Economic appraisal of transport measures with a transport microsimulation

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ABSTRACT
Economic appraisal has a simple concept and can easily be calculated for small transport models. In more complex situations however, dependencies between travellers in a network or other network effects make it nearly impossible to calculate the overall gains or losses. We present a way to measure gains or losses in a complex model based on a multi-agent traffic simulation. We introduce a (hypothetical) toll on the road network of a major city and measure the gains or losses for different groups of inhabitants in the research area. By simulating this scenario with different settings we show that the values retrieved from the economic analysis largely depend on the used model. Models that do not support the adaption of departure times to a toll for example may not be able to model the complete reaction of a population to a change and will thus only be able to provide limited conclusions.

INTRODUCTION

Economic appraisal considers the overall gains (or losses) of a project, and compares them with the monetary costs. This paper will concentrate on the gains/losses.

For simple situations, the concept is straightforward to explain. Assume a transport facility that provides transport between A and B which takes 10 hours and is currently used by 2000 users per day. Now assume that the facility is improved so that the transport takes only 9 hours. Also assume that this is the only effect of the improvement (i.e., say, no increased noise emissions etc.) Computing resulting gains is typically done in a two-step procedure:

1. **Gains/losses of existing users.**
   In the example, those are 2000 users times 1 hour of time savings = 2000 hours of time saving per day.
2. **Gains/losses of new users.**
   For this, one first needs the number of additional users, i.e. those users that are attracted to the facility because of its improvement.
   Let us assume that we know the elasticity for the situation under consideration. For example, a time elasticitiy of demand of –0.5 would indicate that our 10% of travel time savings increases demand by 5%, i.e. by 100 users.
   For these 100 new users, typically the "rule of the half" is applied. This will be well known to people in the field, but let us re-state the argument for the sake of completeness: It is assumed that those new users switch one by one to the new facility when travel time is slowly reduced; and the points of switching is exactly when their previous alternative is as good as switching at this point. All further improvements after their switch is, in consequence, their consumer benefit. In consequence, the first new user reaps nearly the same benefits as the existing users, the last new user reaps nearly no benefits at all, and all others are somewhere in between. Under the assumption of sufficient linearity in the process, this mans that new users in the average reap half the benefits of the existing users. In this case, 100 new users times 1 hour of time savings times 1/2 = 50 hours of time savings per day.

Often, the changes of the system are not only in terms of travel time, but include price changes, service quality changes, etc. In such cases, it is common to translate all utility gains in monetary units. Such conversions come, for example, from discrete choice models that allow to derive, say, a "value of time".

Economic appraisal should look at *all* effects of the modification in the system. If one now assumes that the modification of the facility does not only decrease travel time, but also increases noise emissions, then these need to be taken into account. In principle, the noise change for every affected person is computed, then every such noise change is translated to monetary units, and then these monetary units are added to the benefits. Since noise increase is typically considered a negative effect, those monetary units will be negative, reducing the overall benefit of the project. This allows, at least in principle, to include all effects of the modification in the system into one number.

Considerable problems do, however, occur with regards to existing/new users in more complex situations. Here are some examples:

- *Network effects.* Assume that the connection from A to B is part of a network. Some of the new traffic will indeed come from parallel routes, *de*creasing congestion on those routes, and in consequence producing an economic benefit there (and possibly additional users).

Similarly, routes upstream and downstream of the A-B-connection will now suffer *in*creased congestion from the new users, producing a negative benefit for existing users on those facilities.

- *Mode switches.* If, say, the connection from A to B is a fast train but the parallel routes are roads, then these network effects would include mode switches.
- *Multiple choice dimensions.* Many measures that are currently discussed generate adaptation in many more choice dimensions. A typical example is a geographically and temporally differentiated toll, say a congestion charge on certain links from 7am to 10am and 3pm to 7pm. Such a toll may not only trigger the re-routing and mode choice effects described above, but also the following ones:
  - Temporal adaptation, e.g. drive to work before 7am or after 10am.
  - In consequence, temporal adaptation also in other parts of the day.
  - Locational adaptation, e.g. avoid shopping in tolled areas.

  But is someone who uses a facility at a different time-of-day an existing user or a new user? Technically, one would need to include the time-of-use into the definition of the facility, in which case one time slot would lose a user and another one would gain one. However, obtaining numbers for such effects from elasticities seems increasingly hopeless.
- *Equity issues.* Even if two people gain the same amount of time, it may not carry the same utility to them; a similar (and related) argument holds for the utility of money. In consequence, monetarizing all effects with the same conversion factors introduces biases, typically understating the gains/losses of lower income people.

