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A hybrid and multiscale approach to model and simulate mobility in the context of public events

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Abstract

Organizers of large events have to ensure efficient mobility to guarantee a smooth and secure event course. Traffic and crowd simulations help to predict weak spots on the event's infrastructure. Thus, we propose a hybrid and multiscale approach to provide realistic and computationally efficient simulations. Our approach is able to predict traffic and crowd flow on different spatial resolutions. Events can be modeled on three spatial scales: macroscopic, mesoscopic, and microscopic. Each scale has individual characteristics according to spatial resolution and computational efficiency. Our approach combines these scales to model multimodal aspects of mobility during an event course. For the macroscopic scale, a public transport approach, which combines network based optimization with simulation techniques, is presented. This optimization approach for bus transport was integrated into a crowd simulation platform, which simulates the behavior of visitors after having arrived at the event site.

Keywords: Multiscale, Crowd Control, Optimization

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1. Introduction

The size and relevance of festivals has increased considerably over the last decades (Betz and Hitzler, 2011). The larger an event gets, the more important is an efficient mobility to ensure a smooth and secure event course. Weak spots in the infrastructure may lead to unforeen and dense crowds. In these cases, fatal accidents, like the tragedy on the Love Parade in Duisburg (Helbing and Mukerji, 2012), can occur. The simulation, control, and optimization of traffic flow and pedestrian dynamics helps to forecast and prevent bottlenecks and crowded areas. A public event simulation model can be separated into three different parts: the arrival behavior to the event site, the simulation of uncritical regions, and the simulation of potentially critical situations on the event site. We define these complimentary parts as macroscopic, mesoscopic and microscopic. In this paper, we propose a multimodal multiscale simulation model, which combines public transport service optimization and simulation with a crowd simulation platform. For this multiscale approach, we developed a new optimization and simulation based shuttle bus service approach (see Section 4), a new cellular automaton for pedestrian dynamics simulations (see Section 3.2) and a new model coupling framework (see Section 5). These new developments were combined with existing methods and simulation models to realize a holistic modeling and simulation of mobility in the context of public events.
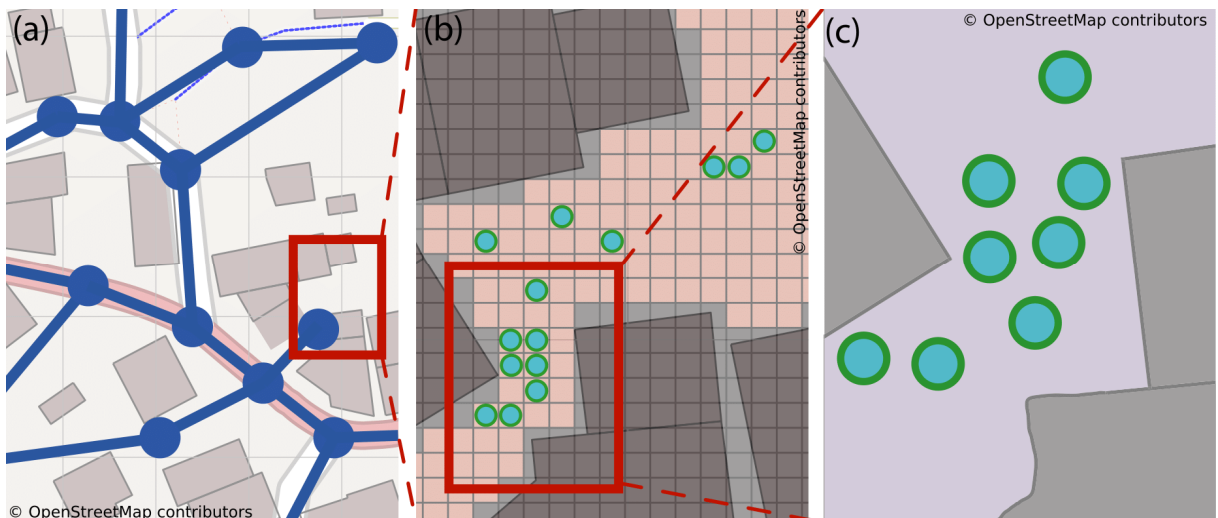
2. Multiscale nature of public events

Fig. 1. The three spatial scales of a public event: macroscopic (a), mesoscopic (b) and microscopic (c).

2.1. Macroscopic scale

The successful management of urban events is a complex problem, because processes take place on different spatial and temporal scales. Macroscopic models of pedestrian dynamics consider the subject of investigation from an all-inclusive perspective (Kneidl, 2013). Nevertheless, one should keep in mind that macroscopic phenomena emerge from microscopic processes (Schelling, 2006). Models on the macroscopic scale consider mostly accumulated values instead of singular and discrete objects. For example, these models use the cumulated number of pedestrians instead of singular and discrete pedestrian objects. To model phenomena on the macroscopic scale, two different modelling techniques are helpful.

First, the method System Dynamics focuses on feedback relationships and causal dependencies, such as the origination processes of mass events or the causal interdependencies that led to the Love Parade tragedy (Handel et al., 2014). Important within this methodology are stocks and flows. A stock is a variable such as the current amount of pedestrians on the festival and flows are then the arriving or departing visitors. With the help of auxiliary variables, the drivers of

these flows can be mapped through System Dynamics to get to a forecast of the amount of visitors at the festival over time.

Second, network-based approaches (see Figure 1a) can be used to model arterial-based pedestrian walkway dynamics, if pedestrians are limited in their spatial movement to walk along paths and streets. Hence, these models simplify the real world to a one dimensional network of nodes and edges. Another possibility is to map motorized traffic with network-based models. The aim is to endogenize the arrival and departure processes from and to the microworld that covers the pedestrian dynamics (e.g. the urban event under investigation).

One example of this macroscopic models is the Lighthill, Whitham (Lighthill and Whitham, 1955) and Richards (Richards, 1956) model. This so called LWR-model is based on the continuity equation and describes traffic as a dynamic fluid. The LWR-model was adapted to pedestrian dynamics by Colombo and Rosini (2004). Another established type of macroscopic modeling is the network flow model (Ahuja et al., 1993). Models of this type are mainly useful to solve optimization problems efficiently.

