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Preliminary results

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Abstract

As part of the recent integration of destination choices for discretionary activities, mechanisms to explicitly treat unobserved heterogeneity in MATSim were developed. This potentially introduced a large amount of randomness to the model as so far the MATSim utility function was deterministic. Adding randomness to a model clearly makes necessary variability analysis. In this paper first steps in assessing the variability of MATSim results are undertaken. The results are preliminary and need comprehensive verification and elaboration.

Keywords

Variability analysis, autocorrelation, microsimulation

1 Problem Description and Research Goal

MATSim is based on utility maximization implemented by econometric discrete choice models (McFadden, 1978). However, until recently the utility function of MATSim was deterministic. As part of the recent integration of destination choices for discretionary activities the random error term has been added, finally making MATSim compatible with discrete choice theory. This potentially introduced a large amount of randomness to the model. Obviously, it is now at latest required to perform a variability analysis or in other words a sampling error analysis.

1.1 Sampling Error Analysis: State-of-Practice and State-of-Art

In practice large-scale microsimulation results are not seldom given on the basis of one single run Hale (1997) owed to the very high computation costs (see e.g., (Balmer *et al.*, 2009)). E. g. in MATSim simulating 7 Million person days takes minimally $4.5h/iteration \times 50$ iterations ~ 10 days (Balmer *et al.*, 2010, see). This procedure is justifiable as policy decisions based on a single microsimulation run are still preferable to those missing this peace of information. Furthermore, relying on a single simulation run is *not* necessarily a problem as long as the results are given at the appropriate aggregation level as aggregation in general reduces variance, i.e., reduces the sampling error as given by Equation 1.

However, when trying to reach a certain confidence, exclusively relying on aggregation done for a single simulation run is problematic. This is particularly true when very heterogeneous elements are aggregated. Making the aggregates very large, may lead to aggregation of e.g., rural and urban areas with very different infrastructure levels. This introduces again a large amount of systematic variance. Furthermore, aggregation clearly reduces model resolution. This is may problematic as many current planning questions (e. g. road pricing) require a certain minimal model resolution. Thus, aggregation is strictly limited.

Concluding, this means that relying on a single simulation run is at least questionable. In any case, be it that the results are produced by a single run or multiple runs, sampling issues need to be analyzed for different spatial and temporal resolutions.

A few papers exist, where sampling issues have been investigated in the context of microsimulations such as Ziems *et al.* (2011); Cools *et al.* (2011); Veldhuisen *et al.* (2000); Castiglione *et al.* (2003); Hackney (2009). The investigations focus on the required number of microsimulation runs to reach stable results to reach a given level of confidence. Thereby only the random seeds are mutated whereas the inputs are held fixed. Castiglione *et al.* (2003) concludes his investigations: "*It would be useful to conduct analyses similar to those presented here with other model systems, both to examine the transferability of the conclusions and to provide*

analysis specific to those models for future reference as they are used in application. Performing such analyses for MATSim is the first goal of this paper. This continues the work of Hackney (page 128ff 2009) who has investigated small ensembles of MATSim runs, where unobserved heterogeneity was *not* yet included in MATSim.

The conclusion of the papers cited above is that sampling error is essentially a *non-issue* for the simulators in question and the investigated temporal and spatial resolution levels. I.e., only a relatively small number of simulation runs (i.e., samples) is required to reach results given a certain practically useful confidence level. This means that the simulation results only feature little variability (as derived from Equation 1). A follow-up analysis must thus compare the variability in the microsimulation with the variability measured in the transport system. Getting some first insights regarding this, is the second goal of this paper.

1.2 Sources of Variability in Microsimulations

Travel demand is characterized by substantial intra- and interpersonal variability (see e.g., (Buliung *et al.*, 2008; Kitamura *et al.*, 2006; Susilo and Kitamura, 2005; Schlich, 2001; Schlich and Axhausen, 2003; Pas and Koppelman, 1987; Pas, 1988; Jones and Clarke, 1988; Hanson and Huff, 1988b,a; Huff and Hanson, 1986; Hanson and Huff, 1982; Burnett, 1977; Golledge, 1970)). This variability is due to changing endogenous motivations of the individuals (such as needs, preferences or personal experience) and due to a varying environment, including the feedback behavior of the other transport system participants.

For modeling purposes variability is often divided into a *systematic* and a *random* part (see e.g., Vovsha *et al.*, 2002). The microsimulation model variability can thus be categorized as follows.

- Systematic observed variability: It has rational sources in reality which are identified by the model at hand (observed). It is included either as model input or directly in the model formulation or both.
- Random variability:
 - inherently random (i.e., unobservable) variability: A certain share of the individuals' decisions are might performed on the basis of chance.
 - unobserved, but actually systematic variability: The decision is actually made on a rational basis. But the modeler misses knowledge about the idiosyncratic rationales of the decision makers.
 - true random model variability: This variance is caused by algorithmic difficulties. For large-scale systems finding the global optimum is not trivial. One might get stuck local optima dependent on the random seeds chosen. This variability is present even if no other sources of random exist.

While true random model variability reduces the model quality in general and should be minimized, all the other variabilities mentioned above are necessary parts of the model. The random parts of the variability are included in the model by means of random sampling mechanisms. As sampling is the constitutive process of microsimulations Wolf (2001a,b), they are a productive tool in this context, and they are increasingly applied in transport modeling.

Before the variability included in MATSim is analyzed in detail in Section 1.4, a short introduction of the simulation framework is given.

1.3 MATSim—In Brief

The Multi-Agent Transport Simulation Toolkit, MATSim (MATSim-T, 2011) is an activity-based, easily extendable, open source, multi-agent simulation toolkit implemented in JAVA and designed for large-scale scenarios. A good overview of MATSim is given in Balmer *et al.* (2006).

