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Mode choice and ride-pooling simulation: A comparison of mobiTopp, Fleetpy, and MATSim

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Abstract

On-demand ride-pooling systems have gained a lot of attraction in the past years as they promise to reduce traffic and vehicle fleets compared to private vehicles. Transport simulations show that automation of vehicles and resulting fare reductions enable large-scale ride-pooling systems to have a high potential to drastically change urban transportation. For a realistic simulation of the new transport mode it is essential to model the interplay of ride-pooling demand and supply. Hence, these simulations should incorporate (1) a mode choice model to measure demand levels and (2) a dynamic model of the on-demand ride-pooling system to measure the service level and fleet performance. We compare two different simulation frameworks that both incorporate both aspects and compare their results with an identical input. It is shown that both systems are capable of generating realistic results and assessing mode choice and ride-pooling schemes. Commonalities and differences are identified and discussed.

Keywords: transport models; agent-based models; model comparison; on-demand mobility; ride-hailing; shared mobility

1. Introduction

Transportation models are a common tool for measuring, understanding, and evaluating transportation systems and the complex interactions among various actors. They support the evaluation of the status quo and potential measures

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at a much lower cost than the real-world implementations themselves. In recent decades, there has been great progress in the development of model capabilities. Kagho et al. [11] present multiple agent-based transport models and the challenges that come with their increased complexity, particularly when comparing multiple models. The main challenges presented are *input data*, *cost of computation*, *transparency*, *validation*, *reproducibility* and *standardization*.
In this paper, we face these challenges by comparing two agent-based simulation frameworks, (1) mobiTopp [13] and (2) MATSim [9], which rely on the same input data and model parameters. mobiTopp is coupled with the agent-based fleet simulation Fleetpy[1] to allow the detailed simulation of ride-pooling. Parts of the mobiTopp results are input for the simulation with MATSim. Both simulation frameworks are used to simulate one day of Hamburg's transportation system and evaluate the introduction of a ride-pooling service. The mobiTopp/Fleetpy framework and the mode choice model were developed in the course of a recently concluded long-term study assessing the implications of the ride-pooling service MOIA on the mobility in Hamburg [10].
Previous studies showed the compatibility of mobiTopp with Fleetpy [15] and mobiTopp with MATSim [4]. However, no studies comparing the two frameworks are available. In general, studies comparing results from different transport models are scarce. We contribute a critical evaluation of results generated by the two different simulation frameworks that are supposed to model the interplay of demand, supply and traffic assignments in a similar way. The focus of our comparison will be on mode choice and the adaptation and performance of an implemented ride-pooling system. The paper helps to classify and contextualize model results and shows the importance of critically questioning, calibrating and comparing model results with reality and further findings.

2. Simulation frameworks

The schematic functionality of both simulation frameworks is shown in Figure 1 considering all steps of the 4-step model. A detailed description of both models and their differences is provided in the following subsections.

