MATSim Model Vienna: Analyzing the Socioeconomic Impacts for Different Fleet Sizes and Pricing Schemes of Shared Autonomous Electric Vehicles

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ABSTRACT

Shared Autonomous Electric Vehicles (SAEVs) are expected to enter the transportation market in the upcoming decades. In this paper, we describe the preparation of a MATSim model for Vienna in which we add this new service as a new transportation mode. We simulate different pricing schemes for various SAEV fleet sizes and analyze their impacts. Our focus is on the impacts in regards of socioeconomic heterogeneity.

One main finding of our paper is that the number of SAEV trips does not necessarily decrease for higher fares. It is instead the average travel time of SAEV rides which decreases if the service gets more expensive. Our simulation results for higher pricing schemes show that many people switch from bike or walk mode to SAEV. Public transport is also highly cannibalized by this new service regardless of the price, whereas SAEVs would always replace no more than 10% of car trips.

SAEVs help reduce travel times significantly. People who do not have a car available in their household experience the greatest savings in travel time. A similar high share of SAEV trips is done by people older than 35 years. In regards of gender, our results reveal that women tend to use SAEVs for shorter trips.

Keywords: MATSim; SAEV; demand responsive transportation; subpopulations; socioeconomic heterogeneity

INTRODUCTION

Shared, autonomous, electric vehicles (SAEVs) are expected to be gradually released to the market in the upcoming decades. There is a broad consensus that they will play a substantial role in future transport systems. The typically strong path-dependencies in the transport sector and, as a consequence, the risk of sub-optimal equilibria render it essential to investigate the potential effects of different policies related to SAEVs before their market introduction (Adler et al. (1)).

It is particularly important to investigate which socioeconomic groups are likely to benefit from the introduction of SAEVs in terms of accessibility. Just as other transport modes, SAEVs are likely to have heterogeneous impacts on different population groups, depending on their home location, trip patterns, as well as their mobility-related preferences (for instance, the extent to which they value travel time savings). For instance, Meyer et al. (2) show that persons living in sub-urban areas will have over-proportionally large gains from the arrival of SAEVs. The same is true for persons who can use their commuting time productively (Malokin et al. (3)).

In this paper, we conduct various simulations which have in common that SAEVs, which are assumed to be fleet ownership, are added to the transport system of the city of Vienna (Austria) and surrounding areas. We use the well-known MATSim software for the simulations (Axhausen et al. (4)). The scenarios differ in terms of SAEV fleet size and the pricing of the SAEVs, as these two factors are expected to have substantial implications on the usage of SAEVs (e.g. Hörl et al. (5)). In contrast to macroscopic traffic assignment software such as VISUM, the traffic demand can be traced back to the single agent. This enables us to characterize the potential user of SAEVs in the future. For each scenario, we show to which extent the availability of SAEVs leads to mode switches among specific population groups, which are assumed to differ in terms of their socioeconomic characteristics and, based on these, their time and mode preferences, as well as their home location and demand for travel on an average day. The results of these scenarios provide us with an indication of the heterogeneous accessibility impacts of SAEVs. These can provide guidance to policy makers regarding regulative (e.g. fleet size limitations, SAEVs limited to specific areas) as well as pricing measures (e.g. road tolls).

We contribute to the literature on heterogeneity of SAEV impacts, which so far has been mostly derived from preference studies at the level of the individual traveler (e.g. Spurlock et al., Zhou et al. (*6, 7*)), and hence approached mostly from the demand side. The supply side of SAEVs has been captured in various simulation models, the most well-known ones probably being Austin (e.g. Chen and Kockelman (8)), Berlin (e.g. Bischoff and Maciejewskia (9)), and Zurich (e.g. Hörl et al. (5)). While these models pay much attention to spatial heterogeneity, little emphasis is placed on socioeconomic heterogeneity. Our model combines a demand-side component that is able to represent heterogeneity in various dimensions (not limited to spatial heterogeneity) and a supply-side component where SAEVs are added to the existent transport network of Vienna and surrounding regions.

