Policy evaluation in multi-agent transport simulations

2009-jul-31

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Words: 6010 + 4 figures

ABSTRACT
Standard economic appraisal allows projects to go forward if the aggregated benefit is larger than the cost, independent from distributional effects. Thus, it may for example be possible that a measure provides huge benefits to a small number of people, while cuasing small losses to a large number of people. Under many circumstances, this may not be desired. The microscopic simulation approach presented in this paper is capable to help design better solutions in such situations. In particular, it is shown that it is possible to connect the behavioral model to income levels in a meaningful and data-driven way. Simulations of simplified scenarios with those behavioral parameters lead to plausible and justifiable results. In addition, and going beyond other work, it is shown that the approach works in a full-scale real world example. This will, in future studies, be used to do full distributional analysis of transport policy measures.

INTRODUCTION

Measures and policies in transportation systems aim at improving the system as a whole. Changes to the system that provide huge benefits for a few while causing disbenefits to broad masses, however, are hard to implement in democratically organized societies, even if they provide an overall benefit. Studies indicate that, e.g., tolls can be regressive if the toll revenue redistribution scheme is not considered at the same time, and may so increase the inequality in wealth distribution *(*e.g. *1).* An option to reach broad acceptance for such policies may be to include the redistribution of total gains into the scheme. Then, methods and tools are needed that simulate welfare changes due to policies on a highly granulated level, i.e. considering each individual person of society. With such tools, policy makers would be able to consider different redistribution schemes before submitting the proposed policy to public discussion.

Traditional transport planing tools using the four-step process combined with standard economic appraisal methods *(*e.g. *2)* are not able to provide such analysis. In order to bridge this gap, multi-agent microsimulations can be used. Large-scale multi-agent traffic simulations are capable of simulating the complete day-plans of several millions of individuals (agents) *(3).* In contrast to traditional models, all attributes that are attached to the synthetic travelers are kept during the simulation process, thus enabling highly granulated analysis *(4).* Being aware of all attributes enables the possibility to attach to every traveller an individual utility function that is used to maximize the individual return of travel choices during the simulation process.

In the context of policy evaluation, the simulation results can immediately be used to identify winners and losers, since the utility scores of the individual agents are kept and can be compared between scenarios agent-by-agent. They can also be aggregated in arbitrary ways, based on any demographic attributes that are available including spatial information of high resolution. Welfare computations, if desired, can be done on top of that, without having to resort to indirect measures such as link travel times or inter-zonal impedances. The usual problems when wishing to monetarize the individual utility measures still apply *(5)*, but at least there is a consistent framework of what these things mean for each individual agent, similar to efforts to base such analysis directly on discrete choice models *(6).*

In this paper we focus on the measurement of welfare using multi-agent approaches in more detail. We study how income can be included in utility calculations, and describe the implications on the simulation model. The paper describes what person-based travel behavior simulations can do to address such problems, and provides simulation results for the issues.

SIMULATION STRUCTURE

Overview

In our simulation, each traveler of the real system is modeled as an individual agent. 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 choose 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. *7)*:

A **plan** contains the itinerary of activities that 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.

A plan can be modified by various **modules**. In the test scenario, the Time Adaptation module is used, while the large-scale application additionally uses a Router module. The *Time Adaptation* module changes the timing of an agent's plan. A very simple approach is used which just applies a random "mutation" to the duration attributes of the agent's activities *(8)*. The *Router* is a time-dependent best path algorithm *(9)*, normally using as link costs the link travel times from the previous iteration. *Mode choice* will not be simulated by a module per se, but instead by making sure that every agent has at least one "car" and at least one "public transit" plan *(10)*.

One of the plans is of every agent is marked as "selected". The **traffic flow simulation** executes all agents' selected plans simultaneously on the network, and provides output describing what happened to each individual agent during the execution of its plan. The *car traffic flow* simulation is implemented as a queue simulation, where each street (link) is represented as a first-in first-out queue with two restrictions *(11, 12)*: 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 *public transit simulation* simply assumes that travel by public transit takes twice as long as travel by car on the fastest route in an empty network *(10)*, and that the travel distance is 1.5 times the beeline distance. Public transit is assumed to run continuously and without capacity restrictions.

The modules base their decisions on the output of the traffic flow simulation (e.g. knowledge of congestion) using **feedback** from the multi-agent simulation structure *(13, 14)*. 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.

