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LARGE-SCALE AGENT-BASED TRAVEL DEMAND OPTIMIZATION APPLIED TO SWITZERLAND, INCLUDING MODE CHOICE

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ABSTRACT

This paper presents the application of the agent-based transport simulation toolkit MATSim-T to a large-scale scenario of Switzerland. The scenario is called large-scale because ca. 6 million synthetic persons, “agents”, are simulated on a high-resolution network model with >1 million links. MATSim-T is able to compute a relaxed state of the simulation system within 60 iterations of the learning-based solution procedure with regard to mode choice, car route choice and choice of activity timing. This is achieved by applying improved optimization algorithms in the replanning stage. A genetic algorithm is used for times and mode choice optimization of activity plans, together with an efficient implementation of time-dependent shortest path search for route choice.

The improvements of the behavioral model reported in this paper are focused on the scoring function which can process individualized parameters for measuring the quality of all-day activity plans. Combined with disaggregate input data for population and land use, it was possible to build a heterogeneous and thus more realistic scenario. Furthermore, four modes of transport (car, public transit, bike, walk) are considered in the presented application. The generalized cost of the car option is determined by a queue simulation of traffic flow. In order to prove the concept of mode choice optimization in a multi-agent microsimulation, the other modes are modelled as abstract alternatives with static travel costs constant throughout the modeled average workday. It is shown how the model is calibrated against observed modal split data. The results are validated with average workday count data. Despite the simple cost structure of the mode alternatives, and due to a mode choice concept based on subtours, the observed spatial distribution of the modal split can be reproduced within ± 10 percentage points per mode.

Keywords: agent based transport simulation, large-scale system optimization, MATSim, parallel computing, activity plans, multi-modal traffic model, Switzerland

MOTIVATION

Location-based services provide information and other services depending on the temporal and spatial position of the end user. A precise mapping of the end users' travel behavior is therefore crucial to the effectiveness of this kind of services. It would be ideal for the provider of location-based services if every potential end user was equipped with a mobile device whose position can be accessed on a regular basis. Modern information technology provides the devices to precisely locate individuals, e.g. with GSM and GPS technology. Despite mobile phones with an integrated GPS device having entered the retail market at a large scale, the coverage is far from the required level to assess frequencies of people at a given location and time of day. Important information for marketing purposes, such as the activity type a person is engaged in, are difficult to obtain. Moreover, privacy issues restrict the automated storage and processing of individual information.

An alternative to processing real-time positioning data in order to locate individuals is the simulation of their travel behavior. Conceptually it provides a comprehensive travel behavior analysis, including the decision making process of individuals. On the other side, simulation is a statistical method whose purpose it is to reproduce observed distributions of travel behavior variables. The spatio-temporal path of a simulated individual does not necessarily match the actual movement of the real person, therefore the requirement of privacy protection is fulfilled. As long as the aggregate analysis of distinct population groups is valid, the result of the travel simulation of individuals can be used for the dimensioning of location-based services.

A promising approach to generate the desired data is multi-agent microsimulation. Large-scale multi-agent traffic simulations are capable of simulating the complete day-plans of several millions of individuals called *agents* (Meister *et al.*, 2009). In contrast to traditional models, all attributes that are attached to the synthetic travelers are retained during the simulation process, thus enabling analysis on the level of the individual traveler. This paper reports on the results of a research project which uses the open source multi-agent transport simulation toolkit MATSim¹ in order to generate a base case of individual travel demand for all of Switzerland. The project was a cooperation between IVT, ETH Zurich and the privately owned company Axon Active AG (formerly Datapuls AG) which is a business consultant for providers of location-based services, amongst others (Balmer *et al.*, 2010). The industry partner wants to use the result of the base case in order to generate visiting frequencies for location-based services of their clients. The scientific and computational challenges to generate these results are detailed in this paper. These are (i) the handling of a scenario with a population of 10^6 agents and a high-resolution network with 10^6 links which poses high performance requirements to the software implementation, (ii) the efficient use of optimization algorithms for mode choice, car route choice and choice of activity timing in order to obtain reasonable network flows, and (iii) an improved behavioral model of the agent in order to meet the requirements of the industry

¹See <http://www.matsim.org>, accessed on May 5, 2010

partner.

The paper starts with a classification of the agent-based approach in the context of large-scale dynamic transport modelling. This is followed by a description of the Swiss data which were used to model demand and supply, as well as of the steps towards the modelling of the individual travel demand. In the next section, the implementations of elements of the agent-based simulation are specified. The calibration and the validation of the base case are presented in the results section. Policy evaluations, i.e. parameter variations of the base case are not part of this study. The paper closes with a summary and conclusions.

MULTI-AGENT TRANSPORT SIMULATION

From a transport modelling perspective, multi-agent simulation is a method to integrate activity-based demand generation with dynamic traffic assignment.

Activity-based demand generation (ABDG) models generate a sequential list of activities and trips connecting these activities for every person in the study area. Demand generation is embedded in a concept of daily activity demand from which the need for transport is derived (Kitamura, 1988). A major advantage of ABDG drawn on in this study is that the spatial and temporal consistency of travel behavior can be ensured. For example, the mode chosen for one trip may influence the mode choice for other trips of the daily plan. This is superior to traditional demand generation where aggregate traffic quantities represent isolated trips. Several operational packages with a wide variety of methods have been developed, each of which is applied to a different typical region. On the one hand, random utility theory is used to generate daily activity plans. Examples are SACSIM for the Sacramento Area, California, and the comprehensive econometric microsimulator for daily activity-travel patterns (CEMDAP) applied to the Dallas-Fort Worth Area (Bradley *et al.*, 2010; Bhat *et al.*, 2004). On the other hand, in a rule-based approach demand generation is based on psychological decision rules observed in stated-adaptation or other types of surveys. Examples include the travel activity scheduler for household agents (TASHA) for the Greater Toronto Area, and the learning-based simulation system ALBATROSS recently applied to the Netherlands in the context of an air-quality study (Roorda *et al.*, 2008; Beckx *et al.*, 2009). An approach to introduce ABDG in traditional demand generation uses hourly origin-destination (OD) matrices which are segmented by activity type (Vrtic *et al.*, 2007a). It is the state-of-the-art currently employed by the Swiss government authorities responsible for mid- to long-term transport planning (Vrtic *et al.*, 2005).

Most of the above approaches to generate a regional transport model have in common that only the first three steps of the traditional four-step model are performed on the basis of individual travelers. For the traffic assignment step, the trips listed in the activity plans are independently aggregated to time-dependent (typically hourly) OD matrices which are fed into a dynamic

traffic assignment (DTA). It assigns routes to time-dependent O-D flows so that the routes, in conjunction with their resulting traffic pattern, fulfill some predefined criterion (Peeta and Ziliaskopoulos, 2001). For example, the routes may fulfill a Nash equilibrium, meaning that at no time of day can any O-D flow find a faster path than those that are already used. An often-used alternative criterion is a time-dependent stochastic user equilibrium, meaning that each O-D flow is distributed across possible routes following a prespecified distribution function at each point in time. The typical way to solve the DTA problem is to use iterations between a router and a traffic simulation (also called network loading algorithm). Flows on routes that do not fulfill the prespecified criterion are slowly adjusted into the right direction. The iterations stop when no more adjustments are necessary — that is, when the iterations have reached a fixed point (Watling, 1996). Examples of DTA implementations are a dynamic version of VISUM (Vrtic and Axhausen, 2003), DynaMIT (Ben-Akiva *et al.*, 2002)² and Dynasmart (Mahmassani *et al.*, 1992)³.

Conceptually, the iterative procedure of DTA can be extended to other dimensions of travel decisions beyond route choice. Examples are “best-reply” models for departure time choice (de Palma and Marchal, 2002; Ettema *et al.*, 2005) or optimal mode choice. Elements of demand generation are thus elevated from a simple pre-process to an integrated part of demand-supply equilibration, as mode choice, departure time choice or even the activity sequence may be susceptible to changes in traffic patterns. In the context of ABDG, the entire activity plan becomes the unit of decision. At this point, multi-agent microsimulation is introduced. It is used in this study such that the software objects representing travelers (“agents”) are retained not only in the demand generation stage, but also in the assignment step (Rieser *et al.*, 2007). Personal attributes such as sociodemographic properties, the activity plan, and other internal variables can be accessed during the entire modeling process. An agent-based approach to iterative route assignment has been developed early in TRANSIMS (Simon *et al.*, 1999) which has recently been moved to open source⁴. Temporally consistent daily activity plans can be directly implemented as the strategy of the agent. This is the main motivation for the use of agent-based simulation in this study.

