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Modelling and simulation of a morning reaction to an evening toll

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INTRODUCTION

The modelling of traffic tolls becomes more and more important in transportation planning as there is usually no possibility to test toll schemes in reality. Time-dependent tolls are often preferred, as they allow for more fine-grained control of traffic flows. But the modelling of time-dependent tolls requires special attention to ensure that the model stays consistent with human behavior.

Traditional transportation planning tools work macroscopically, distributing static traffic flows onto a network. While this is a well-established technology, it is not able to fully model all aspects that are of interest when modelling tolls. In particular, they usually lack any meaning of time-of-day.

Dynamic traffic assignment (DTA) explicitly models the temporal development of the traffic. Demand, however, is typically given as fixed-period (e.g. hourly) OD matrices, and does, in consequence, not adapt to the toll. Adaptation would need to happen in the demand generation modules that generate the OD matrices, but that implies rather intricate coupling between demand generation and DTA.

Every model that uses single trips only will have problems predicting useful reactions of travellers that span the whole day. This is because trips in real life are embedded in a complete day plan. This means that travellers cannot escape a toll at their will, but have to trade off between different utilities (working eight hours, being at a shop when it has opened, ...) and disutilities (paying a toll, being late for work, ...). Thus a toll may influence the whole day schedule of a person, and not only the duration the toll is active.

Our approach uses multi-agent simulations to model and simulate full daily plans. This allows us to research the influence of time-dependent tolls more thoroughly than traditional tools are able to.

SIMULATION STRUCTURE

Our simulation is constructed around the notion of agents that make independent decisions about their actions. Each traveler of the real system is modeled as an individual agent in our simulation. The overall approach consists of three important pieces:

- Each agent independently generates a so-called *plan*, which encodes its intentions during a certain time period, typically a day.
- All agents' plans are simultaneously executed in the simulation of the physical system. This is also called the *traffic flow simulation* or *mobility simulation*.
- There is a mechanism that allows agents to *learn*. In our implementation, the system iterates between plans generation and traffic flow simulation. The system remembers several plans per agent, and scores the performance of each plan. Agents normally chose the plan with the highest score, sometimes re-evaluate plans with bad scores, and sometimes obtain new plans by modifying copies of existing plans.

The simulation approach is the same as in many of our previous papers *(*e.g. *1, 2)*. The following exposition is a shortened and simplified description of key elements to limit the length of this paper. The results of this paper are based on a re-implementation of the MATSim framework in Java *(3)*.

A **plan** contains the itinerary of activities the agent wants to perform during the day, plus the intervening trip legs the agent must take to travel between activities. An agent's plan details the order, type, location, duration and other time constraints of each activity, and the mode, route and expected departure and travel times of each leg. This paper concentrates on "home" and "work" as the only activities, and "car" as the only mode.

A plan can be modified by various **modules**. This paper will make use of two modules only:

- *Activity Times Generator:* This module is called to change the timing of an agent's plan. At this point, a very simple approach is used which just applies a random "mutation" to the duration attributes of the agent's activities.
  Although this approach is not very sophisticated, it is sufficient in order to obtain useful results. This is consistent with our overall assumption that, to a certain extent, simple modules can be used in conjunction with a large number of learning iterations *(*e.g. *4)*.
- *Router:* The router is implemented as a time-dependent Dijkstra algorithm. It calculates link travel times from the output of the traffic flow simulation. The link travel times are encoded in 15 minute time bins, so they can be used as the weights of the links in the network graph.

The **traffic flow simulation** executes all agents' plans simultaneously on the network, and provides output describing what happened to each individual agent during the execution of its plan. The traffic flow simulation is implemented as a queue simulation, which means that each street (link) is represented as a FIFO (first-in first-out) queue with two restrictions *(5, 6)*. First, each agent has to remain for a certain time on the link, corresponding to the free speed travel time. Second, a link storage capacity is defined which limits the number of agents on the link. If it is filled up, no more agents can enter this link.

