MODELLING PEDESTRIAN BEHAVIOUR IN DOWNTOWN SHOPPING AREAS

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Abstract: This paper presents a model to simulate individual route choice behaviour of pedestrians in downtown shopping areas. The model assumes that 1) pedestrians enter the downtown network at entry points: 2) pedestrians exit the downtown area where they entered the area, and 3) given a pedestrian's current link in the downtown network, the pedestrian chooses one of the connecting links to move onwards. This choice is driven by the physical characteristics of the links (e.g. supply of shops), distance, some variables representing the history of the trip, and other variables. The model employs an endogenous, utility-driven mechanism to finish the trip. The model is calibrated using observed route choice data in two medium sized Dutch cities: Eindhoven and Maastricht. The model simulates individual behaviour and aggregated link loadings reasonably well.

Keywords: pedestrian behaviour, downtown shopping areas, link-to-link decision making.

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1 INTRODUCTION

Recent models of pedestrian behaviour focus on pedestrian movement at the microscopic level. These models can be used to assess the effects of detailed design decisions, like the positioning of street furniture or the shape of a building, requiring a detailed description of the spatial environment. Not all decisions related to the design of pedestrian environments need that kind of detail. For example, one might be interested in assessing the likely effects of policy measures related to urban traffic infrastructure, parking facilities, and upgrading of urban retail environments on pedestrian flows in shopping areas. Changing pedestrian flows in shopping areas may result in changing turnover figures and changing real estate values. Therefore, the aim of this paper is to develop a model that is able to predict the likely effects of urban planning policies on pedestrian flows in downtown retail environments at the level of shopping streets.

This paper is organized as follows. In the next paragraph, we will discuss some of the relevant literature on modelling pedestrian behaviour. Then, we will present the theory and assumptions underlying our model in section 3. In section 4, we will describe the data we collected to estimate the parameters of the model. Section 5 specifies the model in more detail and section 6 reports the estimation results. A discussion and some directions for further extensions of the model will conclude the paper.

2 LITERATURE

Models for predicting pedestrian behaviour or the number of pedestrians in public urban areas have been developed since the 1970's. One of the first models was developed by Sandahl & Percivall (1972) to assess the effects of larger retail and parking facilities on pedestrian traffic in a Swedish town. They regressed the observed number of pedestrians on the links of the central area network against characteristics of the links, such as retail floor space, parking facilities, accessibility by bus, centrality of the link in the network, number of street stalls and seating places. Likewise, Puskarev & Zupan (1975) analysed pedestrian presence in avenues and streets in Manhattan. They related pedestrian counts on block sectors to building floor space, walkway area, and proximity to transit facilities.

In contrast to using characteristics related to objects along the links as explanatory variables, Hillier and his co-workers (Hillier et al.; 1993; see also Teklenburg et al.; 1994) used characteristics of the network itself. According to their space syntax model, measures representing topological characteristics of lines are assumed to be related to observed numbers of pedestrians in streets. Consequently, the space syntax approach cannot account for the effects of, for example, changing retail floor space as the approach assumes that morphological characteristics as opposed to functional characteristic determine pedestrian patterns. Desyllas et al. (2003) used topological and non-topological variables to explain observed numbers of pedestrians by means of regression analysis. Visibility appeared to be the most important variable in their study.

The models discussed above might be able to predict pedestrian volumes, but they are less appropriate, if at all, to predict pedestrian movement. Borgers & Timmermans (1986a, 1986b) proposed a model to predict pedestrian movement at the level of links in a downtown shopping area. Their model consists of three modules. Given a list of types of shops to be visited and an entry point for each pedestrian, the destination module selects a destination-link from the set of links providing a particular type of shops. This link will be the next destination. The route choice module then predicts the route from the current position to the selected destination. Having reached this location, the destination module selects a next destination and so on, until all types of shops on the list have been visited. The last destination will be the exit-link, which is assumed to be the entry-link. The third module predicts possible impulse stops along the route through the shopping area. This model can be used to simulate individual pedestrian behaviour (Borgers & Timmermans, 1986b).