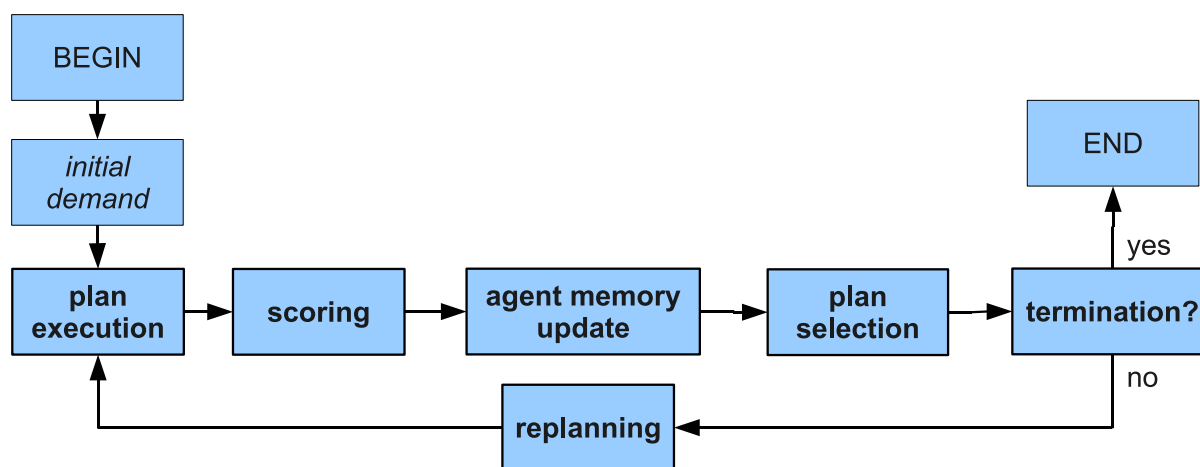
The repeated realization of ABDG in an iterative process becomes computationally more expensive the more dimensions of travel behavior are included, and the more complex the demand calculation becomes. Think e.g. of shortest-path search in high-resolution networks or the calculation of complex random utility models for ABDG such as the model by Bowman and Ben-Akiva (2001). To resolve this issue, *learning* is introduced in the feedback cycle: An agent can hold a set of activity plans in its “memory”, and chooses one of them for the traffic simulation (Raney and Nagel, 2006). The agent will thus not immediately “forget” the activity plan it executed the iteration before, but may use it again in later iterations. The evaluation of the plan may change from iteration to iteration, depending on the respective traffic conditions.

²<http://mit.edu/its>, accessed on May 5, 2010

³<http://mctrans.ce.ufl.edu/featured/dynasmart/>, accessed on May 5, 2010

⁴<http://www.transims-opensource.net>, accessed on May 5, 2010

Figure 1: Structure of the MATSim-T simulation system



The simulation structure of the resulting coevolutionary system is depicted in 1, and can be summarized as follows.

Initial demand For every agent, one initial activity plan is generated. Input data such as population and land use data, as well as network data are processed to generate this initial demand. The agent database, which holds the agents and all their attributes in the RAM, reads the initial plans file, creates the agent objects and loads their plans into their memory as specified by the file. Since each agent usually has only one plan, it marks that one as “selected”, indicating it has chosen that plan for execution (see next step). The data used in this study and the initial demand generation process are outlined in section *Data base and initial demand generation* on page 7.

Plan execution In the plan execution step, the selected activity plans are simulated along the timeline in the model representation of the physical world. Implementations of the plan execution have to take into account boundary conditions of the infrastructure in which activities and movements are performed. These are e.g. the maximum storage and flow capacities of the road network, or opening times of activity facilities. Moreover, activity plans force an agent not to leave an activity before it has arrived there. The result of the plan execution is a list of events which are localized in time and space. They contain information about when an agent was performing an activity, travelling, entering or leaving a network link etc. These events are handled by the subsequent elements of MATSim-T (scoring, replanning, analysis etc.). The details of the traffic simulation are presented in section *Plan execution* on page 12.

Scoring The agent database reads the events information from the plan execution step and sends each event to the agent which generated it. Each agent uses its events to calculate the new score of its selected plan — the one which was most recently executed. The

scores of the other, not selected plans is not modified. The scoring function used in this study is described in section *Scoring* on page 13.

Agent memory update The initial demand typically consists of one activity plan per agent. Every time an agent is selected for replanning (see next step), another plan is added to its memory. An agent can maximally hold n_{plans} in its memory, plus another one if the agent was selected for replanning in the current iteration. In this case, one plan will be removed at the beginning of the next iteration. In this study, the plan with the worst score is removed from the memory. This is a variation of elitist selection in genetic algorithms, which guarantees that the individual with the highest fitness will survive the selection process to the next generation (De Jong, 1975). In this study we use a value of $n_{plans}=2$. The value had to be chosen that low because many agents with very long route descriptions had to be handled in a limited quantity of RAM. Generally, values of 3 or above are desired.

Plan selection Each agent decides which plan to select from its memory for execution in the next iteration. It chooses from the following options:

Replanning With a probability of $p_{replan,m}$, the agent is chosen for replanning by replanning module m . It selects a random plan from its memory, and sends a copy of it to the replanning module. After this copy will have been modified by the replanning module, it is added to the agent memory. The modified copy is then marked as selected for execution in the next iteration. While the probabilities $p_{replan,m}$ may have different values, and may differ from iteration to iteration, in this study the same value is used for all replanning modules across all iterations.

Probabilistic selection For agents not chosen by a replanning module, one existing plan is selected for execution according to the following equation:

$$P(i) = \frac{e^{\beta_{score} \cdot S_i}}{\sum_j e^{\beta_{score} \cdot S_j}}$$

with $P(i)$ being the selection probability of plan i out of all j plans in the agent's memory, given their scores S_j . β_{score} is the score parameter for plan selection. The higher the value of β_{score} , the more the agent tends to choose the plan with the best score. In this study we use a value of $\beta_{score}=2.0$ which was also used in previous studies (Raney and Nagel, 2006). If a plan has no score for any reason, it is selected automatically. The purpose of this selection strategy is to reevaluate existing strategies in order to make them comparable to new activity plans generated by replanning modules. The logit-type formula achieves an agent-based stochastic user-equilibrium, with the activity plan being the unit of choice (Nagel and Flötteröd, 2009).

Termination The iteration cycle is stopped after the properties of the system fulfill some stopping criterion. Conceptually, the system has to run until the agents cannot significantly

improve the score of the executed plans, that is when an agent-based stochastic user-equilibrium is reached. As no formal stopping criterion was available for this study, the iteration cycle is stopped after a fixed number of 60 iterations. See section *Termination* on page 19 for details.

DATA BASE AND INITIAL DEMAND GENERATION

This section describes the data that are available for the generation of travel demand and supply. Usually, data are delivered in different formats and levels of detail. The MATSim-T software used to model the initial individual demand is able to combine these various data sources via standardized XML formats in order to generate daily activity plans (Balmer *et al.*, 2006).

Network model

A major objective of this study is to simulate car traffic on a high-resolution model of the Swiss road network. These networks provide the basis for GPS navigation devices. While there are open-access alternatives⁵, the network used in this study is based on the proprietary TeleAtlas MultiNet Specification 4.3.2.1⁶. It describes the Swiss road infrastructure for the period from the autumn of 2008 to the spring of 2009. While network topology and maximum link speeds are very precise, the number of lanes per driving direction and the flow capacities are not part of the dataset. These data are imputed based on the TeleAtlas road classification.

The high resolution of the network model is expected to substantially increase the computational burden of the simulation system, mainly of the algorithms for shortest-path search and the simulation of the traffic flow (see later). It is therefore a part of the performance optimization that the level of detail of the network data is minimized without losing essential information for the traffic flow simulation and for the comparison of simulated and actual traffic flows. Two steps were taken in order to free the network model from unused information: First, the original polyline encoding of the road segments was deleted. This was possible because the actual topology of the road segments is irrelevant to the implementation if the traffic flow simulation used in this study. The lengths of the polyline elements were summed up as the length of the road segment. Second, adjacent road segments with equal attributes and without junctions in between were merged to a single road segment. The resulting MATSim XML network model consists of 472'819 junctions (MATSim *nodes*) and 1'035'305 road segments (MATSim *links*).

⁵For example, <http://www.openstreetmap.org>, accessed on May 5, 2010.

⁶<http://www.teleatlas.com/OurProducts/MapData/Multinet>, accessed on May 5, 2010.

Count data

The simulated traffic flows are validated with average hourly workday flows calculated from semi- and fully automated counting stations. The counts used here are provided by several government authorities which are responsible for different parts of the Swiss road network. The counts are from the years 2004–2008, depending on the source and covers the following regions/road types: (i) Motorways and other federally funded roads, provided by the Swiss Federal Roads Office (ASTRA), (ii) major roads of the Cantons Basel-Land, Grisons, Neuchâtel, and Zurich, and (iii) the City of Zurich.

Overall, 665 series of average hourly counting data were manually mapped to the network described in section *Network model* on page 7. The hourly averages of each counting station take into account all data of Tuesdays, Wednesdays and Thursdays, except holidays, and omitting the respective upper and lower 2.5% percentiles.

Activity facilities

Besides the network, the study region is mainly characterized by its land use. It determines what types of activities can be performed in which places. For an activity-based travel demand model with a high-resolution network, the land use information should be of high resolution, too. In MATSim-T, each activity is mapped to exactly one *activity facility*, a spatial entity with a coordinate and additional attributes such as opening times or capacity. The activity facility itself is mapped to exactly one network link. Several activity facilities can be mapped to the same link. This is equivalent to a zone-based traffic supply model with each link being a traffic analysis zone.