Network effects can be treated with traditional (static) assignment models, or their newer variants, dynamic traffic assignment (DTA) models. They do, however, have problems with the other choice dimensions, since the fixed OD matrices are not able to accomodate temporal effects. Such effects are, if at all, typically included by using elasticities for those temporal OD matrices, with the same problem as above of obtaining believable and consistent numbers for this.

In addition, one needs to ensure that the assignment model and the economic appraisal work according to the same principles. If, say, the route choice model inside the assignment looks at travel time only, but the economic appraisal includes the distance of travel as well, then these two models are not consistent. It is important that the basis on which the synthetic travelers in the assignment make their decisions is the same as the basis of the economic appraisal *(*e.g. *5)*. Finally, even if individual utility (or welfare) functions were known and correctly applied within the simulation model, their "correct" aggregation to population level is a non-trivial and unresolved task.

ECONOMIC APPRAISAL IN MULTI-AGENT SIMULATIONS OF TRANSPORT

This paper discusses a methodology which, in our view, is considerably more consistent and robust than the method of having separate assignment and appraisal procedures. It is the method of multi-agent simulation. The overall approach is explained quickly: Assume a synthetic version of the real world, with many synthetic persons going about their lives. These synthetic persons have a scoring function, and they attempt, by learning and adaptation from one day to the next, to optimize their score. Eventually, they do not find better solutions any more, at which point they all stick with the solution they have found.

Now assume a modification in the system, e.g., as discussed above, a speed increase of a facility, or a toll. All agents attempt to react to this change, by learning and adapting again, until they have once more found a state in which they do not find better solutions any more. In the sense of what was said above, it is important to note that this adaptation will occur also to 2nd, 3rd, ...-order effects of the modification, such as reduced congestion elsewhere, and it will include temporal and locational adaptation.

Clearly, the difference between the sums of all scores for the two scenarios (or the difference between the average scores) is an indicator for the quality of the modification of the system. If the average score increased a lot, then the change was very beneficial for the (synthetic) society as a whole. If it only increased a little, then the change was not very beneficial. In addition, it is easy to identify winners and loosers from the change, since it is possible to identify for each individual agent if he/she has gained or lost.

If one now replaces "score" by "utility", one obtains *immediately* the (internal) benefits of the modification. There is no need to run additional appraisal calculations on top of the simulation. The only thing that is necessary is to use a person-based utility function that is consistent with the economic appraisal. If the individual utility functions are adequately corrected for income, then this aggregation will even take equity issues into account. The details of this will be described in more detail below.

Also the "external" effect of congestion costs is automatically included, since that effect may not be internal to each traveler's decision, but it is certainly internal to our simulation approach (since congestion is modelled explicitly). True external costs are, for example, imissions. But even these are easier to compute from multi-agent simulations because, for example: since every vehicle and traveler is followed individually, it is much easier to obtain emissions values based on vehicle type and engine temperature; since it is known where people are as a function of the time-of-day, it is much more straightforward than with traditional models to include an *im*missions model.

SIMULATION STRUCTURE

Overview

As pointed out before, 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* (and sometimes the 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. Further details will be given below.

The simulation approach is the same as in many of our previous papers (e.g. *22, 3)* on the same subject. The following exposition thus borrows heavily from those papers. Particularly important for the present paper are the sections on the scoring function, since they relate the agent decision-making to the economic appraisal. In addition, the results of this paper are based on a re-implementation of the MATSim framework in Java *(18)*. This has made the computational performance of the code somewhat slower (in particular, distributed computing is no longer supported), but allows faster conceptual progress.

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. Our implementation already at this point supports additional activity types (see, e.g., *(19)*) and additional modes of transport, but more time is needed to validate results with 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 "stringing", the input to a given module is a (possibly incomplete) plan, and the output is a plan with some of the decisions updated. This paper will make use of two modules only: "activity times 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 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 *(15, 4)*. 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.

In the following sections we describe the used modules in more detail.

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 just applies a random "mutation" 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 min, +30 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 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. *20)*. Since each module is implemented as a "plugin", this module can be replaced by a more enhanced implementation if desired.

MATSim contains already a more sophisticated activity scheduling module *(19)*. This will be used in future studies.

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 *(11)*. With this and the knowledge about activity chains, it computes the fastest path from each activity to the next on in the sequence as a function in time.

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 *(10, 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.

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.

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" based on how it performed in the traffic flow simulation.