Models on the macroscopic scale consider accumulated values instead of singular and discrete objects. Exemplarily, these models use the cumulated number of pedestrians in form of density and simplify the real world to a one dimensional network. Thus, these models have a low level of detail, but are highly computational efficient. Therefore, they are useful to simulate the traffic on large scale scenarios. In the context of public events, macroscopic models are used to model the arriving traffic to the event site. For the simulation of the event site itself, more detailed models are necessary.

2.2. Mesoscopic scale

Mesoscopic models are the intermediate level between microscopic and macroscopic simulations (see Figure 1b). In pedestrian dynamics, these models are based on cellular automata (Biedermann et al., 2014). Each pedestrian is simulated as an individual and discrete object (Blue and Adler, 2001). The pedestrians do not move in a continuous space, but on a two dimensional, cellular grid. Quadratic or hexagonal cell shapes are normally used for mesoscopic pedestrian dynamic simulations. Birch et al. (2007) describe the advantages of these cell shapes. Due to computational efficiency reasons, each cell of the grid has one of the following states: the cell is free, occupied by a pedestrian, or occupied by an obstacle. This "one object per cell"-concept is widely used for pedestrian dynamics simulations with cellular automata (Burstedde, 2001). Thus, the spatial resolution of mesoscopic models is limited by the size of one unit cell. These models are quite computationally efficient, since the space of possible incidents is limited by the number of grid cells.

In the context of public events, mesoscopic models are mainly useful to simulate the behavior of visitors on the event site in non-critical situations. Critical situations can occur, if the local density exceeds five persons per square meter (Löhner and Haug, 2014). In these cases, microscopic models should be applied to achieve more accurate simulation results. Densities, which are higher than one pedestrian per cell, cannot be simulated by mesoscopic models, due to the maximum capacity of one pedestrian per cell. Therefore, the boundary to simulate dense crowds with cellular automatons depends on the area of the unit cell. We obtain a maximal boundary density of approximately $4.7 \; ped/m^2$ for quadratic cells and $5.5 \; ped/m^2$ for hexagonal shaped cells, under the assumption that the grid cell contains a circular formed human body with a radius of $0.23 \; m$ (Weidmann, 1993).

Another weakness of mesoscopic models is if a cell is only partly occupied by an obstacle. Then, the cell has to be considered either as free or as occupied. If we consider it as free, pedestrians would walk on areas which are not accessible in the real world. This leads to unrealistic results. Therefore, we have to consider the cell as occupied (Abdelghany et al., 2016). In this case, we restrict the movement space of the pedestrian more than in real life. This only has a small influence on the walking behavior in the case of wide and open areas, but leads to unrealistic results for narrow bottlenecks. In these cases, microscopic pedestrian dynamic models should be used.

2.3. Microscopic scale

Microscopic models describe fine and detailed pedestrian movement behavior (see Figure 1c). They model the pedestrian's change in position in a two-dimensional plane without technical introduced boundaries. Hence, simulated pedestrians can walk freely on the available surface. Typical examples for microscopic modeling are force-based

approaches that find the change in the pedestrian's position by computing a force between the superposition of pedestrians and obstacles, and a self-driving force (Helbing et al., 2002; Chraibi et al., 2012). Other advanced concepts for microscopic pedestrian movement modelling are for example predictive behavior concepts (Paris et al., 2007), or approaches that introduce psychological findings (Park et al., 2013).

By applying microscopic simulations, the behavior of pedestrians is modeled in high spatial resolution. Therefore, microscopic movement models provide detailed simulation results. Detailed simulations can predict pedestrian flows and behavior in environments with small and complex geometries (Klügl et al., 2009) or in high density situations (Alonso-Marroquín et al., 2014). Hence, trains, office buildings, and clubs are typical application scenarios for microscopic models. Unfortunately, the high spatial resolution of microscopic models introduces the problem of computational burden. The well-known force-based microscopic models have a computational complexity of $O(n^2 \cdot m)$, where n refers to the number of pedestrians and m to the number of geometric obstacles in the simulation. The complexity can be deduced by the typical modelling approach of microscopic models: for each pedestrian n a term needs to be computed for each of the other $n − 1$ pedestrians and for m obstacles, in order to find the next walking position (Quinn et al., 2003). Despite potential computational optimization approaches for microscopic simulations, cellular automata concepts are by far faster due to a complexity of $O(n \cdot k)$. For these mesoscopic models, k is the number of cells evaluated before changing a pedestrian's position. Due to the tradeoff between computational complexity and high spatial resolution, microscopic model are the perfect approach for small scale scenarios with a limited amount of simulated pedestrians.
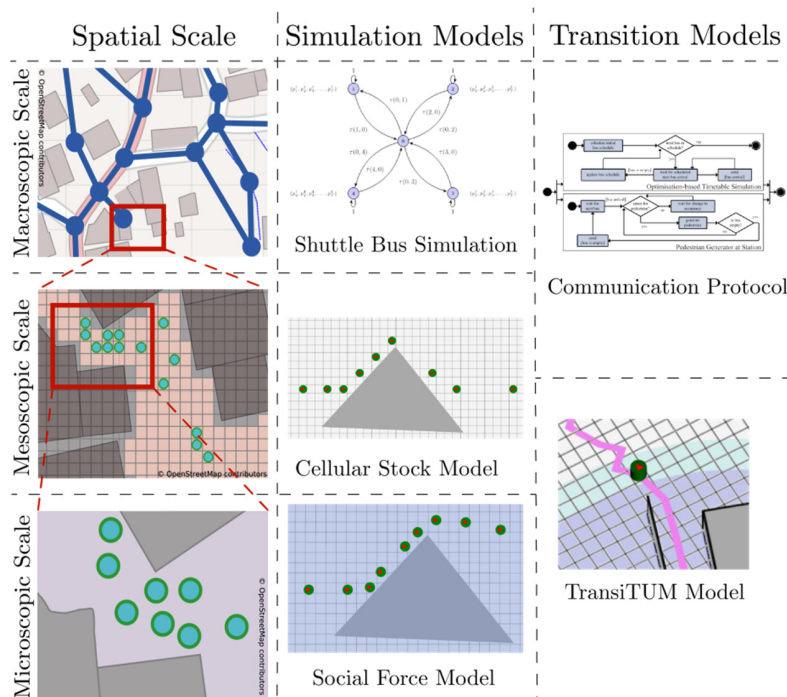
2.4. *Hybrid approaches*

Fig. 2. The three spatial scales of a public event and the corresponding simulation and transition models for our hybrid approach.

