Integrating a simple model for mode choice into a multi-agent simulation of travel behavior and traffic flow

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Abstract

This paper describes an approach how mode choice can be integrated into a multi-agent simulation of travel behavior and traffic flow. This is achieved by giving every agent multiple plans with different modes, have the agents try out these plans in the "synthetic reality", adapt the time structure of the plans, and eventually settle on good plans. The approach is tested with a real world base case for the city of Zurich, and a sensitivity study concerning the "disutility" of travelling by a non-car mode. The main results are that the integration is conceptually straightforward, that the model behaves in a plausible way, and that the microscopic nature of the model allows detailed analyses that are impossible with more aggregated models.

1 Introduction

The traditional transportation planning forecasting process is the four-step process, consisting of the following four steps (e.g. Ortúzar and Willumsen, 1995):

1. **Trip generation**, where sources and sinks of travel are computed
2. **Destination choice**, where sources and sinks are connected to trips. This results in the so-called origin-destination (OD) matrix
3. **Mode choice**, where the trips are differentiated by mode
4. **Assignment**, where routes are found for the trips, taking into account that much-used streets become slower ('congested assignment').

It has been clear for quite some time now that this approach is at odds with anything that is time dependent. At best, seperate runs of the four step process are made for, say, morning peak, mid-day, evening peak, and night. Within the periods, everything is "static" (or steady-state), in the sense flow rates are constant throughout the periods.

The biggest barrier to time dependence is arguably the assignment step, for which a lot of mathematical theory is known (e.g. Sheffi, 1985). Much of that mathematical theory, however, is no longer valid when physical queues, i.s. spillback that uses up physical space, are introduced (Daganzo, 1998). Phyisical queues, however, seem indispensable for a more realistic description of the traffic system. One way to address this problem is *dynamic* traffic assignment (DTA) (Peeta and Ziliaskopoulos, 2001; Bliemer, 2003; Mahut et al., 2003). Although there are different formulations, a standard formulation is to have time-dependent OD matrices, e.g. one matrix for every hour. This sequence of matrices is then loaded onto the network, in such a way that traffic that does not arrive during one time slice is carried into the next time slice, and routes are assigned such that some normative behavioral model (e.g. a Nash equilibrium) is reached.

In order to generate these time-dependent OD demand matrices, there seem to be two mainstream approaches:

- Lohse (1997) (also see Lohse et al., 2006), now implemented into the software VISEVA (PTV www page, accessed 2004; Beuck et al., 2007), generates separate OD matrices for different "trip purpose pairs". Trip purpose pairs are, for example, home→work, home→shop, work→leisure, work→home, etc., i.e. the trip purposes at *both* ends. These OD matrices are then multiplied, for every time period, with a weighting function that describes how much traffic of this specific trip purpose pair happens at that time period. For example, home→work traffic probably mostly happens in the morning, while work→leisure traffic probably mostly happens in the afternoon. The data for this can be derived from time use surveys.

- The second mainstram approach to generate time-dependent OD demand matrices is activity-based demand generation (e.g. Bowman et al., 1999; Bhat et al., 2004; Pendyala and Kitamura, 2005; Arentze and Timmermans, 2000; Timmermans, 2005) generates travellers' daily plans, and transport appears as a derived demand to connect activities at different locations. There are many methods to achieve this, ranging from random utility modelling (Bowman et al., 1999; Bhat et al., 2004) to (partly) rule-based approaches (Arentze and Timmermans, 2000).

In both cases, any feedback of congestion effects to the demand generation is done using aggregated quantities such as aggregated link travel times, or zone-to-zone impedances (Ettema et al., 2003; Lin et al., in press). This can fail rather badly, since the aggregation errors can lead to implausible behavioral responses. For example, a router using link travel times that are aggregated into 15 minute bins can, at the onset of congestion, predict rather wrong travel times, and in consequence try to avoid congestion that in synthetic reality does not exist when the vehicle is actually there (Raney and Nagel, 2004).

An alternative is to use the iterations which are already done on the level of the route assignment routine and to extend them to other choice dimensions. de Palma and Marchal (2002) describe an early step in this direction, where not only routes but also departure times are adjusted individually for each trip, based on performance in previous iterations. MATSim (MATSIM www page, accessed 2008) takes this approach further:

- The simulation system does not only consider trips, but full daily plans and in consequence individual travellers.