In contrast to these models, models of much more detailed, microscopic, pedestrian behaviour have come into fashion during the 1990’s (Batty, 2001). These models offer very detailed descriptions of pedestrian behaviour, e.g. avoidance of obstacles, movement of crowds, at the scale of grid-cells in links. Examples of such models are the Cellular Automata based models suggested by Blue & Adler (2001), the social force model for pedestrian dynamics developed by Helbing & Molnar (1995), and the agent-based models proposed by Kerridge et al. (2001) and Dijkstra et al. (2002).

Haklay et al. (2001) developed STREETS, a system which models pedestrian movement at different spatial levels. Their model consists of two sub-models. The first model operates at the level of sub-regional, urban districts; it populates the gate-ways (like parking garages, train stations, bus stops) of the downtown area with populations of agents (pedestrians), having predetermined activity schedules/route plans. In the second phase, an agent-based model simulates the movement of the agents in the downtown area under influence of spatial configuration, predetermined activity schedules, and the distribution of land uses. The agents are ‘operated’ by five behavioural modules. The mover module determines the very local moving to the next grid square. Medium range (maintaining a proper direction) and longer range (to the next destination) movement is taken care of by the helmsman and navigator module. The chooser module enables an agent to search a nearby area and to recognize buildings near its route. A building, which an agent has seen, might distract an agent from its predefined activity schedule. Changes in the agent’s plan are managed by the planner module. The first three modules deal with tactical movement, while the latter two deal with strategic movement and planning.

Hoogendoorn (2003) described a model for activity scheduling and trajectory choice based on the assumption that pedestrians are subjective utility maximizers who schedule their activities, the areas where activities will be performed, and the trajectories between the activity areas. The trajectories are assumed to be continuous in space and time.

3 MODEL DESCRIPTION

Most recent models of pedestrian behaviour assume a grid based space or even continuous public space to move around. According to Hoogendoorn (2003), facilities like airports and large shopping malls offer pedestrians freedom of movement by providing an infinite number of route alternatives through the facility. However, the aim of this paper is not predicting microscopic pedestrian behaviour rather than predicting pedestrian behaviour at the level of links in downtown retail areas.

Most models of pedestrian behaviour assume that pedestrians have a predefined set of destinations to visit, activities to perform or a route to follow through the public space. In contrast, we assume in this paper that we do not know the aims of pedestrians visiting the downtown area. We assume people go downtown for shopping, stroll around, or other reasons. They enter the downtown area at entry links near car parks, bus stops, bike sheds, railway station, or other locations. An entry link is just a link of the downtown area network. After having entered a link of the downtown area, a pedestrian has to choose one adjacent link to proceed. This process of choosing links from a set of adjacent links continues until the pedestrian reaches the entry link where he leaves the downtown area. In fact, it is assumed (at this stage of model development) that a pedestrian walks some circuit through the downtown network.

The pedestrian's decision on the next link of his trip likely depends on a set of variables. First of all, distance will be an important variable. In the beginning of the trip, we expect pedestrian prefer moving away from the entry link into the downtown area. This desire to move away from the entry link likely diminishes when the pedestrian moves further away from the entry link. At some moment, the desire to move back to the entry link will become apparent. Ultimately, the pedestrian just wants to return to the entry link. Thus, in the beginning of the trip pedestrians tend to choose a link in the network that will increase the distance from the entry link, while towards the end, pedestrians tend to decrease the distance to the entry link. This implicates that at any decision moment in the route choice process, we need to take into consideration the distances walked thus far and the distance back to the entry link.

A central assumption of the model is that pedestrians are driven back to their entry link as discussed above. Eventually, pedestrians will reach their entry link. At that moment, they have the opportunity to end their trip. The probability the trip will be ended increases with the distance walked. If a pedestrian (accidentally) approaches his entry link at a premature stage, he probably will continue his trip.

Apart from these distance effects, other variables are expected to be relevant. These variables can be broken down into two groups. The first group of variables is related to the history of the pedestrian's trip through the downtown area, while the second group is related to physical characteristics of the links. The first history-related variable we expect to be important is whether a link has been passed before during the trip. We assume that ceteris paribus, pedestrians do not like passing twice the same link. However, it is possible that people prefer to walk back to the entry link the same way they walked away from the entry link. In this case, passing a link for a second time induces no negative impact, while passing a third time might do so.