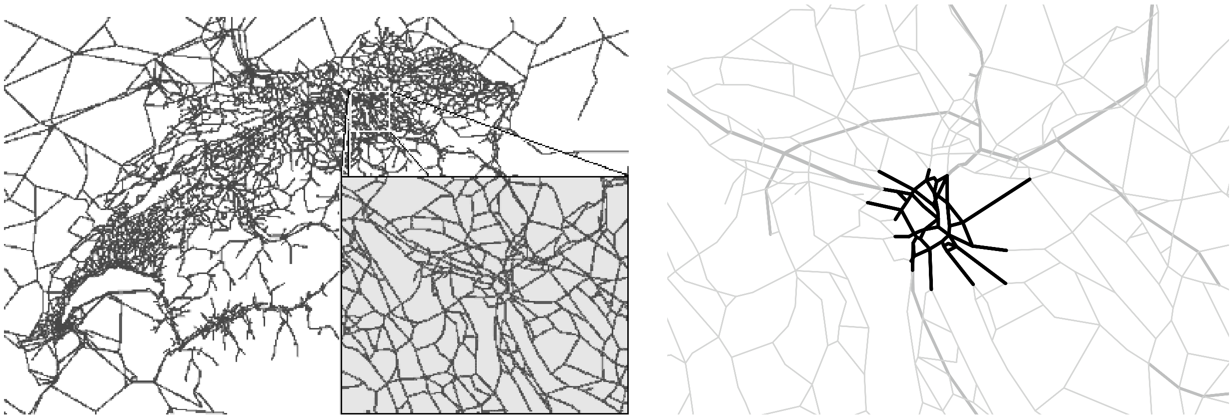
The outcome of the traffic flow simulation (e.g. congestion) depends on the planning decisions made by the decision-making modules. However, those modules can base their decisions on the output of the traffic flow simulation (e.g. knowledge of congestion) using **feedback** from the multi-agent simulation structure *(7, 8)*. This sets up an iteration cycle which runs the traffic flow simulation with specific plans for the agents, then uses the planning modules to update the plans; these changed plans are again fed into the traffic flow simulation, etc, until consistency between modules is reached.

The feedback cycle is controlled by the **agent database**, which also keeps track of multiple plans generated by each agent, allowing agents to reuse those plans at will. The repetition of the iteration cycle coupled with the agent database enables the agents to learn how to improve their plans over many iterations. This circle continues until the system has reached a relaxed state. At this point, there is no quantitative measure of when the system is "relaxed"; we just allow the cycle to continue until the outcome seems stable.

In order to compare plans, it is necessary to assign a quantitative **score** to the performance of each plan. In principle, arbitrary scoring schemes can be used (e.g. prospect theory *(9)*). In this work, a simple utility-based approach is used. The elements of our approach are as follows:

- The total score of a plan is computed as the sum of individual contributions, which consist of positive contributions for performing an activity, and negative contributions for travelling and for schedule delays.
- A logarithmic form is used for the positive utility earned by performing an activity.
- The (dis)utility of traveling is assumed as linear in the travel time.
- The (dis)utility of being late is assumed as linear in the delay.

It is important to note that the score thus takes into account the complete daily plan. More details can be found in *(2, 10)*.



(a) Switzerland network, area of Zurich enlarged (b) hypothetical toll links in Zurich area

FIGURE 1 Scenario: Switzerland network and toll links for Zurich

Our approach is related to the Vickrey bottleneck model *(11)*. When comparing the approaches, care needs to be taken to correctly factor in the effect of the opportunity cost. For example, when an agent is waiting (no score), it could, by a different arrangement of its schedule, have done an activity (positive score) instead. That foregone score is the effective penalty of waiting. A related argument holds for the time spent travelling.

