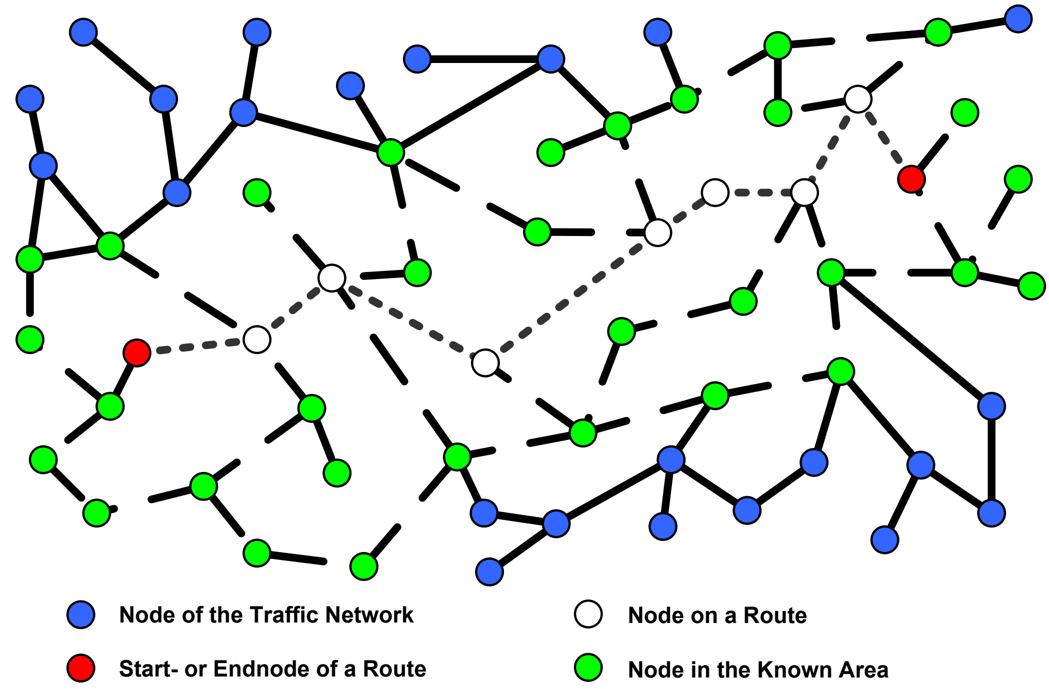

Transport Simulations: Knowledge Levels and System Outcomes

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Abstract

How does knowledge about a traffic system influence the behavior of people and the state of the traffic system they are acting in? The individual perception of the current traffic situation exerts an essential influence on the decision-making of road users and—in return—their behavior effects the state of the traffic system. The key element of modeling traffic systems is to understand the impact of different personal knowledge levels regarding the local and global state of road traffic. To evaluate this relationship, models of different levels of knowledge are constructed and implemented with the simulation toolkit MATSim. Simulations based on a real world scenario show the relation between the mean travel time and the road user's amount of knowledge about the network structure as well as the amount of information about the loading of the links. A key result is that all drivers (statistically) benefit, even if only the half of them re-plan their routes according to current traffic information.

Keywords

Information oriented traffic systems, simulation of transport systems, transport-planning, behaviour of road users, knowledge models, knowledge levels, routing strategies, activity end re-planning, leave link re-planning

Preferred citation style

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1 Introduction

Simulating transport explores the interaction of demand and supply in terms of traffic flows. Both parts, demand and supply, are in correlation with the load of a transport network as an input and as an output component at the same time: If the actual capacity of the network turns out to be lower than estimated, the demand is expected to change by a shift to other destinations, modes, times or routes (Ortúzar and Willumsen, 2001).

The research on traffic flow describes aspects which look similar in physical systems (e.g. Lighthill and Whitham, 1955; Nagel and Schreckenberg, 1992; Lübeck *et al.*, 1997). Although the dynamic of traffic flows have characteristic features, vehicle densities and travel times are hard to predict, due to different sources of uncertainty. For example, recent studies show that the ensemble acting of drivers and physical mechanisms are essential to explain the phenomena of traffic flow. Sugiyama *et al.* (2008) demonstrate the formation of a traffic jam. They found that the collective effect of vehicles causes congestion, even in a free flow state without bottlenecks or incidents. The experiment shows that solely fluctuations caused by drivers are able to induce jams. Also the demand side of a transport system has different parameters which can not all be expressed on a metric scale, like the details of travel behavior, especially route choices based on individual preferences of drivers and their level of knowledge at the point of decision.

Since congestions cannot be avoided, drivers should be informed regularly about the current state of the network, but it is not obvious that information can distribute traffic over the whole network and will reduce the level of congestion (Ziegelmeyer *et al.*, 2008). Some previous research shows that public information about traffic jams can cause a welfare-decreasing adjustment and may lead to an unforeseeable outcome (Ben-Akiva *et al.*, 1991; Arnott *et al.*, 1999).

The literature covers various aspects of the behavior of road users and the role of information in general. Investigations on Advanced Traveler Information Systems (ATIS) suggest changing the mode, the departure time or the route are the most common response to information on congestion (Ziegelmeyer *et al.*, 2008). A class of studies primarily analyse the effects of behavioral changes that are based on modal choices like shifts between private car and public transport (e.g. Reed and Levine, 1997; Gärling and Axhausen, 2004; Klöckner and Blöbaum, 2010). Changes of departure times are mainly discussed in the context of route choice (e.g. Abdel-Aty *et al.*, 1995; Noland and Small, 1995; Hensher, 1997; Cohen and Southworth, 1999). The main stream of research on ATIS reflects potential effects of changing routes where the decisions of drivers are simulated initially (pre trip) or dynamically (en-route). The value of ATIS for route choice is described by numerous authors: Levinson (2003) concludes on previous research (e.g. Khattak *et al.*, 1994; Al-Deek *et al.*, 1998) that ATIS not only reduces the drivers travel time and vehicle operating costs, but also affects the travel time of other users; Levinson (2003) specifies that dynamic route guidance has most opportunities to save time when traffic flow is at a rate of 95% of the capacity and that ATIS provides travel time benefits to users (although it may increase the time for selected non-informed travelers).