The study distinguishes five main activity types: *home*, *work*, *education*, *shop* and *leisure*. For the locations of homes, building information related to the population data was used (see section *Activity based initial demand generation* on page 9). The activity facilities for *work* were generated from the Swiss National Enterprise Census (Swiss Federal Statistical Office, 2001). This dataset contains, per hectare, the exact number of full-time equivalents (FTE) in industry and services, as well as the exact number of employers in different size classes concerning the number of FTE. For each employer, one activity facility was generated with a random coordinate in its hectare. The FTE were distributed among all employers in that hectare proportionally to their size class. For all of Switzerland, 382'979 work facilities were generated. Depending on the type of the employer, they were assigned additional activity types *education*, *shop*, or *leisure*. The opening times, which are important boundary conditions for the scoring of daily activity plans, are based on simple assumptions about working hours, and publicly available data on shop opening hours (Meister, 2008).

Public transport

The result of the car traffic flow simulation is a fully agent-based, link-level description of car trips. There was no large-scale activity-based equivalent operational for public transport at the time this study was conducted. However, it is possible to implement mode choice in MATSim-T without the microscopic simulation of public transport. In this project, public transport travel times are estimated with input data from the transport model employed by the Swiss Federal Government (Vrtic *et al.*, 2005). This model provides a list of $\approx 15'000$ public transport stops. It also provides a travel time matrix between the centers of the 3'114 Swiss municipalities. The travel times are calculated searching for the shortest path in the timetabel of public transport services.

Activity based initial demand generation

The modeling of the initial demand comprises the generation of a synthetic agent population as well as the generation of one complete initial daily activity plan of an average workday. Usually, the generation of the synthetic population is based on Public Use Microdata Samples which are extrapolated to the full population of the study region, using the method of Iterative Proportional Fitting (Beckman *et al.*, 1996). In this study, an existing data set of 5'986'051 Swiss persons hosted by the industry partner was used, which is an 88% sample of the Swiss population⁷. Each record in this data set could straightly be converted to one agent of the simulation. The extrapolation of a subsample was thus not necessary.

For each agent, one initial activity plan is constructed according to the following procedure (Ciari *et al.*, 2008):

Distribution of activity chains The Swiss Microcensus on Travel Behavior is used as the data basis for distributing activity chains to the synthetic agent population (Swiss Federal Statistical Office, 2006). A very simple but effective and robust solution is to uniformly draw an activity chain from the Microcensus based on the individual sociodemographics. The survey is therefore divided into 80 groups based on “gender”, “has work”, “has education”, “has driving license” and 5 different “age” groups (≤ 6 , 7-14, 15-17, 18-65, ≥ 66). The random draw is weighted according to the person weight of the Microcensus. As a result, the relative bias of the distributed chains compared to the Microcensus chains lays below 0.7%. In this step, the 5 main activity types mentioned before are segmented into overall 10 activity types: *home*, *work* (industry/sector 2, services/sector 3), *shop*, *leisure*, *education* (kindergarten, basic primary school, secondary school, higher education, and other).

⁷In order to obtain valid results, the values for storage and flow capacities of the network are adapted proportionally. A sample size of 88% is expected to be large enough in order to give meaningful results.

Assignment of primary activity locations The location of the *homes* of all agents is given by the dataset provided by the industry partner. Next, the activity locations for *work* and *education* are chosen. Aggregate numbers on the municipality level of detail are given by the Swiss National Census (Swiss Federal Statistical Office, 2000). Therefore, the primary locations are directly converted from the census. In a microscopic view, Swiss municipality level of detail is actually too rough. By using the information about activity facilities described above, a weighted random draw of work and education location is performed to distribute the locations inside the given municipality.

Assignment of secondary activity locations There is no information available in the National census about the locations of *shop* and *leisure*-type activities. Based on the given locations of the primary activities, and the dataset on activity facilities, a “neighbourhood search” algorithm is adopted such that it selects given facilities around the primary locations and draws one of them weighted, based on the capacities of the facilities.

While the above attributes will remain fixed during the iterations, the following are variable and will be optimized according to the behavioral model formulated in a scoring function. Although arbitrary (e.g., random) initial values could be used, these attributes are initialized close to the supposed final values.

Activity durations Just like the distribution of activity chains, the initial activity durations are drawn from observations of the Microcensus. Furthermore, it is assumed that the observed distribution of time among the activities is close to the preferred time budget per activity, which is an important parameter of the behavioral assumptions described in section *Scoring* on page 13.

Initial mode choice The following five transport modes are considered in the initial demand: *car*, *public transport* (pt), *bike*, *walk*, and *ride*. In this study, the decision unit related to mode choice is the *subtour*⁸. The initial mode distribution is calculated with a discrete choice model estimated with observed data again from the Swiss Microsensus. The average trip rate per person is 3.7 which conforms with the observation average.

Initial route choice The routes in the initial plans are calculated with a shortest-path algorithm also used in the iteration process, assuming free speed network conditions (see section *Router* on page 17).

See Fig. 2 for an example agent with one initial daily activity plan.

⁸The term *subtour* is defined as follows. A *tour* is a set of consecutive trips in an activity plan where the origin activity of the first trip and the destination activity of the last trip are performed at the same location. A tour may consist of several subtours if another tour can be identified within it. Thus a *subtour* can be defined as a tour within another tour, while its trips not necessarily have to be consecutive.

Figure 2: Example initial daily activity plan in the MATSim XML plans format.

```
<person id="98765" sex="f" age="32" license="yes" car_avail="always"
  employed="yes"> <travelcard type="unknown" />

<desires>
  <actDur type="leisure" dur="01:00:00" />
  <actDur type="work_sector2" dur="07:45:00" />
  <actDur type="home" dur="15:15:00" />
</desires>

<plan score="" selected="yes">
  <act type="home" link="l1" facility="f1" x="609873.0" y="192409.0"
    start_time="00:00" dur="07:47" end_time="07:47" />
  <leg mode="car" dep_time="07:47" trav_time="00:00" arr_time="07:47">
    <route dist="1000.0">node4-node8-node14</route>
  </leg>
  <act type="work_sector2" link="l2" facility="f2" x="609594.0" y="190841.0"
    start_time="07:47" dur="04:00" end_time="11:47" />
  <leg mode="pt" dep_time="11:47" trav_time="00:00" arr_time="11:47">
    <route>stop8571621-zone616-zone35101-stop8507110</route>
  </leg>
  <act type="leisure" link="l3" facility="f3" x="600643.0" y="199514.0"
    start_time="11:47" dur="01:00" end_time="12:47" />
  <leg mode="pt" dep_time="12:47" trav_time="00:00" arr_time="12:47">
    <route>stop8507110-zone35101-zone616-stop8571621</route>
  </leg>
  <act type="work_sector2" link="l2" facility="f2" x="600438.0" y="199855.0"
    start_time="12:47" dur="03:45" end_time="16:32" />
  <leg mode="car" dep_time="16:32" trav_time="00:00" arr_time="16:32">
    <route dist="1100.0">node15-node9-node5</route>
  </leg>
  <act type="home" link="l1" facility="f1" x="609873.0" y="192409.0"
    start_time="16:32" />
</plan>
</person>
```

It consists of the sociodemographic agent description, the preferred time budget per activity type (*desires*), and the initial activity plan. The plan is essentially a list of activities in chronological order. The trips connecting the activities are denoted by *leg*.

In this example, agent #98765 leaves its home at 07:47 AM in order to go to work by car on a route via the network nodes 4, 8, and 14. After 4 hours, it goes on a subtour by public transport (pt) for a leisure activity with the duration of 1 hour. This leisure activity is located in a different zone (616) than the work activity (35101), whereas "zone" means municipality in this application. The agent leaves the second work activity at 16:32.

All attribute values in normal face are predefined and will not be altered during the iterations. The attribute values in bold face (leg modes, activity and leg time information, routes) can be modified by the replanning modules.

For better readability, route descriptions have been simplified. Also, time information is presented in the format HH:MM, while it originally is HH:MM:SS.

IMPLEMENTATION OF MATSIM ELEMENTS

This section presents in some more detail implementations of the MATSim simulation system (Fig. 1) which have been adopted/improved for the study at hand.

Plan execution

Each trip with the mode *car* will be executed in a traffic flow simulation. This simulation consists (i) of loading the agent on the network link at which the previous activity is located at a given departure time, (ii) of moving the agent along a given route through the network, where it might interact with other agents under way, and (iii) unloading the agent from the network at the link of the destination activity. There is a variety of models for the simulation of car traffic with discrete entities such as agents, including car-following models or cellular automata (for a comprehensive review, see Helbing, 2001). These simulations directly model the driving behavior, and thus are quite complex and have too high computing requirements for the repeated simulation in large-scale scenarios. Mid-to-long term transport planning requires a method which generates valid approximations of link speeds and link travel times without the costly detailed simulation of driving behaviour. This requirement is fulfilled by the queuing model (Simon *et al.*, 1999). In this model, each road segment is modelled as a FIFO waiting queue, with a minimum service time of the length of the road segment divided by the maximum travel speed. The maximum number of vehicles that a queue can release equals the road capacity, depending on the number of lanes etc. The maximum flow capacity is thus a predetermined value, as opposed to models with on-link dynamics where the maximum flow emerges from the number of vehicles and their interactions.

In this project, an event-driven implementation of the queue simulation is used. Event-driven refers to the fact that only events are simulated when a vehicle enters or leaves a road segment (Charypar *et al.*, 2007). This implementation is much more efficient than a parallel link update simulation of the network with equidistant timesteps which is typically used for the simulation of on-link-dynamics (Cetin, 2005). The only concept related to on-link dynamics integrated into the queueing simulation is a gap between vehicles travelling backwards at constant speed in the case of traffic jam resolution, bringing in some notion of kinematic waves represented in their full scale in macroscopic traffic models based on fluid dynamics (Helbing, 2001).

