Report

Multi-agent transport simulations and economic evaluation

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1. INTRODUCTION

In many cities in Europe, tolls are discussed as a means to reduce the amount of traffic during peak hours or in a city in general. But only few cities (e.g. Singapore, Bergen, Trondheim, Durham, London, Stockholm, Bologna, Roma) have been able to implement a toll scheme, as tolling requires substantial upfront investment and is likely to be an unpopular policy. Thus, many cities have an interest in transportation planning tools and traffic models to thoroughly test different toll schemes to find one that solves their problems best — and provides hints about popular acceptance.

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 model all aspects that are of interest when modelling tolls. In particular, they usually lack any meaningful representation of the time-of-day dynamics. The models usually calculate traffic flows for a complete day, or at best for certain periods (morning peak, evening peak), but in all cases without any feedbacks between the different times-of-day. This makes it essentially impossible to model time-dependent tolls, as the reaction of the travellers (e.g. driving before/after the toll) cannot be captured endogenously within the planning model, but must be pre-specified by the user. This reduces the usefulness of such a tool enormously.

Dynamic traffic assignment (DTA) explicitly models the temporal dynamics of travel demand over the day. Demand, however, is typically given as fixed-period (e.g. hourly) OD matrices, and, in consequence, does 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. In addition, the DTA is no longer aware of travel characteristics, such as income or time constraints, and, in consequence, cannot base any kind of toll route acceptance/rejection decision on such attributes.

A partial way out is offered by the approach chosen within METROPOLIS (de Palma and Marchal 2002), which selects departure times of trips based on desired arrival times and schedule delay penalties. Given a time-dependent toll, travellers can react by selecting new departure times. A remaining problem is, however, the fact that trips and in consequence, decisions are not related to demographics. In addition, every model that uses single trips 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 and are not meaningful just as stand-alone trips. Trips lead people from one activity to another, and in most cases the activities have a higher importance in the daily schedule than the trips do: Stores have opening and
closing times, work places have fixed times when one has to be present, a full-time employee has to work about eight hours a day. This means that travellers cannot escape a toll at will, but have to trade off between different utilities (working eight hours, being at a shop when it has opened, etc.) and disutilities (paying a toll, being late for work, etc.). Thus, a toll may influence the complete daily schedule of a person, and not only the period where the toll is charged.

Our approach uses multi-agent simulations to model and simulate full daily plans. The agents are generated as a synthetic version of the real population living in the area of interest, matching as many demographic attributes as are available. Every agent then plans his/her day. These plans are simultaneously executed in the synthetic world, and the interaction between the agents (e.g. congestion) is computed. Agents are then given a chance to modify their plans, the plans are executed again, etc., that is, the agents adapt (co-evolution). Since the agents are virtual representations of real people, and since they move in a virtual representation of the real world, aspects of reality such as those discussed in the previous paragraph can be included in a conceptually straightforward way.

Each of our agents has a (possibly individual) scoring function, based on the agent’s performance during plan execution (i.e. including interaction). This scoring function plays the same role as the fitness function in co-evolutionary genetic algorithms: Every agent attempts to improve his/her fitness, which, however, is based on the behaviour of the other agents. In economic terms, it can be interpreted as a utility function. In consequence, changes in an agent’s utility in reaction to a policy change can be directly interpreted as that agent’s welfare change caused by the policy change. Since agents can adapt, their utility change reflects indirect utility: the utility change after agents have optimally adapted to the new circumstances. This adaptation takes place along those choice dimensions that are allowed by the simulation system, thus allowing fine-grained control over the reactions that are to be included into the scenario. Since the score is based on the performance in the synthetic world, it is conceptually straightforward to include constraints such as opening times: If an agent remains at a facility while the facility is closed, no utility will be accumulated during that time, and thus the agent will most probably search for a different time structure for his/her day.