SCENARIO

The scenario is the same as in *(1)*. It covers the area of Zurich, Switzerland, and has about 1m inhabitants. The network is a Swiss regional planning network, extended with the major European transit corridors (figure 1(a)). It has the fairly typical size of 10k nodes and 28k links.

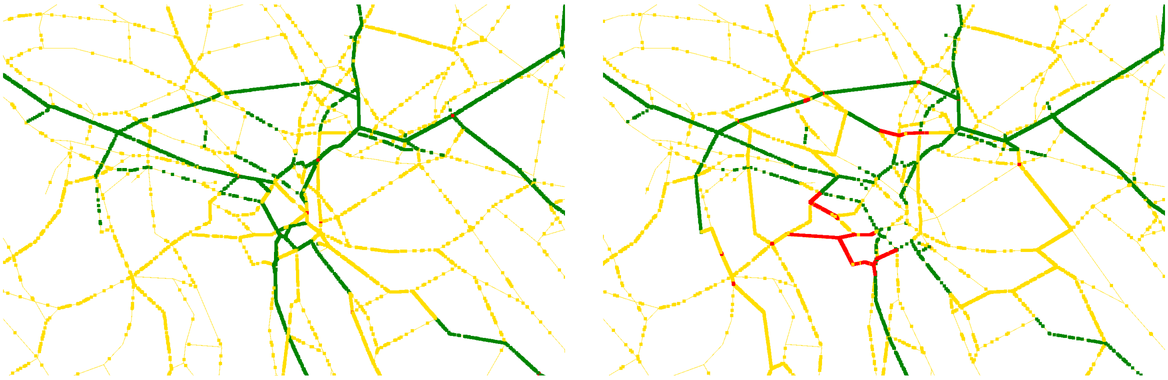
The simulated demand consists of commuters only that travel by car in the aforementioned region, resulting in 260k agents, all with an activity pattern home-work-home. The initial time structure has the agents leaving home in the morning at a randomly chosen time between 6am and 9am, work for 8 hours, and then returning to home. For the work activity a starting time window is defined between 7am and 9am.

We defined a hypothetical toll area that covers the inner city of Zurich (figure 1(b)). The diameter of the toll area is about 6km. The toll is restricted to the evening (3pm to 7pm) only, and the toll amount of 2 Euro/km is subtracted from the plan's score. Restriction of the toll to the evening is done to illustrate that the agent-based approach is able to consider ramifications throughout the whole day. In particular, it will be shown that the morning traffic is significantly affected by the evening toll. As was discussed earlier, this is an effect that a trip-based model cannot represent. The covered area has a high density of offices and other work places, so the in-bound traffic is larger in the morning than the out-bound traffic, and vice versa in the evening.

A base case without the toll was first iterated until a relaxed state was reached. Based on this state, a new run was started with the toll switched on, again until a (new) relaxed state was reached. This allows researching the specific influence the toll has on the behavior of the travellers.

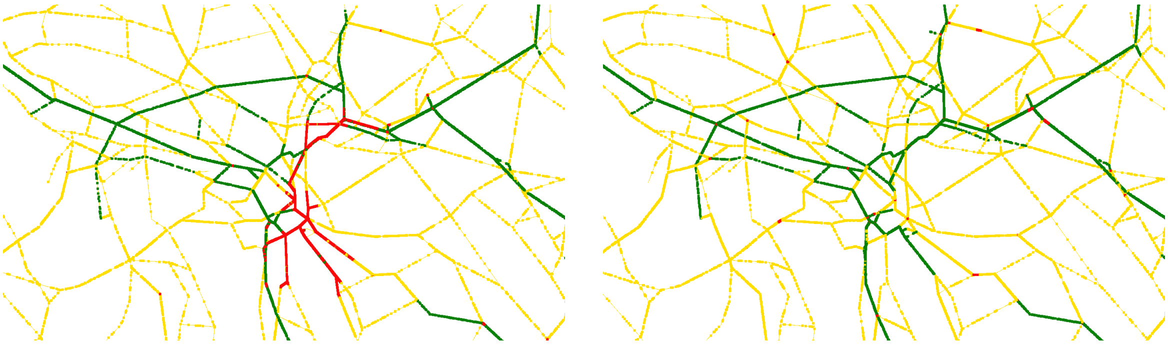
RESULTS

A first visual validation is done by looking at the traffic volumes and velocities. Figure 2 shows the velocity of agents at 5:30pm, during the toll hours. One can clearly see that there are more agents