It is very important to note that our framework always uses *actual plans 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. *24, 9)*. 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 displayed *(21)*.

The procedure of the feedback and learning mechanism is described in detail in *(3)*. 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 by the next 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 $p \propto e^{\beta \cdot S_j}$, where S_j is the score of plan j, and β is an empirical constant. This is similar to a logit model from discrete choice theory.

After this step, the newly selected plans are executed again by the simulation. 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. ns. When the agent generates a new plan using either the

Scores for plans

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 *(2)*). In this work, in order to be consistent with economic appraisal, a simple utility-based approach is used. The approach is related to the Vickrey bottleneck model *(1)*, but is modified in order to be consistent with our approach based on complete daily plans *(7, 22)*. The elements of our approach are as follows:

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

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

  where U_{total} is the total utility for a given plan; n is the number of activities, which equals the number of trips; $U_{perf,i}$ is the (positive) utility earned for performing activity i; $U_{late,i}$ is the (negative) utility earned for arriving late to activity i; and $U_{travel,i}$ 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:

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

  where t_{perf} is the actual performed duration of the activity, t_* is the "typical" duration of an activity, and β_{perf} is the marginal utility of an activity at its typical duration. β_{perf} is the same for all activities, since in equilibrium all activities at their typical duration need to have the same 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 $t_{perf,i}$, implying that the agent should rather cut short other activities. This paper uses

$$t_{0,i} = t_{*,i} \cdot \exp(-\zeta/t_{*,i}) \ .$$

where ζ is a scaling constant set to 10 hours. With this specific form, $U_{perf,i}(t_{*,i}) = \beta_{perf} \cdot \zeta$ is independent of the activity type.[1]

- The (dis)utility of being late is uniformly assumed as:

  $$U_{late,i} = \beta_{late} \cdot t_{late,i} \ ,$$

  where β_{late} is the marginal utility (in Euro/h) for being late, and $t_{late,i}$ is the number of hours late to activity i.
- The (dis)utility of traveling is uniformly assumed as:

  $$U_{travel,i} = \beta_{travel} \cdot t_{travel,i} \ ,$$

  where β_{travel} is the marginal utility (in Euro/h) for travel, and $t_{travel,i}$ is the number of hours spent traveling during trip i.

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 $-\beta_{perf}$. Similarly, that opportunity cost has to be added to the time spent traveling, arriving at an effective (dis)utility of traveling of $-|\beta_{travel}| - \beta_{perf}$.

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 β_{late}. – These values (β_{perf}, $\beta_{perf} + |\beta_{travel}|$, and $|\beta_{late}|$) are the values that would correspond to the consensus values of the parameters of the Vickrey model *(1)* if MATSim would just look for late arrival.

Discussion of the scoring function

In previous work, we have interpreted the scoring function as one of many possibilities to rank alternatives, since ranking is strictly all that was needed. The present paper is significantly different since the scoring function will be used to derive population-wide gains or losses. If these gains or losses are to be interpreted in an appraisal framework, they need to be meaningful within that framework.

In particular, it is important to use scoring functions that score full 24-hour-days, not just parts of them. Only in this way it is possible to move the complex adjustments that travelers can perform—route choices, time choices, mode choices, location choices, activity sequencing, etc.—into one common quantitative framework.

In this context, it is interesting to look at the work of Jara-Díaz and coworkers. In *(14)*, they derive a utility function that covers an arbitrary period of time, and that includes competition between time, money, and consumption. Although their practical model starts with a Cobb-Douglas

[1] This “consequence” is actually the motivation for the specific mathematical form of the activity performance utility contribution. The reason for this motivation is not relevant to this paper, but is described in Charypar and Nagel *(7)*.

type utility function, which is multiplicative instead of additive in its contributions, it should nevertheless be possible to linearize that function and then compare it to our approach. Since as a result of this one obtains just the marginal utilities, the results of this can be taken directly from table 2 of the above paper. One obtains (both for Karlsruhe in Germany and for Thurgau in Switzerland) both for work and for other activities a β_{perf} of approximately w, where w is the wage rate. The *additional* disutility of travel besides the opportunity cost of time (i.e. our β_{trv}) was only estimated for Karlsruhe, and was $-2.5\,w$. Compared to our own value, the value of the paper is large, but the paper itself states that this "value can seem high". Since the MATSim approach will work without problems with other values for β_{trv}, we can safely wait until this discussion is more settled.

One important difference between that work and ours is that we take schedule constraints such as a time window when work should begin explicitly into account. Clearly, without some such time constraints for some of the activities, people would allocate their worktimes all over the day, thus eliminating the rush hours. This would not be realistic.

