

Location choice modeling for shopping and leisure activities with MATSim

Combining micro-simulation and time geography

Journal Article

Author(s):

Horni, Andreas; Scott, Darren M.; Balmer, Michael; [Axhausen, Kay W.](#) 

Publication date:

2009

Permanent link:

<https://doi.org/10.3929/ethz-b-000019518>

Rights / license:

[In Copyright - Non-Commercial Use Permitted](#)

Originally published in:

Transportation Research Record 2135, <https://doi.org/10.3141/2135-11>

Location Choice Modeling for Shopping and Leisure Activities with MATSim

Combining Microsimulation and Time Geography

Andreas Horni, Darren M. Scott, Michael Balmer, and Kay W. Axhausen

The activity-based multiagent simulation toolkit MATSim adopts a coevolutionary approach to capturing the patterns of people's activity scheduling and participation behavior at a high level of detail. Until now, the search space of the MATSim system was formed by every agent's route and time choice. This paper focuses on the crucial computational issues that have to be addressed when the system is being extended to include location choice. This results in an enormous search space that would be impossible to explore exhaustively within a reasonable time. With the use of a large-scale scenario, it is shown that the system rapidly converges toward a system's fixed point if the agents' choices are per iteration confined to local steps. This approach was inspired by local search methods in numerical optimization. The study shows that the approach can be incorporated easily and consistently into MATSim by using Hägerstrand's time-geographic approach. This paper additionally presents a first approach to improving the behavioral realism of the MATSim location choice module. A singly constrained model is created; it introduces competition for slots on the activity infrastructure, where the actual load is coupled with time-dependent capacity restraints for every activity location and is incorporated explicitly into the agent's location choice process. As expected, this constrained model reduces the number of implausibly overcrowded activity locations. To the authors' knowledge, incorporating competition in the activity infrastructure has received only marginal attention in multiagent simulations to date, and thus, this contribution is also meant to raise the issue by presenting this new model.

Behaviorally precise and computationally efficient modeling of people's location choices for shopping and leisure activities is clearly of great importance, not only for science but also for planning, in which different disciplines, such as transportation planning, marketing, and geography, to name a few, benefit from improved location choice models. However, descriptive empirical data for shopping and leisure activity location choice are sparse, and moreover, they are not easily transferable spatially. Thus, behavioral models capturing the underlying factors that drive the decision process have to be designed, which is the objective of MATSim [Multi-Agent Transport Simulation Toolkit (1)] and its location choice module in particular.

A. Horni, M. Balmer, and K. W. Axhausen, Institute for Transport Planning and Systems (IVT), ETH Zürich, CH-8093 Zurich, Switzerland. D. M. Scott, Center for Spatial Analysis, School of Geography and Earth Sciences, McMaster University, Hamilton, Ontario L8S 4K1, Canada. Corresponding author: A. Horni, horni@ivt.baug.ethz.ch.

Transportation Research Record: Journal of the Transportation Research Board, No. 2135, Transportation Research Board of the National Academies, Washington, D.C., 2009, pp. 87–95.
DOI: 10.3141/2135-11

COEVOLUTIONARY SYSTEM MATSim

Transportation and activity location infrastructure is generally limited, which means that users are in competition for time slots to use the infrastructure. Even though the idea of *homo oeconomicus* clearly needs to be extended by altruism, bounded rationality, satisficing principles, incomplete information, and choice heuristics, the assumption that people in general do not act against their own good is close to consensus. As a consequence, it can be deduced that choices expected to bring less subjective benefit than others disappear from people's minds. This can be seen as a coevolutionary mechanism with respect to people's choices.

Although coevolutionary systems exhibit a variety of behaviors, ranging from convergence to a fixed point to periodic or even chaotic behavior, for transport demand modeling, traditionally the attractive fixed points Nash equilibria, the states in which no individual improvement is possible due to unilateral change [Nash (2)] are relevant. Even though the individual dynamics of real travelers are not known, building a coevolutionary system model shows promise for potentially capturing the patterns of people's activity scheduling and participation behavior at a high level of detail in relation to space and time. This coevolutionary approach is adopted in MATSim.

COMPUTABILITY OF LARGE-SCALE SCENARIOS

Before efforts are made to bring the MATSim simulation results closer to reality by iterative extension, calibration, and validation of the model, two crucial conceptual problems need to be solved. First, practical computability of large-scale scenarios needs to be achieved, and second, further light needs to be shed on the question of the uniqueness of a computed solution (i.e., an equilibrium that is related to the Nash equilibrium). The first part of this paper addresses the computability problem by combining microsimulation and time geography.

Being confronted with large location choice sets and large numbers of agents to be modeled on one hand and knowing that in reality people's choices are in general subject to constraints on the other, researchers recognize that the idea to confine the agent's location choices through time-space constraints is natural and that it has already been applied both in simultaneous and in sequential operational microsimulations such as PCATS [e.g., Kitamura et al. (3)] and Albatross [e.g., Arentze and Timmermans (4)]. Nevertheless, the effects on computational efficiency and behavioral accuracy, as well as the methodological needs of incorporating space-time constraints derived from exogenous data or defined by preceding stages of the model, define a scientific problem for each model in its own right.

For example, for the simultaneous model discussed here, constraining the choice set is mainly for efficiency, as explanatory power related to human behavior is based on the utility function, whereas, in sequential models such as Albatross, behavioral realism is partially produced by its choice heuristics.