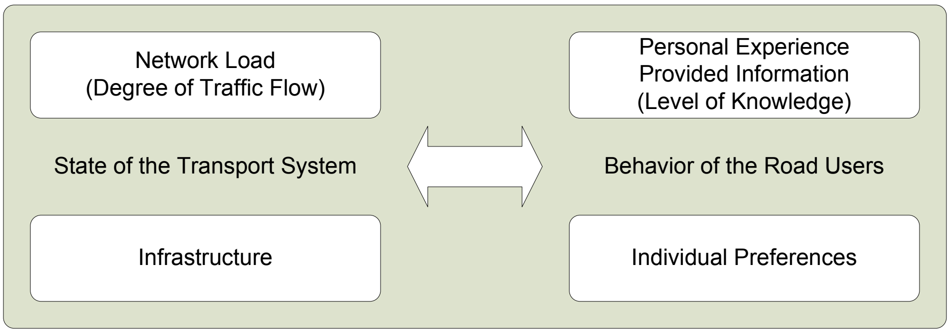
Even if it is evident that information on infrastructure and traffic load will allow a person to find a route with less traffic and will help to avoid traffic jams, questions should be discussed like: To what extent do the drivers who have low degree of knowledge gain some benefit from the behavior of the drivers who are better informed? Or which percentage of well informed road users is needed to improve the capacity use of the network? Consequently, the objective of this study is to understand the impact of different knowledge levels of road users with regards to the local and global state of the transport system. Fundamental questions in this context are "How is the quality of a person's routes affected by her limited information about its environment?" and "How does the traffic flow within a transport system change if the knowledge levels of the road users in the system is varied?" An attempt to answer such questions leads to the usage of knowledge models which consists of timing strategies and different levels of knowledge. A knowledge level is understood as the information that is used in the decision process for the route choice of a certain class of road users. At the highest level of knowledge, the road users are perfectly informed about the condition of the traffic system before every decision they make. Finally we check the assumption: If a certain percentage of drivers are able to re-plan their routes according to an ideal router dynamically, the condition of the system changes in the way, that all road users (even the non-informed) make a profit.

The following chapters describe the design and implementation of a model that respects the knowledge of infrastructure and information about the current state of the transport system. Using the results of several sets of simulation runs the implications of different levels of knowledge are analyzed and examined. The simulation toolkit MATSim enables us to evaluate the consequences of knowledge based behavior with larger-scale scenarios than similar former studies (e.g. Emmerink *et al.*, 1995a). But even such smaller simulation experiments have shown the potential of information provision in transport systems. The results of Emmerink *et al.* (1995b) already indicate that, if drivers are not provided with information, the road network will not be used efficiently in terms of travel time, particularly in networks with non-recurrent congestions. Further research which is linked thematically with the study at hand as well as the position of this topic within the field are described in the review of literature concerning the use and effects of travel information among car drivers (Chorus *et al.*, 2006).

2 Knowledge Models

The behavior of people within transport systems depends on different factors. Probably the two strongest ones are how familiar a person is with the infrastructure and how much information about the current state of the traffic system is available. Typically a person's knowledge is based on different sources like personal experience, information from a traffic management system or traffic jam warnings from the media (Figure 1).

Figure 1: Relationship model



The implemented model is based on the idea that the agents are able to re-plan their routes at any time during the simulated day. This allows a person to choose a route respecting information about the current state of the transport system, mainly link travel times based on current traffic flows. The static part of the model concerns the knowledge of the infrastructure of the road network. For example a person that lives and works in Zurich will know the roads there and in the surrounding areas but not each single road in a different city like Basel or Bern. Therefore, a person will use only known streets when planning a route. To take account of this fact, for each person an area is created that contains all parts of the road network that this person knows. By varying the size of these areas, different knowledge levels can be simulated.

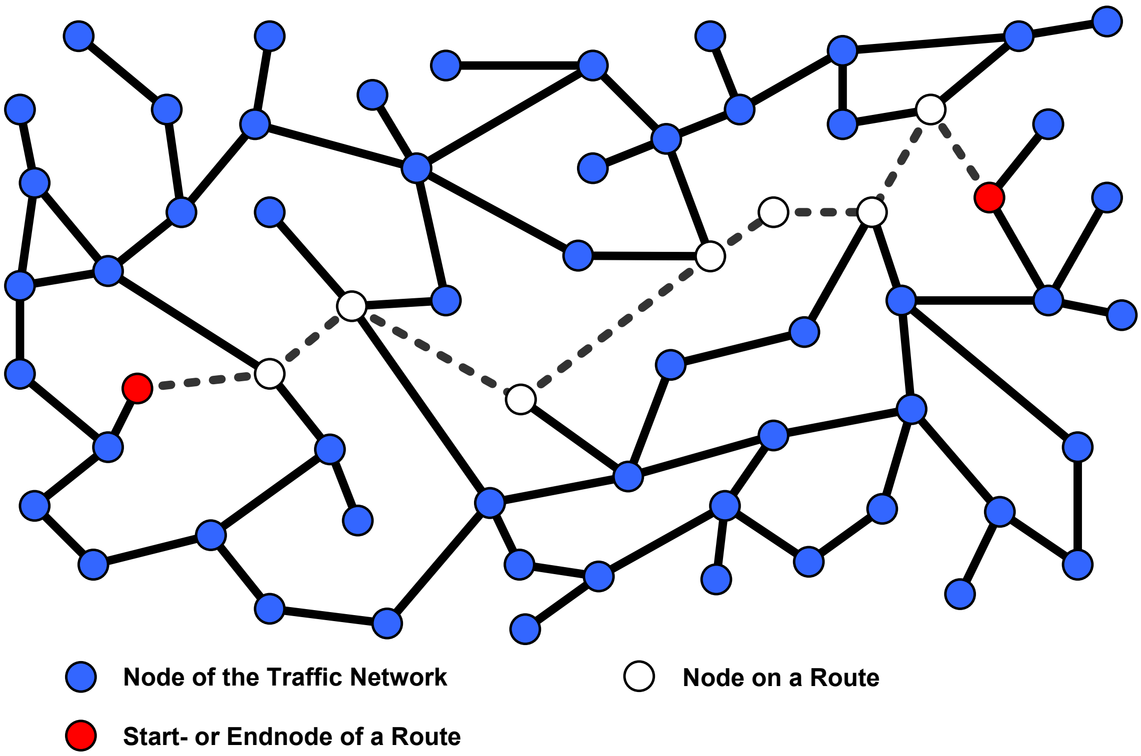
The definition of the areas of a road network known is based on a least cost path algorithm. In a first step, the least cost path from point A to point B is created which results in a route with cost C. To create the known area, the cost C are multiplied with a factor $F \geq 1$. All routes from A to B that have costs less or equal than $C \cdot F$ are contained in the known part of the network. In this context, F can be understood also as the threshold factor below which drivers would accept to deviate from the least cost path. An example for a network with a least cost path and the known area within that network is shown in Figure 2.