- Additional choice dimensions are added one by one. Time choice has been added in earlier work (Balmer et al., 2005); in this paper, the addition of mode choice will be described.

This addition of mode choice will be achieved in the following way:

1. Each agent obtains multiple initial plans, one for every mode.

2. The agents try those plans in different settings, modify the time and routing structure of those plans, etc.

3. The agents eventually settle down on a set of plans that suits their needs best.

Conceptually, MATSim agents individually follow genetic algorithms (GA) (Goldberg, 1989; Holland, 1992), where the MATSim plans correspond to the genes in a GA, the execution of the traffic flow simulation together with the scoring that follows corresponds to the computation of the fitness function in a GA, the MATSim selection between different plans corresponds to selection in a GA, and the algorithms that modify existing MATSim plans correspond to mutation operators in a GA. The MATSim system as a whole, consisting of these adaptive agents, is a co-evolutionary adaptive system (Hraber et al., 1994; Palmer et al., 1994; Arthur, 1994; Hofbauer and Sigmund, 1998; Drossel, 2001). This abstract computational system is then filled with meaning from transport engineering and travel behavior research. For example, the traffic flow simulation is constructed from transport engineering principles (e.g Gerlough and Huber, 1975); the scoring function and the related selection operation follows a utility-based approach (e.g. Ben-Akiva and Lerman, 1985); and the generation and mutation of the plans follows concepts from travel behavior research, in particular activity-based demand modelling (e.g. Timmermans, 2005).

The paper is organized as follows. Section 2 describes the overall approach, concentrating on conceptual aspects, the co-evolutionary adaptation, and the scoring. Section 3 then describes the mode choice model. Section 4 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 and the specific simulation runs that were undertaken. Finally section 5 summarizes the results and provides an outlook to future work.

2 Simulation Structure

The following describes the structure of the simulation that is used. It is the standard structure of MATSim, as described at many places (Raney and Nagel, 2006b; Balmer et al., 2005). Readers familiar with the MATSim approach can skip this section.

2.1 Overview

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

- Each agent independently generates a so-called *plan*, which encodes its intentions during a certain time period, typically a day.
- All agents' plans are simultaneously executed in the simulation of the physical system. This is also called the *traffic flow simulation* or *mobility simulation*.

- There is a mechanism that allows agents to *learn*. In our implementation, the system iterates between plans generation and traffic flow simulation. The system remembers several plans per agent, and scores the performance of each plan. Agents normally chose the plan with the highest score, sometimes re-evaluate plans with bad scores, and sometimes obtain new plans by modifying copies of existing plans.

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.

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 (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 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.

2.2 Activity Time Allocation Module

This module is called to change the timing of an agent's plan. At this point, a simple approach is used which 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. Nagel et al., 2004). Since each module is implemented as a "plugin", this module can be replaced by a more enhanced implementation if desired.

2.3 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.

2.4 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 – for example, the 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, at 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, e.g., will be used by the router), trip travel time, trip length, percentage of congestion, and so on.

2.5 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.

Our framework always uses *actual plans performance* for the score. This is in 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 www page, accessed 2007; Ettema et al., 2003).

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

1. The agent database starts with at least one complete plan per agent, with one plan marked as "selected".
2. The simulation executes these marked plans simultaneously and outputs events.
3. 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 $p_j = e^{\beta U_j} / \sum_i e^{\beta U_i}$, where U_j is the score (utility) of plan j, and β is an empirical constant. This is the familiar logit model (e.g. Ben-Akiva and Lerman, 1985).
4. Next, the simulation executes the newly selected plans, that is, it goes back to 2.

This 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 seems stable.

2.6 Scores (=utilities) 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 Prashker, 2003)). In this work, a utility-based approach is used. The approach is related to the Vickrey bottleneck model (Arnott et al., 1990), but is modified in order to be consistent with our approach based on complete daily plans (Charypar and Nagel, 2005; Raney and Nagel, 2006a). The elements of our approach are as follows:

- The total utility 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 (the first and the last activity on a day are "stitched together"); $U_{perf,i}$ 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, the utility at the typical duration, $U_{perf,i}(t_{*,i}) = \beta_{perf} \cdot \zeta$ is independent of the activity type.[1]

[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 (2005).

- 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 need to be compared to the values of the parameters of the Vickrey model (Arnott et al., 1990).