IMPROVING BEHAVIORAL REALISM OF MATSim LOCATION CHOICE MODULE

The second main point of the paper is the improvement of the behavioral realism of the MATSim location choice module. This improvement is achieved by creating a constrained model that introduces competition for slots on the activity infrastructure. Modeling this competition is relevant as it has an effect on duration of activity participation and choice of activity location in the sense of avoidance actions similar to the effect of road load on people's route choices. As mentioned earlier, competition arises because the activity infrastructure is generally limited (e.g., a limited number of parking spaces or tables in a restaurant or limited availability of sales staff). To the authors' knowledge, the only comprehensive implementation of a constrained model for a microsimulation framework is introduced in Vovsha et al. (5). There a sequential-choice process is proposed in which alternatives are removed from the choice set of later travelers if the locations are already occupied by earlier travelers. Thereby, the order of the travelers is specified arbitrarily, and thus the last-record problem (the last travelers have to travel far to find an available location) is not negligible when heterogeneous travelers are modeled. This problem does not appear with the algorithm presented in this paper, as it is based on a simultaneous-choice process in which every agent in an overcrowded facility gets penalized equally and simultaneously.

The rest of this paper is organized as follows. The section on method gives an overview of MATSim and presents the implementation details of its location choice module, especially the incorporation of the time–geographic approach. The synthetic simulation scenario is also described. The section after that presents the results of the simulation runs for which four configurations are used. Conclusions and ideas for future research are given in the last section.

METHOD

MATSim Simulation Toolkit

MATSim is an activity-based, easily extendable, open-source multi-agent simulation toolkit implemented in Java and constructed to handle large-scale scenarios. It falls under the category of utility-maximizing models, as opposed to sequential rule-based decision-making models [e.g., Timmermans (6)]. As mentioned earlier, MATSim is designed as a coevolutionary system model. This means that while being in a competition for time slots on the infrastructure with all the other agents, every agent iteratively optimizes its daily activity chain by trial and error. To do this, every agent possesses a memory of a number of day plans in which each plan contains a daily activity chain and a utility value. In every iteration before the execution of the microsimulation [e.g., Cetin (7)] (in MATSim called Mobsim), that is, before the selected plans are processed on the infrastructure, every agent selects one plan from its memory with probability proportional to $e^{\beta S_j}$, where S_j is the utility of plan j and β is an empirical constant. A certain share of the agents (usually 10%) is then allowed to modify its selected plans, in which time, route,

and location choices for shopping and leisure activities can be made. Time choice is based on local random mutation [e.g., Balmer et al. (8), Raney (9)]; route choice uses a best-response module, namely the A-star algorithm [Lefebvre and Balmer (10)]; and location choice, described later in more detail, uses a local search based on time–space constraints derived from the plans. An iteration is completed by evaluation of every agent's daily routine, performed following its selected day plan, with a utility function. This function is compatible with microeconomic foundations and computes the sum of all activity utilities $U_{act,i}$ plus the sum of all travel (dis)utilities $U_{trav,i}$ [Charypar and Nagel (11)]:

$$F = \sum_{i=1}^n U_{act,i}(\text{type}_i, \text{start}_i, \text{dur}_i) + \sum_{i=2}^n U_{trav,i}(\text{loc}_{i-1}, \text{loc}_i)$$

where type_i , start_i , and dur_i are the type, start time, and duration of the activity, respectively.

The utility of an activity is defined as follows:

$$U_{act,i} = (U_{dur,i} + U_{wait,i} + U_{late.ar,i} + U_{early.dp,i} + U_{short.dur,i})$$

where

- $U_{dur,i}$ = utility of performing the activity,
- $U_{wait,i}$ = disutility of waiting,
- $U_{late.ar,i}$ and $U_{early.dp,i}$ = disutility of late arrival and early departure, respectively, and
- $U_{short.dur,i}$ = penalty for too short an activity participation time.

For real-world scenarios (time and route choice), the procedure described above has so far shown convergence toward a unique Nash equilibrium, although coevolutionary systems in general exhibit a variety of behaviors. Simulation results are validated against traffic count data, in which an average working day is computed by using the data of one complete year with an hourly resolution. Further details about MATSim are available in Balmer (12) and Balmer et al. (13, 14).

Achieving Computability by Integrating Time–Geographic Approach

Computation Time

If one assumes for a moment that the agents' choices are restricted to location choice, the required computation time for exhaustively searching the phase space is given as

$$\# \text{locations}^{\# \text{activities}} \times t_{\text{per iteration}}$$

This is a huge number even for medium-scale scenarios. Hence, it is obvious that MATSim cannot be based on enumeration or a global random search, which is likely to be even worse than enumeration as solutions might be sampled multiple times. In numerical optimization, the general way of handling prohibitively large search spaces is to implement local search methods capable of escaping local optima [e.g., simulated annealing, Kirkpatrick et al. (15)]. This idea is adapted to the MATSim coevolutionary system by confining the agents' choices to local steps per iteration, which means that the available range of day plan modifications per iteration is constrained for every agent.

Implementation Details

Activity chains of travel demand models consist of a sequence of activities and connecting trips in which activities are usually defined by the following attributes: start time and duration, location, position in the chain, and group composition. Trips are defined by route and travel mode information. In the context of location choice models, it is common practice to distinguish between primary and secondary activities. This research followed a similar classification, but due to the lack of a consistent definition in the literature, it classified activities as fixed and flexible, with flexible activities being ones for which location choice is applied (i.e., in this model, shopping and leisure activities). Both fixed and flexible activities are modified in the time choice step. Nevertheless, in the location choice step, besides the spatial dimension, the temporal dimension of the fixed activities is also tentatively taken as fixed, whereas for flexible activities, for example, the start time is obviously dependent on the chosen location. This fixation is needed to define the origin and the terminal vertex of the space–time prisms confining the flexible activities that are taking place between two consecutive fixed activities according to Hägerstrand’s time geography [Hägerstrand (16), Landau et al. (17)]. In this model, to confine the search space further, the duration of the flexible activity is additionally defined to be fixed in the location choice step. Doing so defines a travel time budget for the flexible activities between two fixed activities.

