Multi-agent simulation used in a real world scenario on environmentally-oriented road pricing schemes

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ABSTRACT

In multi-agent traffic simulations all travelers are resolved. In contrast to the aggregated approach, travelers are always represented with properties like age, employment, or home location, and the simulation always keeps track of each individual traveler throughout the simulation. The latter gives us the possibility to offer new evaluation techniques for project or policy evaluation. The paper reports on an application of a multi-agent traffic simulation in a real world scenario of large dimensions—namely Berlin, Germany, with almost 3.5 million inhabitants. The developed model uses comparable data as a traditional model following the 4-step-process in order to develop average weekday traffic. The results of the Berlin scenario prove that real world scenarios, even those of large dimensions, are feasible. An extensive amount of data is not necessarily needed when building a multi-agent model and making use of its advantages. As an application, we present a study currently conducted on road-pricing as a transport policy. Especially the impact of different modeling techniques on evaluation results is illuminated. The range of output of the multi-agent simulation which could be retrieved of a real-world scenario will be presented, and their use for political decision making evaluated. Preliminary results of our study on road-pricing in urban areas depending on noise and air-borne pollution will be part of the paper as well.

1 BACKGROUND

Pricing measures are expected to contribute greatly to an implementation of a sustainable future urban transport policy. Designing an appropriate pricing system targeting at livable cities is a complex task and depends on local conditions regarding the spatial configuration of the road network and the main residential areas. Spatial-temporal structures of a toll, i.e. which reduce noise during sleeping hours in residential areas, diminish effects due to noise and airborne pollutants for the most densely populated zones, and decrease congestion in peak hours, have to be developed. In January 2005 Germany introduced a new GPS-based toll system on the German highways for HDV (High Duty Vehicles) that could allow differential charging on very fine temporal and spatial scales. This leads to the question in how far these instruments could be fine-tuned in order to fight emissions and congestion where they matter, above all in urban residential areas.

Simulation and evaluation of possible pricing schemes are important and necessary in order to make a solid decision about the introduction of pricing measures. Especially the assessment of reduced noise and congestion effects due to the chosen pricing scheme requires a temporally differentiated traffic modeling. Recent studies dealing with the potential consequences of environmentally or congestion oriented road charges for certain cities give useful insights, but the underlying traffic modeling often lacks important features of urban transport systems in reality. Applying state-of-the-practice 4-step-process models is not sufficient in this context, since for example they do not allow to evaluate the consequences of different tolling schemes at the individual level (coupled with individual demographic data, and coupled with complete daily activity plans). Micro-simulations of travel behavior and traffic flow are a promising method here, since they allow modeling both the human behavior and the noise aspects microscopically. Micro-simulations are capable of analyzing the reactions of all travelers—and therefore of the city as a whole—to different pricing schemes. They also allow computing of individualized immissions. For example, a noisy vehicle in a residential area at night has a much larger impact than a noisy vehicle in a rural area during daytime.

Agent-based microscopic simulation systems are still relatively new, but recent developments have shown that such models can be applied to real-world scenarios of large dimensions. This paper addresses the issue of applying such an agent-based microscopic model to a real-world scenario of large dimensions. Additionally, the scenario is described with respect to an application in a road pricing study.

2 INTRODUCTION

As already mentioned, recent studies dealing with the potential consequences of environmentally or congestion oriented road charges make use of transport models applying the four-step process. The first three steps—trip generation, destination choice, mode choice—concern modeling the demand. In these three steps, various characteristics of the traveler, the land-use, and the network are brought together. In the fourth step, the demand is assigned to the network. A problem with the four-step process is that information is not consistently maintained: For example, while the trip generation step may know something about demographic characteristics, the destination/mode/route choice steps typically do not possess such knowledge. Such an approach will not allow to model reactions to tolls which are differentiated by demographics.

An alternative to the four-step process is an activity-based demand generation (ABDG) together with a dynamic traffic assignment (DTA). ABDG typically starts from a synthetic population (Beckman et al. 1996), and then adds, to every potential traveler in the synthetic population, status (work/school/other), full activity patterns, activity locations, activity times, and possibly mode choice. Other sequences to add these elements are possible, and some or all of them may be generated jointly. Examples of practical applications of activity-based models can be found in San Francisco (Jonnalagadda et al. 2001), Portland/Oregon (Bowman 1999), Toronto (Miller and Roorda 2003), or The Netherlands (Arentze and Timmermans 2000, 2005). The typical outputs of an ABDG are time-dependent, e.g. hourly, origin-destination (OD) matrices. Information like demographic data or tight activity chains get lost in the process of writing OD matrices: After the activity chain is translated into trips, it is perfectly possible that a person leaves an activity location before it arrives. Finally, demand is loaded onto the network (dynamic traffic assignment, DTA). In order to close the feedback loop, spatial impedances—often in the form of inter-zonal travel times—are fed back from assignment to the ABDG, and the feedback is iterated until a self-consistent solution is found.

Unfortunately, also this “state-of-the-art” approach can have several shortcomings especially in the context of simulation and evaluation of pricing schemes. In reaction to a time-dependent toll, traffic may have temporal patterns that go beyond hourly resolution. Hourly OD matrices cannot pick up such effects. When tolls are charged on certain links, the routing decision may depend on the travelers’ attributes, e.g. on income and/or on time pressure given by activities later during the day. Access to such information gets lost through the OD matrix. A delay in the morning may affect activity timing of the whole day. Such an effect is not picked up when travelers are converted into OD-streams. In fact, even when feeding back 15-minute-averaged link travel times, the resulting travel time map can be highly distorted (Raney and Nagel 2004). Furthermore, some “higher level” decisions, such as mode choice or secondary activity location choice, may depend on relatively small details of the trip, such as walking distance to the public transit stop. Alternatively, mode choice may depend on one element of a complete tour, such as one location being not reachable by public transit. Also such effects are impossible to pick up once travelers are aggregated into OD matrices.

Multi-agent simulations (MASim) of traffic process individualized traveler information at every level. Every modeled agent is assigned at least one “plan”. A plan is a sequence of activities, connected by trips. Since that information is typically already available inside the ABDG, it is possible to retain the full agent information from the ABDG throughout the whole simulation process when making use of MASim. Instead of writing OD matrices, agents' plans (their intentions) have to be written at the end of ABDG.