In every iteration, 10% of the agents generate new plans by taking an existing plan, making a copy of it, and then modifying the copy with the Time Adaptation or the Router module. The other agents reuse one of their existing plans. The probability to change the selected plan is calculated according to

$$p_{change} = min(1, \alpha \cdot e^{\beta \cdot (s_{random} - s_{current})/2}) \ , \tag{1}$$

where

- α: The probability to change if both plans have the same score, set to 1%
- β: A sensitivity parameter, set to 20 for the tests and to 2 for the Zurich runs
- $s_{\{random,current\}}$: The score of the current/random plan (see later)

In the steady state, this model is equivalent to the standard multinomial logit model $p_j = \frac{e^{\beta \cdot s_j}}{\sum_i e^{\beta \cdot s_i}}$, where p_j is the probability for plan j to be selected.

The repetition of the iteration cycle coupled with the agent database enables the agents to improve their plans over many iterations. As the number of plans that one agent may have is limited by memory constraints, the plan with the worst performance is deleted when a new plan is added to a person which already has the maximum number of plans permitted. The iteration cycle 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 is stable.

Scoring Plans

In order to compare plans, it is necessary to assign a quantitative score to the performance of each plan. In this work, in order to be consistent with economic appraisal, 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:

  $$U_{total} = \sum_{i=1}^{n} U_{perf,i} + \sum_{i=1}^{n} U_{late,i} + \sum_{i=1}^{n} U_{tr,i} \ , \tag{2}$$

  where U_{total} is the total utility for a given plan; n is the number of activities, which equals the number of trips (the first and the last activity are counted as one); $U_{perf,i}$ is the (positive) utility earned for performing activity i; $U_{late,i}$ is the (negative) utility earned for arriving late to activity i; and $U_{tr,i}$ is the (usually negative) utility earned for traveling during trip i.
- A logarithmic form is used for the positive utility earned by performing an activity:

  $$U_{perf,i}(t_{perf,i}) = \beta_{perf} \cdot t_{*,i} \cdot \ln\left(\frac{t_{perf,i}}{t_{0,i}}\right) \tag{3}$$

  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. As long as dropping activities from the plan is not allowed, $t_{0,i}$ has essentially no effect.

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

$$U_{late,i} = \beta_{late} \cdot t_{late,i} \ , \tag{4}$$

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. β_{late} is usually negative.
- The (dis)utility of traveling used in this paper is estimated from survey data. It will be explained in an extra section.

In principle, arriving 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 $-\beta_{perf}\, t_{*,i}/t_{perf,i} \approx -\beta_{perf}$. Similarly, that opportunity cost has to be added to the time spent traveling.

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}.

ESTIMATED UTILITY FUNCTION

Estimation Data

Data for estimation of the utility function presented in this paper is taken from stated preference surveys run by Institut for Transport Planning and System at ETH Zurich *(15)*. Estimation of the late arrival penalty is retrieved from a time and route choice survey. All other estimations use data from a mode and route choice survey.

Functional form

There is some agreement that income effects play an important role in transport policy, see, e.g., *(16, 17, 18, 5***?** *, 1)*. The argument essentially is that monetary price changes affect different income groups differently. Conversely, if different income groups need to be compensated for losses or should be taxed for gains from non-monetary policy measures, these offsetting payments are income-dependent. This paper demonstrates how these insights can be used constructively in an agent-based approach.

The travel (dis)utility function used here is loosely based on *(***?** *)* and *(1)*:

$$\begin{array}{lcccccc} U_{car,i} & = & & & \beta_{cost} \cdot \ln(y_i - c_{i,car}) & + & \beta_{tt_{car}} \cdot t_{i,car} \\ U_{pt,i} & = & \beta_{income} \cdot \ln(y_i) & + & \beta_{cost} \cdot \ln(y_i - c_{i,pt}) & + & \beta_{tt_{pt}} \cdot t_{i,pt} \ , \end{array} \tag{5}$$

where y is average per-trip income, c is monetary cost, and t is travel time. Note that utilities are computed in true "utils"; a possible conversion into units of money or "hours of leisure time" *(19)* needs to be done separately. Income per trip y_i is obtained by the following calculation:

$$y_i = \frac{y_{year,HH}}{n_{HH} \cdot 240 \cdot 3.5} \ ,$$

where $y_{year,HH}$ depicts the income of the household per year, n_{HH} the number of persons in the household, 3.5 is the average number of trips per day, and 240 the number of work days.

It was, however, not possible to use this form directly, since the survey data contains relatively long trips, meaning that $y_i - c_i$ can become negative, in which case the logarithm does not work.[1] To circumvent this problem, Taylor's theorem is used to approximate the logarithm,

$$\ln(y_i - c_i) \approx \ln(y_i) - c_i \cdot [ln(y_i)]' = ln(y_i) - \frac{c_i}{y_i} \,, \tag{6}$$

which results into the quite normal $1/y$ dependency of the cost term and thus seems quite plausible.