When people create routes from a location to a different one, the term $C \cdot F$ determines the degree of flexibility of their behavior. In the following, some behavioral strategies are described and their interactions with the underlying knowledge are characterized.

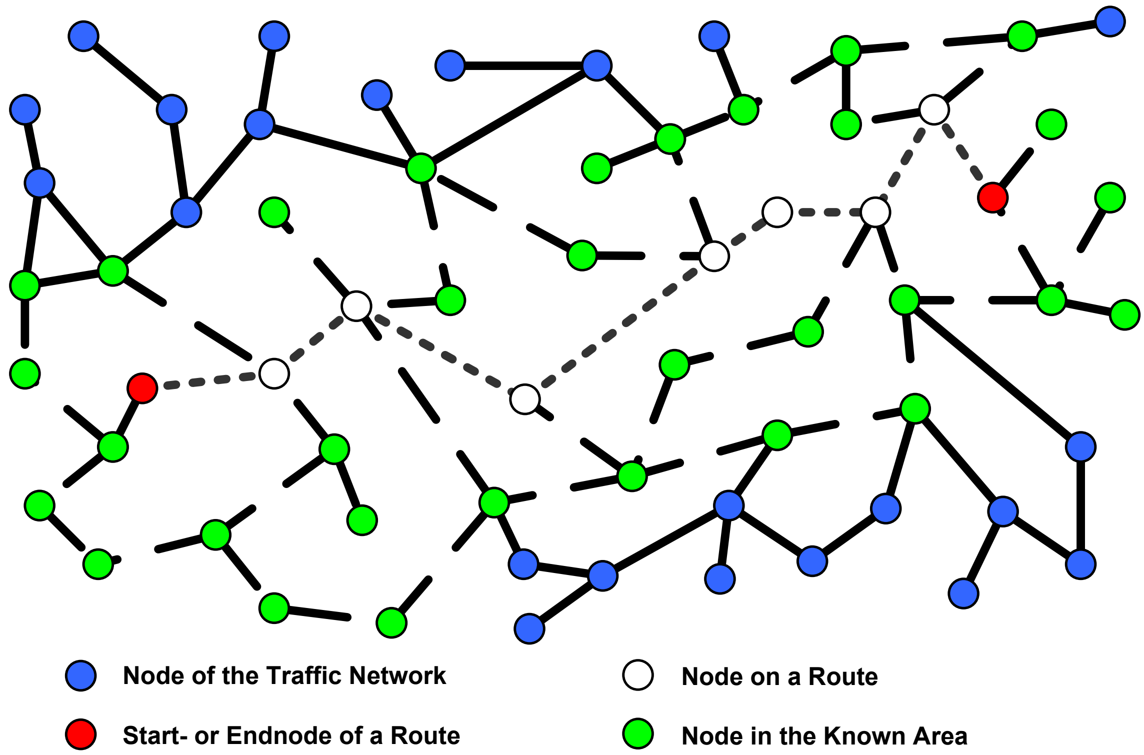
- Random Router
  At each node of the network the router randomly chooses the next link. Due to the fact that the router has no memory, it is possible to turn or to create loops.

Figure 2: Example traffic network

(a) Example traffic network with least cost route



(b) Example traffic network with route and known area



- Tabu Router
  The *Tabu Router* is an extended version of the *Random Router*. It also chooses the next link randomly but it knows the previous node in the route and will only return directly to it if there is no link available that leads to another node.
- Compass Router
  This router uses a compass to generate routes. At each crossing the router chooses that link whose direction is closest to the destination of the route. Depending on the origin and destination of the route and the traffic network it is possible that the router gets stuck in a dead lock and will not find a valid route.
- Random Compass Router
  As its name says, this router is a combination of a *Random* and a *Compass Router*. Based on a probability factor, the router chooses the next link of a route based on a *Random* or a *Compass Router*. This should avoid that the router gets stuck in a dead end.
- Least Cost Router
  There are several implementations of *Least Cost Routers* available. Commonly used variants implement the Dijkstra algorithm (Dijkstra, 1959). This router uses a cost calculator to determine the costs of the links within a road network. Based on the type of cost calculator, different attributes like the travel time and the travel distance are taken into account. Unlike the other described routers, a *Least Cost Router* can also take the actual load of a traffic network into account when creating a route.

To analyze the influence of re-planning the routes during a day (called *within-day re-planning*) three different timing strategies are used. Each timing strategy defines one or multiple points in time, when agent can replan their plans.

- The first strategy is based on an *Initial Creation* of routes before the simulation starts. By doing so, an empty network is used for the calculation of the travel times and costs. Therefore, it is assumed, that each link can be passed in free speed travel time. This strategy uses only structural network information and does not take actual network load—as the real, dynamic factor—into account. Hence, re-planning during a simulation will not produce a different route and is therefore not used.
- The *Activity End Re-planning* strategy is to create a new route when a person has ended an activity and just starts to travel to the next scheduled activity. When doing so, the actual traffic load of the known parts of the network can be interpreted.
- The *Leave Link Re-planning* strategy allows to re-plan a route every time the end of a link is reached, what means, that the next link of a route is chosen just before it is entered—a highly dynamic way of re-planning. Again, the load of the known parts of the network can be taken into account. Axhausen (1988) describes a comparable approach but with the condition that all agents have total information.

Due to the different function of the described routers not every combination of router and timing strategy is reasonable. For example a *Random Router* does not take the load of the network into account. Creating an initial route would result in the same route as using a within-day re-planning strategy. On the other hand a *Least Cost Router* must be run using within-day re-planning in order to take the network load into account. The reasonable combinations that are used in this study are listed in Table 1.

