}_{ij}^{\,\mathrm{phys}}(t) + \vec{f}_{ij}^{\,\mathrm{att}}(t) \right] + \sum_b \vec{f}_{ib}(t) + \sum_k \vec{f}_{ik}^{\,\mathrm{att}}(t)$$

The forces acting on an individual are the intrinsic motivation (first term) acting towards the desired velocity and direction. The pedestrians i and j are keeping distance to each other (social), might desire to get close to each other (attractive), and cannot intersect (physical). Finally, there is a repulsive force from boundaries and an attractive force to landmarks and the like (last term) (Figures 10.20 and 10.21).

10.4.2. Flow Models

Flow models treat crowds as (laminar) fluids. To this end, several assumptions are made:

- Continuity equation (inflow = outflow).
- The flow is spatially and temporarily constant for a specific element.
- All flows into a transition point last for the same time.

These assumptions are the starting point and can of course be further enhanced, i.e., turbulent flows, where the capacity is no longer constant. In general, the influence of high pressures is taken into account by the identification of congestion (inflow > outflow) and by a decreased walking speed. For detailed descriptions of these issues, please refer to IMO (2002), Mehl (2003), and DiNenno (1995). Figure 10.22 illustrates the principle of hydraulic modeling for evacuation processes.

10.4.3. Microscopic Models and Simulations

Microscopic models represent the geometry of a building, the population, and the sequence of events (time) in detail. All three (space, time, agents) are represented on a

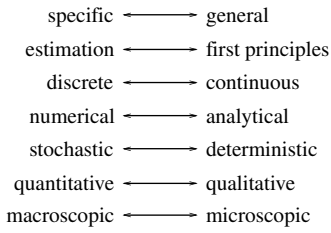


Figure 10.20: Modeling criteria.

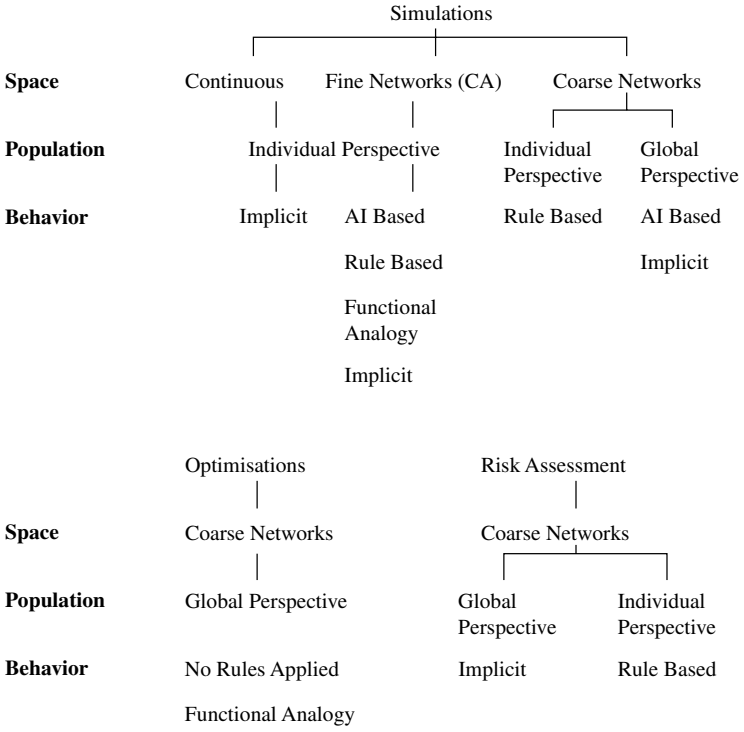


Figure 10.21: Classification of models.

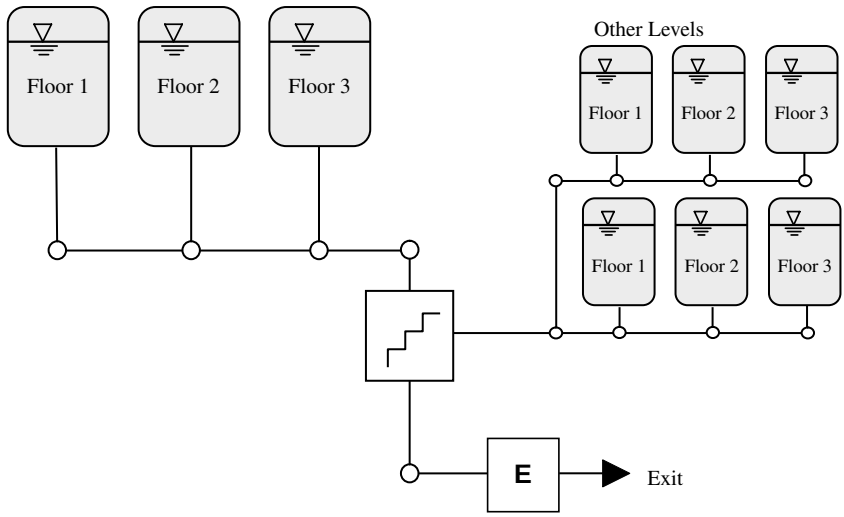


Figure 10.22: Schematic representation of the geometry in a flow model.

microscopic level in the model and the simulation. The term microscopic is a qualitative one. The following criteria can be used, though:

- length scale smaller than 1 m
- time scale in the order of 1 s
- population: single person

This approach is therefore fundamentally different from the previous one (macroscopic or flow models). The flow–density relation, e.g., is not an input parameter in microscopic models. It is an output, i.e., simulation results can be used to calibrate model parameters or validate the model assumptions. Further details of microscopic models will be discussed in the next section.

10.4.4. Comparison of Different Model Classes and Selection Criteria

In summary, the different types of models are shown in *Fehler! Verweisquelle konnte nicht gefunden werden*. The basic distinction between simulation, optimization, and risk analysis has the following consequences. A simulation aims at the representation of the state of a system in detail, whereas an optimization aims at minimizing a specific quantity (e.g., the overall egress time). To this end, a functional relation between this quantity and the relevant influences must be established. This function is varied to find the optimum values for the parameters (influences).

Risk analysis is a method to cover all relevant values determining the risk and assessing them. Risk analysis is usually based on a quantitative safety concept: actual risk $<$ acceptable risk.

The different approaches are designed for specific purposes. For rough calculations (which are fast and easy to handle) flow calculations are well suited. For the simplest case, the sum of the exit widths is divided by a constant specific flow to obtain a rough estimate of the overall egress time. One has to keep in mind, though, the assumptions and limitations which are in this case going beyond those mentioned in the previous section.

Nevertheless, such calculations are useful for plausibility checks of simulation results. They can provide a lower limit for overall egress times. If detailed results are required, e.g., about the sequence of an evacuation and spatial and temporal distribution of congestion, hydraulic models are not sufficient in most cases. In this case influences like population characteristics (and a reaction time distribution) are decisive. These can be represented in sufficient detail in microscopic models only.

The representation of space (i.e., the geometry), time, and the population corresponds to the range of application. Simulation and simplified analyses are always a simplification of reality. This is also true for evacuation exercises. Simulations, if calibrated on the basis of evacuation trials and other empirical data, can extrapolate to areas beyond evacuation trials by adapting the personal parameters or taking into account the influence of hazards. Such a change might be a reduced

orientation capability or an increased reaction time. Due to practical and ethical constraints, such extrapolations are usually not possible in the former.

In summary the comparison of the different approaches provides insights into assessment criteria for which model to choose. They have first of all to fulfill the requirements of the user. For a rough estimate of egress times simple flow models might be sufficient. This can be a simple multiplication of the sum of exit widths with a constant specific flow. For more detailed analyses and the comparison of different scenarios (with different door and hallway widths, adapted escape way geometry, etc.) simulations are much more appropriate, though.

10.5. Application of Crowd Dynamics and Simulation

The comparison of simulation and calculation results with empirical data has two aims: (1) calibration of models and (2) validation of models. As stated before, the verification is the low-level checking of the correct implementation of a model into a simulation and can basically be done without using empirical data. In the context of calibration, specific measurements like the flow–density relation are crucial. Validation, on the other hand, is usually based on more comprehensive data like the actual or trial evacuation of a building. The following section presents such an example: the evacuation exercise in a movie theater.

10.5.1. Evacuation Exercise of a Movie Theater

For the detailed investigation of an evacuation exercise, information about the floor plan, the population characteristics, and the behavior of the persons has to be recorded.

10.5.1.1. Floor plan The floor plan of the theater and the relevant areas in the first floor are shown in Figure 10.23.

The sequence of the events was filmed with four cameras, two inside the room and two outside, as shown in the previous figure. Figure 10.24 shows the scale and the details of the seating arrangement.

The theater had 152 seats, 102 persons took part in the evacuation trial. The persons were individually marked by paper hats with numbers. Figure 10.25 shows the screenshots from video recordings in comparison with simulation results. The simulations were performed with the software package PedGo (described in Klüpfel, 2003). After 65 s all persons had left the theater. The simulation came to the same result. Of course, for the trial as well as for the simulation, the overall time depends strongly on the reaction time distribution. In the trial, the emergency exit in front of the room as well as the regular entrance/exit at the rear were used by approximately the same number of persons.

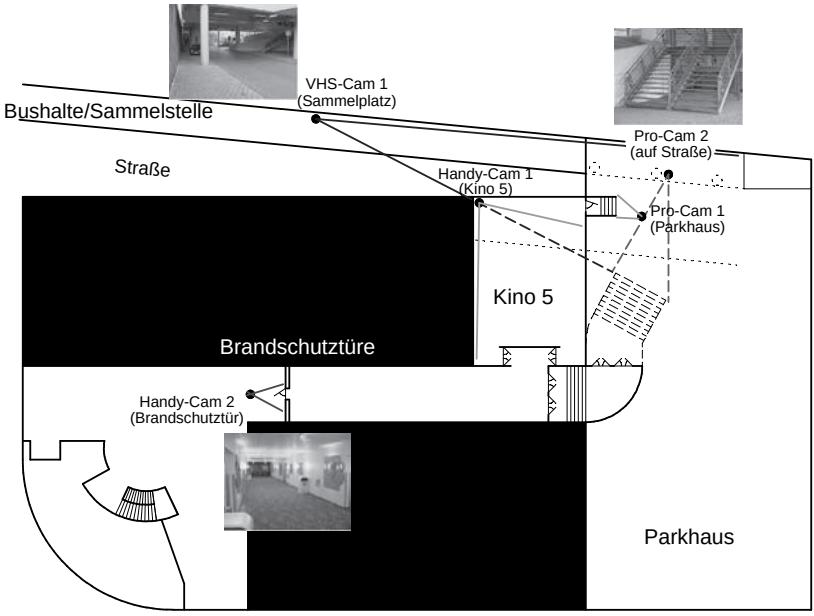


Figure 10.23: Floor plan of the movie theater and camera positions.

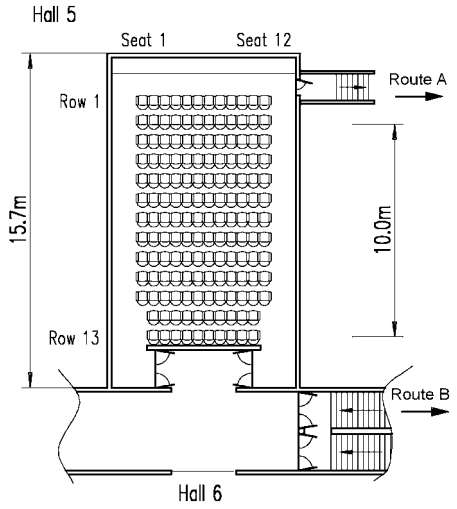


Figure 10.24: Detailed floor plan and seating arrangement.

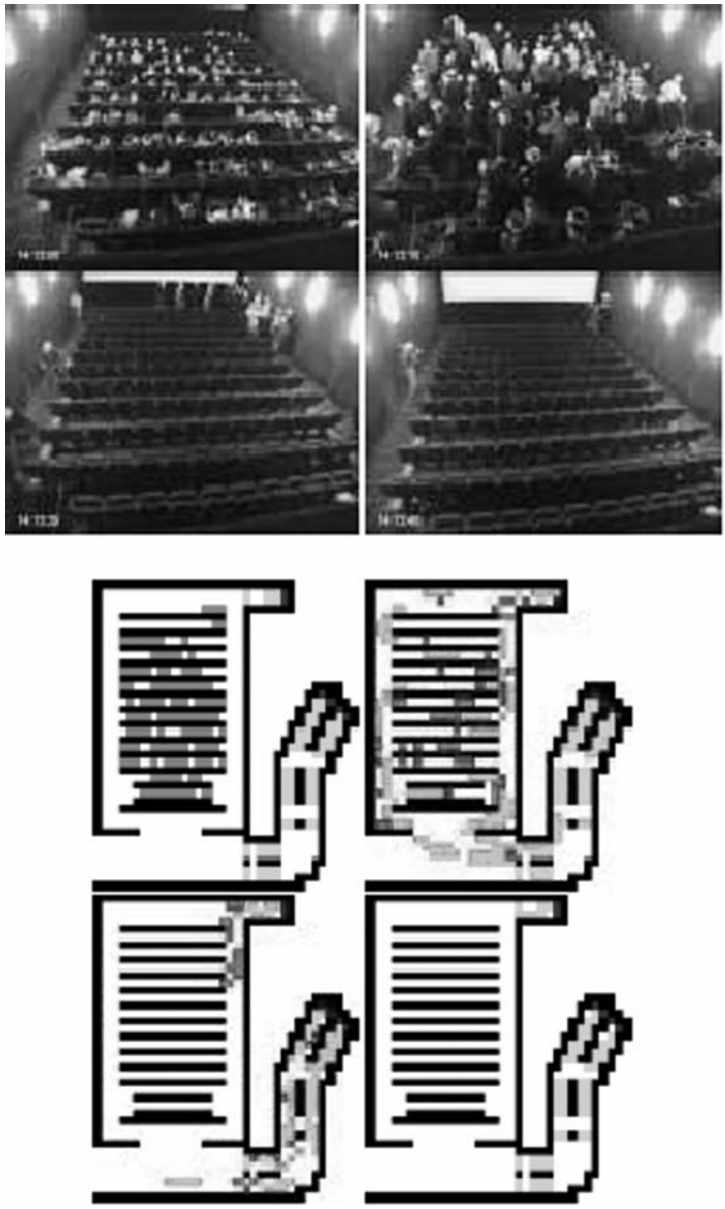


Figure 10.25: Video recordings and simulation screenshots at $t = 0\,\text{s}$, $t = 10\,\text{s}$, $t = 60\,\text{s}$, and $t = 65\,\text{s}$.

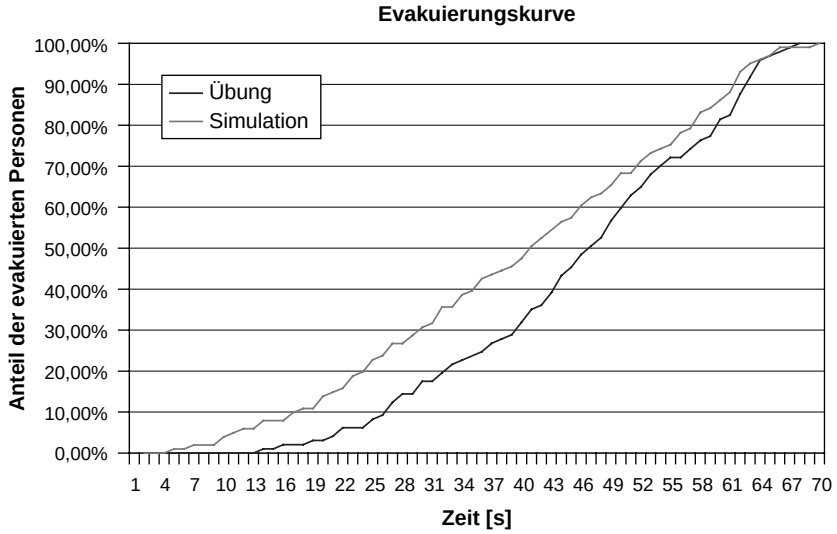


Figure 10.26: Evacuation curve.

10.5.1.2. Simulation results When comparing the evacuation sequence, the difference between the simulated flow at the doors and the experimental flow is prominent: In the simulation, the outflow at the doors is steadier. This can be seen from the evacuation curve in Figure 10.26. The simulations have been performed by the PedGo model described elsewhere.

In the simulation, the orientation was more effective. In spite of the same reaction time, the first person reached the exit earlier than in the exercise. In summary, the results for simulation and reality (exercise) are in good agreement. Differences are mainly due to high flow at high densities for the exercise, which is not the case in the simulation (Figure 10.26). Such a "synchronized flow" can also be observed at railway stations for commuter traffic. Such "synchronized flow" might be unstable, i.e., small disturbances might lead to a breakdown of the synchronized state and a substantial decrease in flow.

10.5.2. High-Rise Building: Phased Evacuation and Elevators

10.5.2.1. Phased evacuation Phased evacuation refers to the fact that the evacuation process is divided into separate phases for different groups of persons within the building. This is mainly applied for high-rise buildings since the stair capacity is not designed for an immediate and concurrent evacuation.

10.5.2.2. Use of elevators for evacuation The use of elevators for evacuation is discussed in the recent years more and more in the affirmative. General resources can be found on www.evacmod.net.

10.5.3. Hospital Evacuation

Hospital evacuation is a very specific case. It is first of all not determined by pedestrian movement but by the movement of persons lying in bed or being impaired in their mobility. Hospital evacuation poses special challenges. A general scheme for determining evacuation times for hospitals is given in Wolf (2001).

10.6. Summary, Outlook, and Conclusions

We have addressed several topics of pedestrian and crowd motion. In the following section, recommended reading and information resources are listed.

10.6.1. Information Resources

10.6.1.1. Literature databases

- www.evacmod.net/literature
- www.safetylit.org
- www.ped-net.org/literature

10.6.1.2. Bulletin boards

- http://www.ped-net.orgwww.ped-net.org
- www.ped-net.org/forum
- www.evadmod.net/forum

10.6.1.3. Internet groups

- www.linkedin.com/ped
- www.xing.de/net/fed

10.6.1.4. Model surveys

- www.firemodelsurvey.com
- www.wikia.com/ped
- www.evacmod.net/models

10.6.1.5. Books and review articles

- Schadschneider et al., Pedestrian and Evacuation Dynamics. In: Springer Encyclopedia of Complexity and Systems Science. Springer, Berlin, 2009.
- Helbing: Fußgängerdynamik. Springer, Berlin, 1999.
- Fruin: Pedestrian Planning and Design.
- SFPE Handbook on Fire Protection Engineering.
- Tubbs: Egress Design Solutions.
- NFPA 101, Life Safety Code.
- Predtetschenskii and Milinskii: Foot Traffic for Building Design.

References

Clarke, L. (2002). Panic: Myth or reality? *Contexts*, *Fall*, 21, http://www.e-noah.net/ASA/MO/articles/clarke.pdf

DiNenno, P. (Ed.). (1995). *SFPE handbook of fire protection engineering*. (2nd ed.; 3rd ed. 2002). Quincy, MA: National Fire Protection Association.

Forell, B. (2004). Bewertung von Evakuierungen in Diskotheken und ähnlichen Vergnügungsstätten, vfdb-Zeitschrift 2/2004, Seiten, pp. 95–103.

Forsyth, D. R. (1999). *Group dynamics*. New York, NY: Wadsworth Publishing.

Graat, E., Midden, C., & Bockholds, P. (1999). Complex evacuation: Effects of motivation level and slope of stairs on emergency egress time in sports stadium. *Safety Science*, *31*, 127–141.

Helbing, D., Farkas, I., Molnàr, P., Vicsek, T., Schreckenberg, M., & Sharma, S. (Eds). (2002). *Simulation of pedestrian crowds in normal and evacuation situations* (pp. 21–58). Pedestrian and Evacuation Dynamics. Berlin: Springer.

International Maritime Organization (IMO). (2002). Interim guidelines for evacuation analyses for new and existing passenger ships. MSC/Circ. 1033.

Klüpfel, H. (2003). *A cellular automaton model for crowd movement and egress simulation*. Dissertation, Universität Duisburg.

Mehl, F. (2003). Bauaufsichtliche Akzeptanz von Ingenieurmethoden im baulichen Brandschutz — Anwendungsbereiche, Grenzen. Promat Fachbeitrag, Ratingen. Available at: www.promat.de

Muir, H. (1996). Effects of motivation and cabin configuration on emergency aircraft evacuation behavior and rates of egress. *International Journal of Aviation Psychology*, *6*, 57–77.

Müller, K. (1999). Die Evakuierung von Personen aus Gebäuden auf der Grundlage von Modellversuchen. *VFDB-Zeitschrift*, *38*, 131–140.

Predtechenskii, V. M., & Milinskii, A. I. (1978). *Planning for foot traffic flow in buildings*. New Delhi: Amerind Publishing.

Wolf, G. (2001). Simulation eines Warteschlangensystems mit Anwendung auf ein Betriebsrestaurant. Master's thesis, Universität Duisburg, Duisburg.

Yamori, K. (1998). Going with the flow: Micro-macro dynamics in the macrobehavioral patterns of pedestrian crowds. *Psychological Review*, *105*, 530–557.

Chapter 11

The MATSim Network Flow Model for Traffic Simulation Adapted to Large-Scale Emergency Egress and an Application to the Evacuation of the Indonesian City of Padang in Case of a Tsunami Warning

Gregor Lämmel, Hubert Klüpfel and Kai Nagel

Abstract

The evacuation of whole cities or even regions is an important problem, as demonstrated by recent events such as the evacuation of Houston in the case of hurricane Rita or the evacuation of coastal cities in the case of tsunamis. This paper describes a complex evacuation simulation framework for the city of Padang, with approximately 1,000,000 inhabitants. Padang faces a high risk of being inundated by a tsunami wave. The evacuation simulation is based on the MATSim framework for large-scale transport simulations. Different optimization parameters like evacuation distance, evacuation time, or the variation of the advance warning time are investigated. The results are given as overall evacuation times, evacuation curves, and detailed GIS analysis of the evacuation directions. All these results are discussed with regard to their usability for evacuation recommendations.

11.1. Introduction

The evacuation of whole cities or even regions is an important problem, as demonstrated by recent events such as the evacuation of Houston in the case of

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hurricane Rita or the evacuation of coastal cities in the case of tsunamis. As a consequence of these events, disaster and evacuation planning has become an important topic in science and politics.

Congruent with the importance of the topic, there is a large body of research regarding emergency evacuations. As a first classification, one may differentiate between two situations: (i) evacuation from within buildings, ships, airplanes, etc.; (ii) large-scale citywide or regional evacuations, e.g., because of nuclear power plants failures or because of hurricanes. Case (i) usually concerns pedestrian evacuation; case (ii) usually uses traffic-based evacuation.

A good overview of pedestrian evacuation modeling and software can be found in the books of the bi-annual conference series "Pedestrian and Evacuation Dynamics" (Schreckenberg & Sharma, 2002; Galea, 2003; Gattermann, Waldau, & Schreckenberg, 2006). Pedestrian evacuation simulations can be classified into microscopic and macroscopic ones. Microscopic models represent space, time, and persons on a fine-grained level. Possible microscopic approaches are Cellular Automata (CA) (Klüpfel, Meyer-König, Keßel, & Schreckenberg, 2003), discretized differential equations (molecular dynamics, MD) (Helbing, Farkas, Molnar, & Vicsek, 2002; Helbing, Buzna, Johansson, & Werner, 2005), or movement rules based on random utility modeling (Bierlaire, Antonini, & Weber, 2003). Examples of software packages based on microscopic models are Exodus (Galea, 2002), Myriad (www.crowddynamics.com), Egress (www.aeat-safety-and-risk.com/html/egress.html), and PedGo (Klüpfel, 2006). Macroscopic models use the analogy of flows of pedestrians and liquids. Examples of software packages based on macroscopic models are Aseri (Schneider & Könnecke, 2002) and Simulex (www.iesve.com) (see, e.g., Jafari, Bakhadyrov, & Maher, 2003; Kuligowski, 2004, for surveys). Compared to what is known in terms of field measurements (e.g., Predtetschenski & Milinski, 1978; Weidmann, 1993), most if not all packages lead to similar results (Rogsch, 2005).

Once the pedestrian movement model is selected, it is necessary to define the evacuation directions. For more complex geometries, this is no longer a single movement toward one or two exits, but may involve rather complex movements in a building or in a street network. The arguably simplest solution is a grid-based potential function where the "uphill direction" leads to the nearest exit (Nishinari, Kirchner, Nazami, & Schadschneider, 2004). The same can be done using essentially continuous spatial variables, at the expense of much larger computing times (Hoogendoorn, Bovy, & Daamen, 2002). Alternatively, routing can be done along graphs (Hamacher & Tjandra, 2001; Gloor, Stucki, & Nagel, 2004a), which is a much faster technique when the abstraction to a graph is possible.

Another line of research concerns citywide or regional evacuations, i.e., case (ii). The development of these tools was much influenced by the development of tools in the areas of transport planning and traffic management. At the core of many of these methods is a static assignment routine (e.g., Sheffi, 1985; Ortúzar & Willumsen, 1995). A typical example for traffic-based evacuation simulation based on static concepts is MASSVAC (Hobeika & Kim, 1998) although later versions contain dynamic aspects.

A severe shortcoming of static assignment is that it does not possess any consideration of the time-of-day dynamics. Dynamic traffic assignment (DTA) is defined as a distribution of time-dependent trips on routes. A typical approach to implement DTA is day-to-day replanning. The traffic flow simulation (also called network loading) is run with prespecified routes, route costs are extracted, some or all of the routes are modified, the traffic flow simulation is run again, etc., until some stopping criterion is fulfilled. Examples of stopping criteria are that either every trip uses a route, which minimizes expected travel time (time-dependent Nash equilibrium, NE), or it selects between different route alternatives following a prespecified distribution function (time-dependent SUE).

Many DTA packages have been tested in the evacuation context: MITSIM (Jha, Moore, & Pashaie, 2004), Dynasmart (Kwon & Pitt, 2005; Chiu, Korada, & Mirchandani, 2005), PARAMICS (Chen & Zhan, 2004), and VISSIM (Han & Yuan, 2005). Oak Ridge National Laboratory has a package named "OREMS" (cta.ornl.gov/cata/One_Pagers/OREMS.pdf) explicitly for evacuation traffic. Publications stressing dynamic aspects of traffic-based evacuation as a novelty can be found as recent as 2000 (e.g., Sattayhatewa & Ran, 2000; Barrett, Ran, & Pillai, 2000) (for a review, see, Alsnih & Stopher, 2004).

A further distinction is if travelers can reroute while they are on their way (within-day replanning; en-route replanning), or only before their trip (day-to-day replanning; pre-trip replanning) (Cascetta & Cantarella, 1991). Clearly, en-route replanning capability is more realistic. It is, however, also more demanding. Adaptation of the plans needs to be called frequently from within the network loading, rather than only having to alternate between the network loading and the mental layers as one does in day-to-day replanning.

A large body of work (e.g., Theodoulou & Wolshon, 2004; Lim & Wolshon, 2005) uses microsimulation to investigate the issues of contraflow evacuation, i.e., the reversal of inbound lanes of a freeway in order to obtain additional outbound capacity.

To our knowledge, none of the above approaches is able to simulate large-scale scenarios (with millions of entities) while remaining microscopic:

- With a CA model, an area of 40 km × 40 km translates into cells. Even if every cell only needs 1 byte, this still translates into 10 Gbyte of memory, resulting in large simulation times.
- For the MD approach, the problems are the sub-second time resolutions that are typically used (Farkas, accessed 2008).
- DTA approaches seem the most likely candidates, but to our knowledge their implementation of the traffic flow dynamics usually is still too time-consuming for scenarios of that size. Sbayti, Lu, and Mahmassani (2007) reports a study using Dynasmart-P consisting of 1347 nodes and 3004 links. 200,000 vehicles were loaded onto the network. The runtime for about 30 iterations of 2 h of simulation was almost 8 h. This means running one iteration with this 1347 nodes/3004 links scenario takes about 16 min. If the runtime scales with the scenario size it would be very time-consuming to run larger scenarios. In Wen, Balakrishna, Ben-Akiva, and

Smith (2006), the DynaMIT framework was applied to a real-time scenario but on a small network (243 nodes and 606 links). In that study a rolling horizon approach was chosen to have a 5 min estimation and 30 min prediction on that network. Two iterations of estimation and two iterations of prediction took about 1 min. If the runtime scales with the size of the network the performance is comparable to the Dynasmart-P approach and again too slow for large-scale scenarios.

One way to achieve faster computation with a microscopic model is to use a model with deliberately large time steps and to computationally concentrate on those areas (links) where the pedestrian movement actually takes place (Gloor, Stucki, & Nagel, 2004b). Another approach is based up on a modified queuing model (Gawron, 1998; Simon, Esser, & Nagel, 1999). The queuing model simplifies streets to edges and crossings to nodes; the difference to standard queuing theory is that agents (particles) are not dropped but spill back, causing congestion. This graph-oriented model is defined by lengths/widths, free speed and flow capacity of the edges. This simplification leads to a major speedup of the simulation while keeping results realistic. The combination of these two approaches (switching off unused links; queue model) is used in this paper.

A robust simulation framework will help to find feasible solutions for arbitrary evacuation scenarios. The aim of this work is to find feasible evacuation solutions for an evacuation of large cities or regions by foot. This means we are looking for solutions from which it is possible to derive recommendations for the real world. This work is part of the current multi-disciplinary project ''Last-Mile'' (Birkmann et al., 2007). The overarching goal of ''Last-Mile'' is to develop jointly with local partners a numerical last mile tsunami early warning and evacuation information system on the basis of detailed earth observation data and techniques as well as hydraulic numerical modeling of small-scale flooding and inundation dynamics of the tsunami including evacuation simulations in the urban coastal hinterland for the city of Padang, West Sumatra, Indonesia. It is well documented that Sumatra's third largest city with one million inhabitants is located directly on the coast and partially sited beneath the sea level, and thus, is located in a zone of extreme risk due to severe earthquakes and tentatively triggered tsunamis.

To develop an evacuation simulation for such a big city one needs much preparatory work, i.e., one needs detailed picture of the walkable area of the city, the socio-economic profile and of the expected extension of the inundation. In this article, we will not go into detail how this information was explored. The interested reader is referred to (Lämmel et al., 2008) for more information about how to get the necessary input data.

11.2. Simulation Framework

The simulation framework is based on the MATSim framework for transport simulation (MATSIM, www page, accessed 2008). Since MATSim is focused

on simulation of motorized traffic, several adaptations were necessary. The key elements are:

- The agent database, where every agent represents one evacuee.
- The simulation network, based on links and nodes.
- The traffic flow simulator, where all the agents plans are executed.
- The plans generator, which generates an escape plan for every agent.
- There is a mechanism that allows improving the performance of the agents' plans by repeatedly trying to find faster evacuation routes.

11.2.1. Synthetic Population, Plans, Agent Database

MATSim always start with a synthetic population of all involved individuals. A synthetic population is a randomly generated population of individuals, which is based as much as possible on existing data such as census data. For evacuation, the synthetic population is the collection of all synthetic individuals that are involved in the evacuation.

Every synthetic individual possesses one or several plans. These plans are "intentions" of the synthetic individuals, to be tested in the traffic flow simulation described later, and scored afterwards. For evacuation, the plans are evacuation strategies. For example, such a strategy may be to leave the building 5 min after a second warning, and follow a predetermined route to safety. The collection of agents together with their plans is sometimes called an agent database.

People can have different positions within the city when a warning occurs. For example, they can be at home or at work. Therefore, also in the evacuation context it makes sense to consider MATSim plans in their more conventional meaning, as a description on what a synthetic traveler intends to do during a normal day. One can then run a regular traffic flow simulation with these plans, stop it at the time of an evacuation warning, and use the positions of all agents at the time of that warning as the initial condition to the evacuation.