Applying (6) to (5) results in the functional form estimated for this study:

$$U_{car,i} = \qquad \beta_{cost} \cdot \left(\ln(y_i) - \frac{c_{i,car}}{y_i} \right) + \beta_{tt_{car}} \cdot t_{i,car} \tag{7}$$

$$U_{pt,i} = \beta_{income} \cdot \ln(y_i) + \beta_{cost} \cdot \left(\ln(y_i) - \frac{c_{i,pt}}{y_i} \right) + \beta_{tt_{pt}} \cdot t_{i,pt} \tag{8}$$

As β_{income} was estimated not significantly different from zero *(20)*, the model was re-estimated without that term. This results in *(20)*

$$\beta_{cost} = 1.31 \,, \qquad \beta_{tt_{car}} = -2.83/h \,, \qquad \text{and} \qquad \beta_{tt_{pt}} = -1.86/h \,,$$

i.e. a model

$$\begin{aligned} U_{car,i} &= + \; 1.31 \ln(y_i/CHF) \; - \; 1.31 \frac{c_{i,car}}{y_i} \; - \; \frac{2.83}{h} t_{i,car} \\ U_{pt,i} &= + \; 1.31 \ln(y_i/CHF) \; - \; 1.31 \frac{c_{i,pt}}{y_i} \; - \; \frac{1.86}{h} t_{i,pt} \end{aligned} \tag{9}$$

It may be a bit surprising that the disutility of travel time comes out larger for car than for public transit. It is, however, consistent with the higher costs of $c_{pt} = 0.28 CHF/km \cdot l_{pt}$ assumed for public transit than for car ($c_{car} = 0.12 CHF/km \cdot l_{car}$), which were used in the survey *(15)* and will be used in the simulations. Clearly and somewhat unusual, for Switzerland public transit is the higher value mode compared to car.

An open question at this point is how much of the the travel time disutility is the opportunity cost of time, and how much is an additional disutility caused by the travel. This approach is consistent with economic approaches where there is an inherent opportunity cost of time and additional utilities or disutilities depending on how the time is spent (e.g. *(19)*), but these values cannot be obtained from the survey as it was taken. Because of this, it was assumed that being in a car neither adds nor subtracts from the opportunity cost of time. This implies a $\beta_{perf} = 2.83/h$ in (2), and modifies the trip portions of the utility functions to

$$\begin{aligned} U_{car,i} &= + \; 1.31 \ln(y_i/CHF) \; - \; 1.31 \frac{c_{i,car}}{y_i} \\ U_{pt,i} &= + \; 1.31 \ln(y_i/CHF) \; - \; 1.31 \frac{c_{i,pt}}{y_i} \; + \; \frac{0.97}{h} t_{i,pt} \end{aligned} \tag{10}$$

Recall that now additional disutility of travel is caused by the opportunity cost of time.

[1] One may argue that in such cases the model should reject the journey completely, at least if it is a daily journey (M. Wegener, personal communication).

Adding income utility on a per-trip basis is a result of starting with (5). As long as the number of trips per day is kept constant for every traveller in the model, this has no influence on the results.

Income Generation

Estimation of income for the synthetic population is based on data from Kanton Zurich.[2] Income distribution is retrieved from a Lorenz curve for the year 2006.[3] The median income for that year is 46300 CHF.

First the functional form of the Lorenz curve was approximated. Then the income curve, i.e. the first derivative of the Lorenz curve, was calculated *(21)*.[4] To generate personal incomes for the agents, a random number in $[0, 1]$ is drawn from a uniform distribution. For this number, the corresponding value on the income curve is calculated and multiplied by the median income. Doing this for all members of the synthetic population we derive an income distribution similar to the Lorenz curve.

TEST SCENARIO

Network

To test the estimated utility function choice model, a simple test network was used (see Fig. 1), consisting only of a cycle of one-way links. The capacity of the links is (unrealistically) high as to minimize the influence these links have on the traffic, essentially making it possible for most agents to drive with free speed. One link before the work location has reduced capacity of 1000 veh / h, building a bottleneck.

