1. Introduction

Predicting passenger behavior using pedestrian movement simulations can efficiently support the planning of public transport infrastructures and the evaluation of operational processes. Since the complexity of mass transit hubs such as subway stations is steadily increasing, a better understanding of pedestrian route choice in order to further improve these simulation tools becomes more important. A common example for route choice in public transit infrastructures is the decision between adjacent stairs and escalators. Typically, passengers prefer to use the escalator but based on various factors such as distance, congestion level and personal preferences, they might switch to the staircase (see Cheung and Lam (1998) and Zeiler et al. (2010)). Route choices can be modeled on the tactical level (see definition in Hoogendoorn and Bovy (2004)) and affect the spatial and temporal distribution of pedestrian
flows. Hence, simulation results can significantly differ when changing the tactical model, although the same operational model and input data such as origin-destination (OD) relationships of pedestrian flows are used.

The importance of route choice has also been investigated within the scientific community. Daamen (2004) provides a detailed overview of pedestrian route choice models which are based on utility maximization calculations (e.g. Gipps et al. (1986), Cheung and Lam (1998), Hughes (2000), Hoogendoorn and Bovy (2004), Daamen et al. (2005), Asano et al. (2010)). Wagoum et al. (2011) present a dynamic route choice model for pedestrian simulation in evacuation scenarios, which includes the possibility that individuals can continuously try to identify a “better” route than their current one. This is achieved using an observation principle, where pedestrians adjust their decisions based on continuous observation of their environment. Therefore, pedestrians combine the knowledge of both, local and global information, and dynamically choose the paths which are most favorable for them at the given moment.

Due to the difficulty of obtaining data, many of these route choice models were not validated at all, or only validated on data obtained from experiments instead of large-scale real world observations. In this work, based upon the principles of related scientific work, we therefore make the following two main contributions towards the pedestrian simulation community:

1. We describe our dynamic route choice model which is based on local utility maximization. Pedestrians can choose alternative routes based on continuous observation of the situation ahead of them.
2. We validate our model with three case studies which include real world data from events in a subway station. Therefore, we have measured OD matrices and pedestrian route choices in the subway station with automatic counting sensors.

The remainder of this paper is structured as follows: Section 2 outlines the venue used within our case studies for applying and validating our model approach. In Section 3 we describe our route choice model. Section 4 provides the main findings of our comparison between the simulation results and the data sets obtained in our case studies during three real events. Finally, in Section 5 we give a conclusion and outline future work.

2. The U2 subway station “Stadion”

The U2 subway line in Vienna includes the station “Stadion”, which is adjacent to the Ernst-Happel-Stadium. The Ernst-Happel-Stadium is Austria’s biggest stadium with a capacity of up to 50,000 visitors during sport events and an additional 19,000 on the pitch for concerts. After major events, as many as 30,000 passengers are directed towards the especially build entrances of the subway station (see orange arrows in Fig. 1). During these times, the normal entrances of the station are closed and are only available to mobility restricted passengers. The design of the subway station includes several facilities to control the passenger inflow, including a set of 15 meanders, each of which provides a passageway where people can walk on abreast, keeping the main pressure outside the station (Seer et al. (2008)). After the meanders, four specially constructed door units lead to corridors that give access to the upper-level platforms via staircases. Each door unit has two sliding doors, and different door width can control passenger inflow during transportation.

Automatic counting sensors mounted above the staircases measure quantitative flow data, thus replacing subjective and possibly biased human assessments of overcrowding. The counting sensors provide input for the sliding doors’ controller, combining the current inflow with information from the public transport authority, like the next train’s departure and the next train’s capacity, to determine the optimum door width for the door units. The system thus automatically avoids overcrowding in the station, especially on the platforms and ensures an efficient passenger transport.

In this work we use the data sets captured by the counting sensors to validate our modeling approach for pedestrian route choice.
3. The dynamic routing model

Similar to other models from scientific literature our dynamic route choice model follows a decision-theoretical approach embedded on the tactical level within our simulation framework. We describe the principle of our route choice model based on the subway station “Stadion” (see Section 2), which we also use in our case studies presented in Section 4.

