Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 151 (2019) 782–787

Procedia Computer Science

www.elsevier.com/locate/procedia

The 8th International Workshop on Agent-based Mobility, Traffic and Transportation Models, Methodologies and Applications (ABMTRANS 2019)
April 29 – May 2, 2019, Leuven, Belgium

Effects of scaling down the population for agent-based traffic simulations

Carlos Llorca[a]*, Rolf Moeckel[a]

[a]*Technical University of Munich, 80333 Munich, Germany*

Abstract

Agent-based transport models simulate the travel demand of individuals at a fine resolution. However, when large road networks and numerous agents are simulated, they require long runtimes. In order to achieve reasonable runtimes, a common strategy is to randomly subsample the entire population. The capacity of the road network is scaled down proportionally. Previous studies have found that scaling affects the simulated agents' travel time and distance, although the reasons behind that and the size of the impact remain unclear for the scientific community. In this paper, we present a systematic analysis of the consequences of scaling down the synthetic population. With this goal, we simulate a scenario with different scale factors between 1 and 100% using the multi-agent simulator MATSim. Different numbers of model iterations and two road network resolutions are compared. The output of the simulations shows how the scaling process modifies the model runtime, the travel times or the link volumes.

Keywords: agent-based simulation, large scale model, sampling

* Corresponding author. Tel.: +49 89 289 28443
E-mail address: carlos.llorca@tum.de

1877-0509
10.1016/j.procs.2019.04.106

1. Introduction

Agent-based (AB) transport models simulate the travel demand at the scale of individuals. In general, this level of detail requires higher computational capacity and longer runtimes, compared to aggregated models that simulate traffic flows. To reduce runtimes, most AB applications in transportation use a random subsample drawn from the entire population or simplify the level of detail of the network by removing the links of the lowest road hierarchy levels. MATSim [1] is one of the most commonly used AB transport models. Like others, it is computationally expensive when it simulates large scenarios with large populations (at the scale of entire cities or regions, representing Millions of agents), requiring long runtimes and large amounts of memory. For instance, a large-scale simulation in Florida applying MATSim with more than 1 Million agents reported a model runtime of 147 h [2].

To run large-scale AB scenarios in reasonable times, the use of small subsamples of the population is common practice. This requires to proportionally scale down the capacity of the network. MATSim link capacity is controlled by the flow capacity (how many vehicles can exit the link by time unit) and storage capacity (how many vehicles can be stored at the same time in the link). Scaling down the population has been applied in most of the MATSim implementations found in the literature: Berlin (1% and 10%) [3], Switzerland (1, 10%) [4], Zurich (10%) [5], Munich (1% and 10%) [6], Baoding (20%) [7], Brussels (1%) [8], Dublin (25%) [9], Germany (8.5%) [10], Santiago de Chile (0.65%) [11], etc. Some of the authors reported certain inconsistencies when analyzing the results, such as unexpected too high average travel times or distances. Based on non-systematic tests, it has been recommended that if the scenario is scaled down by the scaling factor f_{Scale} (between 0% and 100%), the flow capacity factor (multiplies flow capacity) and the storage capacity factor (multiplies storage capacity) should be calculated using the equations 1 and 2 [12]. The flow capacity factor increases the gap between consecutive vehicles and the storage capacity factor increases the length of the vehicles.

$$f_{CapacityFlow} = f_{Scale} \quad (1)$$

$$f_{StorageCapacity} = f_{Scale} \wedge \alpha \quad (2)$$

The motivation of the transformation introduced in Equation 2 is to reduce less than proportionally the maximum storage capacity of a link. If the size of the vehicles is increased too much, it is possible for short links that not even one vehicle fits in the link [13]. The value proposed for the exponent α was 0.75 [12]. With this α value, the value of $f_{StorageCapacity}$ is 59% for $f_{Scale} = 50\%$, or the value of $f_{StorageCapacity}$ is 3% for $f_{Scale} = 1\%$. Therefore, the ratio between $f_{CapacityFlow}$ and $f_{StorageCapacity}$ is higher for smaller scale factors but equal to one for the full-sample simulation. Not having this transformation can produce network breakdowns because of excessively congested links [14]. Additionally, other authors recommended to adjust the flow capacity factor f_{Scale} as well. In an analysis in a Berlin scenario [3], the population was scaled down to 1% but the flow capacity factor was set at 2% to obtain a correct representation of the observed travel distance distribution.