Trips with modes other than *car* can also be interpreted by the implementation used in this study (Waraich *et al.*, 2009). They are not executed in the physical environment. Instead, the travel time is a predetermined value which is generated by the replanning module which generates the routes (see section *Router* on page 17). The execution of such trips is reduced to “teleporting” the agent from the origin to the destination activity in exactly the planned time, which means that trips with a mode other than *car* do not generate any interaction in the physical world.

The complete integration of the traffic flow simulation in MATSim-T allows it to directly read activity plans from the agent database which is entirely held in the RAM. Moreover, the generated events can be immediately transferred to the subsequent tasks that handle them. Time consuming saving of temporary results on the hard disk or any (de)compression of data as in previous versions become unnecessary. The implementation used in this study exploits

the opportunity of parallel computation on multi-core processors such that the handling of the events can happen immediately after they have been generated. The more processor cores are available, the more event handlers can be run in parallel.

Scoring

In order to compare activity plans, they are evaluated with a measure of general utility, called *score*. The related scoring function describes the agent's preferences.

The score of a daily activity plan, U_{plan} , is

$$U_{plan} = \sum_{i=1}^n (U_{act,i} + U_{travel,i} + U_{wait,i} + U_{short,i})$$

with n being the number of activities, $U_{act,i}$ being the score performing activity i , $U_{travel,i}$ being the score of traveling to activity i , $U_{wait,i}$ being a penalty for waiting instead of performing activity i , and $U_{short,i}$ being a penalty for performing activity i for a too short duration (Charypar and Nagel, 2005). See the sections below for a detailed description of the various scoring elements.

Performing an activity

The (usually positive) score of performing activity i , $U_{act,i}$, is

$$U_{act,i} = (U_{cum,j} - U_{cum,j-1}) \cdot f_p$$

with $U_{cum,j}$ being the cumulative score of all activities of the same type as activity i , of which i is the j th instance when ordered ascending temporally. This cumulative score is

$$U_{cum,j} = \begin{cases} \max\left(0, \beta_{perf} \cdot t^* \cdot \ln\left(\frac{\sum_{k=1}^j t_{perf,k}}{t_0}\right)\right) & j > 0 \\ 0 & j = 0. \end{cases}$$

β_{perf} is the marginal utility of another unit of time spent performing an activity. t^* is the externally defined desired time budget of the agent for spending time performing one or more activities of the same type as activity i . $t_{perf,k}$ is the time spent performing the k th activity of the same type as activity i (see `desires` section of the activity plan in Fig. 2). t_0 is the zero of the logarithmic function and is proportional to t^* . In other words, this scoring function cumulates scores by activity type and does not require a time allocation between several activities of the same type beforehand. The advantage is that one does not have to define a large set

of parameters for desired activity durations as it was necessary in previous studies (Meister *et al.*, 2009). Moreover, the values of t^* are defined per agent and thus represent random taste variations whose consideration has been put forward also in discrete choice analysis (Chesher and Silva, 2002).

f_p denotes a factor which may negatively influence the score of a shop or a leisure activity if the related facility is too crowded (Horni *et al.*, 2009):

$$f_p = \begin{cases} \min \left(\beta_{load,1} \cdot \left(\frac{load}{capacity} \right)^{\beta_{load,2}}, 0.5 \right) & , \text{ if activity type } \in \{\text{shop, leisure}\} \\ 1.0 & \text{ otherwise.} \end{cases}$$

with $\beta_{load,1}$ and $\beta_{load,2}$ being the parameters of the capacity restraint function, $load$ being the number of agents that perform an activity of the same type at the same facility and the same time as activity i , and $capacity$ being the maximum number of agents that the facility can accommodate for that activity type.

Traveling

The score for traveling from activity $i-1$ to activity i by the transport mode $mode$, $U_{travel,i,mode}$, is

$$U_{travel,i,mode} = U_{access/egress,mode} + \beta_{tt,mode} \cdot t_{mode} + \beta_{cost,mode} \cdot c_{mode}$$

with $\beta_{tt,mode}$ being the marginal utility of another unit of time traveling by $mode$, $\beta_{cost,mode}$ being the marginal utility of another unit of money spent on traveling by $mode$. t_{mode} denotes the in-vehicle travel time, and c_{mode} is the expenditure of money required for traveling with $mode$. $U_{access/egress,mode}$ denotes the (usually negative) score of access/egress to/from a vehicle if the $mode$ is different than *walk*.

The calculation of the score for traveling is most simple for the mode *walk*. With no access/egress costs, and no monetary expenditure, only the term for travel time has to be considered. In the case of the mode *bike*, a fixed score $U_{access/egress,bike}$ is added to the term for travel time, which reflects the access and egress from/to the means of transportation. Note that access and egress do not take simulation time, only the related score of the opportunity cost is added.

For the mode *car*, the in-vehicle travel time t_{car} is obtained from the traffic flow simulation described in section *Plan execution* on page 12. The monetary expenditure c_{car} is $c_{car} = c_{km,car} \cdot d_{car}$ with $c_{km,car}$ being the (constant) cost of traveling 1km by car, and d_{car} being the trip distance, which is the sum of the lengths of the route's road segments. As for the mode *bike*, the score for access and egress is added.

For the public transport alternative (mode pt), the monetary costs c_{pt} are

$$c_{pt} = \begin{cases} d_{pt} \cdot c_{km,pt} & \text{without public transport season ticket} \\ d_{pt} \cdot c_{km,pt,travelcard} & \text{with public transport season ticket} \end{cases}$$

with $c_{km,pt}$ being the cost of travelling one kilometer by pt without a season ticket, accordingly $c_{km,pt,travelcard}$ with a season ticket. d_{pt} is the trip distance which equals the crow-fly distance between the two public transport stops closest to activities $i-1$ and i , respectively, multiplied with a factor of 1.5. The in-vehicle travel time t_{pt} equals the average travel time between the centers of the Swiss municipalities in which the public transport stops are located (Arendt and Vrtic, 2006). If both stops are located in the same municipality, a constant public transport travel speed v_{pt} is assumed. This value is based on speed measurements of public transport vehicles in the Canton of Zurich, as well as observed door-to-door travel times of public transport trips (Hackney, 2005). For access and egress to/from the public transport stop, the required time for walking from/to the closest activity location is added to the in-vehicle travel time. These imaginary walk trips are scored with the parameters related to the *walk* mode.

Penalties

Two penalties are applied if the agent spent time in an undesired manner. First, an agent must spend time waiting if it planned to perform an activity outside the opening time of the related activity facility, e.g. waiting before a shop opens. The score of waiting instead of performing activity i , $U_{wait,i}$ is

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

with β_{wait} being the marginal utility of waiting time, and t_{wait} being the actual waiting time. Note that it is possible that e.g. an agent arrives at 7:50 AM, waits for ten minutes for the shop to open at 8:00 AM, and immediately starts to perform a planned activity of the type *shop* for the rest of the planned activity duration.

The penalty for performing activity i short is

$$U_{short,i} = \beta_{short} \cdot \max(0, (0.5h - t_{perf,i}))$$

with β_{short} being the marginal utility of another unit of time which is missing to the minimum activity duration of 0.5h, and $t_{perf,i}$ being the time spent performing activity i . This penalty is necessary in order to prevent that activity i is assigned the entire desired activity duration if there are further activities of the same type as activity i , which would possibly have a duration of 0s. This parameter would not be necessary if an agent could decide to add or remove activities from its plan. In this study, the activity chains are fixed.

Summary of scoring parameter values

The values of the scoring function parameters are based on different sources of information. They are deduced as follows.

- The marginal utility values for performing an activity, waiting, and travelling by car are taken from a parameter estimation exercise for a bimodal (car/pt) MATSim study of Switzerland (Kickhöfer, 2009):

$$\beta_{perf}=2.26/h; \beta_{tt,car}=0.0/h; \beta_{wait}=0.0/h$$

As long as $\beta_{perf} > \beta_{tt,car}$ and $\beta_{perf} > \beta_{tt,car}$, the opportunity costs of traveling by car and waiting are negative, which is an incentive for the agent to spend as much time as possible performing activities.

- The parameters of the capacity restraint function of activity locations are taken from (Horni *et al.*, 2009):

$$\beta_{load,1}=0.13; \beta_{load,2}=5.0$$

- Performing an activity short is penalized very hard, compared to the value of β_{perf} , in order to maintain minimum durations in the fixed activity chain:

$$\beta_{short}=-180.0/h$$

- The values of the marginal utilities for spending time traveling by modes other than car, as well as the marginal utilities for monetary expenditures of all modes are the result of a manual calibration procedure. The purpose of the calibration procedure is to reproduce observed modal split distributions with respect to trip distance and trip duration. See section *Results of the modal split calibration* on page 21 for a short description, as well as the results concerning the modal split.

$$\beta_{tt,pt}=-2.0/h; \beta_{tt,bike}=-16.0/h; \beta_{tt,walk}=0.0/h$$

$$\beta_{cost,car}=0.0/h; \beta_{cost,pt}=-0.8/h; \beta_{cost,walk}=-0.1/h$$

A behavioral interpretation of these values cannot be given here because they are not the result of a model estimation, but are inferred from the calibration procedure which imposes a desired modal split. It is not the purpose of this study to find meaningful parameters for the scoring function. As a consequence it is important to note that it is possible to calibrate the large-scale multi-agent transport simulation system presented here in order to obtain a meaningful modal split.