MATSim (our own package, MATSIM www page) takes such plans as input. It iterates between the traffic flow simulation and the behavioral modules. The currently implemented behavioral modules are route finding, and time adjustment. Activity re-sequencing or activity dropping are conceptually clear but not yet implemented. Such a system will react to a time-dependent toll by possibly re-arranging the complete day; in consequence, it goes far beyond DTA (which just does route adaptation).

3 SIMULATION STRUCTURE

MATSim is based on TRANSIMS (TRANSIMS www page) but differs from it in several aspects, among other: giving performance scores to full 24-hour plans based on the execution of those plans in the physical layer (traffic flow simulation) and using these scores for agent learning, and the use of a more lightweight, less data-hungry, and faster simulation of the physical layer – the queue simulation (Cetin et al. 2003).

The traffic flow simulation computes the physical aspects of movement, such as limits on capacity, storage, or speed. In particular it computes the aspects of interaction, such as congestion. The mobility simulation needs information about where travelers enter and leave the network, which turns travelers take at intersections, etc. These aspects can be called plans, or strategies. For the transportation simulation, this means that travelers know where they are going to, when they want to be there, and the route they want to take to get there. This kind of strategic knowledge is in contrast to, say, the simulation of ants in an ant-hill. It also makes the simulation design considerably more demanding, since the generation and handling of strategies is a whole problem of its own. Once complete plans are available, e.g. by extracting them from an ABDG, the simulation can start. It includes the following steps (Raney and Nagel 2005):

1. The system begins with that initial set of plans, one per agent; these plans are submitted to and executed by the mobility simulation.

2. During the mobility simulation, the performance of every agent is recorded, e.g. by noting departure and arrival times at activity locations as events. This performance information is stored for all the agents, associated with the plan that was used.

3. A fraction of the population requests re-planning from the behavioral modules. The new plans are selected for execution in the next iteration.

4. Agents who did not request new strategies choose their highest scored plan from their repertoire.

5. The mobility simulation is executed with the selected plans.

6. This cycle (i.e. steps 2 through 5) is repeated until the agents' average score does no longer significantly improve.

During repeated iterations between the mental (constructing/changing plans) and the physical layer (mobility simulation), every agent attempts to modify its plan so that it obtains a higher score. The choice dimensions along which the agents can learn are configurable. In this way, the simulation system can emulate dynamic traffic assignment (by only allowing the routes to adapt), or it can, for example simulate a system where agents' residences, status, and primary activity locations are fixed, but everything else (secondary activity types and locations, mode, route, time scheduling) is adapted. Similarly, the scoring function is configurable, its only requirement being that it needs to allow to rank plans. In this way, not only standard utility functions (Jara-Diaz et al. 2003) but also, say, prospect theory (Avineri and Prashker 2003) can be included in a conceptually straightforward way.

4 DERIVING PLANS' SCORES AND LEARNING

By allowing the agents to re-adjust, they can learn from the previous iteration (feedback learning). Scoring a plan is a precondition so that agents learn and react toward congestions or tolling. Different plans can be compared and an agent can pick the one with the highest value. A higher score implies that the agent makes better use of its day.

In other words, agents adapt to their environment and learn how to improve their plans over many iterations. In the simulation all agents learn at the same time, since their plans are executed simultaneously. This also means, that an agent's environment changes due to the effect of the other agents in the system. Thus a plan's score has to be updated. A scoring function needs to be defined, which evaluates complete day plans. As scoring function, the traditional utility function based on the Vickrey bottleneck model is used (Arnott et al. 1993), but modified to be consistent with complete day plans. Scoring is based on events information from the physical layer. Performing an activity is rewarded, travel times and late arrival are punished. The overall equation is:

$$U_{plan} = \sum_i U_{act,i} + \sum_i U_{trav,i} + \sum_i U_{late,i} \tag{1}$$

We assume the utility of performing an activity as increasing logarithmically:

$$U_{act,i}(x) = \max\left[0, \alpha \cdot \ln\left(\frac{x}{t_0}\right)\right] \tag{2}$$

where *x* is the duration that one spends at the activity. We take $\alpha = \beta_{dur} \cdot t^*$, where β_{dur} is uniformly the same for all activities and only t^* varies between activity types. With this formulation, t^* can be interpreted as a "typical" duration, and β_{dur} as the marginal utility at that typical duration:

$$\left.\frac{\partial U_{act,i}}{\partial x}\right|_{x=t^*} = \beta_{dur} \cdot t^* \cdot \frac{1}{t^*} = \beta_{dur} \qquad (3)$$

t_0 can be seen as a minimum duration of an activity, but is better interpreted as a priority: All other things being equal, activities with large t_0 are less likely to be dropped than activities with small t_0 (for details, see Charypar and Nagel 2005).

The utilities of traveling and of being late are both seen as disutilities which are linear in time:

$$U_{trav,i}(x) = \beta_{trav} \cdot x \qquad (4)$$

(where *x* is the time spent traveling) and

$$U_{late,i}(x) = \beta_{late} \cdot x \qquad (5)$$

(where *x* is the time an agent arrives late at an activity). β_{trav} is set to -6 €/h, and β_{late} is set to -18 €/h.

In principle, arriving early or leaving early could also be punished. There is, however, no immediate need to punish early arrival, since waiting times are already indirectly punished by foregoing the reward that could be accumulated by doing an activity instead (opportunity cost). In consequence, the effective (dis)utility of waiting is already -6 €/h. Similarly, that opportunity cost has to be added to the time spent traveling, arriving at an effective (dis)utility of traveling of -12 €/h. No opportunity cost needs to be added to late arrivals, because the late arrival time is already spent somewhere else. In consequence, the effective (dis)utility of arriving late remains at -18 €/h. These effective values are the standard values of the Vickrey model (Arnott et al. 1993).

It would make sense to consider an additional punishment (negative reward) for leaving an activity early. This would describe, for example, the effect when there are, on a specific day, better things to do than to continue to work, but some kind of contract (e.g. shop opening hours) forces the agent to remain at work.