The route choice problem that we model on the tactical level is illustrated in Fig. 2. Passengers enter the subway station from the right coming from the event location. All passengers walk towards the station and have to choose one of the open meanders which are linked to four corridors leading to the platforms via staircases. We observed that at the beginning and the end of the transport pedestrian inflow is lower as less people are leaving the event and heading to the subway. During this phase of low inflow, the first corridor is used almost exclusively, since it is the nearest and not congested at these times. With an increase of the passenger flow, the area in front of the station becomes more crowded and it is more likely that passengers also use meanders in front of corridors 1, 2 and 3.
For our routing approach the spatial layout of the environment has to be transformed into a graph representation. The infrastructure contains several facilities like meanders, doors and stairs (see Fig. 2, green and blue circles). To each facility two nodes are assigned – one to the entrance and one to the exit of the facility. For each pair of nodes with a walkable path in between, we add an edge (black lines in Fig. 2). The result is a graph \( G = (V, E) \), \( V \) denoting the \( M \) nodes, and \( E_{ij} \) the edges of the graph connecting nodes \( V_i \) and \( V_j \) \((i \neq j, 0 \leq i < M, 0 \leq j < M)\). The graph generation can be achieved automatically, for instance by building a visibility graph as described in Kneidl et al. (2012). In our case study, applied “soft” measures during real transportation, such as security personnel actively prohibiting some routes, make a manual generation of the routing graph more suitable.

Our route choice model calculates pedestrians’ decisions on routes in a two stage process: At the start of the simulation, our model calculates an initial route from start node \( V_0 \) to destination node \( V_N \) for each pedestrian using the Dijkstra (1959) algorithm. During the simulation, our model continuously updates the routes for each pedestrian - the optimal path as perceived by the pedestrian when created.

For each pedestrian, an initial route, consisting of a list of nodes \( V_0 \ldots V_N \in G \), connected by a set of edges \( E_{01} \ldots E_{N-1, N} \in G \), is assigned when the pedestrian is created. \( V_0 \) represents the start node, in our case study the event location, and \( V_N \) the end node, in our case one of the two platforms. The initial route forms a valid path with the minimum perceived travel time for the whole path. The pedestrian is not necessarily assigned the global optimal path, but the optimal path as perceived by the pedestrian when created.

For a pedestrian \( P \) the perceived travel time \( T_P \) for using an edge \( E_{ij} \) connecting two nodes \( V_i \) and \( V_j \) can be calculated as

\[
T_P = T^\text{exit}_P(V_i) + T^\text{use}_P(E_{ij}) + T^\text{enter}_P(V_j) \tag{1}
\]

with:

- \( T^\text{enter}_P(V_j) \): The perceived time to enter a node \( V_j \) associated with a facility (e.g. a meander). For other nodes, or in case that a node is not visible to the pedestrian, \( T^\text{enter}_P \) is set to zero. \( T^\text{enter}_P \) depends on the number of pedestrians \( N_q \) queuing in front of the node and the number of pedestrians \( N_h \) heading to the node and can be calculated with

\[
T^\text{enter}_P(V_j) = t_1(V_j) + t_2(V_j)N_q + t_3(V_j)N_h \tag{2}
\]

where \( t_1, t_2 \) and \( t_3 \) are time constants depending on the facility associated with node \( V_j \):

- \( t_1 \) represents the cost to enter the facility depending on the pedestrians’ preferences (e.g. desired speed or mobility restrictions). For individuals preferring elevators or escalators over stairs, \( t_1 \) can be used to add penalty costs accordingly.
- \( t_2 \) represents a penalty for already queuing pedestrians at node \( V_j \).
- \( t_3 \) adds a penalty for other pedestrians heading in direction of node \( V_j \).

- \( T^\text{use}_P(E_{ij}) \): The perceived time to use an edge from node \( V_i \) to node \( V_j \). The time on an edge depends on the edge type and its utilization. If the edge is part of a facility, the time to use it depends, besides the pedestrians walking speed, on additional factors like the speed of an escalator or the slope of a staircase.

- \( T^\text{exit}_P(V_i) \): The perceived time to exit a node \( V_i \) associated with a facility (e.g. a meander). For other nodes, or in case that a node is not visible to the pedestrian, \( T^\text{exit}_P \) is set to zero. \( T^\text{exit}_P \) depends on the number of pedestrians \( N_f \) waiting in front of the exit of the node defined by

\[
T^\text{exit}_P(V_i) = t_4(V_i)N_f \tag{3}
\]
where $t_A$ represents a penalty accounting for congested space behind a facility at node $V_i$.

3.2. Dynamic updates with local information

The initial route is calculated upon creation of a pedestrian. However, the environment may change over time as more pedestrians are added dynamically and congestions form, which potentially makes some routes less attractive.