To determine potential locations efficiently for these flexible activities, subject to the travel time budget, the authors propose a novel algorithm based on recursion. This algorithm extends the geographic information system–based algorithm introduced in Scott (18), which serves the purpose of constructing an explicit location choice set for exactly one flexible activity performed between two fixed activities. That algorithm works as follows: One should assume that the locations and the planned start and end times of the fixed activities and the duration of the flexible activity. In turn, this means that the travel time budget t_{tb} is defined. The construction of the travel time–based potential path area (PPA) algorithm has two stages. First, a distance-based approximate subset of locations [in Scott (18) network links are used] for possible inclusion in the PPA is chosen. Second, the network accessibility of the chosen links in relation to the given travel time budget is computed to identify the links of the PPA.

In more detail, in the first step, all links within a circle whose center is the point equidistant to the two fixed locations and with radius $(t_{tb} \times v)/2$ (where v is chosen as a reasonable speed for that region) are included in the subset of potential PPA links. Activity spaces are usually approximated by elliptical regions. However, the existence of efficient implementations of spatial query methods for circular regions makes it advantageous to use a circle whose diameter is equal to the major axis of the underlying ellipse. The algorithm proposed in this paper tailors that earlier algorithm in the sense that, for efficiency reasons, an implicit choice set for chains of arbitrary length for flexible activities is constructed. This is achieved by using the algorithm of Scott recursively and by checking only the feasibility of an alternative in relation to the given travel time budget after that alternative has been randomly and tentatively chosen as an activity location. Given the two fixed activities and n flexible activities with planned activity durations $duration(act_{n,i})$, the algorithm proposed in this paper works as follows.

After the activity location subset in the first stage has been constructed, a location is chosen randomly from it and the travel time budget is reduced by the time it takes to travel from the first fixed activity to that location in the loaded network. As long as the total travel time

is smaller than the travel time budget, the algorithm is applied recursively so that the recently set flexible activity location is taken as the first anchor point. In cases in which the travel time budget is exceeded, the algorithm starts on the first recursion again but with a different random seed. After a certain number of failed trials, the algorithm is initialized with a reduced travel speed (arbitrarily set to 10% reduction), as it is supposed that the assumed average travel speed for that region has been set too high. Termination of the algorithm is guaranteed by random choice within the universal choice set after a certain maximum number of failed trials.

More precisely, the skeleton of the proposed algorithm is given in pseudocode as follows:

1. Set $act_1 \leftarrow$ first fixed activity and
2. $act_2 \leftarrow$ second fixed activity
3. Compute the total travel time budget as

$$t_{tb} \leftarrow starttime(act_2) - endtime(act_1) - \sum_{i=1}^n duration(act_{n,i})$$

4. Set the total travel time $t_t \leftarrow 0$
5. **for** $i = 1$ to n **do**
6. Construct the subset of Stage 1 for act_1 and act_2 by using travel speed v as described below.
7. Randomly choose a location from the subset, and set it as the location for $act_{n,i}$
8. Update the total travel time: $t_t \leftarrow t_t +$ time to travel from $location(act_1)$ to $location(act_{n,i})$
9. **if** $i = n$ **then**
10. $t_t \leftarrow t_t +$ time to travel from $location(act_{n,n})$ to $location(act_2)$
11. **end if**
12. **if** $t_t > t_{tb}$ **then**
13. Start on Line 1 again, but use a different random seed
14. **end if**
15. $act_1 \leftarrow act_{n,i}$
16. **end for**

where $location(act_i)$, $starttime(act_i)$, and $endtime(act_i)$ mean the location and start and end times of activity i , respectively, and t_t is the total travel time.

A good estimate of the travel speed v mentioned on Line 6 could in a future version be derived from travel speed information available from the preceding iteration. If the small speedup produced by the more exact estimation of travel speed is forgone, v can simply be set at a reasonable value. The value that is currently used is computed from the National Travel Survey 2005 (19) and is set at 25.3 km/h.

Improving Behavioral Realism by Applying Capacity Restraints

Activity location load, computed for time bins of 15 min, is derived from events delivered by Mobsim. The load of one particular iteration combined with time-dependent activity location capacity restraints is considered in the agents’ choice process of the succeeding iteration. In detail, this means that the utility function term $U_{act,i}$ described earlier is multiplied by $\max(0; 1 - f_p) \times f_{attractiveness}$, where the first term penalizes agents dependent on the load of the location they frequent and f_p is a power function, as this has proven to be a good choice for modeling capacity restraints. [The well-known

Bureau of Public Roads cost-flow function (20) is a power function.] To introduce additional heterogeneity about the activity locations, attractiveness factor $f_{\text{attractiveness}}$ is introduced that is defined to be logarithmically dependent on the activity location size given by the official census of workplaces (21). Although there is empirical evidence that the attractiveness of shopping locations actually increases with size [e.g., Carrasco (22)] setting $f_{\text{attractiveness}} = f(\text{location size})$ serves the purpose of demonstration and is essentially arbitrary.

As for demonstration purposes, capacity restraints are exclusively applied to shopping locations, where in principle leisure activity locations can be handled similarly. However, for future calibration and validation of the model, derivation of capacity restraints for leisure activity locations is expected to be much more difficult than for shopping locations because the data availability are much smaller for leisure locations and capacity restraints vary much more between leisure locations than between shopping activities (for example, hiking versus going to the movies).