If a pedestrian enters a link at one side, it might be expected he will leave the link at the other side. Of course, pedestrians can make a turn in their current link and leave the link where they entered. We expect that the utility of a turn will be negative. However, this negative effect will decrease if the distance back to the entry link is relative long. Then, pedestrians might prefer to return to the entry point, possibly implying a turn.

Examples of physical characteristics of network links are variables such as land use (retail, housing, etc.), transport modes allowed, dimensions like width and height, type of pavement, indoor/outdoor, architectural design and so on. In case of downtown shopping areas, we expect that the supply of shops at each link is a very important variable. In addition to these local characteristics, global characteristics might be important as well. One such global variable is the accessibility of links. If one link provides good access to other, attractive links, the link will be attractive itself as well. Again, in a shopping environment, links giving good access to attractive shopping streets will have a higher probability to be chosen. A second global variable that might be relevant is visibility (Desyllas et al., 2003). If a link allows pedestrians to see a long line of street segments, it has a higher probability to be chosen.

Most recent Cellular Automata and Multi-Agent based models of microscopic pedestrian movement use rules to decide which of the adjacent grid cells will be selected for the next step (e.g. Blue & Adler, 2001; Kerridge et al., 2001). We could use the assumptions, discussed above, to formulate a set of rules to determine which link from the set of adjacent links will be chosen. A possible drawback of using rules is the difficulty of calibrating the model against observations (Batty, 2001). Although recently algorithms for inducing such rules from empirical observations have been developed (e.g. Arentze and Timmermans, 2000; Moons et al., 2005), we decided to use the still popular, multinomial logit model in this study. According to this model, the probability that an alternative (link) will be chosen from a set of alternatives (the adjacent links) depends on the utility of the alternatives. The utility of an alternative consists of a structural part and a random part. The structural utility is directly related to the characteristics of the alternative. In general, the structural utility is a weighted sum of the scores of the alternative on the selected variables. These weights can be estimated from observed choices. Thus, based on choices made at each link and the scores of the adjacent links on the explanatory variables, we can statistically estimate the weights of the variables. These weights can be used to predict the probability that each of the adjacent links will be chosen.

4 DATA COLLECTION

Data were collected by means of personal interviews. Interviewers were positioned at the exit points of the downtown shopping area. They were instructed to invite only pedestrians who left the shopping area to participate. Each interview consisted of the following items (see also Lorch and Smith, 1993): mode of transport to city centre, destinations (shops) visited, time spent, and personal characteristics. Each respondent was asked to reproduce his route on a map of the downtown area. Main buildings and all streets were identified on the map. First, the respondent had to indicate where he left his mode of transport (car, bike, bus, train). Starting from this point, the respondent had to draw (assisted by the interviewer) his route through the downtown area on the map, also indicating all outlets he visited. The route of each individual respondent was stored in a geographical information system.

Data were collected in two Dutch cities, Eindhoven and Maastricht. Both cities are located in the South of the Netherlands. The population of Eindhoven is just over 200,000, while Maastricht has approximately 120,000 inhabitants. During WWII, the centre of Eindhoven was bombed. As a consequence, Eindhoven has a rather modern downtown shopping centre. In contrast, Maastricht still has a historical city centre. Furthermore, a river is running through the centre of Maastricht.

In March 2002, during two consecutive days, a Friday and a Saturday, data were collected in Eindhoven. In this city, shops close at 21.00 hrs on Fridays and at 17.00 hrs on Saturdays. Both days, data collection started at 11.00 hrs. In total, 848 respondents were interviewed. Response rates were approximately 30% for both days. During these days, weather conditions were relatively mild.

In Maastricht, late night shopping is on Thursdays. Therefore, data were collected on three consecutive days: Thursday from 18.00 to 21.00 hrs; Friday from 10.30 to 18.00 hrs and Saturday from 10.30 to 17.00 hrs. This was done in November 2003, also under mild weather conditions. In Maastricht, 580 respondents were interviewed (response rate just over 40%).

Table 1 presents gender and age distributions of the respondents for both cities. In both cities, but especially in Maastricht, more females than males were interviewed. Also, more elderly respondents were interviewed in Maastricht compared to Eindhoven.