If every agent’s score can be interpreted as his/her own utility, then the sum of these utilities is the system’s welfare. The sum of all utility changes in reaction to a policy change is, in consequence, the change in the system’s welfare. That is, the input of “user benefits” to a cost-benefit analysis can be taken directly from the simulation, and is therefore automatically consistent with the assumptions about the agents’ optimization capabilities. This is in stark contrast to the traditional approach, where there is one model in which the agents react to a policy change, and a second model that assigns economic benefits (possibly negative) to those changes. This approach completely separates the agents’ optimization behaviour from the measurement of the economic benefit, thus making it difficult if not impossible to keep those consistent, but see for example de Jong, Daly, Pieters and van der Hoorn, 2005 for a way to overcome this within an aggregate framework.

This paper describes the agent-based approach in more detail. Section 2 describes the overall approach, concentrating on conceptual aspects, the co-evolutionary adaptation, and the scoring. Section 3 then describes a specific scenario, related to an illustrative study using data from the Zurich metropolitan area. The scenario consists of the geographic and socio-demographic input data, the computational modules, the toll scheme, and the specific simulation runs that were undertaken. In principle, the computational details should be rather unimportant, since agents are assumed to adapt optimally in the choice dimensions that are in-
cluded in the simulation. In practice, however, at this point little is known about the robustness of these results, and for that reason more details are given. Section 4 describes the results of the toll simulation, in particular the reaction patterns that emerge. An important result is that agents react also outside tolled times – as they should. Section 5, finally, comes back to the economic analysis that was shortly sketched in the previous paragraph.

2. SIMULATION STRUCTURE

2.1 Overview

Our simulation is constructed around 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 received a 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 (and sometimes the mobility simulation).
- There is a mechanism that allows agents to learn. In our implementation, the system iterates between plan 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 to test if it now performs better, and sometimes obtain new plans. Further details will be given below.

A plan contains the itinerary of activities the agent wants to perform during the day, plus the intervening trip the agent must travel between activities (see Figure 1). 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 trip. This paper concentrates on “home” and “work” as the only activities, and “car” as the only mode. Our implementation already at this point supports additional activity types (see, e.g., Meister et al 2006) and additional modes of transport, but more time is needed to validate results given those additional complexities.

The task of generating a plan is divided into sets of decisions, and each set is assigned to a separate module. An agent strings together calls to various modules in order to build up a complete plan. To support this incremental process, the input to a given module is a (possibly incomplete) plan, and the output is a plan with one or more decisions added. This paper will make use of two modules only: “activity time generator” and “router”. Other modules will be the topic of future work. Once the agent’s plan has been constructed, it can be fed into the traffic flow simulation. This module executes all agents’ plans simultaneously on the network, allowing agents to interact with one another, and provides output describing what happened to the agents during the execution of their plans.
The outcome of the traffic flow simulation (e.g. congestion) depends on the planning decisions made by the agents and their decision-making modules. However, those modules can base their decisions on the output of the traffic flow simulation (e.g. knowledge of congestion). This creates an interdependency (“chicken and egg”) problem between the decision-making modules and the traffic flow simulation. To solve this, feedback is introduced into the multi-agent simulation structure (Kaufman et al 1991, Bottom 2000). 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 of the results 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 iteration cycles coupled with the agent database enable the agents to learn how to improve their plans over many iterations.

2.2 Co-evolutionary adaptation

The iterative approach outlined above describes co-evolutionary adaptation: Every agent attempts to improve, while everybody around him/her is doing the same. Several conceptual issues are related to this concept:

- If the adaptation ever came to an end (to a fixed point), and if the whole system were deterministic, then the system would be in a Nash equilibrium: No agent could improve by unilaterally doing something else. This notion is important, since it relates our work to standard welfare economics. There is, however, no guarantee that the Nash equilibrium is unique; i.e., depending on the initial conditions and on the exact nature of the adaptation process, different fixed points might be reached (Hofbauer and Sigmund 1998, Watling 1999). Clearly, the possibility of multiple outcomes is important in policy contexts.

- There is not even a need that such a system would go to a fixed point at all. Other possibilities are cycles or chaotic attractors (Hofbauer and Sigmund 1998, Watling 1999).