We showed that a public event consists of three spatial scales: microscopic, mesoscopic and macroscopic. Each scale has different characteristics according to spatial resolution and computational efficiency. Moreover, different stages of transport and movement of visitors can be adequately realized by models with different granularity. The arriving traffic to a public event is often organized via public transport systems, designated shuttle buses or individual traffic. While the optimization of this phase of transport (e.g. in terms of optimized or robust schedules) is crucial to the

efficiency of the overall system, the main data for the event phase is the number of incoming visitors for the event site simulation. Thus, a macroscopic model is sufficient to model transport to the event site, since we are not interested in the specific behavior of single visitors during arrival. As a result, this model provides an inflow which is then used to create pedestrians on the mesoscopic scale for the event site pedestrian movement simulation. In the case of narrow bottlenecks and areas with potentially high densities, a microscopic model has to be used to get realistic simulation results. If we combine these scales into one simulation model, we can lower the computational effort significantly, since only interesting areas are simulated in high detail. Thus, a multiscale approach is the best solution to simulate public events.

Different multiscale approaches already exist in the field of pedestrian dynamics (Ijaz et al., 2015). Nguyen et al. (2012) coupled a LWR approach (Lighthill and Whitham, 1955; Richards, 1956) with a leader-follower model to simulate large street network scenarios. Another hybrid framework for pedestrian dynamics simulations was developed by Lämmel et al. (2016). They combined a force-based and microscopic pedestrian dynamic model with a simple queue model for evacuation scenarios. Most hybrid approaches couple two models of different scales to speed up simulation time. Combined hybrid approaches over all three spatial scales are rare, but exist. For example Chooramun et al. (2012) combined a coarse network, a fine network, and a continuous simulation approach to one combined hybrid evacuation model.

Our hybrid approach of three different scales is made for the modeling of a whole public event (see Section 3). A simulation of an event course is more complex compared to evacuation scenarios. In evacuation scenarios, pedestrians are normally heading towards one target (e.g., the exit of a facility) by using the route with the shortest path. During the course of a public event, the simulated agents vary their targets over time based on their current needs and they have a more complex routing behavior. Additionally, we connected the simulation of the event course with a shuttle bus service to describe the arriving traffic of incoming visitors (see Section 4). To realize this new approach, we developed a new optimization-simulation model for shuttle bus services (see Section 4), a new cellular automaton (see Section 3.2.) and a new coupling framework based on communication protocols (see Section 5). We combined these new developed methods with already existing models like the "Social Force Model" (Helbing et al., 2002), the "Cognitive Model" (Kielar and Borrmann, 2016), the "Unified Pedestrian Routing Model" and the transformation model "TransiTUM" (Biedermann et al. 2014) to enable a holistic simulation of a public event (see Section 3.2.). An overview of our hybrid approach is given in Figure 2.

3. Multiscale view on the event site

3.1. Characterization of the event

A local music festival was used as a case study for our multiscale simulation approach. We observed this annual open air event over two consecutive years (Biedermann et al., 2015). The major share of the approximately 5000 visitors consists of students and people less than 30 years. The festival takes place in the end of July and lasts for one day. It is located on a remote area next to the research campus of the Technical University Munich. Most visitors come to the festival by metro, since a subway station is located close to the event site. In the case of a malfunction of the metro, shuttle buses have to be used to replace the public transport service.

3.2. Multiscale simulation of the event site

According to our definition in Section 1, we divided the all-encompassing modeling in different parts. The modeling of the macroscopic arrival traffic is described in Section 4. The calculated arriving traffic is used to generate the incoming pedestrians for the event site simulation. The event site itself was simulated by the "MomenTUMv2" pedestrian simulation framework, a research simulator developed at the Chair of Computational Modeling and Simulation (Kielar et al., 2016a).

The framework realizes the layer approach from Hoogendorn and Bovy (2004). This approach divides the modeling approach of pedestrian behavior into three interacting, but independent levels: strategic, tactical, and operational. On the strategic level, a pedestrian decides which target he or she will visit next. In the context of public events, targets

are for example bars, dancing areas or sanitary facilities. For the modeling of the strategic level, we used the "Cognitive Model" based on Kielar and Borrmann (2016). The model uses state-of-the-art insights from cognitive sciences to model highly accurate decision processes for the simulated pedestrians.

The tactical level determines the route the simulated pedestrian will take from his current position to the target, which was chosen by the strategic level. Different criteria influence the complex process of human routing behavior (Wolters and Hegarty, 2010). We used the "Unified Pedestrian Routing Model" (Kielar et al., 2016b) on the tactical level. The model combines different cognitive concepts about the processing of spatial information to model a realistic navigation behavior. Based on this, routing information is calculated and handed to the operational level. The routing information is provided through a chain of routing points that lead the pedestrians around obstacles to the target chosen by the strategic model.

The operational level describes the actual walking behavior. Thus, the operational level has to ensure that the pedestrians walk from one routing point to the next in a realistic manner. This means, e.g., that they move with a realistic velocity and avoid collisions with other scenario objects. We used two different operational models to describe the walking behavior on the festival. The largest share of the event site had wide and open areas. Following the concept presented in Section 2, these parts were simulated by a mesoscopic cellular automaton. Only cramped and narrow areas like the entrance area or the sanitary facilities were simulated by a microscopic model. For the mesoscopic scale, we developed the "Cellular Stock Model", a new cellular automaton. This model uses a walking stock, which increases with each simulation time step. A pedestrian is only allowed to move if the stock reached a minimum threshold (normally the distance to a neighboring cell). Each pedestrian p_i of this cellular automaton uses the following rules for each simulated time step:

- Increase the walking stock S by $v_{des} \cdot \Delta t$ (v_{des} is the desired velocity of p_i, Δt the duration of one time step)
- Determine all free neighboring cells, which are closer to the next routing point than the current cell center $\vec{c}_i$
- From these cells, chose the cell c_b which is closest to the beeline between the previous and the next routing point
- If $S \geq |\vec{c}_i - \vec{c}_b|$ move the pedestrian to c_b and lower the stock by $|\vec{c}_i - \vec{c}_b|$
- If the pedestrian did not move and $S > k \cdot v_{des} \cdot \Delta t$ with $k > 1$, choose a random free neighboring cell c_r
- Move the pedestrian to cell c_r and lower the stock by $|\vec{c}_i - \vec{c}_r|$

For the microscopic scale, the established "Social Force Model" from Helbing et al. (2002) was used. This model assigns a potential to each object within the simulated scenario. Obstacles and pedestrians have a repulsive potential, while the next routing point has an attractive one. The superposition of all derived forces moves the pedestrians from one routing point to the next, by applying an additional self-driving force.