MATSim is a co-evolutionary model. While being in a competition for space-time slots on the transportation infrastructure or in destination facilities with all the other agents, every agent iteratively optimizes its daily activity chain by *trial and error*. Every agent therefore possesses a memory of a fixed number of day plans, where each plan is composed of a daily activity chain and an associated utility value (in MATSim called *plan score*).

In every iteration prior to the simulation of the network loading (e. g., Cetin, 2005), every agent selects a plan from its memory. This selection is dependent on the plan utility. In many MATSim investigations, a model that generates a logit model is used. Before the plans are executed on the infrastructure a certain share of the agents (usually 10 %) is allowed to clone the selected plan and to subsequently modify this cloned plan. Thereby three choice dimensions are included for this paper: time choices (Balmer *et al.*, 2005), route choices (Lefebvre and Balmer, 2007), and destination choices.

If an agent ends up with too many plans (here set to “5 plans per agent”), the plan with the lowest score (configurable) is removed from the memory of these agents.

An iteration is completed by evaluating the agent’s day described by the selected day plans. The computation of the plan score is compatible with micro-economic foundations. The basic MATSim utility function was formulated in Charypar and Nagel (2005) which is derived from the *Vickrey* model for road congestion as described in Vickrey (1969) and Arnott *et al.* (1993). The utility of a plan (described in detail in Charypar and Nagel, 2005) is computed as the sum of all activity utilities plus the sum of all travel (dis)utilities.

1.4 Sources of Variability in MATSim

In the MATSim scenarios applied so far, work and home locations are fixed as they are given with high geographic resolution by the Swiss Census of Population 2000 (Swiss Federal Statistical Office, 2000). Variability in terms of model input is introduced by variety of the day chain structures and the desired activity durations. These data are derived from a PUS, namely from the National Travel Survey for the years 2000 and 2005 (Swiss Federal Statistical Office, 2006). Model variability is introduced by the time, route and destination choice modules. For the investigations of this paper car traffic only is modeled. Person attributes other than the home and work locations, such as household type or income are not included in the MATSim replanning modules in a robust manner. I.e., no variability is introduced by such kind of person attributes yet.

One goal of this paper is to investigate the amount of variability generated by the modules while the model input is held constant. However, this is only the starting point for a more in-depth future analysis, which also must include the explicit modeling of temporal variability as described in the next section.

1.4.1 Temporal Variability and Microsimulations Applied as Cross-Sectional Methods

While interpersonal variety in terms of travel behavior is researched to a great extent, intrapersonal or temporal variety has long been neglected in transport literature. The assumption was that individual travel behavior is dominated by repetition. This lack of research stems from high costs for longitudinal studies but also from methodological difficulties in assessing the temporal variability. The assessment of variety is intrinsically tied to the measures chosen, where the measurement resolution is particularly important. Clearly, a higher measurement resolution in general generates larger variability. This makes the assessment of variability methodologically demanding.

Not being paralyzed by this lack of research, people have started building models that are essentially based on cross-sectional data with the "typical (work) day" as the unit of analysis. In these models clearly averages are built over multiple *persons*. In other words, intrapersonal variability diffuses into interpersonal variability (which is incorrect) and also white noise (unobserved heterogeneity). Many microsimulations and also MATSim belong to this group of models.

Recent research has shown that the intrapersonal, i.e. temporal, variability is large. This renders cross-sectional models problematic as large aggregates are necessary to reach stable results.

Furthermore, the spatial (i.e., interpersonal) and temporal dimension are substantially correlated (known as *autocorrelation*) (see Figure 1), which, of course, influence the total variability of the results. In mathematical terms this reads. Given two random variables X_0 and X_1 representing an arbitrary time-dependent decision of individual 0 and 1, i.e., $X_0 = f_0(t)$ and $X_1 = f_1(t)$, the variance of two random variables is $Var(X_0, X_1) = Var(X_0) + Var(X_1) + 2Cov(X_0, X_1)$. The covariance is non-zero for correlated variables, where the covariance is greater than zero if variables are equidirectional. There are a lot of transport-related decisions for which individuals tend to have a positive correlation, i.e., $Cov(X_0, X_1) > 0$. This is given by global rhythms of life. There are also decisions for which correlation is negative i.e., $Cov(X_0, X_1) < 0$. An example might be the avoidance of demand peaks, such as not visiting certain skiing resorts during school holidays. If the positive or negative correlation part dominates is a question for future work.

1.5 Discussion

Small Numbers of Simulation Runs:

As mentioned earlier previous work comes to the conclusion that the sampling error is negligible for the respective simulators and the levels of temporal and spatial resolution analyzed. In consequence, the simulation results only feature little variability. To be more specific, the results are subject to only little *unobserved* heterogeneity. However, if in reality a large variability is measured and if the *unobserved* part of this "true" variability is substantial, then small numbers of required simulation runs means that unobserved heterogeneity is not captured adequately by these models. I.e., then, small numbers of required simulation runs are essentially a weakness of the model. On the other side, if the variability is observed, then it can be introduced to the model as input, for example in the form of different day plans. In this case low required numbers of simulation runs are desirable.

Temporal Variability and Microsimulations Applied as Cross-Sectional Methods:

In the opinion of the authors the strength of microsimulations is that not only averages can be captured but also the fluctuations (see also Esser and Nagel (page 704 2001) or Newman and Barkema (page 11 1999)). However, as mentioned above, if microsimulations are used as cross-sectional methods, intrapersonal (i.e, temporal) variability diffuses into interpersonal variability and also white noise (unobserved heterogeneity). This transformation is random in nature. This makes it impossible to capture the temporal variability consistently by the random error terms. The results might show the same amount of variability as measured in reality but its effects on the network might be completely different. Thus, the presence of temporal variability (and even more so the temporal correlations) actually means that results for the

average working day requires to simulate multiple days. However, MATSim is not yet there. Thus, it is investigated here how much variability is produced by simulating one single day as done up to now.