2.7 Discussion of the scoring function

In our investigations, it turns out that the following aspects of the scoring function are of prime importance:

- The typical duration, $t_{*,i}$ of each activity type.
- The height of the utility function at its typical duration, i.e. $U(t_{*,i})$, for each activity type.
- The slope of the utility function at its typical duration, for each activity type.
- The curvature of the utility function at its typical duration, for each activity type.

In consequence, at first glance it seems that there are four free parameters per activity type. Fortunately, this number can be reduced by the following arguments:

- In order to be optimal, the activity durations need to be selected such that all slopes (= marginal utilities) are the same, at least in the absence of constraints such as opening times or other influences such as strongly variable travel times. This implies that one can, as a first approximation, set all slopes at the typical duration to the same value. This ends up being the marginal utility of leisure time (Jara-Díaz et al., 2004), which can be estimated.

- By the same argument, it should be possible to estimate "typical durations" of activity times from time use surveys: If marginal utilities are the same, then the typical durations need to be set such that the typical durations from time use surveys are recovered. – In our current work, the typical durations are directly taken from actual durations from time use surveys in Switzerland (see below).
- As long as activity dropping is not possible, the absolute height of the utility does not matter. This justifies the arbitrary setting of $U_{perf,i}(t_{*,i}) = \beta_{perf} \cdot \zeta$. It also means that the absolute level of our agent score is meaningless, and *only differences between scores can be interpreted as utility differences.*

The curvature at the typical durations remains as the most problematic parameter. This parameter determines the flexibility of an activity: a large curvature means that the marginal utility increases strongly when the activity duration is reduced, implying that time should rather be saved somewhere else. Conversely, the marginal utility *de*creases strongly when the activity duration is increased, implying that additional time should rather be spent somewhere else. The above utility function has a second derivative of $-\beta_{perf}/t_{*,i}$. This means that, with the above utility function, no free parameter is left to separately adjust the curvature at the typical duration. The second derivative is inversely proportional to the typical duration, meaning that longer activities always have more flexibility than shorter activities.

3 Mode choice model

This section will present and charactarize the mode choice model. This will be achieved by two additional elements in MATSim:

- an extension of the scoring function, now taking into account the (dis)utility of travel by non-car modes
- a mechanism to generate non-car plans

All agents will carry on to maximize personal utility but the calculation of this utility depends on chosen mode.

3.1 Extension of scoring function

The disutility of traveling from chapter 2.6 is $U_{travel,i} = \beta_{travel} \cdot t_{travel,i}$, where $t_{travel,i}$ is the travel time in hours spent for trip i and β_{travel} is the marginal utility of travel. To include alternative modes, it is sufficient to make the (dis)utility of travel dependent on the mode. A simple approach to do this is to use different valuations of the time for the two modes:

$$U_{travel,mode,i} = \begin{cases} \beta_{car} \cdot t_{travel,i} & \text{if trip } i \text{ is by car} \\ \beta_{non\text{-}car} \cdot t_{travel,i} & \text{if trip } i \text{ is not by car} \end{cases}$$

where β_{car} and $\beta_{non\text{-}car}$ are the marginal utilities of traveling by car or not by car (in Euro/h), respectively, and $t_{travel,i}$ is the number of hours spent traveling during trip i. For the time being this leaves out all more complicated aspects of non-car travel valuations, such as changing vehicles, schedule restrictions, waiting times, etc.

The task is now to select values for those marginal utilities. For this, it is important to note once more that β_{car} and $\beta_{non\text{-}car}$ are *not* values of time by themselves, but they are *additional* marginal disutilities caused by traveling, in addition to the marginal opportunity cost of time. This is consistent with econometric approaches (Jara-Díaz and Guerra, 2003).

3.2 Generating non-car plans

Besides the separate scoring of the non-car travel, it is necessary to generate plans that use the non-car mode. In all investigations described in this paper, this is done by giving all travellers an additional initial plan that uses the non-car mode on all trips. The duration of every non-car trip is assumed to take approximately twice as long as the car mode at free speed.[2]

This is based on the (informally stated) goal of the Berlin public transit company to generally achieve door-to-door travel times that are no longer than twice as long as car travel times. This, in turn, is based on the observation that non-captive travellers can be recruited into public transit when it is faster than this benchmark (Reinhold, 2006). For the purposes of the present paper, it is assumed that all non-car modes very roughly have the shared characteristics that they are slower than the (non-congested) car mode—this will be further disaggregated in future work. In the same vein, both for car and for non-car trips there are no separate considerations of access and egress.