The structure of the remainder of the paper is as follows. The section *Methodology* discusses the methodology, specifically the MATSim model and its parametrization as well as the simulated scenarios in terms of SAEV fleet size and pricing. In the section *Results*, we present the simulation outcomes. The section *Discussion* discusses the implications and in the final section *Conclusion* we summarize the findings.

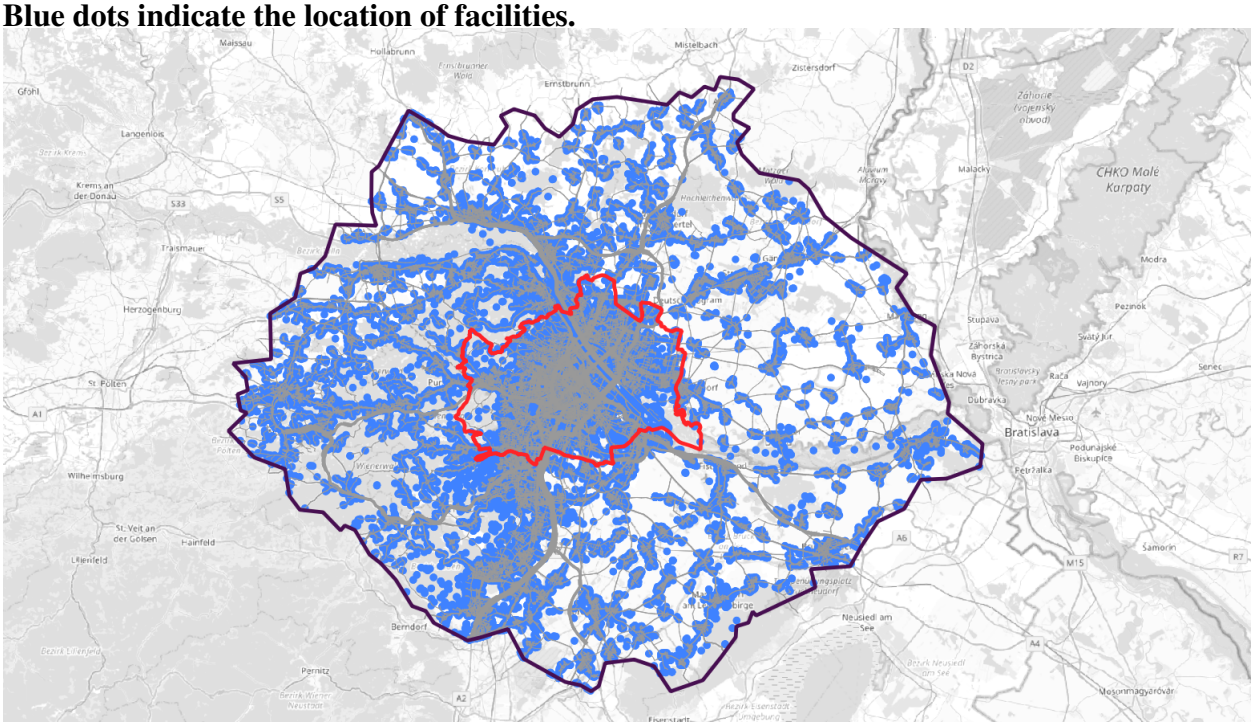
METHODOLOGY

Description of the MATSim model for Vienna

Area and Network

The simulation region of the MATSim model covers the whole city of Vienna as well as the surrounding area within a radius of roughly 30 km around the city center (Fig. 1a)). The boundary is not a perfect circle but was chosen such that infrastructure that is important for traffic in this region is included as well. One example is the Danube crossing near Hainburg. It lies outside of the radius, but since it is the only possibility to cross the river East of Vienna, it is included as well. The population of the city of Vienna and the metropolitan area as of 2019 are 1.91 million and 2.85 million (*10*), respectively. Overall, the simulation area covers $4170 km^2$. The car routing graph for the simulation region is based on OpenStreetMap (OSM) data and consists of around 156,000 links and 71,000 nodes.

FIGURE 1 Maps for the simulation area. The red-framed area marks the city of Vienna. Blue dots indicate the location of facilities.