2 Method

The sampling error is examined by using the 10% Zurich simulation scenario as described in Section 2.1. For illustration purposes a small-scale scenario as described in Section 2.2 is used in addition. The (aggregate) temporal variability in the transport system is assessed and compared to simulation results by using annual count data. The investigations done in this paper as well as future investigations profit from establishing and systematically applying a microsimulation sampling terminology. First steps in this regard are accomplished in Section 2.3.

2.1 Real-world Scenario: 10 % Zurich Scenario

The 10%-Zurich scenario is frequently used for the further development of MATSim but also for projects in Swiss planning practice (e.g., Balmer *et al.*, 2009; Horni *et al.*, 2009). The demand of the simulation scenario is derived from the Swiss Census of Population 2000 (Swiss Federal Statistical Office, 2000) and the National Travel Survey for the years 2000 and 2005 (Swiss Federal Statistical Office, 2006). A 10% sample of the car traffic (including cross-border traffic) that crosses the area delineated by a 30 km circle around the center of Zurich (Bellevue) is drawn, which results in almost 68'000 agents simulated. The activity location data set, comprising more than 10^6 home, work, education, shopping and leisure locations, is computed from the the Swiss Census of Population 2000 and the Federal Enterprise Census 2001 (Swiss Federal Statistical Office, 2001). The network from the Swiss National Transport Model (Vrtic *et al.* (2003)) is used, which consists of 60'492 directed links and 24'180 nodes. An average week day is simulated, where the number of trips per agent averages at 3.35. In total 25'896 shopping activities and 40'971 leisure activities are performed. Comparable data is available in most countries from official sources, such as censuses, national travel diary studies and commercial sources, such as navigation network providers, yellow pages publishers or business directories.

The choice setting comprises the three dimensions, time, route and destination choice for discretionary activities. The random seeds of all choice dimensions are varied simultaneously in this work.

2.2 Small-Scale MATSim Simulation Scenario

To be able to simulate a very large number of simulation runs for illustration purposes a small-scale synthetic MATSim scenario is used. The configuration of the scenario is depicted in Figure 5. The influence of temporal correlations is illustrated with this scenario.

1'000 persons, living in the two residence zones (location 1 and 2) perform one shopping activity with a desired duration of 90 minutes per day. The shopping activity can be performed in the home zones (location 1 and 2) or in the city zone (locations 5-9). 5 consecutive working days are simulated. A variable share of persons does a working activity in the city zone (at location 3) with shares of 0.9, 0.9, 0.9, 0.8, 0.5 (from Monday to Friday). On Fridays all workers have a desired working activity duration of only 7 instead of 9 hours. Time, route and destination choices are performed.

2.3 Sampling Terminology for Transport Microsimulations

Transport microsimulations are applied in activity-based, i.e., disaggregate contexts. Units of simulation, able to make decisions, are the persons or small homogeneous groups of persons. Prominent decision dimensions are time, route, mode and destination choice, where more recently also activity chain choice is researched. This spans a huge range of possible *combinations of decisions*. The number of combinations is essentially infinite as time choice is continuous.

A single microsimulation run represents *one* of these combinations. In sampling terminology, this is the *sampling unit*. *Variables* of interest may be the total vehicle miles traveled in the study area or the total daily load on a specific link. One simulation run provides one realization of these variables. The *sample* contains n simulation runs. The *population parameters* (such as the mean) of these variables are estimated by a *population statistic*. This statistic is accompanied by the *standard error*, also called *sampling error*. The sampling error is the standard deviation of the *sampling distribution*. For the case where the statistic is the mean the sampling error ϵ_s can be estimated by

$$\epsilon_s \sim \hat{\sigma} / \sqrt{n} \quad (1)$$

where $\hat{\sigma}$ is the statistic for the standard deviation and n is the sample size. The derivation of this formula is for example given in Hutchinson (1993).

3 Results

In the following sections results of preliminary experiments and analyses are presented. Comprehensive checks are planned for future work.

3.1 Traffic Count Data

As mentioned earlier the assessment of temporal variability of the transport system is non-trivial. In this paper we use traffic count data. Clearly, in general model assessment must not only base on count data, as also count data for a specific time features a substantial amount of random noise. I.e., random influences such as the weather naturally have a significant effect on counted values. However, the large amount of data provides a large number of sampling points. The data is prepared as described in detail in Balmer *et al.* (e.g., 2009). Additionally, the days between Christmas and new year are filtered out. Using Swiss count data with hourly resolution the volumes of an average working day (Tuesday to Thursday) are calculated. ... respectively ... unidirectional links are measured for Switzerland and the Zurich region respectively. Only count values greater than zero are included.

In Figure 1 the analysis of counted link volumes is given for different spatial and temporal domains, i.e., complete Switzerland and the region of Zurich (area with 12 km radius around the Bellevue in Zurich) is evaluated for the complete year and for single months. The (population) standard deviation is given with respect to the mean for the respective temporal and spatial domain. E.g., monthly volumes are compared to the monthly average and not to the annual average. A substantial variability can be observed, where the annual variability is always larger than the variability of single months. This indicates substantial temporal autocorrelations.

The variability of the Swiss volumes are greater than the values for the Zurich region. Different regions of Switzerland show different annual rhythms. E.g., skiing resorts have high loads in winter while Alpine passes are closed then. This can be interpreted as spatial autocorrelation combined with temporal autocorrelation.

3.2 Small-Scale Scenario

Two different configurations are simulated. For configuration 2 the averaging is done on the input side. E.g., an average share of workers is simulated, where for every day 20 % of the workers has a reduced desired working duration of 7 instead of 9 hours. In configuration 1 temporal correlations are explicitly taken into account by applying the shares of working activities and desired work durations per day. The hourly arrivals and departures plotted in Figure 2 and 3

respectively clearly illustrate that both configurations generate similar averages but different variability. Configuration 1 shows substantially larger variability as discussed in Section 1.4.1.