The non-car plan can undergo time adaptations as all other plans can. In consequence, it is quite possible that an agent will end up having multiple car plans *and* multiple non-car plans. If one mode scores consistently worse than the other mode, most plans of that mode will eventually be deleted. However, the plans deletion mechanism is programmed in a way that the last plan of every mode needs to be kept. In this way, it is ensured that travellers maintain the option to switch modes at all times.

[2]The algorithm to construct the trip durations of the non-car mode was later modified to take *exactly* twice as long as the car mode at free speed. This explains differences between this paper and other publications on the same subject. Eventually, these estimates need to be replaced by real-world data.

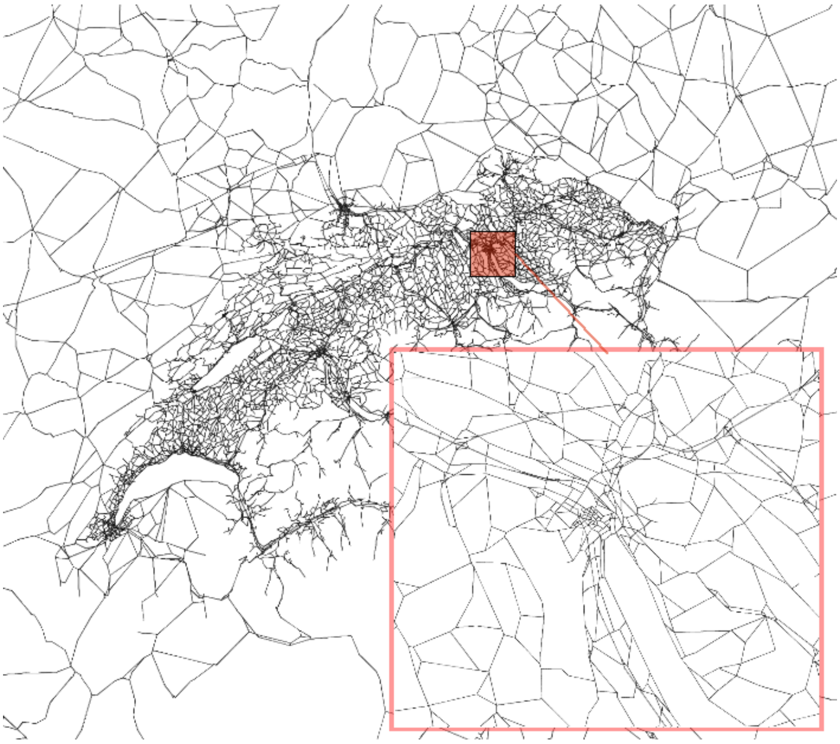

Figure 1: Switzerland network, area of Zurich enlarged

4 Zurich Scenario

4.1 Network

The scenario covers the area of Zurich, Switzerland, which has about 1m inhabitants. It is shown in Fig. 1. The network is a Swiss regional planning network, which includes the major European transit corridors. It consists of 24 180 nodes and 60 492 links.

The links have attributes (flow capacity, free speed, number of lanes, . . .) suitable for static traffic assignment. These turned out to be generated with a view towards *national* forecasts, and were thus not sufficiently detailed within the city of Zurich with its dense road network. Thus, all links within a circle with radius 4 kilometers around the center of Zurich have their attributes modified as follows:

- links corresponding to primary roads in OpenStreetMap[3] get a capacity of at least 2000 vehicles per hour. If the original capacity is higher than that, the capacity is not changed.
- links corresponding to secondary roads in OpenStreetMap keep their original capacity (usually between 1000 and 2000 veh/h).

[3]see `http://www.openstreetmap.org`

Activity type	Opening time	Closing time
Home	00:00	24:00
Work	06:00	20:00
Education	06:00	20:00
Shop	08:00	20:00
Leisure	00:00	24:00

Table 1: Activity opening and closing times used in the scenario.

- all other links get a capacity of at most 600 veh/h. If the original capacity is lower, it is not changed.
- a few single links are manually adjusted based on local knowledge.