Simulated population generation

Initial daily schedules of the simulated mobility population were created by cleaning, geo-constraining and resampling data of the Austrian national mobility-survey "Österreich unterwegs 2013/2014" (*11*), or "ÖU13/14", for the described region of greater Vienna.

Resampling was done to retrieve approximately 12.5% of the total surveyed population within the target area, which results in a set of about 2×10^5 agents in the simulated scenarios. Computation requirements for the simulation are not high: recent consumer-grade hardware can run 100 iterations of the MATSim simulation in less than twelve hours given there is at least 12 GB of RAM available.

Together with a data set of potential activity locations (home, work, education, shopping,

leisure, errand) for the agents, which are based on land use categories and points of interest (both derived from OSM) as well as open data for population density (*12*) and workforce (*13*). An algorithm for spatial dis-aggregation of the survey's activity location information (given as municipal code only) was used to assign realistic coordinates for the simulated agent destinations. The implementation of this algorithm relies on the reported trip times and distances as available in the travel survey data. It finds optimally fitting locations for each agent's chain of activities within the sets of possible locations for each activity type.

Socioeconomic characteristics as described in 3.1.4 were derived from the data in the "ÖU13/14" survey and correspondingly added as binary variables to the mobility population data set. The resulting set of agents and their daily-travel schedules ("plans") was transformed to a valid MATSim mobility-agent population description, consecutively.

Intermodal routing

For intermodal routing we do not use the MATSim router but instead integrate the AIT intermodal routing framework *Ariadne* (Prandtstetter et al. (*14*)) into the simulation cycle. This is done for two reasons: First, MATSim is currently not capable of intermodal routing, which is not trivial to implement. Therefore, leveraging our well tested routing framework reduces the required effort. Second, a tight integration of routing and mode choice while separating this part from the MATSim iterations provides performance benefits as described in (*15*).

Prior to running the MATSim simulations all candidate plans, i.e. plausible intermodal plans for the whole day of the agent, are calculated and cached. The agents' mode availability and location of personal vehicles is respected, i.e. personal vehicles must be brought back home at the end of the day and can only be used at a certain location when the agent drove there before.

The transportation modes drt, car, public transport, bike and walk are covered by our model, of which only cars and drt vehicles are simulated on the MATSim network. The other modes are teleported while retaining the detailed travel time calculated by the intermodal router. Different cycling speeds due to topography and public transport time tables can thus be taken into account.

Subpopulations

To model different behavioral patterns within subpopulations, the synthesized population described above is split into 10 subpopulations based on socioeconomic characteristics. For each subpopulation, we derive a distinct set of parameters that is used in the scoring function of the MATSim model (Axhausen et al. (*4*)) and the model calibration. More specifically, the mode-specific constants, the value of travel time savings (VTTS), the Value of Leisure (VoL), and the disutility associated with transfers vary across sub-populations (we present the parameter values in Section 3.1.6, Table 2). Note that the VTTS equals the VoL (i.e., opportunity costs of time) minus the direct utility (or disutility) derived from the time spent traveling (which typically depends on travel conditions such as crowding, comfort, and the possibility to use the travel time productively).

The parameters of the subpopulations are derived from the Mobility-Activity-Expenditure Diary data described in Hössinger et al. (16). This data source contains a weekly mobility and activity diary as well as expenditures from a representative sample of Austrians. In addition, stated preference data on hypothetical mode choice situations from the same individuals have been collected. The detailed data do not only allow for the estimation of the VTTS and other mobility-related preference parameters, but also for the estimation of the VoL, which is the marginal utility associated with those activities to which more time than the necessary minimum is assigned (such

as leisure activities). The empirical model follows the theoretical framework developed by Jara-Díaz et al. (17).