11.2.2. Simulation Network

The simulation network represents the area that is accessible by the evacuees. In the case of a vehicular evacuation this network consists of all accessible streets. Each street segment defines a link. The parameters of the links are the length, capacity, and the free flow speed. For a pedestrian evacuation the links in the simulation network also consist of squares and sidewalks. The flow capacity is given by the width of a link as described in the next section. A good way of creating the simulation network is by extracting the needed information from satellite imagery.

In the case of an evacuation simulation the network has time-dependent attributes. For instance large-scale inundations or conflagrations do not cover all the endangered

area at once. In fact the spreading of the threat could be seen as a function of time. One solution would be by modeling this as a time-variant network. This means streets, bridges, etc. will be blocked as soon as they no longer passable. In MATSim time-variant aspects of the network are modeled as network change events. A network change event modifies parameters of a link in the network (e.g., free speed or flow capacity). As soon as a link is no longer passable its free speed will be set to zero.

11.2.3. *Traffic Flow Simulator*

The traffic flow simulation is implemented as a queue simulation, where each street (link) is represented as a FIFO (first-in first-out) queue with three restrictions (Gawron, 1998). First, each agent has to remain for a certain time on the link, corresponding to the free speed travel time. Second, a link flow capacity is defined which limits the outflow from the link. If, in any given time step, that capacity is used up, no more agents can leave the link. Finally, a link storage capacity is defined which limits the number of agents on the link. If it is filled up, no more agents can enter this link. The difference to standard queuing theory is that agents (particles) are not dropped but spill back, causing congestion.

An illustration of the queue model is shown in Figure 11.1a. The parameters of the model are:

- Link minimum width w
- Link area A
- Link length l
- Flow capacity $FC = w \times C_{\max} = w \times 1.3$ (p/m $\times$ s)
- Free flow speed $v_{\max} = 1.66$ (m/s)
- Storage capacity $SC = A \times D_{\max} = A \times 5.4$ (p/m^2)

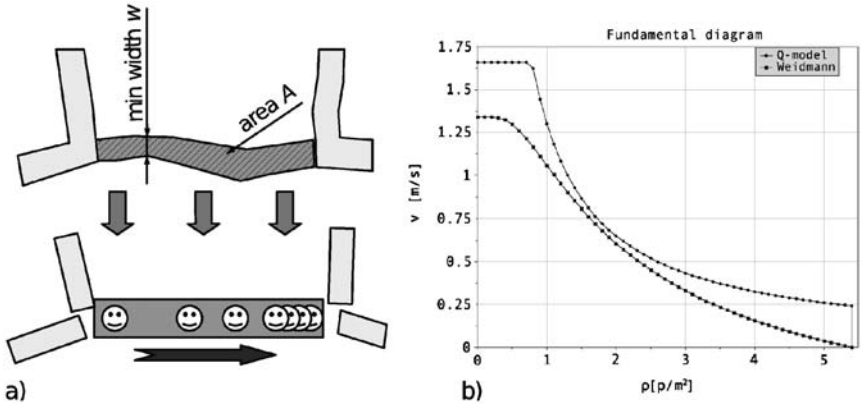


Figure 11.1: Functioning of the queue model is shown in (a) and its corresponding fundamental diagram in (b).

where is the maximum flow capacity per unit width, and is the maximum density per unit area.

The parameters have been chosen to approximate Weidmann's fundamental diagram (Weidmann, 1993).[1] He pointed out that the relation between density and velocity is adequately captured by the so-called Kladek-formula:

$$v_{F,hi}(D) = v_{F,hf} \times [1 - e^{-\gamma \times ((1/D)-(1/D_{\max}))}]$$

with, $v_{F,hi}$ the velocity at a particular density [m/s]; $v_{F,hf}$ the velocity at free flow [m/s]; γ a free parameter [persons/m^2]; D the actual density [persons/m^2]; and $D_{\max}$ the density at which no flow occurs [persons/m^2].

Empirical studies showed the best results with $\gamma = 1.913$, $v_{F,hf} = 1.34$ m/s, and $D_{\max} = 5.4$ (persons/m^2).

Our study uses the same maximum density, but the free flow speed was set to 1.66 m/s. This value is slightly higher then the 1.34 m/s used by Weidmann, but the values presented by Weidmann reflect the pedestrian flow under normal conditions and not in a case of emergency.

Our queuing model, however, generates a speed–density relationship of the form $v = \min[v_{\max}, FC/D]$ (Simon & Nagel, 1999). The flow capacity FC is a free parameter that has to be chosen to fit the desired fundamental diagram. Even if a complete agreement is not possible, with $FC = 1.3(\text{p}/(\text{m} \times \text{s}))$ the flow dynamics produced by our queue model is not too far away from Weidmann's fundamental diagram (cf., Figure 11.1b). Furthermore, Predtetschenski and Milinski's (1978) empirical study supports a value of approx. $1.3(\text{p}/(\text{m} \times \text{s}))$ for the flow capacity.

11.2.4. Plans Generation

Initial plans use the shortest path (according to free speed travel time) out of the evacuation area for all agents. Within the MATSim framework a shortest path router based on Dijkstra's (1959) shortest path algorithm has been implemented. This router finds the shortest path in a weighted graph from one node to any other, whereby the actual weights for a link are defined by a time- and distance-dependent cost function. Since we want to evacuate the city as fast as possible, the weights represents the (expected) travel time. There is, however, no particular node as the target of the shortest path calculation, as the evacuees have more than one safe place to run to. Instead, in the underlying domain every node outside the evacuation area is a possible destination for an agent that is looking for an escape route. To resolve this, the standard approach (e.g., Lu, George, & Shekhar, 2005) is to extend the network in the following way. All links which lead out of the evacuation area are connected,

1. Newer studies (Schadschneider et al., 2009) imply other fundamental diagrams than those from Weidmann. An adaptation of these values could, in consequence, become necessary in future.

using virtual links with infinite flow capacity and zero length, to a special "evacuation node," and all paths are routed to that special evacuation node. Doing so, Dijkstra's algorithm will always find the shortest route from any node inside the evacuation area to this evacuation node and, in consequence, to safety.

11.2.5. Agents Learning

After an execution of the traffic flow simulation, every agent will score the performed plan. The score of a plan is calculated by a scoring function as it is described later. The scored plans remain in the agents' memory for further executions. For the learning procedure two different learning strategies were used. The ReRoute strategy generates new plans with new evacuation routes based on the information of the experienced travel times from the last run. This uses the router described in the previous section, but using time-variant link travel times as link costs. The other strategy is called ChangeExpBeta. This strategy decides if the just performed plan should be used again, or if a random plan out of the memory should be selected for the next iteration. The probability to change the selected plan is calculated by

$$p_{\text{change}} = \min(1, \alpha \times e^{\beta \times (s_{\text{random}} - s_{\text{current}})/2})$$

with, α: the probability to change if both plans have the same score; β: a sensitivity parameter; $s_{\{\text{random,current}\}}$: the score of the current/random plan.

If the system is "well-behaved," this set-up converges to a steady state where the probability that agent a uses plan i is

$$p_{a,i} = \frac{e^{\beta \times s_{a,i}}}{\sum_j e^{\beta \times s_{a,j}}}$$

i.e., the standard multinomial logit model (e.g., Ben-Akiva & Lerman, 1985).

The plans score (utility) is determined by the scoring function:

$$U_i = \beta_{tr} t_{tr,i} + \beta_{\text{dist}} d_i$$

where is the (dis)utility of plan i, is the marginal utility (in $1/h$) for travel (normally negative), is the experienced travel time for plan i, represents the marginal utility (in 1/km) of distance (normally negative), and the distance covered by executing plan i.

Each strategy is selected with a certain probability. These probabilities are assigned before the simulation starts, but they can be varied during the iterations. Typically, ReRoute is called with a relatively small probability, say 10%, and ChangeExpBeta is called in the remaining cases.

After replanning every agent has a selected plan that will be executed in the next iteration. Repeating this iteration cycle of learning, the agentsâ™ behavior will move toward a NE. If the system were deterministic, then a state where every agent uses a

plan that is a best response to the last iteration would be a fixed point of the iterative dynamics, and at the same time a NE since no agent would have an incentive to unilaterally deviate. Since, however, the system is stochastic, this statement does not hold, and instead we look heuristically at projections of the system. From experience it is enough to run 100 iterations until the iterative dynamics has reached a steady state. In most (but not all) evacuation situations, the NE leads to a shorter overall evacuation time than when everybody moves to the geographically nearest evacuation point. On the other hand, a NE means that nobody has an incentive to deviate. The NE in an evacuation situation can therefore be considered as a solution that could be reached by appropriate training.

11.3. Scenarios

The aim of this work is to find feasible solutions for the evacuation of the city of Padang in the case of a tsunami. There are several aspects that have to be taken into consideration. At first one needs a synthetic population for the agent database. In the studies described in this paper, it is assumed that all people are at home. The information about the distribution of the population was derived from existing census data (BPS, 2005). The agent database consists of about 320,000 agents living in the endangered area.

Another important aspect is the information about safe places. In the future it is planned to identify buildings that are suitable for a vertical evacuation. For the time being we use a simpler approach. All areas with an elevation of more than 10 m above sea level are defined as safe.

Figure 11.2 shows an image of the city with the endangered area.

However, just evacuating the so-defined endangered area as quickly as possible is not necessarily the best solution. Based on models of small-scale flooding and inundation dynamics of the tsunami (Goseberg, Stahlmann, Schimmels, & Schlurmann, 2009) it is not expected that all the area below 10 m will be flooded. Based on these simulations, one also learns that the estimated time between the earthquake and the inundation of the city is about 28 min. The results are backed by the results of large-scale tsunami simulations for the west coast of Sumatra Island (McCloskey et al., 2008). Making all links impassable after they are flooded makes the agents learn a more risk-averse behavior, they are not only trying to reach the safe area as fast as possible, but they also try to avoid the flooding. Since this is an additional constraint, this will in general *increase* the evacuation time of the full "endangered" area.[2]

2. We say "in general" since our Nash equilibrium (NE) solution is not the system optimum (SO), and it may happen that the additional constraint pushes the NE toward the SO. The interpretation of the NE is discussed in more detail in Section 11.5.

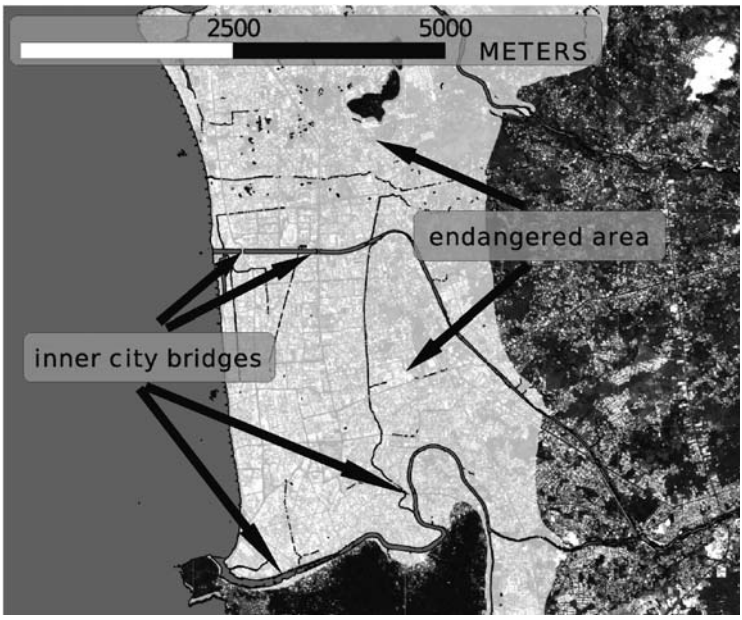


Figure 11.2: Satellite imagery of the city shows the evacuation area (light gray) and some main bridges where bottlenecks are expected during an evacuation. Satellite imagery by the German Aerospace Center, Oberpaffenhofen (2007).

But even in this setup the learned behavior is not necessarily plausible. One can still find simulated people who flee for a long time in parallel to the shoreline, turning inland only shortly before the tsunami approaches. One way to get a more risk-averse behavior is given by the fact that a solution for a scenario where the tsunami reaches the shoreline earlier (e.g., after 10 min) is also a solution for the "28 min" scenario. At the same this solution is more risk averse because the agents are forced to leave the flooding area earlier. Once more, in general this will increase the evacuation time for the full-endangered area.

Another important aspect is the large number of bridges in the city. Bottlenecks often emerge at bridges. The local nonprofit organization KOGAMI (tsunami alert community http://kogami.or.id) suggests to avoid all the bridges in the inner city during an evacuation (cf. Figure 11.2).

As discussed in Section 11.2.5, the agents in the simulation improve their plans by iterative learning. After a simulation cycle is finished all the agents plans will be scored. The scoring function takes both, evacuation time and covered distance, into account. The evacuation time should be the major criterion for the plans scoring. But also the distance costs can important. For example, there could be situations, where two evacuation routes have equal travel time but one route is substantially longer than the other. If the scoring function only took the travel time into account, then both routes would get the same score. In the real

Table 11.1: Setup parameters for the seven different scenarios.

Run	Warning time	Bridges blocked	β_{tr}	β_{dist}
1	28	No	−6	0
2	8	No	−6	0
3	28	Yes	−6	0
4	8	Yes	−6	0
5	8	No	−6	1
6	8	No	−6	5
7	8	No	−6	10

world, one would recommend the shorter route even if there is a bit more congestion than on the longer one.

Taking this all together we define seven different scenarios in Table 11.1.

11.4. Results

For each run 100 iterations of learning were performed. As expected the evacuation time decreases significantly with the iterations. Figure 11.3 compares the initial iteration (top) and the last iteration (bottom) of run 2. It shows the area that has been evacuated after 30 min of evacuation and the maximum expansion of the inundation. In the initial iteration all agents are on the shortest path, while in the last iteration the system has converged toward NE and the agents are on the fastest path under the given circumstances. It is clearly shown that with the NE approach considerably more agents manage to escape in the given time than in the shortest path solution.

In all runs, the evacuation of all areas below 10 m took at least 1 h. Nevertheless, in all runs the highly endangered coastal strip, which is expected to be flooded, was evacuated before the tsunami waves reach the shoreline. However, the runs perform differently in terms of the evacuation progress.

Figure 11.4 shows the evacuation curves for run 1 to run 4. While avoiding potentially flooded areas early (run 2 vs. run 1) makes little difference, it is clearly visible that blocking the bridges during evacuation slows down the evacuation of the full-endangered area. Still, even if the bridges are blocked, there seems to be enough time to evacuate the highly endangered area at the coastal strip.

Adding distance costs (runs 5–7 vs. run 2) results in longer evacuation times. Figure 11.5 compares the evacuation curves. The more distance costs are added, the longer the evacuation takes. This result is not unexpected, because the agents now have to optimize another criterion. They do not only try to find the fastest evacuation route, but a trade-off between fast and short.

But even if the additional distance costs increase the evacuation time, there are also advantages. Without distance costs, an agent chooses with equal probability between two equally fast evacuation routes even if one of the routes is substantially longer than the other. Not only is this counterintuitive, but from those results it is

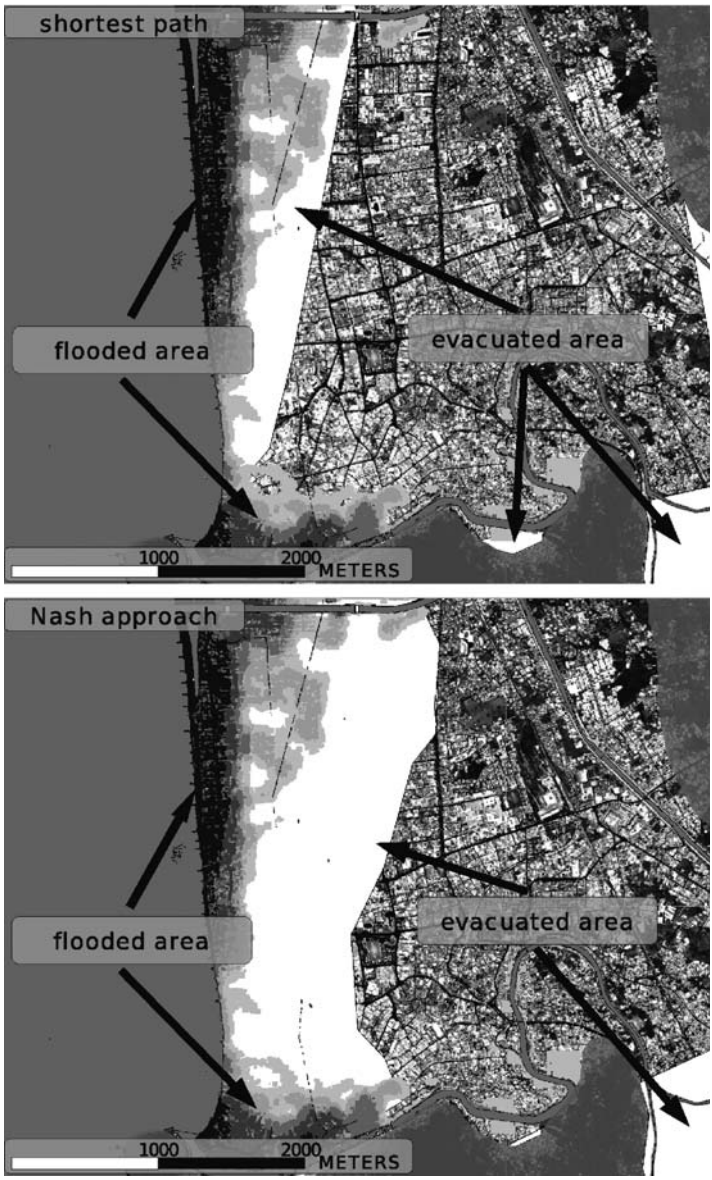


Figure 11.3: The area that could be evacuated within 30 min and the maximum expansion of the inundation for a medium-height tsunami. Top: A solution where every agent is on the shortest path. Bottom: Result of run 2 after 100 iterations of learning (Nash equilibrium approach). The evacuated area in the Nash equilibrium approach is considerably larger than in the shortest path solution. Satellite imagery by the German Aerospace Center, Oberpaffenhofen (2007).

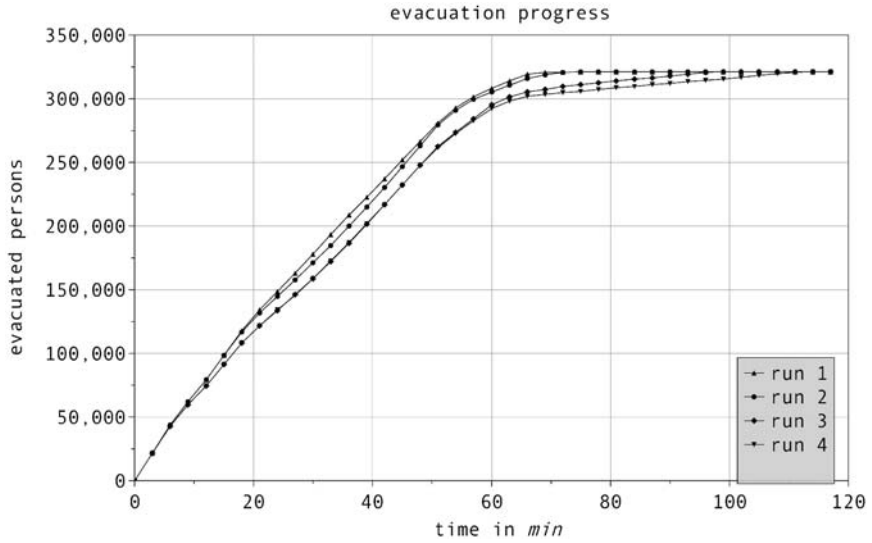


Figure 11.4: Evacuation curves for run 1–4. These curves look similar, but if the bridges are blocked (run 3 and run 4) the overall evacuation time increases by about 40 min compared to run 1 and run 2, where all bridges are open.

difficult to derive specific recommendations for the real world. It is, e.g., not realistic that people living in the same street or even the same household would follow completely different evacuation routes. In emergency situations, people tend to be irrational and to display herd behavior (Helbing, Farkas, & Vicsek, 2000). From this point of view it is better to recommend people living next to each other the same evacuation route. Adding additional distance costs helps to find those solutions. This is shown in Figure 11.6.

Figure 11.6 compares the evacuation destinations between run 2 and run 7. The arrows in this figure point toward the place where the people flee to. Each arrow represents the home location of one person. Arrows pointing to the same destination have the same shade of gray. For run 7 this destination depended colorization is much more grouped and not so mixed up as it is for run 2. The only difference in the setup was the additional distance costs for run 7. This means that from simulation runs with additional distance costs it is easier to derive recommendations for the real world, at the cost of a slower evacuation procedure, as shown in Figure 11.5.

11.5. Discussion

11.5.1. Nash Equilibrium versus Other Solutions

The NE approach is used as a first benchmark. As can be seen from Figure 11.3, the approach allows to evacuate a much larger critical area than with an approach where

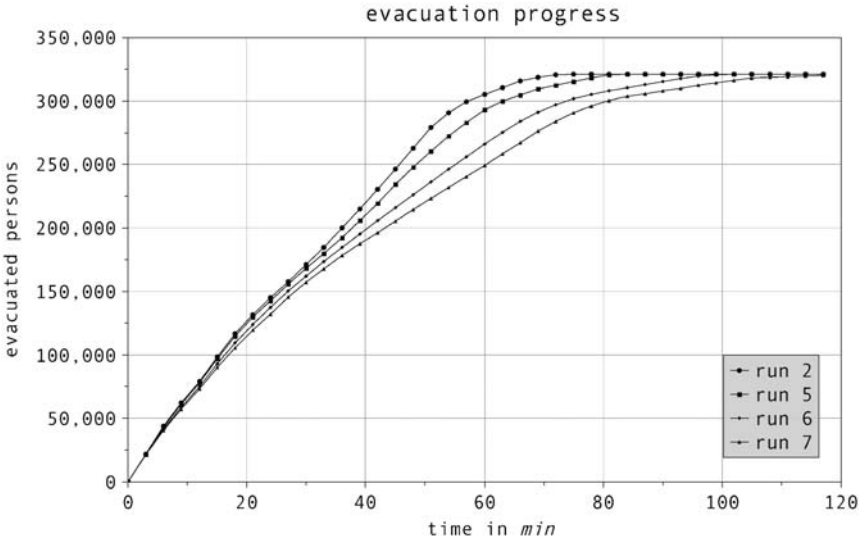


Figure 11.5: Evacuation curves of run 5–7 compared with run 2. The comparison shows that without distance costs (run 2) about 300,000 agents managed to evacuate within 60 min, where in run 7 (distance costs of 10 units/km) in the same time only 250,000 agents managed to escape.

everybody takes the geometrically shortest path to safety. This is clearly a consequence of congestion on *some* of the geometrically shortest paths, making evacuees caught in congestion better off if they use a different, geometrically longer path. This is confirmed by the fact that adding distance into the cost function makes the evacuation take longer again.

Many people argue that the NE approach is not appropriate for evacuation since people will not evacuate often enough for this solution to be plausible. We would argue that the NE approach could, if designed correctly, be established by appropriate training of the population, in particular for a nighttime situation as discussed here, where families can be assumed to be united from the start. Then, the NE solution would have the advantage that nobody in the population would have an incentive to deviate from this solution.

This is in contrast to a system optimal solution, which might be even better than the NE solution, but which might give individuals incentives to deviate.

Nevertheless, it is nothing but a possible benchmark. It may be unrealistic or problematic at least for the following reasons:

- It is probable that people will also display other types of behavior, such as herd behavior or uniting the family (possibly causing counterflows) before evacuating. In fact, personal interviews show that at this point many people do not have the intention to evacuate at all (Hoppe, 2007).

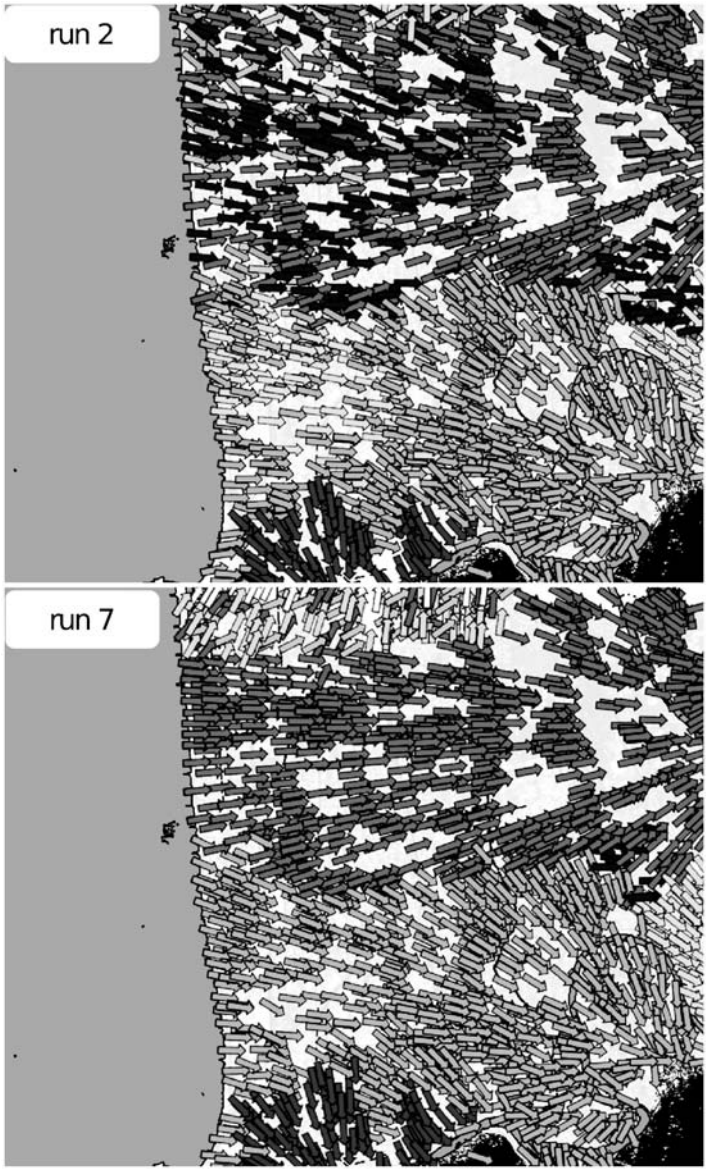


Figure 11.6: Comparison of the evacuation destinations for run 2 and run 7. The arrows point toward the evacuation destinations, with same shade of gray indicates the same destination. Satellite imagery by the German Aerospace Center, Oberpaffenhofen (2007).

- The NE solution for Padang is most probably not a confluent flow solution (see, e.g., Chen et al., 2004). This means that the "correct" direction from any intersection is not always just a single link that remains fixed over time. Instead, the simulation shows that it is quite common in the NE solution that flows split at intersections, or move into different downstream links at different times.
- Although evacuation flows of pedestrians are reasonably stable and thus predictable (Rogsch, 2005), there are still many reasons why the simulation could be wrong: parked cars or other obstacles could reduce the minimum width of links; some people might have difficulty walking; some people might use other means of transport, thus leading to a mix of different vehicles rather than a homogeneous pedestrian population; cars might even be abandoned (and thus convert to obstacles) in the course of an evacuation. Note that pedestrian evacuation reaches a flow rate of 1.3 pedestrian/s/m cross section; the use of individual vehicles (cars, motorcycles, bicycles) will probably *reduce* that flow rate, increasing congestion.

Overall, we believe that it is plausible to say that the simulation at this point is rather a "good case" than a bad case scenario. Still, the fact that one seems to be able to evacuate the "flooded areas" with 30 min to spare (Figure 11.3) gives hope that one may be able to construct a workable solution.

11.5.2. Risk Exposure Over Time

Our simulation has so far been defined in terms of a "minimal time to evacuate." Given the network, the initial distribution of the population, and predefined safe areas, the simulation attempts to answer the question which times are plausibly needed in order to get everybody into the safe areas. Yet, it is not clear which exactly are the safe areas:

- In the case of an actual warning, neither tsunami wave heights not wave patterns nor the time until the wave reaches the shoreline will be known. Therefore, it is impossible to define a "minimal" dangerous area. On the other hand, it would be quite difficult to establish a solution where people need to walk for 30 min or more, especially since it is probable that there will be a fair number of false alarms. At this point, we are considering to take an "envelope" of the inundation (see Figure 11.3) from a number of worst-case scenarios computed by Goseberg et al. (in press). In addition, there will eventually be special "shelters," buildings marked as safe, etc.
- It is unclear how to proceed with the time-dependence of the problem. Clearly, bridges will eventually be unsafe. But so will be certain other streets, and it might be better to use a bridge to get into safety right afterwards than to stay on risky streets for a much longer time. This problem is apparent in all of our situations. Given a certain warning time, it makes sense for some of the evacuees to take a path that increases their risk temporarily in order to be really safe much earlier.

This problem is confounded by the "minimal time to evacuate" approach. There will eventually be a warning time which cannot be reduced any further without accepting loss of life in the simulations. If this, however, is the minimal warning time ever used in the simulations, the simulated agents can assume that all of the city is safe for that amount of time, and route themselves accordingly. If then, in reality, the warning time is even shorter, such routes might not be advantageous.

Our current plan is to investigate approaches where we designate different "risk levels" to different links, and devise evacuation paths where agents always reduce risk. This will avoid the situation described above, but will result in a less efficient evacuation. This efficiency reduction will be tested and quantified by the simulation.

- It is not possible to designate non-flooded areas directly as "safe," since evacuees both in the simulation and in reality would stop there, causing congestion for evacuees that follow.

11.6. Conclusion

This paper describes a microscopic evacuation simulation based on the MATSim framework for transport simulation. The key elements of MATSim are the synthetic population, the simulation network, the traffic flow simulator, and a mechanism that lets the members of the synthetic population improve their evacuation plans. The scenario for this study is the Indonesian city of Padang with approximately 1,000,000 inhabitants. The city faces a high risk of being inundated by a tsunami wave. About 320,000 people live in a highly endangered area. The simulation runs were performed with 320,000 agents forming a corresponding synthetic population.

In this study, seven different runs with different parameters were conducted. Parameters that were varied are the advance warning time, blocking of the bridges, and the distance cost for traveling. With the variation of these parameters the system moves toward different NE. Results regarding the overall evacuation time, evacuation curves, and evacuation directions are given. Section 11.5 discusses under which circumstances a NE would be a good solution for the evacuation problem. Some points that are presently not covered by the simulation framework are also addressed (e.g., abandoned cars in the streets as obstacles). Finally problems with a definition of safe areas are discussed.

In future work we are going to integrate tsunami proof shelters into the simulation framework as additional safe areas. This is of particular interest because in currently running studies the buildings in the city will be classified regarding their usability as shelters. Furthermore we are currently investigating methods for risk-averse evacuations. This will be done by adding additional risk costs to links depending on their direction. Overall we have shown in this paper that the MATSim framework is a good analysis tool for evacuation scenarios, especially if they are large-scale.

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References

Alsnih, R., & Stopher, P. (2004). *A review of the procedures associated with devising emergency evacuation plans*. Working Paper ITS-WP-04-04, Institute of Transport Studies, The University of Sydney and Monash University. See http://www.itls.usyd.edu.au/publications/working_papers/wp2004/its_wp_04-04.pdf

Barrett, B., Ran, B., & Pillai, R. (2000). *Developing a dynamic traffic management modeling framework for hurricane evacuation*. Paper 00-1595, Transportation Research Board Annual Meeting, Washington, DC.

Ben-Akiva, M., & Lerman, S. R. (1985). *Discrete choice analysis*. Cambridge, MA: The MIT Press.