- The average monetary expenditures per kilometer for motorized modes of transport are based on Swiss values documented in Vrtic *et al.* (2007b).

$$C_{km,car}=0.12 \text{ CHF/km}; C_{km,pt}=0.28 \text{ CHF/km}; C_{km,pt,travelcard}=0.14 \text{ CHF/km}^9$$

⁹CHF - Swiss Francs (Swiss currency)

The value for $c_{km,pt,travelcard}$ is a weighted mean between the values for travelers with an all-Switzerland half-fare card (“Halbtax”, 0.15 CHF/km), and an all-Switzerland travelcard (“Generalabonnement”, 0.08 CHF/km).

- The constant average speed of the *pt* mode is based on speed measurements in the City of Zurich (Hackney, 2005). The speeds for *bike* and *walk* are arbitrary assumptions.

$$v_{pt}=15.7 \text{ km/h}; v_{bike}=14.0 \text{ km/h}; v_{walk}=2.8 \text{ km/h}$$

- The assumed access and egress time per trip to/from the means of transportation for the modes *car* and *bike* is

$$t_{access,car/bike}=t_{egress,car/bike}=5 \text{ min (Mogridge, 1997).}$$

The related costs for access and egress for the modes *car* and *bike* are constant opportunity costs. As such, they interact with β_{perf} :

$$U_{access/egress,car} = U_{access/egress,bike} = (\beta_{tt,walk} - \beta_{perf}) \cdot (t_{access,car/bike} + t_{egress,car/bike})$$

For the mode *walk*, the value of this score constant is zero. This is also the case for the mode *pt*, where access to and egress from the closest pt stop are explicitly part of the route description.

Replanning

Two replanning modules are used to generate modified activity plans for the learning procedure. For both modules, p_{replan} is 10% each.

Router

The *router* module generates new routes for all trips, given their mode and departure time.

For the mode *car*, a time-dependent shortest path algorithm is run in order to find the route with the smallest possible negative score. For the estimation of link travel times, events from the previous run of the traffic flow simulation are aggregated in 15 minute time slots¹⁰. The shortest path algorithm used here is a dynamic Landmarks-A* router which finds the same best possible path as a standard Dijkstra algorithm for Euclidean networks (Lefebvre and Balmer, 2007). For the expected size of the road network model (10^5 nodes, 10^6 links), the performance of the A* algorithm is ≈ 10 times better than that of the Dijkstra algorithm.

For the public transport mode (*pt*), the travel time is determined for the Swiss municipalities in which the activities are located, as described in section *Traveling* on page 14. At first the

¹⁰This means that global knowledge of the system is used to generate the new route, which might be an invalid assumption given the limited human capacity to store and process information.

stops closest to the previous and the next activity locations have to be found. In order to make this look-up very efficient for an expected number of 10^4 stops, the stops are sorted in a quad tree (Finkel and Bentley, 1974). The average travel time between the two municipalities where the stops are located is then looked up in the given travel time matrix. This static calculation does not depend on time-of-day dependent travel times as it is the case for the *car* mode. The mapping of stops to activity locations is straightforward and could in principle be performed beforehand. The use of the efficient data structures mentioned becomes crucial as soon as the pt travel time calculation gets more complex. For example, if agents were allowed to change the location of their activities, the public transport alternative would have to be calculated again. The number of calculations would increase even more if the determination of the travel time becomes dynamic as it is the case in state-of-the-art transport models employed in Switzerland (Vrtic *et al.*, 2007b).

For the modes *bike* and *walk*, no path optimization is performed. The travel time is computed simply by dividing the crow-fly distance, multiplied with a factor of 1.5, by the respective assumed average speeds v_{bike} and v_{walk} .

Planomat

The *planomat* is a replanning module for activity durations and departure times, as well as mode choice on subtour level. It uses a genetic algorithm (GA) for function optimization of the daily activity plan scoring function (Meister *et al.*, 2006). This means that while robust results of the stochastic optimization are expected, it cannot be guaranteed that the optimal solution is returned, as it is the case for the router described above. However, it is sufficient to approximate the optimal solution because the traffic conditions in which the optimized plan will be executed may have changed substantially from one iteration to the next, given the 10% share of agents selected for each replanning module. On the one hand, the usage of “approximating best-reply” modules such as the *planomat* replaces a module which only shifted the existing departure time information in a range of ± 30 minutes (the “time allocation mutator”, Balmer *et al.*, 2005). This makes the system independent of the initial conditions, here the time allocation of the initial demand. Furthermore, this leads to a convergence of the learning framework within several dozens of iterations, as opposed to ≥ 200 iterations with mutation-type modules. On the other hand, the choice of a GA allows it to easily include more plan variables into the optimization procedure. In this study, the mode of each subtour of the activity plan is optimized in addition to the times. It is widely acknowledged that the transportation mode choice is one of the most important information that planners want to have from a transportation model. It becomes important for dynamic transport models besides route choice and departure time choice, e.g. for the assessment of peak-hour road pricing (Downs, 2004). Mode choice has already been addressed in the context of MATSim-T with a mutation-type replanning module (Rieser *et al.*, 2009). The choice set for each subtour consists of the four modes *car*, *public transport* (pt),

bike, and walk.

The optimal timing of the daily activity plan depends mainly on the travel times which the agents expects for a given trip. Just like in the router, and for reasons of simplicity, a travel time approximation based on global knowledge is assumed. The travel time will be estimated for the route that is given in the activity plan, which remains unchanged. For the “virtual” assessment of other modes of a given trip, the free-speed route for the respective mode is determined. The actual travel time on this route may still be time-dependent, as for the mode *car* in the application presented here.

Termination

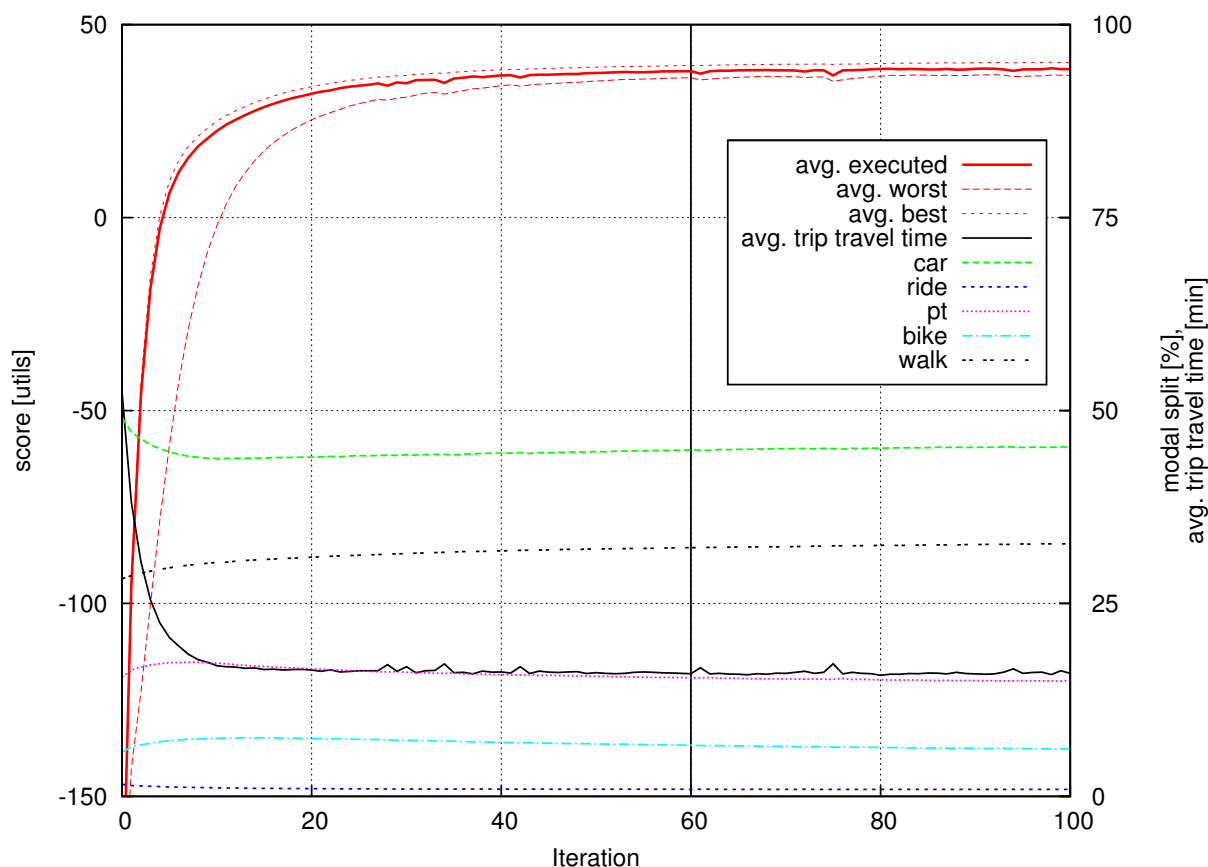
The iterations are stopped after a fixed number of 60 iterations. This number is based on visual inspection of the development of aggregate system indicators across iterations, such as average score of the executed plans, the average travel time, or the mode share (see Fig. 3). The learning procedure is judged complete when these values have reached a plateau for several iterations. In addition, the comparison of traffic patterns as validated by counts data between iterations is used to assess whether substantial changes are still taking place or not. The value of 60 iterations ensures that the agents are selected for replanning several times.