Estimating of the VoL requires fitting the observed expenditures and time use patterns against the utility-maximization framework developed by Jara-Diaz and co-authors, using maximum likelihood estimation. The VTTS and other travel-related preference parameters, in contrast, can be derived from a (discrete) mode choice model applied to all trips contained in the sample. For the Austrian data set, these estimations have been performed separately (the VoL estimation can be found in Hössinger et al. (16) and the VTTS estimation in Schmid et al. (18)), but also jointly in Jokubauskaitė et al. (19), which has the advantage that correlations between time use, expenditure and mode choice behavior can be accounted for in a coherent way. The parameters used in this paper are also derived from a joint estimation, albeit somewhat different from Jokubauskaitė et al. (19) in order to simplify how socioeconomic characteristics can be combined into subpopulations. The parameters presented here are derived from a Latent Class Model - a classification model to assign observable discrete variables to latent classes - (see for instance Greene and Hensher (20)), in which all model components are connected via a joint likelihood function and an overarching class membership equation.

The mode choice model that is part of the joint estimation is a more parsimonious version of the model presented in Schmid et al. (18), and uses actual and hypothetical trip data. The time use and expenditure equations are estimated in a similar way as in Hössinger et al. (16) and Jokubauskaitė et al. (19). We estimate two classes of coefficients for all parameters, since not much explanatory power is gained by introducing more classes. The class membership equation then determines for each individual the class membership probability, i.e. how much weight each class of coefficients has for a specific person. The class membership probability in turn is a linear function of several binary socioeconomic variables *sex, age below 35, age above 55, income higher than median, education high-school or above, living in urban area, kids living in the household, single household and full time work with at least 38 hours a week*. These socioeconomic variables were chosen since they were available both in the estimation data as well as in the synthesised population. An exception is the high income variable for which the self-reported living standard was used as a proxy. An overview of the variable distribution among the agents of our population is shown in Table 1.

The subpopulations are then determined as the 10 regularly spaced quantiles of the class membership probabilities. The characteristics of the different subpopulations can be seen in Fig. 2. Differently pronounced socioeconomic characteristics of the subpopulations become apparent. As an example, Class 1 is dominated by highly educated males in urban areas and in full time employment, while Class 7 mostly contains young urban females with kids, without higher education and without full-time employment. The VoL and mobility-related preference parameters are calculated for each of the ten subpopulations by averaging over the personalised parameter values.

The SAEV fleet

We implemented SAEV vehicles in the simulation as demand-responsive transportation (drt) service by using MATSim's drt module. These vehicles are planned as automated, electric vehicles with a maximum capacity of 4 passengers. Ridesharing will be executed in case there are ride requests in the proximity of the vehicle and the the agents' destinations do not differ too much. The SAEV vehicles have a battery capacity of 20kWh and can be charged at one of the more than 900 charging points (587 in the city of Vienna), each of which have 2 plugs. Existing charging

TABLE 1 Descriptive statistics by sub-populations

	Mean	SD
Gender (1=Male)	0.478	0.499
Urban (=1)	0.744	0.436
Single (=1)	0.217	0.412
Kids (=1)	0.356	0.479
Age >= 35 (=1)	0.248	0.432
Car (=1)	0.612	0.487
Education (=1)	0.337	0.473
Employed (=1)	0.509	0.500
Income high (=1)	0.426	0.494
Observations	200,036	

stations as well as gas stations and taxi stands, all taken from OSM, were considered as charging locations.