Table 1: Combinations of knowledge levels and timing strategies

Knowledge Level of Router / Timing Strategy	Random	Tabu	Compass	Random Compass	Least Cost
Initial Creation	x	x	x	x	x
Activity End Re-planning	-	-	-	-	x
Leave Link Re-planning	-	-	-	-	x

3 Simulations

3.1 Implementation with MATSim

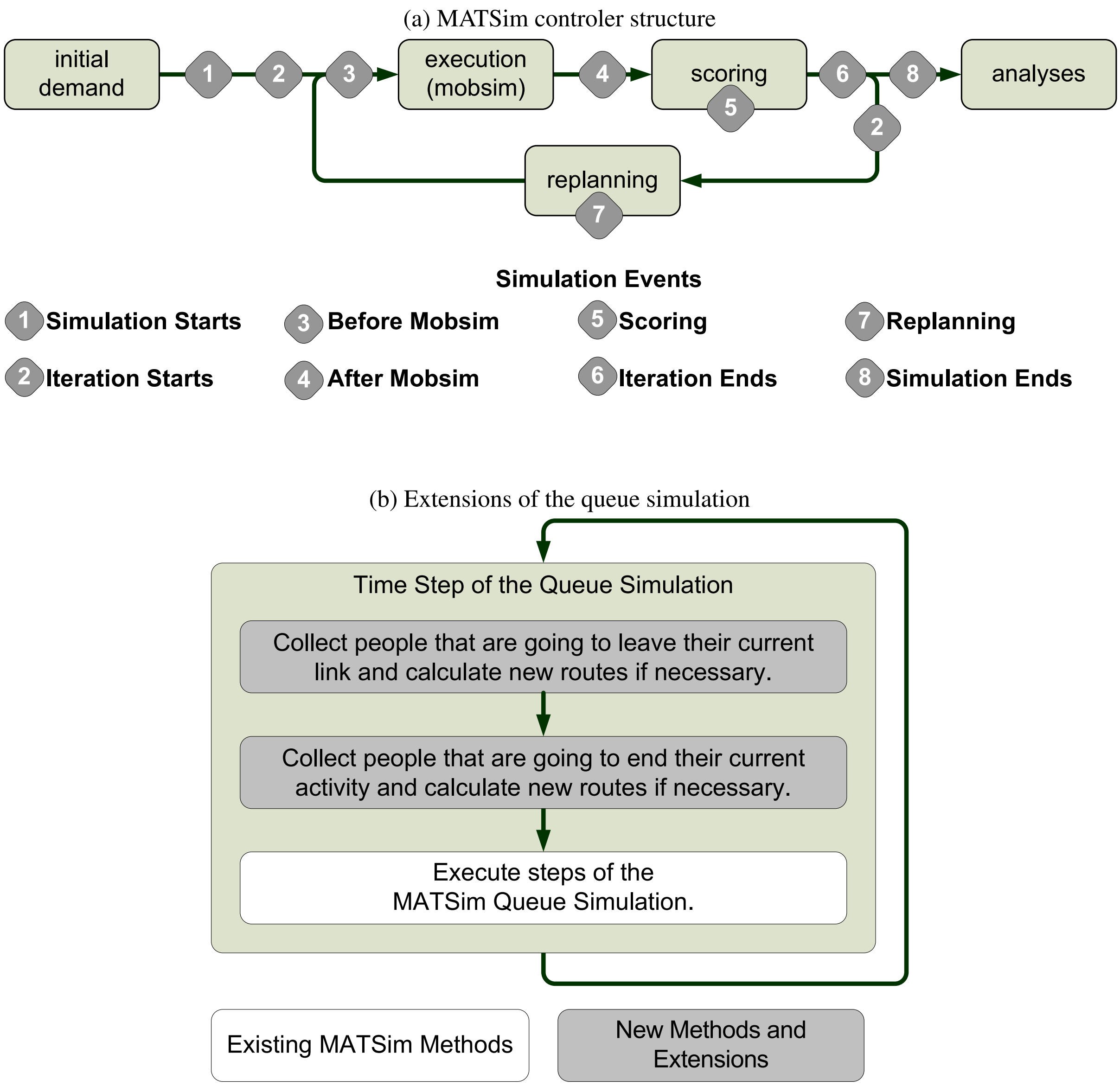
To analyze the behavior of road users, the knowledge models described are implemented in the iterative, agent-based micro-simulation framework MATSim (Multi Agent Transport Simulation) that is developed by teams at ETH Zurich and TU Berlin as well as the senozon AG, a spin-off company founded by former members of both institutes. It consists of several modules that can be used independently or as part of the framework. It is also possible to extend the modules or replace them with further implementations. Balmer (2007) gives a detailed description of the framework, its capabilities and its structure. Meister *et al.* (2010) presents the application of MATSim to a large scale scenario of Switzerland (over 6 million agents simulated on a high resolution network with 1 million links).

Because of its agent-based approach, each person in a transport system is modeled as an individual agent in the simulated scenario. Each of these agents has personal attributes like age, sex, available transport types and scheduled activities per day. Klügl (2001), Eymann (2003) and Ferber (1999) give a detailed overview on the topic of multi-agent-systems and simulations.

The modular structure of the MATSim framework allows to add further attributes to the agents. A new attribute could for example define which kind of timing strategy an agent uses. Another attribute could describe whether an agent knows only the road network or has also information about the traffic load. A third attribute could define that an agent knows only certain areas of the road network and therefore does not create route outside those areas. By adding such attributes, the previously described knowledge models are implemented in the MATSim framework.

The queue-based traffic flow simulation module that is used for the simulation runs is deterministic and time-step based (Balmer, 2007). Figure 3(a) shows the structure of a typical MATSim simulation run. After the creation of the initial demand the agents' plans are modified and optimized in an iterative process until a relaxed state of the system has been found and the analyzing of the results can be done. Typically, this relaxed state is a *Stochastic User Equilibrium* (Nagel and Flötteröd, 2009).

Figure 3: MATSim overview



Due to the fact that the agents are able to change their routes depending on the current load of the traffic system, the MATSim controler structure was slightly changed. By extending the simulation module, every agent can now decide in each simulated time-step if re-planning is necessary. Re-planning means in this context, that a route which is used to travel from one activity to another is planned again. Changing the duration of an activity or its scheduled start and end times must be still done before the queue simulation runs. In Figure 3(b) the extensions of the queue simulation module are illustrated.

By extending the routing modules, the agents are able to consider their knowledge of the traffic system. The routers will take a link only into account if the re-planning agent knows the link—otherwise it is ignored. The travel time of a link is estimated by averaging the travel times of all vehicles that have passed that link within the last 15 minutes. Agents that are creating new routes will try to avoid links with too high travel times.

3.2 Scenario

For the simulation runs a 10% square cut of Zurich with an edge length of 100 km is used which includes about 87'600 people and 64'380 facilities (a facility is a place where activities can be performed). As a constraint, a person is only considered in the simulation if all scheduled activities take place within the simulated area. The used road network is based on the Swiss National Traffic Network (Vrtic *et al.*, 2003). The focus of this study lies on individual transport, therefore public transport is not simulated. This scenario contains a high amount of traffic which increases the differences in the mean travel times between the different timing strategies depending on the quality of the created routes.

The underlying, daily plans of the population result from an earlier simulation run with 150 iterations for which the Charypar-Nagel-Scoring Function (Charypar and Nagel, 2005) was used, which created a realistic distribution of the scheduled activities over the simulated time period. The plans of the last iteration are used as input plans for the simulations with the different timing strategies and knowledge levels. The routes in those plans are ignored because they are replaced when the agents do their re-planning.