- Our system, however, is not deterministic. Although this is probably more realistic, and makes the system more robust, it makes the interpretation more complicated. One could argue that the system is ergodic and should thus go to a steady state phase space density (Cantarella and Cascetta 1995). Yet, the phase space is huge and our typical iteration numbers comparatively small, and thus an instance of pseudo-stability (Watling 1996) or “broken” ergodicity (Palmer 1989) is much more probable. In practical terms, this means

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\[1\] This term common in aviation is used here instead of trip. A full specification of the trip as a sequence of stages (see Axhausen, 2007) will added later.
that the iterations might find a state that is locally stable, but there is no guarantee that running the iterations longer might not lead to completely different solutions.

The uniqueness of the Nash equilibrium solution of traditional transport modeling was one of its most important features: Although static assignment does not necessarily have much to do with reality especially in heavily congested situations, at least it allows a conceptually sound comparison of different policy scenarios. Multi-agent simulations do not possess this uniqueness property, as can be shown already with simple but plausible examples (Daganzo 1998). It is as of yet unclear what the agent-based models will be able to put forward instead. One possibility is to not only consider the relaxed state, but also to pay closer attention to the realism of the initial condition and the adaptation behavior itself. Such models, then, would attempt to predict the full dynamic trajectory of the learning behavior of the simulated population when faced with a policy or infrastructure change.

2.3 Scores for plans

In order for adaptation to work in a meaningful way, it is necessary to be able to compare the performance of different plans. This is easiest achieved by assigning scores to plans. This is the same as the fitness function in genetic algorithms, or the objective function in optimization problems. Note once more that every agent has its own scoring function, and attempts to optimize for her/himself.

In principle, arbitrary scoring schemes can be used (e.g. prospect theory, Avineri and Praschker 2003). Much of the approach, in fact, would still function even if agents were only able to rank plans. In this work, a utility-based approach is used. The approach is related to the Vickrey bottleneck model (Arnott et al 1993), but is modified in order to be consistent with our approach based on complete daily plans (Charypar and Nagel 2005, Raney and Nagel 2006). The elements of our approach are as follows:

- the total score of a plan is computed as the sum of individual contributions:

\[ U_{\text{total}} = \sum_{i=1}^{n} U_{\text{perf},i} + \sum_{i=1}^{n} U_{\text{late},i} + \sum_{i=1}^{n} U_{\text{travel},i} \]

where \( U_{\text{total}} \) is the total utility for a given plan; \( n \) is the number of activities, which equals the number of trips, as we consider the stay at home before the first departure; \( U_{\text{perf},i} \) is the (positive) utility earned for performing activity \( i \); \( U_{\text{late},i} \) is the (negative) utility earned for arriving late to activity \( i \); and \( U_{\text{travel},i} \) is the (negative) utility earned for traveling during trip \( i \). In order to work in plausible real-world units, utilities are measured in Euro.

- a logarithmic form is used for the positive utility earned by performing an activity:

\[ U_{\text{perf},i}(t_{\text{perf},i}) = \beta_{\text{perf}} \cdot t_{**} \cdot \ln \left( \frac{t_{\text{perf},i}}{t_{0,i}} \right) \]

where \( t_{\text{perf}} \) is the actual performed duration of the activity, \( t_{**} \) is the “typical” duration of an activity, and \( \beta_{\text{perf}} \) is the marginal utility of an activity at its typical duration. \( \beta_{\text{perf}} \) is the same for all activities, since in equilibrium (and in the absence of constraints) all activities at their typical duration need to have the same marginal utility (since otherwise an agent could gain by expanding the activity with the largest marginal utility while shrinking the activity with the smallest marginal utility).

\( t_{0,i} \) is a scaling parameter that is related both to the minimum duration and to the importance of an activity. If the actual duration falls below \( t_{0,i} \), then the utility contribution of the
activity becomes negative, implying that the agent should rather completely drop that activity. A \( t_{0,i} \) only slightly less than \( t_{*,i} \) means that the marginal utility of activity \( i \) rapidly increases with decreasing \( t_{\text{perf},i} \), implying that the agent should rather cut short other activities. This paper uses \( t_{0,i} = t_{*,i} \cdot \exp(-\zeta / t_{*,i}) \) where \( \zeta \) is a scaling constant set to 10 hours. With this specific form, \( U_{\text{perf},i}(t_{*,i}) = \beta_{\text{perf}} \cdot \zeta \) is independent of the activity type.