To combine the mesoscopic and microscopic model into one encompassing simulation, we used the "TransiTUM" transition approach (Biedermann et al., 2014b). This approach uses transition zones to enable generic multiscale simulations of coupled microscopic and mesoscopic pedestrian dynamics models. Specific parts of the event site can be assigned as microscopic areas, which means, that all pedestrians inside this area are simulated by the microscopic model. The remaining areas are simulated by the computational more efficient mesoscopic model. The "TransiTUM" framework surrounds each microscopic area with a transition zone. If a microscopic or mesoscopic pedestrian enters the transition zone, the framework checks if the pedestrian will leave the sphere of the current simulation model. If this is the case, the pedestrian gets transformed from the microscopic model to the mesoscopic model and from the mesoscopic model to the microscopic one, respectively.

4. Modeling of the arriving traffic

4.1. Optimization-based timetable simulation

The studied local music festival is situated at a university campus outside Munich. Students and visitors get to the event site mainly by car or metro. If the metro breaks down, it is substituted by a specially designated shuttle bus service. Since there is no practical experience in serving the region around the university by shuttle busses, macroscopic mathematical models help to design optimized timetables. When setting up such a bus service, several

decisions have to be made. In this paper, we only deal with the design and simulation of the timetable, using both optimization and simulation techniques (see e.g. Hamacher et al. (2011) or Kneidl et al. (2011) for related approaches). The two macroscopic models fulfill complementary purposes in practice: using the optimization model described in the next subsection, the practitioner may calculate a timetable from scratch, which is optimal for the expected input data. In particular no timetable is needed as input for the computation. Afterwards, the practitioner may test the robustness of the calculated timetable against fluctuations in the input data using the simulation model. In Subsection 4.4, the synergy between the two approaches is discussed in more detail.

First, we describe the used optimization and simulation models and discuss coherence between them. Afterwards, we illustrate how a practitioner can profit from combining both approaches. The coupling between the macro- and mesoscopic simulation is explained in Section 3.
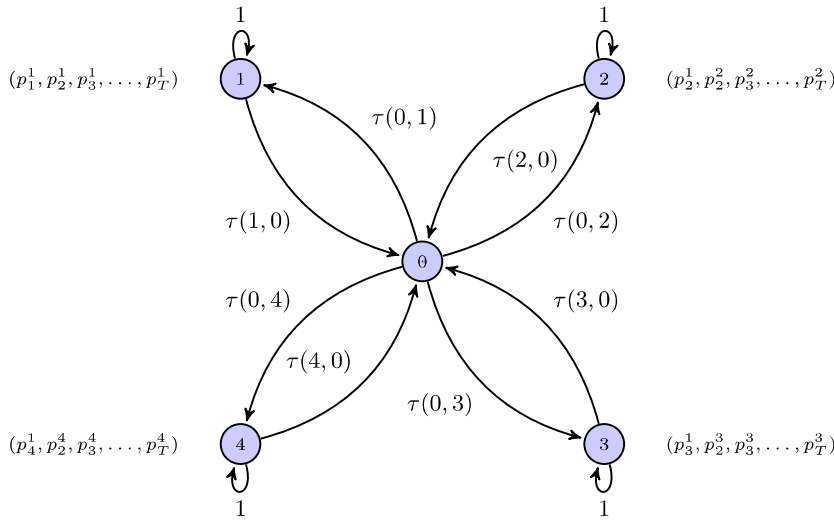
4.2. A dynamic network flow model

Fig. 3. Example of star graph on which a shuttle bus service operates. In addition to node $\mathbf{0}$, the stop at the event, there are four more nodes $\mathbf{1}, \mathbf{2}, \mathbf{3}, \mathbf{4}$ where passengers get on the bus. The numbers on the arcs represent the travel times, the numbers next to the nodes stand for the number of arriving passengers over time.

For calculating a timetable, a dynamic network flow model with a discrete time horizon is used (Ahuja et al., 1993; Ford and Fulkerson, 1962; Hall et al., 2007). We denote the number of shuttle buses by $B \in \mathbb{N}$ and assume that B is fixed. The bus capacity is denoted by $C \in \mathbb{N}$. The bus stops are modeled as nodes of a directed graph $G = (V, A)$, where the arcs represent the bus routes between the stops. Additionally, there are waiting arcs $(v, v) \in A$ for each node $v \in V$, which model that a bus or passenger can spend a whole time step at a node. Each arc $a = (v, w) \in A$ and each node $v \in V$ is equipped with a set of parameters. For every arc $a = (v, w) \in A$, the model requires a parameter $\tau(a) = \tau(v, w) \in \mathbb{N}$ which is the (average) time needed for traveling from v to w along the route represented by a. The waiting arcs $(v, v) \in A$ have travel time one. In the optimization model, the travel time is assumed to be constant over time. The parameter set of each stop $v \in V$ includes the estimated passengers supply over time $p(v) = (p_1^v, p_2^v, \ldots, p_T^v)$, called the supply at v, and the number of buses $b(v)$ that can be served simultaneously at a time at stop $v \in V$. The passenger supply at the destination d is zero.

Since we deal with a shuttle bus system, we make the following assumptions compared to general bus systems:

- The set of nodes is partitioned into $V = \{d\} \,\dot\cup\, \{s_1, \ldots, s_n\}$ for fixed $n \in \mathbb{N}$.
- The nodes $s_1, \ldots, s_n \in V$ represent the stops where passengers get on the bus. We denote this set by $V_S = \{s_1, \ldots, s_n\}$

- All passengers get off the bus at node $d \in V$ situated in the vicinity of the event.
- At each node $v \in V$ passengers get either on or off the bus - but not both.
- Busses directly head for the event after picking up passengers.