The proposed model allows the assignment of individual time-dependent capacities to the activity locations. However, for the sake of demonstration, the capacities of all shopping facilities are set equal, so that the values are derived from the shopping trip information given in the National Travel Survey of 2005 (19) (Figure 1). The total daily capacity is set so that the activity locations in the region of Zurich (see next section) satisfy the total daily demand with a reserve of 50%. In detail, the capacity restraint function for location i is as follows:

$$f_{p,i} = \alpha_i \times \left(\frac{\text{load}_i}{\text{capacity}_i} \right)^{\beta_i}$$

where

$$\alpha_i = 1/1.5^{\beta_i},$$

$$\beta_i = 5, \text{ and}$$

$$f_{p,i} = \text{penalty factor as described in the text above.}$$

Simulation Scenario

As real-world application and therefore validation is not an issue in this paper, a completely synthetic simulation scenario could be used. However, to ensure consistency with future steps, a real-world scenario was chosen; it is described in detail in Balmer et al. (23). The initial demand of this simulation scenario is derived from the Swiss Census of Population 2000 (24) and the National Travel Survey for 2000 and 2005 (19). For this scenario, a 10% sample was chosen of Swiss car traffic that crosses the area delineated by a 30-km circle around the center of Zurich (the Bellevue area).

The activity location data set is computed from the Federal Enterprise Census 2001 (21), and the network is an updated and corrected version of the Swiss National Transport Model [Vrtic et al. (25)]. An average weekday is simulated. The locations for the flexible activities are initially assigned randomly within the Zurich region. Comparable data are available in most countries from official sources, such as censuses and national travel diary studies, and commercial sources, such as navigation network providers, yellow pages publishers, or business directories.

In detail, the following data form the basis of the scenario:

- Total number of agents simulated: 61,480;
- Total number of facilities for
 - Shopping activities: 1,162 and
 - Leisure activities: 6,662;
- Total number of activities performed for
 - Shopping: 25,896 and
 - Leisure: 40,971;
- Total number of persons doing
 - Shopping activities: 22,639,
 - Leisure activities: 32,229, and
 - Shopping or leisure activities: 42,962;
- Activities:
 - Fixed: home, work, and education and
 - Flexible: shop and leisure;

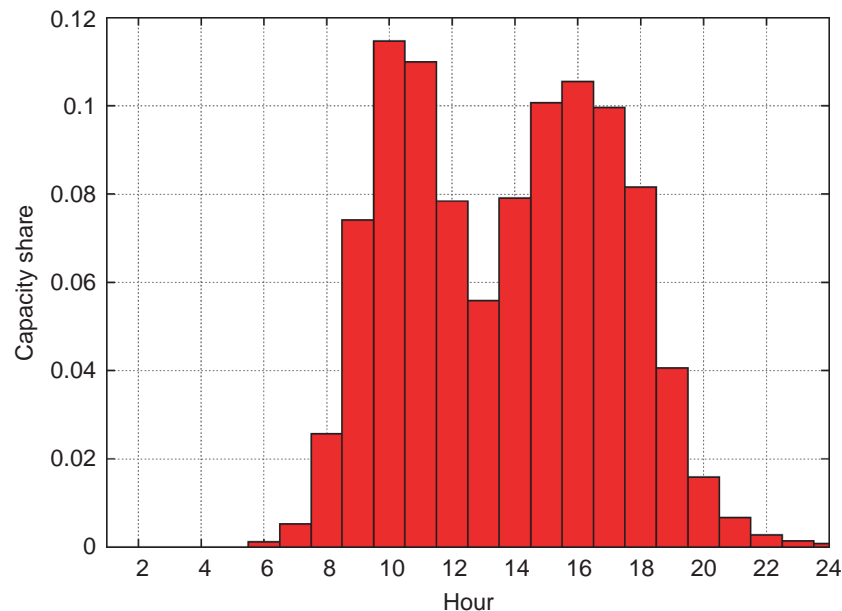


FIGURE 1 Time-dependent capacity share.

- Average number of trips per agent: 3.35; and
- Network, number of
 - Directed links: 60,492 and
 - Nodes: 24,180.

RESULTS

One goal of this work was to achieve computability, that is, to drive the coevolutionary system to a fixed point within a reasonable time (even though uniqueness of a found solution has not yet been studied). A second goal is to improve the behavioral realism of this model by including activity capacity restraints that are expected to reduce the number of implausibly overloaded activity locations. Simulation results are produced for the following four configurations, spanning the relevant combinations of choices and choice sets:

Configuration 1:

- Replanning: rerouting and time choice and
- Scoring: no capacity restraints;

Configuration 2:

- Replanning: rerouting, time choice, and location choice (universal choice set) and
- Scoring: no capacity restraints;

Configuration 3:

- Replanning: rerouting, time choice, and location choice (universal choice set) and
- Scoring: including capacity restraints; and

Configuration 4:

- Replanning: rerouting and time choice and
- Scoring: including capacity restraints.

As mentioned in the section on the simulation scenario, all flexible activity locations were initially assigned randomly within the Zurich circle. During the replanning phase, location choice for Configurations 2 and 3 were made by random choice from the universal choice set that contains the locations within the Zurich circle. Configuration 4 used the authors' novel algorithm, which constrained the choice set with respect to the agents' travel time budget. For Configuration 1, no location choice was performed during the replanning phase. The replanning step was carried out for 10% of the agents in each iteration. As no precisely defined termination criterion (i.e., a general measure for the relaxation of the system) existed yet for MATSim, the scenario runs were terminated after 500 iterations, which was sufficient to evaluate the actual achievement of the above-mentioned goals.

As Figure 2 shows, in all four configurations, the average plan score (utility), shows a strong increase during the first iterations, then a short attenuation phase, and finally a long phase of small increases. This is the typical progress of evolutionary algorithms [Eiben and Smith (26)], and this, in general, gives an indication of the effective operation of the coevolutionary algorithm of MATSim.