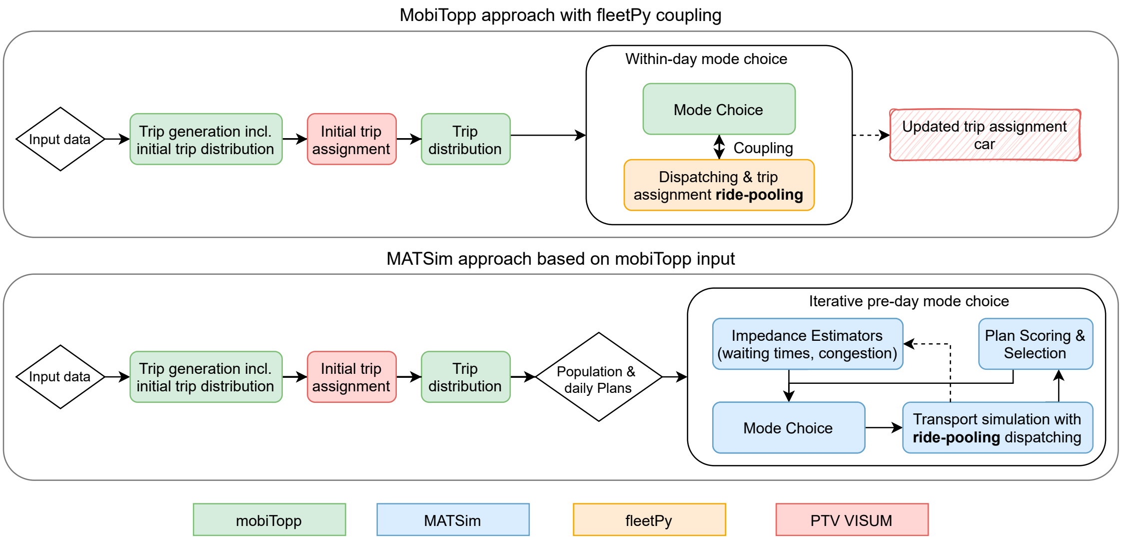

Fig. 1. Schematic representation of both model functionalities

2.1. *mobiTopp approach with Fleetpy coupling*

mobiTopp's origins date back to the project EUROTOPP from 1990 [7] and was re-developed starting from 2011 [13]. Nowadays, mobiTopp is an open-source activity- and agent-based travel demand modeling framework. It consists

[1] https://github.com/TUM-VT/Fleetpy

of two main stages, (1) a long-term module and (2) a short-term module. During the long-term module, the population including its activity schedules, activity locations such as the workplace, and access to mobility tools are generated. During the short-term-module, a time period between one and seven days is simulated chronologically. The agents perform destination and mode choice when moving from one place of activity to another. The choices are influenced by the current state of the simulation (e.g., availability of car). mobiTopp typically simulates one week of activities, allowing to understand multimodal travel behaviour over a longer period of time. However, in the present study only the excerpt of one day of simulation is used.

mobiTopp was coupled successfully with the agent-based fleet simulation Fleetpy. The novelty in this interaction of ride-pooling supply and demand is a live-coupling between these two simulation frameworks [15, 16]: Each mobiTopp agent with access to the ride-pooling app creates a travel request, which triggers the fleet operator to check how the new request can be accommodated by the current fleet and builds an offer (including fare, wait and travel time) based on an insertion heuristic. If the mobiTopp agent accepts the offer, the fleet state is updated. To improve the assignments made by this sequential insertion heuristic, the ride-pooling assignments are re-optimized every minute with an algorithm based on Alonso-Mora et al. [1] and Engelhardt et al. [6].

Travel times for the mobiTopp simulations are calculated beforehand and saved in origin-destination-matrices for small time-slices, which for the present model are generated using PTV Visum [14]. These travel times are valid for all direct connections on the car network. However, since ride-pooling involves detours and waiting times are determined by current vehicle states (positions, on-board and waiting passengers), Fleetpy calculates them dynamically from assigned vehicle routes and current network travel times. Although the network travel times could, similarly to the MATSim approach, be updated over several iterations, we consider them to be constant here, as the ride-pooling demand is rather small and effects on the car network are expected to be small. In this way, mobiTopp does not require additional iterations for ride-pooling, as the live-coupling in the discrete choice model inherently balances ride-pooling demand and supply.

2.2. MATSim approach based on mobiTopp input

The applied MATSim [9] approach handles the initially generated mobility demand from mobiTopp's long-term module in terms of population and each agent's daily plan. The central approach of MATSim is based on an iterative, co-evolutionary optimization of an agent's daily experienced mobility. The utility of a day of mobility gets expressed in a score. Mode choice, traffic assignment and the ride-pooling dispatching are executed in a closely coupled manner. Within the iterative approach of MATSim a certain share of agents is allowed to explore a new mode of transport. Other agents are executing an existing unchanged plan. The score of an agent is optimized due to a plan selection mechanism over several iterations.

In contrast to the default MATSim process, the random mode choice exploration has been replaced by a new incremental mode choice approach, inspired by the discrete mode choice implementation of Hörl et al. [8]. For a randomly selected share of the population, an implementation of a multinomial logit (MNL) mode selection is applied for a randomly selected trip of an agent's plan. The applied MNL utility function and its parameters are congruent to the previously explained mobiTopp approach with Fleetpy coupling.

A key difference to the above mentioned approach with within-day mode choice is the iterative pre-day mode choice in MATSim. To allow an impedance responsive mode selection, impedance estimators have been added for mode choice relevant factors. Those factors are public transport (PT) and ride-pooling waiting times and in-vehicle travel times for car, ride (i.e., passenger in a car), PT and ride-pooling trips. During traffic assignment, all trips for which agents choose ride-pooling, are served by the ride-pooling fleet using the dispatching algorithm by Bischoff et al. [3]. Due to the fact that mode choice and traffic assignment stages are closely coupled in an iterative manner, the MATSim approach permits to generate reasonable insights about potential rebound effects between both stages. Such a rebound effect could be caused by the introduction of a new mode, e.g. ride-pooling, which potentially changes the number of vehicles and travel times in the car network, and thus leads to new mode choice decisions.