Bierlaire, M., Antonini, G., & Weber, M. (2003). Behavioral dynamics for pedestrians. In: K. Axhausen (Ed.), *Moving through nets: The physical and social dimensions of travel* (pp. 1–18). Amsterdam: Elsevier, available at: http://infoscience.epfl.ch/record/86990/files/Bierlaire2003_283.pdf

Birkmann, J., Dech, S., Hirzinger, G., Klein, R., Klüpfel, H., Lehmann, F., Mott, C., Nagel, K., Schlurmann, T., Setiadi, N., Siegert, F., & Strunz, G. (2007). Numerical last-mile tsunami early warning and evacuation information system. In: L. Stroink (Ed.), *GEOTECHNOLOGIEN Science Report No. 10* (Vol. 10, pp. 62–74). Early Warning Systems in Earth Management, Die Deutsche Bibliothek, available at: http://www.geotechnologien.de/Download/pdf/Science_Report/SR10.pdf

BPS. (2005). *Kecamatan Dalam Angka-Subdistricts in Numbers*. Padang, Indonesia: Statistical bureau (BPS) Kota Padang.

Cascetta, E., & Cantarella, C. (1991). A day-to-day and within-day dynamic stochastic assignment model. *Transportation Research A*, *5*(25A), 277–291.

Chen, J., Kleinberg, R. D., Lovász, L., Rajaraman, R., Sundaram, R., & Vetta, A. (2004). (Almost) tight bounds and existence theorems for confluent flows. In: L. Babai (Ed.), *STOC '04: Proceedings of the thirty-sixth annual ACM symposium on Theory of computing* (pp. 529–538). New York, NY, USA: ACM.

Chen, X., & Zhan, F. (2004). *Agent-based modeling and simulation of urban evacuation: Relative effectiveness of simultaneous and staged evacuation strategies*. Paper 04-0329, Transportation Research Board Annual Meeting, Washington, DC.

Chiu, Y.-C., Korada, P., & Mirchandani, P. (2005). *Dynamic traffic management for evacuation*. Paper 05-2369, Transportation Research Board Annual Meeting, Washington, DC.

Dijkstra, E. (1959). A note on two problems in connexion with graphs. *Numerische Mathematik*, *1*, 269–271.

Farkas, I. (accessed 2008). Pedsim source code. See http://pedsim.elte.hu

Galea, E. (2002). Simulating evacuation and circulation in planes, trains, buildings and ships using the EXODUS software. In: M. Schreckenberg & S. D. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 203–225). Berlin: Springer.

Galea, E. (Ed.) (2003). *Pedestrian and evacuation dynamics*. Proceedings of the 2nd international conference, London. UK: CMS Press, University of Greenwich.

Gattermann, P., Waldau, N., & Schreckenberg, M. (Eds) (2006). *Pedestrian and evacuation dynamics*. Proceedings of the 3rd international conference, Vienna. Berlin: Springer.

Gawron, C. (1998). An iterative algorithm to determine the dynamic user equilibrium in a traffic simulation model. *International Journal of Modern Physics C*, *3*(9), 393–407.

Gloor, C., Stucki, P., & Nagel, K. (2004a). Hybrid techniques for pedestrian simulations. In: P. Sloot, B. Chopard & A. Hoekstra (Eds), *Cellular automata, proceedings. Lecture notes in computer science, 3305* (pp. 581–590). Berlin: Springer, available at: http://www.springerlink.com/content/ng75m5lyyd8b617p/

Gloor, C., Stucki, P., & Nagel, K. (2004b). Hybrid techniques for pedestrian simulations. *Proceedings of Swiss Transport Research Conference (STRC)*, Monte Verita, CH (see, http://www.strc.ch).

Goseberg, N., Stahlmann, A., Schimmels, S., & Schlurmann, T. (2009). Highly-resolved numerical modeling of tsunami run-up and inundation scenarios in the city of Padang, West Sumatra. *Proceedings of the International Conference on Coastal Engineering*, Hamburg.

Hamacher, H., & Tjandra, S. (2001). Mathematical modelling of evacuation problems: A state of art. *Berichte des Fraunhofer ITWM*, *24*, 1–38.

Han, L., & Yuan, F. (2005). *Evacuation modeling and operations using dynamic traffic assignment and most desirable destination approaches*. Paper 05-2401, Transportation Research Board Annual Meeting, Washington, DC.

Helbing, D., Buzna, L., Johansson, A., & Werner, T. (2005). Self-organized pedestrian crowd dynamics: Experiments, simulations and design solutions. *Transportation Science*, *39*, 1–24.

Helbing, D., Farkas, I., Molnar, P. & Viesek, T. (2002). Simulation of pedestrian crowds in normal and evacuation situations. In: M. Schreckenberg & S. D. Sharma (Eds), Pedestrian and evacuation dynamics (pp. 21–58). Berlin: Springer.

Helbing, D., Farkas, I., & Vicsek, T. (2000). Simulating dynamical features of escape panic. *Nature*, *407*, 487–490.

Hobeika, A., & Kim, C. (1998). Comparison of traffic assignments in evacuation modeling. *IEEE Transactions on Engineering Management*, *2*(45), 192–198.

Hoogendoorn, S., Bovy, P. & Daamen, W. (2002). Microscopic pedestrian wayfinding and dynamics modelling. In: M. Schreckenberg & S. D. Sharma (Eds), Pedestrian and evacuation dynamics (pp. 123–154). Berlin: Springer.

Hoppe, M. (2007). *Early warning experiences in Padang after first Bengkulu earthquake on 12 September 2007*. Technical report, GTZ-International Services.

Jafari, M., Bakhadyrov, I., & Maher, A. (2003). *Technological advances in evacuation planning and emergency management: Current state of the art*. Final Research Reports EVAC-RU4474. Center for Advanced Infrastructure and Transportation (CAIT), NJ: Rutgers University, available at: cait.rutgers.edu/finalreports/EVAC-RU4474.pdf

Jha, M., Moore, K., & Pashaie, B. (2004). *Emergency evacuation planning with microscopic traffic simulation*. Paper 04-2414, Transportation Research Board Annual Meeting, Washington, DC.

Klüpfel, H. (2006). The simulation of crowd dynamics at very large events — Calibration, empirical data, and validation. In: Gattermann et al. (Eds), pp. 285–296.

Klüpfel, H., Meyer-König, T., Keßel, A., & Schreckenberg, M. (2003). Comparison of an evacuation exercise in a primary school to simulation results. In: M. Fukui, Y. Sugiyama, M. Schreckenberg & D. Wolf (Eds), *Traffic and granular flow '01* (pp. 449–454). Berlin: Springer.

Kuligowski, E. (2004). *Review of 28 egress models*. Technical report, National Institute of Standards and Technology (NIST), Gaithersburg, MD.

Kwon, E., & Pitt, S. (2005). *Evaluation of emergency evacuation strategies for downtown event traffic using a dynamic network model*. Paper 05-2164, Transportation Research Board Annual Meeting, Washington, DC.

Lämmel, G., Rieser, M., Nagel, K., Taubenböck, H., Strunz, G., Goseberg, N., Schlurmann, T., Klüpfel, H., Setiadi, N., & Birkmann, J. (2008). Emergency preparedness in the case of a tsunami — Evacuation analysis and traffic optimization for the Indonesian city of Padang. In: *Pedestrian and evacuation dynamics*. Proceedings of the 4th international conference.

Lim, E., & Wolshon, B. (2005). Modeling and performance assessment of contraflow evacuation termination points. *Transportation Research Record*, *1922*, 118–128.

Lu, Q., George, B., & Shekhar, S. (2005). Capacity constrained routing algorithms for evacuation planning: A summary of results. In: C. Medeiros, M. Egenhofer, & E. Bertino (Eds), *Lecture notes in computer science* (Vol. 3633, pp. 291–307). Berlin: Springer.

MATSIM. www page (accessed 2008), MultiAgent Transport SIMulation, available at: http://ww.matsim.org

McCloskey, J., Antonioli, A., Piatanesi, A., Sieh, K., Steacy, S., Nalbant, S., Cocco, M., Giunchi, C., Huang, J., & Dunlop, P. (2008). Tsunami threat in the Indian Ocean from a future megathrust earthquake west of Sumatra. *Earth and Planetary Science Letters*, *265*, 61–81.

Nishinari, K., Kirchner, A., Nazami, A., & Schadschneider, A. (2004). Extended floor field CA model for evacuation dynamics. *IEICE Transactions on Information and Systems*, *3*(E87-D), 726–732.

Ortúzar, J. deD., & Willumsen, L. (1995). *Modelling transport*. Chichester: Wiley.

Predtetschenski, W., & Milinski, A. (1978). *Planning for foot traffic in buildings*. New Delhi: Amerind Publishing Co. Pvt. Ltd.

Rogsch, C. (2005). *Vergleichende Untersuchungen zur Simulation von Personentrömen*. Diploma thesis, Universität Wuppertal.

Sattayhatewa, P., & Ran, B. (2000). *Developing a dynamic traffic management model for nuclear power plant evacuation*. Paper, Transportation Research Board Annual Meeting, Washington, DC.

Sbayti, H., Lu, C.-C., & Mahmassani, H. (2007). Efficient implementation of method of successive averages in simulation-based dynamic traffic assignment models for large-scale network applications. *Transportation Research Record*, *2029*, 22–30.

Schadschneider, A., Klingsch, W., Klüpfel, H., Kretz, T., Rogsch, C., & Seyfried, A. (2009). Evacuation dynamics: Empirical results, modelling and applications. In: B. Meyers (Ed.), Encyclopedia of Complexity and System Science. Berlin: Springer.

Schneider, V., & Könnecke, R. (2002). Simulating evacuation processes with ASERI. In: M. Schreckenberg & S. D. Sharma (Eds), *Pedestrian and evacuation dynamics* (pp. 303–314). Berlin: Springer.

Schreckenberg, M., & Sharma, S. D. (Eds) (2002). *Pedestrian and evacuation dynamics*. Proceedings of the 1st international conference, Duisburg, 2001, Springer.

Sheffi, Y. (1985). *Urban transportation networks: Equilibrium analysis with mathematical programming methods*. Englewood Cliffs, NJ: Prentice-Hall.

Simon, P., Esser, J., & Nagel, K. (1999). Simple queueing model applied to the city of Portland. *International Journal of Modern Physics C*, *5*(10), 941–960.

Simon, P., & Nagel, K. (1999). *Simple queueing model applied to the city of Portland*. Paper 99-0861, Transportation Research Board Annual Meeting, Washington, DC.

Theodoulou, G., & Wolshon, B. (2004). Alternative methods to increase the effectiveness of freeway contraflow evacuation. *Transportation Research Record*, *1865*, 48–56.

Weidmann, U. (1993). Transporttechnik der Fussgänger.In: *Schriftenreihe des IVT* (2 ed., Vol. 90). ETH Zürich: Institute for Transport Planning and Systems (In German).

Wen, Y., Balakrishna, R., Ben-Akiva, M., & Smith, S. (2006). Online deployment of dynamic traffic assignment: Architecture and run-time management. *Intelligent Transport Systems, IEE Proceedings*, *153*, 76–84.

Chapter 12

Comparative Study of Pedestrian Behavior in Central Shopping Areas of East Asian Cities

Shigeyuki Kurose, Atsushi Deguchi and Shichen Zhao

Abstract

The objective of this paper is to investigate and compare pedestrian behavior in the central shopping areas of Fukuoka (Japan), Busan (Korea), and Tianjin (China). Pedestrians were interviewed in these cities and provided data on shopping destinations and routes that were chosen. These data were analyzed for trip length, choice heuristics, and shortest routes. In addition, relationships between these statistics and pedestrians characteristics were investigated. Finally, the relationship between pedestrian behavior and physical conditions like the road network pattern, and the location pattern of shops along the street were examined. Findings indicate that pedestrian behavior may depend on pedestrian characteristics such as age and occupation. Young students have more free time than other pedestrians, and complete more return trips. Street characteristics also affect pedestrian behavior. Pedestrians in the central shopping areas of Busan and Fukuoka, where many shops are distributed in a rectangular shape make more trips than those in Tianjin, where shops are concentrated along a line. Compared with Fukuoka, pedestrians in the central shopping area of Busan, which has shorter links and a more densely distributed pattern of shops and vendors, make more return trips.

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12.1. Introduction

12.1.1. Background and Objectives

Especially in Europe, there has recently been a trend, of stimulating the use of public transport and the planning public spaces for pedestrians. These initiatives were triggered by environmental concerns and the policy of revitalizing inner city centers. For example, Gehl and Germzøe (2001, 2004) showed that public spaces were created in Copenhagen and in many other European cities. Also in Japan and East Asia, the development of public spaces in the central shopping area of a city for pedestrians has become an increasingly more important issue. Because such spaces are supposed to contribute to the revitalization of inner city areas, it is important to better understand pedestrian behavior in these areas. What are common aspects? What are differences between cities and to what extent are these differences associated with characteristics of the urban environment? Answers to such questions provide urban planners and designers with input to improve the quality of pedestrianized spaces. Work of this kind is still rather limited, especially in East Asia.

The objective of the study, reported in this chapter, therefore is to obtain basic knowledge about pedestrian behavior for creating pedestrians' spaces in central shopping areas of cities in East Asia. To that end, we analyze and compare data on pedestrian behavior in the central shopping areas of Fukuoka (Japan), Busan (South Korea), and Tianjin (China). These cities are located close together and therefore share some common variables such as temperatures and general weather conditions. On the other hand, these cities differ in terms of urban morphology and the nature of the pedestrian network, allowing the analyses of the association of urban morphology and pedestrian behavior, controlling for socio-demographic variables.

12.1.2. Methodology and Scope

In order to examine the interrelationships between aspects of pedestrian behavior, socio-demographic and urban characteristics, data on pedestrian behavior is required. In the present study, on-site interviews were used selecting pedestrians, who finished shopping, to collect data on their characteristics and the routes they followed when shopping. The survey method and modeling pedestrian movements were based on previous work of Borgers and Timmermans (1986a, 1986b). Only pedestrians who were leaving the city center were asked to complete the questionnaire. Each respondent was asked to mark on a map the route taken within the city center, the links of the network where they stopped, and the type of shop associated with each stop.

In urban planning, most original modeling of pedestrian movements in shopping areas was based on gravity models (e.g., Hagishima, Mitsuyoshi, & Kurose, 1987). The route choice component of the model was typically based on sequential shortest routes, assuming that pedestrians minimize distance between consecutive stops. It has been argued that this approach may be too simple and that pedestrians may

apply different temporal and spatial heuristics. A heuristic can be viewed as a rule which describes some principle underlying the choice behavior of pedestrians. For example van der Hagen, Borgers, and Timmermans (1991) differentiated between temporal heuristics and spatial heuristics. As for temporal heuristics, they distinguished the local-distance-minimizing (LDM) heuristic, the total-distance-minimizing (TDM) heuristic, and the global-distance-minimizing (GDM) heuristic. In terms of spatial heuristics, the LDM heuristic indicates that pedestrian choose the shortest route between consecutive stops. In contrast, the TDM heuristic is equivalent to the traveling salesman problem: pedestrian minimize the total distance traveled. The GDM heuristic is in-between, in the sense that a reordering of the sequence of stops would result in longer distances, but actual distance traveled is higher than the minimum total distance and sum of sequential shortest distances between successive stops. In terms of spatial heuristics, a distinction was made between the farthest-destination-oriented heuristic, and the nearest-destination-oriented heuristic. The first heuristic indicated that pedestrian first visit the destination farthest away from their entry point and then trace back, while the second heuristic suggest that they start with the nearest destination. This characterization was used by Kurose, Borgers, and Timmermans (2001) to classify pedestrians' behavior and then progressively move to the farthest destination (Kurose et al., 2001). This method was applied to analyze pedestrians who use both ground level sidewalks and also underground pedestrian ways in Fukuoka (Kurose, 2008). Note that this classification of route choice strategies is wider than that used in most studies, which often rely on simple distance minimizing strategies (e.g., Helbing, Molnár, Farkas, & Bolay, 2001; Kukla, Kerridge, Willis, & Hine, 2001; Kerridge, Hine, & Wigan, 2001), although more encompassing empirical models also exist (e.g., Daamen, 2004; Borgers & Timmermans, 2005; Antonini, Bierlaire, & Weber, 2006; Robin, Antonini, Bierlaire, & Cruz, 2009).

These principles underlying pedestrian behavior were also used in the present study. More specifically, we analyzed the features of pedestrian behavior, analyzing mainly trips in terms of trip length (not including the first leg from the entry point to the first destination), heuristics, and shortest routes. In addition, we investigated the relationship between pedestrians' characteristics and pedestrians' behavior, and between pedestrian behavior and physical conditions such as the road network pattern and the location pattern of shops along the street.

12.2. Study Areas

The study area chosen in Fukuoka, Japan is the Tenjin-Daimyo area which is surrounding Tenjin station of the Nishitetsu-Omuta line (Figure 12.1). This area contains many office buildings, big commercial facilities, and many small shops and restaurants. The area has two main subareas. Daimyo is situated on the western side of Nishi-douri. It is well known for its Masugata (Japanese traditional clunk type road pattern), and has many new shops for young people, often located in old

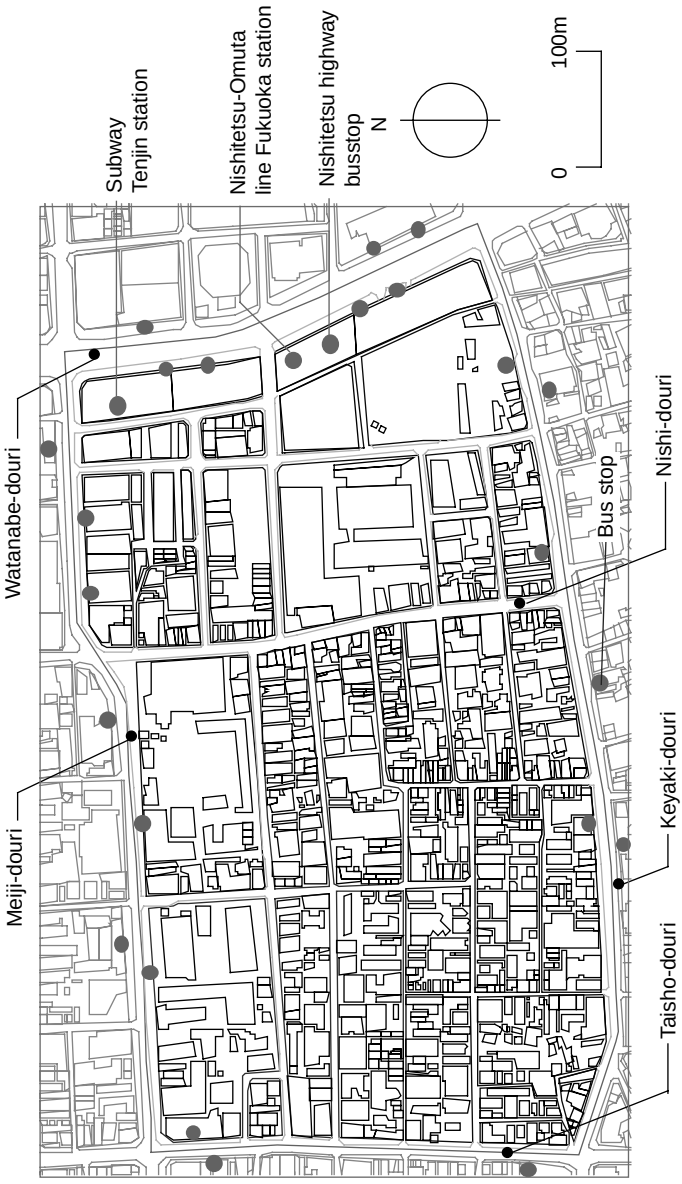


Figure 12.1: Tenjin-Daimyo area of Fukuoka (Japan).

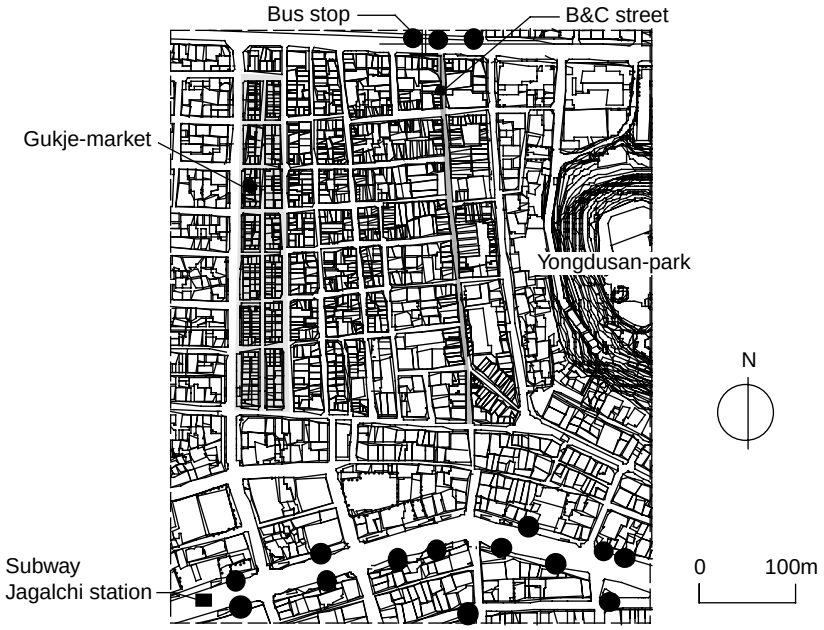


Figure 12.2: Nampo-dong area of Busan (Korea).

houses. The second subarea is Tenjin area on the eastern side of Nishi-douri, with the major department stores. The northern side of the study area has many high-rise office buildings. The area gives the impression of a big scale townscape. The total area is about 800 m long from east to west, and 450 m long from north to south. The area is surrounded by four wide streets: Meiji-douri, Taisho-douri, Keyaki-douri, and Watanabe-douri.

The central shopping area, selected in Busan, Korea, is called the Nampo-dong area. This area is bustling with many temporary shops and pedestrians (Figure 12.2). The area neighbors Jagalchi-market subway station on the south side, and Gukje-market on the west. It contains B&C-street which is favored by young people. The area is 350×450 m, and its road network has a grid pattern. The road density is very high, and many street vendor shops are doing business from 11 a.m. to 8 p.m. B&C-street is the center of these vendor shops.

Tianjin is one of four Chinese biggest national administrative cities, located on the ocean, east from Beijing. As a central shopping area, we chose a long pedestrian shopping mall, redeveloped in 2000 as a part of Tianjin international construction project. This shopping mall is the longest in China, and is called Heping-road and Binjiang-road. This area differs from the other two areas in that it is much larger in scale, and in that car traffic is prohibited (Figure 12.3). The study area is 2000×2050 m. In this mall, electric mini buses are operated. Only pedestrians and these buses can go through the mall.

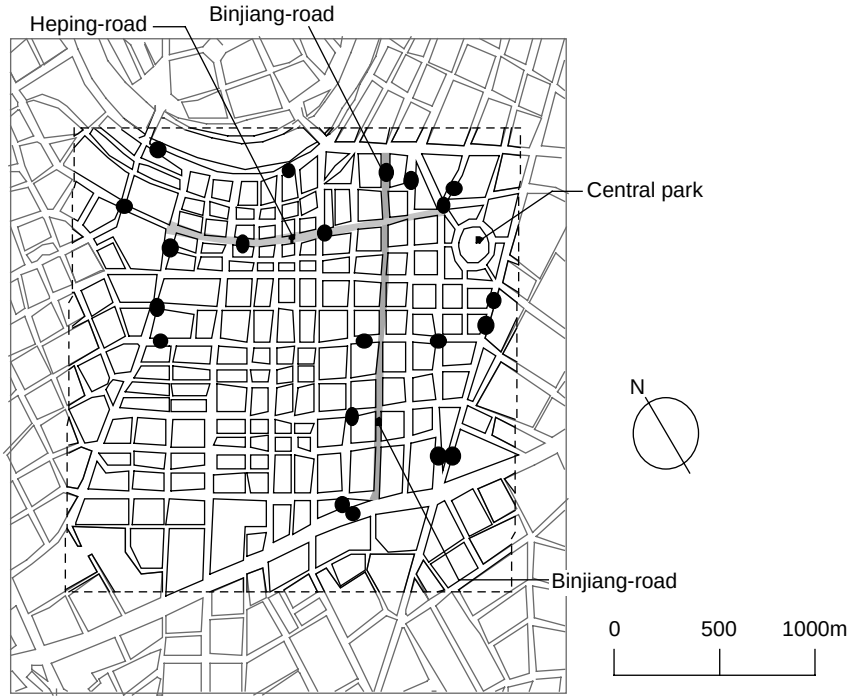


Figure 12.3: Heping-road and Binjiang-road area of Tianjin (China).

12.3. Pedestrian Behavior Survey

Pedestrians in Fukuoka were interviewed in October and November 2002. In Tianjin, they were interviewed in November 2002, while in Busan interviews were conducted in November 2003. Interviewers were instructed to sample pedestrians of every generation, but some rejected to be interviewed. It implies that the samples are not necessarily representative of the larger population of these cities. Weather conditions were similar in all cities: cloudy, sometimes with light rain. Pedestrians were interviewed when they had finished their shopping. They were interviewed at exit points such as bus stops, subway stations, and at the boundary of the survey area.

Pedestrians were invited to provide three types of information: (i) data about socio-demographic variables such as age, gender, occupation, and address; (ii) information about the trip and their behavior in general, including purpose, visiting frequency, previous planning of activities, etc., and (iii) data on routes and stop sequences indicated on the survey area map, and the duration of their stay in the survey area. Sample sizes obtained were 208 in Fukuoka, 80 samples in Busan, and 261 in Tianjin.

12.3.1. Pedestrian Characteristics

Figures 12.4–12.6 give an overview of sample characteristics. These figures show that most pedestrians are teens or people in their twenties. Most are students or company employees. They have much time to spend, and are physically strong. In addition to socio-demographic information, respondents also indicated whether their activities in the area were planned. Results indicated that many pedestrians in Tenjin-Daimyo area of Fukuoka previously planned the shops they intend to visit. In the Nampo-dong area of Busan, many pedestrians did not plan their trip at all, and a few pedestrians planned shops to visit (see Figure 12.6). It suggests that pedestrians in

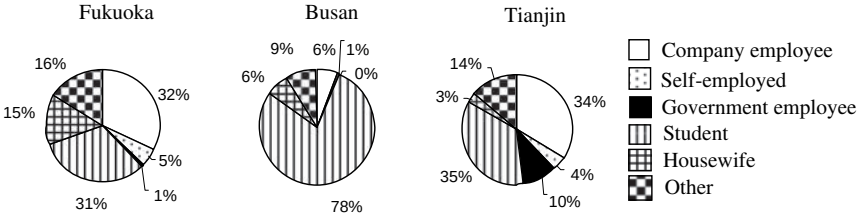


Figure 12.4: Distribution of occupations of pedestrians in each area.

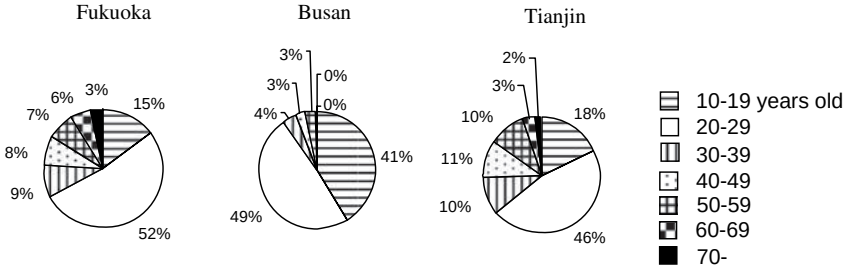


Figure 12.5: Age distribution of pedestrians in each area.

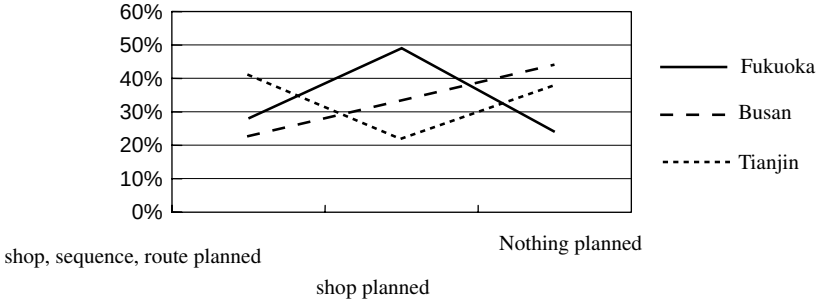


Figure 12.6: Previous planning of pedestrians in each area.

Busan are less anxious to plan their activities. In the Heping-road and Binjiang-road area of Tianjin, many pedestrians previously planned in the shops to visit, the sequence of visiting shops, and the route. The percentage of pedestrians who planned the full trip, that is, shops, the sequence of visiting shops, and the route choices, is 41%. This is the highest ratio for these three areas.

12.3.2. Features of Pedestrians' Routes

Figures 12.7–12.9 show the results of pedestrians' route choice decisions in each city based on intensity of link use. The routes of pedestrians in Fukuoka and Busan are distributed in a plane. On the other hand, the pedestrians' routes in Tianjin are concentrated in Heping-Road and Binjiang-Road, and show a T-shaped pattern.

Next, we divided the data into two types of pedestrians: pedestrians who visited stores and those who did not. Analyses were then conducted for each group separately. Figure 12.10 shows the ratio of pedestrians who stopped at shops. It is 96% in Busan, and 83% in Tianjin. In these two areas, the vast majority of pedestrians visited a store. This ratio was 74% for Fukuoka. It is low because of many pedestrians who changed public transportation mode in Fukuoka. These transfer pedestrians were included in this stage of the analysis; after this stage they were removed.

We also calculated mean trip lengths in each area. Table 12.1 shows that the mean trip length of pedestrians in Tianjin is the longest. In Tianjin, it is five times larger than in Busan, and four times larger than in Fukuoka.

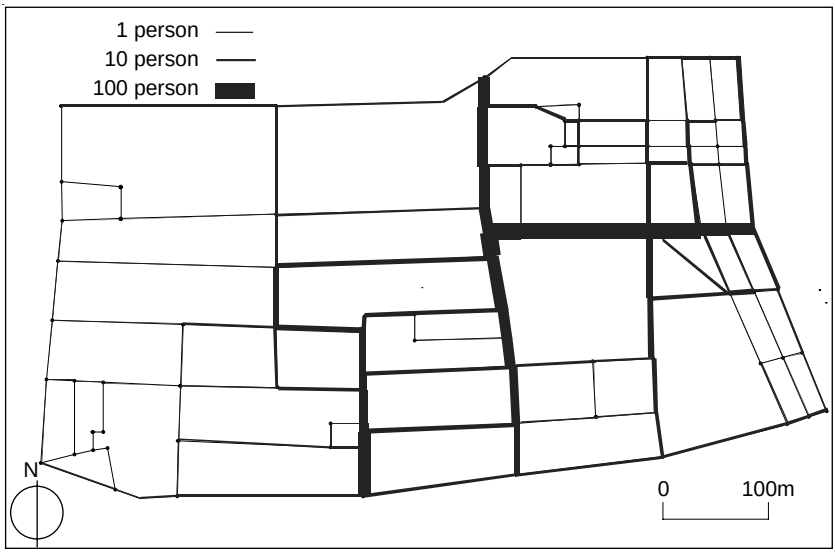


Figure 12.7: Pedestrian routes in Fukuoka.