A comparison of Configurations 3 and 4 in Figure 2 shows a much faster decrease of the average travel times and distances for Configuration 4 and hence a faster increase of the average plan's score than random choice from the universal location choice set as made for Configuration 3. This comparison reveals the strongly needed speedup of the relaxation process toward practical computability. The urgent need for this speedup is further illustrated by the results of running Configuration 3 for 4,000 iterations (i.e., more than 25 days)

(Figure 3a). Under the assumption that Configurations 3 and 4 reach the same Nash equilibrium, it is expected that finally the average travel distances are equal for both configurations. For Configuration 3, it can be seen that, at between 3,000 and 4,000 iterations, the decrease in average travel distance still goes on. However, the value after 4,000 iterations is still much higher than the value that is reached for Configuration 4 after only 500 iterations (Figure 2b). This means that it takes a very long time until the average travel distance for Configuration 3 is at the level of Configuration 4. Thus, it can be concluded that, when the modelers of a system are being confronted with phase spaces that are prohibitively large for exhaustive search, confining the agents' choices to local steps per iteration by using a time–geographic approach actually is productive, similar to local search methods in numerical optimization. Nevertheless, the crucial question about uniqueness of a found fixed point (Nash equilibrium) and the follow-up discussion on local optimal needs to be researched.

The effect of explicitly incorporating the activity location load, coupled with capacity restraints, into the agents' location choice process is visible in Figure 4. Figure 4a shows the distribution of $f_{\text{attractiveness}}$ with respect to the activity locations. In relation to the distribution of visitors on the activity locations (Figure 4b), a strong shift toward the activity locations with a high $f_{\text{attractiveness}}$ can be observed for Configuration 2, whereas this shift is much smaller for Configuration 3, where capacity restraints are applied. Given the distribution of $f_{\text{attractiveness}}$ with respect to the activity locations (Figure 4a), the strong shift for Configuration 2 suggests an overload of the highly attractive locations. In fact, Figure 4c shows many heavily overloaded activity locations for Configuration 2, whereas, for Configuration 3, this implausible overload is not observed. These observations lead to the conclusion that designing a constrained model with respect to activity location load improves behavioral realism in general.

In addition to affecting the activity facility load, the constrained model shows two further effects that will have to be the subject of evaluation steps in the future. The comparison of Configurations 2 and 3 in Figure 2 shows that the constrained model produces a small increase in travel distances (and times). In addition to that spatial effect, constraints produce a temporal effect. Besides a general reduction of the load (shortening of the shopping duration), comparison of Figure 3b to Figure 1 shows that the aggregated hourly load of activity locations is adjusted to the time-dependent capacity restraints.

Table 1 gives the average computation times per iteration for the four configurations. [The data in Table 1 were computed with four CPUs (Dual-Core AMD Opteron Processor 8218 with 2,600 MHz and 1,024 KB cache size) and 18 GB of RAM]. Due to shorter routes, which have to be handled in the microsimulation, computation times are generally reduced by performing location choice (compare Configurations 1 and 2). In particular for Configuration 4, which produces short routes after a few iterations, it can be seen that the additional replanning effort is more than compensated by shorter microsimulation computation times. In other words, applying the time–geographic approach in the simulation not only reduces the total number of needed iterations but is also expected to lower the average computation time per iteration.

CONCLUSIONS AND OUTLOOK

Through the incorporation of location choice, MATSim is capable of simultaneously modeling time, route, and location choice for shopping and leisure activities.

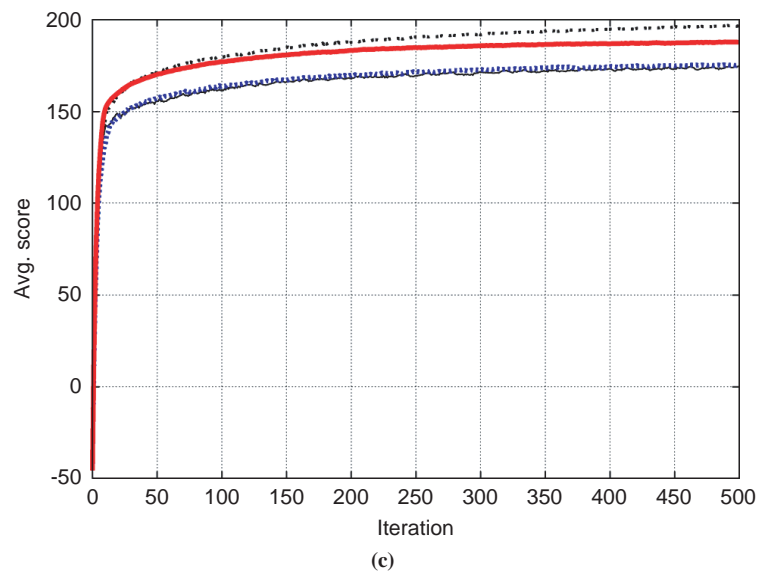
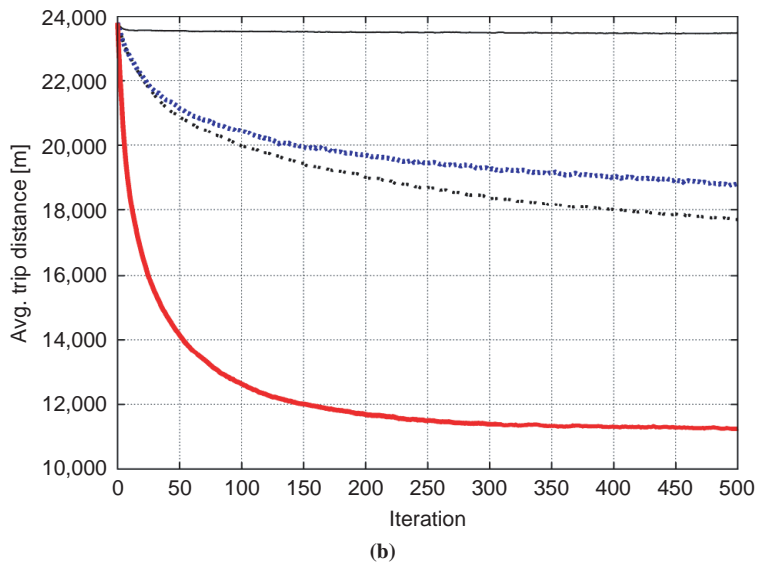
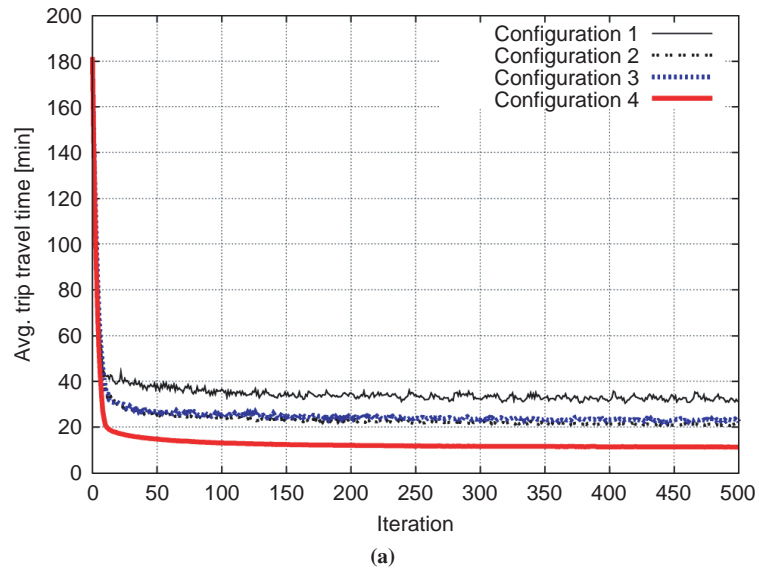