4.2 Population, initial demand

The simulated demand consists of all travelers within Switzerland that cross at least once during their day an imaginary boundary around Zurich. This boundary is defined as a circle with a radius of 30 kilometers and with its center at “Bellevue”, a central place in the city of Zurich. To speed up computations, a random 10 % sample was chosen for simulation, consisting of 181 725 agents.

The travelers have complete daily activity patterns based on microcensus information (Balmer et al., 2006; Meister et al., 2008). Such activity patterns can include activities of type *home*, *work*, *education*, *shopping*, and *leisure*. Each agent gets two plans based on the same activity pattern. The first plan uses only “car” as transportation mode, while the second plan uses only “non–car”.

This demand was then extended with people crossing the borders of Switzerland and travelling within the region of Zurich, either because they live in neighboring countries but work in Switzerland, because they live in Switzerland but work outside, or because they travel through Switzerland on transit. Again, a 10% sample was taken, adding 5759 agents to the demand. This part of the demand is important to get more realistic traffic volumes especially on highways. These agents of our population have no option to switch from mode car to non–car. We will refer to them as “transit” traffic in the following paragraphs.

To specify opening and closing times for the facilities where activities are performed, activities are classified by type, i.e. it is distinguished between home, work, education, shop and leisure activity types. Opening and closing times for the facilities where those types are performed are shown in Table 1.

Parameter	Value
β_{perf}	6 Euro /h
β_{car}	-6 Euro /h
$\beta_{non\text{-}car}$	-3 Euro /h and -6 Euro /h
β (existing plans)	4

Table 2: Behavioral parameters used in the scenario.

4.3 Simulation runs and base case

The simulation is run for 250 iterations, to retrieve a relaxed state in which the initial plans are adapted to the traffic conditions. In each iteration, 10 % of the agents adapt routes and 10 % adapt activity times. With the remaining probability of 80%, agents select one of the existing plans as described in Sec. 2.5. In doing so they can choose between modes car or non-car. This is done until iteration 200 is reached. In the last 50 iterations route and time adaption is switched off and 100% of the agents select plans based on the experienced performance. Thus all agents stop to try new options and return to the plans that have been experienced as best ones. The used parameter values are summarized in Tab. 2.

For the Zurich region, data from 159 traffic counting stations is available. The hourly measured traffic volumes can be compared with the amount of traffic of the $\beta_{non\text{-}car} = -3$ Euro/h scenario simulation runs. This comparison is shown in Fig. 2. Most important is the red curve which is calculated for each hour by following formula:

$$\frac{\text{Simulated traffic volume} - \text{Real traffic volume}}{\text{Real traffic volume}} * 100$$

During the night, i.e. from 00:00 am till 07:00 am, the simulation deviates from reality with 50% to 100%. However the simulation results for the daytime, i.e. from 07:00 am till 09:00 pm, have a relative deviation of about 30%. After 09:00 pm the deviation is 40% or slightly higher.

4.4 Sensitivity

In order to test the model's sensitivity, exactly the same set-up was run again, from the same initial conditions, but this time with a $\beta_{non\text{-}car}$ of -6 Euro/h. Since at this point the model does not differentiate between public transit and other non-car modes, such a change is a bit difficult to interpret in practical terms, but it might be loosely taken as a price increase of all non-car modes.

The results of the two simulation runs of the Zurich scenario are summarized in Tab. 3. The first and second column contain the data for the $\beta_{non\text{-}car}$ of -3 and -6, respectively.