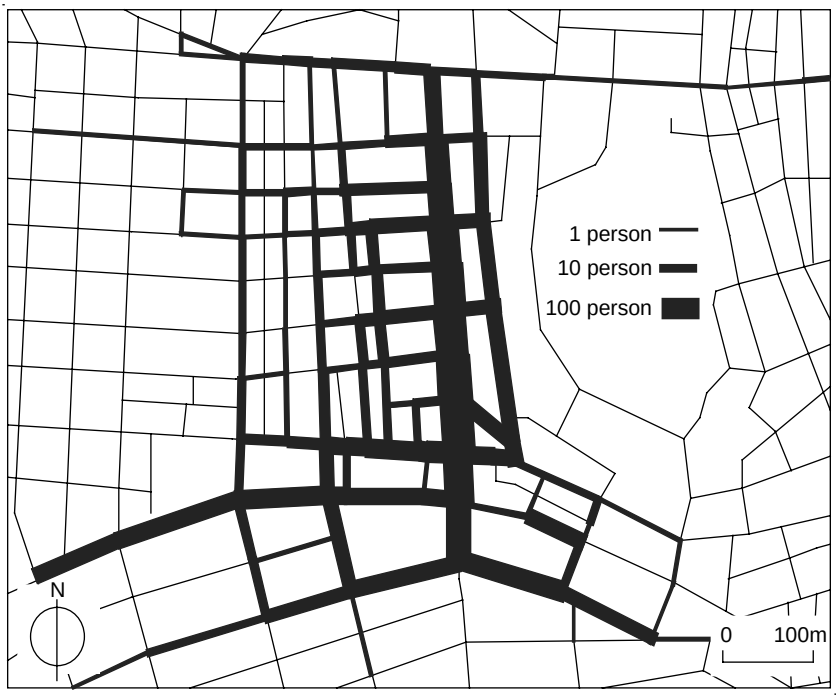


Figure 12.8: Pedestrian routes in Busan.

12.4. Data Analyses

12.4.1. Analyses by Heuristic Choice Rules

If a pedestrian uses the LDM heuristic, he/she uses the shortest route between two consecutive stops. If a pedestrian use the TDM heuristic, he/she moves along the network such as to minimize the total distance of the route. If a pedestrian use the GDM heuristic, he/she acts according to the same sequence as the TDM heuristic but the total distance is not minimized. The remaining cases cannot be classified according to any of these temporal heuristics.

Table 12.2 shows the mean trip lengths of each pattern of heuristic choice rules and area. It suggests that pedestrians not applying the LDM, TDM, or GDM indeed exhibit considerably longer trip lengths in every area. It might be true that pedestrians, who move by not using LDM, TDM, or GDM, make more return trips than other pedestrians do. In Fukuoka, the mean trip length for this group of pedestrians is 2.8 times longer than the mean trip length of those using the TDM heuristic.

The trip length of pedestrians applying the GDM heuristic, that is choosing the same sequence as implied by the TDM heuristics but using more distance, is 382.3 m longer than the mean trip length associated with the TDM heuristic in Fukuoka, 144.2 m longer in Busan, and 564.2 m longer in Tianjin. The shortness of links in the

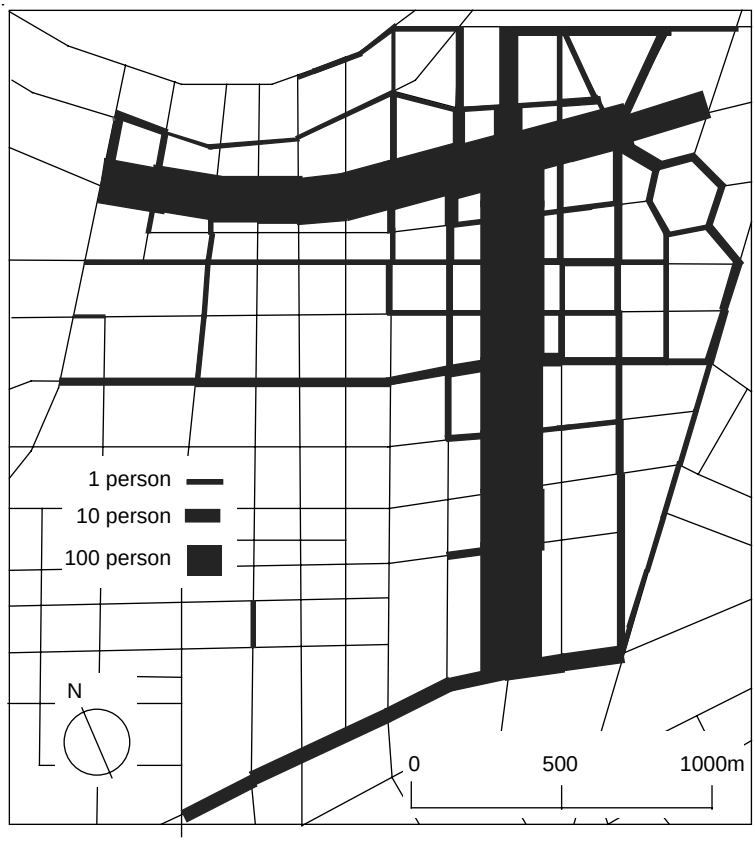


Figure 12.9: Pedestrian routes in Tianjin.

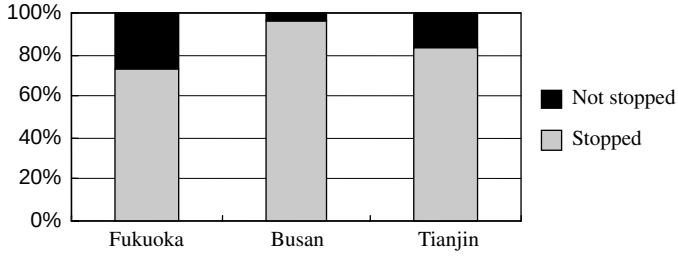


Figure 12.10: Stopping behavior of pedestrians in each area.

road network pattern of Busan might be the reason why this difference is smallest in Busan. Table 12.3 shows that in Busan the mean length of links is short. It may indicate that this area offers many opportunities to choose alternatives routes at every corner of the short links, allowing pedestrians to return back to the shortest route immediately.

Table 12.1: Mean trip length of each area in meters.

	Fukuoka	**Busan**	**Tianjin**
Average	824.5	1073.8	1744.3
Stopped	924.8	1010.5	1764.5
Not stopped	545.5	897.3	1396.4

Table 12.2: Mean trip length in meters of each area and heuristic.

	Fukuoka	**Busan**	**Tianjin**
LDM	500.4	892.4	1101.9
TDM	500.4	785.8	1101.9
GDM	882.7	930.0	1666.1
Not LDM, not TDM, not GDM	1414.6	1169.0	2859.9
GDM–TDM	382.3	144.2	564.2

Table 12.3: Mean length of links in meters in each area.

Fukuoka	68.3
Busan	43.9
Tianjin	110.1

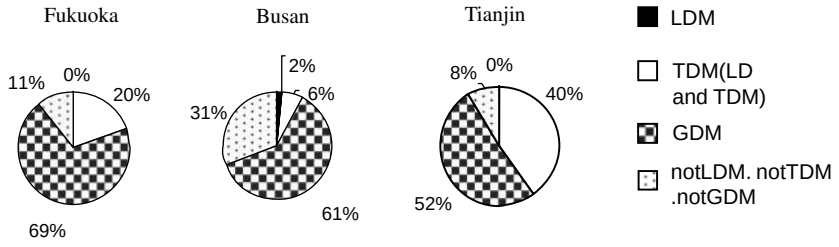


Figure 12.11: Heuristic rule patterns in each area.

According to Figure 12.11, the percentage of pedestrian applying the GDM heuristic is highest in Fukuoka (69%). In Busan, few pedestrians apply the TDM heuristic, and 92% do not use the shortest route. Even 31% cannot be classified in terms of either the LDM, TDM, or GDM heuristic. These facts suggest that in Busan some pedestrians make many return trips. Finally, in Tianjin, 40% of the pedestrian use the shortest route, and this is the highest of the three areas. Consequently, the

percentage of pedestrians not applying the LDM, TDM, or GDM heuristic is lowest. After all, Tianjin is the shopping area where pedestrians make less return trips.

12.4.2. Analysis on the Shortest Routes and the Chosen Routes

Next, we concentrated on the routes from the starting point to the exit point, and we calculated the proportion of pedestrians who take the shortest route. Note that the shortest route is the route implied by the TDM heuristic. Moreover, we calculated the degree of similarity between the chosen and the shortest route.

Figure 12.12 shows that the proportion of pedestrians who take the shortest route is the lowest in Fukuoka (7%). This proportion in Busan is 10%, whereas in Tianjin it is 40%. Thus, there is a significant difference between Tianjin and the other two cities. Next, for the pedestrians who did not take the shortest route, we calculated the degree of similarity between the chosen and shortest routes in terms of the number of common links between the chosen route and the route implied by the TDM heuristic. The mean percentage of common links between chosen and shortest route in each area is respectively 48.9% in Fukuoka, 58.6% in Busan, and 54.6% in Tianjin. It suggests that the similarity between the chosen and shortest route is higher in Busan than in Fukuoka.

12.4.3. Location of Stops

A final analysis concerned a classification of shops by the number of pedestrians who stopped there. The results shed light on why pedestrians did not choose the shortest route. Figures 12.13–12.15 plot the stops that pedestrians made. Figure 12.13 pertaining to Fukuoka illustrates that stops shops are scattered across the whole area. Consequently the spatial pattern of stops is dispersed and not very dense. In contrast, the distribution for Busan, represented by Figure 12.14 is concentrated in a small area near B&C-street. The pattern is very dense. However, in both these areas, stops are dispersed in a plane; the pattern is not linear. In Tianjin, on the other hand,

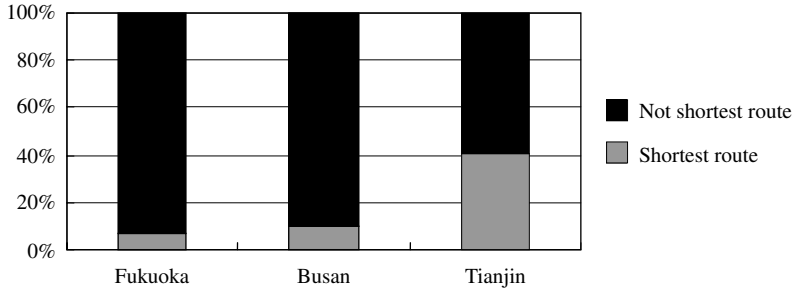


Figure 12.12: Ratio of the shortest routes chosen in each area.

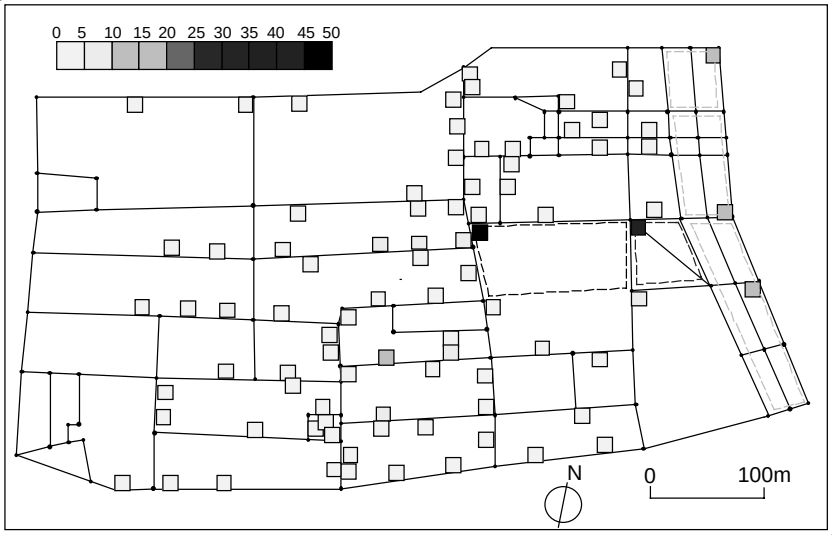


Figure 12.13: Distribution of stopped shops in Fukuoka.



Figure 12.14: Distribution of stopped shops in Busan.

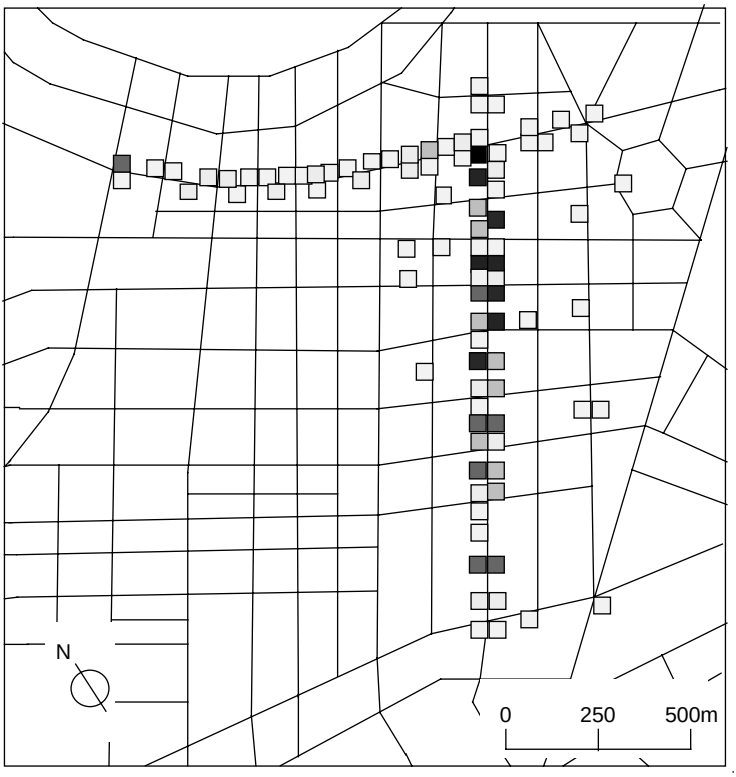


Figure 12.15: Distribution of stopped shops in Tianjin.

the spatial distribution of stops is concentrated according to a T-shaped pattern, and then pedestrians also move along this T-shaped route.

Both in Fukuoka and Busan, more than 90% pedestrians did not take the shortest routes, and it is a common feature of these two areas that stops are located along a line distributed across a plane. On the other hand, in Tianjin, stops are located along a line. This may suggest that if stops are dispersed in a plane, pedestrians make more return trips and do not take the shortest routes. If stops are located along a line, pedestrians make less return trips, and take the shortest routes.

12.5. Conclusions

In this paper, we investigated and analyzed pedestrians' behavior by using the data from the interview surveys collected in Fukuoka, Busan, and Tianjin. Obtained results are as follows:

(1) Pedestrians in Busan and Fukuoka make more return trips. On the other hand, pedestrians in Tianjin show the longest mean trip length because of the longest links and the large area, but pedestrians make less return trips.

(2) Compared with Fukuoka, pedestrians in Busan make more return trips because of short links and small width of streets bustling with many street vendor shops.

Thus, overall, it seems that there is a relationship between urban form and characteristics of pedestrian behavior. Destination choice and route choices seem primarily influenced by the utility that pedestrian derive from visiting certain destinations and choosing particular routes. However, the physical properties of urban form sometimes constrain the available choice options and more or less dictate pedestrians to exhibit a particular kind of behavior. Urban planners and designers should be aware of such relationships as their design will influence pedestrian movement and in turn trade-over in stores. A multi-agent model, incorporating these principles would be of interest and would make an innovative contribution to the literature.

References

Antonini, G., Bierlaire, M., & Weber, M. (2006). Discrete choice model of pedestrian walking behavior. *Transportation Research B*, *40*, 667–687.

Borgers, A. W. J., & Timmermans, H. J. P. (1986a). City centre entry points, store location patterns and pedestrian route choice behavior: A micro-level simulation model. *Socio-Economic Planning Sciences*, *20*, 25–31.

Borgers, A. W. J., & Timmermans, H. J. P. (1986b). A model of pedestrian route choice and the demand for retail facilities within inner-city shopping areas. *Geographic Analysis*, *18*, 115–128.

Borgers, A. W. J., & Timmermans, H. J. P. (2005). Modelling pedestrian behaviour in downtown shopping areas. Paper presented at the 10th International Conference on Computers in Urban Planning and Urban Management, London, UK.

Daamen, W. (2004). *Modelling passenger flows in public transport facilities*. Ph.D. thesis, TRAIL Research School, Delft.

Gehl, J., & Germzøe, L. (2001). *New city spaces*. Copenhagen: The Danish Architectural Press.

Gehl, J., & Germzøe, L. (2004). *Public spaces public life*. Copenhagen: The Danish Architectural Press & The Royal Danish Academy of Fine Arts School of Architecture Publishers.

Hagishima, S., Mitsuyoshi, K., & Kurose, S. (1987). Estimation of pedestrian shopping trips in a neighbourhood by using spatial interaction model. *Environment and Planning A*, *19*, 1139–1153.

Helbing, D., Molnár, P., Farkas, I. J., & Bolay, K. (2001). Self-organizing pedestrian movement. *Environment and Planning B*, *28*, 361–383.

Kerridge, J., Hine, J., & Wigan, M. (2001). Agent-based modeling of pedestrian movements: The questions that need to be asked and answered. *Environment and Planning B*, *28*, 327–341.

Kukla, R., Kerridge, J., Willis, A., & Hine, J. (2001). PEDFLOW: Development of an autonomous agent model of pedestrian flow. *Transportation Research Record*, *1774*, 11–17.

Kurose, S. (2008). A study on pedestrian behavior in the central shopping area with the underground shopping streets. *Proceedings of the 6th International Symposium on City Planning and Environmental Management in Asian Countries* (pp. 157–165).

Kurose, S., Borgers, A. W. J., & Timmermans, H. J. P. (2001). Classifying pedestrian shopping behavior according to implied heuristic choice rules. *Environment and Planning B*, *28*, 405–418.

Robin, Th., Antonini, G., Bierlaire, M., & Cruz, J. (2009). Specification, estimation and validation of a pedestrian walking behavior model. *Transportation Research B*, *43*, 36–56.

van der Hagen, X., Borgers, A. W. J., & Timmermans, H. J. P. (1991). Spatiotemporal sequencing processes of pedestrians in urban retail environments. *Papers in Regional Science*, *70*, 37–52.

Chapter 13

The Pedestrian Itinerary–Purposes, Environmental Factors and Path Decisions

John Zacharias

Abstract

Pedestrian itineraries can be conceived as flexible decision chains for movement through space. Decisions refer simultaneously to conceptualizations of the trip and the environment at different environmental scales. The purposeful or exploratory nature of the trip as well as early conceptualization of its execution impact on mode and path choice before the individual embarks on the trip. Decision points are decided *a priori* or are inserted into the itinerary as new information or events modify the set of opportunities available. At the scale of directional decisions and visit locations, information from the proximate environment acts on spatial behaviour decisions. The original trip purpose and subsequent modifications to the plan weigh significantly in how the individual draws information from the global scale of the walking environment and from the micro-scale of direction and activity decisions. The ambient environment weighs into decision-making consciously and in more automatic ways, but clearly plays a significant role in local walking environments. The transport and land use structure of the larger environment plays a preponderant role in spatial choices at the urban scale and when considering collective behaviour. At the finer scale of blocks and streets, different physicalist descriptions of the walking network layout relate significantly to local choices, as do sensory inputs and the social meanings. A review of the findings with regard to the formation of the itinerary is accompanied here with some illustrative analysis. The relative importance of these sets of factors as well as possible pathways between them is central in research on pedestrian itineraries.

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13.1. Introduction

This chapter is primarily concerned with a conceptualization of the pedestrian itinerary as means to organizing and understanding factors in itinerary decisions. The pedestrian itinerary is conceived as a decision and activity chain, in which certain environmental features have significant weight but where it is also likely that the whole has certain qualities not commensurable with micro-scale decision-making. The decision-making that accompanies the emergence of the pedestrian itinerary is dynamic and causal in nature (Alfonzo, 2005). The pedestrian trip, in contrast to motorized trips, generally involves more potential decision points, resulting in greater uncertainty in outcome and greater potential for impinging factors to impact on decision-making.

The focus on micro-scale, individual behaviour is necessary to help understand how individual decisions are chained and how the whole trip is conceptualized, then executed. While many pedestrian trips are short, purposeful and executable as planned, an important proportion of trips are sufficiently complex such that they cannot be entirely imagined before enactment when such predictability might be desired. The generally high levels of actual choice as well as the possibility of almost infinite variation in itinerary contrasts with the preponderance of shared itineraries in observed walking behaviour in specific environments. Potentially infinite complexity is thus reduced to limited sets of stochastic choices, prompting the enquiry into reasons for this shared decision-making. Since such choices are anchored in the physical environment, it is reasonable to presume that environment plays a significant role in formation of itineraries for certain purposes and at a certain scale.

While much attention has been focussed on the social, gendered and purpose-related aspects of walking trips, the physical environment has received much less attention, with exceptions as discussed here. Earlier reviews tend to show the importance of environmental factors in the literature, with broad characteristics or aggregate descriptions showing associations with the physical environment (Saelens, Sallis, & Frank, 2003). Overall, the environmental effects are important although varying in strength among environments and mediated notably by trip purpose. Causality remains an elusive target, however, so that specific measures taken in the environment cannot easily be related to observed increases in walking frequency and distance. The research tends to suggest that certain types of environments are supportive of walking while others host remarkably lower walking rates (Naess, 2006), but attempts at isolating specific variables in these outcomes have not produced large effects attributable to any one isolable factor. A bundle of likely factors in the physical realm cannot easily be decomposed, rendering difficult the transferability of outcomes from one environment to another and leaving unanswered fundamental questions about how we interact with the environment when we move about on foot.

Research supports the role of certain kinds of physical environment factors in walking behaviour outcomes. General layout of the walking environment, land use mix and transportation management are all evidently related to the great variation in walk frequency and distance observable across environments. The initial decision to walk is conditioned by an assessment of alternatives, such that variations in the accessibility, ease or cost of an alternative transport mode may easily inflect

positively on non-motorized trips (Brown, Werner, Amburgey, & Szalay, 2007; Loukopoulos, Jakobsson, Gärling, Schneider, & Fujii, 2004). Presumably, the subsequent enactment of the non-motorized trip could be conceptualized and evaluated to some degree at this initial stage of making the decision to walk, which suggests a decision-making structure at two levels.

The choice to walk in the first place over other available alternatives is dependent on contextual factors that ultimately give character to the collective walking behaviours of local populations. The range of trip purposes, frequency of walking trips and their eventual length can vary significantly between neighbouring localities, apparently because of important differences in urban form (Schwanen, Dijst, & Dieleman, 2004). Within such urban areas, variations in land use distributions and the layout of the public environment also result in varying participation levels in non-motorized transportation (Cervero & Duncan, 2003). In Asian cities where variations in land use distribution, block and street dimensions and density are generally greater than in the Occident, the observed variations in the selection of non-motorized modes are proportionally greater (Zacharias, 2005). In that study, local people made 250% more trips in one district than in another in the same city, after accounting for personal characteristics, while such walking trips were also 160% longer. The elasticities in walking frequency and distance for various purposes as a function of environment remains relatively undefined, but the collected evidence so far suggests a greater range of possible responses than expected, as seen in the following literature.

The general findings on the importance of urban form characteristics on pedestrian walking itineraries have focussed on issues of connectivity and to some extent metric properties of the walking network (An & Chen, 2007). The revealed relationship between walking rates on the one hand and higher connectivity and low distances between streets on the other seems to suggest that access and time economy prevail in pedestrian decision-making. While the findings support higher connectivity and low distances between streets, they do not exhaust the possibilities of urban form or the significance of other urban form characteristics such as variable geometries, curvilinear pathways and hierarchically organized space. Moreover, the observed deviation from such protocols in some environments suggests that there is more at work than mechanistic path minimization, though path minimization may in fact characterize some of the itineraries in a given setting.

This chapter is written with the intention of clarifying the role of purpose and scale in decisions within the pedestrian itinerary, and relating environmental factors to these decisions. The chapter begins with a conceptualization of the itinerary, as a function of purpose, in its global properties and at the micro-scale. The evidence giving form to these conceptualizations of itinerary, especially those that come from the proximate environment at the scale of walking itinerary, is discussed.

13.2. The Pedestrian Itinerary

In theory, the walking trip should be considered as a chain of decisions and actions, in recognition of the fact that decisions must be staged in time and space. Complex

trips involve too many phases to be comprehensible both in detail and as a connected system, leaving some decisions to points within the itinerary. Such decisions may be influenced by previous decisions, the experience *en route* and prospects for later experience. Unlike much other travel behaviour, decisions at certain points in the environment have multiple possibilities, more than one of which has no differential cost in time or energy expenditure. The relative volatility of such a choice environment makes it vulnerable to proximate influences, closely associated with the stream of experiences while the individual is in motion. For these reasons, a conceptualization of the pedestrian itinerary as a chain of actions and decisions also allows us to introduce uncertainty and thus stochastic process. While it is feasible to relate a large proportion of the variability in pedestrian behaviour to a limited set of factors, there remains a part of observed behaviours that remain unexplained.

For the purposes of understanding how the itinerary varies, it is necessary to consider three possibilities: travel with the goal of reaching a familiar destination, exploration with the purpose of returning to the point of origin and travel to a novel destination (Allen, 1999). The question is the extent to which the pedestrian draws information differentially from the environment as a function of these trip purposes. The next sections consider how each of these trip types impinges on choices.

13.3. Purposeful Itineraries

Shopping trips in the retailing literature are widely recognized as classifiable on a continuum of organization and purpose. At one end of this continuum, shoppers have definite purchase plans and destinations, tending to execute the plan without alteration. At the other end are sensation-seekers, for whom purchasing decisions are secondary if not irrelevant. In between are shoppers with general or specific visit plans, but who are also open to suggestion (Bloch, Ridgway, & Nelson, 1991). The initial decision to walk is contingent on plans and purposes determined *a priori*. It is also clear that the local environment at origin influences the decision to walk.

Shopping trips constitute a major part of the walking trips made by individuals. Some proportions of such trips are purposeful, that is, have specific visit plans and destinations (Bellenger, Robertson, & Greenberg, 1977). In a tracking study of 722 visitors to a shopping centre, 20% never entered a store, while a questionnaire applied to 283 visitors revealed that 30% were there for non-shopping purposes (Zacharias & Schinazi, 2003). However, even non-shopping visits acquire purposes and destinations as they unfold. In general, it is suggested that the pedestrian itinerary develops in three stages: selection of destination, route choice and impulse stops (Borgers & Timmermans, 1986). Walking to a single destination for a planned activity usually involves finding the fastest path or the one requiring the least physical and cognitive effort, moving towards the target without deviation and with reduced attention to the surrounding environment. In a shopping environment, visitors were observed to minimize their steps with respect to revealed destination, with regular protocols for direction change and moving around others (Bitgood & Dukes, 2006). Such utility-driven behaviours at the micro-scale do not hold up as well at the scale

of the larger walking environment, where distance minimization may be more difficult to achieve, or where other decision-making factors become salient (Gärling, 1988; Muraleetharan & Hagiwara, 2007). Multiple purpose trips cannot be so easily planned since it is often difficult to determine a minimal or least-effort path that minimizes the individual path segments between destinations (Säisä & Gärling, 1987). On the other hand, path minimization does describe well the itinerary as a whole, when it is a shopping trip. Exploring an environment for the first time cannot involve planning since little or nothing is known yet about the environment. Information must be gleaned at first hand and only a small part of the environment can be understood at one time. A cursory glance at the observed itineraries of purposeful and exploratory walkers illustrates the differences in behaviour. Travel to a novel destination involves planning the itinerary based on incomplete survey information with gaps completed through prior experience and derived apparent relationships.

Planned trips to known destinations call on stored information to support a planned itinerary. Stops and behaviour episodes may intervene, leading to path deviations and a completely revamped itinerary. Environmental attractors may induce the pedestrian to deviate from a minimized path. This intervention in the series of spatial decisions may explain why on some longer walking trips in local environments, pedestrians will opt for a path that is substantially longer than the minimal-distance one (Muraleetharan & Hagiwara, 2007). Pedestrians can alter their itineraries to respond to opportunities, collective decision-making and new objectives for the itinerary.

For planned trips to novel destinations, greater levels of uncertainty lead to more decision-making *en route* to destination. The pedestrian must scan the environment for available clues with regard to the apparent, inherent advantages of various choices for the presumed but unknown destination.

A second major category of purposeful trips involves travel to public transport. There are utilities associated with various forms of transit that predispose users to extend or shorten their walking trip. Walking distance to rail-based transit is proving to be greater in many cases than the planning standards suggest (Canepa, 2007; Alashalalfah & Shalaby, 2007; O'Sullivan & Morrall, 1996), while bus transit may generate as little as half the walking distance to rail. In the suburban example in Calgary (O'Sullivan & Morrall, 1996), the 75th percentile of walks to light rail transit (LRT) stations generated a pedestrian environment of 2.2 km^2. The substantial variation in the extent of the walking environment is evidently related to environmental qualities that can be quantified. For example, the selection of public transport, and in particular bus, over private motorized transport alternatives was positively associated with the presence of sidewalks in local areas in a study in the eastern US (Rodríguez & Joo, 2004).

The general search for physical parameters supportive of walking frequency and distance are often grouped under the term transport-oriented development (TOD). Measures known to extend walking distances and frequency include a clearly marked, continuous pathway with a high-quality destination (Sugiyama, Ward Thompson, & Alves, 2008). Shaded and sheltered pathways, seating provisions and

more elaborate pedestrian crossings of motorized traffic all result in significant increases on both scores.

Of course, the question remains just how far people can be induced to walk to public transport. The measured distances vary substantially and generally exceed the usual planning standards. The elasticities in these walking itineraries suggest that local design efforts may have substantial effects in terms of walk frequency, but it remains unknown just how far people will be willing to walk, when the ultimate goal is public transport (Schlossberg & Brown, 2004). The impact of facilities supporting a multiple purpose trip as well as the impact of environmental enhancements of various kinds on walk distance have not been explored to a significant extent. The need to isolate such interventions in order to measure effect makes necessary before–after studies and multiple cases with identical study protocols.

To this extent, then, the pedestrian itinerary incorporates a relative mix of pre-determined spatial decisions in series with modifications in the specific series of choices occurring as a consequence of new information. That new information may adjust the relative value of stored choices or an unforeseen and superior alternative behaviour. The susceptibility of the individual to such stimulus may account for much of the behavioural difference but pre-disposition by pre-assigned trip purpose appears to account for a substantial part of the variance in such walking trips locally. For example, the walking itineraries of locals and visitors could easily be distinguished in the tracked trips within an indoor market, presented below. The unbounded nature of many tourist itineraries lends them characteristic complexity, the consequence of many successive decisions.

In the main, it seems likely that spatial behaviour varies as a consequence of the purposes and intentions of the pedestrian.

13.4. Exploratory Itineraries

Exploratory trips have no planned destinations for which the movement itinerary is merely the means to the end, although destinations may present themselves *en route*. Exploration implies openness to environmental stimulus, although there is no clear demarcation between exploratory trips and those with pre-ordained but unknown destinations. Rather, the relative importance of environmental stimulus will vary according to the purpose-related or exploratory nature of the trip. First-time visits to novel environments without cartographic aids and without a specific agenda — the presumed conditions surrounding the leisure travel experience — constitute the most exploratory and least structured itinerary on its initial launch. But of course, the insertion of destinations and choices, some of which begin to constitute a structure of chained experiences, inevitably condition later decisions. The extent to which these chained experiences do impact subsequent choices is not well explored in the literature, however, but such impacts are widely assumed to exist.

It seems highly likely that various anticipated trip segments have been conceived in relation to each other, since there are benefits and costs to combinations of segment choices independent of those associated with individual segments. Repeated,

voluntary trips are of this kind. For example, in a study of trips to the public market, visitors often prepared a complex travel itinerary involving others to the market location, including economies of various sorts along the way, most of which could be assumed to be repetitive and proven, given the frequency of visits to the location (Zacharias, 1997). Collected itineraries within the market varied significantly by entry point, however, prompting the inference that the trips were constituted, at least in part, while being enacted.