For further simulations, the start and end times as well as the durations of the activities are fixed because only the quality of the created routes matters in the conducted experiments (and not an optimal distribution of the activities and traffic over the day). By doing so, the only parts of an agent's plan that can be changed, are the routes.

As mentioned above, the simple routers (random, compass and random compass routing) do not use any traffic load related information. Therefore, running them multiple times with the same random number seed will return always the same routes. Thus, only one a single iteration has to be conducted. The least cost router based strategy is only used in combination with within-day re-planning. There, the link travel times, that are used by the router, are collected within each iteration from scratch, but they are not reused from previous iterations. Therefore, performing multiple iterations will again produce identical results in each iteration. Thus, for each scenario setup, which is a combination of the applied timing strategy, the share of agents that use that strategy and the size of the known area, only a single iteration is performed.

To make the results of the simulations more comparable, a scoring function is used that only accounts for the travel time of the executed daily plans, although a typical scoring function includes aspects like the duration of executed activities, travel distance and travel time. So, the quality of the routes is measured and compared by the different trip durations.

As a reference value for the quality of the routes created by the implemented timing strategies and knowledge levels, an additional series of iterative simulations is run that is using the traditional MATSim optimization strategy without the added within-day re-planning modules. The agents are able to optimize their routes within their known areas of the network using the travel time based scoring function but they are not allowed to change the duration or the starting and ending times of their activities. The mean travel times per person and day of the relaxed system depending on the size of the known areas are taken as comparative values for the other simulation runs (called *Stochastic User Equilibrium* in the analysis).

As a second reference value, a simulation is run where every agent creates its routes on an empty network using a least cost path algorithm with a time based scoring function (called *Initial Creation* in the analysis). This simulates a scenario where every driver uses a typical navigation system that knows the entire network but has no information about the traffic load.

3.3 Hardware

The experiments employed to compare the effects of different timing strategies and levels of knowledge are run on a computer with two quad core CPUs (each an AMD Opteron 2380) and 24 GB of shared memory. Table 2 shows the computation times per iteration of a representative subset of the conducted simulation runs.

3.4 Analysis of the Results

In the first set of simulations, those routers are used that do not take the current load of the traffic network into account. The agents' routes are created before the simulation is started. The behavior of the routers is analyzed separately, which means that in each simulated scenario

Table 2: Computation times overview

(a) Initial creation timing strategies

Run setup	Computation time [mm:ss]
Stochastic User Equilibrium	01:50
Initial creation	03:14
Random Router (Size Factor F = 1.05)	14:49
Random Router (Size Factor F = 1.50)	31:53
Random Router (Size Factor F = 3.00)	63:43
Tabu Router (Size Factor F = 1.05)	08:02
Tabu Router (Size Factor F = 1.50)	21:27
Tabu Router (Size Factor F = 3.00)	50:02
Random Compass Router (Size Factor F = 1.05)	09:12
Random Compass Router (Size Factor F = 1.50)	15:18
Random Compass Router (Size Factor F = 3.00)	23:32

(b) Within-day timing strategies

Run setup	Computation time [mm:ss]
Stochastic User Equilibrium	01:50
Initial creation	03:14
Activity End Replanning (Size Factor F = 1.05)	03:39
Activity End Replanning (Size Factor F = 1.50)	06:01
Activity End Replanning (Size Factor F = 3.00)	15:49
Leave Link Replanning (Size Factor F = 1.05)	07:00
Leave Link Replanning (Size Factor F = 1.50)	20:10
Leave Link Replanning (Size Factor F = 3.00)	36:38

(c) Mixed usage of initial creation and within-day re-planning

Run setup	Computation time [mm:ss]
Stochastic User equilibrium	01:50
Initial creation	03:14
50% Activity End Replanning (full knowledge)	05:16
100% Activity End Replanning (full knowledge)	06:18
50% Leave Link Replanning (full knowledge)	10:35
100% Leave Link Replanning (full knowledge)	16:12

all agents use the same timing strategy. For each strategy, a series of simulations is run where the size of the known parts of the road network of the agents is varied. Doing this allows to determine the influence of the knowledge on the created routes. The results of the simulations are shown in Figure 4(a) which compares the mean travel time of the different routers. The results of the *Compass Router* are not shown because almost every agent got stuck and therefore was not able to create a valid route. For comparison, additionally the results of the reference simulations are also included in the figures (*Initial Creation* and *Stochastic User Equilibrium*).

The results show that even if the persons can use only very small parts of the traffic network (e.g. size factor F < 1.10), the created routes are significantly worse than the ones in the reference simulations. It also can be seen, that the mean travel times increase almost linearly. Comparing the performance of the three timing strategies shows, what one could have expected: The *Random Compass Router* performs better than the *Tabu Router* which in turn performs better than the *Random Router*. The results also show that the quality of the created routes increases significantly when additional information is provided. Presumably, the results of the *Random Compass Router* could be further improved by using an intelligent algorithm for the random choice. Currently, a fixed rate defines, how often a link is chosen randomly or by using the compass. However, using the random selection is only necessary to prevent the router from being stuck in a loop. Therefore, a logic could be implemented that activates the random selection only when a loop is detected.

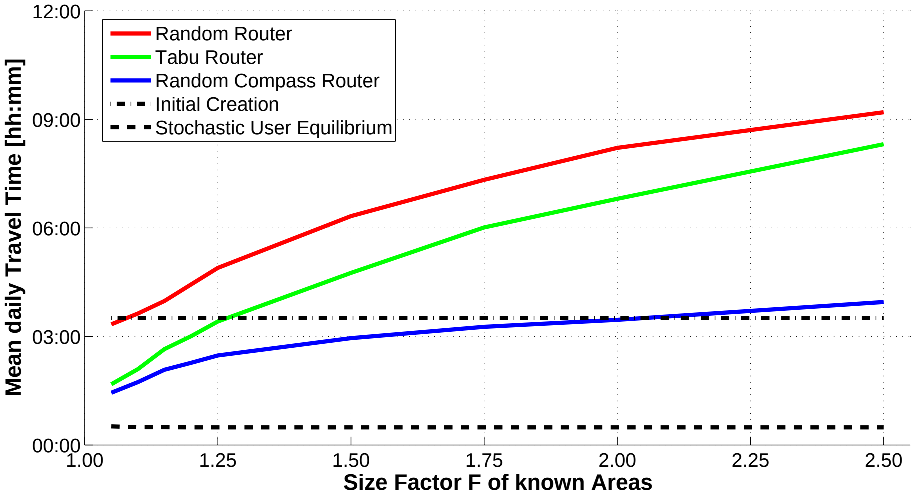
Having a look at the computation times in Table 2(a) shows, that they increase with the size of the known area and decrease with the level of information that a router uses, which is reasonable.