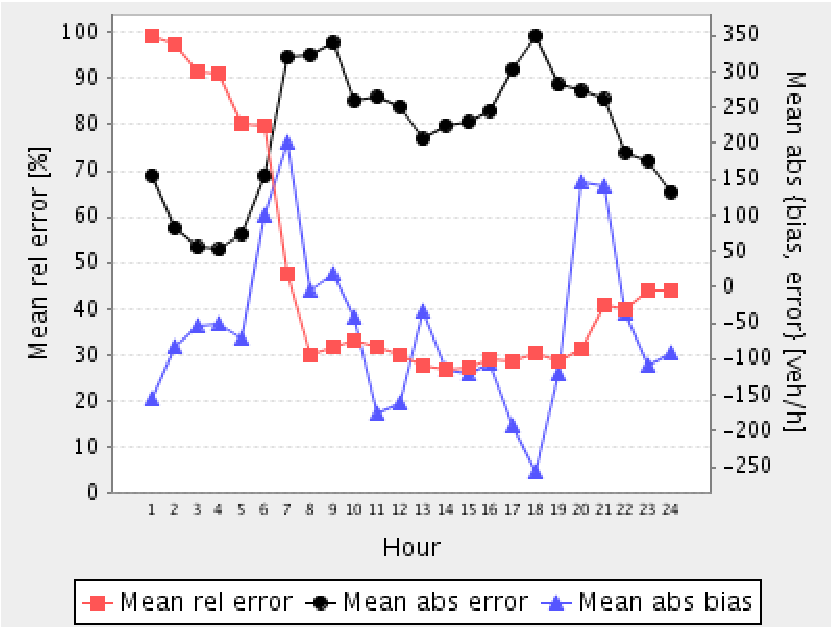

Figure 2: Realism of the $\beta_{non\text{-}car} = -3$ Euro /h simulation run. 159 traffic counting stations provide real traffic counts for the Zurich area. The three curves show mean relative error (red), mean absolute error (black) and the mean absolute bias (blue) when comparing the traffic volumes of the base case with the real values.

The third column contains the difference between the $\beta_{non\text{-}car} = -3$ and the $\beta_{non\text{-}car} = -6$ values.

The first line contains the number of agents used for simulation. The next two lines contain indicators for the performance of the system as a whole. While the average trip duration increases a non-significant 2 seconds, the average score decreases by 0.84 Eu. This is plausible, since an effective price increase in the system without compensation elsewhere needs to lead to a decrease in utility.

4.5 Winner-loser analysis

It is immediately possible to identify the winners and losers of a policy. An example of such an analysis, which shows the spatial distribution of losers, is Fig. 3. The map pictures the greater Zurich area, whereby each dot symbolizes an agent's home location. Colorization is based on the relative change using the $\beta_{non\text{-}car} = -3$ scenario as base and the $\beta_{non\text{-}car} = -6$ scenario as compare case. Red colored dots stand for agents that lose more than 1 % utility.

A look at the spatial distribution of the losers in Fig. 3 shows that losers are more likely to reside at the border of the city area. In the base scenario, where $\beta_{non\text{-}car}$ is set to -3,

	$\beta_{non\text{-}car} = -3$	$\beta_{non\text{-}car} = -6$	Difference
Size of population	181725	181725	0
Avg. trip duration [s]	714	716	+2
Avg. score [EUR]	177.36	176.53	−0.84
Car rate [%]	42.31	60.25	+17.94
non-car rate [%]	54.62	36.68	−17.94
Transit rate [%]	3.07	3.07	0

Table 3: Results for the Zurich scenarios with a $\beta_{non\text{-}car}$ of −3 and −6. The third column displays the difference, i.e. values of $\beta_{non\text{-}car} = -3$ scenario are subtracted from the scenario for $\beta_{non\text{-}car} = -6$.

non-car traveling is a profitable option for them. Changing $\beta_{non\text{-}car}$ to −6 forces them to either "pay" more, or to switch to car, which results in more congestion on streets and thus longer traveltimes for everybody.

This is reflected by Fig. 4. Red and green dots symbolize home locations of agents that stay at the choosen mode despite the change of $\beta_{non\text{-}car}$. Yellow dots depict the agents changing from car to non-car while blue dots stand for the contrary mode swap. One can see that most of the agents living in the city area stay with their original non-car mode. Residents living at the borders of the metropolitan area tend to switch more often from non-car to car. The reason is that most of their trips are longer than the trips of their inner city counterparts. And with longer trips, the change of $\beta_{non\text{-}car}$ has a stronger effect, and the time advantage of the car (in non-congested conditions) plays a larger role.

These images are meant as a first illustration of what will be possible with microscopic methods. Future analysis should probe more deeply into the details of the behavioral mechanics. For example, one could imagine the following approach:

1. Introduce the policy measure but force every traveller to behave as before.

   This should identify those people who presumably feel most threatened by a policy measure; let us call them "directly affected".

2. Allow all agents to re-compute their route choice *once*.

   In the example discussed in this paper, this would presumably lead to a relatively large initial mode change reaction.

3. Let the system relax along all relevant choice dimensions by doing a large number of iterations.

   In the example discussed in this paper, this would presuambly lead to some of the the initial mode changes being reversed, because of increased congestion in the car mode.