In contrast to the mobiTopp approach, multiple iterations allow the agents to explore multiple plans from which the one with the highest utility is finally selected. The integrated simulation of all modes within one framework allows to consider all mutual interactions for traffic assignment and mode choice.

3. Scenario setup

The simulations are carried out on an agent-based model of the city of Hamburg that has been developed during the long-term study of the ride-pooling service MOIA [10]. Due to computational reasons, the population is simplified as follows: Only Hamburg inhabitants are considered, only main modes and ride-pooling are simulated, no calibration took place and only one day (Thursday) is simulated, although mobiTopp provides results for an entire week. Furthermore, no group bookings are considered and vehicles do not require operational tasks at hubs. Thus, the results must not be compared to the calibrated results that have been provided in the mentioned long-term study.
The street network is based on the transport model of the city of Hamburg and was synchronized between both simulation frameworks. The modes *ride*, *bike* and *walk* are teleported in MATSim. However, the travel speeds are synchronized between both simulation frameworks. A public transit schedule for the *public transport* mode is extracted from a General Transit Feed Specification (GTFS) file from a Thursday in November 2020.
The ride-pooling service operates within MOIA's current (November 2021) 195 km^2 service area in the city of Hamburg using MOIA's virtual stop network with roughly 6,000 stops. We supply 200 autonomous 6-seater vehicles throughout the entire simulation and do not consider any operational tasks such as charging, cleaning or shift breaks.
The two frameworks use different ride-pooling dispatching algorithms. A previous study from Zwick and Axhausen [17] compared both algorithms and found a similar pooling performance when enough vehicles are deployed. Both algorithms use a repositioning algorithm that is, in the case of FleetPy (Alonso-Mora et al. [1]) based on real-time demand, and in the case of MATSim (Bischoff et al. [3]) based on historical demand of previous iterations [2]. The maximum wait time is set to 10 minutes and the maximum detour is 50% of the direct ride time and additionally 5 minutes. The customer (de-)boarding time is 1 minute. The mode choice decisions are based on an MNL model estimated on a survey with over 12,000 participants that were asked about their mobility behaviour and the usage of ride-pooling in November 2019 [12].
With each simulation framework, we simulate two scenarios to discover and compare sensitivities of both models. To isolate effects, we only implement a change in ride-pooling fare across the scenarios. In the first scenario the ride-pooling fare is 2 € + 0.5 €/km, in the second scenario 2 € + 1 €/km.

4. Results

We analyze the simulations with respect to the mode choice results and the ride-pooling system. Table 1 shows the modal share for each scenario with the mobiTopp/Fleetpy and the mobiTopp/MATSim setup.

Table 1. Mode share in [%] for both scenarios and frameworks.

	MOIA fare: 2 € + 0.5 €/km		MOIA fare: 2 € + 1 €/km	
Mode	mobiTopp & Fleetpy	mobiTopp & MATSim	mobiTopp & Fleetpy	mobiTopp & MATSim
Car	23.5	25.9	23.5	25.9
Ride	4.3	3.2	4.3	3.2
PT	26.0	25.9	26.0	26.0
Bike	27.7	26.1	27.7	26.1
Walk	18.4	18.8	18.4	18.8
Ride-pooling	0.068	0.113	0.056	0.073

Overall we observe that the mode choice results do not differ a lot within the same framework across the scenarios, which is expected as the only change is a fare increase of ride-pooling and the overall mode share of ride-pooling is almost always below 0.1%. Comparing the results across both frameworks, we observe a higher car share with mobiTopp/MATSim and a higher ride and bike share with mobiTopp/Fleetpy. However, the maximum absolute difference is 2.4 percentage points for the mode car. A high relative difference is observed for the mode ride (4.3% vs. 3.2%). For the ride-pooling mode, the mobiTopp/MATSim simulations result in higher mode shares (0.113% vs 0.068% and

0.073% vs. 0.056%) and a larger relative decrease when the fare is raised (35% vs. 18%). This indicates a higher price elasticity in the mobiTopp/MATSim framework, which is surprising since the same mode choice model was used as for the mobiTopp/FleetPy framework. One possible reason for this is that the agents are more sensitive over multiple MATSim iterations than in the mobiTopp mode choice approach with one iteration. However, this needs further investigation. Table 2 shows results of the ride-pooling services.