The hypothesis of serial vision impacting on the series of spatial decisions is based on an information-processing model of environmental experience. Theories to explain such successive choices are developing slowly, perhaps because it remains challenging to distinguish whether it is as the consequence of an emerging cognitive map for which spatial decisions serve a purpose in place and time, or whether planned itineraries suggest the succession of decisions.

Walking pathway layout, dimensions and design characteristics have substantial impact on evaluations of the walking environment (van der Waerden, Borgers, & Timmermans, 2007). Path choices in virtual environments also strongly suggest the importance of these physical characteristics of the local, visible environment (Matsumoto, Koyanagi, & Seta, 1997; Kent, 1989). For example, pathways with more complex structure, curves and multiple outlets tend to be preferred over simple, orthogonal layouts with limited further choices. Hidden outcomes and visual clues for anticipated walking experiences are also attractive, along with upward sloping pathways, at least in virtual environments. Such preferences for stimulation in virtual environments and those represented by photographic surveys may also carry over into real settings where other factors, including physical effort may moderate such choices. For example, habitual recreational walking behaviours of elders in their local environments showed a marked tendency to choose routes offering topographical and visual variation, with path or effort minimization playing a minor role (Joseph & Zimring, 2007). The routes chosen were generally centrally located in the walking system and were well connected with the surrounding environment. The inherent interest of the landscape was a significant motivation for the executed recreational walking trip. It is apparent that the search for visual interest and stimulation is fundamental in many walking trips with recreational and exploratory purposes. It is also evident that the search for novel experience is a primary motivation for trip execution, which by definition, cannot be planned in advance. In the virtual visit to Montpellier, France (Zacharias, 2001a), visitors tended to avoid repeating trips once they had experienced certain pathways, suggesting the impact of environmental learning on decision-making and the drive to acquire more knowledge of the environment.

Preponderant in the choices of these visitors to a virtual environment were the presence of signs of human activity — number of people in the view, the number of signs, awnings and moveable planters. In that study, the preferred path choices were altered to remove signs of human activity, which were then inserted in those views of path choices that were least preferred. There was a shift in preference from the most preferred toward the least preferred as a result of removing and adding respectively the signs of human activity (Zacharias, 2001a). In a follow-up test the original photos

representing the path choices were again modified to see whether certain architectural features also inflected choices.

The visual relationship between the building walls lining the pathway and the walking surface has long intrigued designers, prompting a variety of design theories and practices. In the follow-up study on path choices in Montpellier, 6 of the 13 choice sets were modified this time by narrowing the street digitally. All individuals, signs, planters and awnings were retained in the altered images. The most preferred path choices were narrowed, suggesting a high aspect ratio, or ratio between the height of the bounding walls and the width of the pathway. Least preferred pathways were altered by widening the pathway and reducing the number of floors in the buildings bounding the pathway (Figure 13.1).

A new group of 45 participants made choices according to the protocol of the original experiment. Five of the six intersections showed no change in pathway preference. A sixth intersection did reveal a significant shift to another path choice, but not the choice where a broader pathway was digitally created. In this choice set, the most preferred choice was bounded by a treed park, which was digitally built up with a solid row of buildings. It can be concluded that altering the apparent relationship between the dimensions of the buildings and the open space had no impact on the choices made by the participants, when all else was retained. What is clear is that the impact of human activity on path choices was much greater than the represented architectural variations, although the operative range of the variables was undoubtedly important in this outcome. This result contrasts with that of Wang and Seo (2008) and Herzog and Flynn-Smith (2001) where a wider walking pathway and more open sky were preferred over the alternatives.

While aspect ratio may have minor effect, other candidate variables remain relatively unexplored, including the effect of level changes and enclosure on path choice. Understanding the frictional effect of unaided and mechanically aided climb on pedestrian choices is much in demand for the planning of transport termini and other multiple level pedestrian environments.

The bulk of the reported experimental data on reference systems for pedestrians suggest that pedestrians have an egocentric reference system with the reference direction straight ahead. If enough of the environment is visible, they will see various structures and features in plan and in depth to enable a volumetric understanding of the visible environment, through which a straight trajectory can easily be imagined and executed. If only a close view is permitted, then the pedestrian must rely on dead reckoning, compensating for deviations. The micro-scale evidence from psychology is replicated in urban-scale environments. When asked to traverse an environment, pedestrians executing a virtual trip through an artificial environment tended to follow a simple line biased to forward movement (Conroy Dalton, 2003). The relative precision of the straight-line trajectories through a non-orthogonal grid appears to support the thesis that the movement impulses of participants is largely directional in nature, with a bearing determined at the point of origin. Movements may involve many minor adjustments in heading but deviations are minor when compared with potential deviations in this virtual walking network. This tendency to find what appears to be a direct route leads to many diagonal trajectories in the urban



Figure 13.1: In Zacharias (2001a), signs of human activity were added (a2) to least preferred path choices (a1). In Zacharias (2001b), the open space was reduced (b2) on preferred path choices (b1).

environment which, it has been suggested, are a means to reduce traversed distance and maintain a sense of direction (Khisty, 1990).

The itineraries of people relatively unfamiliar with the layout of the local environment display affinities and differences with respect to the itineraries of habitual visitors. The literature suggests that people will follow others, being attracted to public presence in general. Of course, a major part of human presence is a consequence of the organization of the environment but also for certain individuals or certain situations an instantaneous response to an impinging factor introduced at a particular time and place. Human presence alone would conger up a multiplicity of choices, which is particularly useful in a purposeful search, while also maintaining high levels of choice. Ultimately in an open search maximizing the size of the choice set describes an optimal search strategy if the fundamental motivation is level of choice.

People familiar with the local walking environment are effecting repeated itineraries with relatively fixed spatial itineraries or purposeful visits without fixed spatial itineraries. While the difference may be discernible in investigations of trip-planning protocols, these various purposes also appear in the detailed tracks of pedestrians. Micro-scale spatial behaviour displays varying interest in local attractions, in adherence to efficient movement and in attention to other persons.

The configurational properties of walking itineraries are evidently related to the configurational properties of the physical environment, although they seldom map one over the other in entirely understandable ways. At the same time, the level of complexity of the itinerary also varies substantially within the same set of trips. Some of this variation appears to relate to the trip purpose; for example, preplanned trips with a single destination and purpose are more likely to be executed as a simple, direct trajectory to destination with a return along the same path. Exploratory trips tend to be more complex in configuration because they must be by definition to some extent experimental. These variations can easily be detected in the pedestrian itineraries collected in a festival market, with 72 itineraries (Figure 13.2a) and one fairly complex itinerary (Figure 13.2b). The preponderance of paths coalesce around a handful of walking segments within the market. Moreover, these paths are tributary of choices at key points, which in this case consist of the lobbies inside the main doors where vertical circulation and a choice of pathways at the same level are grouped together. Such varied visits nevertheless tend to be played out in the same places within this particular setting for popular consumption. More complex itineraries did not tend to "fill in" those spaces less visited by the majority of visitors on a mission or quickly passing through (Zacharias, 1993).

The shape made by the collected paths of pedestrians in environments will vary more significantly between environments than within one environment. Within one environment, the great majority of itineraries can be reduced to a handful of distinct shapes, when metric distance is suppressed and only turn radius is considered. Consider the collected tracks from three studies ($n = 155$, 74, and 250) and their categorization by path shape. The observation that the vast majority of itineraries in large, popular public places with many choices of pathway reduce to a small set of simple shapes (Zacharias, 1997) stems possibly from the cognitive need to

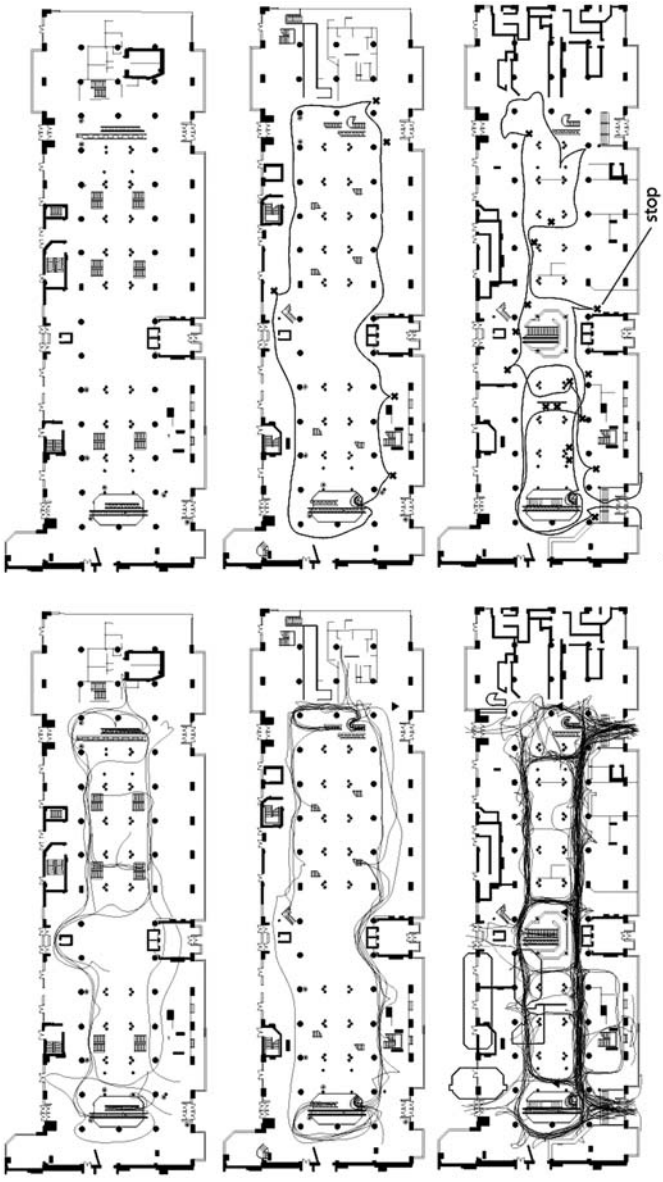


Figure 13.2: In the tracking study in the festival market in Montréal, the cumulative patterns of tracked visitors acquired particular form (a), although individual itineraries might be highly complex with multiple stops (b).

remember the way (Conroy Dalton, 2003), shared preferences at key decision points and the preponderance of simple, single-destination trips for the majority of visitors. It seems likely that all three reasons may operate simultaneously, although perhaps not for all individuals. By reducing itineraries to path shapes according to directional decisions at choice points, metric aspects are suppressed, while characteristic manoeuvres can be observed, even if they do not map precisely onto the same spaces. With categories as unique shapes, the frequency distribution across the three tracking studies shows a preponderance of a handful of unique trajectories in urban space (Figure 13.3).

High levels of agreement about particular pathways to choose as well as agreement in the overall configuration of the itinerary are suggestive of general agreement in the approach to the trip, evaluation of its possibilities and finally, its execution. Whether the mechanism underlying this pattern of movement is largely one at the scale of the walking environment or whether it is an outcome of a preponderance of micro-scale decisions remains to be determined.

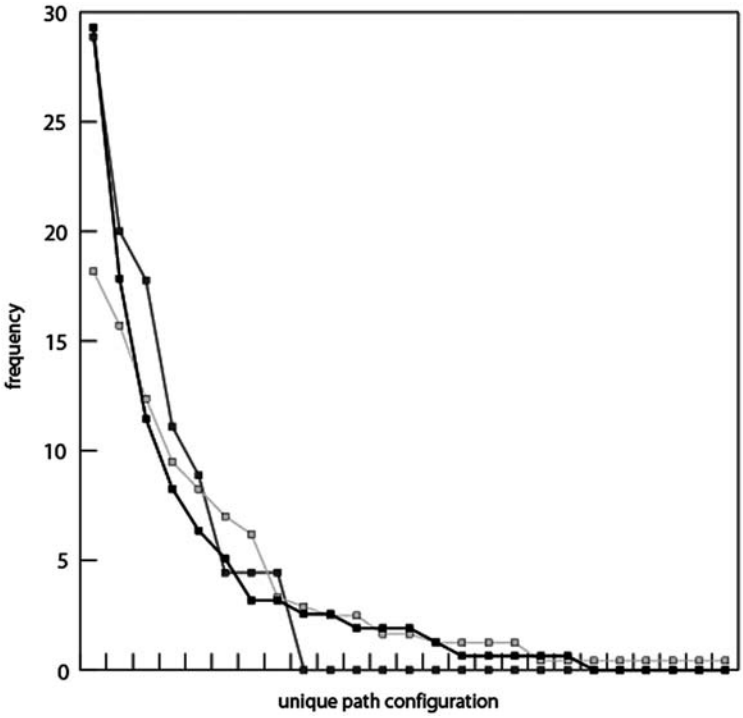


Figure 13.3: The frequency distribution of unique configurations of walking itineraries in three environments shows that a high proportion of trips can be described by a small number of unique spatial configurations across environments of varying complexity.

13.5. Environmental Factors in Walking

This section looks in more detail at the various components of the walking environment that impinge on pedestrian spatial behaviour and attempts to put them in relation to each other. Before the individual components are examined through the research literature, general effects of environmental factors on behaviour are presented. In particular, we examine the effect of facilities on walking, the effect of reduced access by car on walking trips and land use relationships as support for the walking environment.

Urban design measures at the urban scale including improving connectivity of the pathway network and linking walking systems to daily activities have proven positive effects on walking rates overall (Southworth, 2005; Rodríguez & Joo, 2004). As rates vary so do the proportions given to various purposes and the organization of modes of travel to carry out those purposes. Those most dependent on non-motorized modes are particularly sensitive to conditions on offer. The provision or absence of appropriate supportive facilities have corresponding consequences on distances traversed and the frequency of such trips (Sugiyama et al., 2008). Suitable destinations are needed and at intervals to extend the walking trips and complete the network. But in general it is easier to enhance walking conditions for a specific pathway or segment, while the constitution of a wider network of suitable pathways and destinations is more difficult although certain to deliver more substantial results.

Alterations to the traffic environment have important effects on the presence and movement behaviour of pedestrians. Appleyard (1981) among others showed early on that greater traffic volume was associated with fewer pedestrian trips and less sociability. The car-removal and car-traffic reduction schemes of the 1970s in Europe were shown in the 1980s to have resulted in increased pedestrian traffic in those projects (Bentham & Haynes, 1985; Weisbrod, 1982). In the Boston case, pedestrian traffic and retail sales increased respectively 11% and 26% two years after the traffic measures, in a downtown area with a captive worker population (Weisbrod, 1982). That case, along with others (e.g. Guo, Bhat, & Copperman, 2007) show that modal split can be substantially altered through land use, design and traffic management at the local level; namely, for the purposes of reducing the automobile portion of travel to such locations.

In more walking-oriented environments, are non-motorized trips different than those where there is a higher motor share? Researchers have asked whether motorized trips are substitutable with pedestrian trips. A strong suggestion in the literature is that increased pedestrian trips in local environments are associated with voluntary activity. The evidence for substitutability of auto-based trips points in both directions. For example, Handy suggests that some local driving trips are replaced with walking when the environment is sufficiently supportive (1996). Cervero and Radisch (1996) also found that some residents substituted a walking trip to a local service or store for an automobile trip. On the other hand, Guo et al. (2007) show that motorized trips are not reduced when the local environment has features associated with more non-motorized trips. However, the evidence cannot be

considered definitive because the environments themselves may not allow the exercise of choice, due to distance and density limitations in many of the published cases.

On the other hand, certain physical characteristics of local environments predispose local people to make more pedestrian trips, often of short duration and with multiple purposes. Mixed land uses, more sidewalks and a well-connected walking environment tend to raise pedestrian numbers overall (Schlossberg & Brown, 2004; Vernez-Moudon, Hess, Snyder, & Stanilov, 1997; Shriver, 1997). In the San Francisco Bay area, street layout patterns and land use mix accounted for 21% of the variance in the choice to walk or bicycle (Cervero & Duncan, 2003). Such environments produce substantially different kinds of trips than those without these pedestrian-oriented characteristics. For example, Saelens, Sallis, Black, and Chen (2003) showed that neighbourhoods with higher residential density, land use mix and street connectivity also had substantially higher levels of walking, even after controlling for income, educational level and ethnicity. Higher levels of walking were also seen related to density and land use mix in Atlanta (Frank, Andresen, & Schmid, 2004).

At the individual choice level it is also seen that pedestrians tend to choose pathways that have more generous and better quality pedestrian provisions, even if such choices are not the most time-efficient (Muraleetharan & Hagiwara, 2007). For very short trips, time is more important than pedestrian provision. But other factors of the walking experience also affect path choice. Path obstructions and long waits for the green cycle at intersections militate in favour of other pathways. Heavy pedestrian traffic, such that usual walking speed is reduced, and car-traffic crossing through the pedestrian traffic militate in favour of less travelled pathways and those without intermodal conflicts. In environments with those features of supportive pedestrian design, overall urban density and multiple land uses, walking distance is increased, although it remains to sort out the specific factors leading to extended walking trips (Greenwald & Boarnet, 2001). Aesthetic qualities also tend to increase the walking distance within such environments (Canepa, 2007), strongly suggestive of the elasticities in time and distance latent in many pedestrian itineraries.

13.6. Connectivity and Centrality

Because of the serial nature of pedestrian path choices and statistical probability of certain pathways capturing higher levels of pedestrian traffic, all else equal, it has been reasoned that such preferences and statistical choices could be decoded from a reading of layout. Layout factors thought to lead this statistical choice include connectivity, centrality, directionality and metricity.

A highly connected walking environment offers potential variations in itinerary. A connected environment also demands more choices and greater cognitive awareness to execute those choices. In the bulk of the empirical studies walks tend to take a central trajectory through a highly connected and extensive walking network. In a study of a complex, indoor walking environment, longer, more central and highly connected corridors tended to be adopted (Haq & Zimring, 2003). Such corridors

coincidentally harboured more choice points. Moreover, all else equal, such a walking strategy for entering an environment offers the greatest likelihood of achieving the shortest possible path. It seems likely the considerations that do enter play are several, though their relative importance is uncertain.

Models for measuring pathway centrality have as their purpose the prediction of collective pedestrian choices. A topological representation of the environment with pathway centrality (Hillier & Hansen, 1984) has been augmented for metric distance (Salheen & Forsyth, 2001), for visibility analysis (Turner & Penn, 2002), and for standardized coding of the environment (Batty & Rana, 2004). Such systematic coding of the environment in graph-theoretic terms has produced variance in pedestrian presence and pedestrian volume-flow varying from less than 10% to nearly half. Local factors not yet considered in these spatial models, including structural aspects of the larger transport system and retrenched land uses may explain the substantial variation in the performance of these spatial models.

While most of the studies have involved volume counts, from which movement patterns can be deduced approximately, tracking studies also reveal that individuals make certain spatial decisions at the micro-scale consistent with the observations of collective movement (Zacharias, Bernhardt, & de Montigny, 2005). In the cited tracking study in a shopping centre, there was a strong tendency to move towards a central location in the shopping centre even when the trip was purposeful and destination-bound.

In real environments, more than path centrality is at play in the distribution of walks because of spatially recursive processes. Central, connected spaces acquire uses that best exploit high levels of accessibility, their presence then generating increased flow. Alternate routes acquire properties that not only differentiate them but also structure a permanent relationship of uses and linkages.

13.7. Path Geometry

People exhibit a strong tendency to move forward once engaged in that movement. From the point of view of task, it is much easier to maintain the course than to turn, re-orient and search for useful information in a scene not yet viewed. The tendency to change directions diminishes as angular change increases at the choice point, leading to strong biases for forward movement, all other things equal. At least some part of the walking experience, for all but the most simple and planned, involve impulse movement behaviour that can be described as continuous, chained and systematic, with few instances of sharp changes in direction or plan.

The tendency to move forward has been seen in several studies in different environments. In a virtual navigation task through an artificial urban environment, there was a marked tendency to strike a straight course launched from the initial directional impulse (Conroy Dalton, 2003). This pattern of splitting the space by striking a heading is also observed in tracking in a real environment. For example, a centrally located pathway was also selected for a given trajectory that provided an overall direction that also constituted a bearing with minimal change from current

bearing (Chang, 2002). For example, more peripheral pathways with regard to this bearing, even though of the same length or even shorter receive fewer visits. This result may be related to a cognitive image of the potential space where a bisecting pathway clearly offers the greatest opportunity for understanding and exploiting the possibilities inherent in that walking environment. A peripheral path also entails diverting from a straight-ahead protocol, and thus a necessary greater shift in direction. Large angular shifts in direction are difficult to encode. Also, an apparently peripheral pathway offers fewer insights into the local walking environment. In a setting dominated by commuting trips by regular visitors, it was observed that most chose centrally located pathways which were not always shorter than alternative, less central pathways (Chang, 2002). In that same elevated walkway setting in London, visitors apparently joined the trajectories of habitual travellers.

To navigate effectively in an urban setting one must have a certain level of survey knowledge — remembered straight-line distances and spatial angles connecting behaviourally relevant landmarks — that may be acquired with relative facility depending on the challenges faced by the environment or the computational abilities of individual persons. The greater challenges posed by variably angled environments over orthogonal ones (Sadalla & Montello, 1989) may oblige the person to simplify or "regularize" the perceived environment. The ability to capture mentally the dominant spatial relationships in the local environment undoubtedly introduce a more complex, relational understanding of the spatial decisions required, whereas rudimentary knowledge of the local environment is more liable to result in simple approximations and heuristics to derive decisions that best respond to a defined purpose.

It has long been observed that people prefer wider pathways in the absence of other meanings that might attach to choices (Herzog & Flynn-Smith, 2001; Zacharias, 1998). Spaciousness may be a fundamental characteristic desired by pedestrians, although it is also likely that certain meanings attach to spatial dimensions, including the importance of the pathway in the network. The assessment of a pathway, when memory of it is not available, includes an association between its dimensional and configurational properties on the one hand and the potential for certain activities, levels of safety and comfort on the other (Herzog & Flynn-Smith, 2001), although the desire for enclosure may be a competing motivation in path choice. While it is possible that such metric preference refers to atavistic memory, meanings derived from context have obvious influence when, as in the cited examples above, the study environments consist of open space, urban alleys or shops. Since wider pathways offer less hidden information than narrower ones, such preference does not seem to align with the revealed preference for complexity and hidden outcomes in the walking environment.

Finally, the itinerary trajectory is preceded by an assessment of the channel for movement resulting in generally curvilinear paths of least resistance, although such paths are often encased in architectural forms that little resemble the shape of movement. A research effort on the effective width of designated pedestrian channels, the negotiation of barriers and the dynamics of movement interchange mark the recent effort to understand how pedestrian spatial behaviour intersects with architectural frames.

13.8. Walking Environment Aesthetics

Relatively little research has investigated how perceptions of the local walking environment impact on pedestrian behaviour, although some inferences might be drawn from stated preference studies for these environments. Pedestrians can easily make qualitative judgements about an environment's attraction for walking (Isaacs, 2000), which may translate into more or less walking in those variously evaluated urban landscapes. A review of research on the importance of aesthetics in walking decisions shows that the role of aesthetics is contingent on the walk purpose (Owen, Humpel, Leslie, Bauman, & Sallis, 2004). For example, general aesthetic appreciation of the landscape was strongly associated with recreational walking in self-reports on motivational factors in walking, but not in purposeful trips to known destinations. Aesthetic experience is an integral part of the recreational trip, but may play a more subliminal role in spatial behaviour with ostensibly non-recreational purposes.

Muraleetharan and Hagiwara (2007) did find that pedestrians selected pathways that they found more pleasant to walk, even though this meant a somewhat longer trip altogether. In that case study in Sapporo, Japan, it was seen that on average pedestrians' paths were 1.21 the length of the shortest and quickest path. A similar result obtained in Australia where it was found that pedestrians tended to walk longer when they judged the streets to be of high quality (Giles-Corti & Donovan, 2003).

Such individual responses and expressed preferences with regard to enhanced environmental qualities are observable at the urban scale, where collective preference finds expression in the generalized movement pattern. For example, the presence of street trees and small commercial buildings accounted for about 31% of the variance in pedestrian presence in streets in Lille (Foltête & Piombini, 2007). In that study, layout topology accounted for 25% of the variance in pedestrian presence. To a certain extent, such citywide distributions of pedestrian trips also expresses the degree to which pedestrian trips are voluntary and spontaneously arranged. The research so far into urban aesthetic preference suggests the simultaneous operation of multiple variables that span scales, environments and purposes. Preferences for spatial and volumetric relationships, visual content, greenery and public animation, while all candidates for general agreement among individuals, are likely to remain a vast range of feature combinations.

The aesthetics of the walking environment need to be understood in dynamic terms, which implies that aesthetic evaluations on particular aspects of space will comprise the sum of an accumulation of percepts. Such aesthetic response is fundamentally the modalities of sensory experience (Moles, 1973). Sensory experiences relate directly to their objects but also have multiple pathways among them, notably within and between the senses. As a consequence, it is a major challenge to separate out aesthetic responses ranging across the senses. It may be impossible to separate out, for example, aesthetic response to the built form landscape from response to the culture that inhabits it. Therefore, how such responses combine is of interest in the study of aesthetic response to the walking environment.

Pedestrians are exposed to multiple sensory inputs at close range during their walks, prompting a subliminal response, which may enter consciousness if the

experience is consequential. Landscape qualities prompt memory and relevant associations, contributing to affect and finally to evaluations of the walking environment. Lynch (1980) demonstrated early on that pedestrians are attentive to minute details of the walking environment and especially those elements that are very close at hand. Such accumulated perceptions can be related to physical features of the environment and ultimately to affect (Brown et al., 2007; Sheets & Manzer, 1991; Herzog & Flynn-Smith, 2001). Components of affect that link directly with the sensorial content of the walking path include feelings of comfort, aesthetic pleasure, impressions of social control and arousal, including apprehended danger. Maintenance and cleanliness will also link to an overall impression of societal values with respect to the specific walking place and to the concept of social control. The stream of inputs and affective responses constitutes a major part of the walking experience, particularly in first-time visits where the senses are more attentive to these details.

Such complex, accumulated impressions are a vital component of path making on exploratory and first-time visits where little else is available to inform decision-making. In commented exploratory itineraries in a case study of walking behaviour in an indoor environment, certain perceived elements or qualities were instrumental in decision-making (Zacharias, 2006). The most important elements motivating path choice were the land uses, represented by the shops along the pathway, along with the accumulated presence of others associated with the path choice. Also significant, however, were elements of design, including materials, colours and landscaping details, lighting colour and level, music and odours. Altogether, these qualitative aspects of the walking experience constituted 29% of the comments made by the participants in this study as they walked about. Similarly, the evaluations made of shopping centre options in a study from the Netherlands revealed the extent important items in the conscious evaluation of these centres could be described as aesthetic response, nevertheless bound up with associated expectations (Oppewal & Timmermans, 1999). Signs for food and drink are also mnemonics for the associated experiences, or their expectations.

13.9. The Presence of Others

The presence of others often provides the reason for being in a space or continuing to another space. Spatial meaning can be derived directly from the apprehension of others in the environment, particularly when that presence is associated with specific purposeful activity, such as shopping or conversation. The individual joins the pedestrian stream and adapts to prevalent spatial behaviours. The relative presence of others in space is itself a factor in spatial choice, especially in novel environments and on exploratory visits. The presence of others may also positively impact choices for individuals effecting habitual itineraries. In a study of walkway systems in London, Chang (2002) observed that visitors unfamiliar with the walking system tended to follow those who were apparently familiar with it. In other words, the presence of others was key information not only for first-time visitors but also for habitual visitors.

The presence of others confers specific meaning on the space. The importance of the space is affirmed by multiple individuals, which provides assurance in the absence of any other information. Heavy pedestrian flow suggests an accessible space and thus one that also has more choices for further walking decisions. The heavier flow also suggests dense coverage of services. But dense pedestrian traffic can also be a source of comfort, security and sociability. The attraction to greater presence of others that characterizes many walking environments is self-reinforcing, contributing to the consolidation of preferred pathways into a characteristic hierarchy.

Research shows that pedestrian walking speed is affected by the presence of others, but that this relationship is not monotonic. In fact, low speeds are associated with very low and very high pedestrian volume, with higher speeds attained in a steady stream of pedestrians (Al-Azzawi & Raeside, 2007). Pedestrian behaviour is thus directly impacted by the presence of others and not necessarily their specific behaviours, but simply their presence in proximity.

13.10. Ambient Conditions, Place and Tempo

A variety of ambient environmental factors have direct impact on observable behaviours of pedestrians, displaying some sensitivity to these conditions as well as a high level of agreement among individuals. Many studies have examined pedestrian tempo. Lam and Cheung (2000) found variations in walking speed between indoor and outdoor walking facilities, and between office and shopping areas. It is well known that pedestrian tempo is keyed to the density of pedestrian traffic. Of course, high pedestrian density mechanically lowers overall pedestrian speed, but there is also a tendency to lower speeds in low density walking environments. Similarly, relatively higher density produces more uniform walking speed. These relationships reveal aspects of collective walking experience that form part of the ambient environment.

Also important in the ambient environment is air temperature. Although a fast walking pace at high air temperature will produce heat that cannot be easily dissipated, walking pace will not necessarily decline (Rotton et al., 1990). Even though walking may generate discomfort, the automatic response is not necessarily to slow down. A recent study on walking pace suggests Singaporeans, while inhabiting one of the hottest cities on earth, are also the fastest walkers in the world (Wiseman, 2007), although the study did not control for location within the city and time. In an unpublished study of observed walking trips at noon in the CBD of Montréal, it was seen that walking distance to destination or a long stop was unrelated to actual walking distance through a temperature range of $-21\,^{\circ}\mathrm{C}$ to $+31\,^{\circ}\mathrm{C}$. On the other hand, a higher proportion of the total walking distance was indoors when the outdoor temperature was lower. Tarawneh (2001) found that pedestrians picked up speed when they traversed a large space or a wide street and slowed down in small spaces and narrow streets.

The variations in walking pace as a function of place and air temperature illustrate the latent effects of environment on walk choices. Ambient conditions are often felt

only subliminally and may also be felt to be normal in their range at the particular time and place. Thus attention is not necessarily drawn to such ambient factors, even though behaviour is clearly and in a complex way related to these same conditions. By extension, the observed effects support the idea that the pedestrian itinerary is subject to substantial modification without conscious effort.

13.11. Conclusion

The pedestrian itinerary, in this characterization, has spatial and temporal structure. Before embarking on the trip, a person must conceive some kind of plan, where trip purpose figures prominently, along with those conditions that support the particular purpose. A plan to execute the trip on foot necessitates judgements about alternative means of travel and appropriate linkage between the primary purpose and other purposes that might be joined to it. Supportive environments clearly raise the frequency of walking trips, extend the distances covered and the reasons for walking. Thus, the experience of walking for such individuals operating in a walkable environment will be reinforced. At the other end of the spectrum of walk-supportive environments, people may have little daily experience of walking, such that the range of walking options that appear to be available to them are reduced. Thus, the perceptions of walks and factors surrounding walking decisions may be strongly affected by exposure.

Once engaged on the walk, individuals are exposed to choices, some of which may be seriously considered by the pedestrian. Relative distance, activity options, environmental qualities and the presence of barriers enter explicitly or subliminally into decision-making, depending on the relative susceptibility of the individual to suggestion. Such susceptibility is related to defined trip purpose, either at the outset of travel or as redefined in the course of the itinerary itself. The walking environment, even in highly controlled settings such as shopping malls where efforts are taken to guide movement, involves many possible choices that can be engaged in different orders. Thus, the high potential for a distinct series of spatial decisions for each individual also suggests that trips have a high degree of unexplained variation. At least, it would be difficult to take apart every segment of a path and relate the decisions to distinct stages and modalities of evaluation.

Interestingly, the relative complexity of path structure, and by inference the complexity of the environment itself, has little impact on the overall agreement on spatial choices among participants in the same environment. In other words, complexity in terms of highly local directional changes, stops and visual inspections are subsumed in the larger pattern of spatial choices over which there is general agreement.