Table 1: Gender and Age (in %)

	Eindhoven	Maastricht
Male	45	40
Female	55	60
< 18 years	6	1
18-55 years	80	73
> 55 years	14	26
N	848	560

In addition to the interviews, the numbers of pedestrians leaving the downtown area were counted at each exit point. This was done during two time intervals (of 5 minutes) on the late shopping nights and during 3 intervals on Friday and Saturday. These counts were used to estimate the total number of respondents leaving the downtown area at each exit point during periods of the day. These estimated numbers were used to weigh the interviews.

Moreover, data about shopping supply on each link of the downtown area were collected. In fact, the local Chambers of Commerce provided lists of shops in the downtown shopping areas, indicating the kind of store. The municipalities of Eindhoven and Maastricht provided detailed maps of their downtown area. These maps were used to determine the floor space of each individual shop.

Link networks were constructed using a geographical information system. For each link, the following characteristics were collected: type of traffic modes allowed, type of pavement, use of space along each side of the link (buildings, square, traffic, water). In addition, some more specific variables were listed. In the 1970's, both cities added a relatively small indoor mall to the open air shopping area. Neither of these malls was successful. The one in Eindhoven was under reconstruction during the period of data collection, while the Maastricht mall was closed shortly after data collection, also to be reconstructed. In the 1990's, Eindhoven extended the downtown shopping area by a second, larger and more successful mall. Links inside that mall were coded 'indoor'. Some links in the network specifically facilitate crossing main roads. These links were coded 'pedestrian crossing'. The Eindhoven mall is a multi storey building. Links representing escalators and stairways are coded 'stairway indoor'. Finally, some links in Maastricht contain stairways. These are coded 'stairway outdoor'.

5 MODEL SPECIFICATION

To simulate pedestrian route choice behaviour, a series of consecutive choices has to be predicted. As explained in section 3, given a current link l, the pedestrian has to choose one alternative link from the set of adjacent links. The set of links adjacent to link l is represented by $\mathbf{L}_l$. However, if the current link l is equal or adjacent to the link of entry (e), the pedestrian has the opportunity to STOP his trip. Hence, in general, the choice set of a pedestrian in link l, who started at entry link e, will be represented by $\mathbf{S}_{el}$. Formally, $\mathbf{S}_{el}$ is defined as $\{\mathbf{L}_l, STOP\}$ if $l=e$ or $l \in \mathbf{L}_e$ and as $\mathbf{L}_l$ otherwise. The probability that a pedestrian chooses the j^{th} alternative from $\mathbf{S}_{el}$ is then equal to (multinomial logit model):

$$p_{el,j} = \exp(V_{el,j}) / \sum_{j' \in \mathbf{S}_{el}} \exp(V_{el,j'}) \qquad (1)$$

where $p_{el,j}$ is the probability that a pedestrian at link l who started at entry link e will choose alternative j;

$V_{el,j}$ is the utility of alternative j for a pedestrian at link l who started at entry link e.

If alternative j induces the end of the trip (j=$STOP$), the structural utility is defined as

$$V_{el,j} = \alpha_1 D^W \qquad (2)$$

where D^W is the total length of the path traversed by the pedestrian from the entry link to the current link, including the current link itself (also referred to as 'Distance Walked').

If alternative j is a link ($j \neq STOP$), the structural utility $V_{el,j}$ is defined as a weighted summation of scores of link j, given the trip history of the pedestrian.

$$V_{el.j} = \alpha_2 D_j + \alpha_3 B1_j + \alpha_4 B2_j + \alpha_5 B3_j + \alpha_6 T_j + \alpha_7 S_j + \sum_k \beta_k F_{jk} + \sum_k \gamma_k A_{jk} + \sum_n \delta_n X_{jn} \quad (3)$$

where Dj = $(1-(D^W/D^T))\ d_{je}$ (4)

D^T is the Threshold Distance;

d_{je} is the shortest distance from link j to link e (the final link);

$B1_j$ is 1.0 if the pedestrian passed link j already once, else 0.0;

$B2_j$ is 1.0 if the pedestrian passed link j already twice, else 0.0;

$B3_j$ is 1.0 if the pedestrian passed link j already more than 2 times, else 0.0;

T_j = $1.0/d_{le}$ if choosing link j implies a turn in link l, else 0.0 (5)

S_j is equal to the total length of the line of sight link j is part of;

F_{jk} is equal to the floor space of shops in branch k in link j;

A_{jk} = $\Sigma_{j' \neq j} F_{j'k}/d_{jj'}$ (6)

Note that according to equation 4, the effect of distance is positive if the walked distance D^W is less than the threshold distance D^T. This effect however is decreasing with increasing D^W. If D^W is larger than D^T, the distance effect will be negative, implying that the pedestrian will prefer links heading to the entry link. This effect will increase with increasing D^W.