INPUT DATA & BASIC SCENARIO

Also the scenario is the same as in *(3)*. The following overview are nevertheless included for completeness; further details can be found in *(3)*.

Network

The street network is essentially a Swiss regional planning network, extended with the major European transit corridors (figure 1(a)). It has the fairly typical size of 10 564 nodes and 28 624 links. Also fairly typical, the major attributes on these links are type, length, speed, and capacity.

Counts Data

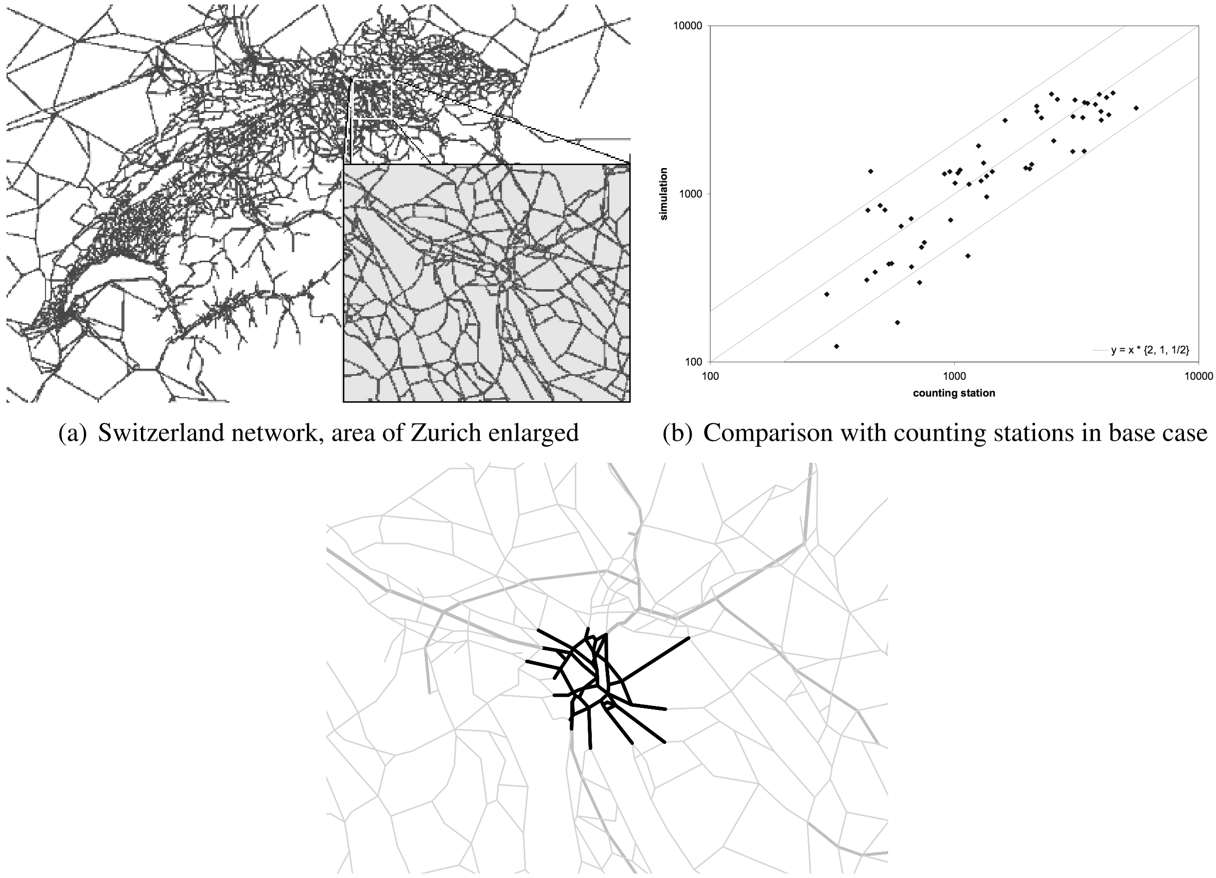
There are about 230 automatic counting stations registered at the Swiss Federal Roads Authority (Bundesamt für Strassen). Of those, we had hourly counts data for 101 stations which we could locate in our network. Since we are just interested in the Zurich area, only a subset of 29 counting stations can be used. Since they are bi-directional, this means that we can compare 58 links to reality.