3.3 Zurich Scenario

A set of 10 simulation runs of the Zurich scenario are performed with identical input but varying random seeds. This corresponds to the Method of replication as described in Benekohal and Abu-Lebdeh (1994). At the moment a 10 % random draw of the complete population is simulated. Work started recently will look at different sampling rates (including oversampling).

3.3.1 Analyses

Population Level: At population level only little variability between simulation results exists. The mean score (averaged over agents) of all executed plans of the final iteration 100 averages at 180.871 with a sample standard deviation of 0.230 (i.e., 0.127 % of the mean).

Link Level: In Figure 4 the sample standard deviations of the link volumes for three different hours of the day are shown. When looking at a single iteration (here the final iteration 100) (Figure 4(a)) one can see substantial variability. However, when looking at the link volumes which are averaged over 5 iterations (here 96-100)(Figure 4(b)) this variability is at least halved. This means that results are subject to a relatively large intra-run variability. This can either mean that the system is far from a relaxed state or that the replanning modules add too much variability per iteration in general. In this work the replanning shares are quite high (20 % of the agents perform destination and route choice with time adaptations accordingly and additionally 20 % of the population performs time choice), which potentially introduces a large intra-run variability. In any case much intra-run variability is undesirable and makes further model improvements necessary. In this vein, this paper also fulfills first steps of model verification.

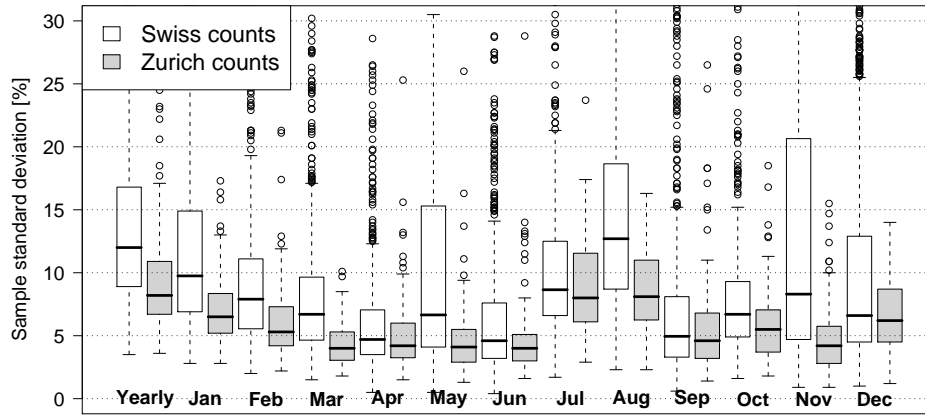
Person Level: In Figure 6 the sample standard deviations of the plans executed in iteration 100 are shown. The vast majority of agents shows a relatively small variability.

4 Conclusions and Outlook

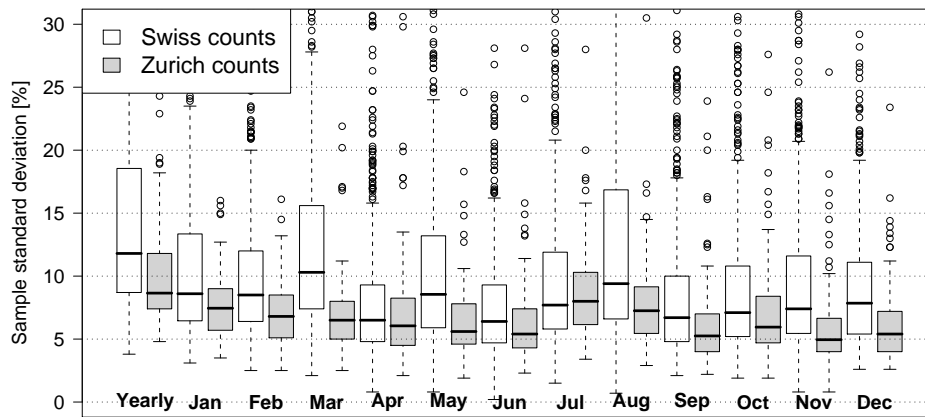
This paper undertakes first steps in evaluating the variability of MATSim results. This is especially important now as recently mechanisms to explicitly treat unobserved heterogeneity

Figure 1: Standard Deviation [%] of Swiss Annual Count Data.