Splitting the perceived travel time as described in Section 3.2 allows us to dynamically update the travel time by reusing the time estimation $T_p^{\text{enter}}$ for entering congested nodes. In the routing graph in Fig. 2 we have marked several nodes to be equivalent alternatives (indicated by the blue colors of the nodes). Whenever a pedestrian’s next goal is a node which has at least one alternative, we periodically check for better local routes by calculating the perceived travel time for reaching and entering an alternative node $V_a$ according to

$$T_p(V_a) = \frac{d}{s} + T_p^{\text{enter}}(V_a)$$

(4)

where $d$ denotes the distance of the pedestrian to the alternative node and $s$ the current speed of the pedestrian.

We calculate $T_p$ for all alternatives $V_a$ every 5 seconds and an alternative node is used once it can be reached at least 30 seconds faster than the current assigned node. Both thresholds have been determined experimentally based on our case studies.

4. Case studies

We applied our dynamic route choice model in three case studies in the U2 subway station “Stadion” (see Section 2) with various event types, thus including different audience (football fans vs. concert visitors) and a varying number of visitors. For each event, the real passenger flows inside the subway station were measured at the staircases of each corridor (see Fig. 1). The selected events with the corresponding number of visitors are:

1. Austrian football association cup final (30.05.2013): 16,500 spectators, 6,850 heading to the subway station
2. Pink Floyd concert (23.08.2013): 40,000 spectators, 18,400 heading to the subway station
3. Bon Jovi concert (17.05.2013): 50,000 spectators, 25,900 heading to the subway station

In order to simulate the passenger movement starting from the stadium up to the platforms inside the subway station we need to define the passenger behavior on the strategic level. Since passengers can only decide between the two platforms (inbound or outbound), this can be encoded as the travel demands in the OD matrix based on the measured distribution from real world data and is assigned to each passenger upfront.

On the operational level we use two different modeling approaches depending on the environment: to model interactions in free walking space, we use a Social-Force model based on the principles described by Helbing and Johansson (2009). The pedestrian radius is set to 0.25 m and the desired speed is drawn from a Gaussian distribution with mean speed $\mu = 1.34$ m/s and standard deviation $\sigma = 0.26$ m/s. The pedestrian behavior in facilities (e.g. meanders, staircases) is modeled with a macroscopic approach which uses a maximum flow rate derived from observing the video data. For instance, meanders are assigned with a maximum flow rate of 50.96 pedestrians per minute (see Seer et al. (2008)) and sliding doors use a maximum flow rate of 1.3 pedestrians per meter and second (Gwynne et al. (2009)).

For each simulation run, we need to predefine several input data, i.e. the layout of the infrastructure (see Section 2), the graph representation for the dynamic routing model (see Section 3) and the OD matrix. We estimated OD matrices based on the real world counting sensor data at the corridors and their correlation to the pedestrian influx into the station. The results for a single simulation run are illustrated in Fig. 3. The remainder of this section describes the validation results of our dynamic routing model based on comparisons of the passenger flow distribution to the corridors between simulation and real world observations.
Fig. 3. Screenshots every 5 minutes of a simulation run.
4.1. Football cup final

After the football cup final, 6,850 football fans used the subway station where the total transportation time took roughly 40 minutes. Fig. 4 shows the comparison between real world data and simulation results: since corridor 4 is the closest to the stadium, it can be seen in the real world observations that this corridor is the first one that is used as well as the one with the highest number of passengers. Approximately 20 minutes after the start of transportation, the maximal passenger flow is reached and all 4 corridors are used. In case of using the initial routing only, we can observe a strong deviation with respect to the real world observations, which is particularly high for corridor 4 immediately after the beginning of the transportation process. When applying our dynamic route choice model the accumulated passenger counts match much closer to the real world observations (see Table 1).

![Fig. 4. Usage of corridors in the football cup final event.](image)

4.2. Pink Floyd concert

The Pink Floyd concert was attended by about 40,000 spectators, and approximately 18,000 people used the subway after the concert, in a constant stream of about an hour. As can be seen in Fig. 5, the distribution of people to the four corridors is homogenous due to a constant influx. 35% of the audience of the Pink Floyd concert used the further away corridors 1 and 2 when the nearer corridors 3 and 4 are congested. During the football cup final only 31% used corridors 1 and 2. Our dynamic rerouting approach shows significantly closer passenger counts compared to real world observations than the initial route only model (see Table 1).