The second set of simulation runs analyzes the traffic system when drivers take the current load of the network into account. To do so, two different timing strategies are used. People who use the first one can re-plan their routes when they have just ended an activity. Before they enter the network to travel to the location of the next activity, the route to that activity is re-planned considering the current traffic load (*Activity End Re-planning*). The second approach allows people to change their routes each time they reach the end of a link. By doing so, they can choose the next link of their route just before they enter that link (*Leave Link Re-planning*). Doing this allows an agent that is at a traffic intersection to decide "Link A seems to be congested, so take link B instead". In a real world scenario, a timing strategy like this could for example be realized with a traffic management system that communicates with the people to inform them about the current traffic load of the road network.

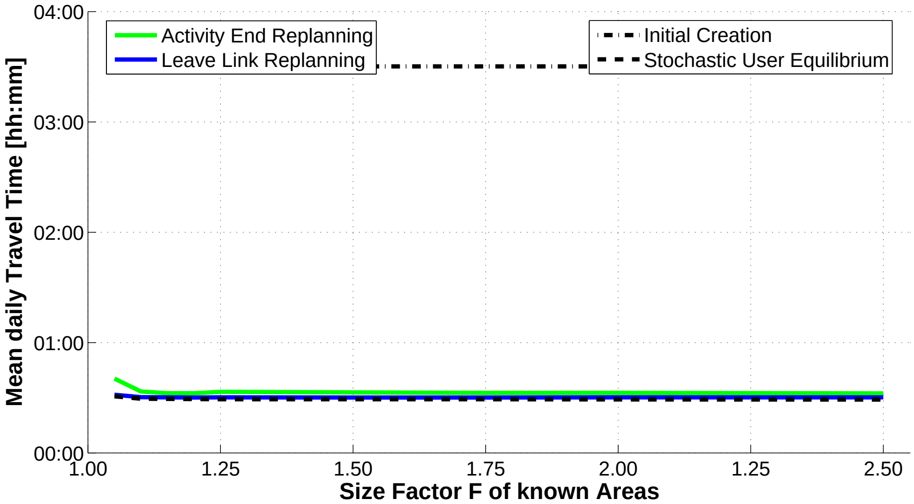
Figures 4(b) and 4(c) again show the mean travel times of a person as function of the size of the known parts of the road network. In 4(b) additionally the values from both reference simulations are shown. 4(c) gives a closer look at both within-day timing strategies and compares them with the relaxed system state.

Figure 4: Comparison of timing strategies

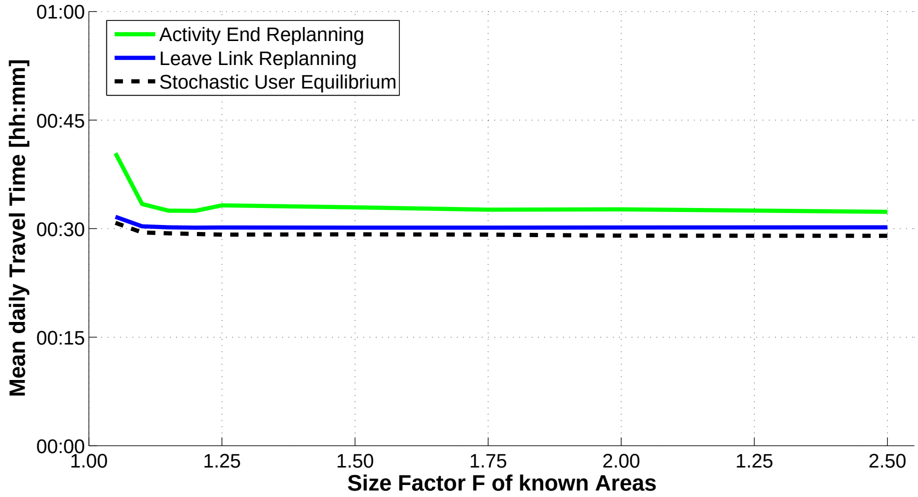
(a) Initial creation timing strategies



(b) Within-day timing strategies



(c) Within-day timing strategies (enlarged)



As expected, the results of the timing strategies that respect the knowledge of the people lie between the reference values. The considerable longer travel times when using an initial timing strategy are a result of the high traffic load that causes some congestion. The persons are able to reduce their travel times when the size of the known areas reaches a certain value (size factor F of ~1.20 in the simulated scenario). If the size factor further increases beyond this value, no further noticeable reduction of the travel times can be achieved.

The influence of the size of the known parts of the traffic systems depends highly on the traffic situation. If there is a lot of traffic or even a traffic jam (as in the used scenario), people who know bigger areas are able to find routes that avoid the jammed links which are faster even if the traveled distance is longer. On the other hand, persons will not need that knowledge if they are traveling in an almost empty network because their travel time is not influenced by other drivers.

The small time difference between the two within-day timing strategies results of the short mean trip duration of about 9 minutes per trip. Within this time, the load of the traffic system usually does not change significantly. Therefore the amount of people that change their route while they are driving is quite small. A very interesting point is, that even if people have only a very limited knowledge, they are able to create routes that are significantly better than those created without any knowledge. Using better routes leads to a better balanced traffic load in the network which in turn also reduces the travel times.

Comparing the computation times of both within-day re-planning strategies (see Table 2(b)) shows, that *Activity End Re-planning* is approximately three times faster. This is obvious, because the *Leave Link Re-planning* strategy requires multiple least cost route calculations per trip whereas *Activity End Re-planning* requires only a single one. However, the performance of the *Leave Link Re-planning* could be improved by checking, whether a re-planning is necessary or not (see Axhausen, 1988). This could be e.g. decided based on changes in the network load. If the link travel times have not changed since the last re-planning, an agent will not find a better route than the one currently selected. Therefore, no re-planning is required.

The third set of the simulation runs investigates the influence of the distribution of the knowledge among the persons within a traffic system. In the previous mentioned scenario with the traffic management system that informs the people about the network's state, typically not all people would use the possibility to get information from that system. Reasons could be that they do not have the technical equipment or that they just do not use it because they are afraid that their data could be collected and abused or that they know better. So in reality the usage of such a system would be somewhere between 0% and 100%. The central question is in which manner the state of a traffic system is affected, if the amount of people with knowledge on the traffic system is varied.