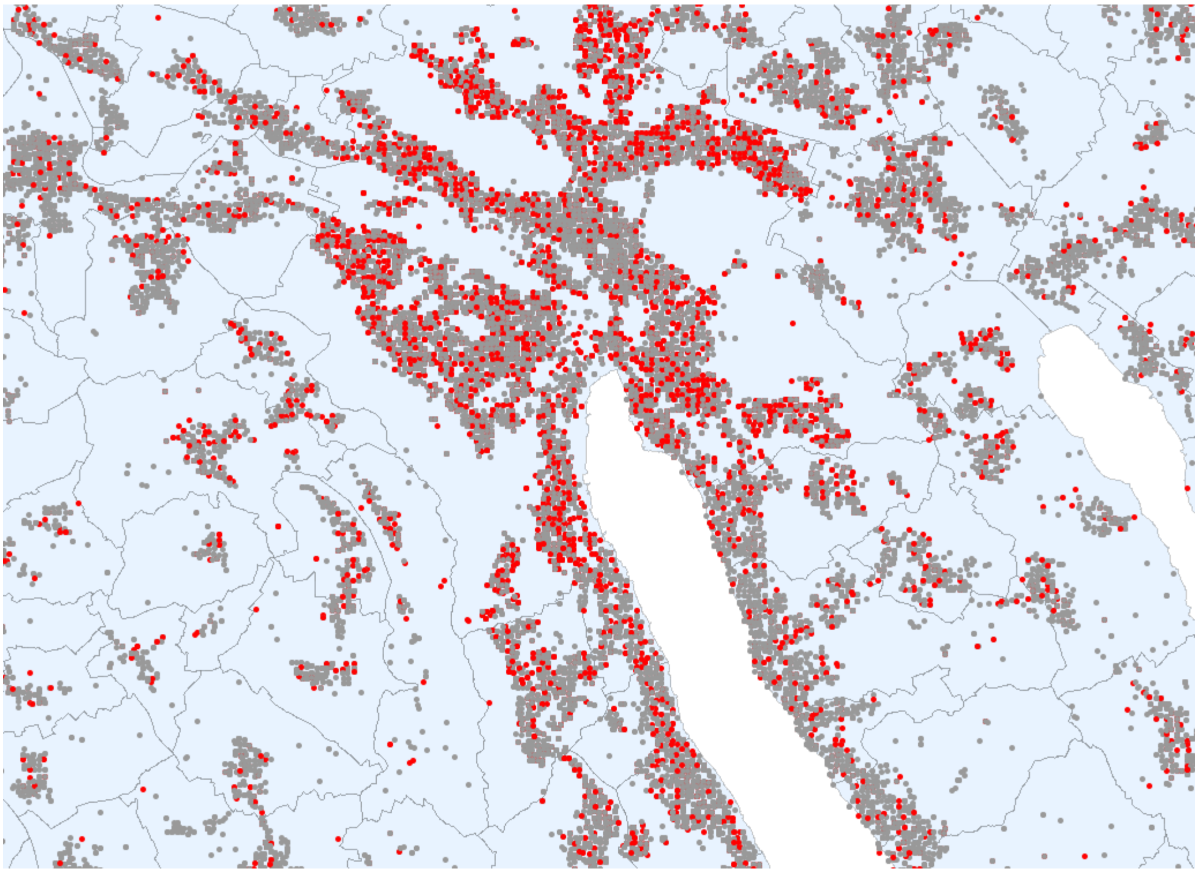

Figure 3: Map of the greater Zurich area. Each dot locates a home location of an agent. Red colored dots stand for agents losing more than 1 % of utility due to the raise of $\beta_{non\text{-}car}$

> The final result would identify the distribution of winners and losers after the system has adapted to the policy measure. It may be important to find out in how far the gains and losses have shifted from those that were "directly" affected to those that are now indirectly affected (e.g. via increased car mode congestion).

5 Conclusion

In this paper, a mode choice model for the MATSim framework was presented. The model provides a possibility to analyze car vs. non-car travel decisions. To achieve this, our scoring function was extended by one parameter, $\beta_{non\text{-}car}$. In addition, initial plans using the non-car mode were generated by assuming that they take approximately twice as long as the car in an empty network. Nothing more is needed to simulate mode choice. The parameter $\beta_{non\text{-}car}$ can be interpreted as the agents' disutility of using the non-car mode; it needs to be compated with a similar parameter for the car, β_{car}.