Initial plans

The synthetic population consists of 2000 agents. All agents start at their home activity, which they initially leave at 06:00. They initial drive to work with a car, where they initially stay for 8 hours, after which they drive home again. The home to work trip has a length of 17.5 km while the way back is 32.5 km long. Speed limit is at 50 km / h so the free speed travel time from home to work by car is 21 minutes while 39 minutes are needed for the way back home. Thus the total free speed travel time driving by car is 60 minutes. As the agents are forced to remain on that route, the scenario is similar to the well-known Vickrey bottleneck scenario *(22, 23)*; also see below for more details.

In addition, each agent possesses an initially non-active plan that uses the public transit mode for both trips. These trips take twice as long as by car at freespeed, i.e. 42 minutes from home to work, and 78 minutes for the way back. The total public transit travel time is 120 minutes. In contrast to the car travel times, these transit travel times are not affected by congestion. Since public transit is assumed to run continuously and without capacity restrictions, a home departure at time t will always result in a work arrival at $t + 42min$.

Work opens at 07:00 am and closes at 06:00 pm. In order to obtain the similarity to the Vickrey scenario, an additional behavioral parameter of $\beta_{late} = -1.52/h$ is used, i.e. deducting $-1.52/h \cdot t_{late}$ for arriving late. This value is obtained from estimating a model with time and route choice

[2] `http://www.statistik.zh.ch/themenportal/themen/index.php`, last access 01.08.2009

[3] `http://www.statistik.zh.ch/themenportal/themen/aktuell_detail.php?id=2752&tb=4&mt=0`, last access 01.08.2009

[4] The Lorenz curve is $L(x) \propto \int_0^x y(\xi)\, d\xi$. Therefore, $L'(x) \propto y(x)$. The correct scaling is given by the fact that $y(0.5)$ is the median income.

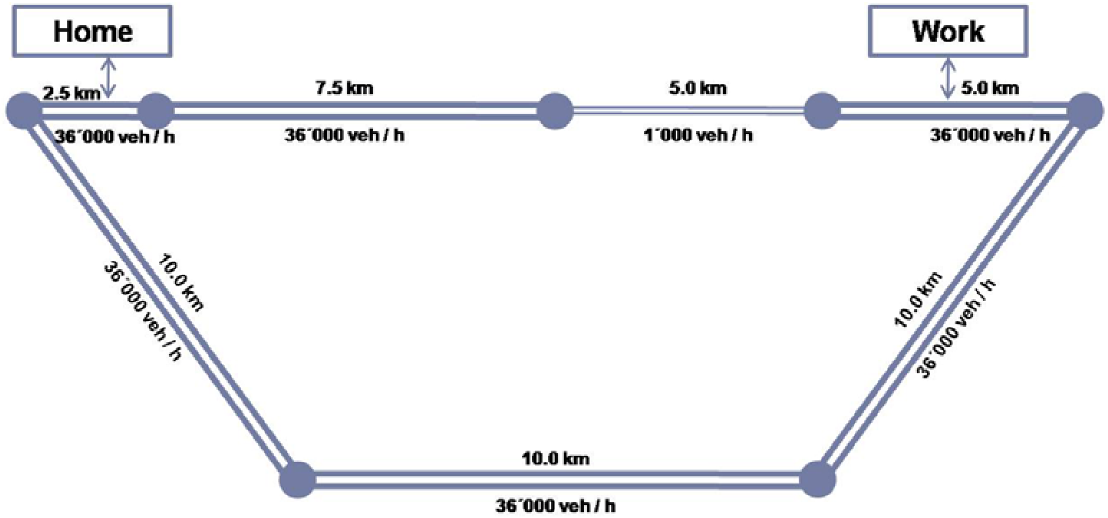


FIGURE 1 The layout of the testnetwork with the attributes of the links. Traffic runs clockwise starting at the home location. Between home and work location lies a bottleneck link with a capacity restriction to 1000 veh / h.

survey data from *(15)*.

Behavioral parameters
The behavioral parameters are set and can be interpreted as follows:

- utility of performing an activity at its typical duration: $\beta_{perf} = 2.83/h$
- marginal disutility of arriving late: $\beta_{late} = -1.52/h$
- marginal utility offset for traveling with a car: $\beta_{tr,car} = 0$
- marginal utility offset for traveling with public transit mode: $\beta_{pt} = +0.97/h$
- factor in logit process (1): $\beta = 20$
- "typical" durations of $t_{*,w} = 8$ and $t_{*,h} = 12$ hours for work and home mean that work and home times have a tendency to arrange themselves with a ratio of 8:12 (i.e. 2:3).
  The activity of the home activity is "wrapped around", i.e. a departure at 6am and a return at 5pm results in a home activity duration of 13 hours.