The environment impinges on the spatial decisions of pedestrians at several levels. A conceptualization of the possible walk environment and the central elements of the proposed itinerary will be organized according to an assessment of perceived utilities and hedonic benefits associated with various choices. Ability to differentiate all aspects of the projected trip, at least when it is relatively complex, varies but is nearly always sub-optimal. For purposes of exploration and general search, there is less

need to map out an itinerary beforehand than for specific actions at specific places within a certain time frame. But even loosely structured trips are organized around key activities and key decision points, in part because it is impossible to store all the possible elements of the trip even if they were known, in part because we apparently find it convenient to do so.

Given the relatively strong relationship between physical and spatial descriptions of the environment on one hand and the patterns of movement of pedestrians on the other, it is reasonable to presume strong and transferable relationships between environment and behaviour at the walking scale. The characterization of the whole itinerary in a single set of related terms would help to sort out the causality that weighs heavily in the results but is so hard to pin down in its various components. But progress in this sense brings us closer to understanding why pedestrian itineraries have invariant properties as well as character that relates to the spatial frame in which they take place. Making environments that take into account invariant properties of pedestrian behaviour while admitting of a great range of possible behaviours and behaviour settings strikes a delicate balance and calls in general for sound understanding of human motivations while walking.

References

Alashalalfah, B. W., & Shalaby, A. S. (2007). Case study: Relationship of walk access distance to transit with service, travel, and personal characteristics. *Journal of Urban Planning and Development*, *133*(2), 114–118.

Al-Azzawi, M., & Raeside, R. (2007). Modeling pedestrian walking speeds on sidewalks. *Journal of Urban Planning and Development*, *133*(3), 211–219.

Alfonzo, M. (2005). To walk or not to walk? The hierarchy of walking needs. *Environment and Behavior*, *37*(6), 808–836.

Allen, G. (1999). Spatial abilities, cognitive maps, and wayfinding. In: R. G. Golledge (Ed.), *Wayfinding behavior: Cognitive mapping and other spatial processes* (pp. 46–80). Baltimore, MD: John Hopkins Press.

An, M., & Chen, M. (2007). Estimating nonmotorized travel demand. *Transportation Research Record* (2002), 18–25.

Appleyard, D. (1981). *Livable streets*. Berkeley, CA: University of California Press.

Batty, M., & Rana, S. (2004). The automatic definition and generation of axial lines and axial maps. *Environment and Planning B: Planning and Design* (31), 615–640.

Bellenger, D., Robertson, D., & Greenberg, B. (1977). Shopping center patronage motives. *Journal of Retailing* (53), 29–38.

Bentham, C. G., & Haynes, R. M. (1985). The effects of vehicular traffic restriction on pedestrian numbers. *Traffic Engineering + Control*, *26*, 210.

Bitgood, S., & Dukes, S. (2006). Not another step! Economy of movement and pedestrian choice behavior in shopping malls. *Environment and Behavior*, *48*(3), 394–405.

Bloch, P., Ridgway, N., & Nelson, J. (1991). Leisure and the shopping mall. *Advances in Consumer Research* (18), 445–452.

Borgers, A., & Timmermans, H. (1986). A model of pedestrian route choice and demand for retail facilities within inner-city shopping areas. *Geographical Analysis* (18), 115–128.

Brown, B., Werner, C., Amburgey, J., & Szalay, C. (2007). Walkable route perceptions and physical features. *Environment and Behavior*, *39*(1), 34–61.

Canepa, B. (2007). Bursting the bubble: Determining the transit-oriented development's walkable limits. *Transportation Research Record* (1992), 28–34.

Cervero, R., & Duncan, M. (2003). Walking, bicycling, and urban landscapes: Evidence from the San Francisco Bay Area. *American Journal of Public Health* (93), 1478–1483.

Cervero, R., & Radisch, C. (1996). Travel choices in pedestrian versus automobile oriented neighborhoods. *Transport Policy* (3), 127–141.

Chang, D. (2002). Spatial choice and preference in multilevel movement networks. *Environment and Behavior*, *34*(5), 582–615.

Conroy Dalton, R. (2003). The secret is to follow your nose: Route path selection and angularity. *Environment and Behavior*, *35*(1), 107–131.

Foltête, J.-C., & Piombini, A. (2007). Urban layout, landscape features and pedestrian usage. *Landscape and Urban Planning* (81), 225–234.

Frank, L., Andresen, M., & Schmid, T. (2004). Obesity relationships with community design, physical activity, and time spent in cars. *American Journal of Preventive Medicine*, *27*(2), 87–96.

Gärling, T., & Gärling, E. (1988). Distance minimization in downtown pedestrian shopping. *Environment and Planning A* (20), 547–554.

Giles-Corti, B., & Donovan, R. (2003). Relative influences of individual, social environmental, and physical environmental correlates of walking. *American Journal of Public Health*, *93*(9), 1583–1589.

Greenwald, M. J., & Boarnet, M. G. (2001). Built environment as determinant of walking behavior: Analyzing nonwork pedestrian travel in Portland, Oregon. *Transportation Research Record* (1780), 33–41.

Guo, J. Y., Bhat, C. R., & Copperman, R. B. (2007). Effect of the built environment on motorized and nonmotorized trip making: Substitutive, complementary, or synergistic?. *Transportation Research Record* (2010), 1–11.

Handy, S. (1996). Urban form and pedestrian choices: Study of Austin neighborhoods. *Transportation Research Record* (1552), 135–144.

Haq, S., & Zimring, C. (2003). Just down the road a piece: The development of topological knowledge of building layout. *Environment and Behavior* (35), 132–160.

Herzog, T., & Flynn-Smith, J. (2001). Preference and perceived danger as a function of the perceived curvature, length and width of urban alleys. *Environment and Behavior*, *33*(5), 653–666.

Hillier, B., & Hanson, J. (1984). *The social logic of space*. Cambridge, UK: Cambridge University Press.

Isaacs, R. (2000). The urban picturesque: An aesthetic experience of urban pedestrian places. *Journal of Urban Design*, *5*(2), 145–180.

Joseph, A., & Zimring, C. (2007). Where active older adults walk. *Environment and Behavior*, *39*(1), 75–105.

Kent, R. (1989). The role of mystery in the preference for shopping malls. *Landscape Journal: Design, Planning and Management* (8), 1–28.

Khisty, C. J. (1990). Non-Euclidean metrics in nonmotorized transportation. *Transportation Research Record* (1281), 102–111.

Lam, W. H. K., & Cheung, C. (2000). Pedestrian speed/flow relationships for walking facilities in Hong Kong. *Transportation Engineering*, *126*(4), 343–349.

Loukopoulos, P., Jakobsson, C., Gärling, T., Schneider, C., & Fujii, S. (2004). Car-user responses to travel demand management measures: Goal setting and choice of adaptation alternatives. *Transportation Research D* (9), 263–280.

Lynch, K. (1980). A walk around the block. In: K. Lynch (Ed.), *City sense and city design. Writings and projects of Kevin Lynch*. Cambridge, MA: MIT Press.

Matsumoto, N., Koyanagi, E., & Seta, S. (1997). Physical and mental factors of anticipation in the streetscape. *Proceedings of the International Conference on Environment-Behavior Studies for the 21st Century*, Tokyo, 4–6 November (pp. 283–286).

Moles, A. (1973). *Théorie de l'information et perception esthétique*. Paris: Denoël.

Muraleetharan, T., & Hagiwara, T. (2007). Overall level of service of urban walking environment and its influence on pedestrian route choice behavior: Analysis of pedestrian travel in Sapporo, Japan. *Transportation Research Record* (2002), 7–17.

Naess, P. (2006). *Urban structure matters: Residential location, car dependence and travel behaviour*. London: Routledge.

Oppewal, H., & Timmermans, H. (1999). Modeling consumer perception of public space in shopping centers. *Environment and Behavior*, *31*(1), 45–65.

O'Sullivan, S., & Morrall, J. (1996). Walking distances to and from light-rail transit stations. *Transportation Research Record* (1538), 19–26.

Owen, N., Humpel, N., Leslie, E., Bauman, A., & Sallis, J. (2004). Understanding environmental influences on walking: Review and research agenda. *American Journal of Preventive Medicine*, *27*(1), 67–76.

Rodríguez, D., & Joo, J. (2004). The relationship between non-motorized mode choice and the local physical environment. *Transportation Research Part D* (9), 151–173.

Rotton, J., Shats, M., & Standers, R. (1990). Temperature and pedestrian tempo. *Environment and Behavior*, *22*, 650–674.

Sadalla, E. K., & Montello, D. R. (1989). Remembering changes in direction. *Environment and Behavior*, *21*, 345–363.

Saelens, B., Sallis, J., Black, J., & Chen, D. (2003). Neighborhood-based differences in physical activity: An environment scale evaluation. *American Journal of Public Health*, *93*(9), 1552–1558.

Saelens, B., Sallis, J., & Frank, L. (2003). Environmental correlates of walking and cycling: Findings from the transportation, urban design, and planning literature. *Annals of Behavioral Medicine*, *25*(2), 80–91.

Salheen, M., & Forsyth, L. (2001). Addressing distance in the space syntax syntactical model. *Urban Design International*, *6*, 93–110.

Säisä, J., & Gärling, T. (1987). Sequential spatial choices in the large-scale environment. *Environment and Behavior*, *19*(5), 614–635.

Schlossberg, M., & Brown, N. (2004). Comparing transit-oriented development sites by walkability indicators. *Transportation Research Record* (1887), 34–42.

Schwanen, T., Dijst, M., & Dieleman, F. (2004). Policies for urban form and their impact on travel: The Netherlands experience. *Urban Studies*, *41*(3), 579–603.

Sheets, V., & Manzer, C. (1991). Affect, cognition and urban vegetation: Some effects of adding trees along city streets. *Environment and Behavior*, *23*(3), 285–304.

Shriver, K. (1997). Influence of environmental design on pedestrian travel behavior in four Austin neighborhoods. *Transportation Research Record* (1578), 64–75.

Southworth, M. (2005). Designing the walkable city. *Journal of Urban Planning and Development*, *131*(4), 246–257.

Sugiyama, T., Ward Thompson, C., & Alves, S. (2008). Associations between neighborhood open space attributes and quality of life for older people in Britain. *Environment and Behavior*, *41*, 3–21.

Tarawneh, M. (2001). Evaluation of pedestrian speed in Jordan with investigation of some contributing factors. *Journal of Safety Research*, *32*, 229–236.

Turner, A., & Penn, A. (2002). Encoding natural movement as an agent-based system: An investigation into human pedestrian behaviour in the built environment. *Environment and Planning B: Planning and Design*, *29*, 473–490.

van der Waerden, P. J. H. J., Borgers, A. W. J., & Timmermans, H. J. P. (2007). User evaluation of pedestrian infrastructure functional or design-led?. *Traffic Engineering and Control*, *48*(2), 6–9.

Vernez-Moudon, A., Hess, P. M., Snyder, M. C., & Stanilov, K. (1997). Effects of site design on pedestrian travel in mixed-use, medium-density environments. *Transportation Research Record* (1578), 48–55.

Wang, W., & Seo, I. (2008). Extracting features of sidewalk space using the rough sets approach. *Environment and Planning B: Planning and Design*, *35*, 920–934.

Weisbrod, G. (1982). Business and travel impacts of boston's downtown crossing automobile-restricted zone. *Transportation Research Record*, *882*, 25–32.

Wiseman, R. (2007). Pace of life project. Available at http://www.paceoflife.co.uk/

Zacharias, J. (1993). Reconsidering the impacts of enclosed shopping centres: A study of pedestrian behaviour around and within a festival market in Montreal. *Journal of Landscape and Urban Planning*, *26*, 149–160.

Zacharias, J. (1997). The impact of layout and visual stimuli on the itineraries and perceptions of pedestrians in a public market. *Environment and Planning B: Planning and Design*, *24*(1), 23–35.

Zacharias, J. (1998). Path choices and the layout of a shopping centre. In: H. Timmermans (Ed.) *Design and decision support systems in architecture and urban planning. Proceedings of the 4th Conference*, Maastricht, The Netherlands, 26–29 July.

Zacharias, J. (2001a). Path choice and visual stimuli: Signs of human activity and architecture. *Journal of Environmental Psychology*, *21*, 341–352.

Zacharias, J. (2001b). Visual stimuli and pedestrian path choices. Presentation at the Environmental Design Research Association 32, Edinburgh, 3–6 July.

Zacharias, J. (2005). Non-motorized transportation in four Shanghai districts. *International Planning Studies*, *10*(3), 323–340.

Zacharias, J. (2006). Exploratory behaviour in real and virtual environments. *Landscape and Urban Planning*, *78*, 1–13.

Zacharias, J., Bernhardt, T., & de Montigny, L. (2005). Simulated pedestrian behavior in shopping environment. *Journal of Urban Planning and Development*, *131*(3), 195–200.

Zacharias, J., & Schinazi, V. (2003). The impact of an entertainment retrofit on the performance of a shopping center. *Journal of Shopping Center Research*, *10*(1), 29–44.

Chapter 14

Visitors' Behavior in World Expo 2010 Shanghai: An Application of Discrete Choice Models and Web-Based Survey

De Wang, Li Ma and Wei Zhu

Abstract

Research on visitor behavior in the World Expo and other similar large exhibition events are crucial for planning site layouts and providing service facilities. However, empirical studies and data on visitor behavior in such events are scarce. In this paper, we discuss a case study of modeling and simulating visitor behavior for the Expo 2010 in Shanghai, conducted to support the planning of the Expo site. Data on virtual visits to the site were collected using a web-based experiment. A multinomial logit model was applied to predict destination choice behavior of visitors. Model estimation results were very satisfactory with all factors significant in the hypothesized directions. The model was taken as the backbone of a simulation framework with additional behavior modules such as resting, queuing, and dining. We simulated the visits of 4000 individual visitors and predicted the spatio-temporal distribution of visits, visitor flows, and dining demands at the Expo site. Suggestions for site planning and service provision were given, based on these predictions.

14.1. Introduction

World Expo 2010 Shanghai China will attract a large number of visitors. According to The Bureau of the Shanghai World Expo Coordination (2005), the average number of visitors will be 400,000 per day and the peak could be over 700,000 per

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day. Therefore, in order to organize a successful Expo, it becomes crucial to guarantee that, within the Expo site of approximately 3 km^2, such a large number of visitors can smoothly complete their activities and that visitor flows and other traffic are well organized.

Visitors' routes are primarily influenced by the layout of the exhibition site, which includes the positions of the exhibition pavilions, service facilities, road networks, and so on. Some visitors may find their way during the visit, receiving and processing information from the surrounding environment and constantly making decisions about which pavilion to visit, which route to take, and whether to end the whole visit trip. Some more organized visitors may plan their visits before starting the trip according to some map or information guide of the site, and more or less follow their schedule during the visit. In either way, a reasonable site layout can guide visitors to complete their visits in good order. In contrast, a poor site design could result in disordered visitor behavior, and negatively influence in-site traffic and overall experience of convenience.

In the process of planning the site, planners should not only decide the appropriate positions of the exhibition pavilions for guiding visitor flows, but also should estimate any imbalanced distributions of activities in space and allocate sufficient space to specific places in order to keep potential dangers due to high spatial activity concentration under acceptable levels. It will also be beneficial for providing service facilities in appropriate places with appropriate quantities, if the planners can grasp the regularities in visitor activities such as dining, resting, and using transports. Modeling visitor behavior is a very useful approach for the planning process as the planners can predict the potential problems of visitor activities under certain site plans through computer simulation and adjust the plan until the planning objectives are attained.

Although research about in-site traffic at Expo's or large-scale exhibitions are scarce, the general approach adopted in pedestrian behavior research in shopping environments fits our research objective very well. Pedestrian research has dominantly relied on rational choice models since the breakthrough of the random utility theory (e.g., McFadden, 1974; Train, 2003). These models allow simulating individual decisions and behavior as a function of the characteristics of commercial environments. For example, Oppewal and Timmermans (1997) used detailed environmental factors such as store variety, window layout, price, quality, and shopping atmosphere in their choice experiment which presented respondents alternative scenarios for choosing a shopping center. Zhu, Wang, and Saito (2005, 2006) used consumer spatial choice models to explain how the pedestrians move consecutively through blocks of shopping streets, and simulated aggregate activity patterns. Borgers and Timmermans (2004, 2005) abstracted shopping district into links, which represented streets and nodes connecting the links. Under this representation, pedestrian behavior was modeled as the choice of link at the nodes. The utility of a link was composed of the distance to the link, the retail floorspace of stores along the link, the visit history of the pedestrian, and others. Choice models were also used for modeling more complicated behavior and cognitive processes. Dijkstra, Timmermans, and de Vries (2005) estimated perception fields of pedestrians

in shopping streets using a logistic regression model (a special form of multinomial logit model), to determine the stores that are included in the perception fields of pedestrians. Except for conventional environmental factors such as store size, type, and distance, they also differentiated pedestrian behavior in terms of motivational states, personal characteristics, and familiarity with stores. Borgers, Smeets, Kemperman, and Timmermans (2006) extended the link-node type spatial representation from the meso destination choice level to the micro level. They systematically identified nodes along a street, and assigned to each node a set of links, connecting the node with its neighboring nodes. They assumed that the movement of a pedestrian is the result of sequentially choosing at each node the link with the highest utility, which consists of the type of link (entry, exit, transfer, center), the length of the link, the attraction that the link leads to, the heading of the link relative to the current heading, the side of the street relative to the heading of the link (right- or left-hand side), etc.

Besides modeling choices, properties of microscopic pedestrian behavior have also been examined over the years, including walking pace (e.g., Walmsley & Lewis, 1989), speed (e.g., Willis, Gjersoe, Havard, Kerridge, & Kukla, 2004; Daamen & Hoogendoorn, 2007), speed–flow relationship (e.g., Lam, Morrall, & Ho, 1995; Lam & Cheung, 2000), travel time (e.g., Lam & Cheung, 1999), and interpersonal interactions (e.g., Hughes, 2002). The results of these studies constitute a sound foundation for simulating individual spatio-temporal behavior.

This short review shows that methodologies in pedestrian shopping behavior are relatively mature and can be easily adapted to model visitor behavior at Expo sites as the two phenomena are quite similar. Choosing an exhibition pavilion is in principle not too different from choosing a store. Therefore, one purpose of this study is to apply discrete choice models to predict visitors' choice of exhibition pavilions at the Expo site and investigate the influence of environment factors on behavior. The estimated model is then used to simulate visitor behavior under different design scenarios and suggest the best site layout. Although the modeling principles in pedestrian shopping behavior can be borrowed, models of shopping behavior cannot be used for simulating visiting behavior since they occur in very different contexts, which suggests that our model must be tailored to visitor behavior. This leads to the data collection problem as Expo is a rare event and few experiences have been accumulated. Borgers et al. (2008) showed that a questionnaire-based on-site survey method is the main data collection method in pedestrian shopping behavior research, but it is not applicable to our case. Using stated preference methods seems to be the only viable alternative way. To improve the efficiency of data collection in conventional paper-based choice experiments, we developed a web-based survey method, which allows respondents to make virtual visits on personal computers based on a map of the Expo site. This constitutes the other contribution of this study since, to our knowledge, no research has used the web survey to collect visitor behavior, although the method has been applied prevalently in others fields (e.g., Iragüen & Ortúzar, 2004; Chorus, Arentze, & Timmermans, 2007). We must admit that it is far from an ideal survey method. Nevertheless, it is still a practical method balancing realness, efficiency, data quantity, and quality.

14.2. Model

We model the whole chain of visits of a visitor as the result of consecutive choices of destinations. First, when the visitor enters the Expo site at one of the entrances, he/she considers where to go by evaluating the utilities of alternative destinations (choice set) and chooses the destination with the highest utility. After the activities at the first destination are finished, the visitor makes the decision to visit a second destination. This process is repeated until after the last visit the visitor decides to end the visit and leave the site. This framework implies that we mainly model the behavior of visitors who make decisions on the site rather than those who follow some predetermined schedule. Nevertheless, even the behavior based on such plans may be more or less affected by the environment.

The choice set, by definition, includes 55 destinations represented by $j = 1, \ldots, J|J = 55$. The first 43 destinations ($j = 1, ..., 43$) are exhibition pavilions (or clusters of pavilions), squares, and entertainment facilities. The other 12 destinations ($j = 44, ..., 55$) are entrances/exits, which means that for each decision (except the first one) there is the possibility that the visitor decides to end the trip and leave the site through one of the exits. We assume that the choice process can be modeled by a multinomial logit model. That is, visitors are assumed to evaluate the utility of each destination, which is represented by $u_{ij} = v_{ij} + \varepsilon_{ij}$. u_{ij} is the utility of alternative j evaluated at the current location of i, and is composed of a deterministic (observable) part v_{ij} and a stochastic (unobservable) part ε_{ij}. Assuming that the visitor chooses the alternative with the highest utility and ε_{ij} is an independently and identically distributed Gumbel distribution, the probability of choosing destination j equals $p_{ij} = \exp(v_{ij})/\sum_{j'=1}^{J} \exp(v_{ij'})$. The deterministic utilities of the alternatives are specified as follows,

$$v_{ij} = \beta^s s_j + \beta^c c_j + \beta^t t_j + \beta^d \ln(d_{ij}) + \beta^a a_{ij} + \beta^b b_{ij} + \beta^r r_j + \beta^w w_j + \beta^h h_j + \beta^e e_j \quad (14.1)$$

with the following meanings.

14.2.1. Size

Size, s_j, refers to the floorspace of exhibition pavilions, which represents the attractiveness of each destination. We hypothesize that larger size will bring higher attractiveness to the visitor and therefore that the parameter β^s should be positive. Considering that visitors are not sensitive to small floorspace differences between the pavilions and more naturally cognize pavilions as small, medium, and large, size was operated in the model as 1 ($<20{,}000\,m^2$), 2 (20,000–40,000 m^2), and 3 ($\geq 40{,}000\,m^2$), respectively.

14.2.2. Feature

Feature, c_j, indicates destinations with distinct exhibitions. Expo 2010 is designed to have many featured exhibitions and activities such as pavilions designed or

constructed by hosting countries, themed exhibitions, cultural centers, gardens and squares, and so on. These featured destinations may give additional attraction to visitors. We coded this variable qualitatively, using 1 to represent destinations with such distinct features and 0 for other normal destinations. The hypothesis is that the parameter β^c should be positive.

14.2.3. Type of Space

Type of space, t_j, differentiates gardens and squares from exhibitions. This differentiation is important because, in a pilot study, we found that gardens and squares were infrequently visited by visitors, while gardens and squares occupy notable proportions of the space at the Expo site and are supposed to be important elements for activities such as orientation, rest, gathering, and transfer. Therefore, in order to properly design gardens and squares, it would be valuable to quantify their influence relative to exhibitions in the model. As we coded destinations of exhibitions as 1 and destinations of gardens and squares as 0, the hypothesized sign of parameter β^t is positive if exhibitions are more preferred in general.

14.2.4. Distance

Distance, d_{ij}, refers to the shortest route distance between the visitor's current location i and destination j. *Ceteris paribus*, one would intuitively expect that visitors prefer destinations that are closer to them. In pedestrian research, distance has almost always been a significant factor influencing behavior. Therefore, we hypothesize that the parameter for distance, β^d, is negative. We took the natural log of distance to represent the notion of marginally decreasing utility, which means that the disutility of further distance has a limit.

14.2.5. Adjacency to the Origin

Adjacency, a_{ij}, refers to the spatial relationship describing whether the origin and the destination are adjacent to each other. Adjacency could be correlated to distance, but there is still a difference. Even if two destinations have the same distance to the origin, the adjacent destinations could be more valued than the non-adjacent destinations because visitors in general are less willing to skip some intermediate destinations. Therefore, if we code adjacent destinations as 1 and non-adjacent destinations as 0, parameter β^a should be positive.

14.2.6. Side of the River

The Expo site is designed to be separated by a river, and exhibition pavilions and entrances are located at both sides of the river. Although ferries and tunnels will be

used for cross-river transportation, the river could still be a hindrance to visitors when they want to visit the exhibits at the other side of the river. For this reason, we hypothesize that destinations at the same side of the river as the visitor's current location are preferred to destinations at the other side. Variable b_{ij} is used to represent this relationship with a value of 0 if the destinations are on the same side and a value of 1 if they are located on different sides of the river. Parameter β^b is expected to be negative.

14.2.7. Adjacency to the River

This variable, r_j, indicates whether the exhibition pavilions are adjacent to the river (1 for adjacent and 0 for non-adjacent). It is assumed that the river banks offer special landscapes which may attract visitors, leading to more opportunities of visits to those exhibitions located along the river bank. Parameter β^r is hypothesized to be positive.

14.2.8. Adjacency to High-Rise Walkways

A high-rise walkway system exclusive for pedestrians is designed for the whole Expo site. This special facility may not only serve as traffic infrastructure but also be a special attraction in its own right due to new experiences that it may bring to visitors. Therefore, we conjecture that destinations adjacent to the walkways may take advantage of the accessibility and attractiveness that the system offers and enhance their own attractiveness. Destinations adjacent to the walkways are coded as 1 for variable w_j and destinations non-adjacent to the walkways are coded as 0. Parameter β^w is hypothesized to be positive.

14.2.9. Visit History

Visitors' decisions and behavior are no doubt influenced by the history of their visits. Apparently, if an exhibition has been visited, the probability of revisiting this exhibition later during the stay at the Expo site will likely be much smaller. We use variable h_j to indicate whether an exhibition destination has been visited by the visitor before (with value 1 if yes and 0 if not). A negative value is expected for parameter β^h.

14.2.10. Exit

Exit, e_j, is a dummy variable indicating whether the destination is an exit or not (1 for yes, 0 for no). It represents the alternative-based utility of ending the visit relative to continuing the visit. Hence, the sign of parameter β^e could either be negative or positive. If the visitor chooses an exit, the visit to the Expo ends.

14.3. Data

The Expo site has not been finished yet. Hence, stated preference methods seem to be the only viable way of collecting visitor behavior. After giving the respondents relevant background information, we asked them to take a virtual visit to the Expo site. This virtual environment was implemented through the web, which is convenient for providing rich information through multimedia technologies (e.g., images, movies) to respondents and flexible for interaction through queries. Respondents have more freedom to select the information that interests them compared to traditional paper-based surveys, which must present a large amount of information within limited available space, forcing respondents to process all information simultaneously. We believe a virtual experiment provides a more realistic environment for collecting visitor behavior.

14.3.1. Survey Method

We designed an interactive webpage for data collection. The whole survey file was developed using Flash technology (by Macromedia), which was selected for its superior multimedia functions, interactive abilities, and programmable environment. When the file was uploaded onto the web, it provided background information about the Expo, interactive queries, questionnaires, and data transmission. When data were sent to the server, a response program on the server was activated. This program was responsible for receiving data and detecting responses implying repeated participation of the survey by the same respondent. Perl language was used for developing this response program.

The respondent first opened the survey webpage on his/her personal computer (downloading the Flash page through the server) and read the background information. Then he/she filled in the questionnaire. After completion, the program checked the validity of the answers before submitting them back to the server. Because the survey was open for a period of time and respondents might participate multiple times, which could cause biased data, the server inferred whether the respondent had participated the survey by checking whether the IP address of the response was recorded before and only recorded the response that was not. This completed the survey of one respondent.

The link address of the survey webpage was stored on the Expo official website. To increase the number of responses, the link was referred at other gate websites.

14.3.2. Survey Content

The survey used a map that was based on the Expo site plan made around April 2006 (Figure 14.1). For ease of presentation during data collection, we simplified the map (Figure 14.2). For example, the numbers of floors of the pavilions were omitted and

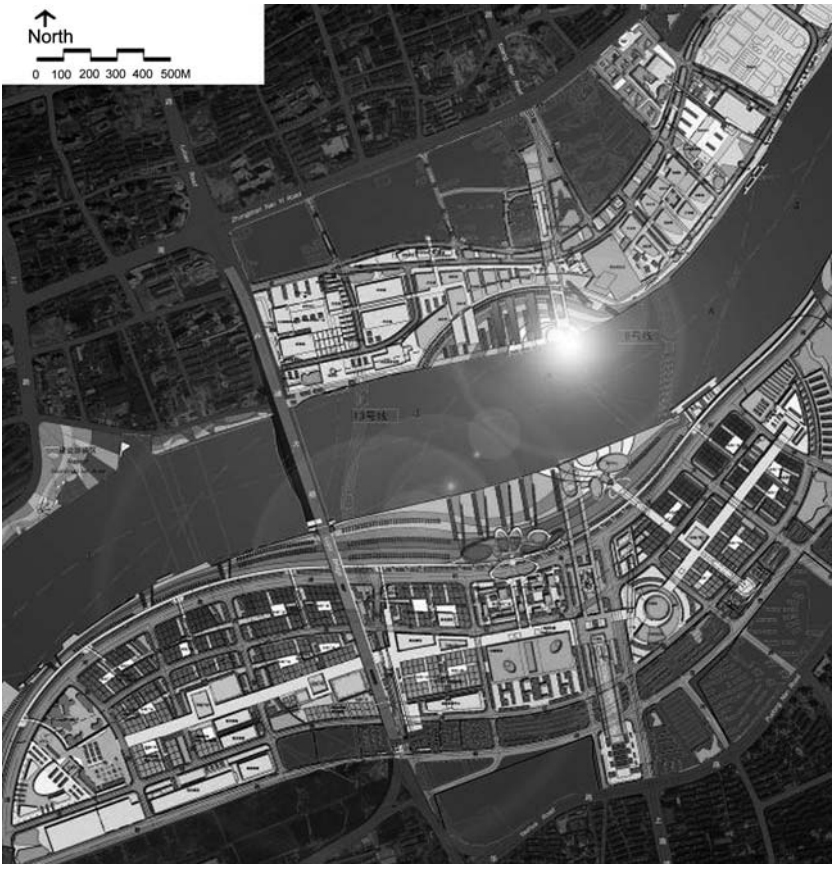


Figure 14.1: The site plan of Expo 2010.

instead floorspace was used to reflect the size of the pavilions. Similarly, distance information was replaced by estimated walking time to overcome the difficulty of distance estimation on a map.

The survey questionnaire included three parts. To give enough background information to respondents, the first part introduced the Expo, including the location of the site, size, surrounding transportation facilities, positions of entrances/exits, in-site transportation system, cross-river transportation, high-rise walkway system, and the layout of the exhibition pavilions. The second part was the main part of the survey and consisted of two components: (1) the respondent started the virtual visit trip by selecting an entrance. Then he/she indicated consecutively which exhibition pavilions or squares to visit by clicking the destinations with a mouse. These actions were recorded in the database. The information provided during the decision making included the distance and walking time from his/her current location to the destinations that the mouse was pointing to. Repeated visits of one destination were allowed. The trip ended when the respondent selected an exit. (2) Respondents were

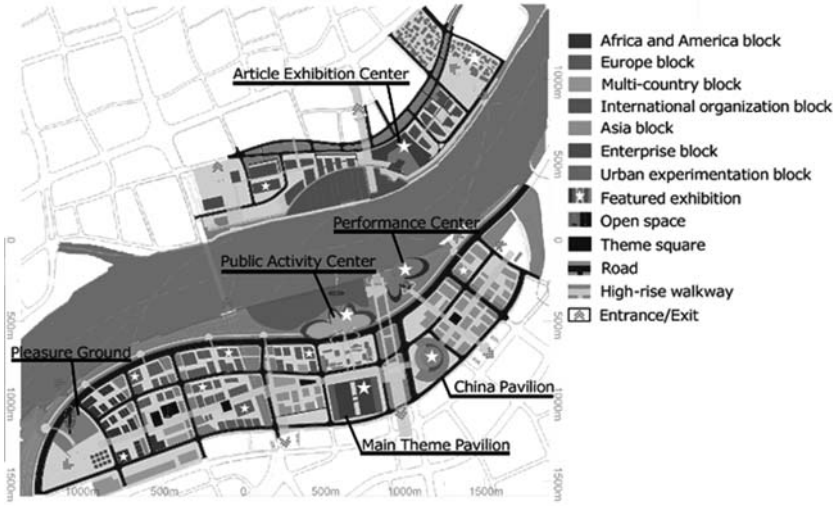


Figure 14.2: The main interface of the survey webpage.

asked to indicate underlying intentions such as the start time, the duration of the trip, the interval and duration for rest, and the acceptable waiting time when queuing. The third part of the survey recorded respondents' socio-demographics such as gender, age, income, occupation, and residence.