According to equation 5, the effect of turning back in a link decreases if the pedestrian is further away from the entry link. Note that the value of T_j will be relatively high if the pedestrian just started his trip or is about to finish his trip. At these instances, it does not make sense to turn around. So, we expect a negative parameter value for this variable.

The *S*-variable represents the total length of sight the link provides. If a link is part of a long straight line of connected links, the link is probably preferred over links in a short line. If there are no other links connected in a straight line to link j, the value of S_j is equal to the length of link j itself. So, even if a long link is not connected in a straight line to other links, the S_j-value can be relatively high.

Shopping supply is likely to be a very important variable in choosing a link. The supply of shops per link is measured in square meters per branch. The following types of stores are distinguished: 1) food products; 2) personal care 3) fashion; 4) shoes; 5) household articles; 6) appliances; 7) books & stationery 8) CD's & DVD's; 9) department stores; 10) other shops; 11) restaurants & café's; 12) services & entertainment. The latter two categories do not represent shops, although we expect these type of outlets to influence route choice behaviour. The floor space for these outlets was arbitrarily set to 100 m^2 each. Links providing no or few shops might still be attractive for pedestrians in the sense that links also provide access to shops in other links. The *A*-variables account for these effects. The store types are defined similar to the *F*-variables.

Finally, the *X*-variables represent physical characteristics of the links, as discussed in section 4.

6 MODEL ESTIMATION

To estimate the parameters of the model, the routes reported by the respondents in Eindhoven and Maastricht were used. As it was assumed that pedestrians walk a circuit through the shopping area, all reported routes not ending at or adjacent to the entry link were excluded from the estimation set. In total, 1,073 reported routes were used to estimate the model (637 and 436 reported in Eindhoven and Maastricht respectively). Each selected route was used to create choice sets $\mathbf{S}_{el}$. For each link in a route, one choice set is generated, resulting in 28,030 choice sets in total. The mean number of alternatives per choice set is approximately 5.6. In a perfect grid-network, each link would have six adjacent links. As might be expected, the downtown networks are not perfect, resulting in less adjacent links on average. The parameters of the multinomial logit model were estimated by LIMDEP (Greene, 2003).

Due to quite some interdependencies among the explanatory variables, some operational decisions were made regarding the estimation process. First of all, it was decided to estimate the remaining parameters, conditional on preset values for the distance threshold D^T. The threshold was set to 3.0, 4.0, up to 8.0. For each value, the remaining parameters were estimated. It appeared that with increasing D^T, the parameter for *D*-variable increased as well. In fact, the D-variable seems to compensate, at least partially, for an increasing threshold. However, the optimal value for D^T seems to be somewhere in between 4.0 and 6.0. We arbitrarily set the value to 5.0.

As might be expected, the shopping supply variables are interdependent. A link providing a large amount of floor space in one particular branch is likely to offer a large supply in some of the other branches as well. Therefore, we reduced the number of branches. In addition, there is spatial dependency between the supply of links. If a link provides a large shopping supply, neighbouring links probably provide large shopping supplies as well, implying spatial correlations between the floor space variables *F* and the accessibility variables *A*. Summing the *F*- and *A*-variables for each type of shops solved this problem. All together, a new set of variables was compiled: Q_1 (daily products: F_1+F_2+A_1+A_2); Q_2 (fashion: F_3+F_4+A_3+A_4); Q_3 (home: F_5+F_6+A_5+A_6); Q_4 (department stores: F_9+A_9); Q_5 (other shops: F_7+F_8+F_{10}+A_7+A_8+A_{10}); Q_6 (restaurants & cafés: F_{11}+A_{11}); Q_7 (services & entertainment: F_{12}+A_{12})

The downtown areas of Eindhoven and Maastricht are quite different, especially regarding their networks of links. It might be expected that the parameters for both cities are different. To test for this kind of differences, so called contrast parameters were estimated. For each variable, an additional variable is constructed:

$Z'_i = Z_i \times (+1.0)$ if the data is related to Eindhoven (7a)

$Z'_i = Z_i \times (-1.0)$ if the data is related to Maastricht (7b)

The corresponding contrast parameters (if significant) identify differences between both cities.