This scoring function already allows simulating simple toll scenarios: By decreasing the marginal utility for traveling, the time agents spend traveling gets more expensive. This initially means that a plan's score would be reduced. An agent could react towards this new situation by adjusting its plan. How to implement other tolling schemes is conceptually clear, and necessary adjustments of the scoring function are already implemented but not yet tested. The new scoring function includes an additional tolling term.

5 SET-UP OF THE REAL-WORLD SCENARIO—BASE CASE

Our real-world application of a multi-agent simulation as described in the previous sections focuses on the city of Berlin, Germany. In order to simulate average traffic conditions we model and simulate Berlin's surrounding as well but with a lower level of detail. All together the study region covers an area of 150 km x 250 km and has a population of about 6 million inhabitants.

Given the large investments in terms of data and software of Berlin's planning department into the 4-step process, it is undesirable to abandon those investments and to start over with an agent-based approach. It is therefore also of importance to base our multi-agent traffic simulation on available data commonly used by the official transport model developed by and for the planning department.

Thus, network and demand are derived from data used and produced by the aggregated macroscopic model that Berlin's planning department is working with. In contrast to this official transport model used for mid and long term forecasts, in our simulations all travelers are resolved as agents generating trips while following their day plans. The following sub-sections describe the set-up of the Berlin scenario.

5.1 The network

The provided network has been used as part of the forecast model for the year 2015. Since we aim to model and simulate Berlin's current traffic of an average workday, we had to adapt the network manually in order to exclude modifications planned to be realized until 2015 (e.g. expansion of the inner city highway southward). The final network consists of almost 30,000 links connecting more than 10,000 nodes, described by their coordinates. For our simulation we need, for each link, the attributes free flow speed, length, number of lanes and flow capacity. The network does indeed contain these attributes, but the usefulness of the data is variable. For example, the number of lanes in uniformly set to one, presumably because the number of lanes does not matter for traditional assignment models. We calculated a more realistic number of lanes based on the original link capacities on the network.

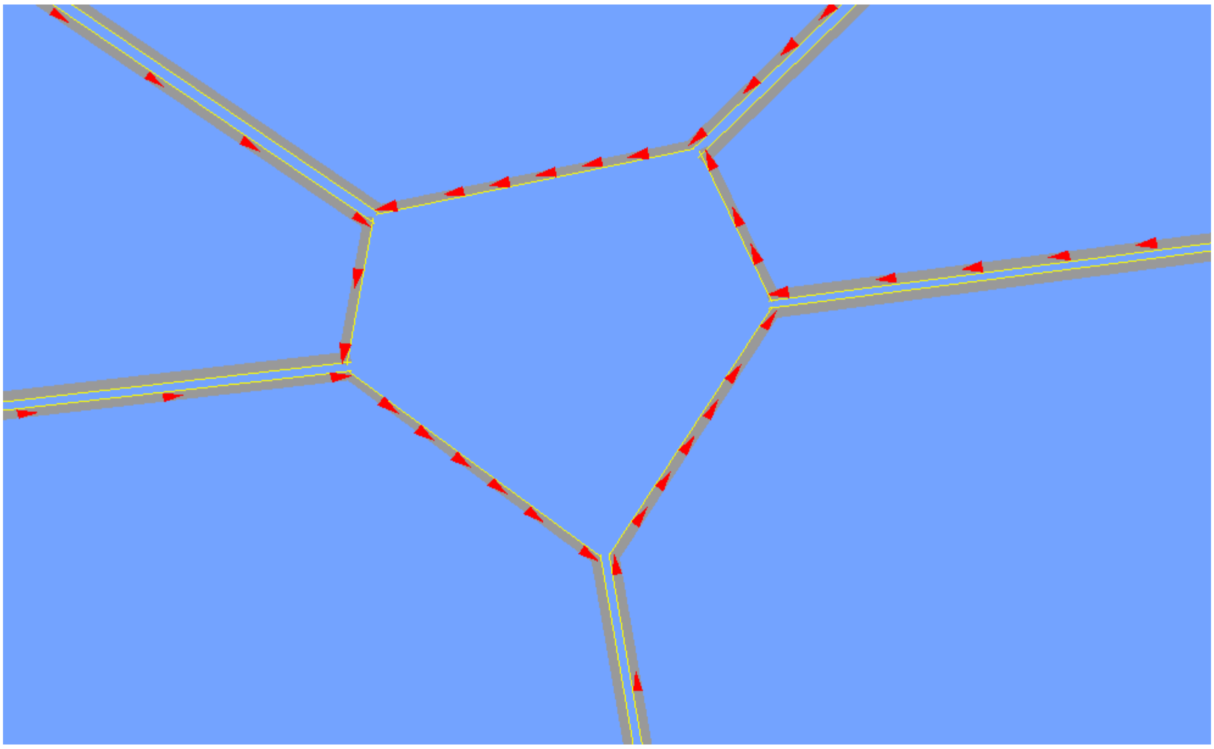

Fig. 1 Gridlock at Grosser Stern in Berlin

Another issue is that link capacity is interpreted very differently by the aggregated model used by the planning department of Berlin and by our multi-agent simulation. While in our simulation, capacity is understood as maximum outflow of a link in a given time period, the aggregated model does not treat a link's capacity as hard constraint. Thus, we had to adapt these capacity values that were the basis for a 24 hours static assignment. Additionally, in some simulations gridlocks appeared as shown in Fig.1. The problem here is that all links along the loop are full, and all vehicles that are at the respective downstream ends of links want to enter the next link of the loop. In this situation, no vehicle along the loop can move, which is why it is called gridlock. Such situations can in principle occur along any closed loop of the network graph, but have a much higher probability along short loops. We have been aware of the gridlock issue for many years, and have conventionally resolved it by the introduction of "lost vehicles": Vehicles that could not move for a certain amount of time were taken out of the simulation. This approach, however, does not seem to be sufficient for the Berlin simulations. When we detected such a situation the flow capacities were increased manually along the loop (usually a roundabout). A justification for this approach is that capacities on roundabouts indeed seem to be too low – one of these situations where low capacities on short links to not matter much for traditional assignment with soft capacity constraints but matter a lot when capacities are hard. After this adjustment the vehicles along the loop can move and congestion may appear along the approaching lanes.