To investigate the behavior of the traffic system, simulation runs with varying number of people with knowledge are performed. In each simulated scenario there are two groups of people. One group employs a timing strategy that respects the traffic load on the network and the other group does not do it. Due to the fact that we are now interested in the systems behavior and not in the movement of single persons, we ignore the knowledge of areas of the network (now every person knows the entire network, which is equal to a F factor of ∞) and focus on the knowledge of the network load instead. For both within-day timing strategies a set of simulations is run where the amount of people using the router is varied from 0% to 100%.

As the results in Figure 5(a) show, it is not necessary that every person uses a router that respects the load of the network. Even if 40% of the people do not use such a router, the remaining 60% are able to keep the system in a near optimal state with no significant change of the mean travel time of a person per day. Again, both within-day re-planning strategies produce comparable results at which the *Leave Link Re-planning Router* performs slightly better as before.

Figures 5(b) and 5(c) show in addition to the overall mean daily travel times also the mean travel times of the agents with and without a within-day re-planning strategy. If only few agents use within-day re-planning, they are able to reduce their travel times dramatically compared to those agent without re-planning. However, the more agents use within-day re-planning, the smaller the differences between the mean travel times becomes. If over 60% of the agents re-plan their routes, the mean travel times are almost equal. Therefore, an agent cannot further reduce his travel time by switching from initial creation to within-day re-planning.

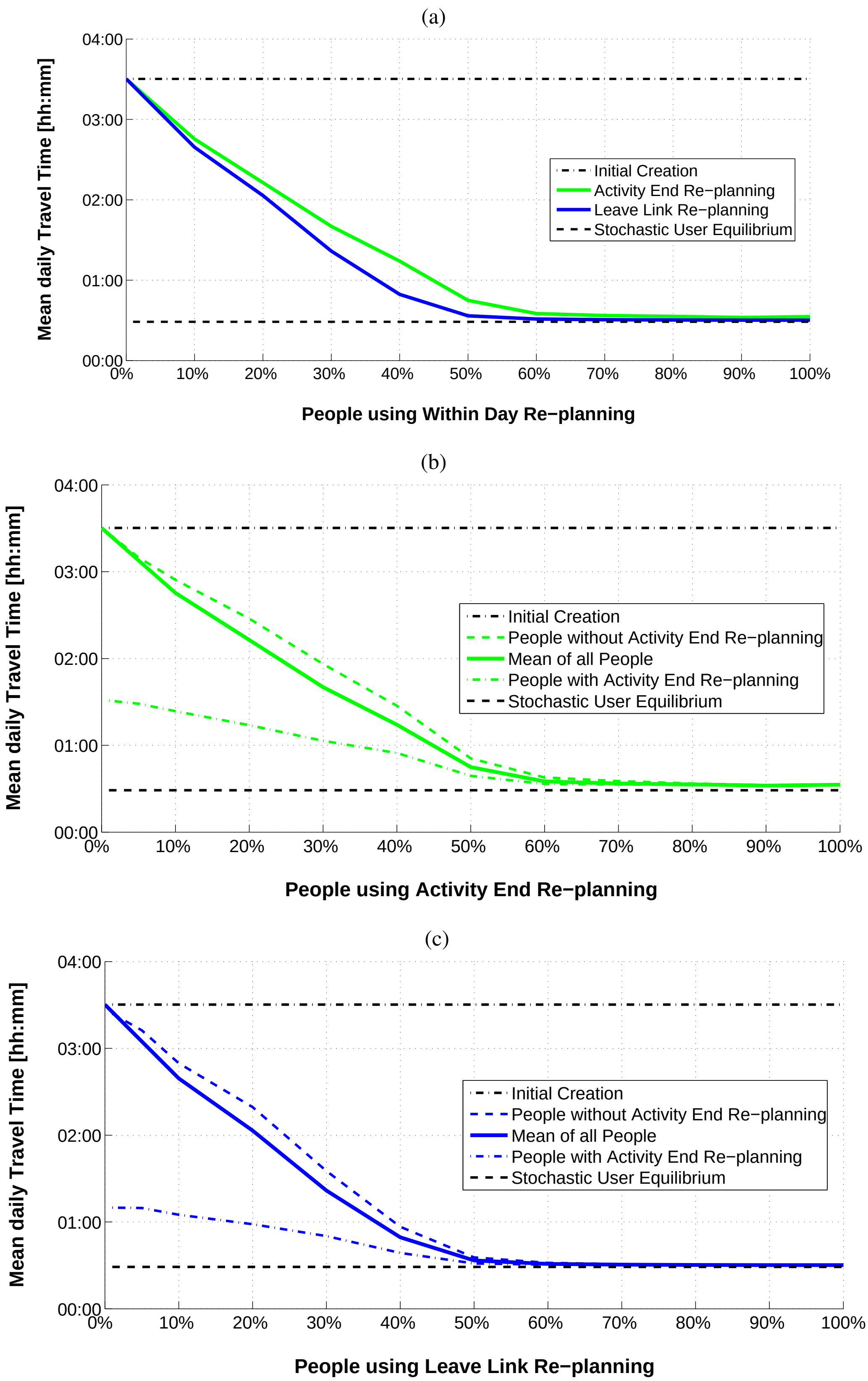
4 Conclusions and Outlook

The individuals within a traffic system have different levels of knowledge about its infrastructure and its current traffic load. The relations between the knowledge of the road users and the state of the traffic system are analyzed.

As one would expect, the results of the simulations show basically that people without a router that takes the structure of the road network into account are not able to find reasonable routes. The mean travel time is reduced significantly if a person has information about the network structure. Even better results can be achieved if information about the load of the links within the network is available additionally.

We also found that it is not necessary that the people know the entire network and its state. Depending on the load of the network, even a low degree of flexibility when choosing routes (small size factor F, e.g. 1.10) can be enough to keep the system in a user equilibrium where no further significant improvements of the traffic situation are possible.

Figure 5: Mixed usage of initial creation and within-day re-planning



An interesting detail that should be analyzed further is that in the simulated scenario the usage of within-day re-planning strategies that respect the current load of the network seems to be able to approximate the equilibrium of the transport system. Even if a certain number of people within the system (as shown in Figures 5(b) and 5(c)) use an initial creation strategy—what typically causes more traffic and slower routes—the mean travel time per person stays almost constant. Furthermore, the differences in the mean travel times of users with and without re-planning disappears. One would not suspect absolutely what the results clearly show in Figure 5: all drivers (statistically) make a profit from a router, if only the half of them uses the router to re-plan their routes taking current traffic flows into account.