![Fig. 5. Usage of corridors in the Pink Floyd event.](image)
4.3. Bon Jovi concert

The Bon Jovi concert was attended by 50,000 visitors and over 25,000 people used the subway afterwards. However, with an overall duration of two hours, the time span of people using the station after the Bon Jovi concert was twice as long as after the Pink Floyd concert (Fig. 6). Low inflow at the beginning of the scenario led to an exclusive usage of corridor 3 and 4. The total usage of corridor 1 and 2 after the event could be determined as only 28%. In our simulations people used corridors 1 and 2 significantly more than in the real world event. Due to the longer influx, estimation of pedestrian insertion times from the counting sensor data becomes more complex, which might have affected the route choice and our simulation results. The short plateau in the real data at 21:58 was caused due to problems with a broken train and closed doors to avoid overcrowding on the platform. In our simulations, these doors were not closed, which might also have an influence on the route choice.

![Fig. 6. Usage of corridors in the Bon Jovi event.](image)

4.4. Summary of Results

Table 1 shows the detailed numbers on the corridor usage of the real events compared to our simulations. Without any calibration of the model towards the infrastructure of our use cases, the presented generic dynamic route choice model is suitable to reproduce the corridor choice.

<table>
<thead>
<tr>
<th>Event</th>
<th>Total number of pedestrians</th>
<th>Data Set</th>
<th>Corridor 1 Pedestrians/ Avg. Dev. (Std)</th>
<th>Corridor 2 Pedestrians/ Avg. Dev. (Std)</th>
<th>Corridor 3 Pedestrians/ Avg. Dev. (Std)</th>
<th>Corridor 4 Pedestrians/ Avg. Dev. (Std)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cup Final</td>
<td>6850</td>
<td>Real world</td>
<td>779/- (-)</td>
<td>1379/- (-)</td>
<td>1783/- (-)</td>
<td>2909/- (-)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Initial route only</td>
<td>934/+73.0 (73.7)</td>
<td>1690/+103.6 (133.4)</td>
<td>2028/+66.4 (93.1)</td>
<td>2187/-418.3 (237.6)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Dynamic rerouting</td>
<td>858/+29.8 (49.4)</td>
<td>1422/-34.6 (88.8)</td>
<td>1874/-17.7 (76.8)</td>
<td>2683/-154.0 (106.8)</td>
</tr>
<tr>
<td>Pink Floyd</td>
<td>18398</td>
<td>Real world</td>
<td>2889/- (-)</td>
<td>3551/- (-)</td>
<td>5109/- (-)</td>
<td>6849/- (-)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Initial route only</td>
<td>2912/-81.9 (150.4)</td>
<td>4672/-418.7 (373.2)</td>
<td>5228/-78.1 (84.2)</td>
<td>5574/-505.3 (313.7)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Dynamic rerouting</td>
<td>2707/-219.7 (162.1)</td>
<td>4136/-202.5 (257.1)</td>
<td>4988/-143.8 (68.5)</td>
<td>6557/-188.0 (68.3)</td>
</tr>
<tr>
<td>Bon Jovi</td>
<td>25869</td>
<td>Real world</td>
<td>2936/- (-)</td>
<td>4526/- (-)</td>
<td>7616/- (-)</td>
<td>10791/- (-)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Initial route only</td>
<td>3989/+617.0 (293.8)</td>
<td>6389/+1231.5 (318.1)</td>
<td>7428/-203.0 (158.1)</td>
<td>8051/-2117.5 (319.9)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Dynamic rerouting</td>
<td>3640/+357.7 (246.5)</td>
<td>5589/+660.5 (237.4)</td>
<td>7134/-425.3 (144.9)</td>
<td>9493/-1071.8 (191.1)</td>
</tr>
</tbody>
</table>
5. Conclusion

We have presented our dynamic route choice model and compared the simulation results to counting data obtained from three different real world events. By introducing dynamic rerouting based on local observations, better results than with static route assignments can be achieved. The average error between simulated and observed counting data is significantly lower. This demonstrates the importance of local information and continuous travel time estimations.

The used route choice models are very sensitive to the timing when the pedestrians are created as the choice is affected by the local densities in front of the meanders. The OD matrix estimation from the counting sensors seems like a reasonable approach, but has its limitations when all meanders are used equally which is the case when the space in front of the station becomes crowded.

Future work also needs to address the calibration of the model parameters with additional real world data sets. That includes performing a sensitivity analysis on the influence of the individual parameters. Based on the initial results, the presented approach of a dynamic rerouting model using continuous travel time estimations is the first step to realistically model pedestrian behavior in large scale scenarios.

Acknowledgements

The authors want to thank the ‘Wiener Linien’ for their support, in particular for the allowance to use the counting data of the U2 station ‘Stadion’ in this study.

References