Another network attribute necessary for mobility simulation is free flow travel time. It is calculated as link length divided by the free flow speed of the link. Additionally, the storage of a link is constrained. The storage of a link is calculated as length times the number of lanes (the corrected value) divided by the space a vehicle occupies in a jam (7.5 m). In order to speed up the computation of the Berlin scenario, the demand and the network capacities (both flow and storage) were scaled down to 10 % of the actual values.

5.2 Initial plans

As already described, we need initial plans which will be executed in the mobility simulation. These initial plans should be derived from the existing planning data used by the planning department as well. As the official forecasting model makes use of OD matrices, these were considered first for provision of initial conditions.

It is straightforward to extract individual trips from OD matrices, and to generate for each trip a “pseudo”-agent, whose complete plan consists of that single trip. In this way all previously described drawbacks of making use of OD matrices in assignment would also apply to the multi-agent simulation. Generating initial MATSim plans and not only one-trip-plans from OD matrices is possible when one can couple residences and work-places (Balmer et al 2005a). But this approach is not applicable in Berlin since the coupling between residences and work-places is not available: To our knowledge there is no such information available from the census or from the micro-data sample. This is a problem that not only agent-based packages have, but in fact all transport planning tools.

Fortunately, Berlin’s official 24 h OD matrix is derived from an ABDG (Kutter1984, Kutter and Mikota 1990, Kutter et al. 2002). And as described previously, ABDG internally use concepts that are close to agents. It seems possible to extract agent plans from an ABDG instead of a single OD matrix.

The ABDG providing Berlin’s forecast model with OD matrices differentiates 72 person groups with similar demographic attributes and homogeneous behaviors. The model was modified to output activity chains to be used to produce initial agents’ plans for our multi-agent simulation (Rümenapp and Steinmeyer 2006).

Each activity chain contains information about the start location, up to four activities, and the frequency of occurrence of that chain. Activities are described by their type, location, and the transportation mode used to reach that location. The home location is the start and end location of each activity chain (round trips or tours). Information on location refers to traffic analysis zones (TAZ), since these represent sources and sinks of traffic streams in the macroscopic model. Before transforming activity chains into agents’ plans, location information and data had to be disaggregated. As in MATSim every trip starts and ends at a link we had to assign a link to every activity location. Additionally, activity chains lack time information. For initial plans, all activities are assigned a random activity duration within a type-dependent range. In Balmer et al (2005b) it is shown that feasible timings of given schedules can be generated by simple initial departure times and durations of activities.

As a result of the plan extracting process, over 7 million “virtual” agents are generated from the tours in the ABDG data. Each of these agents has a plan corresponding to an activity chain generated by the ABDG model. Since MATSim is currently only able to simulate individual car traffic, only plans making use of a car are considered as initial plans. The simulation of other transport modes is under implementation.

As already mentioned, to speed up the Berlin scenario we also scaled network capacities as well as demand down to 10 %. Additionally only chains containing at least one activity in Berlin or its close surroundings were transformed into plans. At the end a total of about 205,000 car travelers with complete day plans are the population of our Berlin simulation.

5.3 Behavioral Modules

Route finding and time adjustment are currently the only implemented behavioral modules. Using route finding, agents try to find better routes, but do not change their departure times or the duration of activities. To find better routes, they make use of the events to calculate actual travel times and thus recognize jammed links. Using time adjustment, the departure times and activity durations are modified with the goal to optimize the individuals' plans score (Meister et al 2006). As already said, additional behavioral modules are conceptually clear, but not yet implemented: Activity re-sequencing would change the order of activities (e.g. shopping after work instead of before work), while activity dropping would remove certain activities in an overloaded plan. Such a system with several different behavioral modules, including activity re-sequencing and activity dropping, will react to a time-dependent toll by possibly re-arranging the complete day. This goes far beyond just route adaptation in DTA.

The agents have three different re-planning possibilities: route re-planning, time re-planning, choosing an already existing plan. The latter requires an agent memory; its size is set to five in our simulations. Only a certain share of agents re-plan and this share is not fixed. The simulation starts with 15 % of agents re-planning; each of the options is adopted by 5 % of the agents. Later in simulation, single re-planning options are switched off at certain iterations. This reduces fluctuations and can increase average score (see Fig.2 and related text).

5.4 Results—base case

First results from our base case scenario, which represents Berlin's average workday car traffic, will give an impression about applicability of a MASim to a real-world scenario of large dimensions based on available transport planning data used in traditional forecasting models. A good overview of the iterations' progress can be given by the average score of all agents' plans. From a very low level of average score in the first iterations, when the system is far away from being relaxed, the average score increases to a stable level, although fluctuations cannot be suppressed completely. What happens is that with ongoing iterations, the agents learn how to avoid traffic jams by choosing different routes or starting their trips at different times of day.