The aim of this paper is to quantify the effects of scaling down the number of agents on the results of the transport simulation. We systematically analyze the use of diverse scale factors, network resolutions and number of iterations in a real-world implementation of MATSim.

2. Method

The study is based on a real implementation of MATSim. It is carried out for the Munich metropolitan area, which includes the five core cities Munich, Augsburg, Ingolstadt, Landshut and Rosenheim and their respective hinterland. The study area is delineated to ensure that every municipality is included from which the share of commuters to at least one of the five core cities is 25% or higher. A synthetic population for the entire study area was generated, including the socio-demographic characteristics and geolocation of households and jobs [15]. A travel demand model predicts the trips made by the synthetic population using the household travel survey Mobilität in Deutschland [16]. Trips not made by car or as a car passengers are discarded. This model has not been calibrated but has been used only for the purpose of this paper. The analysis described here requires reasonably congested conditions, but precise link volumes are not crucial for the purpose of this paper. The total number of trip legs made by car is 2.9 Million per day. The road network is downloaded from the OpenStreetMaps (OSM) service. Two different network resolutions are compared in this paper. The fine network contains all the roads (except of roads tagged as *service* in OSM), while the coarse network also discards roads tagged as *residential*. The fine network has three times more links than the coarse.

MATSim replanning functionality is limited to changes of route; thus the agents cannot change the transportation mode. We define different simulation setups. The simulation setups differ combine two networks (fine and coarse), with six scale factors (1, 5, 10, 20, 50, 100%), with three storage factor exponents (0.75, 0.85, 1.00) and with five number of iterations (50, 100, 200, 300, 500).

3. Results

The analysis is focused on runtime, average travel time, travel time distribution and MATSim scoring.

3.1. Runtime

Firstly, the runtime of each simulation is recorded. The runtimes are obtained on a 64GB RAM, Intel® Xeon® E5-2640v @2.60GHz desktop computer. The runtimes shown in Figure 1 include only the MATSim runtime (discarding demand generation). Figure 1a shows that the model runtime increases linearly with the number of simulated agents (scale, in x-axis) and with the number of iterations (line width). The size of the network (if described by the number of links) is proportional to the runtime as well, as seen in Figure 1b. As identified by most of previous research on AB models, the observed high runtime motivates the use of scaled scenarios.

3.2. Average travel time

The average travel time is defined as the average of the travel time of all trips made by every agent for every purpose. Figure 2 shows the average travel time for different scales (horizontal axis) by varying the network resolution (2a), the number of iterations (2b) and the exponent of the storage capacity factor (2c). As seen in the three sub-plots, the average travel time depends strongly on the scaling factor of the scenario. In general, a U-shaped curve is found, where the minimum travel time is found for scale factors around 10% to 20%. Scale factors of 1% are significantly different from the general trend, with higher average travel times in all simulations.

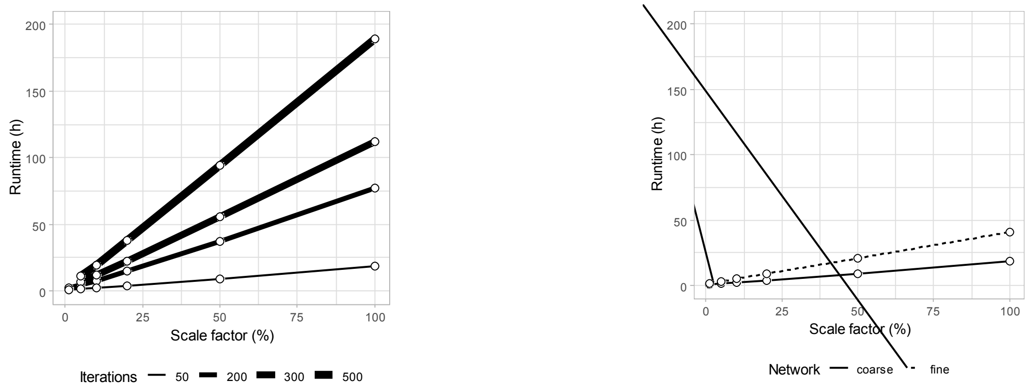
As seen in Figure 2a, the network resolution is a relevant factor, too. Using the finer network resulted in lower average travel times, and a lower variation of them across different scales (fewer differences in average travel time obtained from different scale factors). The higher average times of the coarse network may be related to an excessive load (same agents on a smaller network). Moreover, very short trips may be routed on major roads of the coarse network, although they would use only minor roads if they were routed on the fine network. Previous research [17] suggested to scale down short-distance trips for coarser zone systems. The same might be true for coarser networks, where short-distance trips should be deleted if they reached such network.