(a) 07:00-08:00



(b) 11:00-12:00



(c) 17:00-18:00

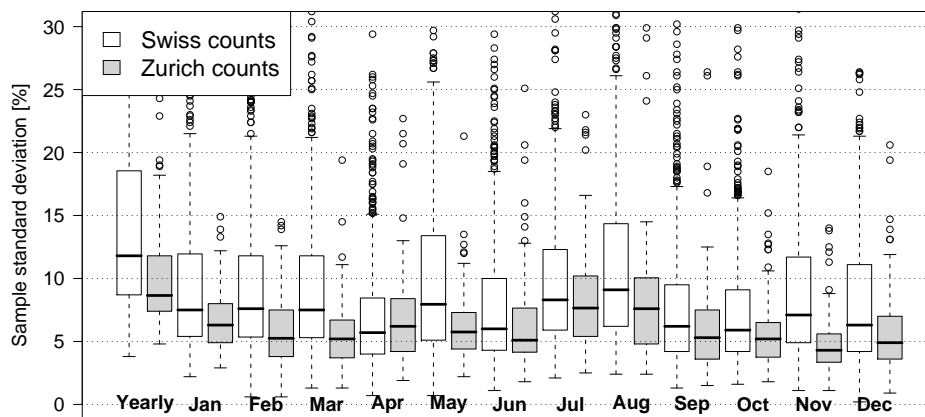
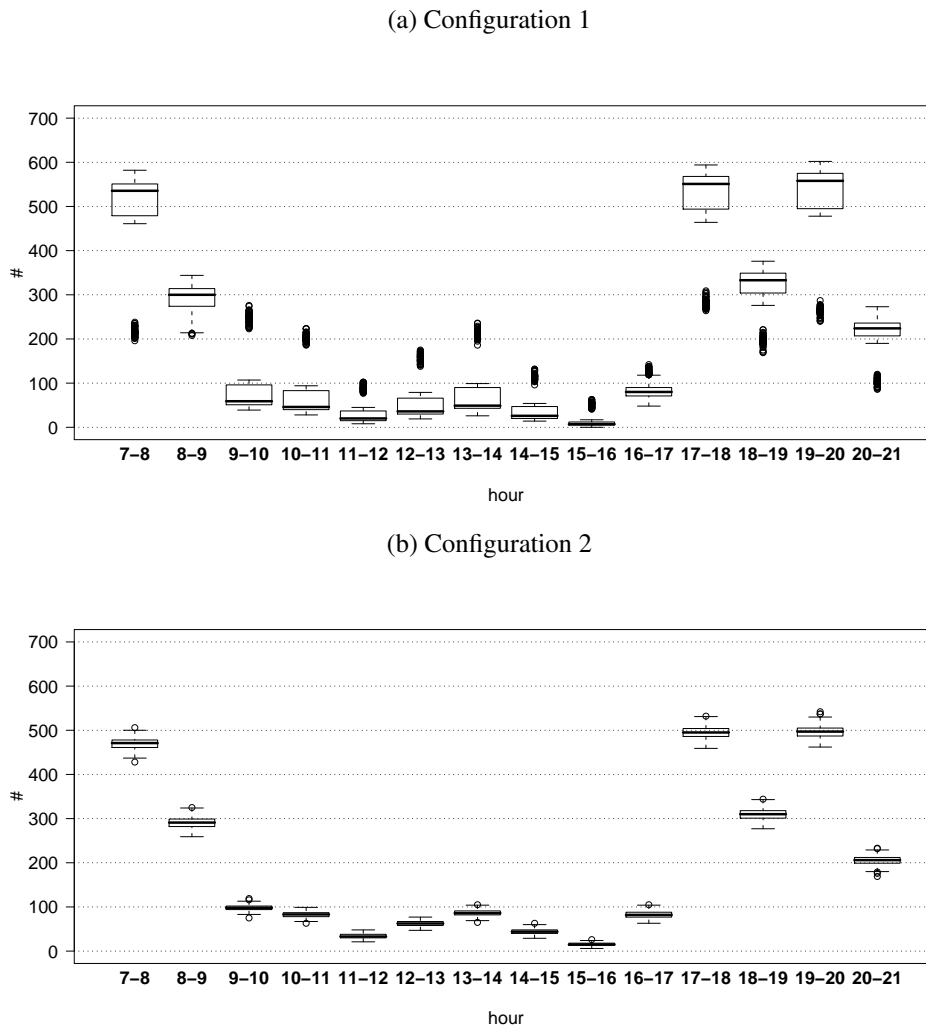


Figure 2: Arrivals for Configuration 1 and 2 (Iteration 100)



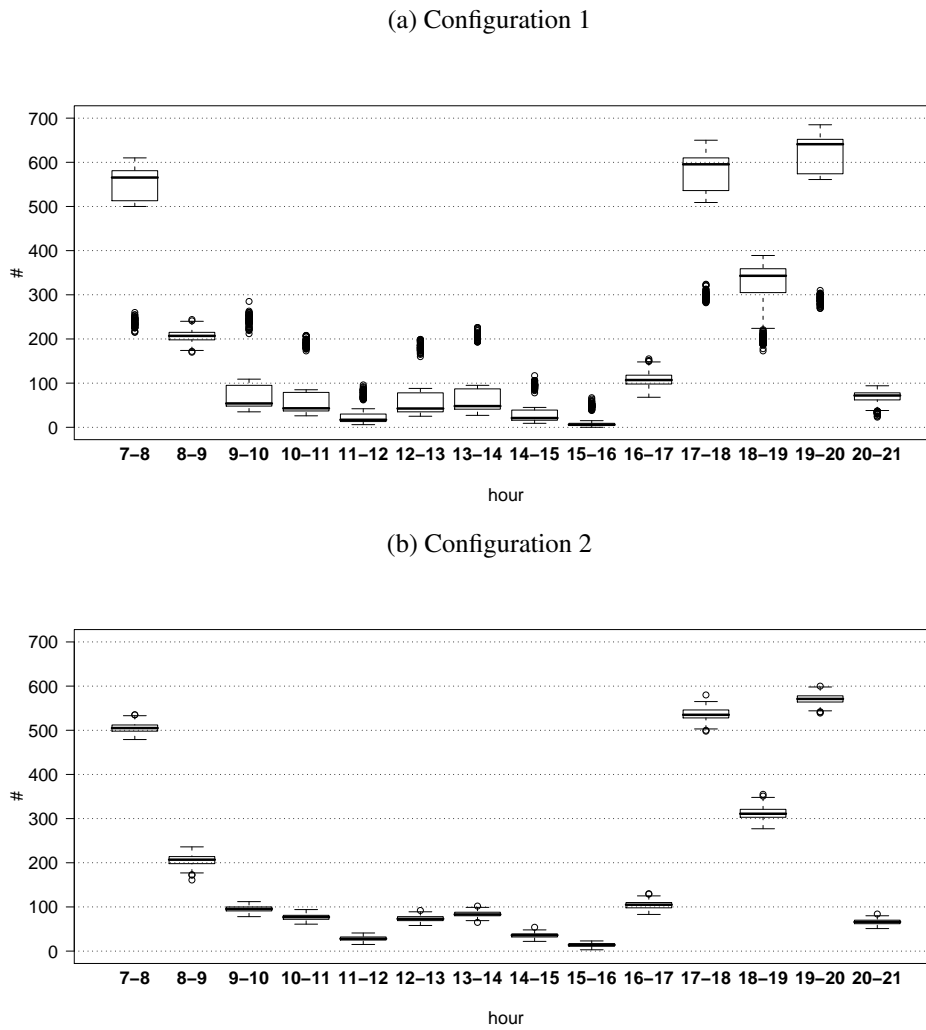
were added to the MATSim destination choice utility function. The results are preliminary and need comprehensive verification and elaboration.