(a) base case (b) toll case

FIGURE 2 Travel speeds at 5:30pm during the toll time on the network: green are high speeds, red marks traffic jams.



(a) base case (b) toll case

FIGURE 3 Travel speeds at 8am when no toll has to be paid: green are high speeds, red marks traffic jams.

travelling around the toll area in the toll case by the traffic jams they produce.

We can also compare the two runs in the morning hours at 8am. Note that at this time of the day, there is no active toll either case. As can be seen in figure 3, there are traffic jams in the base case, but none of them in the toll case. This clearly shows that the toll in the evening rush hour has an influence on the morning rush hour.

Figure 4(a) shows the departure time distribution for the base case and the toll case. Comparing the toll case with the base case in the evening peak, one can see how the number of travellers departing from work is higher in the toll case than in the base case in the time before the toll starts. It is also slightly higher after the toll ends. However, during the time the toll is active, the number of travellers departing is lower in the toll case than in the base case.

As each traveller tries to work eight hours a day, the same characteristics can also be seen in the morning rush hour, as agents planning to leave before 3pm will also have to arrive at work earlier than the others. This leads to a general broadening also of the morning peak. Without full daily plans, there would be no difference in the morning peak.

If the peaks of departing travellers are broader but less high, this means also that there are likely fewer people travelling at the same time. Figure 4(b) shows the number of travellers simultaneously on the road. Especially in the morning rush hour it is apparent that the area below the curve is