The increase in the number of iterations (Figure 2b) produces lower average travel times, less influenced by scale, although the minimum average travel times is always found at 10% or 20% sampling rates. At 10% or 20% sampling rates, an increase of iterations has limited impact, while at full sample simulation the reduction of travel times is still significant when iterations increase. This might be caused by random variations of the travel demand, which can quickly saturate certain links of the network. For instance, if a network has two different routes of equal capacity, it is much more likely to randomly assign two vehicles to only one of the routes (scale equal to 1%) than to randomly assign 200 vehicles to only one of the routes (scale equal to 100%).

Lastly, the impact of the exponent α (Equation 2) is less relevant compared to the other variables (Figure 2c).

3.3. Travel time distribution

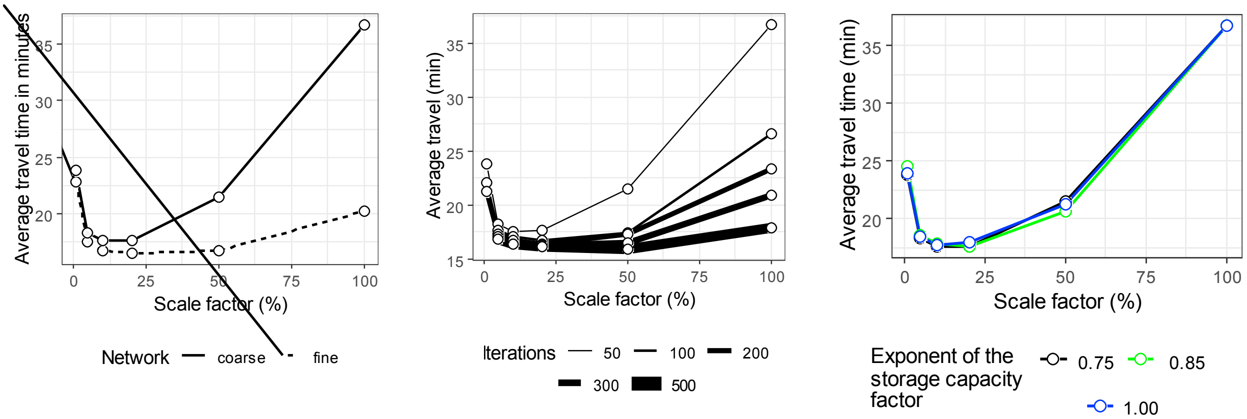
Thirdly, Figure 3 analyzes the agents' travel time distribution for different numbers of iterations and different scale factors. Regarding the 100% simulations (gray series), the plots indicate a significant proportion of trips longer than 1 h, which is not the case for the rest of scales, suggesting that some agents may not yet have found the best route possible. The percentage of trips longer than 1 h at full-sample simulations decreased from 11% with 50 iterations until less than 1% with 500. Regarding the 5% scaling factor (pink series), the travel time density function does not change when iterations increase. The density function of the 100% sample gets progressively closer to the 5% distribution when iterations increase.



(a) by scale and number of iterations (coarse network)

(b) by scale and network resolution (50 iterations)

Figure 1. Runtime comparison



(a) by network resolutions (50 iterations, α exponent equal to 0.75)

(b) by number of iterations (coarse network, α exponent equal to 0.75)

(c) by α exponent (50 iterations, coarse network)

Figure 2. Average travel time vs. scale factor

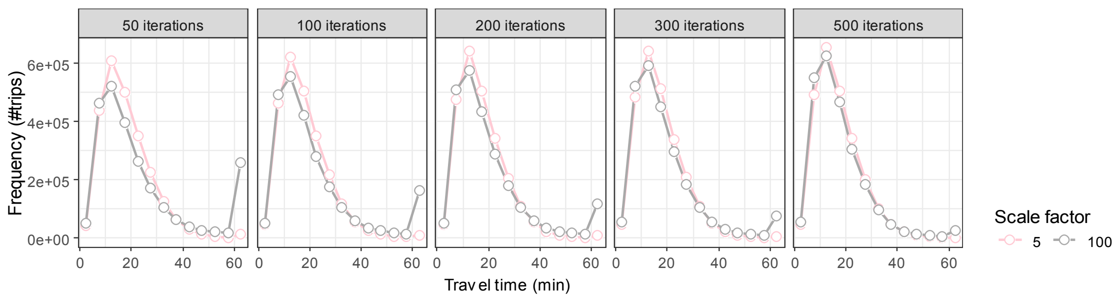


Figure 3. Travel time distribution vs. number of iterations and scale factor.