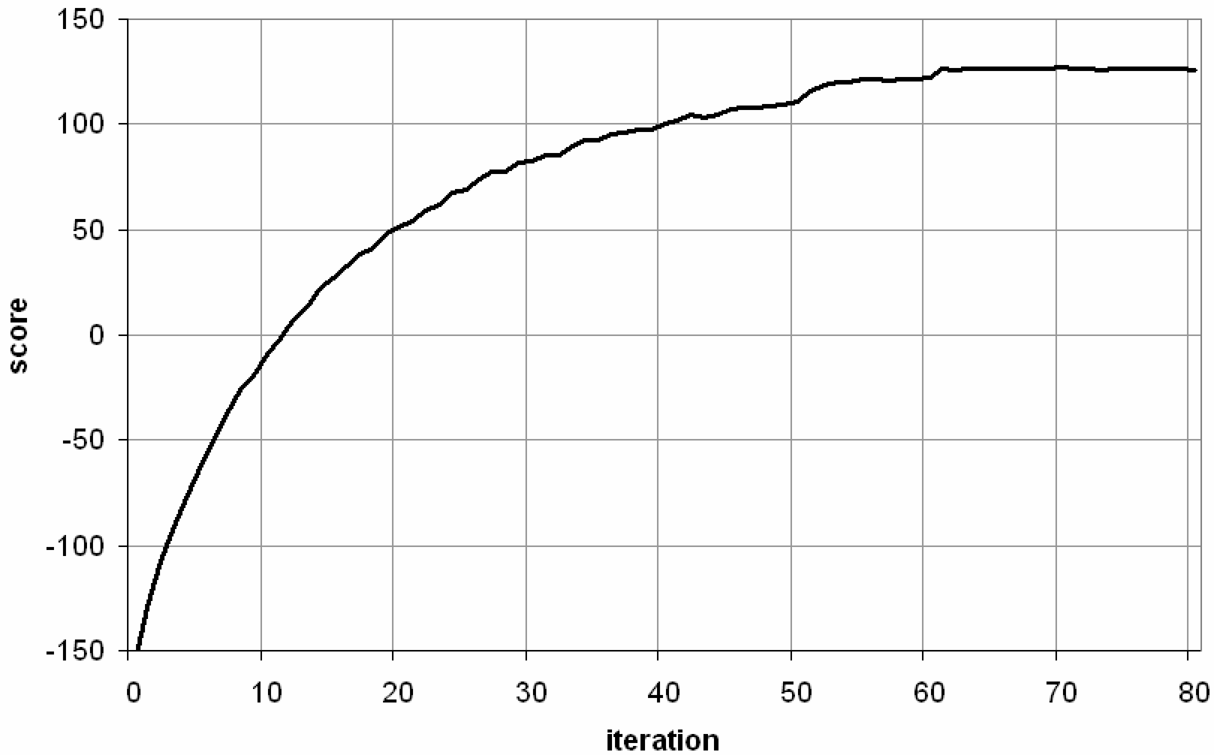

Fig. 2. The agents' average score

The re-planning process is also reflected in a comparison of departure times of different iterations. Initially, all agents are assigned random start time for the first activity and random activity durations, each within a certain range of time. The range depends on the type of the activity. The re-planning modules described earlier in the paper lead to a differentiated distribution of trip departure times. Fig.3 shows the number of trip departures over the course of a day, iteration 0 (in the upper part) and iteration 80 (in the lower part) are compared. The number of trip departures is furthermore differentiated by trip purposes; plans having work or education as primary activity and plans having other primary activities like shopping or leisure are differentiated. It can be seen that the agents try to avoid traffic jams in the morning by leaving home earlier than initially assigned. Additionally, agents that do not have to work or go to school and thus are more flexible, try to avoid the evening rush hour by performing activities before or after the peak hour.

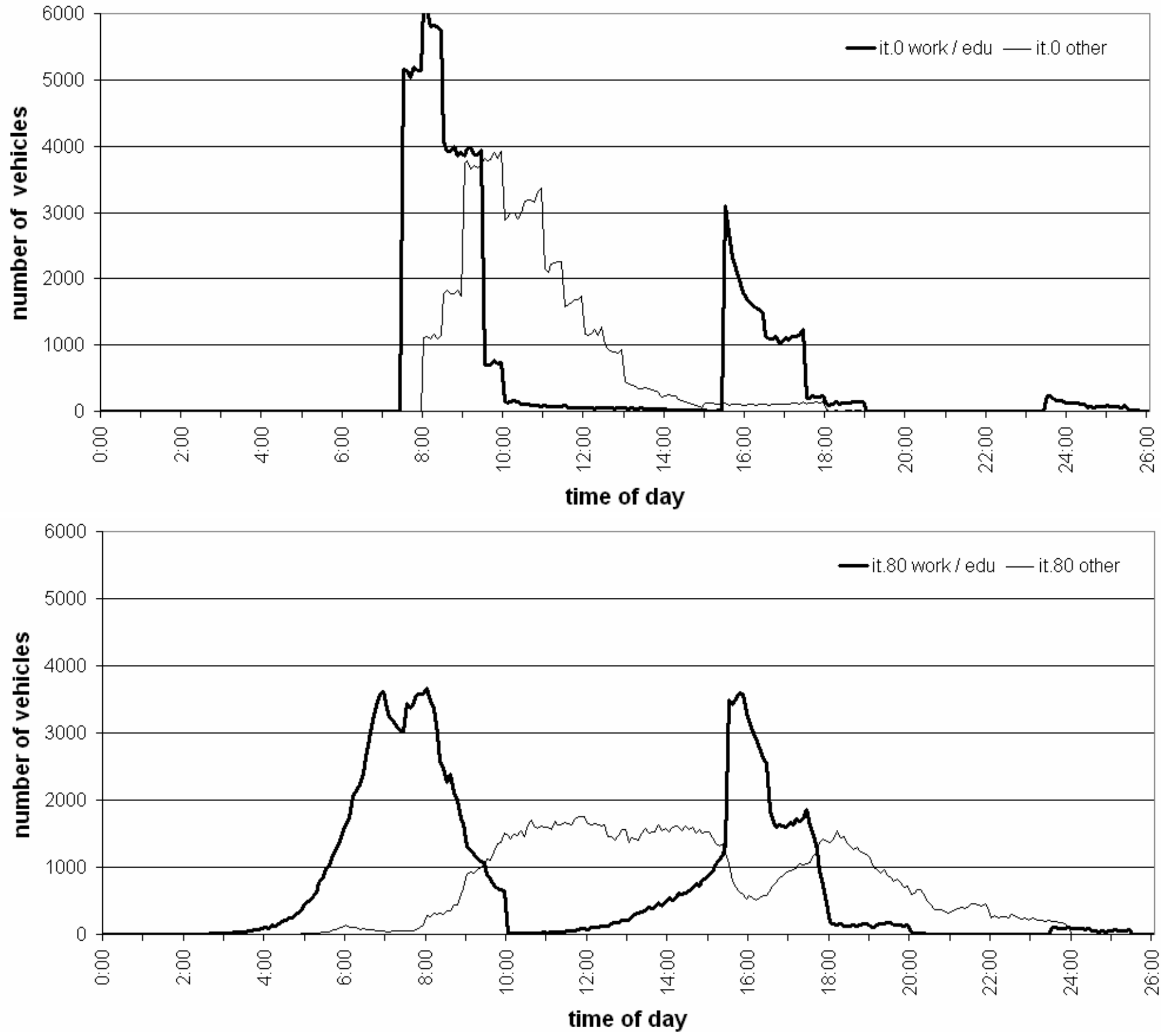

Fig. 3. The number of trip departures over the course of a day in iteration 0 (top) and iteration 80 (bottom), differentiated by the type of the primary activity of the corresponding plan

Fig.4 shows daily flows of vehicles. Flows below 15,000/day are displayed in green, flows of 30,000/day are displayed in orange, flows above 60,000/day are displayed in red. Flows in between are displayed in interpolated colors. The figure shows average values for the iterations 76 to 80. Since the simulation uses only 10 % of the population, the numbers from the simulation were multiplied by 10 in order to have the same scale as real world numbers.