An evaluation of annual Swiss count data shows substantial temporal and spatial variability. Microsimulation procedures must be developed to *efficiently* model not just the average statistics but also this variability.

The MATSim results also show substantial variability. A large intra-run variability is observed. As the development of the destination choice module is in an early stage the sources of the variability are not yet fully identified. It might be that some of the variety is introduced by the replanning configuration (e.g., large replanning share), which is of course undesirable.

Recommendations on required numbers of random runs for practice will be developed, when the verification of the destination choice module is finished. Future work will include the

Figure 3: Departures for Configuration 1 and 2 (Iteration 100)



investigation of different sampling rates (including oversampling of the population). Data for finer analyses will be available by a recent GPS survey conducted at the institute at the moment. In the far future mode choice and activity chain choice will be included.

Figure 4: Standard Deviation of Simulated Link Volumes

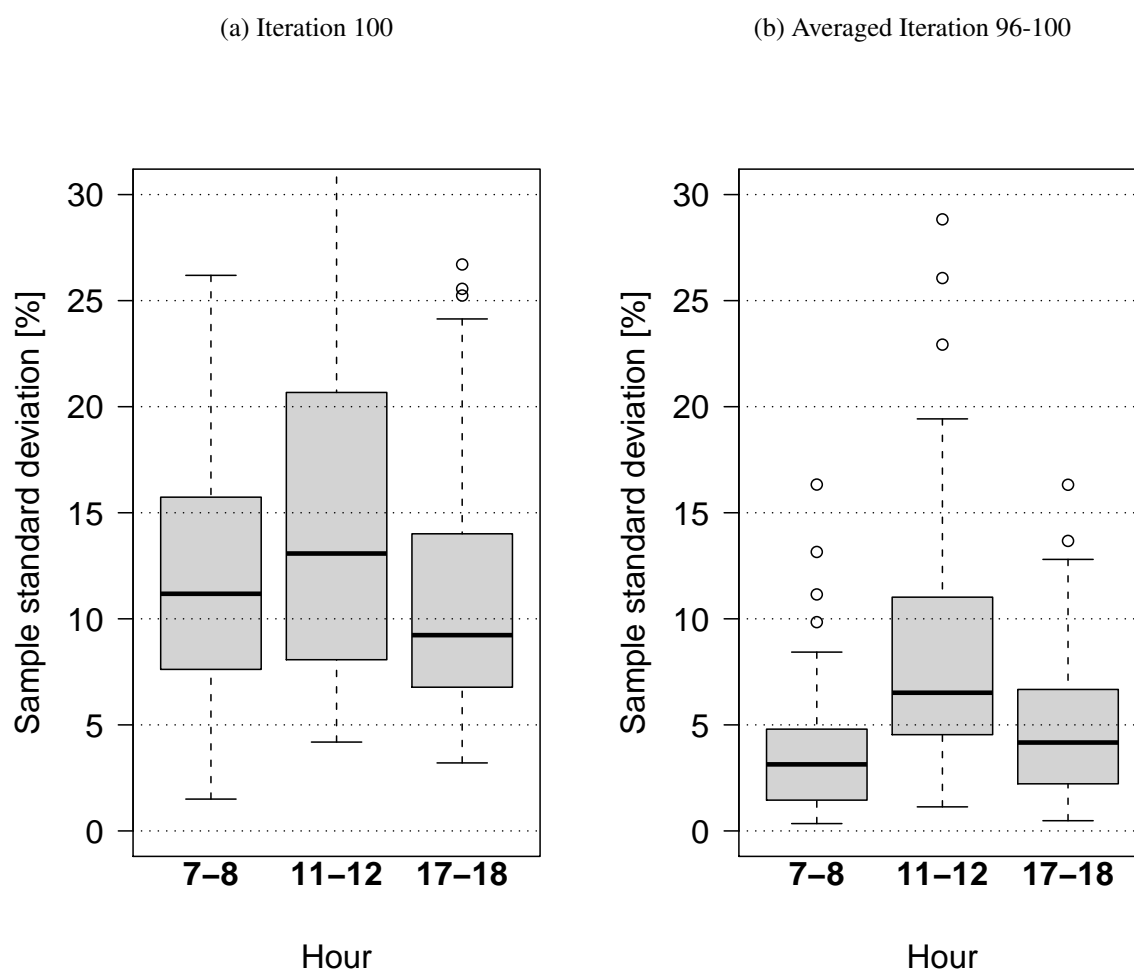


Figure 5: Small-scale Scenario

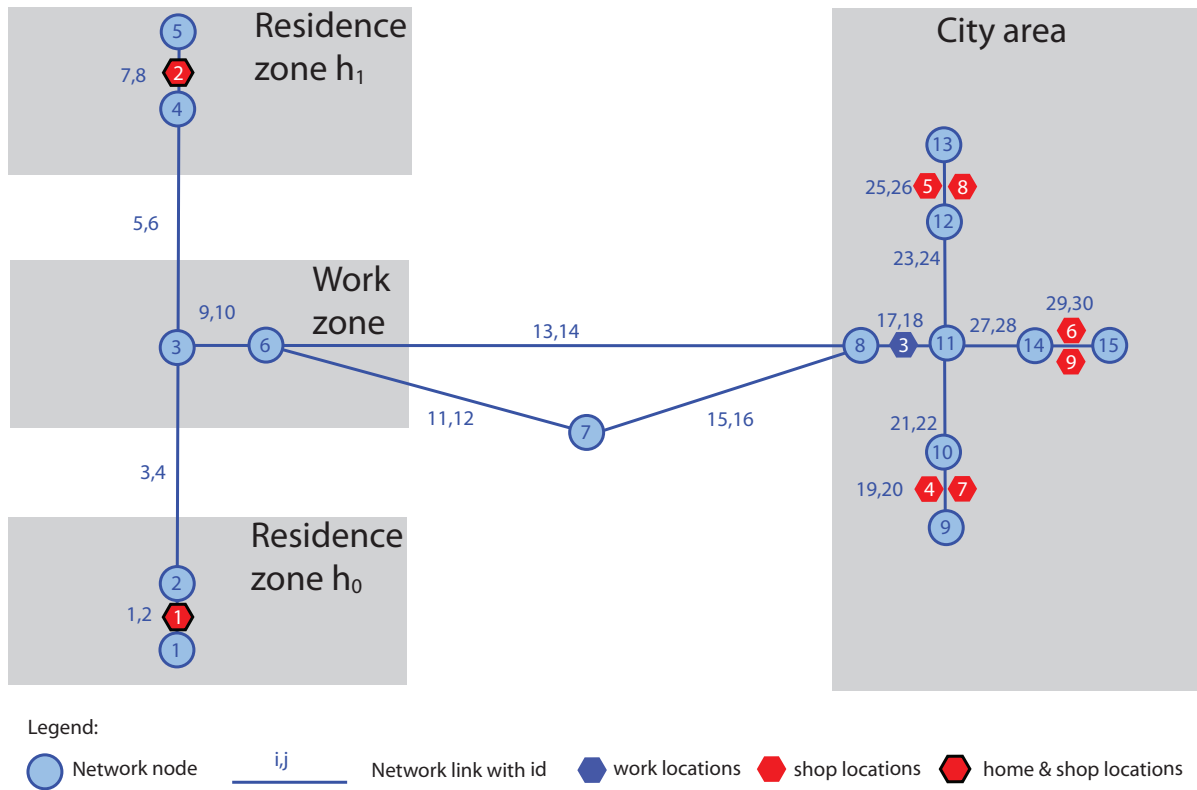
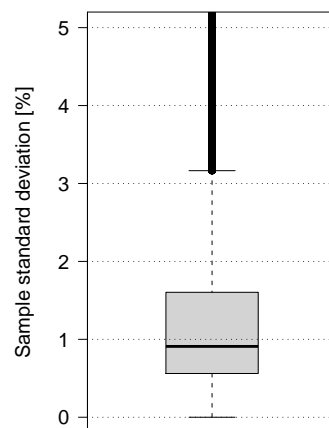


Figure 6: Standard Deviations of Executed Plans Scores



5 References

- Arnott, R., A. de Palma and R. Lindsey (1993) A structural model of peak-period congestion: A traffic bottleneck with elastic demand, *The American Economic Review*, **83** (1) 161–179.
- Balmer, M., K. W. Axhausen and K. Nagel (2006) An agent-based demand-modeling framework for large scale micro-simulations, *Transportation Research Record*, **1985**, 125–134.
- Balmer, M., A. Horni, K. Meister, F. Ciari, D. Charypar and K. W. Axhausen (2009) Wirkungen der Westumfahrung Zürich: Eine Analyse mit einer Agenten-basierten Mikrosimulation, *Final Report*, Baudirektion Kanton Zurich, IVT, ETH Zurich, Zurich, February 2009.