3.4. Scoring

We analyze the evolution of scoring along iterations as well. In MATSim, the scoring represents how good the plans selected by agents (routes) are. The evolution of scoring along iterations may be used as an indicator whether more iterations are required or not. Figure 4 shows the average executed plan scores for the same two scale factors 5% and 100%, by number of iterations. For each run, the last 30% of iterations is almost flat since the generation of new plans is deactivated in MATSim, and only changes between already existing plans are possible. Figure 4 reveals that the evolution of scoring is clearly different for different scale factors. When the full sample (100%, in gray) is simulated, the required number of iterations is higher. This is not only due to an overall lower score but also because the slope is still positive, showing that there is still room for improvement. In general, the results of simulations with even 500 iterations suggest that more iterations are needed. Such large sample do not reach stable average agents' score. However, the 5% simulations (pink lines) show almost horizontal score lines from the beginning, and especially from 100 iterations. This suggests that the lower scale factor simulations need fewer iterations than the full samples. As MATSim is based on an evolutionary algorithm that depends on randomly generated plans, random choices and scoring of selected and non-selected plans, a higher number of agents in the simulation might cause the need of more random replications until an optimum solution is found. Following the previous example with a network with two different routes of capacity equal to 100 vehicles, it requires fewer iterations for one agent to be assigned to each route at least once (1% simulation) than exactly 100 agents to be assigned to each one the two routes (100% simulation).

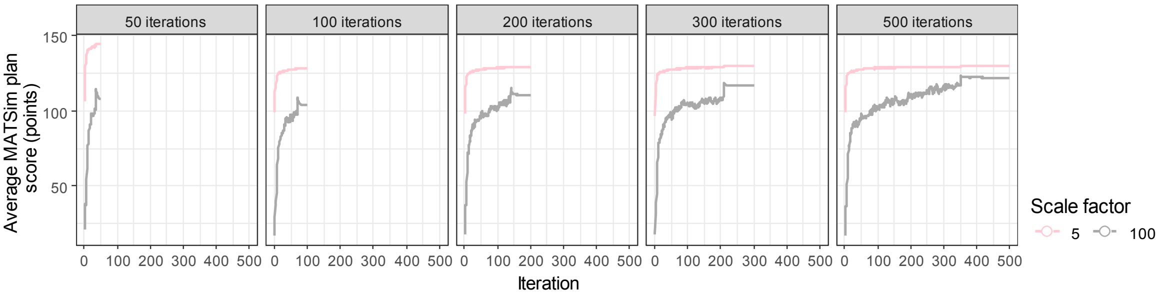


Figure 4. Scoring by number of iterations (note that MATSim deactivate the generation of new routes in the last 30% of the iterations).

4. Conclusions

Taking into account the analyses of this paper, the first result is that scaling down large populations is required because of long runtimes, both in model development and model application phases. However, the use of very small sampling rates (1%) may produce undesired effects, such as a proportion of agents with too high travel times.

Different scaling factors require different number of iterations to achieve equivalent results (from the travel time perspective). As small scaling factors need fewer iterations, runtimes may be reduced additionally. In relation with the network resolution, the results indicate that the finer networks produce lower deviations with respect of the full-sample simulations, though they increase the runtime proportionally to the number of links or nodes. If coarser networks are used, further analysis is needed to determine whether some trips have to be removed because they would never use the roads of the coarse network.

In the example for the Munich metropolitan area, 5% of agents and 50 iterations produced similar travel time distributions than 100% of agents and 500 iterations (but 50 times faster). Accordingly, scale factors around 5% seem reasonable. The requirements of the policy scenarios may affect, however, the most suitable scale factor and network density for each application. Testing a scenario where results are analyzed only at a highly aggregate level, smaller scaling factors may be acceptable. The analyses of traffic flows for a single corridor, however, likely require a 100% sample. For detailed analysis of small areas, the random effects across simulation runs should be also taken into account [18]. Ultimately, the correct sampling rate can only be derived through iterative testing of variations between the 100% (with e.g. 500 iterations) and smaller samples for a given application of the model. Other approaches for scaling the capacities, such as using different passenger-car-equivalents or modifying the road network are not tested in this paper. Similarly, the effects of scaling on public transport trips require further attention, since vehicle capacities cannot be scaled down in the same proportion. Although the study area is large and contains both dense urban and sparse rural zones, the results might be different for different networks or with a different travel demand. Therefore, these recommendations should be extrapolated with caution.