Fig. 4. Daily flows of vehicles.

One observes that the pattern in the south-western sector is significantly different from the pattern in the north-eastern sector: While in the south-western half there is considerable traffic on the peripheral freeway, the patterns in the north-eastern sector are considerably more radial. This is due to extended freeway construction in the western sector during the division of the city, and the lack of such construction in the eastern sector.

Finally, we are comparing simulation results to observed data. Fig.5 shows the distribution of simulated trip travel times for all purposes. This distribution can be compared to an observed distribution (Fig.6) of car trip travel times from the German travel survey “Mobilität in Deutschland (MiD)” for trips performed in Berlin (DIW and Infras 2004).

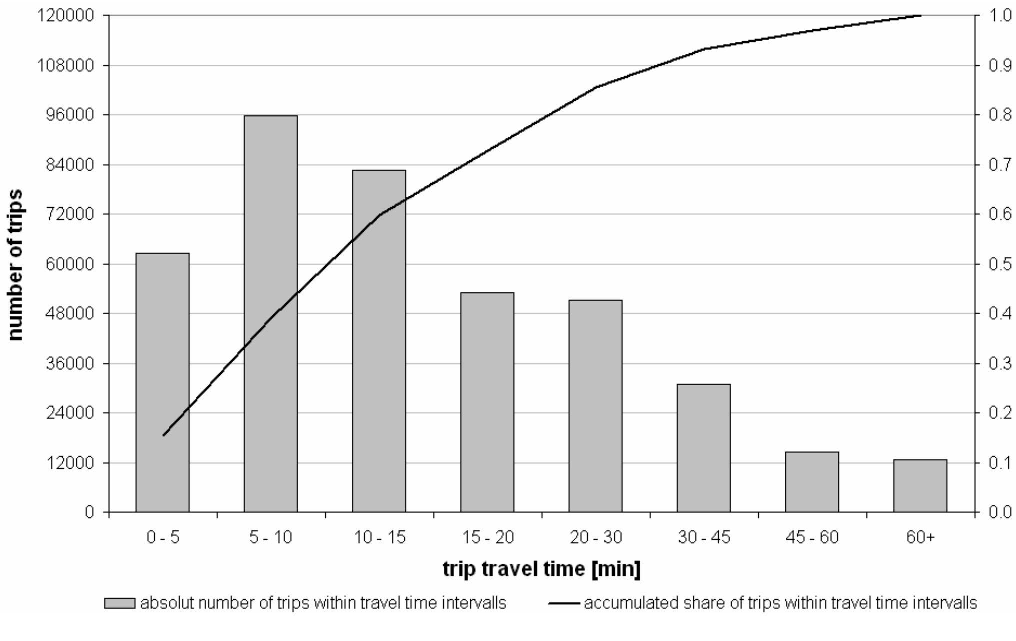

Fig. 5. Simulated car trip durations (iteration 80)

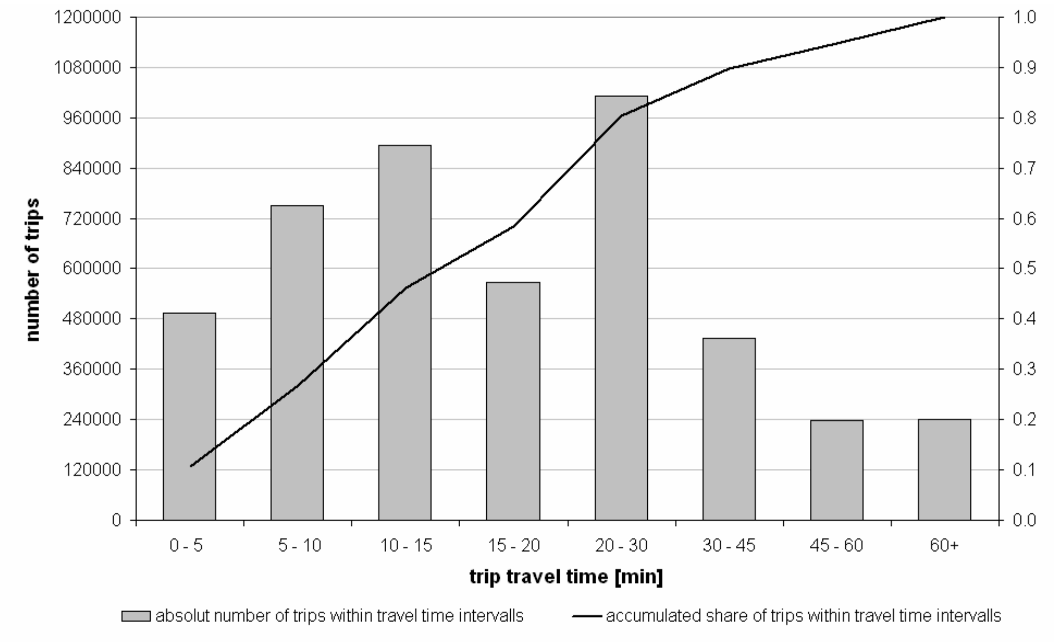

Fig. 6. Observed car trip durations

The simulation network does not contain all links of the real network—especially smaller roads are missing. Since activity locations are assigned to links in the simulation network and trips start and end at links, the simulation tends to underestimate access times. Thus, compared to the observed trip travel times (Fig.6) the simulated ones (Fig.5) are a bit shorter but their distribution is realistic.