FIGURE 2 Agents' best plan: (a) average trip travel times, (b) average trip travel distances, and (c) average plan score.

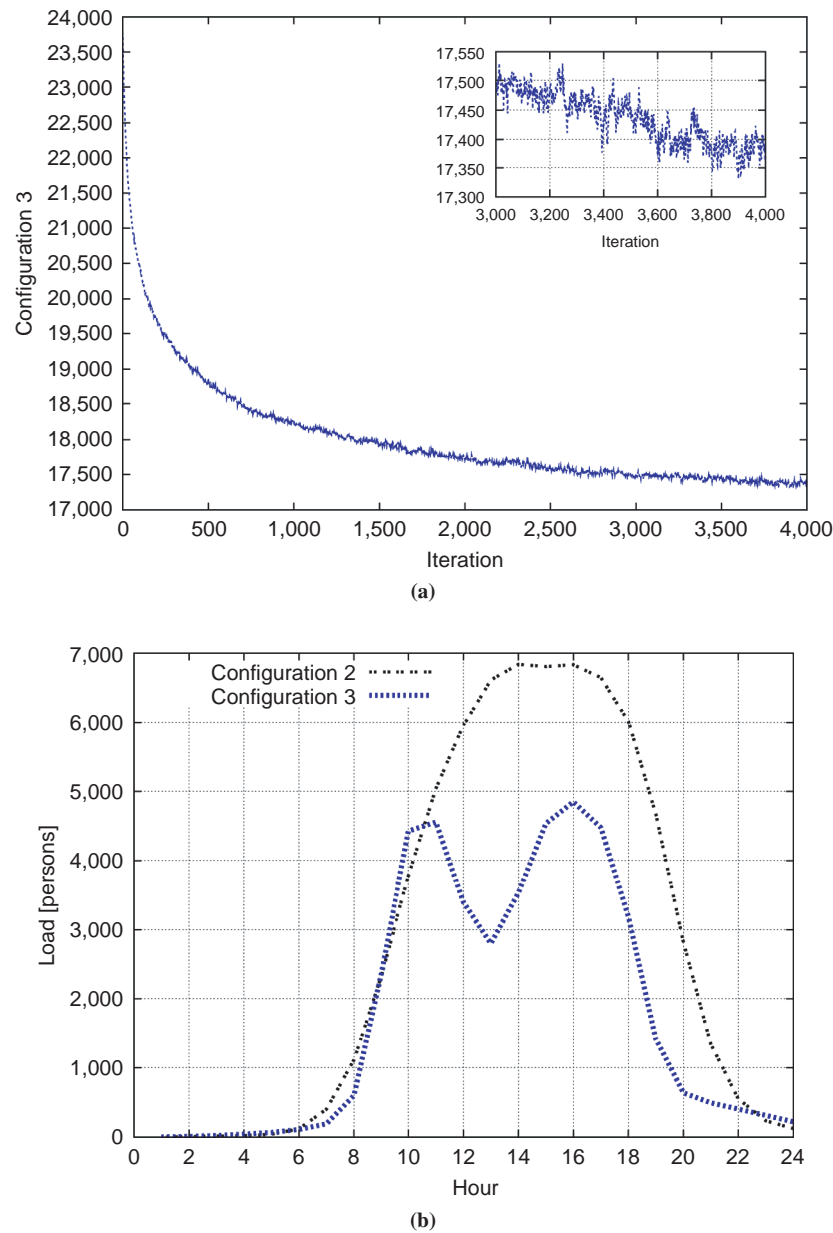


FIGURE 3 Results for Configuration 3 (Iterations 0 to 4,000): (a) average travel distance of agents' best plan and (b) aggregated hourly load of the shopping activity locations.

The results presented, on the one hand, emphasize that random location choice made from the universal choice set is not possible for large-scale scenarios in relation to computability, which is particularly important when a complete scenario is being simulated for Switzerland with 7 million agents and 1.7 million activity locations, which is the long-term aim of MATSim. On the other hand, the results exemplify that confining the agents' choices to a local range per iteration by including the time–geographic approach is actually a useful step on the way to computability. In addition, the paper shows that the time–geographic approach can easily be integrated by using a simple and efficient recursive algorithm that successively generates an implicit choice set for shopping or leisure activities.