Table 2: Estimated Parameters

Variable	Parameter	Sig	Contrast parameter	Sig
D (distance)	0.5672	0.0000	0.1533	0.0000
D^W (STOP-alternative)	0.02958	0.0000		
B1 (passed before once)	0.1144	0.0000		
B2 (passed before twice)	-0.8363	0.0000		
B3 (passed before >2 times)	-0.6034	0.0001		
T (turn in current link)	-0.4025	0.0000		
S (length of line of sight)	0.1555	0.0000		
Q_1 (daily products)	0.00006986	0.0137		
Q_2 (fashion)	0.0001183	0.0000		
Q_3 (home)	0.00005289	0.0239		
Q_4 (department stores)	0.00001160	0.0000		
Q_5 (other shops)			0.0001477	0.0000
Q_6 (restaurants & cafés)	-0.0002439	0.0000	-0.0001279	0.0000
Q_7 (services & entertainment)	0.0003867	0.0000	-0.0002846	0.0000
X_1 (traffic)	-0.2227	0.0000	-0.1870	0.0000
X_2 (indoor)	-0.4455	0.0000	0.3117	0.0000
X_3 (through shop)	-0.3886	0.0000	0.5781	0.0000
X_4 (stairway indoor)	-2.4940	0.0000		
X_5 (stairway outdoor)	-0.8066	0.0000		
X_6 (water)	0.3658	0.0000		
X_7 (along a square)	-0.3336	0.0000	-0.2785	0.0000
X_8 (crossing a square)	-0.3116	0.0000	-0.4363	0.0000

The results of the estimation (see Table 2) are very encouraging as the goodness of fit of the multinomial logit model is rather high (ρ^2=0.505) and most estimated parameters are in anticipated direction. For a number of variables, the effect on route choice behaviour is different between the two cities, as indicated by a significant contrast parameter.

First of all, the parameter for the distance variable is positive. This is as expected, because the value of the distance variable will be positive in the beginning of the trip and will be negative after 500 meters (D^T was set to 5.0). A positive parameter means that pedestrians first walk away from their entry point and walk back later on. Note that the corresponding contrast parameter is positive. This means that pedestrians in Eindhoven are more sensitive to distance than pedestrians in Maastricht. As the threshold D^T was set to 5.0 and the distance parameter is dependent on the value of D^T, a significant contrast parameter for distance might also indicate that the threshold values differ between the two cities.

If the pedestrian's current link is equal or adjacent to his entry link, the pedestrian can stop his trip. According to the positive D^W parameter, the probability of stopping increases with the length of the route walked thus far. The pedestrians do not mind to choose a link a second time again. However, the pedestrians are not inclined to select links that were passed twice or three times before. Altogether, the three 'passed before' parameters confirm that some pedestrians make roundtrips using the same links. Also, pedestrians do not make turns in a link when they are close to their entry link. If the distance according to the shortest path from the current link to the entry link is short, the reciprocal of this distance will be relatively high and the negative parameter for T induces a negative utility. Links that are part of a long straight line offer a long view. According to the S-parameter, such links are appreciated.

Overall, shopping supply has a positive effect on choosing a link. However, pedestrians do not prefer links with restaurants, lunchrooms, bars and the like. These types of shops have a negative main parameter. The corresponding contrast parameter indicates that especially pedestrians in Eindhoven dislike these links, while those in Maastricht do not care. The contrast parameters for the Q-variables indicate two more differences. First, the utility of 'other shops' is positive in Eindhoven, and negative in Maastricht. Second, pedestrians in Maastricht appreciate the 'services & entertainment'-type of establishments much more than pedestrians in Eindhoven do. The results regarding the Q-variables suggest that the motivation of pedestrians in Maastricht is more hedonic in nature than in Eindhoven.