A work start exactly at 7:00am means that (a) no utility can be accumulated from an arrival earlier than 7:00am, and (b) any late arrival is immediately punished with $\beta_{late} = -1.52/h$.

Because of the argument made earlier regarding the opportunity cost of foregone activity time when arriving early, the *effective* marginal disutility of early arrival is $\beta_{early,eff} = -\beta_{perf}\, t_{*,i}/t_{perf,i} \approx -\beta_{perf} = -2.83/h$. The effective marginal disutility of car traveling is, by the same argument, $\beta_{travel,eff} = -\beta_{perf}\, t_{*,i}/t_{perf,i} \approx -\beta_{perf} - |\beta_{tr,car}| \approx -2.83/h$. The return trip has no influence since there is no congestion.

Overall, the *effective* values of time of our study would correspond to the values $(\beta_{early,eff}, \beta_{travel,eff}, \beta_{late,eff}) = (-2.83, -2.83, -1.52)$ of the Vickrey scenario *(23, 22)*. This has the consequence that all travellers that arrive early do not care if they sit in congestion or wait at the entrance, and that travellers are willing to arrive $1/1.52 \approx 0.66$ min later in order to save

$1/2.83 \approx 0.35$ min of travel or waiting time. These values are a bit unusual in comparison with the usual Vickrey values; they were left in place since they come from the data and they seem plausible with respect to a region with a highly qualified mostly white-collar work force.

Simulation runs

First, a "preparatory run" is performed by running the base case for 2000 iterations. During the first 1000 iterations, 10% of the agents perform "time adaptation", i.e. they make a copy of an existing plan and shift each element of its time structure by a random amount between zero and 7.5min. The other 90% of the agents switch between their existing plans according to (1), which means that they potentially also switch the mode. During the second 1000 iterations, time adaptation is switched off; in consequence, agents only switch between existing options according to (1). That is, their choice set now remains fixed to what they have found in the first 1000 iterations, and they choose within this set according to a logit model.

After this, the policy is introduced. Every policy case is run for another 2000 iterations, starting from the final iteration of the preparatory run. For the first 1000 iterations of the policy case, the time adaption module is again switched on, with the same 10% replanning fraction. The final 1000 iterations are once more with a fixed choice set. At the same time, the base case is continued with that same treatment as the policy case.

The following policies are investigated:

public transit price increase: The price of public transit, i.e. $c_{i,pt}$, is raised from 0.28 to 0.36 CHF/km, i.e. by more than 28%.

public transit speed increase: Speed of public transit is increased, now taking only 1.8 (instead of 2.0) times as long as the freespeed car, i.e. a speed increase of 10%.

combined: Combination of the two.

Results

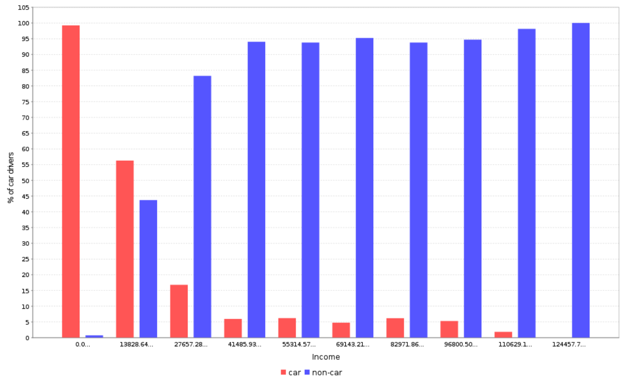
Since car is the low value and public transit the high value mode, low income people predominantly use the car while high income people predominantly use public transit (Fig. 2a). When the public transit price is increased, the mode split predictably shifts from public transit to car, from 40%:60% to 43%:57% (car:pt). Also predictably but importantly, this shift happens through a shift of the income level that divides the two regimes – this level, naturally, moves to higher incomes (Fig. 2b).

Conversely, a public transit speed increase shifts the mode split from car to public transit, to 34%:66% (car:pt), and again, this is achieved by a shift of the income level that divides the two regimes, this time to lower incomes (Fig. 2c).

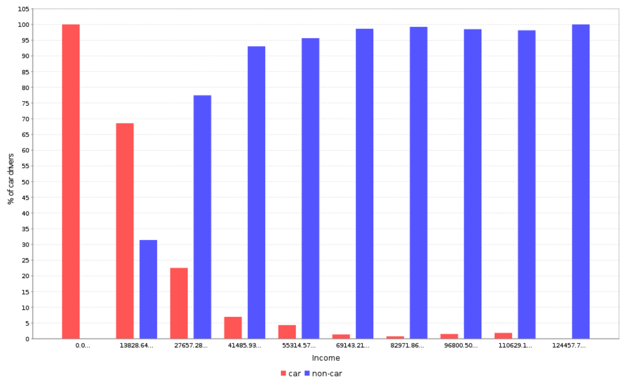
Combining public transit price and speed increase leads to a mode split of 38%:62%, and a mode split across income groups that resembles the base case (Fig. 2d).