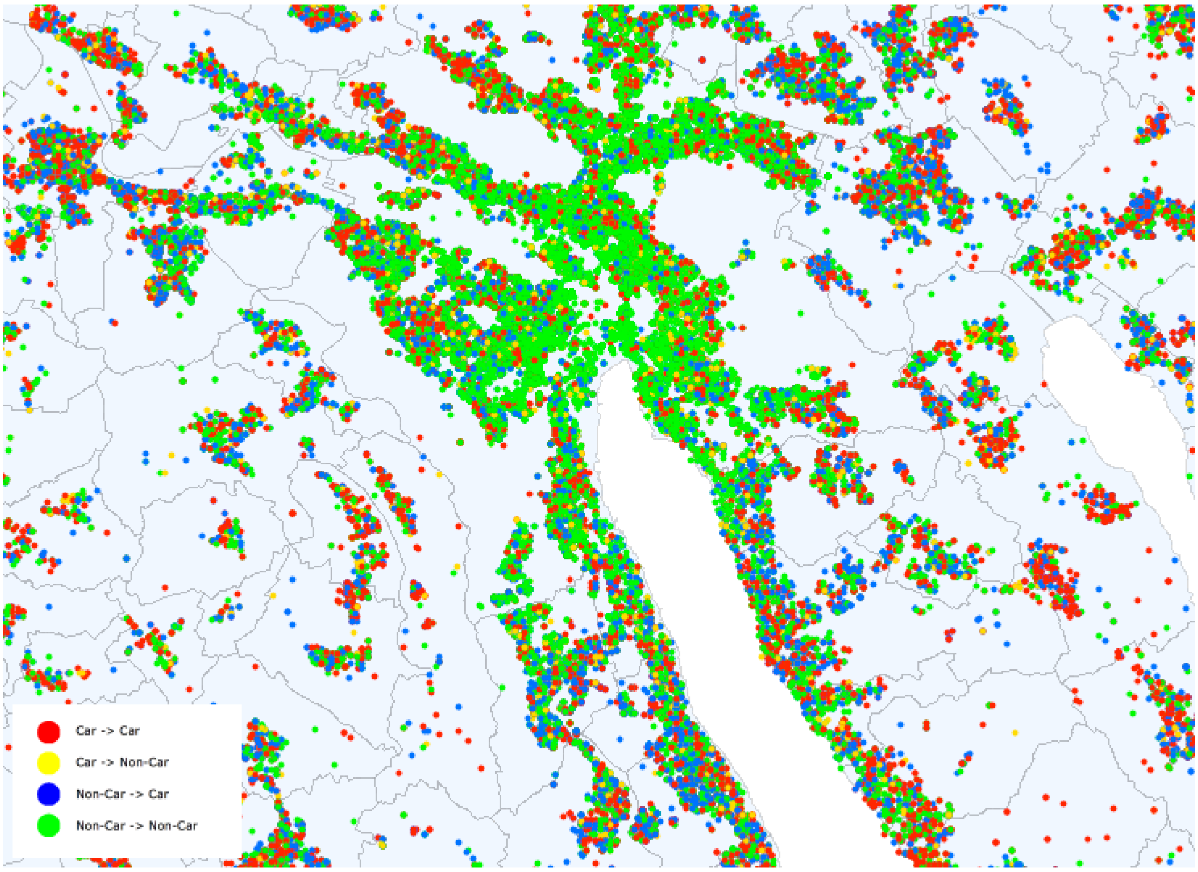

Figure 4: Map of the greater Zurich area. Dots symbolize home locations of agents colorized by the mode change due to the raise of $\beta_{non\text{-}car}$. Note that agents living at the border of the metropolitan area are most likely forced to switch from non-car to car (blue dots).

The model was applied to the city of Zurich. Starting from a plausible base case, the parameter $\beta_{non\text{-}car}$ was doubled. As expected, car usership went up. Because of the agent-based approach, it was easy to allocate gains and losses to the agents' home locations; the result was shown in a graphical way. Similarly, the geographic distribution of mode switchers was shown.

In the longer run, the simple model for the non-car mode will be replaced by a detailed model that includes the effects of the actual public transit schedule. That model will then be able to compute the populations' reaction to changes in the schedule, the routing, the fare system, etc.

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