RESULTS

This section presents selected aggregate simulated traffic results which are compared to real-world observations.

First, the modal split of the simulation results after 60 iterations is compared to the reported modal split of the Swiss Microcensus of Travel Behavior, a representative one-day travel survey (Swiss Federal Statistical Office, 2006). The scoring parameter values were manually adjusted such that the difference in the modal split with respect to trip distance and trip travel time distribution between the observation and the iterated activity plans is minimized (for the final values, see section *Summary of scoring parameter values* on page 16). That means, the model was calibrated to fit the observed modal split. This was not achieved by imposing a fixed modal split in the initial demand. Instead, the sensitivity of the results to the scoring parameters for travelling was studied by performing several runs of the simulation system with different parameter settings. The calibration focused on the modal split because mode choice optimization based on subtour-level has been performed for the first time in this study (see section *Planomat* on page 18). Route equilibration and departure time optimization are already known to work well (Meister *et al.*, 2009). The main goal of the model calibration is to achieve

Figure 3: Relaxation of the transport model.



The score averages of all executed activity plans, and of each agent's best and worst plans are plotted against the left x axis. Iteration 60 is chosen as the result iteration because there is no significant change in scores afterwards. Aggregate indicators of the transport system are plotted to the right axis. While the score values and the average trip travel time are stable, a slight gradual shift in mode shares can still be observed visually. The shares of the various transport modes in the relaxed state do not differ very much from those of the initial demand (iteration 0), because the latter is modelled on the basis of observations. Conceptually, a random modal split could be used in the initial demand. See section *Results of the modal split calibration* on page 21 for a discussion of the modal split results.

a realistic share of the *car* mode, and thus a reasonable amount of demand in the traffic flow simulation *without* imposing a fixed modal split beforehand. In the second part of this section, counts comparisons are presented in order to check to what extent this goal was achieved.

The results presented in this section were produced with the simulation of a 25% sample of the initial demand in order to minimize the computational burden. The sensitivity analysis required dozens of MATSim runs. In order to simulate the entire scenario, 90 GB of RAM are required. When using the 25% sample, three runs can be performed at the same time. Each of those sample runs takes about 4 days to calculate the required 60 iterations. Our experience shows that the simulation of only a subsample of the agent population produces meaningful results while the capacities of the infrastructure, primarily the road network, are proportionally reduced

(Gao *et al.*, 2010). Simulation of subsamples is also applied in other activity-based demand generation models such as TASHA (Roorda *et al.*, 2008). Furthermore, the simulation of the entire agent population was not mandatory from the perspective of the industry partner for their aggregate analyses of the results.

Results of the modal split calibration

Fig. 4 shows comparisons of the observed and the calibrated simulated modal split. Cumulative mode shares across both trip distance and trip duration are shown. The rightmost columns of both subfigures show that the overall modal split can be reproduced quite well not only for the car mode (43.3% observed vs. 44.1% simulated), but also for the other modes.

The modal split with respect to the trip distance is depicted in Fig. 4(a). While the quality of the distribution, as well as the overall modal split are generally acceptable, there are several deviations of the simulated modal split of the observed numbers:

- The number of trips with the mode *ride* is almost zero in the simulation results. This result was expected as this mode only exists in the initial demand, and is excluded from the choice set for the mode choice optimization during the learning iterations. There was no mature method for the large scale agent-based simulation of the *ride* mode available at the time this study was conducted. With the ongoing iterative simulation and replanning, the initial ride share of overall 4.4% is reduced to 0.9% after 60 iterations. The figure suggests that the initial ride trips are distributed to both the *car* and *pt* modes.
- Generally, the simulation produces too few short trips with a distance <2km and instead, produces too many trips with longer distances. Particularly for the *walk* and the *car* modes, the simulation overestimates the trip distance, while it is underestimated for the mode *pt*. The main reason for these deviations is suspected in the inadequate distance calculation based on approximate crow-fly distances for all modes except *car*. Furthermore, it is unclear to what extent the interdependence of subtours influences the real world modal split. For example, a person cannot choose to go by *bike* or *car* if the vehicle is not available at the anchor point of the subtour (e.g. go to work by bike, and choose the car for a work-based subtour to a leisure activity). This interdependence is not considered by the mode-choice optimization presented here, and thus violates the boundary conditions of the physical simulation. Other implementations of activity-based demand generation, such as TASHA, explicitly consider this interdependence (Miller *et al.*, 2005).

One notices the leftmost column of Fig. 4(a) representing the number of trips with a distance of zero meters, in both the observed and the simulated data. While no trip in reality has a distance of 0m, it occurs when the activities at both ends of the reported trip are mapped to the same

Figure 4: Comparison of observed and simulated modal split

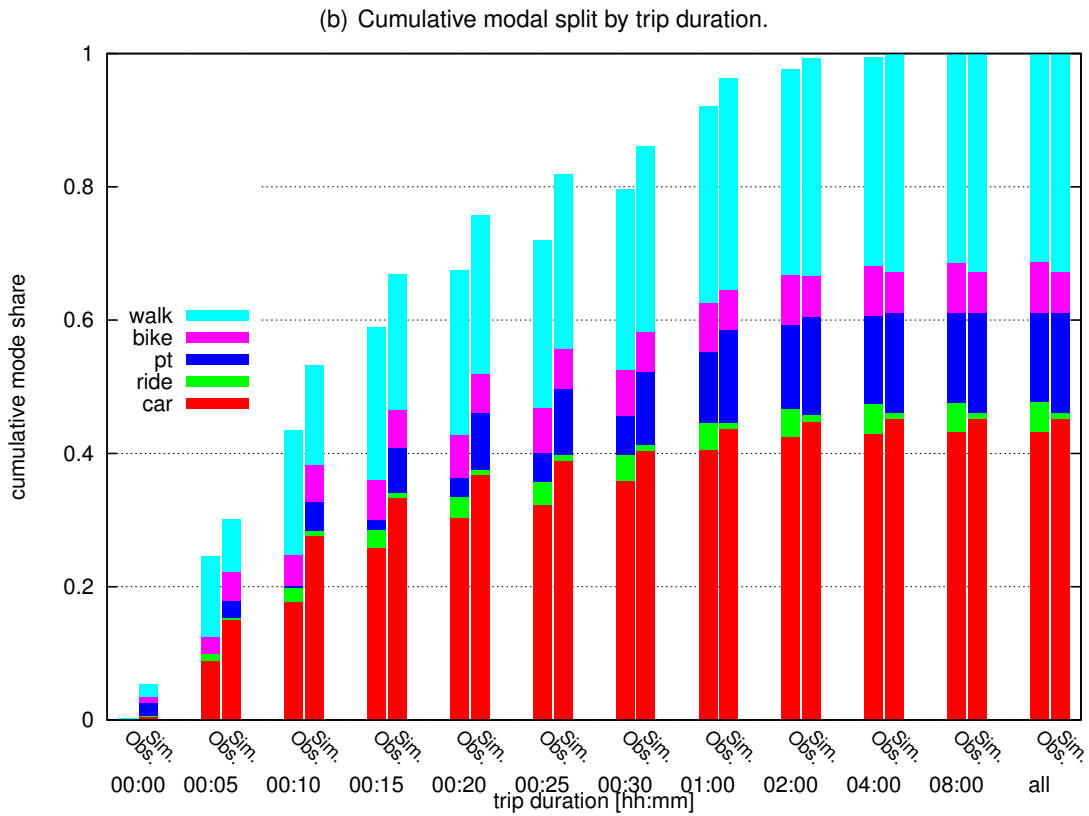
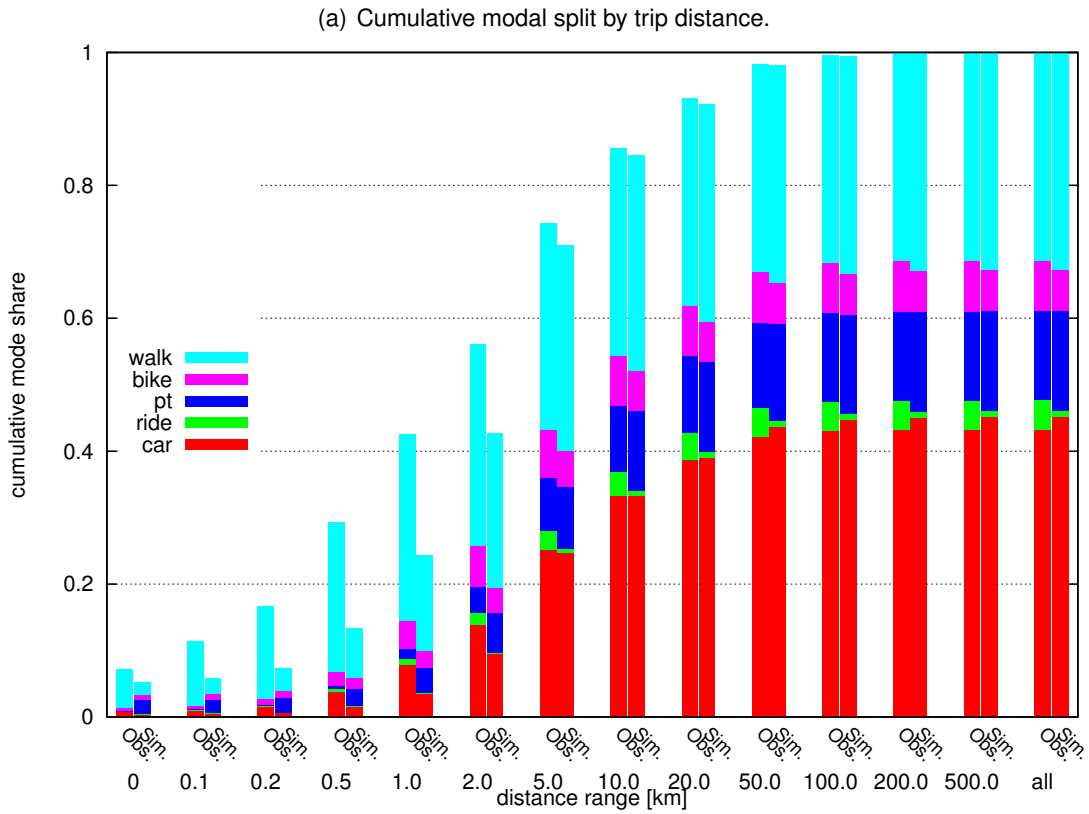
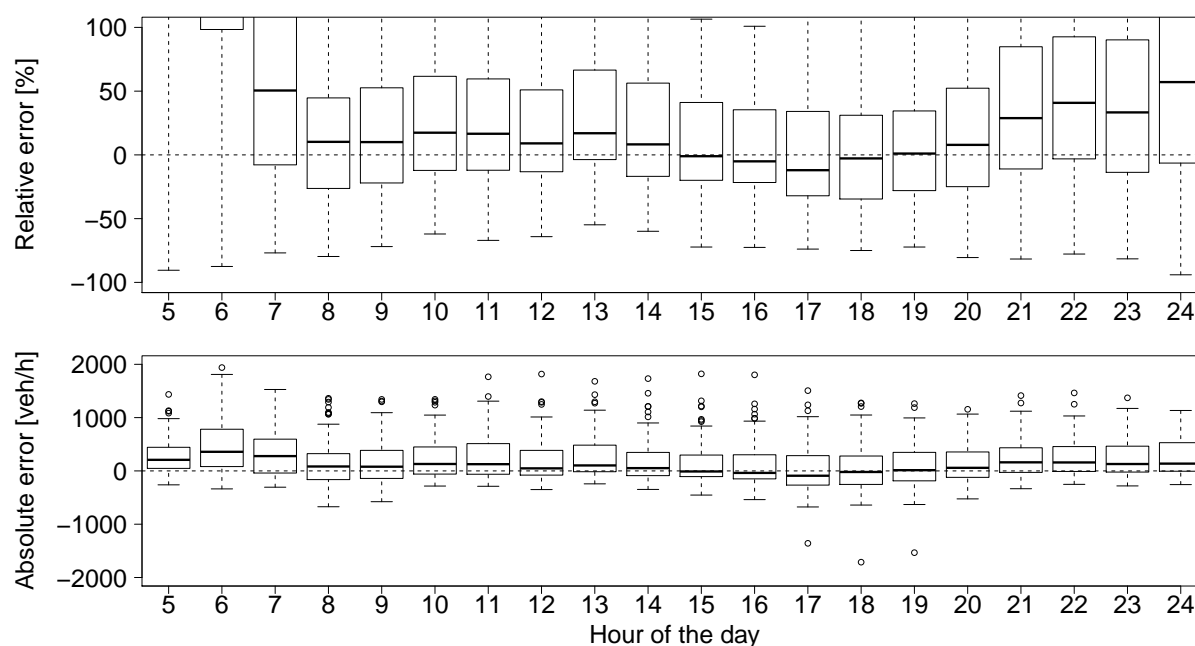