Table 2. Ride-pooling results for both scenarios and frameworks.

	MOIA fare: 2 € + 0.5 €/km		MOIA fare: 2 € + 1 €/km	
Mode	mobiTopp & Fleetpy	mobiTopp & MATSim	mobiTopp & Fleetpy	mobiTopp & MATSim
Rides	4065	6695	3341	4327
Med. wait time (min)	2:49	3:52	2:33	3:29
Avg. wait time (min)	3:33	4:30	3:16	4:06
95-perc. wait time (min)	7:53	9:23	7:17	8:36
Avg. direct dist. (km)	4.7	8.3	4.4	7.9
Avg. dist. detour (%)	19.2	28.0	16.4	25.0
VKT (km)	24 251	54 326	20 643	35 808
empty ratio (%)	31	19	36	21

The median, average and 95 percentile wait time, and the average detour are similar across both simulation frameworks. Substantial difference are observed for the number of rides, average distances and empty ratios. In the FleetPy simulation, distances are shorter with only 4.7/4.4 km compared to 8.3/7.9 km in the MATSim simulation. Both do not exactly match the observed average direct trip distance from MOIA, which is between 6 km and 7 km with an average MOIA fare between 6 € and 9 €. The impact of the fare increase has similar effects across the frameworks with less rides, shorter wait times and shorter trips. The difference in VKT for both fleets can be explained by the differing average direct distance and fleet utilization.

5. Limitations

Although the simulation frameworks presented are similar in structure and the input variables and parameters are harmonized, there are numerous challenges in aligning them. Some, but not all, of the limitations are discussed here.
In general, the presented agent-based models are not suitable to predict the exact behaviour of a single agent but rather represent a comparable behavior at the population level. Thus, inaccuracies are always part of the models. Both simulation frameworks are software projects that have been growing over decades and contain complex functionalities for routing, mode choice and interactions between modes. It is nearly impossible and not required to harmonise all of these functionalities.
The route choice in the car network is different across both models and consequently travel times and mode choices differ. The routing of bike and walk is done differently in both frameworks. While these modes are teleported in MATSim, they are routed through the network in mobiTopp. However, the travel times are not expected to differ a lot across the models. For the mode ride, an additional complexity has to be considered with regard to mode choice as choosing to ride with another person highly depends on social networks that are difficult to model.
Another difference across the models is the consideration of a week in mobiTopp, from which a day is extracted for MATSim. This leads to daily schedules that do not always start and end with a home activity that MATSim usually requires. An essential difference is also the simulation of iterations in MATSim while only one iteration is simulated in mobiTopp. While both approaches have advantages, iterations are required to measure the impact of large-scale ride-pooling systems on the network load. However, an adaptation of mobiTopp when large-scale ride-pooling systems are simulated is also possible.
Finally, for the simulation of ride-pooling, two different ride-pooling algorihtms are used, which also leads to different results. A detailed analysis of the two dispatching strategies used can be found in [17]. The empty ratio, for instance, highly depends on the applied repositioning algorithm and the optimization target.

6. Discussion

The presented results from two agent-based simulation frameworks and scenarios show that they, in general, perform in a similar way and provide comparable results in terms of mode choice and ride-pooling performance indicators. This shows the general validity of the models to generate and reproduce realistic results from similar input data. Both models contain demand-supply interactions and estimate the ride-pooling service quality based on the fleet and demand. The balance of demand and supply is crucial when investigating the impacts of regulatory measures on the transportation system and the ride-pooling system in particular [5].
However, there are many limitations when comparing both simulation frameworks, which is also true for the general analysis of simulation and model results. Typically, model results are compared and validated against observed values from reality. By calibrating the input parameters, the models are tuned to provide realistic results, which then form the basis for investigating further scenarios. This study is intended to create an awareness of the need to calibrate any model that is intended to reflect reality and that any model results must generally be treated with caution.
We observed that the agent-based models mobiTopp, FleetPy and MATSim function well together and complement each other for certain parts of the simulation of the transport model and ride-poooling in particular.

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