- The (dis)utility of being late is uniformly assumed as: \( U_{\text{late},i} = \beta_{\text{late}} \cdot t_{\text{late},i} \) where \( \beta_{\text{late}} \) is the marginal utility (in Euro/h; usually negative) for being late, and \( t_{\text{late},i} \) is the duration of being late to activity \( j \) [h].

- The (dis)utility of traveling is uniformly assumed as: \( U_{\text{travel},i} = \beta_{\text{travel}} \cdot t_{\text{travel},i} \) where \( \beta_{\text{travel}} \) is the marginal utility (in Euro/h; usually negative) for travel, and \( t_{\text{travel},i} \) is the number of hours spent traveling during trip \( i \) [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 \(-\beta_{\text{perf}}\). Similarly, that opportunity cost has to be added to the time spent traveling, arriving at an effective (dis)utility of traveling of \(-|\beta_{\text{travel}}| - \beta_{\text{perf}}\).

No opportunity cost needs to be added to late arrivals, because the late arrival time is spent somewhere else. In consequence, the effective (dis)utility of arriving late remains at \( \beta_{\text{late}} \).

These values (\( \beta_{\text{perf}} \), \( \beta_{\text{perf}} + |\beta_{\text{travel}}| \), and \( |\beta_{\text{late}}| \)) are the values that would correspond to the values of the parameters of the Vickrey model (Arnott et al 1993) if MATSim would just look for late arrival.

3. SCENARIO

In this section, a specific scenario will be described in some detail. The purpose of this section is to illustrate the more general concepts described above, but also to provide some intuition as to what is feasible when dealing with real world scenarios.

3.1 Geographical area; population

The scenario covers the area of Zurich, Switzerland, which has about 1m inhabitants. The network is a Swiss regional planning network, extended with the major European transit corridors (Figure 2 (a)). It has the fairly typical size of 10 564 nodes and 28 624 links.

The simulated demand consists only of commuters that travel by car in the aforementioned region, resulting in 260 275 agents, all with a simplified activity pattern of 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.
eventually come up with a calibrated and validated model that describes that physical reality in sufficient detail; and in fact, our own experience (unpublished) indicates that the results do not hinge critically on the selection of the traffic flow simulation. Yet, also the selection of the decision modules should, as long as they are able to scan the search space in a meaningful way, not be absolutely critical, since it is the scoring function described above that ultimately determines the agents’ behavior. There is indeed some indication that simple mental modules, together with many iterations (= very long computing times), can lead to plausible results (Nagel et al 2004, Balmer et al 2005). Yet, the issue of computing times remains important (Meister et al 2006, Charypar et al 2006).

3.2.1 Activity Time Allocation Module

This module is called to change the timing of an agent’s plan. At this point, a very simple approach is used which applies random “mutations” to the duration and end time attributes of the agent’s activities. For each such attribute of each activity in an agent’s plan, this module picks a random time from the uniform distribution $[-30 \text{ min}, +30 \text{ min}]$ and adds it to the attribute. Any negative duration is reset to zero; any activity end time after midnight is reset to midnight.

Although this approach is naive, 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. Nagel et al 2004). Clearly, it is important to have a behaviorally realistic scoring function, in conjunction with knowledge about the locations of the facilities for the different activity types, and their opening times.

Since each module is implemented as a “plugin”, this module can be replaced by a more sophisticated implementation if desired. MATSim contains already a more sophisticated activity scheduling module (Meister et al 2006). This will be used in future studies.