Demand

Demand was generated essentially by the following steps:

- 24 one-hourly origin-destination matrices were obtained from a more conventional study *(25)*.
- Only the three matrices between 6 and 9 am were retained. It was assumed that those matrices mostly contain trips to work or to education.
- All these trips were routed on the empty network; only those trips using at least one link within 26km of Zurich were retained.
- Trips were converted to agents by assuming that each trip belonged to an agent, and that the agent would do an inverse return trip in the evening.

This resulted in 260 275 agents, all with an activity pattern home-work-home. The initial time structure of those plans had a starting time randomly chosen between 6am and 9am, and a work duration of 8 hours. These were the "initial plans" to all simulations that follow.



(a) Switzerland network, area of Zurich enlarged

(b) Comparison with counting stations in base case

(c) hypothetical toll links in Zurich area

FIGURE 1 Scenario: Switzerland network with validation and toll links for Zurich

Simulation Parameters

Here we describe some of the specific parameters used in the simulation setup for the results presented in the next section.

The maximum number of plans that agents are allowed to keep in the agent database, N, is set to 4 plans. This number results from the scenario size in conjunction with computer memory limitations.

The value of the empirical constant β used to convert plan scores to selection probabilities, is 2.0/Euro.

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

$$\beta_{perf} = +6 Euro/h \;, \;\; \beta_{travel} = -6 Euro/h \;, \quad \text{and} \;\; \beta_{late} = -18 Euro/h \;.$$

Although it is not obvious at first glance, these values mirror the standard values of the Vickrey scenario *(1)*: An agent that arrives early to an activity must wait for the activity to start, therefore forgoing the $\beta_{perf} = +6 \; Euro/h$ 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 $18\ Euro$ per hour late.

In addition, this paper will only look at daily activity chains that consist of one home and one work activity. The optimal times will be set to

$$t_{*,h} = 16\ hours \text{ and } t_{*,w} = 8\ hours\ .$$

With these assumptions, the maximum score is $120\ Euro$ ($60\ Euro$ per activity).

For the work activity a starting time window is defined between 7:08am and 8:52am. These values were set to correspond with those used in a similar study *(17)*.

TOLL CASE

We defined a distance toll for the inner city of Zurich. The toll area includes all the links of the inner city region, but is small enough not to include highways (see figure 1(c)). This gives agents the possibility to drive around the toll area on highways where such are available (Zurich has no closed highway-circle around the city). The diameter of the toll area ranges from 5–7 km. *The toll is restricted to the evening (3pm to 7pm)* and is set to $2\ Euro/km$. This may sound steep, but we wanted a clear signal in this already synthetic scenario. The restriction to the evening was done to demonstrate that with our approach, also an evening-only toll can trigger changes in the morning traffic.

RUNS

A base case without the toll was first run until a relaxed state was reached. Based on this state, three different simulations with the toll applied were run. The three runs differ in the available choice dimensions:

Times-Only 5% of the population adapt the times of their plans in each iteration, all others chose one of their existing plans. Routes need to be maintained from the base case.

Routes-Only 5% of the population adapt the routes of their plans in each iteration. All others chose one of their existing plans. Times need to be maintained from the base case.

Times-And-Routes 5% of the population adapt the times, and 5% of the population adapt the routes of their plans in each iteration. Thus, an agent could adapt times and routes of its plan in different iterations. The remaining 90% of the agents in each iteration chose one of their existing plans. In consequence, both routes and times are adapted in reaction to the toll

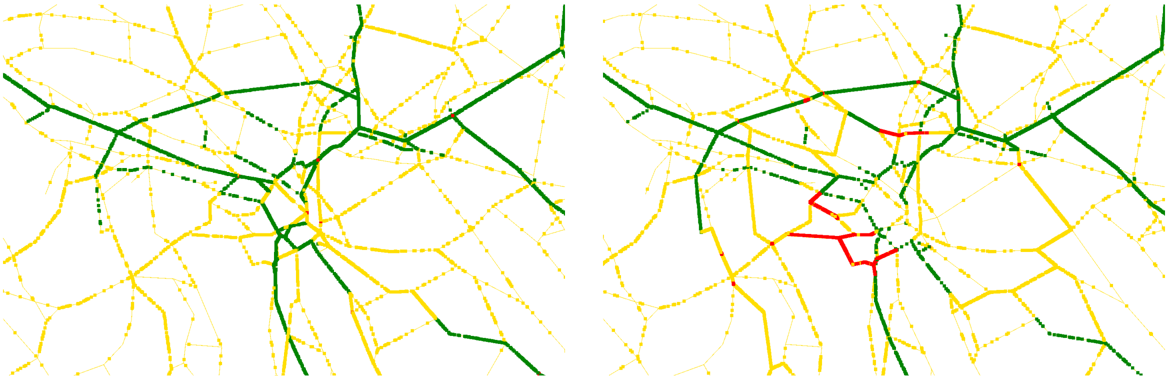
These runs were also run until they reached a relaxed state. Then, the final states of these runs were analyzed and compared to the base case and each other.