Fig. 3 shows, for every agent, the score difference between the base case and the policy case, as a function of the income level. In all three cases, one notices a "fan" of points at the lower income levels, and a more correlated structure stretching across nearly all income ranges except for the lowest. The "fan" can be traced back to the car users, who, because of stochastic congestion effects, face rather strong fluctuations of their utilities. In contrast, the correlated structure is caused by the public transit users.

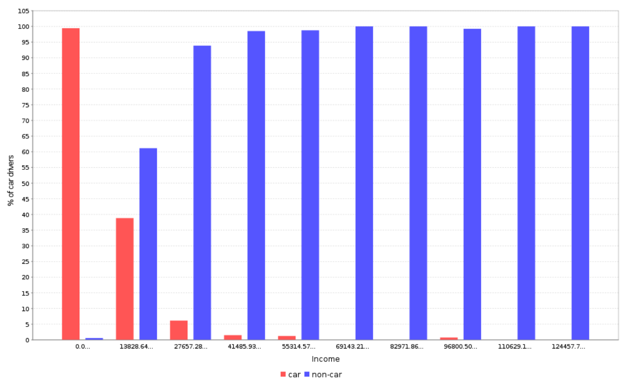
Predictably, the public transit users lose from the price increase, and they gain from the speed increase. Note, however, how nicely the simulation picks up the effect that the price increase affects lower income people more than higher income people, while the inverse is true for the