Figure 5: Aggregate hourly counts comparison for 78 counting stations within a 5km radius around Bellevue, Zurich



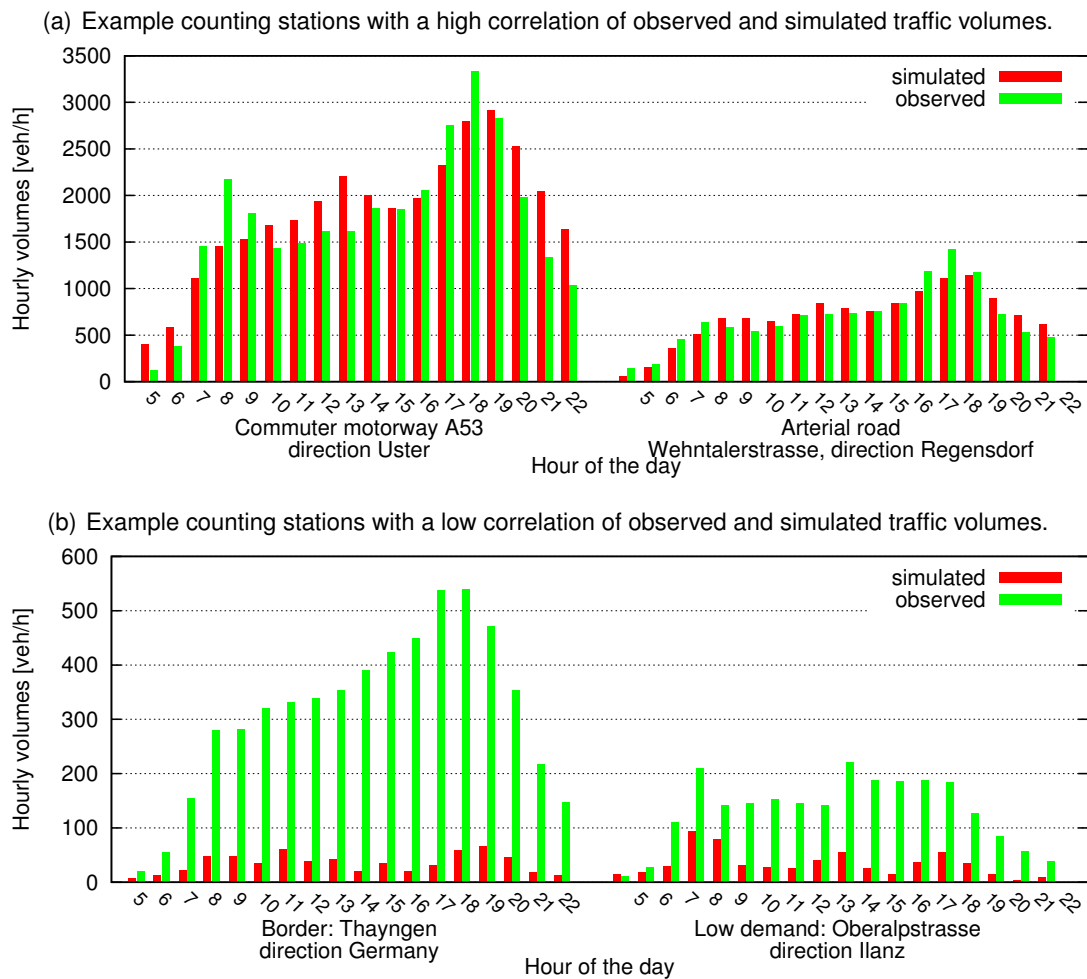
activity facility in the geocoding step (e.g. due to “vertical” transportation in the same building). Trips with zero distance are explicitly allowed in the simulation, where a trip can connect two activities in different activity locations at the same coordinate.

The modal split distribution across trip durations shows a similar result (Fig. 4(b)). The overall qualitative distribution is reproduced well. The quantities of trips per trip duration slot are hit slightly better than in the trip distance distribution. In general, trip durations are underestimated by the simulation, in particular for very short *car* trips with a duration <10min and short *pt* trips with a duration <20min. Again, one notices an artifact of $\approx 6\%$ of simulated trips with a trip duration of 00:00, which are caused by zero-distance trips as explained above.

Validation with count data

The simulation results are validated by comparing simulated traffic volumes with counts from different Swiss government authorities (see section *Count data* on page 8). The focus of the study is to model the personal travel behaviour of the Swiss population. Cross-border traffic as well as freight traffic are not included in the description of the simulated demand. A more or less substantial underestimation of traffic volumes is therefore expected, depending on the location of the counting station. The validation thus concentrates on qualitative count comparisons.

Figure 6: Counts comparisons of selected roads



The maximum flow capacity of each road is 4000 vehicles/h.

Fig. 5 depicts the results of count comparisons of hourly traffic volumes for counting stations located in the City of Zurich. Zurich is located in the center of the biggest Swiss metropolitan area. It is furthermore not close to a national border like other large Swiss cities such as Basel or Geneva are, whose workforces substantially consist of cross-border commuters. Most counting stations are located on urban roads instead of freeways, where possibly many transit travellers are counted. It is therefore expected that the observed counts are matched quite well by the traffic simulation. The median relative error of the simulated traffic volumes does not exceed $\pm 15\%$ for the hours from 7:00 to 20:00, which are the hours with the highest traffic volumes. The simulation model tends to slightly overestimate traffic volumes especially for urban roads. In the early morning as well as in the late evening hours, traffic volumes are smaller. It is typical for the simulation of small quantities that the relative error increases while the absolute error remains negligible.