The presented simulation results of our base case scenario did prove feasibility of such a large-scale real-world scenario, so that we intend to apply our MASim to different mobility pricing scenarios in order to provide decision makers with a more solid basis for their decision about introduction and scheme design than traditional models could do.

6 APPLYING TO PRICING MEASURES—PRELIMINARY RESULTS

This part of the work is still in progress. We want to explore environmentally-oriented road pricing schemes for livable cities, using our agent-based micro-simulation model. The main objective of our work is the definition of local pricing policies in favor of livable cities in Europe. The agent-based model will be cross-tested with the traditional traffic-flow-based model. So a realistic evaluation of the delivered model qualities will be achieved, which should demonstrate the specific advantages of micro-level modeling in comparison to the traditional approaches.

From the model results, proposals for the best suiting policy for future urban transport systems can be derived, which shall be used in the guidance process for citizens and politicians on local transport measures.

In this section we present preliminary results of our first toll scenario implemented in our multi-agent simulation. As already described, the first toll scenario assumes that time spent in traffic gets more expensive. Compared to our base case scenario the marginal utility of traveling is decreased further. Network and demand (initial plans) do not change for the different pricing scenarios. The available re-planning strategies are already described for the base-case scenario.

In order to speed up our simulations, we started all simulations with plans that were derived from an earlier base case run (Rieser et al. 2006). This means, that activity duration and scheduling as well as routes started from an already realistic basis compared to initial conditions with assigned timing based on activity types and routes based on an empty network. The iterative process of MATSim was started and the agents adapted their strategies to the situation on the network. Network and also the behavioral modules experienced changes after the run reported in Rieser et al. (2006), but as the Fig.7 shows the agents adapt their strategies to the new conditions.

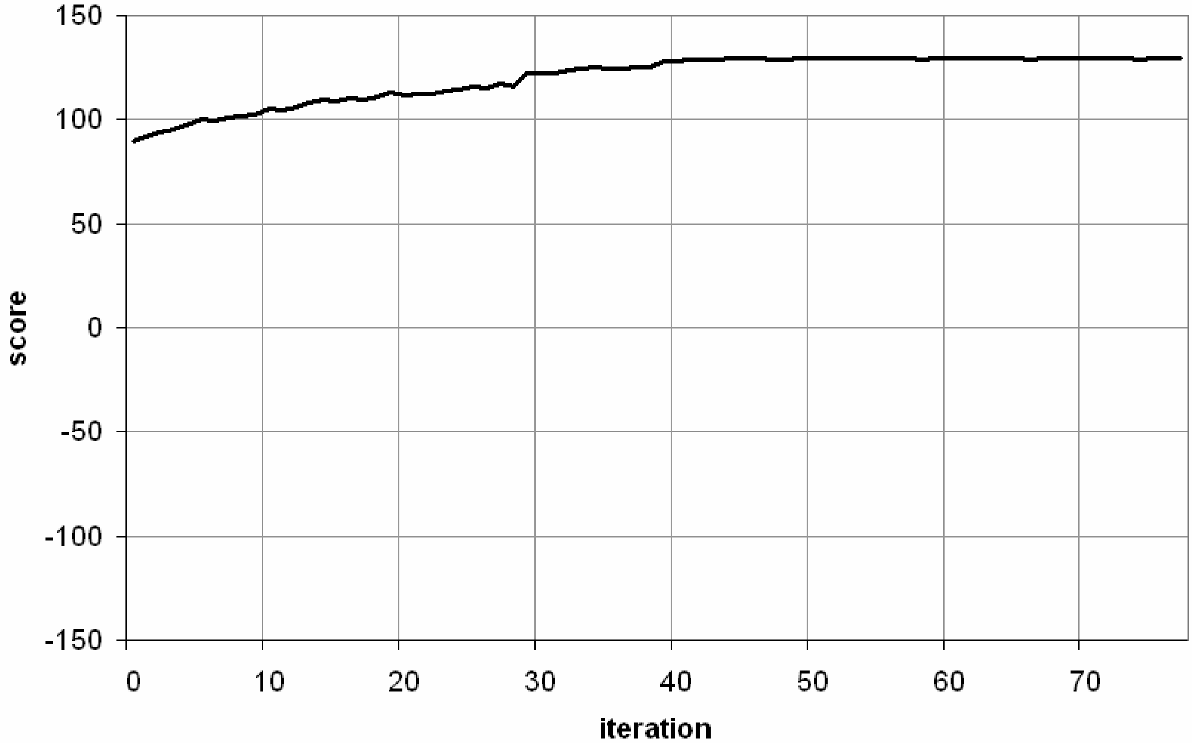

Fig. 7.The agents' average score

Two pricing levels are simulated; both scenarios only differ in their values for the marginal utilities of travel time. The low disutility scenario uses a value of -6 €/h in the scoring function and in the time adjustment module. In contrast, the high disutility scenario uses a value of -66 €/h.