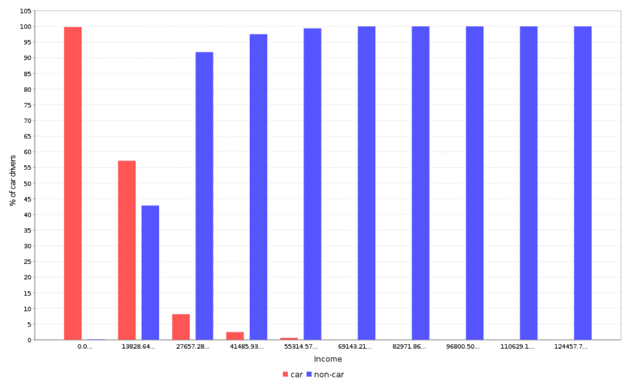
(a) base case



(b) policy price only

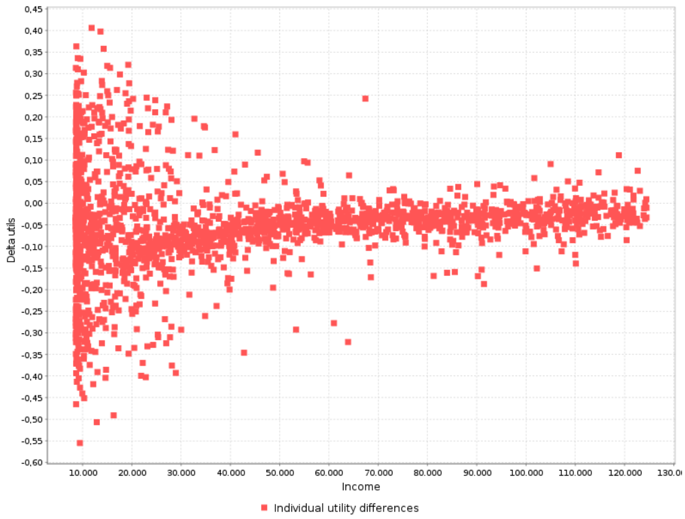


(c) policy speed only

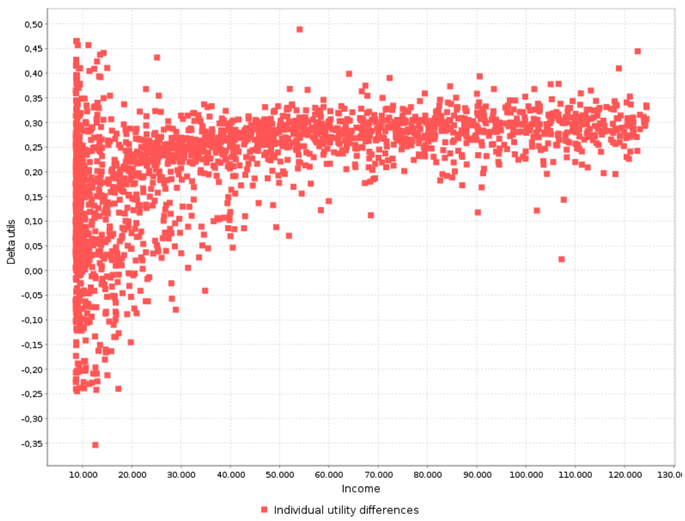


(d) policy price and speed

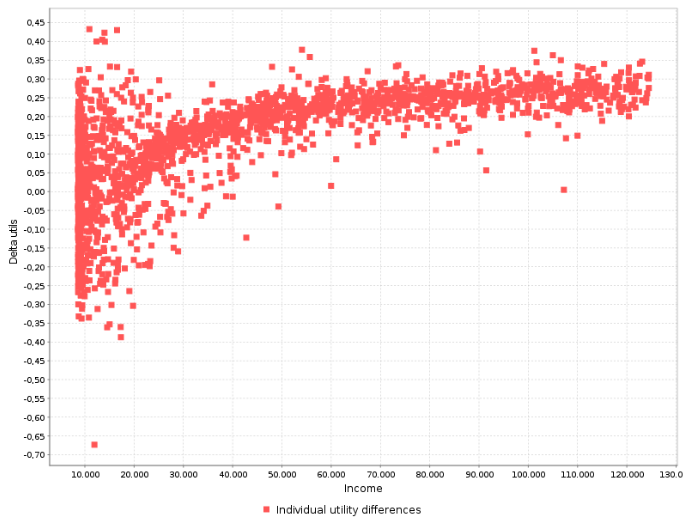
FIGURE 2 Mode choice over income classes. Red bars depict car drivers, blue bars public transit users



(a) price increase



(b) speed increase



(c) price increase and speed increase

FIGURE 3 Utility differences of agents between policy case and base case by income.

speed increase. In the combined scenario, incomes up to 10k neither gain nor lose, while higher income groups increasingly gain.

Car users are affected by the congestion effects: The price increase leads to an increased car share, thus more car congestion, thus utility losses for car users; the speed increase leads to a reduced car share, thus less car congestion, thus utility gains for car users. The gains and losses of the car users, however, are much weaker than the stochastic fluctuations.

Overall, the results demonstrate that the approach picks up the distributional effects of transport policy measures. While both price and quality-of-service changes affect mode share, achieving this with price changes affects the lower income groups more, while achieving this with quality-of-service changes affect the higher income groups more.

SCENARIO – ZURICH SWITZERLAND

Network and Population

The income-dependent utility function was also applied to a large-scale, real-world scenario. We used the area of Zurich, Switzerland, for this application, which has about 1 million inhabitants. The following paragraphs only give a simplified description of the scenario. A full description of the scenario can be found in *(24)*.

The network is a Swiss regional planning network that includes the major European transit corridors. It consists of 24 180 nodes and 60 492 links.

The simulated demand consists of all travelers within Switzerland that are inside an imaginary 30 km boundary around Zurich at least once during their day *(24, 25)*. All agents have complete day plans with activities like *home*, *work*, *education*, *shopping*, *leisure*, based on microcensus information *(26, 27)*. The time window during which activities can be performed is limited to certain hours of the day: *work* and *education* can be performed from 07:00 to 18:00, *shopping* from 08:00 to 20:00, while *home* and *leisure* has no restrictions. Unlike the test scenario described above, there is no punishment for being late. This is not possible because agents can have more than one work activity, e.g. one in the morning and one in the afternoon. In such a case it is complicated to specify when an agent starts an activity late or not.

To speed up computations, a random 10% sample is taken from the synthetic population for simulation, consisting of 181 725 agents. In this large-scale application, the agents cannot only perform time adaptation as described in a previous section, but can also do route adaptation, which is essential for the car mode.

Traffic counts

Simulated traffic volumes are compared with the hourly traffic volumes from 159 real-world counting stations. Fig. 4 shows, in blue, the mean relative error of previous Zurich scenario runs *(24)* between hourly flows in reality and hourly flows from the simulation. That run was based on $\beta_{perf} = 6/h$, $\beta_{tr,car} = -6/h$, $\beta_{pt} = -3/h$, and no dependence on travel distance or income.