- Balmer, M., K. Meister, R. A. Waraich, A. Horni, F. Ciari and K. W. Axhausen (2010) Agenten-basierte Simulation für location based services, *Final Report*, F&E Förderung: Science to Market, **KTI 8443.1 ESPP-ES**, Datapuls AG, IVT, ETH Zurich, Zurich, February 2010.
- Balmer, M., B. Raney and K. Nagel (2005) Adjustments of activity timing and duration in an agent-based traffic flow simulation, in H. J. P. Timmermans (ed.) *Progress in Activity-Based Analysis*, chap. 5, 91–114, Elsevier, Oxford.
- Benekohal, R. F. and G. Abu-Lebdeh (1994) Variability analysis of traffic simulation outputs: Practical approach for TRAF-NETSIM, *Transportation Research Record*, **1457**, 198–207.
- Buliung, R. N., M. J. Roorda and T. K. Rummel (2008) Exploring spatial variety in patterns of activity-travel behaviour: Initial results from the Toronto Travel-Activity Panel Survey (TTAPS), *Transportation*, **35** (6) 697–722.
- Burnett, P. (1977) Tests of a linear learning model of destination choice: Applications to shopping travel by heterogeneous population groups, *Geografiska Annaler*, **59** (2) 95–108.
- Castiglione, J., and M. A. Bradley (2003) Systematic investigation of variability due to random simulation error in an activity-based microsimulation forecasting model, *Transportation Research Record*, **1831**, 76–88.
- Cetin, N. (2005) Large-scale parallel graph-based simulations, Ph.D. Thesis, ETH Zurich, Zurich.
- Charypar, D. and K. Nagel (2005) Generating complete all-day activity plans with genetic algorithms, *Transportation*, **32** (4) 369–397.
- Cools, M., B. Kochan, T. Bellemans, D. Janssens and G. Wets (2011) Assessment of the effect of micro-simulation error on key travel indices: Evidence from the activity-based model feathers, paper presented at the *90th Annual Meeting of the Transportation Research Board*, Washington, D.C.