The survey lasted from July 10, 2006 to November 8, 2007. The recorded number of responses was 1086 within which 978 responses were valid. Most of the responses were returned within the first half-year and 74.2% of them came from respondents living in Shanghai. Due to the media used for the data collection, 33% of the respondents were young people (<30) and 46% were middle-aged people (30–60). Fifty-eight percent of the respondents reported that they were male, 26% were female, and the remaining 16% did not indicate their gender. An interesting phenomenon is that most respondents lived in the district where (most part of) the Expo site is located.

14.4. Model Estimation and Simulation

The statistical software SAS was used for estimating the model based on the 978 records of visits, from which 11,732 destination choices were derived. Table 14.1 shows the estimation results that are quite satisfactory. The general goodness-of-fit statistic (McFadden's Likelihood Ratio Index, equivalent to ρ^2) reaches 0.33 and all parameters are significant with proper signs. This model is used as the major component in simulating visitor behavior and evaluating and adjusting the site layout.

14.4.1. Simulation Framework

The destination choice model is the main part of the simulation framework. Other behavior such as resting, queuing, and taking meals is also indispensable for planning service facilities. Moreover, if the visit and route choice simulation are only carried out statically, they are insufficient for optimal planning because they do not provide dynamic changes of visitor activities across a day, which are crucial for allocating resources according to the time-varying demands. Therefore, additional behavioral modules were incorporated into the simulation framework, taking the destination choice simulation as the core process.

We simulated the behavior of each visitor in sequential time slots using SAS. In each time slot, the simulation of each visitor behavior is as follows. First, the system checks whether the visitor needs rest according to the time that he/she has spent on the site, or whether it is the time (*a priori* set) for taking meals. If neither rest nor dining is needed, the system checks whether the visitor is visiting some exhibition or is on the way to a destination. If the visitor is still visiting an exhibition, the system checks whether this visit should continue. If not, the choice model will generate a new destination for the next visit. If the visitor is still on the way, the system checks whether he/she has reached the destination. If yes, the system checks whether queuing is necessary according to the service level of the destination in the previous time slot. A visitor may choose to queue or not according to the pre-set probability in case of a queuing situation. Those rejecting queuing will skip this exhibition and choose the next destination from the current location. The simulation records the location, activity, and other information of each visitor in each time slot until the simulation for this visitor ends.

Table 14.1: Model estimation results.

Parameter	Estimate	*t* value	Significance
β^s: size	0.4102	27.80	$<.0001$
β^c: feature	0.7532	29.23	$<.0001$
β^t: type	0.8129	22.77	$<.0001$
β^d: distance	−0.6968	−76.06	$<.0001$
β^a: adjacency to destinations	1.4691	65.54	$<.0001$
β^b: side of the river	−1.7633	−36.68	$<.0001$
β^r: adjacency to the river	0.2202	8.00	$<.0001$
β^w: walkway	0.1537	5.57	$<.0001$
β^h: history	−4.7523	−63.69	$<.0001$
β^e: exit	−0.7459	−15.00	$<.0001$
Number of records	11,732		
Log-likelihood	−31,496		
McFadden's LRI	0.3301		

14.4.2. Simulation Settings

Some conditions were assumed prior to the simulation. Most of them were derived from the distributions of the answers and behavior obtained from the survey or referred to existing literatures. They are not the foci of this study and need further justification in future research.

14.4.2.1. Walking environment We only simulated walking behavior of visitors. Although several means of transports will be available such as shuttle bus and ferry, this assumption can still hold at large because walking was the major means of visit in past Expos.

14.4.2.2. Time unit Considering the scale of this study and the moving speed of visitors, the time unit for each simulation was set to be 1 min.

14.4.2.3. Entry The number of visitors entering the Expo site varies across the day, which significantly influences the activity distributions on the site. The simulation took the distribution of the visit start times collected through the survey as the template for generating the number of visitors in each half hour.

14.4.2.4. Service capacity, walking speed, visit speed, and visit area Service capacity refers to the number of visitors an exhibition pavilion can serve under normal conditions. Taking into account this factor is important because queuing behavior occurred in each past Expo, which means visitors were under-served. Therefore, simulating service level will be helpful for generating balanced pavilion designs between under-service and over-service. We assumed that each visitor occupies 3.5 m^2 in space. Walking speed refers to the speed of visitors walking on the route to the destination and was set to be 1.1 m/s. Visit speed refers to the area visited by each visitor in unit time, which was set to be 0.5 m^2/s. These are the average speeds, although in reality they vary from person to person. Visit area refers to the area that a visitor visits in one pavilion. It differs between building area (the whole floorspace of the exhibition pavilion) and exhibition area (the floorspace for exhibition). We assumed in the simulation that visit area = building area × the ratio of exhibition area (60%) × the ratio of visit area (60%), which means 36% of the pavilion area is visited.

14.4.2.5. Queuing and leaving behavior Since the service capacities of exhibition pavilions were constrained, queuing behavior could occur. The simulation needs as input the proportion of visitors who will queue and how much time they would like to spend for queuing before turning to another destination. These answers were given by the survey, which showed that 35% of the respondents indicated to wait and the maximum time for queuing was 1 h. The simulation of leaving (the site) behavior was on one hand realized through the choice of exit and on the other hand coordinated with time. One assumption was that after visiting 12 exhibitions (the average number of visits in the survey) the utility of leaving would increase substantially; the other assumption also increased this utility after 22:00.

14.4.2.6. Taking rest and meal The time interval and duration of rest are the two main factors for simulating rest-taking behavior. They were taken from the sample, which showed on average that each visitor rested for 10–20 min every 1.5 h. To avoid over-simplification of rest behavior, we set the probability of taking a rest at 90%. The occurrence of dining behavior was more regulated. In the sample, lunches began around 12:00 and suppers began around 18:00. The simulation also took 90% as the probability of deciding the occurrence of the dining behavior. If it occurred, the start time was determined by adding the base time with a random time between 0 and 2 h. The duration for dining was between 20 and 30 min. Dining behavior was assumed to have the same effect as resting.

14.4.3. Simulation Results

Because simulating all visitors is resource consuming, we simulated 4000 visitors. Accordingly, the service capacities of the exhibition pavilions were scaled down from the actual design capacities so that queuing behavior may occur. The results were scaled up proportionally for making sense in real situations. The simulation was carried out in three scenarios: normal days (400,000 visitors/day), peak days (600,000 visitors/day), and ultra peak days (800,000 visitors/day) in each of which the spatial distributions of visits and visitor flows are analyzed.

14.4.3.1. Number of visits Aggregating the visits of individual visitors results in the distribution of overall visits across the site, which is helpful for planning site layout and facilities in general. Figure 14.3 shows such a distribution on peak days. There seems little difference between the pavilions in the upper side of the site. The variation in the lower side of the site is much larger. High concentrations of visitors are found in several important pavilions (the main theme pavilion, the China pavilion, the performance center, and the activity center), which suggest that relatively more service facilities should be arranged in these locations. More specifically, three pavilions require more attention, the main theme pavilion, the China pavilion, and the article exhibition pavilion in the upper site, which receive about 250,000, 240,000, and 210,000 visits, respectively on peak days and 340,000, 310,000, and 270,000 visits, respectively on ultra peak days. On normal days, the number of visits in several main pavilions can reach 150,000.

The temporal variation of the visitor distribution can be seen in Figure 14.4. Because the start time of the visitors concentrates before noon, the peak hour of visit starts at 11:00 and maintains until 16:00. In these peak hours, many visitors are in the large pavilions near the main entrances. The highest number of instant visits (in 1 min) occurs in the article exhibition pavilion, which reaches 40,000 visits on normal days and 50,000 visits on peak and ultra peak days. The instant visits of the main theme pavilion and the China pavilion are lower, with 35,000 visits on normal days, 40,000 visits on peak days, and 45,000 visits on ultra peak days, although they have the largest number of daily overall visits because the variation of the instant visits of

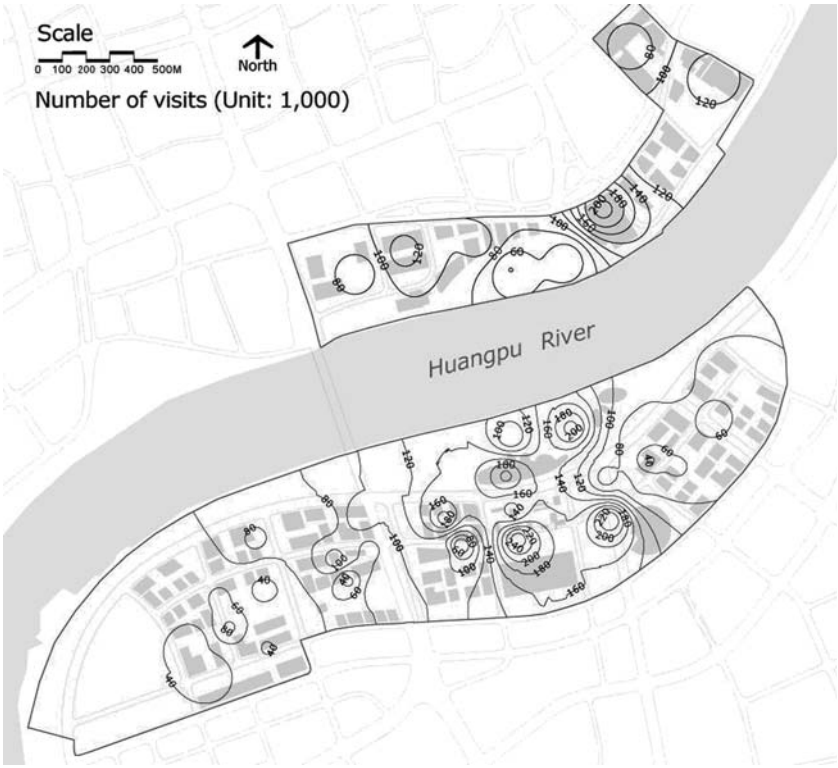


Figure 14.3: The distribution of visits in peak days.



Figure 14.4: The distribution of visits over time.

the two pavilions are smaller, keeping constant the total of between 30,000 and 35,000 visits. The other normal pavilions have only 1/10–1/20 of the overall visits of the main pavilions. Therefore, the arrangement of space and service facilities must consider the activity distributions in peak hours.

14.4.3.2. Visitor flows Studying visitor flows is very important for planning road networks and transportation facilities because these facilities should have enough capacity for the flows and the layout should be consistent with the main directions of the flows. The distribution of visitor flows in peak days is shown in Figure 14.5.

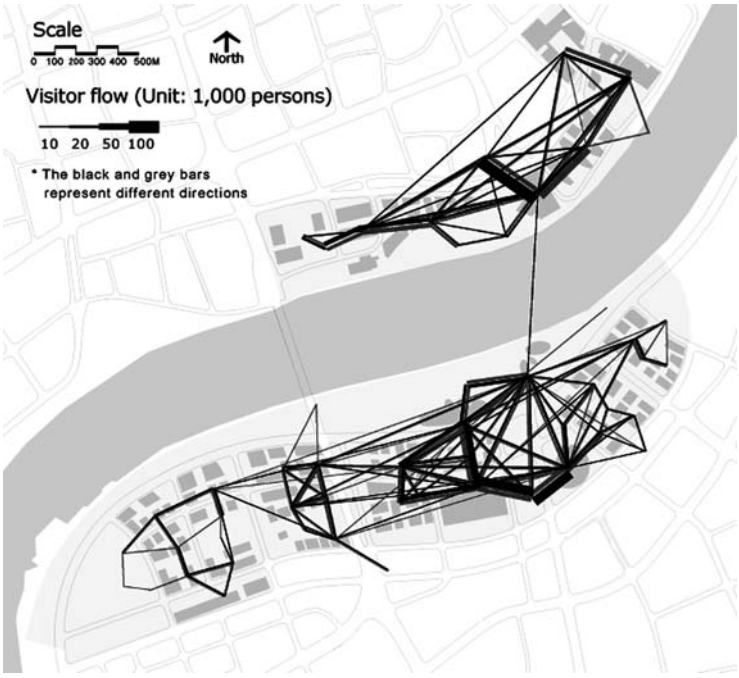


Figure 14.5: The distribution of visitor flows in peak days. *Note*: Only those flows whose one-direction number of visitors larger than 4000 are shown.



Figure 14.6: The distribution of visitor flows over time. *Note*: Only those flows whose one-direction number of visitors larger than 500 are shown.

In the upper site, the distribution is largely linear in shape, which is consistent with the plan of the road network. In the lower site, high concentrations of flows can be found between several main pavilions, which do not conform very well with the plan of a linear artery road along the river, suggesting that more space and paths should be arranged between these pavilions.

The temporal distributions of the flows (Figure 14.6) show a clear pattern of entry behavior before 10:00. The pattern of the flows in the upper site is generally well ordered, while more leaping flows (skipping adjacent pavilions) appear in the lower site when the number of visits increases, partially due to the saturation of the services in the main pavilions near the entrances. Since 10:00, the intensity of the flows



Figure 14.7: The distribution of dining demands in peak days.

gradually decreases and the distribution flattens. After 17:00, the flows toward the exits slowly increase because visitors start to leave. More specifically, on peak days, the peak flows (within 10 min) between the main entrance of the upper site and the article exhibition pavilion reaches 20,000 visits. Along the largely linear flows between the pavilions in this area, the peak flows may reach 6000 visits. In the lower site, about 10,000 visits and 15,000 visits can be observed on respectively normal days and peak days between several main pavilions. Besides these flow statistics, the number of visitors who are resting and queuing outside the pavilions should be considered simultaneously in planning. Necessary physical or administrational measures should be introduced to keep different types of activities from interfering with each other.

14.4.3.3. Dining demands The distribution of lunch demands is similar to the distribution of visits (Figure 14.7). The largest demands occur in the main theme pavilion and the China pavilion, which reach 45,000 meals. Pavilions with fewer visits have lunch demands around 2000 meals. The demand for supper is significantly lower than lunch and the distribution is also somehow different. Large decreases are observed in the upper site, while little changes happen in the lower site. These results suggest that space around the main pavilions should be provided with a sufficient amount of catering services. However, the demand for dining in squares may have been under-predicted because we focused more on the behavior of visiting exhibitions, while in fact squares are nice places for resting, taking meals, and enjoying views at the same time. Providing catering services in squares could also be a potentially good solution for satisfying the dining demands.

14.5. Conclusion

Research on visitor behavior in Expo and other similar large exhibition evens are crucial for planning site layouts and providing service facilities. However, empirical

studies of this topic are scarce. In this paper, we introduced a case study of modeling and simulating visitor behavior in Expo 2010 Shanghai for supporting the planning of the Expo site. A dataset about visitors taking virtual visits to the site was collected through a web-based experiment. A multinomial logit model was applied to model the destination choice behavior of visitors. Estimation results were satisfactory with all selected environmental factors significantly influencing choice behavior in hypothesized directions. This model was taken as the backbone procedure of a simulation framework which we developed to simulate the visits of 4000 individual visitors and predict the number of visits, the distribution of visitor flows, and the dining demands on the whole Expo site. Suggestions were given based on these predictions for site planning and service provision.

Many aspects of this study should be improved. Although web survey is a better alternative to conventional paper-based survey, it also introduces specific biases. The most critical one is probably an unrepresentative sample, which consists of respondents who have good computer skills, are relatively young and probably male. Hence, the most important thing is to have data of real-world visitor behavior, which is necessary for reliable models and conclusions. Theoretically better models, such as the nested logit model and mixed logit model, could be applied to capture more elements of visitor behavior. Elements such as entry, queuing, resting, and dining could be subjected to further investigation.

References

Borgers, A., Kemperman, A., Timmermans, H., Zhu, W., Joh, C., Kurose, S., Saarloos, D., & Zhang, J. (2008). Alternative ways of measuring activities and movement patterns of transients in urban areas: International experiences. *Proceedings of the international conference on travel survey methods*, Annecy, France, CD-ROM.

Borgers, A. W. J., Smeets, I. M. E., Kemperman, A. D. A. M., & Timmermans, H. J. P. (2006). Simulation of micro pedestrian behaviour in shopping streets. In: J. P. van Leeuwen & H. J. P. Timmermans (Eds), *Progress in design & decision support systems in architecture and urban planning* (pp. 101–116). Eindhoven, Netherlands: Eindhoven University of Technology.

Borgers, A. W. J., & Timmermans, H. J. P. (2004). Simulating pedestrian route choice behavior in urban retail environments. *Proceedings of Walk21-V Conference*, Copenhagen, CD-ROM (11 pp).

Borgers, A. W. J., & Timmermans, H. J. P. (2005). Modeling pedestrian behavior in downtown shopping areas. *Proceedings of the 9th International Conference on Computers in Urban Planning and Urban Management*, London, CD-ROM (15 pp).

Chorus, C. G., Arentze, T. A., & Timmermans, H. J. P. (2007). Travelers' need for information in traffic and transit: Results from a web survey. *Journal of Intelligent Transportation Systems*, *11*(2), 57–67.

Daamen, W., & Hoogendoorn, S. P. (2007). Free speed distributions: Based on empirical data in different traffic conditions. In: N. Waldau, P. Gattermann, H. Knoflacher & M. Schreckenberg (Eds), *Pedestrian and evacuation dynamics 2005* (pp. 13–25). Berlin: Springer.

Dijkstra, J., Timmermans, H., & de Vries, B. (2005). Modeling behavioral aspects of agents in simulating pedestrian movement. *Proceedings of the 9th International Conference on Computer in Urban Planning and Urban Management*, London, UK, CD-ROM.

Hughes, R. L. (2002). A continuum theory for the flow of pedestrians. *Transportation Research B*, *36*, 507–535.

Iragüen, P., & Ortúzar, J. deD. (2004). Willingness-to-pay for reducing fatal accident risk in urban areas: An internet-based web page stated preference survey. *Accidence Analysis and Prevention*, *36*(4), 513–524.

Lam, W. H. K., & Cheung, C. Y. (1999). Pedestrian travel time functions for the Hong Kong underground stations: Calibration and validation. *Journal of Transactions*, *5*(3), 39–45.

Lam, W. H. K., & Cheung, C. Y. (2000). Pedestrian speed/flow relationships for walking facilities in Hong Kong. *Journal of Transportation Engineering*, *126*, 343–349.

Lam, W. H. K., Morrall, J. F., & Ho, H. (1995). Pedestrian flow characteristics in Hong Kong. *Transportation Research Record*, *1487*, 56–62.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In: P. Zarembka (Ed.), *Frontiers in econometrics* (pp. 105–142). New York: Academic Press.

Oppewal, H., & Timmermans, H. J. P. (1997). Modelling the effects of shopping centre size and store variety on consumer choice behavior. *Environment and Planning A*, *29*(6), 1073–1090.

The Bureau of the Shanghai World Expo Coordination. (2005). The Registration Report of the World Expo 2010 Shanghai China. Available at: http://en.Expo2010.cn/documents/indexn.htm

Train, K. E. (2003). *Discrete choice methods with simulation*. New York: Cambridge University Press.

Walmsley, D. J., & Lewis, G. J. (1989). The pace of pedestrian flows in cities. *Environment and Behaviour*, *21*, 123–150.

Willis, A., Gjersoe, N., Havard, C., Kerridge, J., & Kukla, R. (2004). Human movement behaviour in urban spaces: Implications for the design and modelling of effective pedestrian environments. *Environment and Planning B*, *31*, 805–828.

Zhu, W., Wang, D., & Saito, S. (2005). The entry behavior of consumers on East Nanjing Road (in Chinese). *City Planning Review*, *29*(5), 14–21.

Zhu, W., Wang, D., & Saito, S. (2006). The multi-stop behavior of consumers on East Nanjing Road (in Chinese). *City Planning Review*, *30*(2), 9–17.

Chapter 15

Measurement of Pedestrian Movements: A Comparative Study on Various Existing Systems

Dietmar Bauer, Norbert Brändle, Stefan Seer, Markus Ray and Kay Kitazawa

Abstract

Management of large pedestrian infrastructures such as junctions of mass public transport, airports, or shopping centers needs measurements of pedestrian movements. These measurements are necessary to quantify and monitor the demand for the infrastructure in order to correspondingly adjust supply. Pedestrian movement measurements are also needed to provide services relating to safety (such as temporary access restrictions), security, and convenience of the users.

While a multitude of different sensing equipment is commercially available, knowledge on the relative merits is sparse. This chapter provides an overview of a number of different sensors for measuring pedestrian movement. The main emphasis lies on comparisons of advantages and disadvantages of the various approaches. We investigate properties of the systems with respect to comparative advantages, accuracy, and limitations. The objective is to provide guidelines to support selecting the most appropriate sensing equipment for a given measurement problem. The text also hints at ''blind spots'' indicating the need for further research. As such this chapter is of interest both for practitioners and researchers.

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15.1. Introduction

Many pedestrian infrastructures such as junctions of mass public transport or shopping centers are frequented by a large number of people every day. It is the duty of the management to ensure that these people enjoy a safe and convenient stay in the infrastructure. Consequently, technology to measure the movement of people within the infrastructure is necessary for a number of reasons:

- *Safety*: Overcrowding is a main source of safety threats which potentially leads to dangerous situations already in normal situations. Examples include the threat of being pushed off the edge of a railway platform (Figure 15.1a) and, *a fortiori* in evacuation or panic situations (cf. Helbing, Farkas, & Vicsek, 2000). In order to avoid overcrowding it is necessary to obtain an estimate of the number of persons within a pre-specified region in real time to be able to impose suitable access restrictions.
- *Security*: Large crowds are a main target of criminal activity ranging from pick pocketing to terrorist attacks. Some of these activities could be prevented if suspicious situations were identified early. The large amount of information available from the numerous surveillance cameras typically installed nowadays makes support from automatic systems identifying unusual and suspicious movements automatically highly desirable.
- *Efficiency*: Bottleneck elements within the infrastructure such as staircases, doors, or corridors limit the capacity of the infrastructure in terms of maximum flow rates accommodated by the infrastructure. Congestions due to insufficient supply (see Figure 15.1b) reduce the convenience of users and potentially deter people from using public transport. Furthermore, origin–destination matrices describing the flow between entries and exits of a public transport system are important prerequisites for planning adaptations and extensions of the system. On the other hand, too high supply levels invoke unnecessary costs. Hence public transport



Figure 15.1: (a) Dense crowd of spectators at the subway station next to a soccer stadium in Vienna, Austria, 2008. (b) Queue in front of the security check in Schiphol airport, Amsterdam.

operators are interested in monitoring usage of their infrastructure, in particular the extent of unnecessary delays making public transport less attractive compared to individual traffic.

- *Attractiveness*: Many infrastructures nowadays serve multiple purposes: junctions of mass public transport do not only handle passengers, but also act as shopping arcades. Hence they are of prime interest for marketing companies due to the large number of passers-by. This provides an additional source of income for the infrastructure provider. Some of this income is directly proportional to the number of persons using the infrastructure. Consequently, the rent for billboards or stores inside the infrastructure will depend on the number of potential customers frequenting the area inside the infrastructure. Shop owners have an interest in obtaining information on the so-called conversion rate (i.e., the percentage of persons entering a store that actually purchase something) and the typical duration of stay within the premises. This information can be obtained based on person counts in combination with time stamps recording the times when persons enter or leave the area under study.

The above problems justify the development of tools recording the movement of people within an infrastructure, in particular counting and tracking of pedestrians.

A number of different tools for counting and tracking pedestrians have been developed in recent years. It is the main goal of this chapter to provide a survey of different technologies to measure pedestrian movement inside infrastructures. We discuss the main characteristics of each technology, supporting both researchers and practitioners selecting the best measurement technology for a given task. The survey is based on our experience with numerous systems and deals with the following characteristics:

- Main applications
- Limitations
- Typical accuracy and reliability

The chapter has two main parts. Section 15.2 deals with pedestrian counting, while pedestrian tracking is discussed in Section 15.3. The presentation is divided into separate subsections for each investigated technology. The conclusions in Section 15.4 emphasize the main findings.

15.2. Pedestrian Counting

The most basic measurement of crowds is pedestrian counts at a cross-section. A cross-sectional count is a pair of pedestrian numbers and time stamps indicating the number of people that crossed a particular virtual gate — henceforth called counting line — either since the last measurement or exactly at the indicated time stamp. This offers information on volume flow, flow rates, and (for suitable configuration and directional counts) occupation levels/average pedestrian density. Counting

pedestrians relies on the ability to detect single pedestrians in the vicinity crossing the counting line. This can be accomplished by using "signals" emitted by pedestrians to interact with the environment. Among such signals are visual appearance, heat emission, reflections on the surface of the body, pressure exerted to the ground, and radio signals emitted from devices carried by the pedestrians. All these characteristics have been used in order to detect pedestrians as will be clear from the following sections.

15.2.1. Manual Observation

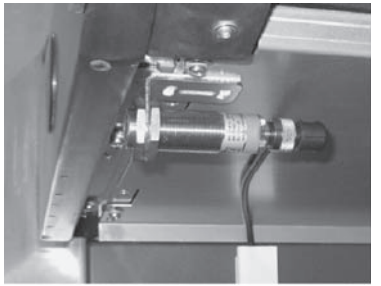
The traditional method for observing pedestrian flows is to use human observers that manually record information. Originally, sheet and paper methods were used, sometimes in combination with so-called tally counters (which continue to be heavily used on ferries, fairs, luna parks, or other similar events). For further analysis, the manual recording must be digitized. Nowadays, modern equipment makes the workflow more efficient by automatically including a time stamp with each recorded counting event and storing the data in digital form. Applications on smart phones are relatively simple to program and can be easily distributed to a number of observers (see Figure 15.2a). Concerning counting accuracy of human observers, Diogenes, Greene-Roesel, Arnold, and Ragland (2007) report an underestimation of volume flows between 8 and 25%, depending on the observer. The complexity of the scene (e.g., the flow rate, the width of the counting line, and the number of lines to be counted simultaneously) is another crucial factor having an impact on counting accuracy. This is documented by the fact that in Greene-Roesel, Diogenes, Ragland, and Lindau (2008) the manual observations in simple scenarios were found to be equally accurate as manual offline video counts.

In order to mitigate these inaccuracies, offline applications have been developed, where the cross-section to be evaluated is recorded with a video camera, and the counts are obtained by manually annotating the video sequences. These manual video annotation applications increase the accuracy and allow defining an arbitrary number of counting lines, as the video material can be viewed as often and as slowly as necessary. Such systems have been documented in the literature (e.g., the ZEUS system of the company Legion, www.legion.com, see Berrou, Beecham, Quaglia, Kagarlis, & Gerodimos, 2005). There are also freeware solutions available, which must be adapted to the counting situation (e.g., VIPER, viper-toolkit.sourceforge.net).

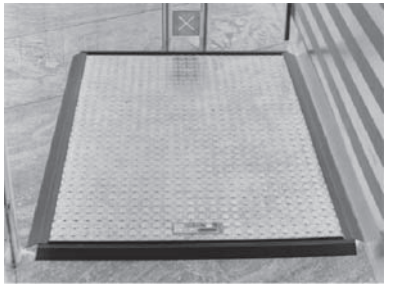
Manual observations do not require much planning and hence are a fast means of obtaining information (except the offline approach, where the positioning of the cameras should be carefully planned). The main cost relates to the personnel and hence costs scale essentially linearly with observation length and complexity (in terms of number of counting lines). Consequently, manual counts are most effective for temporally limited (ranging from hours to a few days) small cross-sections such as doors, staircases, escalators, or narrow corridors.



(a) *Manual counting application on a smart phone (© AIT)*



(b) *Infrared beam sensor.*



(c) *Switching mat*



(d) *IRIS infrared counting system (installed at the subway station Wien Hütteldorf, Austria)*



(e) *DILAX counting sensors (installed at a shopping centre in St. Pölten, Austria)*



(f) *LASE PeCo laser scanner (installed at the Atomium, Brussels)*

Figure 15.2: Various pedestrian counting sensors.

Manual observations can extend to long time spans such as years when they are combined with suitable sampling schemes (see, e.g., Arnberger, Haider, & Brandenburg, 2005, and the references therein). However in that case involve a non-negligible organizational overhead in addition to the personnel required for conducting the observations.

Table 15.1 shows summary of the manual observation characteristics.

15.2.2. *Automatic Single File Movement Counting Methods*

The counting task is significantly simplified when pedestrians can cross the counting line only in single file movement, and moreover are sufficiently separated. In such a situation comparatively low-cost sensors can be used to count pedestrians. Many of such sensors are mechanical, and do not directly provide counting data but have to be read off manually. This is true for most turnstiles typically found at entrances to supermarkets or subway stations.

Alternatives to turnstiles are infrared beams and switching mats. Infrared beams are composed of a sensor (emitting and receiving an infrared light beam, see Figure 15.2b) and a reflector. The sensor detects missing reflected signals as indications of an object being between the sensor and the reflector. These signal interruptions can be detected. Each interruption is interpreted as one person crossing the line. Switching mats (see Figure 15.2c) essentially work as electronic switches. Two electrodes are mechanically connected when a person is standing on the mat exerting pressure onto the mat, and are disconnected when the person leaves the mat.

In both cases counting can only be effective when the headway between consecutive pedestrians (i.e., time between two persons) is sufficiently large, such that two consecutive pedestrians can be separated by the sensors. When the headway is too small, the sensors cannot distinguish between consecutive persons, resulting in too low counts. Additionally, the walking direction cannot be observed based on one sensor only.

Figure 15.3 compares the accuracy of the counting results achieved by infrared beam sensors and switching mats in trials at a security check at the Vienna

Table 15.1: Characteristics of counting by using human observers.

Main applications	Entering and exiting counts on ferries, at fairs and events; situations where immediate results are expected with limited financial support
Advantages	Simple; not much planning involved, no installation/in site power supply needed (except for offline approach); reliable (no sensor failures possible)
Limitations	Sample size is limited (both in time and in extent; typically only hourly counts at a small number of locations are performed); offline methods decrease limitation in terms of complexity
Accuracy	Typically comparatively inaccurate, but depends crucially on the human observer and the complexity of the scene; offline methods increase accuracy considerably

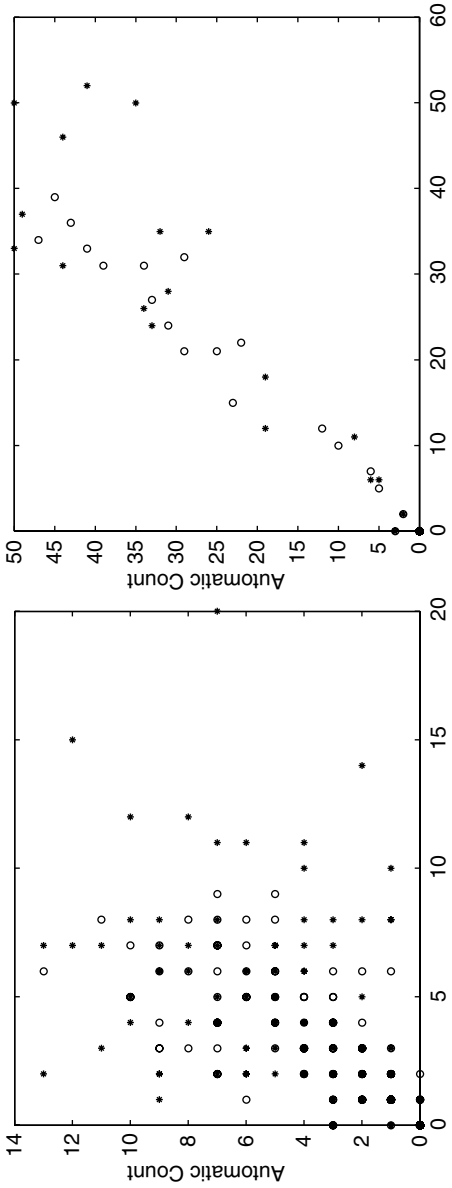


Figure 15.3: Comparison of true and automatic counts using infrared beam sensors (o) and switching mats (x). Left plot: Two-minute time intervals. Right plot: Fifteen-minute intervals.