In order to examine the quality of the validation in more detail, a closer look is taken on the results of particular counting stations. Fig. 6(a) shows the hourly volumes of examples of common road types close to Zurich (high-volume commuter roads, arterial roads). Both the shape and the quantities of the load curve are reproduced quite well. The same is generally true for highways connecting large Swiss cities, as well as urban roads (not shown). Instead, counting stations where the simulated traffic volumes are too low throughout the day are presented in Fig. 6(b). These counting stations are typically located close to the Swiss national border. This result is not surprising because cross-border travel demand is not included in the travel demand description. Traffic volumes are underestimated also in rural regions where the demand is generally low, such as the Cantons Ticino and Grisons. They consist of many tourist trips which are not captured by the Microcensus of travel behavior of the Swiss population. Additional sources of errors in count comparisons are of a more technical nature. For example, the base year of counts of some stations is not the same as the base year of the network model. This may heavily distort the result for this counting station e.g. because the demand drops due to the opening of a new high-capacity alternative. Furthermore, counting stations may have been mapped to the wrong road segment which is not easily detected when working with high-resolution network models.

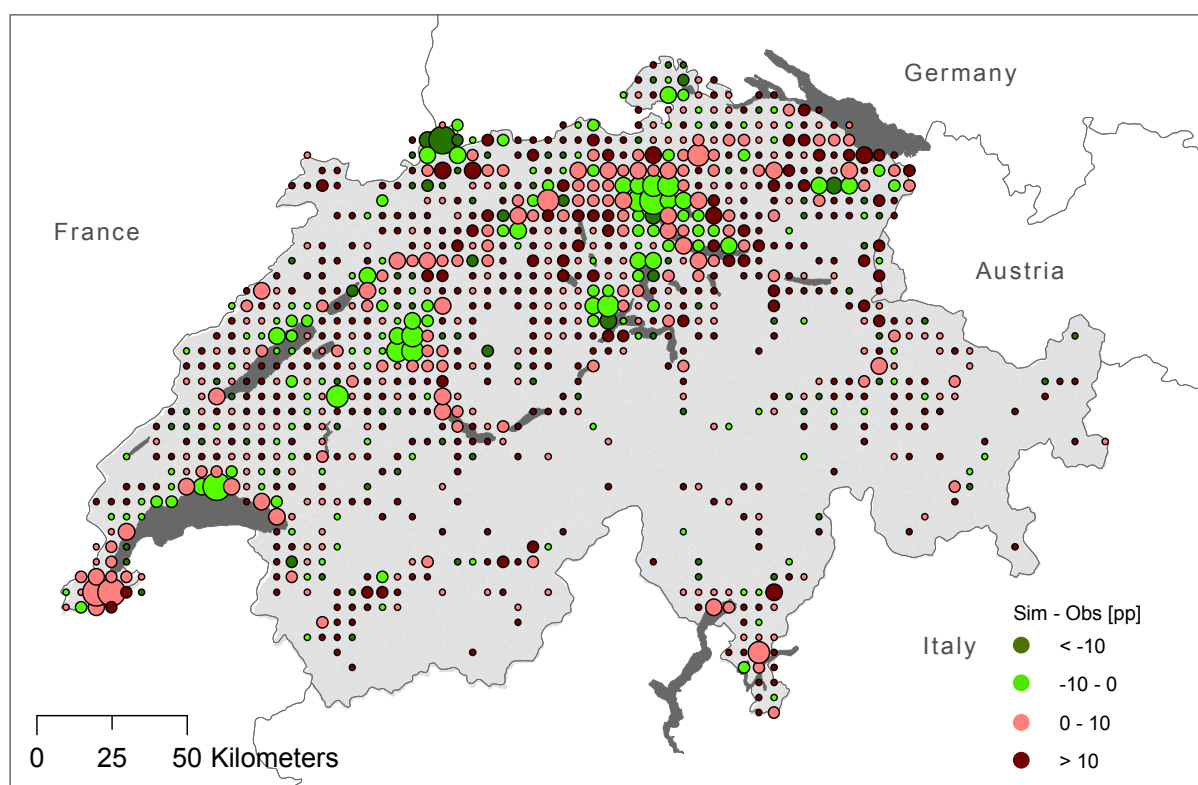
Spatial validation of modal split

Fig. 7 shows the quality of the spatial distribution of the modal split, in the case of public transport. In general, the pt share in most of the greater urban areas such as Zurich, Berne or Lausanne is hit within a range of ± 10 percentage points. This level of quality is considered acceptable for the application presented here. For the large cities the pt share is slightly underestimated, with the exception of Geneva (slight overestimation) and Basel (strong underestimation). As the pt share is highest in such areas due to the high population density it is pleasant to have it reproduced approximately. For second-order agglomerations which also make up a substantial share of the population, the underestimation of the pt share is 10 percentage points maximum, such as the space between Zurich and Berne. Grid cells with major deviations from the observed values ($> \pm 10$ pp) are distributed with no identifiable spatial pattern.

SUMMARY AND CONCLUSIONS

This paper presents the application of the agent-based transport simulation toolkit MATSim-T to a large-scale scenario of Switzerland. The scenario is called large-scale because ca. 6 million synthetic persons, “agents”, are simulated on a high-resolution network model with >1 million links. MATSim-T is able to compute a relaxed state of the simulation system within 60 iterations of the learning-based solution procedure with regard to mode choice, car route choice and

Figure 7: Spatial distribution of public transit share on subtour level - comparison of simulation results to Swiss Microcensus 2005



The figure shows the deviation of the simulated (sim) from the observed pt share (obs) in percentage points (pp) with data aggregated in a 5-km grid. This is the minimum resolution the limited number of observed subtours ($\approx 100'000$ for all of Switzerland) admits in order to generate statistically representative comparisons. The area of a data point is proportional to the number of simulated subtours.

choice of activity timing. This is achieved by applying improved optimization algorithms in the replanning stage. A genetic algorithm is used for times and mode choice optimization of activity plans, together with an efficient implementation of time-dependent shortest path search for route choice.

Computational issues

The computer used to calculate the iterative solution is a shared-memory machine of the type Sun Fire X4600 M2 with 8 dual-core CPUs and 128 GB RAM. For a 25% sample of the full scenario, 30 GB RAM are required. MATSim-T can compute one iteration of such a scenario within 2 hours absolute computation time, of which the traffic flow simulation requires 50%, and both the replanning modules require 25% each. Overhead time is required only in every 10th iteration, when the plans as well as the events are dumped to compressed files. As the software of

the agent database and the traffic flow simulation are now completely integrated, no additional overhead for file exchange is generated as in previous versions. Furthermore, multithreading is used to separate generation and processing of events during the traffic flow simulation, which reduces overhead time for events handling to a negligible level. A starting point for further exploitation of multithreading in the simulation of traffic flow is the re-introduction of domain decomposition of the network assignment (Charypar *et al.*, 2009).

Multithreading can on the other side be used to distribute agents on the available processors in the replanning stage because there no agent interaction takes place. 5 CPU cores are used for each of the three 25% sample runs which were performed in the sensitivity analysis stage of the project as described in section *Results* on page 19. This application of multithreading reduces the share of net CPU core time of $\approx 40\%$ to the mentioned 25% share of absolute computation time per replanning module. This saving increases with a growing number of available CPU cores. The time required for replanning is furthermore reduced by an efficient implementation of an A*-Landmarks routing algorithm for car route choice.

It can be summarized that the simulation system provides a performant software implementation to compute an agent-based equilibrium transport model of the mentioned size with high-resolution network models within a reasonable time. These network models resolve the street network much more realistically than usual planning networks, which results in a ten times higher number of links.

Data and modelling issues

The improvements of the behavioral model reported in this paper are focused on the scoring function which can process individualized parameters for measuring the quality of all-day activity plans. Combined with disaggregate input data for population and land use, it was possible to build a heterogeneous and thus more realistic scenario. Furthermore, four modes of transport (car, public transit, bike, walk) are considered in the presented application. The generalized cost of the car option is determined by a queue simulation of traffic flow. In order to prove the concept of mode choice optimization in a multi-agent microsimulation, the other modes are modelled as abstract alternatives with static travel costs constant throughout the modeled average workday.

The calibration of the model system is focused on the modal split which emerges from the iterative learning procedure. There were no quantitative requirements for the actual numbers of the modal split result from the industry partner. As a first milestone, results correct within a range of ± 10 percentage points could be generated, both for the trip distance/trip travel time distributions shown in Figs. 4(a) and 4(b) as well as the spatial distribution shown in Fig. 7. Potential for improvement exists on the data side (e.g. a more complete list of public transit stops) as well as on the model side (e.g. use of a behaviorally sound location choice module

for flexible activities instead of a simple “neighborhood search”). A near-future outlook on methodic advances includes the agent-based demand generation and simulation also of other modes than just the car mode (Rieser and Nagel, 2009).

An important issue in micro-simulation modeling is the high sensitivity of the results on errors in input data. This is especially true for model regions with a high density of activities, where a high travel demand meets short road segments due to the high network resolution. Besides that, raw population and land use data as used in this study are usually not available to the transport modeler, which poses additional methodic challenges e.g. to initial demand generation. In any case, more attention has to be paid to the correct statistical properties of the demand model than in aggregate transport modelling.

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