- Esser, J. and K. Nagel (2001) Iterative demand generation for transportation simulations, in D. A. Hensher (ed.) *Travel Behaviour Research: The Leading Edge*, 689–709, Pergamon, Oxford.
- Golledge, R. G. (1970) Some equilibrium models of consumer behavior, *Economic Geography*, **46**, 417–424.
- Hackney, J. K. (2009) Integration of social networks in a large-scale travel behavior microsimulation, Ph.D. Thesis, ETH Zurich, Zurich.
- Hale, D. (1997) How many NETSIM runs are enough?, *McTrans Newsletter*, **11** (3) 4–5.
- Hanson, S. and J. Huff (1988a) Repetition and day-to-day variability in individual travel patterns: Implications for classification, in R. G. Golledge and H. J. P. Timmermans (eds.) *Behavioural Modelling in Geography and Planning*, 368–398, Croom Helm, London.
- Hanson, S. and J. O. Huff (1982) Assessing day-to-day variability in complex travel patterns, *Transportation Research Record*, **891**, 18–24.
- Hanson, S. and J. O. Huff (1988b) Systematic variability in repetitious travel, *Transportation*, **15** (1–2) 111–135.
- Horni, A., D. M. Scott, M. Balmer and K. W. Axhausen (2009) Location choice modeling for shopping and leisure activities with MATSim: Combining micro-simulation and time geography, *Transportation Research Record*, **2135**, 87–95.
- Huff, J. O. and S. Hanson (1986) Repetition and variability in urban travel, *Geographical Analysis*, **18** (2) 97–114.
- Hutchinson, T. P. (1993) *Essentials of Statistical Methods in 41 Pages*, Rumsby Scientific Publishing, Adelaide.
- Jones, P. M. and M. I. Clarke (1988) The significance and measurement of variability in travel behaviour, *Transportation*, **15** (1) 65–87.
- Kitamura, R., T. Yamamoto, Y. O. Susilo and K. W. Axhausen (2006) How routine is routine? an analysis of the day-to-day variability in prism vertex location, *Transportation Research Part A: Policy and Practice*, **40**, 259–279.
- Lefebvre, N. and M. Balmer (2007) Fast shortest path computation in time-dependent traffic networks, paper presented at the *7th Swiss Transport Research Conference*, Ascona, September 2007.
- MATSim-T (2011) Multi Agent Transportation Simulation Toolkit, webpage, <http://www.matsim.org>. Accessed on 03/04/2011.

- McFadden, D. (1978) Modeling the choice of residential location, in A. Karlqvist (ed.) *Spatial Interaction Theory and Residential Location*, 75–96, North-Holland, Amsterdam.
- Newman, M. E. J. and G. T. Barkema (1999) *Monte Carlo Methods in Statistical Physics*, Oxford University Press, Oxford.
- Pas, E. I. (1988) Weekly travel-activity behavior, *Transportation*, **15**, 89–109.
- Pas, E. I. and F. S. Koppelman (1987) An examination of the determinants of day-to-day variability in individuals' urban travel behavior, *Transportation*, **14**, 3–20.
- Schlich, R. (2001) Analysing intrapersonal variability of travel behaviour using the Sequence Alignment Method, paper presented at the *European Transport Conference*, Cambridge.
- Schlich, R. and K. W. Axhausen (2003) Habitual travel behaviour: Evidence from a six-week travel diary, *Transportation*, **30** (1) 13–36.
- Susilo, Y. O. and R. Kitamura (2005) Analysis of day-to-day variability in an individual's action space, *Transportation Research Record*, **1902**, 124–133.
- Swiss Federal Statistical Office (2000) Eidgenössische Volkszählung 2000, http://www.bfs.admin.ch/bfs/portal/de/index/infothek/erhebungen/_quellen/blank/blank/vz/uebersicht.html.
- Swiss Federal Statistical Office (2001) *Eidgenössische Betriebszählung 2001 - Sektoren 2 und 3, GEOSTAT Datenbeschreibung*, Swiss Federal Statistical Office, GEOSTAT, Neuchatel, <http://www.bfs.admin.ch/bfs/portal/de/index/dienstleistungen/geostat/datenbeschreibung/betriebszaehlung05.Document.111424.pdf>.
- Swiss Federal Statistical Office (2006) *Ergebnisse des Mikrozensus 2005 zum Verkehrsverhalten*, Swiss Federal Statistical Office, Neuchatel.
- Veldhuisen, J., H. J. P. Timmermans and L. Kapoen (2000) Microsimulation model of activity patterns and traffic flows: Specification, validation tests, and monte carlo error, *Transportation Research Record*, **1706**, 126–135.
- Vickrey, W. S. (1969) Congestion theory and transport investment, *The American Economic Review*, **59** (2) 251–260.
- Vovsha, P., E. Petersen and R. Donnelly (2002) Microsimulation in travel demand modeling: Lessons learned from the New York best practice model, *Transportation Research Record*, **1805**, 68–77.

- Vrtic, M., P. Fröhlich and K. W. Axhausen (2003) Schweizerische Netzmodelle für Strassen- und Schienenverkehr, in T. Bieger, C. Lässer and R. Maggi (eds.) *Jahrbuch 2002/2003 Schweizerische Verkehrswirtschaft*, 119–140, Schweizerische Verkehrswissenschaftliche Gesellschaft (SVWG), St. Gallen.
- Wolf, D. A. (2001a) Note on statistical analysis and microsimulation for studying living arrangements and intergenerational transfers, *United Nations Population Bulletin*, (Special Issue Nos. 42/43) 386–392.
- Wolf, D. A. (2001b) The role of microsimulation in longitudinal data analysis, *Canadian Studies in Population*, **28** (Special Issue on Longitudinal Methodology, 2) 313–339.
- Ziems, S. E., S. Bhargava, J. Plotz and R. M. Pendyala (2011) Stochastic variability in microsimulation modeling results and convergence of corridor-level characteristics, paper presented at the *90th Annual Meeting of the Transportation Research Board*, Washington, D.C.