Base Case

For validation of the base case, the simulated volumes were compared to those of counting stations. Figure 1(b) shows the comparison of the values. With the exception of a few outliers which need more investigations, most of the volumes are within the range of daily fluctuations.

Toll cases

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



(a) base case (b) toll case (routes + times)

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

	Base case	Times-Only	Routes-Only	t + r
avg. score (incl. toll payments)	107.88	104.90	104.61	105.62
avg. score (after redistrib. of toll rev.)	107.88	107.50	105.93	106.64
avg. trip duration [s]	1 538	1 536	1 757	1 637
economic benefit [k-EUR]		-99.9	-54 678	-34 619
total tolls paid [k-EUR]		676.1	342	265

TABLE 1 Key comparison values for the different cases. "including toll payments" means that the toll payments are deducted from each agent's monetarized utility; "after redistribution of toll revenues" means that the per capita toll revenues are added to each agent's score.

The next comparison is based on the average score of all agents. As the score increases with activity durations and decreases with the time spent travelling, it gives a good indication how well an agent makes use of its time. The average scores of the four runs can be seen in table 1. The score difference (after redistribution of the toll revenues) between the base case and the "Times-Only" run is relatively small, what can be interpreted that the agents are able to adapt well to the toll. The score of the "Routes-Only" run is the worst, meaning that the agents cannot adapt well to the toll or that the adaption leads to high other costs (e.g. much longer travel times).

The score of "Times-And-Routes" is between "Times-Only" and "Routes-Only", which may be unexpected as one could assume that the combination of both should be at least as good as "Times-Only" and the additional route choice may help some agents to further improve. This is indeed the case if one looks at the average score without redistribution of toll revenues. Toll revenues are, however, so much lower than in the Routes-Only case that the score after redistribution is smaller than in Routes-Only.

Additionally, one can look at the average trip durations (table 1). One can observe that the trip durations are considerably *higher* when route-adaption is possible, especially if no additional time-adaption is allowed. This is, in effect, a result of the toll area: Travelers accept longer routes if this means shorter trips within the tolled area.

In consequence, with none of the simulated adaptations the synthetic travelers are able to extract an overall economic benefit from the toll. This is most probably a consequence of the lack of public transit as a choice dimension, together with the non-optimal structure of the toll – even within its second-best structure (not every link is tolled; the toll is not finely time-dependent), the toll is probably too high, and neither the time window(s) nor the tolled area are optimally selected. Nevertheless, it points once more to the fact that second-best tolls need to be carefully constructed, or they *reduce* economic performance of the system – even before the cost of collecting the toll is taken into account.

In addition, increasing the choice dimensions (from "Times-Only" to "Times-And-Routes") does not necessarily make the travelers better off; in addition, the differences in the economic benefits between the different traveler adaptations are huge. This points to the dangers of evaluating tolling schemes with models that simulate unrealistically few choice dimensions; it also means that models with few choice dimensions do not necessarily provide lower bounds to the economic benefits.

Finally, the results show that the order of magnitude of the economic (dis)benefit can be considerably larger than that of the toll revenues. That is, although economic benefits of a well-selected tolling scheme are of the order of the toll revenues, economic disbenefits of a badly selected tolling scheme can be considerably larger.

It is clear that not every agent is similarly affected by the toll. But as directly affected agents can affect other agents, a systematic analysis of winners or losers is not easily possible. In our agent-based approach, we can compare the score of each agent before and after the toll as introduced. The change of score can be plotted on a map for each agent, e.g. at the home-location of the agent. In an aggregated view one can then see in which region people are more likely to be affected by the toll. Figure 3 shows such a spatially disaggregated view. As the toll incomes are not redistributed in this example, there are very few agents that gain score by the introduction of the toll. Note also, that we assumed a constant value of travel time savings for all agents. The higher-income winners of travel time reductions are therefore missing. One can clearly see that in the center where the toll area is, most of the agents lose score, as they cannot avoid the toll when leaving home. But it is interesting to see that there is no abrupt change between the toll area and the area around, but a gradual change. This points out that the chance to find a by-pass around the toll area increases with growing distance from the toll area. – The fact that, when continuing outward, there are eventually again more losing agents is probably due to the chosen setup: Only agents that travel into the region of Zurich are simulated and thus scored.