Even if aspects of knowledge levels do not match real drivers, the results of modeling and simulation have a potential value for a planning analyst in the understanding of the relations of individual behavior and system outcomes.

5 References

Abdel-Aty, M. A., R. Kitamura and P. P. Jovanis (1995) Investigating effect of travel time variability on route choice using repeated-measurement stated preference data, *Transportation Research Record*, **1493**, 39–45.

Al-Deek, H. M., A. J. Khattak and P. Thananjeyan (1998) A combined traveler behavior and system performance model with advanced traveler information systems, *Transportation Research Part A: Policy and Practice*, **32** (7) 479–493.

Arnott, R., A. de Palma and R. Lindsey (1999) Information and time-of-usage decisions in the bottleneck model with stochastic capacity and demand, *European Economic Review*, **43** (3) 525–548.

Axhausen, K. W. (1988) Eine ereignisorientierte Simulation von Aktivitätenketten zur Parkstandswahl, Ph.D. Thesis, University of Karlsruhe, Karlsruhe.

Balmer, M. (2007) Travel demand modeling for multi-agent traffic simulations: Algorithms and systems, Ph.D. Thesis, ETH Zurich, Zurich, May 2007.

Ben-Akiva, M. E., A. de Palma and I. Kaysi (1991) Dynamic network models and driver information systems, *Transportation Research Part A: General*, **25** (5) 251–266.

Charypar, D. and K. Nagel (2005) Generating complete all-day activity plans with genetic algorithms, *Transportation*, **32** (4) 369–397.

Chorus, C. G., E. J. E. Molin and B. van Wee (2006) Travel information as an instrument to change car-drivers' travel choices: a literature review, *European Journal of Transport and Infrastructure Research*, **6** (4) 335–364.

Cohen, H. and F. Southworth (1999) On the measurement and valuation of travel time variability due to incidents on freeways, *Journal of Transportation and Statistics*, **2** (2) 123–131.

Dijkstra, E. W. (1959) A note on two problems in connexion with graphs, *Numerische Mathematik*, **1**, 269–271.

Emmerink, R. H. M., K. W. Axhausen, P. Nijkamp and P. Rietveld (1995a) Effects of information in road transport networks with recurrent congestion, *Transportation*, **22** (1) 21–53.

Emmerink, R. H. M., K. W. Axhausen, P. Nijkamp and P. Rietveld (1995b) The potential of information provision in a simulated road transport network with non-recurrent congestion, *Transportation Research Part C: Emerging Technologies*, **3** (5) 293–309.

Eymann, T. (2003) *Digitale Geschäftsagenten - Softwareagenten im Einsatz*, Springer, Berlin.

Ferber, J. (1999) *Multi-Agent Systems: An Introduction to Distributed Artificial Intelligence*, Addison-Wesley, Boston.

Gärling, T. and K. W. Axhausen (2004) Introduction: Habitual travel choice, *Transportation*, **30** (1) 1–11.

Hensher, D. A. (1997) Behavioral value of time savings in personal and commercial automobile travel, in D. L. Greene, D. W. Jones and M. A. Delucchi (eds.) *The Full Costs and Benefits of Transportation: Contributions to Theory, Method and Measurement*, 245–280, Springer, Berlin.

Khattak, A. J., A. Kanafani and E. Le Colletter (1994) Stated and reported route diversion behavior: Implications of benefits of advanced traveler information system, *Transportation Research Record*, **1464**, 28–35.

Klöckner, C. A. and A. Blöbaum (2010) A comprehensive action determination model: Toward a broader understanding of ecological behaviour using the example of travel mode choice, *Journal of Environmental Psychology*, **30** (4) 574–586.

Klügl, F. (2001) *Multiagentensimulation - Konzepte, Werkzeuge, Anwendung*, Addison-Wesley, Munich.

Lübeck, S., M. Schreckenberg and K. D. Usadel (1997) Density fluctuations and phase transition in the Nagel-Schreckenberg traffic flow model, *Physical Review E*, **57** (1) 1171–1174.

Levinson, D. (2003) The value of advanced traveler information systems for route choice, *Transportation Research Part C: Emerging Technologies*, **11** (1) 75–87.

Lighthill, M. J. and G. B. Whitham (1955) On kinematic waves. ii. a theory of traffic flow on long crowded roads, *Proceedings of the Royal Society of London. Series A*, **229** (1178) 317–345.

Meister, K., M. Balmer, F. Ciari, A. Horni, M. Rieser, R. A. Waraich and K. W. Axhausen (2010) Large-scale agent-based travel demand optimization applied to Switzerland, including mode choice, paper presented at the *12th World Conference on Transportation Research*, Lisbon, July 2010.

Nagel, K. and G. Flötteröd (2009) Agent-based traffic assignment: Going from trips to behavioral travelers, paper presented at the *12th International Conference on Travel Behaviour Research (IATBR)*, Jaipur, December 2009.

Nagel, K. and M. Schreckenberg (1992) A cellular automaton for freeway traffic, *Journal de Physique I*, **2** (1992) 2221–2229.

Noland, R. B. and K. A. Small (1995) Travel time uncertainty, departure time choice and the cost of morning commutes, *Transportation Research Record*, **1493**, 150–158.

Ortúzar, J. d. D. and L. G. Willumsen (2001) *Modelling Transport*, 3. edn., John Wiley & Sons, Chichester.

Reed, T. B. and J. C. Levine (1997) Changes in traveler stated preference for bus and car modes due to real-time schedule information: A conjoint analysis, *Journal of Public Transportation*, **1** (2) 25–49.

Sugiyama, Y., M. Fukui, M. Kikuchi, K. Hasebe, A. Nakayama, K. Nishinari, S.-I. Tadaki and S. Yukawa (2008) Traffic jams without bottlenecks-experimental evidence for the physical mechanism of the formation of a jam, *New Journal of Physics*, **10**, 033001.

Vrtic, M., P. Fröhlich and K. W. Axhausen (2003) Schweizerische Netzmodelle für Strassen- und Schienenverkehr, in T. Bieger, C. Lässer and R. Maggi (eds.) *Jahrbuch 2002/2003 Schweizerische Verkehrswirtschaft*, 119–140, Schweizerische Verkehrswissenschaftliche Gesellschaft (SVWG), St. Gallen.

Ziegelmeyer, A., F. Koessler, K. Boun My and L. Denant-Boèmont (2008) Road traffic congestion and public information: An experimental investigation, *Journal of Transport Economics and Policy*, **42** (1) 43–82.