The red curve depicts the same for the new, estimated utility function. One notices a slight increase in the average error using the estimated function. This seems acceptable, given that the results are now obtained from a data-based behavioral utility function. Nevertheless, it is a bit surprising that, at least at the aggregated level, there is so little difference between the runs. Presumably, this is due to the fact that the activity patterns, preferred activity durations, opening times, and transportation network structure are dominating the results. In particular, given the fact that the traffic counts are reproduced much better between 8am and 7pm than the remainder of the day, one may speculate that the need to squeeze all activities into the available opening times is, in fact, the dominating force.

CONCLUSION

Standard economic appraisal allows projects to go forward if the aggregated benefit is larger than the cost, independent from distributional effects. Thus, it may for example be possible that a measure provides large benefits to a small number of people, while cuasing small losses to a large number of people. Under many circumstances, this may not be desired.

The microscopic simulation approach presented in this paper is capable to help design better solutions in such situations. In particular, it is shown that it is possible to connect the behavioral model to income levels in a meaningful and data-driven way. Simulations of simplified scenarios

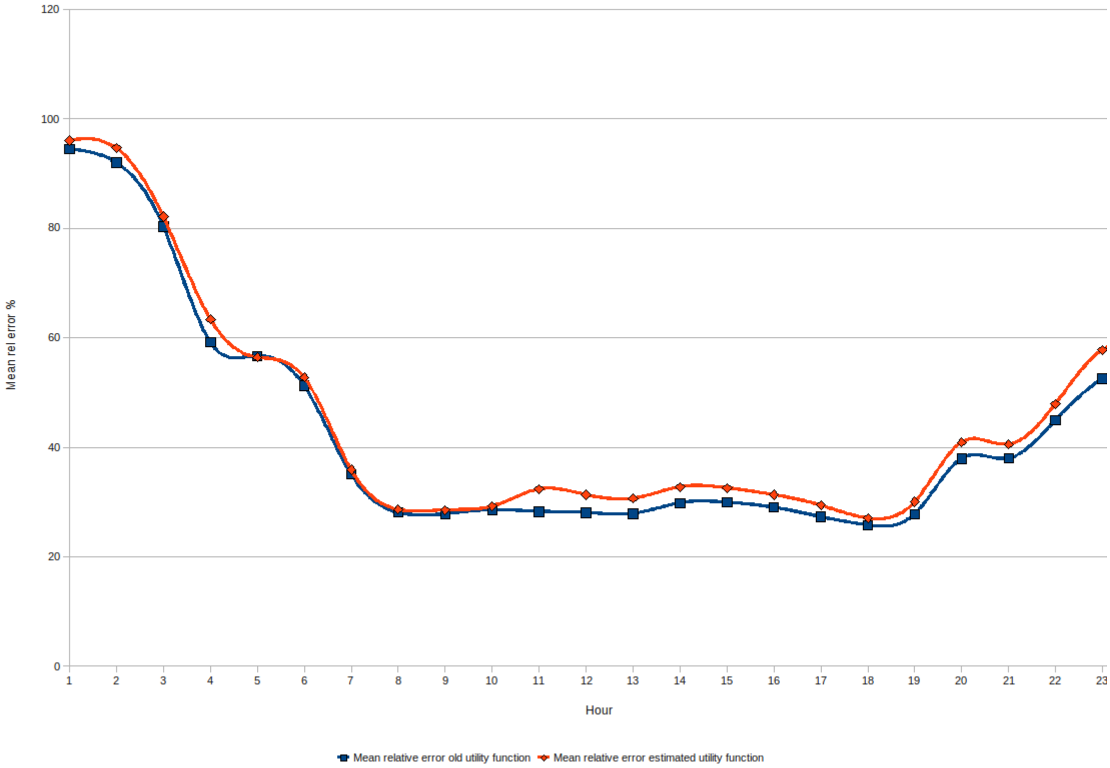


FIGURE 4 Realism of the two runs. 159 traffic counting stations provide real traffic counts for the Zurich area. The blue curve shows the relative error when comparing the simulation traffic volumes of the previously used utility function with real values, the blue curve the comparison using the estimated utility function of this paper.

with those behavioral parameters lead to plausible and justifiable results. In addition, and going beyond *(1)*, it is shown that the approach works in a full-scale real world example. This will, in future studies, be used to do full distributional analysis of transport policy measures.

ACKNOWLEDGMENTS

This work was funded in part by the "Bundesministerium für Bildung und Forschung" (BMBF) within the research project "Adaptive Verkehrssteuerung" (Advest), and in part by the "German Research Foundation" (DFG) within the research project "Detailed evaluation of transport policies using microsimulation". Our compute cluster is maintained by the Department of Mathematics at TU Berlin.

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