3.2.2 Router

The router is implemented as a time dependent Dijkstra algorithm. It calculates link travel times from the events output of the previous traffic flow simulation (see next section). 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. Apart from relatively small and essential technical details, the implementation of such an algorithm is straightforward (Jacob et al 1999; Lefebvre and Balmer, 2007). With this and the knowledge about activity chains, it computes the fastest path from each activity to the next one in the sequence as a function of departure time.

3.2.3 Traffic Flow Simulation

The traffic flow simulation simulates the physical world. It 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 (Gawron 1998, Cetin et al 2003). 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.

Even though this structure is indeed very simple, it produces traffic as expected and it can run directly off the data typically available for transportation planning purposes. On the other
hand, there are some limitations compared to reality, i.e. number of lanes, weaving lanes, turn connectivities across intersections or signal schedules cannot be included into this model.

The output that the traffic flow simulation produces is a list of events for each agent, such as entering/leaving link, left/arrived at activity, and so on. Data for an event includes which agent experienced it, what happened, what time it happened, and where (link/node) the event occurred. With this data it is easy to produce different kinds of information and indicators like link travel time (which i.e. will be used by the router), trip travel time, trip length, percentage of congestion, and so on.

3.2.4 Agent Database – Feedback

As mentioned above, the feedback mechanism is important for making the modules consistent with one another, and for enabling agents to learn how to improve their plans. In order to achieve this improvement, agents need to be able to try out different plans and to tell when one plan is “better” than another. The iteration cycle of the feedback mechanism allows agents to try out multiple plans. To compare plans, the agents assigns each plan a “score”, as explained above.

It is very important to note that our framework always uses actual plan performance for the score. This is in stark contrast to all other similar approaches that we are aware of. These other approaches always feed back some aggregated quantity such as link travel times and reconstruct performance based on those (e.g. URBANSIM 2007, Ettema et al 2003). Because of unavoidable aggregation errors, such an approach can fail rather badly, in the sense that the performance information derived from the aggregated information may be rather different from the performance that the agent in fact experienced (Raney and Nagel 2004).

The procedure of the feedback and learning mechanism is described in detail in (Balmer et al 2005). For better understanding, the key points are restated here.

The agent database starts with one complete plan per agent, which is marked as “selected”. The simulation executes these marked plans simultaneously and outputs events. Each agent uses the events to calculate the score of its selected plan and decides, which plan to select for execution during the next iteration (traffic flow simulation). When choosing a plan, the agent database can either:

• create a new plan by sending an existing plan to the router, adding the modified plan as a new plan and selecting it,

• create a new plan by sending an existing plan to the time allocation module, adding the modified plan and selecting it,

• pick an existing plan from memory, choosing according to probabilities based on the scores of the plans. The probabilities are of the form $p \propto e^{\beta S_j}$, where $S_j$ is the score of plan $j$, and $\beta$ is an empirical constant. This is the familiar logit model (e.g. Ben-Akiva and Lerman 1985).

After this step, the simulation executes the newly selected plans. 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 the long run, measures to stop the iterations automatically and consistently need to be found.
3.3  Tolls

During the rush hours, traffic in Zurich is very dense, and tolls are debated as a possible solution. Thus, we defined a hypothetical toll area that covers the inner city of Zurich, but not the motorways that lead into and partially around the city. Figure 2 (b) shows the tolled links. The diameter of the toll area is about 6km. The toll is restricted to the evening (3pm to 7pm) only and is set to 2 Euro/km. This high level was chosen to demonstrate the possible impact in this artificial and simple scenario. Restriction of the toll to the evening will illustrate that the agent-based approach as is able to consider ramifications throughout the day. In particular, it will be shown that the morning traffic is significantly affected by the evening toll. As was discussed earlier, a trip-based model cannot capture this effect. The tolled 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) Switzerland network, area of Zurich enlarged  
(b) hypothetical toll links in Zurich area.

Figure 2: Scenario: Switzerland network with toll links for Zurich.

3.4  Runs

A base case without the toll was first iterated until a relaxed state was reached. Both routes and activity times were allowed to adapt. Based on this state, new iterations were run with the toll switched on, again until a (new) relaxed state was reached. This allows to identify the specific influence the toll has on the behaviour of the travellers.