Moreover, evidence is given that incorporating activity location load coupled with capacity restraints actually improves the behavioral

realism of location choice models of microsimulations by reducing the number of implausibly overloaded locations.

As mentioned earlier, calibration and validation using empirical data are subjects for future work. In addition, the crucial and highly complex question about the uniqueness of a found fixed point of the coevolutionary system needs to be answered. To improve goodness of fit, the range of attributes included in the utility function will be considerably extended, as the research will draw on recent Swiss work [Carrasco (22)] estimating facility-specific grocery location choice models by means of the geocoded National Travel Survey (19). A possible improvement in the presented algorithm for choice set generation could be to handle the flexible activities on the basis of priority rather than chronologically. On the practical side, tools for easy analysis of time-dependent aggregated and disaggregated

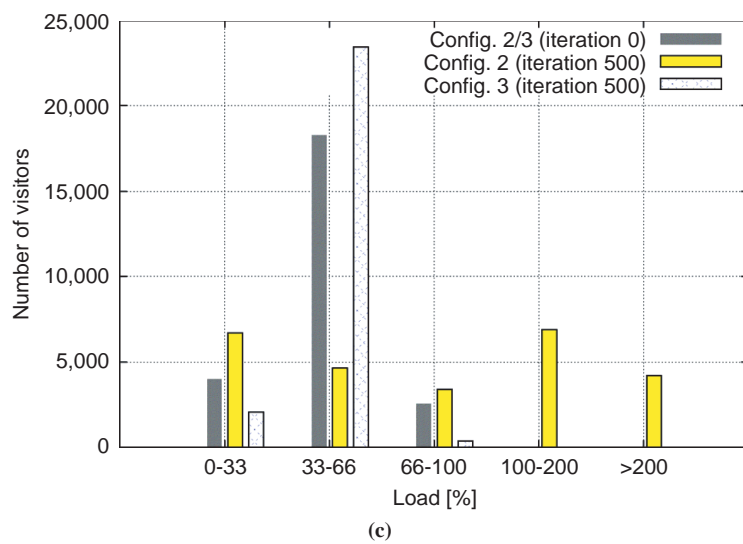
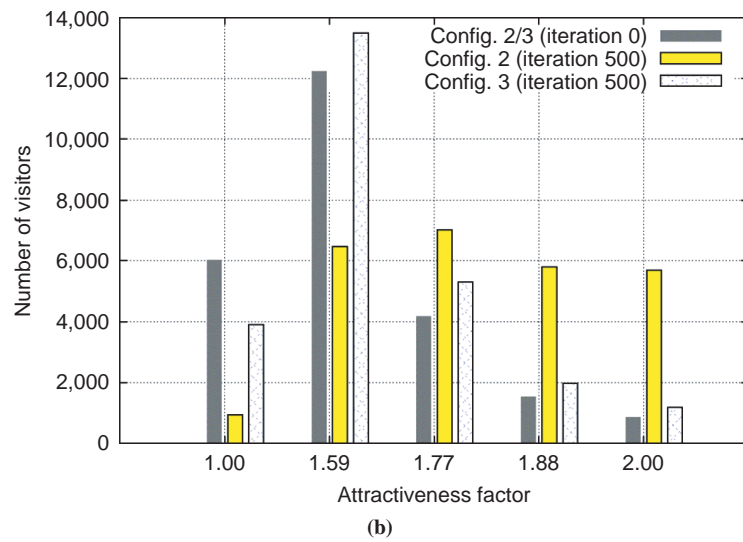
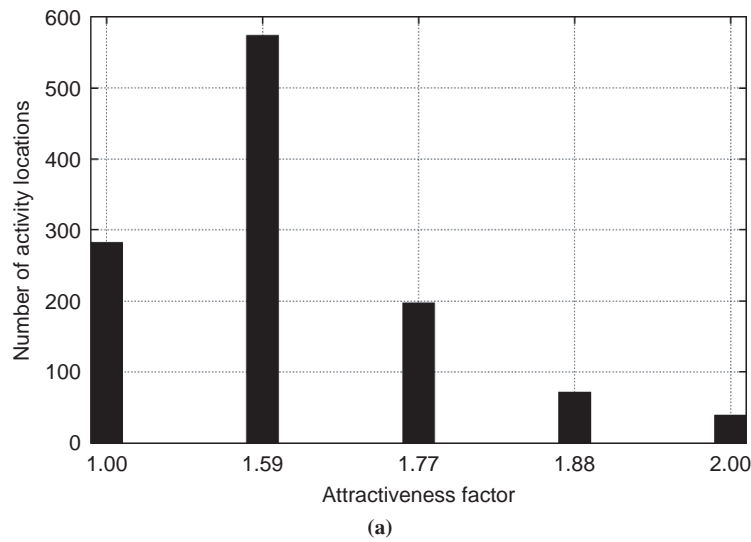


FIGURE 4 Activity location load: (a) number of activity locations with respect to attractiveness factor $f_{\text{attractiveness}}$, (b) number of visitors at the activity locations with respect to $f_{\text{attractiveness}}$, and (c) number of visitors at the activity locations with respect to activity location load.

TABLE 1 Mean Computation Time per Iteration

Configuration	Mobsim	Replanning	Sum
1 Rerouting; time choice no capacity restraints	581	13	594
2 Rerouting; time choice; location choice no capacity restraints	498	49	547
3 Rerouting; time choice; location choice capacity restraints	529	50	579
4 Rerouting; time choice; location choice improved capacity restraints	365	82	447

facility usage and catchment area analysis will be added to the MATSim module for location choice.