In the following, we analyze winners and losers a bit more thoroughly. For this, we split the population into four groups:

Out-Out Agents in this group have both the home and the work location outside the toll area.

Out-In These agents live outside the toll area, but have a work place inside the toll area.

In-Out These live within the toll area, but work outside.

In-In These have both activity locations within the toll area.

For each group, there are some expectations as to how they react to and how they are influenced

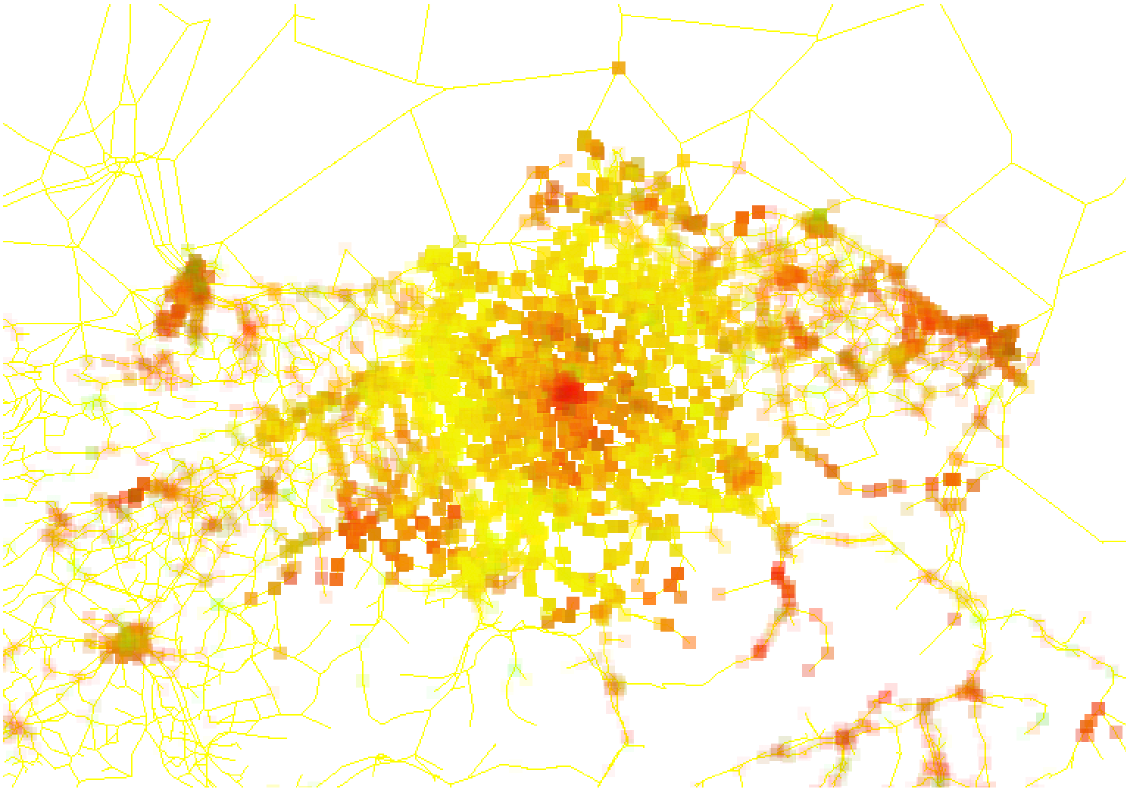


FIGURE 3 The change in agents' score when a toll is applied and agents can adapt their departure times and routes. Red marks agents that lose score, yellow depicts agents not being affected by the toll, and green marks agents that gain score when the toll is introduced.

by the toll. E.g. for the last group, "In-In", one could expect that they have shorter travel times as the traffic volume is lower in the toll area when other agents try to avoid the toll.

Table 2 shows several key values for the different groups and the different simulated cases. In general, the average score in the group "In-In" is much higher than in the other groups. This can be explained with the fact that these agents are likely to have short paths from home to work, and thus not spending much time traveling. It can also be seen that the score is always the lowest in the case where only route-adaption is possible.

If the average morning and evening travel times are compared, one can see that the travel times in the evening increases in all toll cases, with the Routes-Only adaption having the highest travel times among the different cases each time. Of interest is, that the average morning travel times are lower in most cases when time adpation is possible, but higher when only route adaption is possible. *This shows that the toll in the evening has also an influence on the traffic in the morning,* by agents adapting their departure time in the morning to have an optimal work duration and then possibly leaving before or after the toll time in the evening. Although this particular example is a bit artificial, it demonstrates that our approach can pick up temporal changes throughout the day, and not just for a particular trip.