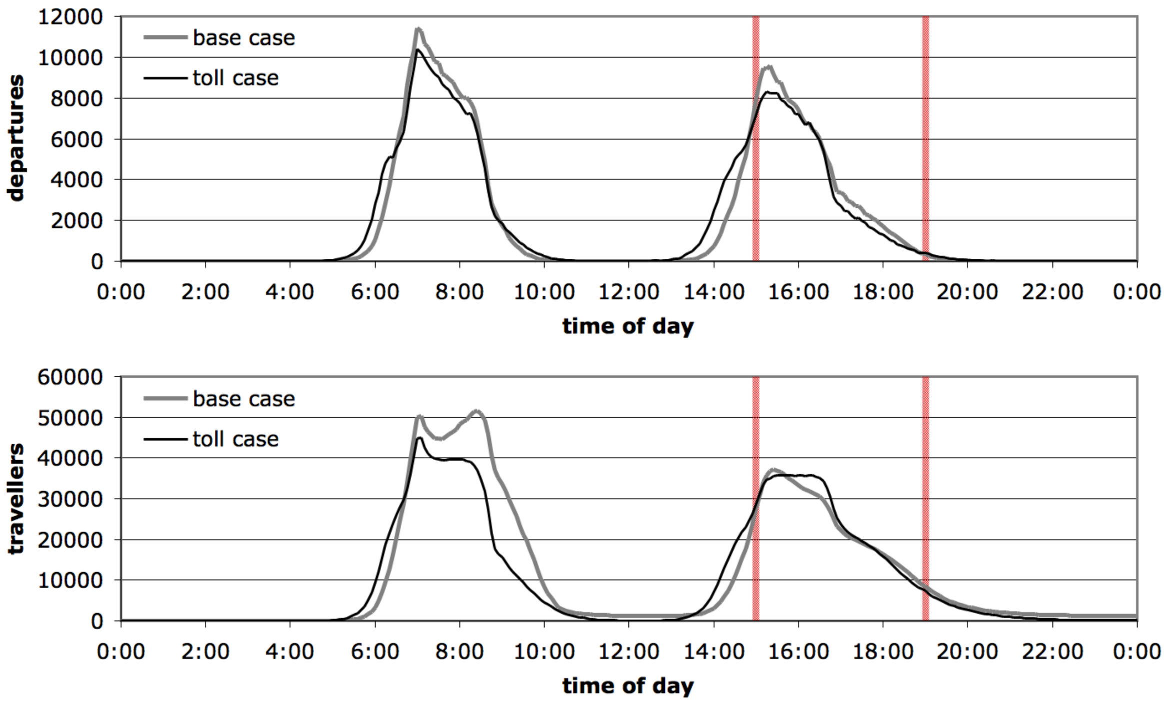


FIGURE 4 (a) Number of departures and (b) number of travellers on the road over the time of day. The red lines mark the start and the end of the time a toll has to be paid.

significantly smaller than in the base case. The area below the curve can be interpreted as the total time agents spend on the road. A smaller area means that people spend less time in total travelling—and all this without a toll in the morning rush hour!

The case is a bit different in the evening rush hour. Around 4pm we actually have more travellers on the road than in the toll case. This can be explained if one remembers that the toll area is only a small part of the whole simulated area: The travellers only have to get out of the toll area before the toll starts (as can be seen in the higher number of departures and travellers between 2pm and 3pm). However, this has the consequence that there may now be more travellers outside the toll area—and that's what can be observed in figure 4(b) at 4pm.

CONCLUSIONS

We have shown that the use of full daily plans in multi-agent simulations can be used to model travellers' reactions to a time-dependent toll in a way most existing transportation planning tools are not able to. In particular, the interdependence of different trips for a single agent throughout the day is taken into account by the simulation.

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REFERENCES

1. M. Balmer, B. Raney, and K. Nagel. Adjustment of activity timing and duration in an agent-based traffic flow simulation. In H.J.P. Timmermans, editor, *Progress in activity-based analysis*, pages 91–114. Elsevier, Oxford, UK, 2005.

2. B. Raney and K. Nagel. An improved framework for large-scale multi-agent simulations of travel behavior. In P. Rietveld, B. Jourquin, and K. Westin, editors, *Towards better performing European Transportation Systems*. Routledge, London, 2006. Similar version TRB preprint number 05-1846.

3. MATSIM www page. MultiAgent Transport SIMulation, accessed 2007.

4. K. Nagel, M. Strauss, and M. Shubik. The importance of timescales: Simple models for economic markets. *Physica A*, 340(4):668–677, 2004.

5. N. Cetin, A. Burri, and K. Nagel. A large-scale agent-based traffic microsimulation based on queue model. In *Proceedings of Swiss Transport Research Conference (STRC)*, Monte Verita, CH, 2003. Earlier version, with inferior performance values: Transportation Research Board Annual Meeting 2003 paper number 03-4272.

6. C. Gawron. *Simulation-based traffic assignment*. PhD thesis, University of Cologne, Cologne, Germany, 1998.

7. J.A. Bottom. *Consistent anticipatory route guidance*. PhD thesis, Massachusetts Institute of Technology, Cambridge, MA, 2000.

8. David E. Kaufman, Karl E. Wunderlich, and Robert L. Smith. An iterative routing/assignment method for anticipatory real-time route guidance. Technical Report IVHS Technical Report 91-02, University of Michigan Department of Industrial and Operations Engineering, Ann Arbor MI 48109, May 1991.

9. E. Avineri and J.N. Prashker. Sensitivity to uncertainty: Need for paradigm shift. Paper 03-3744, Transportation Research Board Annual Meeting, Washington, D.C., 2003.

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

11. R. Arnott, A. De Palma, and R. Lindsey. A structural model of peak-period congestion: A traffic bottleneck with elastic demand. *The American Economic Review*, 83(1):161, 1993.