5. Acknowledgement

The research was completed with the support of the Technische Universität München – Institute for Advanced Study, funded by the German Excellence Initiative and the European Union Seventh Framework Programme under grant agreement n° 291763.

6. References

[1] Horni A, Nagel K, Axhausen KW. The Multi-Agent Transport Simulation MATSim. London: Ubiquity Press; 2016. doi:http://dx.doi.org/10.5334/baw.
[2] Mtoi ET, Moses R, Ozguven EE. An alternative approach to network demand estimation: Implementation and application in multi-agent transport simulation (MATSim). Procedia Comput Sci 2014;37:382–9. doi:10.1016/j.procs.2014.08.057.
[3] Ziemke D, Nagel K, Bhat C. Integrating CEMDAP and MATSim Based On Traffic Counts to Increase the Transferability of Transport Demand Models. Tansportation Res Rec 2015;2493:117–25. doi:http://dx.doi.org/10.3141/2493-13.
[4] Bösch PM, Ciari F, Axhausen KW. The IVT 2015 baseline scenario. 16th Swiss Transp Res Conf 2016.
[5] Balac M, Ciari F, Axhausen KW. Modeling the impact of parking price policy on free-floating carsharing: Case study for Zurich, Switzerland. Transp Res Part C Emerg Technol 2017;77:207–25. doi:10.1016/j.trc.2017.01.022.
[6] Kickhöfer B, Kern J. Pricing local emission exposure of road traffic: An agent-based approach. Transp Res Part D Transp Environ 2015;37:14–28. doi:10.1016/j.trd.2015.04.019.
[7] Zhuge C, Shao C. Baoding: A Case Study for Testing a New Household Utility Function in MATSim. In: Horni A, Nagel K, Axhausen KW, editors. Multi-Agent Transp. Simul. MATSim, London: Ubiquity Press; 2016, p. 393–6.
[8] Röder D, Stratec IC, Nagel K. Simulation-based sketch planning, part III: Calibration of a MATSim-model for the greater Brussels area and investigation of a cordon pricing for the highway ring 2013.
[9] Mcardle G, Furey E, Lawlor A, Pozdnoukhov A. Using Digital Footprints for a City-Scale Traffic Simulation. ACM Trans Intell Syst Technol 2014;5:1–16. doi:10.1145/2517028.
[10] Illenberger J. Germany. In: Horni A, Nagel K, Axhausen KW, editors. Multi-Agent Transp. Simul. MATSim, London: Ubiquity Press; 2016, p. 431–6.
[11] Kickhöfer B, Hosse D, Turner K, Tirachini A. Creating an open MATSim scenario from open data : The case of Santiago de Chile 2016:1–22. doi:10.13140/RG.2.2.25394.40649.
[12] Nicolai TW. Using MATSim as a travel model plug-in to UrbanSim. SustainCity. Deliverable D7.2 2012.
[13] Dobler C. Travel behaviour modelling for scenarios with exceptional events. Methods and implementations. 2013. doi:10.3929/ETHZ-B-000225616.
[14] Rieser M, Nagel K. Network breakdown “at the edge of chaos” in multi-agent traffic simulations. Eur Phys J B 2008;63:321–7. doi:10.1140/epjb/e2008-00153-6.
[15] Moreno A, Moeckel R. Population Synthesis Handling Three Geographical Resolutions. ISPRS Int J Geo-Information 2018;7:174. doi:10.3390/ijgi7050174.
[16] Moeckel R, Llorca C, Moreno AT, Rayaprolu H. Microscopic Travel Demand Modeling : Using the Agility of Agent-Based Modeling Without the Complexity of Activity-Based Models. Transp. Res. Board Annu. Meet., Wasgington DC: 2019, p. 1–6.
[17] Moeckel R, Donnelly R. Gradual rasterization: redefining spatial resolution in transport modelling. Environ Plan B Plan Des 2015;42:888–903. doi:10.1068/b130199p.
[18] Paulsen M, Rasmussen TK, Nielsen OA. Output variability caused by random seeds in a multi-agent transport simulation model. Procedia Comput Sci 2018;130:850–7. doi:10.1016/j.procs.2018.04.078.