REFERENCES

- MATSim-T, Multi-Agent Transportation Simulation Toolkit. 2008. www.matsim.org.
- Nash, J. Non-Cooperative Games. *The Annals of Mathematics*, Vol. 54 No. 2, 1951, pp. 286–295.
- Kitamura, R., A. Kikuchi, and S. Fujii. An Overview of PCATS/DEBNetS Microsimulation System: Its Development, Extension, and Application to Demand Forecasting. In *Simulation Approaches in Transportation Analysis: Recent Advances and Challenges* (R. Kitamura and M. Kuwahara, eds.), Springer, New York, 2005, pp. 371–399.
- Arentze, T. A., and H. J. P. Timmermans. ALBATROSS—A Learning-Based Transportation Oriented Simulation System. *Transportation Research Part B: Methodological*, Vol. 38, No. 7, 2004, pp. 613–633.
- Vovsha, P., E. Petersen, and R. Donnelly. Microsimulation in Travel Demand Modeling: Lessons Learned from the New York Best Practice Model. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1805, Transportation Research Board of the National Academies, Washington, D.C., 2002, pp. 68–77.
- Timmermans, H. J. P. Models of Activity Scheduling Behavior. *Stadt Region Land*, Vol. 71, 2001, pp. 33–47.
- Cetin, N. *Large-Scale Parallel Graph-Based Simulations*. Ph.D. thesis. ETH Zurich, Zurich, Switzerland, 2005.
- Balmer, M., B. Raney, and K. Nagel. Adjustments of Activity Timing and Duration in an Agent-Based Traffic Flow Simulation. In *Progress in Activity-Based Analysis* (H. J. P. Timmermans, ed.), Elsevier, Oxford, United Kingdom, 2005, pp. 91–114.
- Raney, B. *Learning Framework for Large-Scale Multi-Agent Simulations*. Ph.D. thesis, ETH Zurich, Zurich, Switzerland, 2005.
- Lefebvre, N., and M. Balmer. Fast Shortest Path Computation in Time-Dependent Traffic Networks. Presented at 7th Swiss Transport Research Conference, Ascona, Switzerland. Sept. 2007. www.strc.ch/pdf_2007/lefebvre.pdf.
- Charypar, D., and K. Nagel. Generating Complete All-Day Activity Plans with Genetic Algorithms. *Transportation*, Vol. 32, No. 4, 2005, pp. 369–397.
- Balmer, M. *Travel Demand Modeling for Multi-Agent Traffic Simulations: Algorithms and Systems*. Ph.D. thesis. ETH Zurich, Zurich, Switzerland, May 2007.
- Balmer, M., K. W. Axhausen, and K. Nagel. An Agent-Based Demand-Modeling Framework for Large-Scale Microsimulations. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1985, Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 125–134.
- Balmer, M., K. Nagel, and B. Raney. Large-Scale Multi-Agent Simulations for Transportation Applications. *Journal of Intelligent Transportation Systems*, Vol. 8, No. 4, 2004, pp. 205–223.
- Kirkpatrick, S., C. Gelatt, and M. Vecchi. Optimization by Simulated Annealing. *Science*, Vol. 220, 1983, pp. 671–680.
- Hägerstrand, T. What About People in Regional Science? *Papers of the Regional Science Association*, Vol. 24, 1970, pp. 7–21.
- Landau, U., J. N. Prashker, and B. Alpern. Evaluation of Activity Constrained Choice Sets to Shopping Destination Choice Modeling. *Transportation Research Part A: Policy and Practice*, Vol. 16, No. 3, 1982, pp. 199–207.
- Scott, D. M. Constrained Destination Choice Set Generation: A Comparison of GIS-Based Approaches. Presented at 85th Annual Meeting of the Transportation Research Board, Washington, D.C., 2006.
- Ergebnisse des Mikrozensus 2005 zum Verkehrsverhalten*. Swiss Federal Statistical Office, Neuchâtel, Switzerland, 2006.
- Traffic Assignment Manual*. U.S. Bureau of Public Roads, Department of Commerce, Washington, D.C., 1964.
- Eidgenössische Betriebszählung 2001—Sektoren 2 und 3, GEOSTAT Datenbeschreibung*. Swiss Federal Statistical Office, Geostat, 2001. www.bfs.admin.ch/bfs/portal/de/index/dienstleistungen/geostat/datenbeschreibung/betriebszaehlung05.Document.111424.pdf.
- Carrasco, N. *Deciding Where to Shop: Disaggregate Random Utility Destination Choice Modeling of Grocery Shopping in Canton Zurich*. Master's thesis. IVT, ETH Zurich, Zurich, Switzerland, 2008.
- Balmer, M., K. W. Axhausen, A. Horni, K. Meister, D. Charypar, and F. Ciari. *Wirkungen der Westumfahrung Zürich: Eine Analyse mit einer Agenten-basierten Mikrosimulation*. Final report. Baudirektion Kanton Zurich, IVT, ETH Zurich, Zurich, Switzerland, 2009.
- Eidgenössische Volkszählung 2000*. Swiss Federal Statistical Office, 2000. www.bfs.admin.ch/bfs/portal/de/index/infoteh/erhebungen_quellen/blank/blank/vz/uebersicht.html.
- Vrtic, M., P. Fröhlich, and K. W. Axhausen. Schweizerische Netzmodelle für Strassen- und Schienenverkehr. *Jahrbuch 2002/2003 Schweizerische Verkehrswirtschaft* (T. Bieger, C. Lässer, and R. Maggi, eds.), Schweizerische Verkehrswissenschaftliche Gesellschaft (SVWG), St. Gallen, Switzerland, 2003, pp. 119–140.
- Eiben, A. E., and J. E. Smith, eds. *Introduction to Evolutionary Computing*, Springer, Berlin, 2003.

The Traveler Behavior and Values Committee sponsored publication of this paper.