We used the following values for the marginal utilities of the utility function used for calculating scores:

\[ \beta_{\text{perf}} = +6 \text{ Euro/h}, \quad \beta_{\text{travel}} = -6 \text{ Euro/h}, \quad \beta_{\text{late}} = -18 \text{ Euro/h} \]

Although it is not obvious at a first glance, these values mirror the standard values of the Vickrey scenario (e.g. Arnott, de Palma, and Lindsey 1993): An agent that arrives early to an activity must wait for the activity to start, therefore forgoing the \( \beta_{\text{perf}} = +6 \text{ Euro/h} \) that it could accumulate instead. An agent that travels forgoes the same amount, plus a loss of 6 Euro/h for traveling. And finally, an agent that arrives late receives a penalty of 18 Euro/h late.

In addition, this paper will only look at daily activity chains that consist of on home and one work activity. The optimal times were set to \( t^*_{\text{h}} = 15 \text{ hours} \) and \( t^*_{\text{w}} = 8 \text{ hours} \).
Simplifying the work activity’s starting time window is defined as 7:08am and 8:52am. These values were set to correspond with those used in a similar study (17).

4. RESULTS

A first visual validation is done by looking at the traffic volumes and velocities. Figure 3 shows the velocity of agents at 5.30pm, during the toll hours. One can clearly see that there are more agents travelling outside the tolled area in the toll case by the traffic jams they produce.

![Figure 3: Travel speeds at 5:30pm during the toll time on the network. Green are high speeds, red marks traffic jams.](image)

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! As can be seen in Figure 4, 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: Travel speeds at 8am, when no toll has to be paid. Green are high speeds, red marks traffic jams.](image)

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 of the two peaks in the morning and the evening.
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 5 (b) shows the number of travellers simultaneously on the road. Especially during the morning peak it is apparent that the area below the curve is 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 travelling—and all this without a toll in the morning rush hour!

![Figure 5: Number of departures (a) and number of travellers on the road (b) over the time of day. The red lines mark the start and the end of the toll period.](image)

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 tolled area is only a small part of the whole simulated area: The travellers only have to get out of the tolled 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 5 (b) at 4pm.

5. **ECONOMIC INTERPRETATION**

Standard economic appraisal, as is for example used for cost-benefit-analysis (e.g. Pearce and Nash 1981), would now take the above traffic patterns as input, and attach economic valuations to them. One would, for example, for each link count the number of users and the average time they spent on the link. These numbers would then be compared between the base case and the scenario case. Typically, for a link the travel time would go down (say from $t_1$ to $t_2$) and the number of users would go up (say from $n_1$ to $n_2$). The economic gain consists of two contributions (e.g. Pearce and Nash 1981, Button 1993):

- Gains by existing users: $n_1 (t_1 - t_2)$, where the economic interpretation is that this was already the best option for those people before the modification of the system, and so the improvement of the system is fully counted for those people.
• Gains by new users: \((n_2 - n_1) \frac{(t_1 - t_2)}{2}\), where the intuition is the following: New users one by one switch to the facility when the travel time is slowly decreased. A user that is switching is exactly neutral between two options. Any further improvement of the facility after the switch is then counted as benefit to that user. The first user that switches reaps nearly all the benefits from \(t_1\) to \(t_2\), while the last user that switches reaps nearly no benefits; this is overall approximated by \(\frac{(t_1 - t_2)}{2}\) (known as the “rule of the half” in the literature).

The result of this procedure has a unit of time; it is then converted to monetary units by multiplying it with a value of time.