As a consequence, there are no arcs between two different stops s_i and s_j, and the graph G is a star graph, see Figure 3. The bus routes between the nodes are (principally) fixed by the shortest path from stop s_i to d and back. Therefore, the travel time of each passenger, which is the standard objective in timetabling (Schmidt and Schöbel, 2014; Liebchen, 2006; Lindner, 2000), is also fixed. The overall goal is to improve the level of service of a timetable by minimizing the waiting time of the passengers.

$$
\text{(SBP)} \quad \min \left(\sum_{v \in V_S} \sum_{t \in [T]} x_{v,v}^{t,0} \right) \qquad \qquad \text{total waiting time}
$$

$$
\begin{aligned}
s.t. \quad & x_{s,v}^{t,0} = p_v^t & v \in V_S,\, t \in [T] \quad &(1)\\
& \sum_{v \in V_S} \sum_{t \in [T]} x_{s,v}^{t,1} = B & &(2)\\
& x_{v,v}^{t,1} \le b(v) & v \in V,\, t \in [T] \quad &(3)\\
& \sum_{(v,w) \in A} x_{v,w}^{t-\tau(v,w),l} = \sum_{(v,w) \in A} x_{v,w}^{t,l} & w \in V \setminus \{s,d\},\, t \in [T],\, l \in \{0,1\} \quad &(4)\\
& x_{d,v}^{t,0} = 0 & v \in V_S,\, t \in [T] \quad &(5)\\
& C \cdot x_{v,w}^{t,1} \ge x_{v,w}^{t,0} & (v,w) \in A,\, v \in V \setminus \{s\},\, t \in [T] \quad &(6)\\
& x_{v,w}^{t,k} \in \mathbb{N}_{\ge 0} & v, w \in V,\, t \in [T],\, k \in \{0,1\} \quad &(7)
\end{aligned}
$$

$x_{v,w}^{t,0} \in \mathbb{N}_{\ge 0}$ number of passengers traveling from v to w at time t

$x_{v,w}^{t,1} \in \mathbb{N}_{\ge 0}$ number of buses traveling from v to w at time t

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Fig. 4. Mathematical formulation of Dynamic Network Flow Problem SBP.

We set up the following Shuttle Bus Problem (SBP), which is a generalized Dynamic Min-Cost Flow Problem (Ford and Fulkerson, 1958; Fleischer and Skutella, 2003; Klinz and Woeginger, 2004), as integer program (Nemhauser and Wolsey, 1988) for calculating aperiodic timetables which minimize the total waiting time of the passengers. The mathematical equations are given in Figure 4. For modeling purposes, we add an extra node $s \in V$ to the graph, the supersource, which is linked by extra arcs to each node $v \in V$.

There are two sets of flow variables. The flow variables $x_{i,j}^{t,0}$ with 0 in the exponent stand for the passenger flow, while the variables $x_{i,j}^{t,1}$ with 1 in the exponent represent the bus flow. Equation 1 fixes the passenger supply at stop v and time $t \in [T]$ to be p_v^t, while Equation 2 demands that in total B buses enter the network. Equation 3 enforces that at most $b(v)$ buses are served at a time at stop v. Equation 4 represents flow conservation, whereas Equation 5 enforces that passengers who have reached the destination to remain there. Finally, Equation 6 represents the link between bus flow and passenger flow: It ensures that all traveling passengers fit into the traveling buses, i.e. the bus capacity is respected. In the objective function, we sum up the number of passengers waiting at some stop $v \in V_S$ over all time steps $t \in [T]$ in order to get the total waiting time of the passengers.

Remark 4.1: *If Equation 6 is left out, SBP turns into a standard Min-Cost Flow Problem.*

Remark 4.2: *It can be shown that the optimal objective value of SBP does not increase if we leave out constraint 6 and relax the passenger flow $x_{v,w}^{t,0} \in \mathbb{N}_{\geq 0}$ to $x_{v,w}^{t,0} \in \mathbb{Q}_{\geq 0}$.*

Remark 4.3: *In addition to SBP, another optimization model has been implemented which allows to solve the corresponding periodic timetabling problem.*

Solving the optimization model produces an optimal timetable, i.e. a timetable with minimal total waiting time of the passengers. Note that no timetable is required as input for the model.
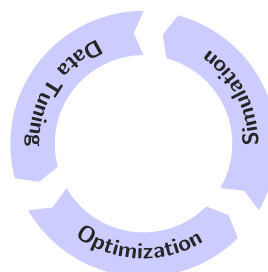
4.3. Shuttle-bus simulation model

We choose a discrete event simulation model that is able to simulate a large number of passengers. Following the optimization model, the simulation produces a sequence of states, one state for each time step. Between two states occurring in consecutive time steps, no change in the system may occur. Each object in the simulation (nodes, arcs, passengers, buses) has a functionality, which is executed at each time step. The functionalities determine how stops, passengers, buses and travel routes interact. The entirety of these functionalities transforms a state into its consecutive one. The simulation terminates, when all passengers have been transported to the event.

The input for the simulation is the same as for the optimization, plus a timetable which constitutes the travel plan for the buses. However, compared to the optimization, the simulation allows for a higher resolution of the process:

- The passengers need time to enter and leave the buses.
- Both the travel times on arcs and the time needed to enter/leave the bus vary stochastically.
- If there are several buses waiting at a stop, passengers may choose which bus they enter.
- Bus drivers may decide to depart although there are waiting passengers in order to catch up on a delay.

The simulation and optimization models display an in-depth coherence. In the simulation and optimization model, the same number of passengers arrives at each stop and each time step, they want to travel to the event in both cases, the number of buses is the same, the graph on which the passengers and the buses travel is identical, including arc and node parameters. The choice of a discrete event simulation further strengthens the coherence between the models: when an optimized timetable is simulated, the results of the simulation coincide with those of the optimization if the time for entering and leaving the bus is set to zero, the travel times remain constant and all passengers choose to enter the bus which leaves first.

Remark 4.4: *For estimating the time needed to enter a bus, two field experiments have been conducted by Hochschule München and Universität Koblenz-Landau (Torchiani et al., 2015).*

4.4. Interactive timetable optimization

Having at hand the optimization and the simulation model, a practitioner may use an iterative optimization/simulation approach for designing a shuttle bus timetable. The procedure is described in the following and illustrated in Figure 5.

Fig. 5. Interactive Simulation-Based Optimization Approach.

The practitioner first fixes the scenario parameters, i.e. number of stops, buses that can be served at a stop at a time and travel times between the stops and the event. Then an iterative cycle starts:

1. The passenger inflow at the stops is estimated, and the number of buses is fixed.
2. Based on this estimation, a timetable is calculated which minimizes the total waiting time using the Min-Cost Flow Model.
3. In several simulation runs, the robustness of the timetable against fluctuations in the passenger inflow is tested.