If in a particular link motorised traffic is involved, the link is preferred less. This effect is much stronger in Eindhoven than in Maastricht. The reason for this difference might be that the downtown area in Eindhoven is surrounded by arterials roads. Indoor links are not preferred, especially not in Maastricht. The reason is straightforward: the indoor mall in Maastricht is less attractive than the one in Eindhoven. Walking through a shop implies a negative utility. However, this only holds for Maastricht. In Eindhoven, walking through a shop induces a small positive utility. The Eindhoven mall is a three-storey building. Pedestrians seem to be very reluctant to switch one floor up or down, as indicated by the X_4-parameter. The X_5-parameter is related to links containing some steps because of height differences, occurring in Maastricht only. Obviously, pedestrians do not like these links. Also in Maastricht, some links are located along or crossing the river. Pedestrians do like these links (X_6). Apparently, pedestrians do not like walking along squares or crossing squares. Although, according to the contrast parameters, this mainly applies to Eindhoven.

It can be concluded that the multinomial logit model performs very well, both in terms of ρ^2-value and face validity. However, to really test the predictive power of the model, we used the model to simulate reported route choice behaviour. To do so, we used each respondent's first reported link as the entry link. Beginning at this link, the pedestrian will walk a circuit through the downtown area. To leave the starting link, the pedestrian has to choose one of the adjacent links or, not likely, finish the trip. The multinomial logit model is used to predict the probabilities for each alternative. Monte Carlo Simulation is used to decide which alternative will be chosen. The probabilities for the alternatives are cumulated and a random number is drawn from a uniform distribution. The alternative having a lower value in the cumulative distribution less than the random number and an upper value greater than the random number will be selected as the chosen alternative. The pedestrian moves into the selected link and the process is repeated. This way, a set of consecutive links will constitute a route. When the route approaches the entry link, the '*STOP*'-alternative can be chosen in addition to the adjacent links. If the '*STOP*'-alternative is chosen, the pedestrian finishes his trip.

The simulation for each reported route was repeated 50 times to cancel out random effects and get stable results. During this simulation process, both observed and simulated link loadings were continuously updated for both cities. The results are shown in Figures 1 and 2.

To compare the simulated routes with observed routes, three indices were calculated. First, the correlation between the observed number of pedestrians per link and the simulated number of pedestrians per link was calculated. The correlation coefficient is equal to 0.767 and 0.791 for Eindhoven and Maastricht respectively. The second index measures the mean absolute difference in number of observed and simulated pedestrians per link. In Eindhoven, this difference is 49 pedestrians per link, while this figure is equal to 39 for Maastricht. The third index to compare observed and simulated pedestrian behaviour is the mean length of the routes. The mean length of observed routes in Eindhoven is approximately 1180 meters. The mean length of simulated routes in Eindhoven is 1340 meters. For Maastricht, these figures are respectively 1770 and 1966 m. In both cities, the simulated routes are longer than observed (14% in Eindhoven, 11% in Maastricht).

Based on the indices, the model seems to reproduce reported route choice behaviour reasonably well. However, Figures 1 and 2 show that there are quite some mismatches. When assessing the predictive power of the model, one should take into consideration that the model does not use any information about plans, motivations, or characteristics of pedestrians visiting the downtown area.

Figure 1 Observed (left) and Simulated (right) Link Loadings (Eindhoven)