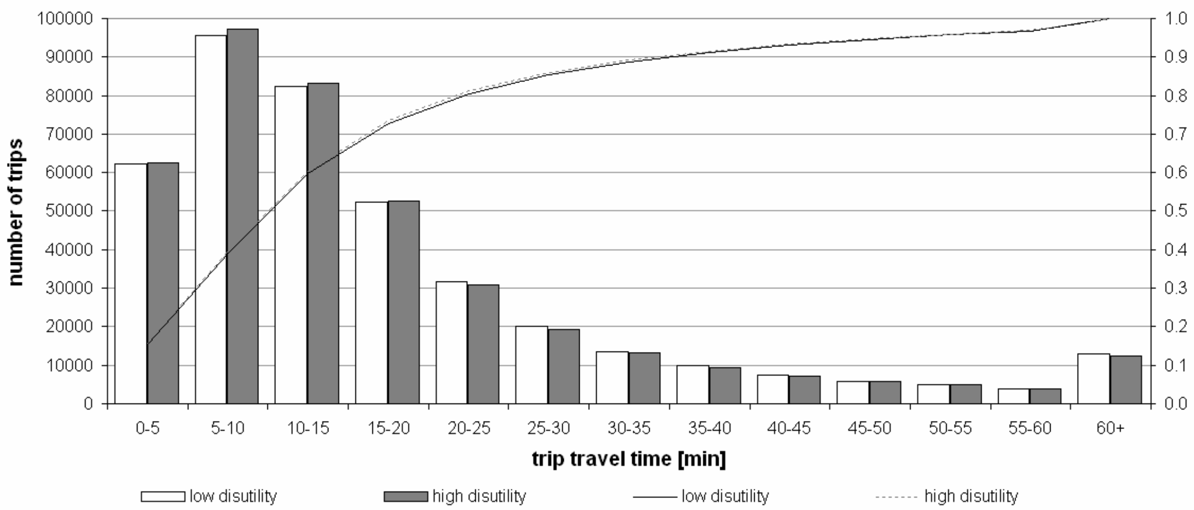

Fig. 8. Trip durations of the high and the low disutility scenario

Fig.8 shows trip time distribution for both scenarios. As one would expect, in the high disutility scenario agents reduce trip times, i.e. the share of trips with short trip times is higher in the high disutility scenario. But only a slight difference can be observed.

In order to reduce trip times, the agents can adjust their departure times to avoid congestions. Fig.9 shows that this happens in our simulation. For the high disutility scenario the volume capacity ratio is lower compared to the low disutility scenario during peak hours and higher compared to the low disutility scenario during off-peak hours. This indicates a better use of the network infrastructure due to adapted and more wide-spread departure times.

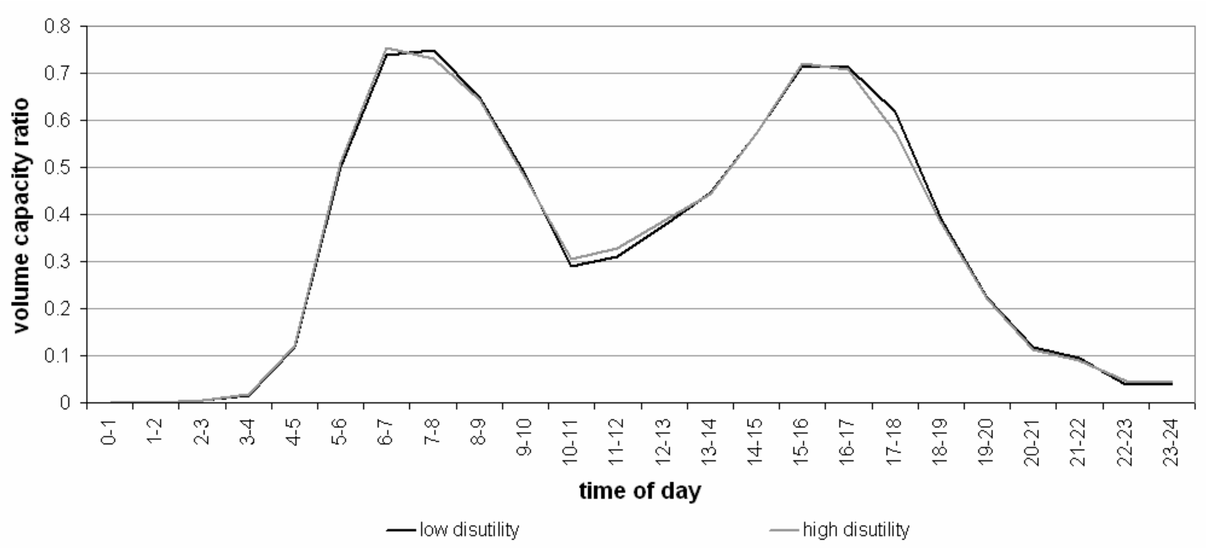

Fig. 9. Volume capacity ratio of the high and the low disutility scenario

But the difference of simulation output of both scenarios is only marginal as seen comparing in trip travel times and volume capacity ratio during the course of the day. One reason for these marginal differences are the limited options to adapt a plan: activity re-sequencing and dropping is not implemented yet, also activity location is not adjusted in the described scenarios.

But also initial plans from ABDG contribute to this situation. Since Berlin's ABDG is tour-based, we can derive only unrealistically short activity plans.

7 DISCUSSION AND FUTURE WORK

Considerable work was necessary to adapt the macroscopic network and demand data to our purposes. Although the data requirements of the queue model are not particularly difficult (apart from the number of lanes, all information is the same as for traditional planning models), it turns out that the queue model is more sensitive to data errors than the conventional models. This is due to the hard limit on the capacity: In a conventional static assignment model, short links with reduced capacities have very little effect, whereas in the queue model, they cause large spillbacks. This effect occurs in all dynamic models with hard capacity limits. We have to investigate further our network configurations in terms of attributes like capacity.

Our demand generation suffers from the fact that the base model is tour-based. Thus, we generate tour plans and not daily plans. In consequence, a person who has, say, the activity chain home-work-home-leisure-home will be divided into two "virtual" agents, one with activity chain home-work-home and the other with activity chain home-leisure-home. There is no reason why those two virtual agents should perform their trips in a sequential order, so in general they will, wrongly, not do so. This issue is due to the orientation of the demand generation towards daily travel, without consideration of the time-of-day. It will probably be necessary to devise a completely new method of demand generation.

An additional problem is that our simulations include passenger car travel only. A first approach is made by extracting heavy duty vehicle (HDV) plans from an HDV OD matrix.

Quite in general, it is difficult to get temporally consistent data—the data that we are currently using as input comes from many different years. In most places, things do not change that quickly, and it is sufficient to have the road network data and the traffic counts from the same year. Berlin, however, is a quickly-changing city due to the re-unification, and in consequence, such differences matter considerably.

When dealing with different tolling schemes it remains a task to adapt also the time adjustment module and the router in order to take tolls into account. For the time being, road toll is included in the scoring function only. Furthermore, plan adapting strategies have to be expanded by activity re-sequencing or dropping and re-location.

With such an enhanced simulation model, we will design scenarios for environmentally oriented road pricing, which will be based on noise and airborne pollutant emissions levels due to traffic. We aspire a fit of these pricing scenarios to the local environmental and socio-economic conditions and to the existing policy measures. Therewith we will show that urban road charging is a real alternative policy measure for the livable city, and can contribute to the reduction of negative effects of traffic.

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