4. If the results are satisfactory, the current timetable is put into practice. Otherwise, another iteration starts, in which the estimated passenger inflow and the number of buses are adjusted according to the simulation results.

By using this innovative interactive simulation/optimization approach, several goals are reached: the practitioner needs not to design a timetable from scratch. Instead, solving the Min-Cost Flow Model provides a complete timetable, which additionally realizes the minimal waiting time for the passengers in the scenario that the practitioner considers most likely. Thus, the calculated timetable fulfills a provable quality criterion. However, the actual passenger inflow may differ from the estimation. Using the simulation, the practitioner may test a timetable previous to an event in order to find out whether a timetable is viable in practice. If this is not the case, e.g. if the waiting time of the passengers is unacceptable, the practitioner may react by adapting the timetable and/or the number of buses prior to the event. For the studied music festival, the presented cycle has been implemented. The timetable, which is simulated on the macroscopic scale, is the outcome of the presented Min-Cost Flow Model.

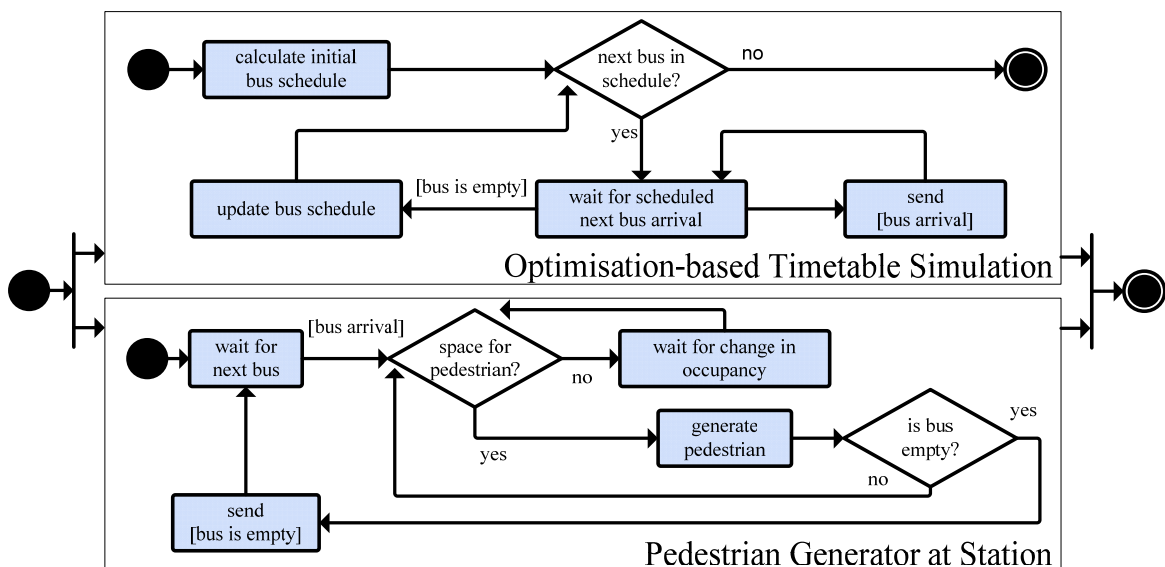## 5. Coupling of the public transport service with the event site simulation

Fig. 6. Coupling process between the optimization-based timetable simulation and the pedestrian generator of the crowd simulation platform.

To achieve an all-encompassing modeling of an event course, we combined the optimization-based timetable simulation of shuttle buses with the crowd simulation platform "MomenTUMv2". The interaction between the singular components can be seen in Figure 6. Two communication protocols are used for the interaction between the singular components: the arrival-protocol contains the list of all buses, which arrived at the event site and the number of passengers they transport. The timetable simulation generates such arrival protocols. The second communication protocol is the departure protocol. It is created by the crowd simulation platform. It contains the departure time of all buses, which departed from the event site. These two protocols are essential for the communication between the singular components.
In the following, we describe the simulation flow of our multiscale approach: the timetable, calculated by the macroscopic optimization-based timetable simulation (Section 4), determines the point in time at which a shuttle bus arrives at the event site. If a shuttle bus arrives, it is added to the arrival-protocol.
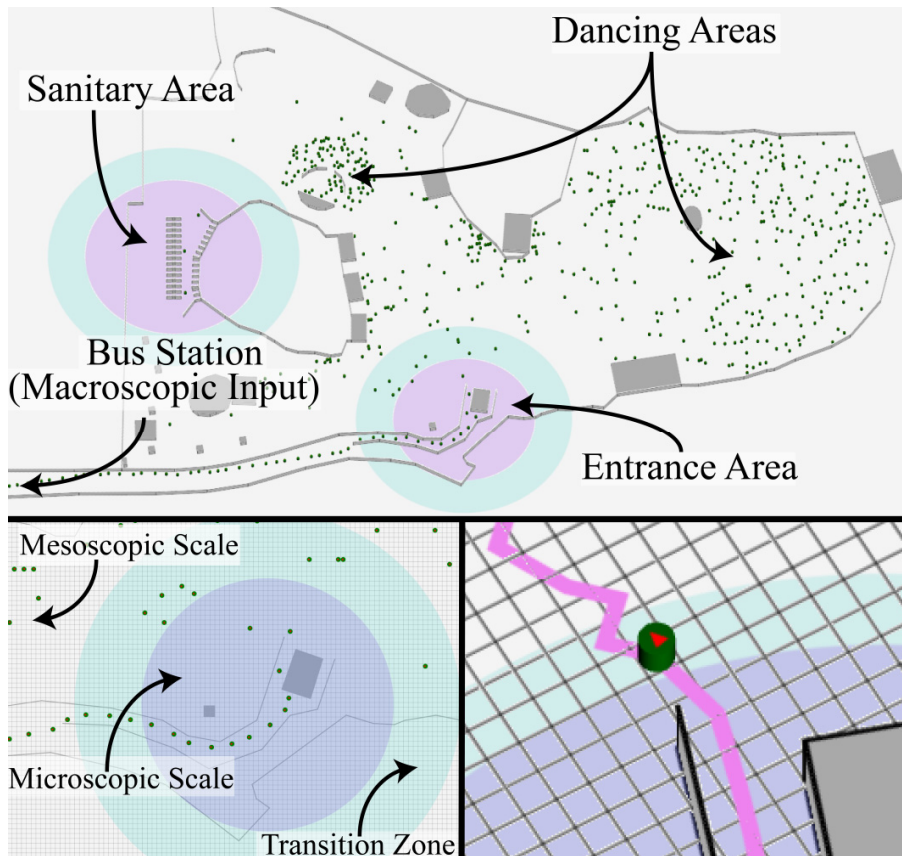
Fig. 7. Snapshot of the all-encompassing simulation of mobility on public events.