It should be clear, however, that this is too simplistic for the above scenario. In particular, the standard approach only counts travel time gains, but not schedule delay effects (caused by people choosing a non-preferred time of travel to avoid the toll). However, research indicates that schedule delay effects might contribute more than half of the economic effects of well-chosen time-dependent tolls (Arnott et al 1990). In addition, the standard approach is unable to look at equity aspects of the toll, since it is not able to differentiate between subgroups. Yet, equity effects, for example by age, income, gender, or race, are increasingly becoming important in any discussion of policy measures. Finally, the approach needs to assume a uniform value of time for all travellers, since the approach is not able to differentiate between trip purposes. Yet, it is well known that the value of time may differ by a substantial factor between leisure trips and business trips (for relevant Swiss results see Axhausen et al forthcoming), which also differentiates by the length of the trip; see Jara-Diaz and Guevara, 2003 for the problem of an equity-weighted value of time.

Fortunately, with our multi-agent simulation, it is, in fact, not necessary to add the economic appraisal as it is conventionally done, since the sum of all agent utilities already is the economic performance of the system. This is because the score is the measure that every agent attempts to improve, and a higher score directly measures the amount of improvement that an agent was able to reach. This automatically includes the schedule delay effects, since every agent will have optimally adjusted to any trade-off between time-dependent congestion, time-dependent toll, and schedule delay, including any personal restrictions that an agent may have, such as specific opening times. The multi-agent approach could also automatically include different values of time, since they would be included as person-specific values of \(\beta_{\text{perf}}, \beta_{\text{travels}}\) and \(\beta_{\text{late}}\).

Table 1 shows one such analysis, for the scenario described above. On the left, one finds the contributions to the average agent score (score per capita), averaged over the whole scenario. For example, when switching on the toll, the score contribution from of late arrivals goes from -1.22 to -1.57, implying a score change of -0.35 per capita. Meanwhile, the score contribution due to travelling goes from -5.16 to -5.46 (a score change of -0.61). The latter means that agents in the average travel longer because of the toll; in this case because of the traffic jams caused by the attempt to avoid the toll area (Figure 3 (b)), which in turn is caused by the geometry of the toll area. The positive score contribution of actually doing an activity is also reduced from 114.27 to 113.66 (-0.61), because the time of doing activities is reduced by the increased travel time. Together with the average toll payment of 1.02, the average agent score is reduced from 107.88 to 105.62 (-2.26). Since, however, toll is just a transfer payment, it cannot be included in the economic analysis. This can be emulated by redistributing the toll revenues to the agents. In this case, the average score still goes down, but only to 106.64 (-1.24).
The three rightmost columns of the table show the sums of all score contributions. This result obviously can also be obtained when multiplying the average agent scores with the number of agents, 260,275. The most important information is that the scheme produces, in the cost categories that are considered, a welfare change (after redistribution) of $27,754,428 - 28,078,454 = -324,026$, i.e. a welfare loss. The toll scheme used in the scenario is badly designed. A challenge for future investigations will be to come up with better schemes.

Table 1: Different contributions to the agent scores. Left: scores per capita. Right: sum of scores.

<table>
<thead>
<tr>
<th>PartialScores</th>
<th>Run w/o toll</th>
<th>Run w/ toll</th>
<th>Difference</th>
<th>Run w/o toll</th>
<th>Run w/ toll</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td># agents</td>
<td>260,275</td>
<td>260,275</td>
<td>n/a</td>
<td>260,275</td>
<td>260,275</td>
<td>n/a</td>
</tr>
<tr>
<td>LateArrival</td>
<td>-1.22</td>
<td>-1.57</td>
<td>-0.35</td>
<td>-318,168</td>
<td>-407,661</td>
<td>-89,493</td>
</tr>
<tr>
<td>Performing</td>
<td>114.27</td>
<td>113.66</td>
<td>-0.61</td>
<td>29,740,644</td>
<td>29,582,509</td>
<td>-158,135</td>
</tr>
<tr>
<td>Traveling</td>
<td>-5.16</td>
<td>-5.46</td>
<td>-0.30</td>
<td>-1,344,021</td>
<td>-1,420,420</td>
<td>-76,398</td>
</tr>
<tr>
<td>Toll</td>
<td>0.00</td>
<td>-1.02</td>
<td>-1.02</td>
<td>0</td>
<td>-264,633</td>
<td>-264,633</td>
</tr>
<tr>
<td>SUM</td>
<td>107.88</td>
<td>105.62</td>
<td>-2.26</td>
<td>28,078,454</td>
<td>27,489,795</td>
<td>-588,659</td>
</tr>
<tr>
<td>SUM after re-distribution</td>
<td><strong>107.88</strong></td>
<td><strong>106.64</strong></td>
<td><strong>-1.24</strong></td>
<td><strong>28,078,454</strong></td>
<td><strong>27,754,428</strong></td>
<td><strong>-324,026</strong></td>
</tr>
</tbody>
</table>