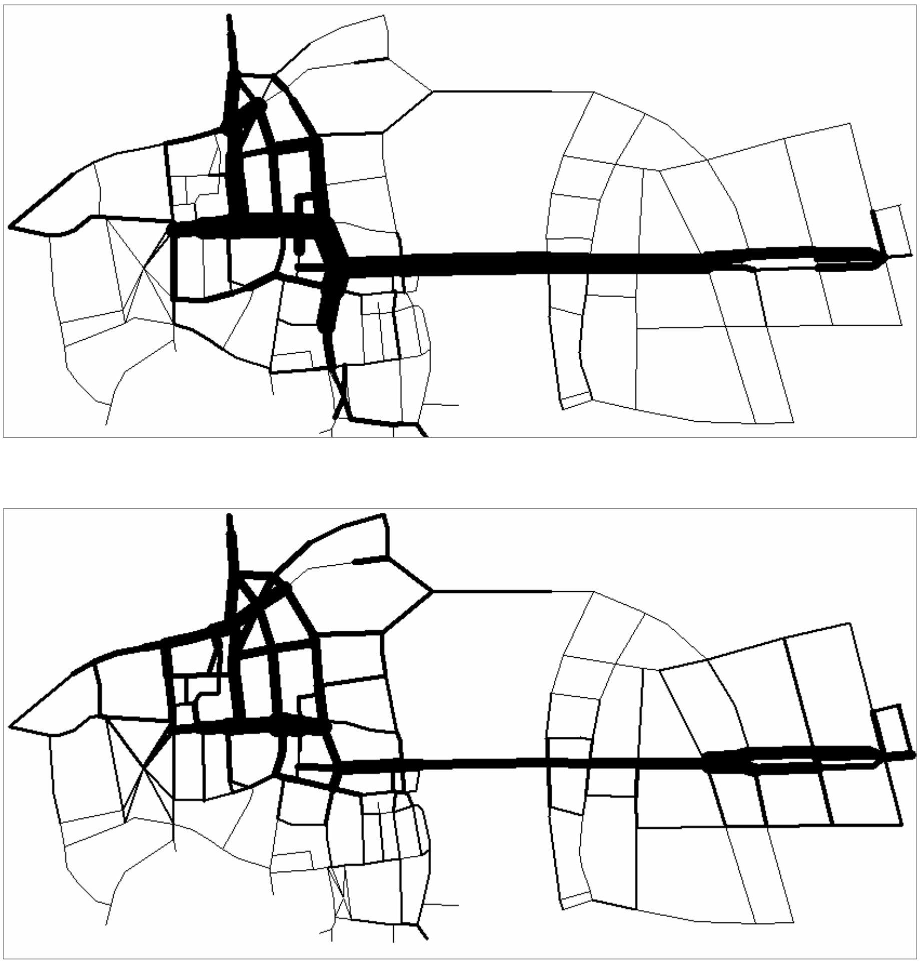

Figure 2 Observed (top) and Simulated (bottom) Link Loadings (Maastricht)

7 CONCLUSIONS AND DISCUSSION

In this paper, we presented a model to predict the number of pedestrians in downtown shopping streets. The main assumption of the model is that an individual enters a shopping area, walks around in the streets of the shopping area and eventually returns to the location of entrance. In each link of the downtown network, the pedestrian chooses one of the connecting links to proceed. The preferences for links are related to shopping supply in the links and the accessibility from each link to shopping supply in other links. Further, distance from and to the entry link and the history of the route are important factors influencing route choice behaviour. Finally, some characteristics of the links are important. The model incorporates an endogenous driven mechanism assuring that pedestrians finish their trip at or near their entry link. The model was estimated and tested using reported routes in two Dutch cities.

The model performs reasonably well. However, it can be extended in several ways. One important extension would be to include shopping agendas into the model. By assuming that pedestrians may have a list of products to buy during the shopping trip, the effect of shopping supply per link could be differentiated into an overall effect of shopping supply on route choice behaviour and specific effects for goods still to be bought. By passing a link supplying a required product, the specific effect for that product will decrease after leaving this link as the pedestrian has had the opportunity to buy the product.

In the reported version, physical characteristics of the links in the retail network such as the width of a street related to the height of facades, the presence of trees, etc are not included in the model. Such characteristics can easily be incorporated into the model by estimating a weight for each additional characteristic. Such extensions would be interesting for designers and town planners.

Pedestrians visiting a shopping centre have different motivations and therefore may behave differently. For example, Bellenger and Korgaonkar (1980) found empirically that recreational shoppers behave different from economic shoppers in that the first do more non-planned purchases and spend more time on a shopping trip. It would be interesting to investigate to what extent the weights estimated in this paper would differ for these groups of shoppers. Some differences in estimated parameters already suggest that the Maastricht pedestrians behave more hedonic than the Eindhoven pedestrians.

Finally, because this project is still in an exploratory phase, we have applied a simple multinomial logit (MNL) model. This means that, in this stage, we accept the independence of irrelevant alternatives assumtion. In future work, once we have explored the extensions mentioned above in the context of a multinomial logit model, we will replace the MNL model with more advanced discrete choice models.

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