Simultaneously, the simulation of the crowd platform is executed. Before pedestrians can be simulated, they need to be created by a pedestrian generator. The pedestrian generator creates pedestrians in specific areas of the simulation scenario (so-called origins). In our case, the shuttle bus station is modeled as the origin of the event site. Each time the pedestrian generator has to generate pedestrians for the simulation, the generator checks the arrival-protocol for arriving shuttle buses. If a bus arrived, the pedestrian generator tries to create one pedestrian for each passenger of this bus. The pedestrians are created on the mesoscopic scale and are simulated by the pedestrian behavior models described in Section 3.

If too many passengers arrive, the origin can get too crowded to place new pedestrians in the origin area. In that case, the pedestrian generator waits until enough free space is available to create an additional pedestrian. This causes a delay of the shuttle bus schedule, since the bus has to wait until all of its passengers left the bus. As soon as all passengers of a bus are out, the bus is added to the departure-protocol. Now, the passengers of the next arriving bus can be transformed to pedestrians of the event site simulation. The optimization-based timetable simulation uses the departure-protocol to update the current shuttle bus schedule. Based on the updated schedule, new arriving times for the shuttle buses are calculated.

The whole procedure continues until no more bus arrivals are planned by the schedule. The simulation of the event site continues until the end of the event course.

As a proof of concept, we simulated the event course for a local music festival (see Section 3.1.). Figure 7 shows a snapshot of our multiscale simulation approach. The orange zone represents the station at which the mesoscopic

pedestrians are generated based on the results from the macroscopic timetable simulation. From this place, the pedestrians enter the event via the entry area. The entry area is a quite narrow place. Thus, we simulated it on the microscopic scale to avoid unrealistic results. On the event site, the pedestrians are transformed back into the mesoscopic scale to decrease the computational effort. They walk around and visit different points of interests, e.g., sanitary facilities, bars, or the dancing area. Based on our observation on this music festival, we simulated particularly interesting parts of the event site on the more detailed microscopic scale. After the end of the event course, the pedestrians leave the event site and are removed from the simulation scenario.

A validation of our proposed multiscale approach is necessary and will be presented in the future. The simulation on the event site can be validated by the measuring of densities on the festival over time (Corbetta et al., 2014). These density maps split the simulation area into a regular grid and represent a cell-wise cumulated density. To validate the simulation result, the density map of the simulation is compared with the density map of the real event course. The density map of the observed event can be obtained by video observations. If the results are similar, the simulation model is able to forecast the density distributions. Thus, the simulation model could detect areas with critical high densities. Another validation technique would be an individual tracking of pedestrians on the event site. We can track visitors' walking paths (e.g. by a mobile GPS-device) over the whole course of an event. If simulate the total event course, we can compare the simulation trajectories with the trajectories of the tracked visitors. A good simulation should reproduce similar trajectories. The similarity of trajectories can be compared by different metrics like the turning angle function (Kneidl, 2013).

6. Future research

For our proposed modeling approach, different smaller shortcomings and possible extensions exist. One major issue is the missing validation with field data (see Section 5). We will present such a validation in future publications.
In the current state, our multi scale simulation approach is not completely suitable for the needs of organizers of public events. Due to its prototype status, the successful use of our approach requires a sufficient amount of knowledge about pedestrian dynamics and computational science. We try to lower this initial hurdle in future developments. However, a pedestrian simulation can never forecast the course of an event in all details. Thus, the safety planning of an event should not be based on simulation results only. A professional and experienced crowd manager is always necessary to interpret the simulation results.
We simulated the arriving traffic of visitors and their behavior on the event site. Thus, our approach is able to model the whole course of an event. In a next step, the multiscale approach could be extended by the inclusion of a shuttle bus service for the departure of visitors. Pedestrians, which leave the event site, would choose and enter a bus to return to the bus station they started at the beginning. For this extension, more complex communication protocols are necessary and the optimization based timetable simulation needs to be extended for multiple targets.

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References

Abdelghany, A., Abdelghany, K., Mahmassani, H. 2016. A hybrid simulation-assignment modeling framework for crowd dynamics in large-scale pedestrian facilities. In: Transportation Research Part A, pp. 149-176
Ahuja, R. K., Magnanti, T. L., Orlin, J. B. 1993. Network Flows
Alonso-Marroquín, F., Busch, J., Chiew, C. 2014. Simulation of counterflow pedestrian dynamics using spheropolygons. In: Physical Review E.
Betz, G., Hitzler, R., Pfadenhauer, M. 2011. Urbane Events, pp. 9-24
Biedermann, D. H., Kielar, P. M., Handel, O. 2014. Betrachtung der Modellierung und Simulation von Fußgängern im Kontext verschiedener Skalen. In: Proceedings of the 26th Forum Bauinformatik, pp. 171-179

Biedermann, D. H., Kielar P. M., Handel, O., Borrmann, A. 2014. Towards TransiTUM: A generic framework for multiscale coupling of pedestrian simulation models based on transition zones. In: Transportation Research Procedia 2, pp. 495-500

Biedermann, D. H., Dietrich, F., Handel, O., Kielar, P. M., Seitz, M. J. 2015. Using Raspberry pi for scientific video observation of pedestrians during a music festival

Birch, C. P., Oom, S. P., Beeccham, J. A. 2007. Rectangular and hexagonal grids used for observation, experiment and simulation in ecology. In: Ecological Modelling 206(3), pp. 293-312

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

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(3), 507-525

Chooramun, N., Lawrence P. J., Galea, E. R. 2012. An agent based evacuation model utilizing hybrid space discretization. In. Safety Science 50, pp. 685-1694

Chraibi, M., Freialdenhoven, M., Schadschneider, A., & Seyfried, A. 2012. Modeling the desired direction in a force-based model for pedestrian dynamics

Colombo, R. M., Rosini, M. D. 2004. Pedestrian Flows and Nonclassical Shocks. In: Mathematical Methods in the Applied Sciences, pp. 1553-1567

Corbetta, A., Bruno, L., Muntean, A., & Toschi, F. 2014. High statistics measurements of pedestrian dynamics. Transportation Research Procedia, 2, pp. 96-104

Fleischer, L., Skutella, M. 2003. Minimum Cost Flows Over Time without Intermediate Storage.In: Proceedings of the 14th Annual ACM–SIAM Symposium on Discrete Algorithms, pp. 66-75

Ford, L. R., Filkerson, D. R. 1958. Constructing Maximal Dynamic Flows from Static Flows. In: Operation Research (3), pp. 419-433

Ford, L. R., Fulkerson, D. R. 1962. Flows in Networks. In: Princeton University Press.