The increase in evening travel time for the group "In-In" is surprising. We would have expected the travel times to be lower or equal to the base case, as there should be fewer other agents traveling

TABLE 2 Key values for the different groups of agents. "avg. score" is after equal redistribution of toll revenues

(a) Out-Out, 176 555 agents

	base	times	routes	t + r
avg. score (after equal redistribution of toll revenues)	109.00	108.82	107.96	108.39
avg. morning travel time [s]	1473	1465	1487	1456
avg. evening travel time [s]	1422	1423	1626	1526
avg. late arrival penalty	-0.94	-1.04	-1.17	-1.15

(b) Out-In, 57 896 agents

	base	times	routes	t + r
avg. score (after equal redistribution of toll revenues)	105.50	104.88	101.55	102.84
avg. morning travel time [s]	1783	1730	1834	1711
avg. evening travel time [s]	1749	1714	2559	2182
avg. late arrival penalty	-1.73	-2.20	-2.16	-2.40

(c) In-Out, 25 331 agents

	base	times	routes	t + r
avg. score (after equal redistribution of toll revenues)	105.33	104.08	101.66	102.96
avg. morning travel time [s]	1843	1827	1866	1822
avg. evening travel time [s]	1724	1740	2450	2118
avg. late arrival penalty	-2.06	-2.75	-2.61	-2.59

(d) In-In, 493 agents

	base	times	routes	t + r
avg. score (after equal redistribution of toll revenues)	115.92	114.80	112.47	113.68
avg. morning travel time [s]	433	440	541	435
avg. evening travel time [s]	460	463	1059	836
avg. late arrival penalty	-0.34	-0.73	-0.50	-0.53

at the same time. Probably some of these agents drive out of the toll area to minimize the toll paid and travel next to their target on non-tolled routes, leading to much longer trips than when travelling through the toll area.

Coming late to the workplace is punished when calculating the score. But agents may prefer to be punished for coming late when it helps them to avoid the toll or helps them otherwise to optimize their schedule. In all toll cases, the agents accept higher penalties (also called schedule delay costs) than they do in the base case. So the agents accept additional schedule delay costs for minimizing the impact of a toll.

DISCUSSION

It is important to note that our approach initially contains the individual changes for each individual agent, and their individual valuation (score) of these changes. Given the choice dimensions that we allowed the agents in the simulation (time choice, route choice, or both), they have tried to find the best reaction to the changed situation. The aggregation method is completely left to the analyst. As examples, we have (a) provided a graphical depiction of winners/losers by their home location, and (b) have differentiated if home and/or work locations lie within the toll area. Given data availability (which we will very soon have for the Zurich area), arbitrary segmentations of the population are possible, for example according to income or to gender. Even the extraction of complete distributions (e.g. according to income) will be possible.

The above *analysis* differs between values of time for performing an activity, doing nothing, or travelling, but uses homogeneous values of those values across the population. Our general *approach*, however, could also differentiate these values across the population, in the extreme giving each member of the population different values (e.g. depending on demographics) *(12, 13, 16)*. It would, for example, make sense to perform the complete calculation in "utils" instead of in monetarized values. This would, for example, pick up the effect that the marginal utility of money may be different across income groups – implying that lower income groups lose more by paying a toll than higher income groups, but conversely that lower income groups gain more by receiving a toll redistribution than higher income groups *(23, 8)*. Alternatively, gains could be weighted according to income in some agreed way. Such analyses are planned for the future – the possibility of such analyses is, in fact, one of the strong arguments for using microscopic models such as MATSim.

Although it has been said before, it is worth re-iterating that mode choice is missing as a choice dimension in the above analysis. Given the importance of the public transit system in Zurich, this may be one of the main reasons why the toll produces no economic benefits. Public transit as a choice dimension is already implemented for MATSim, but needs to be tested.

CONCLUSIONS

We have shown that multi-agent simulations can be used to more easily research economic aspects of planned transport measures than what current models allow for. Because multi-agent simulation is disaggregated, it is possible to calculate for every synthetic traveler individually her/his economic benefits or losses. Data aggregations are then possible in any way the analyst desires; two illustrative examples are shown in the paper. The approach also easily allows to separate the traveler reactions by choice dimensions, most importantly also allowing for consistent adaptation along the time axis (an evening-only toll causing changes in the morning traffic).

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