Finally, any aggregation by sub-groups is possible since the individual scores are attached to every individual of the synthetic population, thus allowing filtering and aggregation by arbitrary criteria. An example of such an analysis is Figure 6, which allocates the gains and losses to the residential locations of the agents. In this case, the inner-city residents lose since they are captive to the toll (and neither public transit nor noise or other environmental effects are considered), while the residents in the suburbs gain, presumably because they now have a choice to trade between time and money. Long-distance travelers mostly lose, because most of them travel to the center of Zurich.
Figure 6: Spatial distribution of gains and losses of the toll. Yellow: households with gains; red: households with losses.

An additional advantage of such an approach is that the simulation and the appraisal are automatically consistent. Assume, for the purpose of illustration, that a toll is introduced for a fast facility, but that the facility can be circumvented by using a slower and untolled facility. Assume furthermore that the value of time is set to a small value in the simulation, but to a large one in the appraisal. In that situation, in the simulation much traffic would be diverted around the toll facility, since most travelers would rather spend more time than pay money. In the economic appraisal, however, that loss in time would be weighted very heavily. The result would be wrong, because if the travelers would use the larger value of time in the simulation, they would rather pay the toll and save time, thus making them better off. This example is arguably a bit trivial, but it is easy to design examples where such “incentive mismatches” can happen quite easily. In fact, the issue of the schedule delay, included in the simulation but excluded from current appraisal, is one example.

Clearly, such an interpretation does no longer allow arbitrary agent scoring functions, but demands that the scoring functions can be interpreted in economic terms. The score is, in one way or other, the quality-of-life indicator that every agent attempts to optimize, and the sum of all quality-of-life indicators needs to be the relevant economic benefit. The following arguments may be brought forward in this context:

- One could argue that it is erroneous to sum up the scores of all agents, since this tends to, say, mix up gains by the rich with gains by the poor. This is a valid criticism; two arguments can be put forward against it: (1) This argument renders any welfare analysis invalid, not just ours. In that case, other indicators need to be found to compare gains and losses between agents. (2) There is research, for example by Jara-Diaz et al (2007) or by Franklin (2006) that makes the utility of money income-dependent, thus arriving at aggre-
gate benefit measures that may be perceived as more fair.

- One could argue that real people do not systematically optimize any scoring function at all (Simon 1997, Moss and Sent 1999). In that situation, what would remain is to replace the behavioral logic of our agents with an alternative logic. If this could be successfully done, the simulation would still be able to predict future outcomes. The indicators, however, would now need to be based on other principles.

- The approach does not seem to include external effects. However, these could be included by computing the emissions caused by the traffic, and then compute the effect that these emissions have on the agents.

6. CONCLUSION

It was shown that multi-agent simulations can be used to model travellers’ reactions to time-dependent toll in a way most existing transportation planning tools are not able to do. As time-dependent tolls are a much-debated subject in transportation politics, the ability to fully model such tolls and the reactions of travellers may help to find better toll schemes or to base the decision for or against a specific toll scheme more thoroughly. It was also shown that the economic benefit of a measure can be directly derived from the agents’ score, since the agent score is the relevant quality-of-life indicator that every agent attempts to improve.

Multi-agent simulations are able to approach a multitude of questions that current transportation tools are not able to answer. In a world where individuals have more and more freedom to schedule their daily plans, agent-based simulations offer an intuitive way to research complex topics with lots of interdependencies—like the interdependence of different trips for a single traveller throughout the day.

7. ACKNOWLEDGMENTS

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8. BIBLIOGRAPHY