International Airport.[1] The plots compare automatic counts with video-based offline manual counts serving as ground truth data. The data is based on the evaluation of 5½ h of video coverage the person counts aggregated to 2-min intervals (a) and 22 fifteen-minutes intervals (b) Note that the situation at security checks is more complex than other counting areas: Since the measurement area is located next to the conveyor belt transporting the hand luggage across the X-ray machine, pedestrians must stop and walk back often (e.g., because they are prompted to do so by the security personnel). Stopping in the area of the counting line might distort counts, as people enter the mat and step back while not crossing the counting line. Such behavior results in multiple counts per person and hence counteracts the underestimation due to insufficient headways. Similar artifacts occur for the infrared beam.

The evaluation shows that for a wide range of flow rates the sensors provide reasonable estimates for aggregation to 15 min counts even in this complicated situation (in particular for small flow rates). As for 2 min aggregation, Figure 15.3a does not show a clear relation. For larger flow rates infrared beams overestimate the number of persons (by approximately 20% on total). This tendency is less clear for the switching mats (overestimation of 5%). In any case the systematic bias could be corrected by post-processing the count data, whereas the random variation (which increases with rising flow rates) is unavoidable.

The lessons to be learned from these investigations are that pedestrian counts with a small aggregation interval are unreliable. This behavior is typical for automatic counting sensors in general (see below and see also Griffith, 2005). Since measurements in different measurement periods appear to be independent, temporal aggregation lowers the relative error. However, for larger flow rates also larger uncertainty (in absolute terms) is to be expected. Again, this situation is typical for all automatic counting technologies as will be clear from below. In this sense, the results for the infrared beam sensors and the switching mats are prototypical.

Since the measurements are obtained automatically, the length of the observation period is unlimited. However, the restrictions on single file movement and separation limit the potential applications. Furthermore, electric power supply and data recording units need to be connected to the sensors. Consequently, the main costs lie in the equipment itself. Table 15.2 gives an overview about the characteristics of automatic single file movement counters.

15.2.3. Active Infrared-Based Counting

The infrared-beam sensors described in section 15.2.2. can only provide good counting accuracy in situations where no occlusion problems (due to sufficiently

1. The experiments have been conducted during the project "PACE-AOM" (financed via the program TAKE-OFF, an initiative of the Austrian federal ministry for transport, innovation, and technology, which is gratefully acknowledged). The authors thank the Vienna International Airport for support during the data collection phase.

Table 15.2: Characteristics of automatic single file movement counters.

Main applications	Situations where turnstiles are accepted or access restrictions are imposed (entries to supermarkets, subway stations, sports facilities, airports)
Advantages	Observation is fully automatic and hence can extend over a long time span at small costs; sensors are of lower costs compared to other counting sensors
Limitations	Only single file movement can be handled; installation of equipment might lead to additional restrictions (placement of sensors are not to interfere with movement: infrared beam sensor may not reach into walking space; switching mats have significant elevation causing troubles for handicapped people, other equipment)
Accuracy	Typically comparatively low for small time intervals; depends largely on the separation of pedestrians

large headways and single file movement) are expected. This can be achieved for sensors mounted above the heads of pedestrians pointing toward the floor. Using two infrared-beam sensors staggered in walking direction allows bidirectional counting of a single file movement. By combining several such "top view" sensors in a linear grid (perpendicular to the walking direction) of distance small enough that most people are not able to walk between two sensors (e.g., 35 cm), counting sensors useable for a general cross-section have been developed. Figure 15.2d shows an image of the IRIS (www.irisgmbh.de) counting system installed at a subway station, Figure 15.2e provides a closer look onto the similar system of the company DILAX (www.dilax.de) installed at a shopping center.

The main challenge with this principle is (beside the determination of the walking direction) to estimate the number of people in situations where more than one sensor records interruptions of the light beam. Hence it is expected that the main difficulty for the technology are dense scenarios as well as cross-sections with a large width.

Figure 15.4a shows plots for 2 min counting intervals using DILAX sensors and 1 min counts IRIS sensors in two different situations. The DILAX sensors were mounted atop a corridor in a shopping center, while the IRIS sensors were mounted in the entrance to a subway platform close to a soccer stadium and analyzed for high levels of pedestrian flow (Seer, Bauer, & Brändle, 2008).[2] While comparing the estimation accuracy is valuable, it would be expected to be only fair when obtained in a systematic study such as the one described in Griffith (2005). This follows from the fact that counting accuracy is not only related to average flow rates, but also depends

2. The experiments with the IRIS system have been conducted in the project "RAVE," the experiments with the DILAX counters in the project "OD-METRICS." Both projects have been financed in the program I2 by the Austrian ministry for transport, innovation, and technology, which is gratefully acknowledged.

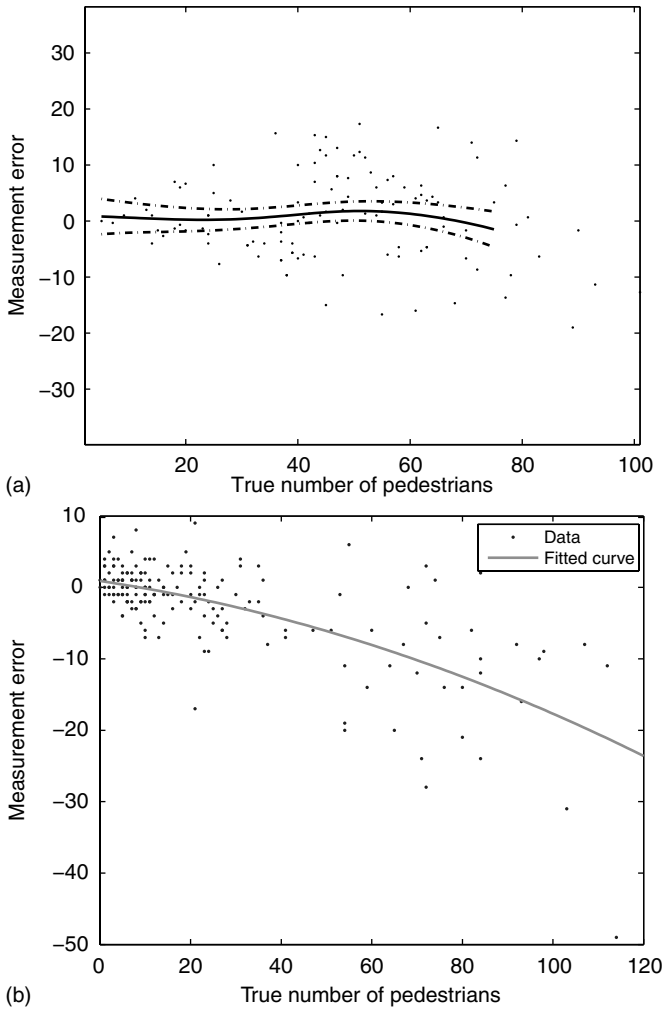


Figure 15.4: Comparison of estimation accuracy for active infrared counting sensors. (a) Accuracy of DILAX sensors in shopping center (2 min aggregation). Superimposed is a kernel estimate of the average error (solid line) with confidence interval (broken lines). (b) Accuracy of IRIS sensors in subway station (1 min aggregation). Superimposed is a quadratic curve fitted using least squares.

on the distribution of flow rates over the observation period (see Figure 15.3 or Figure 15.4). Thus the two plots are not directly comparable and results on the relative merits of the two systems cannot be deduced.

The main message is that both systems are capable of providing fairly accurate estimates of flow rates even for small levels of temporal aggregation. The 2 min counts from the DILAX system (see Figure 15.4a) showed a mean absolute

percentage error of approximately 14% and a ratio of the standard deviation to the average counts of 16%. Under the (reasonable) assumption of measurement errors being independent over time, one obtains a standard deviation to mean ratio for estimates of 12 h counts of less than 1%. Similar remarks are true for the IRIS system in Figure 15.4b with one exception: The plot reveals a substantial underestimation of the number of pedestrians for high flow levels (which has not been observed for comparatively small flow rates). Comparable flow rates did not occur in the shopping center situation. Hence for the DILAX sensors no conclusion in this respect can be drawn. Falk (2005) noted analogous underestimation for large flow rates also for other counting sensors (such as video and laser scanner counting techniques, see below), so this is no particular deficiency of the IRIS system.

It is important to note that systematic underestimation does not average out by aggregating to larger time intervals. However, if such a systematic estimation error is detected (e.g., by means of analyses analogous to the ones presented here), the systematic part of the estimation error can be accounted for. Table 15.3 summarizes the characteristics of active infrared-based counting systems.

15.2.4. Video-Based Counting

Video-based counting techniques capture video data of a scene and analyze the video information with respect to the numbers of individuals crossing a virtual counting line. A number of companies offer products for a wide range of different applications (see, e.g., Acorel, www.acorel.com; Springboard, www.spring-board.info; BlueEyeVideo, www.blueeyevideo.com; ObjectVideo, www.objectvideo.com to mention just a few). Most of these systems use a top view scenario, where the camera is mounted atop the counting line in order to mitigate problems with occlusions of

Table 15.3: Characteristics of active infrared-based counting systems.

Main applications	Counting pedestrians in large infrastructures (junctions of mass public transport, shopping centers) at mid-sized counting lines (up to approximately 5 m)
Advantages	Observation is fully automatic and hence can extend over a long time span; delivers reliable counts also for wider corridors and doors in comparison to single file counters
Limitations	Require top view locations for the sensors in a limited range of height of about 2.4–2.7 m (see the construction in Figure 15.2d); although technically possible typically it is not advisable to use these sensors for wide corridors (wider than approximately 5 m) due to high costs
Accuracy	Pedestrian density and temporal aggregation are the main determinants of counting accuracy; also an influence of the number of sensors induced by varying corridor widths is expected[a]

[a]Data on this question is sparse. Hence no conclusions can be drawn in this respect.

pedestrians. Common to all systems is that the results strongly depend on the environmental conditions, especially on lighting condition (sunlight). Video-based systems also show a degradation for large flow rates, where they substantially underestimate the number of pedestrians.

Bio-inspired stereo sensors such as the ''Universal Counting Sensor (UCOS)'' from the ''Safety & Security'' group at AIT infer height information (Milosevic, Schraml, & Schön, 2007). This improves the distinction between pedestrians and other objects in the scene and consequently the counting accuracy. Table 15.4 provides an overview of the characteristics of video-based counting systems.

15.2.5. Other Sensors

The principle of laser scanners for counting pedestrians is similar to the principle of active infrared detectors: A laser scanner is mounted atop the counting line which provides two height profiles of the vertical plane intersecting the ground plane at two lines surrounding the counting line. Two lines are used to determine the walking direction. The height profile is analyzed to detect and count persons. The mounting height determines the possible width of the counting line. The sensors can be mounted up to 15 m above ground, allowing a counting line of 26 m width.

Falk (2005) compares the accuracy of a number of counting systems including the laser scanner sensors of the company LASE PeCo Systemtechnik (www.people-counter.de). He concludes that the accuracy of the laser scanner sensors is superior to the other tested sensors. However, he also notes that the separation of pedestrians is vital for accurate counting. Closely spaced pedestrians lead to substantial underestimation of the number of persons. Laser scanners are expensive compared to other sensors (a few thousand Euros). Hence they are only competitive for relatively wide counting lines (starting from approximately 5 m).

Passive infrared sensors measure the heat emitted by persons in order to detect people. Such sensors have been developed by the company IRISYS

Table 15.4: Characteristics of video-based counting systems.

Main applications	Counting pedestrians in large infrastructures (junctions of mass public transport, shopping centers)
Advantages	Observation is fully automatic and hence can extend over a long time span; delivers reliable counts also for wider corridors and doors in comparison to single file counters
Limitations	Require top view locations for the sensors (height crucially depends on the camera lens used) and considerable distance between pedestrian heads
Accuracy and reliability	Changing environmental conditions (e.g., lighting) lead to unpredictable performance for most vision-based systems; high crowd densities might pose problems and limit accuracy

(www.irisys.co.uk), and they are used by the company Experian Footfall (www.footfall.com). One sensor covers an area of up to 2.4×4.4 m and currently costs approximately 1000€, excluding recording equipment.

In the course of a large study in London, three sensor technologies have been systematically compared in an outdoor setting (Griffith, 2005): the laser scanners by LASE PeCo, the Footfall system, and a computer vision-based system by the company Springboard (www.spring-board.info). The main conclusion drawn there was that the counts for small temporal aggregation are unreliable for all systems but that for 3 h aggregation also including high flow rates all systems reached an accuracy of less than 5% error. This is well in line with our findings above. The laser scanner turned out to be more accurate.

Finally it should be noted that also other measurement approaches have been tested. Falk (2005), which contains also technical descriptions of the sensors, lists ultra-sonic measurements and radar measurements in addition to the approaches discussed above. To the best of our knowledge these approaches have not yet been proven to work satisfactorily in real-world situations.

15.3. Pedestrian Tracking

We denote pedestrian tracking as the collection of trajectory data in the form of consecutive pairs of (time stamp, location) samples. Such trajectory data contains useful information on the motion behavior of persons. It can be used to classify behavior for monitoring purposes in ambient assisted living (e.g., Morris & Trivedi, 2008), to obtain information on the usage pattern (such as, e.g., OD-matrices) for improving the attractiveness of an infrastructure (e.g., measuring the duration of stay inside various rooms in a museum, Kanda et al., 2007). Trajectory data sets are also useful to calibrate microscopic pedestrian movement models such as the social force model of Helbing and Molnar (1995) as is documented, e.g., in Johansson, Helbing, and Shukla (2007), Hoogendoorn and Daamen (2006), and Bauer and Kitazawa (2008).

Trajectory data sets can also be used to obtain pedestrian counts at arbitrary cross-sections. Consequently, the distinction between pedestrian counting (Section 15.2) and pedestrian tracking approaches is not strict. Some of the technologies used for counting actually rely on extracting the count information from people tracking.

Technology for pedestrian tracking is much less developed than technology for counting. Additionally, precision strongly varies between the different methods. The discussion of the various methods below will be brief and not in the same format as used for the counting methods.

Tracking methods can be categorized into intrusive and non-intrusive approaches. The intrusive approaches require the tracked pedestrians to be equipped with tracking devices and hence are limited to scenarios where distributing and collecting tracking devices is possible. Non-intrusive approaches, on the other hand, either use devices that are already present at a subset of the population (e.g., cell phones),

which subsequently defines the sample, or do not use any special devices (such as visual surveillance methods). In the following sections we describe the most popular tracking approaches.

15.3.1. Shadowing

Shadowing (or stalking) is the oldest form of measuring people tracking data. Human observers physically follow the investigated individual and record significant locations on a map (hardcopy or digital). In addition to tally counters (Section 15.2), PDAs or tablet PCs provide technical aid for shadowing. A software application in this respect developed at the AIT in Vienna allows to load a digital map (represented with standard graphic image formats) into a tablet PC. While observing the subject, its location can be annotated directly on the digital map using a smart pen. Together with the location information, the application records the ID of the tracked subject and a time stamp. Furthermore, supplementary information can be added easily. This greatly reduces the workload for the analysis of the results. For details and an application see Millonig and Gartner (2008).

Trajectory data sets obtained with shadowing have limited spatial accuracy. Furthermore, since data collection is performed by humans, the sample size is heavily limited. In many cases, however, shadowing is still the method of choice due to the lack of attractive alternatives, as will be clear from the following subsections.

15.3.2. Video-Based Tracking

Digital video footage is composed of temporal sequences of two-dimensional pixel arrays having a fixed number of rows and columns, called video frames. In video-based tracking, the first step is usually to detect people in individual frames, where pixel sets are classified to belong to the pedestrian class (see Munder & Gavrila, 2006 for an overview). The second step is to associate detected objects between video frames (and between multiple cameras) in order to obtain trajectories (see Yilmaz, Javed, & Shah, 2006 for a survey).

Contradicting to claims of marketing departments, existing academic and commercial automatic video surveillance techniques can only operate robustly and reliably in limited scenarios with limited camera networks, limited video footage, limited fault tolerance, and small variability of scenes (Remagnino, Velastin, Foresti, & Trivedi, 2007). Difficulties in video-based tracking can arise due to abrupt object motion, changing appearance patterns, occlusions (people-to-objects, people-to-people, people-to-scene), and camera motion.

The performance of automatic monitoring is heavily influenced by the imaging setup. For example, one way to avoid severe occlusions and the resultant problems with pedestrian detection and tracking is to capture the scene from a bird eye's view.

Most of today's commercially available video-based pedestrian *counting* sensors rely on such configurations (see Section 15.2.4).

Many built environments have an architecture which does not necessarily allow full video coverage. Too many cameras might be required to cover an entire building. Additionally, the ceilings are often low (e.g. in subway environments), which will lead to shallow viewing angles with the related severe mutual occlusions. An example for a single camera view from an elevated mounting position in a train station entrance hall is shown in Figure 15.5. The black lines indicate automatically computed people trajectories for a 15-min interval, the crosses indicate calibration points to obtain metric trajectory data where positions relate to a coordinate system on the ground plane (see Brändle et al., 2009 for details).

A large number of cameras might demand an impractical hardware setup. *Smart cameras* combine video sensing, processing, and communication in a single embedded device and can therefore avoid video transmission and hardware resources for video processing. An overview of distributed smart cameras can be found in Rinner and Wolf (2008).

Concerning dense crowds of people, it is widely agreed that the object-based trajectory approach only works up to a certain complexity and density of people. For crowded scenes with many individuals, the mutual occlusions become so severe that currently no tracking algorithms can handle them effectively, even with a multi camera approach. The sub-domain of crowd analysis deals with information

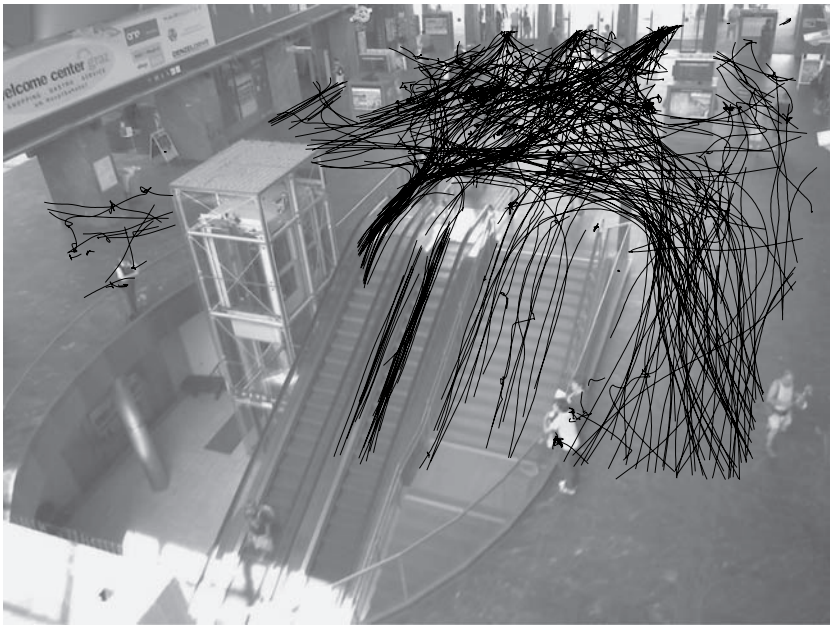


Figure 15.5: Trajectory data of a train station hall computed with automatic video-based tracking (for details see Brändle et al., 2009).

extraction without relying on individual object tracking (Zhan, Monekosso, Remagnino, Velastin, & Xu, 2008).

15.3.3. Passive Infrared-Based Methods

Passive infrared sensors provide data frames of heat maps which are structurally very similar to video sequences (see Section 15.2.5). Consequently, (top view) video-based tracking methods can be employed. First attempts to use passive infrared for pedestrian tracking are described in Kerridge, Armitage, Binnie, Lei, and Sumpter (2004). The problem is simpler than conventional computer vision problems. Since the typical temperature of human beings is known and typically very different from the surroundings, detection of persons in a top view setting corresponds to detections of bright spots.

Also for this technology occlusions at higher levels of density limit tracking accuracy (due to the typically low image resolution). Additionally the sensors cost currently limit the area which can be covered, since each sensor can only monitor an area of a few square meters. The latter is less critical for counting applications, where only the area surrounding the counting line needs to be monitored. No results on the accuracy of the measured trajectories are known.

15.3.4. Horizontal Laser Scanners

Tracking with laser range scanners is different from counting with laser range scanners in the sense that a plane parallel to the ground plane is scanned rather than a vertical plane intersecting the ground plane at the counting line. Rather than on an elevated point close to the ceiling, laser range scanners for tracking are mounted close to the floor, either at hip height or approximately 16 cm above the floor depending on whether the hip or the foot is to be detected. They provide with a frequency of 10 Hz (i.e., one snapshot every tenth of a second) the distance to the nearest object in different directions of an angular domain in a local scanner coordinate system. Combining the output of a number of scanners into a unified real-world coordinate system results in a cloud of points in which pedestrians are represented by a number of dots roughly arranged on an elliptically shaped object. Bauer and Kitazawa (2008) use laser scanners mounted at hip height and obtain trajectories with an HMM (hidden Markov model) tracker to map dots in the outline of an elliptical object to pedestrians. Nakamura et al. (2006) mount eight laser scanners close to the floor and track foot movement to reduce occlusion problems. Depending on the location and number of the laser scanners, up to 150 pedestrians have been successfully tracked simultaneously.

If all pedestrians can be tracked successfully, one obtains for each pedestrian a motion trajectory. The accuracy of this trajectory has been evaluated in Bauer and Kitazawa (2008) using trajectories of pedestrians following prescribed paths in a laboratory environment. The average absolute deviation from the prescribed path

was found to be approximately 3 cm. Such high precision trajectory data sets can be used in order to calibrate microscopic pedestrian movement models.

Nakamura et al. (2006) demonstrate the potential of laser scanning for tracking in a subway station. However, occlusion problems need to be countered by an increase of laser scanners which are expensive compared to video camera equipment. This also hampers commercial application of this approach.

15.3.5. Intrusive localization methods

In some situations it is possible to equip people with devices which allow tracking by interaction with measurement beacons. Such devices are radio frequency identification (RFID) tags, smart phones, PDAs, or other devices emitting signals.

RFID tags have been used as an intrusive method for pedestrian tracking. RFID tags are popular in the area of logistics for identifying objects. There are active and passive approaches for RFID tracking: Active tags require power supply increasing the costs of the tags significantly, while passive tags obtain power supply from signals sent by the RFID reader posing strong restrictions on the capabilities of the tags and limiting the distance from which they can be read. On the other hand, passive tags do not require special maintenance operations. These two classes of RFID tags are consequently suited for very different applications: The signal strengths of one active RFID tag received at a number of RFID readers (minimum of three is necessary) are compared to tabulated "fingerprints" to estimate the position of the tag. This potentially enables measuring the position of the tags on a very fine scale. To date it is insufficiently known how accurate the corresponding localizations are. In particular the effects of environmental conditions such as weather or the presence of other pedestrians are largely unknown.

A passive tag, on the other hand, is registered if it is sufficiently close to a card reader (typically in the magnitude of a few centimeters). This allows detecting pedestrians only in the vicinity of the RFID readers, but not in between. Passive tags are typically used for access controls at offices, museums, etc., where time information is the main point of interest. On the other hand, tracking information is already used in large-scale real-life applications. For example, http://skiline.cc logs the ski lifts a person uses over an entire day including the timing and the elevation skied. Another example for tracking with passive RFID is www.chronotrack.com which provides RIFD tags for timing marathon races.

Other emitted signals such as Bluetooth or WLAN can be used analogously. These signals are emitted by a wide range of devices such as mobile phones, PDAs, or laptop computers. To the best of our knowledge the achievable accuracy using such a system is insufficiently known. These methods can be employed both in an intrusive and non-intrusive manner. In the latter case, the observer has no control over the sample size and the selection of the sample. Sample selection issues are insufficiently known in that case. The accuracy of the resulting trajectory data sets is expected to be subject to the same problems as for RFID.

15.4. Conclusions

Research and practice dealing with the planning and management of infrastructures frequented by pedestrians are "data hungry." In contrast to motorized individual traffic, much less data sources and data history are available. Technology on measuring pedestrian behavior is of a comparatively recent vintage. Surveys and human observers are still predominantly used.

Knowledge on the characteristics of different technologies is still sparse. This is documented by the efforts documented in Griffith (2005), and also by the fact that manufacturers of counting sensors list the resulting accuracy as "bigger than 95%" without specifying the temporal aggregation or the flow rates under which the accuracy can be achieved. As can be seen from the results discussed above for small time intervals counting results can be much worse, which is also documented in Griffith (2005) and Falk (2005). However, since measurement errors appear to be independent over time, the relative error decreases as the temporal aggregation increases: in technical terms this is due to the fact that the average counts increase linearly with aggregation interval, while the standard deviation increases proportional to the square root of the aggregation interval. This argument only works when there are no systematic errors. Such errors cannot be excluded *a priori*, but can be corrected for (which presumably is done in many sensors already). The dependence of the counting accuracy on the temporal aggregation as well as the true flow rate has been observed for all automatic counting devices.

Only a few comparisons of the relative accuracy of counting sensors have been conducted. These studies indicate that for pedestrian counting, there are no "optimal" sensors that are best under all circumstances. Limitations for installation heights, occlusion problems, and cost restrictions are important in this respect. Hence it seems to be appropriate to pick the sensor that best matches the question analyzed. In this text a number of hints can be found that guide this choice.

Pedestrian-tracking technology is much less mature than counting. For pedestrian tracking, knowledge on the accuracy is even sparser. In laboratory environments accuracies of less than 3 cm have been achieved. Most systems are not developed up to a point where they can deal with real-world scenarios. For other systems sample selection issues are unclear or subjects must be equipped with measurement devices. Thus distribution and collection of devices biases the results. In this respect the text demonstrates a strong research need.

References

Arnberger, A., Haider, W., & Brandenburg, C. (2005). Evaluating visitor-monitoring techniques: A comparison of counting and video observation data. *Environmental Management*, *36*(2), 317–327.

Bauer, D., & Kitazawa, K. (2008). Using laser scanner data to calibrate certain aspects of microscopic pedestrian motion models. *Proceedings of the 4th International Conference on Pedestrian and Evacuation Dynamics (PED2008)*, Wuppertal, Germany.

Berrou, J. L. Beecham, J., Quaglia, P. Kagarlis, M. A., & Gerodimos, A. (2005). Calibration and validation of the Legion simulation model using empirical data. *Proceedings of the 3rd International Conference on Pedestrian and Evacuation Dynamics (PED2005)*, Wien, Austria (pp. 167–181).

Brändle, N., Matyus, T. Brunnhuber, M., Hesina, G., Neuschmied, H., & Rosner, M. (2009). Realistic interactive pedestrian simulation and visualization for virtual 3D environments. *Proceedings of the IEEE 15th Conference on Virtual Systems and Multimedia (VSMM2009)*, Vienna.

Diogenes, M., Greene-Roesel, R., Arnold, L., & Ragland, D. (2007). Pedestrian counting methods at intersections: A comparative study. *Transportation Research Record*, *2002*, 26–30.

Falk, S. (2005). Personenzähleinrichtungen für Versammlungsstätten, Diplomarbeit. Masters thesis, *Hochschule für Angewandte Wissenschaften Hamburg* (in German).

Greene-Roesel, R., Diogenes, M., Ragland, D., & Lindau, L. (2008). Effectiveness of a commercially available automated pedestrian counting device in urban environments: Comparison with manual counts. *Proceedings of the TRB 2008 Annual Meeting*.

Griffith, A. (2005). Automatic pedestrian counting trial. Central London Partnership, Stage 3 — Final report.

Helbing, D., Farkas, I., & Vicsek, T. (2000). Simulating dynamical features of escape panic. *Nature*, *407*, 487–490.

Helbing, D., & Molnar, P. (1995). Social force model for pedestrian dynamics. *Physical Review E*, *51*, 4282–4286.

Hoogendoorn, S. P., & Daamen, W. (2006). Microscopic parameter identification of pedestrian models and implications for pedestrian flow modeling. *Proceedings of the 85th Annual Meeting of the Transportation-Research-Board*, Washington, DC, Jan. 22–26.

Johansson, A., Helbing, D., & Shukla, P. (2007). Specification of the social force pedestrian model by evolutionary adjustment to video tracking data. *Advances in Complex Systems*, *10*(4), 271–288.

Kanda, T., Shiomi, M., Perrin, L., Nomura, T., Ishiguro, H., & Hagita, N. (2007). Analysis of people trajectories with ubiquitous sensors in a science museum. *Proceedings of the IEEE International Conference on Robotics and Automation* (pp. 4846–4853).

Kerridge, J., Armitage, A., Binnie, D., Lei, L., & Sumpter, N. (2004). Using low-cost infrared detectors to monitor movement of pedestrians: Initial findings. *Transportation Research Record*, *1878*(1), 11–18.

Millonig, A., & Gartner, G. (2008). Ways of walking — Developing a pedestrian typology for personalised mobile information systems. In: G. Gartner & K. Rehrl (Eds), *Location based services and TeleCartography II — From sensor fusion to context models. Lecture notes in geoinformation and cartography* (pp. 79–94). Berlin: Springer.

Milosevic, N., Schraml, S., & Schön, P. (2007). Smartcam for real-time stereo vision — Address-event based stereo vision, Barcelona, Spain, March 8–11, 2007. *INSTICC — Institute for systems and technologies of information, control & communication*, INSTICC Press, Portugal, ISBN:978-972-8865-74-0, pp. 466–471.

Morris, B. T., & Trivedi, M. M. (2008). Vision-based trajectory analysis for surveillance. *IEEE Transactions on Circuits and Systems for Video Technology*, *18*(8), 1114–1127.

Munder, S., & Gavrila, D. M. (2006). An experimental study on pedestrian classification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *28*(3), 1–6.

Nakamura, K., Zhao, H., Shibasaki, R., Sakamoto, K., Ohga, T., & Suzukawa, N. (2006). Tracking pedestrians using multiple single-row laser range scanners and its reliability evaluation. *Systems and Computers in Japan*, *37*(7), 1–11.

Remagnino, P., Velastin, S., Foresti, G., & Trivedi, M. (2007). Novel concepts and challenges for the next generation of video surveillance systems. *Machine Vision and Applications*, *18*, 135–137.

Rinner, B., & Wolf, W. (2008). An introduction to distributed smart cameras. *Proceedings of the IEEE*, *96*, 1565–1575.

Seer, S., Bauer, D., & Brändle, N. (2008). Design of decision rules for crowd controlling using macroscopic pedestrian flow simulation. *Proceedings of the 4th International Conference on Pedestrian and Evacuation Dynamics (PED2008)*, Wuppertal, Germany.

Yilmaz, A., Javed, O., & Shah, M. (2006). Object tracking: A survey. *ACM Computing Surveys*, *38*(4), 1–45.

Zhan, B., Monekosso, D. N., Remagnino, P., Velastin, S. A., & Xu, L. (2008). Crowd analysis: A survey. *Machine Vision and Applications*, *19*, 345–357.