Hall, A., Hippler, S., Skutella, M. 2007. Multicommodity Flows Over Time: Efficient Algorithms and Complexity. In: Theoretical Computer Science (379), pp. 387-484

Hamacher, H. W., Heller, S., Klein, W., Köster G., Ruzika, S. 2011. A sandwich approach for evacuation time bounds. In: Pedestrian and Evacuation Dynamics. Springer, pp. 503-513

Handel, O., Biedermann, D. H., Kielar, P. M., Borrmann, A. 2014. A System Dynamics based Perspective to Help to Understand the Managerial Big Picture in Respect of Urban Event Dynamics. In: Transportation Research Procedia 2, pp. 669-674

Helbing, D., Farkas, I. J., Molnar, P., Vicsek, T. 2002. Simulation of pedestrian crowds in normal and evacuation situations. In: Pedestrian and Evacuation Dynamics, pp. 21-58

Helbing, D., Mukerji, P. 2012. Crowd disasters as systematic failures: analysis of the Love Parade disaster. In: EPJ Data Science 1(1), pp. 1-40

Hoogendoorn, S. P., Bovy P.H.L. 2004. Pedestrian route-choice and activity scheduling theory and models. In: Transportation Research Part B: Methodological 38(2), pp. 169-190

Ijaz, K., Sohail, S., & Hashish, S. 2015. A survey of latest approaches for crowd simulation and modeling using hybrid techniques. In 17th UKSIMAMSS International Conference on Modelling and Simulation (pp. 111-116).

Kielar, P. M., Borrmann A. 2016. Modeling pedestrians' interest in locations: A concept to improve simulations of pedestrian destination choice. In: Simulation Modeling Practice and Theory, pp. 47-62

Kielar, P. M., Biedermann, D. H., Borrmann, A. 2016a. MomenTUMv2: a modular, extensible, and generic agent-based pedestrian behavior simulation framework, Technical Report

Kielar, P. M., Biedermann, D. H., Kneidl, A., Borrmann A. 2016b. A Unified Pedestrian Routing Model Combining Multiple Graph-Based Navigation Methods. In: Proceedings of the 11th Conference on Traffic and Granular Flow

Klinz, B., Woeginger, G. J. 2004. Minimum-cost dynamic flows: The series-parallel case. In: Networks (43), pp. 153-162

Klügl, F., Klubertanz, G., Rindsfüser, G. 2009. Agent-Based Pedestrian Simulation of Train Evacuation Integrating Environmental Data. In: KI 2009: Advances in Artificial Intelligence (32), pp. 631–638

Kneidl, A., Thiemann, M., Hartmann, D., Borrmann, A. 2011. Combining pedestrian simulation with a network flow optimization to support security staff in handling an evacuation of a soccer stadium. Proceedings of the European Conference Forum 2011.

Kneidl, A. 2013. Methoden zur Abbildung menschlichen Navigationsverhaltens bei der Modellierung von Fußgängerströmen. Ph.D. Thesis

Lämmel, G., Chraibi, M., Wagoum, A. U. K., Steffen, B. 2016. Hybrid multi- and inter-model transport simulation: A case study on large-scale evacuation planning. In: Transportation Research Board 95th Annual Meeting

Liebchen, C. 2006. Periodic timetable optimization in public transport. Ph.D. Thesis

Lighthill, M. J., Whitham, G.B. 1955. On kinematic waves II. A theory of traffic flow on long crowded roads. In: Proceedings of the Royal Society of London. Series A, Mathematical and Physical Sciences (229), pp. 317-345

Löhner, R., Haug, E. 2014. On Critical Densities And Velocites For Pedestrians Entering a Crowd. In: Transportation Research Procedia 2, pp. 394-399

Nemhauser, G. L., Wolsey, L. A. 1988. Integer and Combinatorial Optimization

Nguyen, T. N. A., Zucker, J. D., Nguyen, H. D., Drogoul, A., Vo, D. A. 2012. A hybrid macro-micro pedestrian evacuation model to speed up simulation in road networks. Advanced Agent Technology, pp. 371-383

Paris, S., Pettré, J., Donikian, S. 2007. Pedestrian Reactive Navigation for Crowd Simulation: a Predictive Approach. Computer Graphics Forum, 26(3), pp. 665–674

Park, J., Rojas, F., Yang, H. 2013. A collision avoidance behavior model for crowd simulation based on psychological findings. In: Computer Animation and Virtual Worlds, 24(3-4), pp. 173–183

Quinn, M. J., Metoyer, R. A., & Hunter-Zaworski, K. 2003. Parallel implementation of the social forces model. In Proceedings of the Second International Conference in Pedestrian and Evacuation Dynamics, pp. 63-74

Richards, P. I. 1956. Shock Waves on the Highway. In: OperationResearch (4), pp. 42-51

Schelling, T. C. 2006. Micromotives and Microbehavior

Schmidt, M., Schöbel, A. 2014. Timetabling with passanger routing. In: OR Spectrum,(37), pp. 75-97

Hall, A., Hippler, S., Skutella, M. 2007. Multicommodity Flows Over Time: Efficient Algorithms and Complexity. In: Theoretical Computer Science (279), pp. 387-484

Torchiani, C., Seitz, M., Willems, D., Ruzika, S., Köster, G. 2015. Fahrgastwechselzeiten von Shuttlebussen. Technical Report

Weidmann, U. 1993. Transporttechnik der Fussgänger. Schriftenreihe des IVT Nr. 90

Wolters, T., Hegarty, M. 2010. What determines our navigational abilities?. In: Trends in Cognitive Sciences 14(3), pp. 138-146