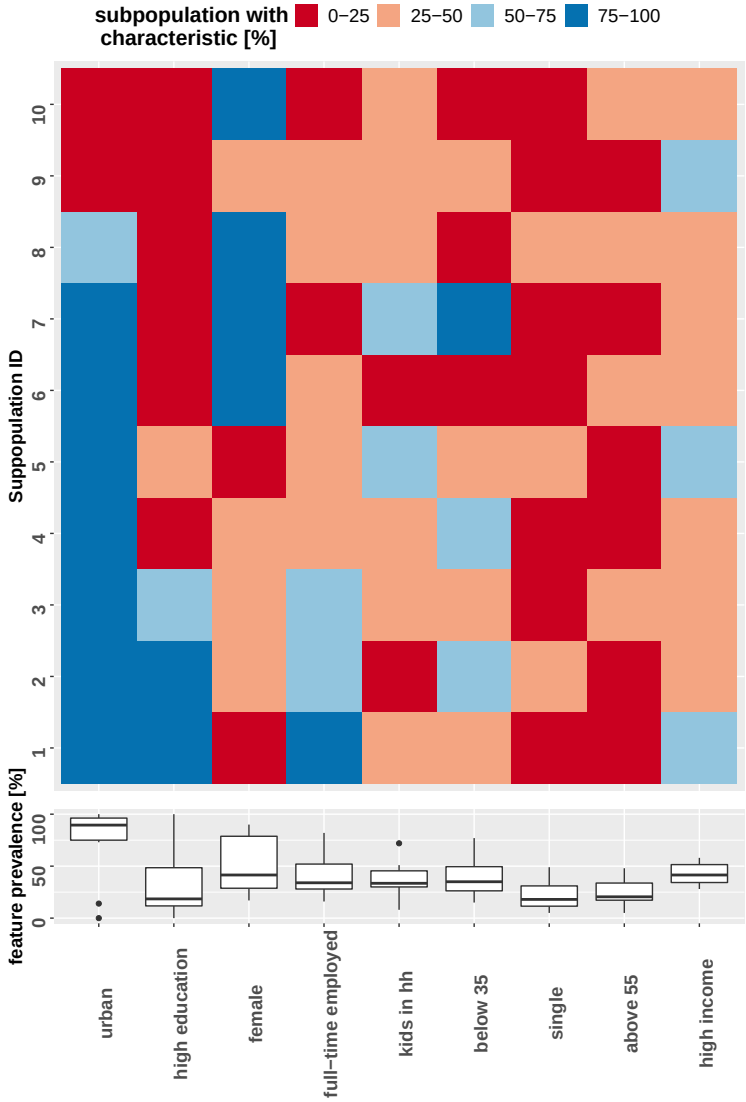
For each of the scenarios that are presented in 3.2 we assume that there is only one fleet operator with one price scheme operating as door2door service. The actual implementation of such a SAEV fleet in real life is difficult to predict as fully-automated vehicles (*21*) will not be available for city traffic for another 10 years (*22*). This is the reason why several parameters relevant for the operation of the fleet (e.g. base fare, minimum fare) could not be chosen based on a business model of an actual fleet operator but were disregarded instead. We assume that there will be a rebalancing of the SAEV vehicles every 30 minutes based on the demand which is aggregated over cells with a size of 500 m. The SAEV vehicles are randomly distributed across the simulation area. Idle vehicles will return to one of these starting locations as they are regarded as depots. At the beginning of each simulation iteration, the SAEV vehicles will again start from these predefined, random locations.

The SAEV rides are simulated on MATSim's car network. The maximum waiting time is set to 10 minutes. If this waiting time is exceeded, the request will be rejected. For boarding and disembarking the drt vehicle one additional minute of travel time is added. The logic of the simulation is that an agent only requests a SAEV vehicle as soon as the previous activity has finished. Then the scheduler of the drt module assigns a vehicle to the agent. This means that agents always have to wait for the drt pickup.

Parametrization of the utility function

Based on the model described in Section 3.1.4, the parameters in Table 2 show the estimated VTTS for every mode (β_{mode}) and the according mode-specific constants (c_{mode}), whereby the c_{walk} is set to 0 for all subpopulations. The values are already standardized by the marginal utility of income of the mode choice model, such that the `marginalUtilityOfMoney` can be left to 1. The VoL, which is in MATSim literature often referred to as β_{dur}, and $\beta_{lineSwitch}$ can be taken directly as MATSim configuration parameter `performing` and `utilityOfLineSwitch`, respectively. The parameter `marginalUtilityOfTraveling_util_hr` for the respective modes and subpopula-

FIGURE 2 Mean prevalence of binary socioeconomic characteristics within the ten subpopulations, determined by application of the class membership model of the latent class model.



tions is however differently implemented (Axhausen et al. (*4*), p.32) and therefore defined as the sum of β_{mode} and β_{dur}.

Additionally, the parameters for `lateArrival`, `waiting` and `waitingPt` are set manually. According to the meta-analysis by Wardman et al. (*23*), the disutility for arriving 10 minutes too late at an activity amounts on average to 1.9 times the disutility associated with a 10-minute increase in *in-vehicle time*, whereas waiting for a facility to open is penalized by 1.83 times *pt-in-vehicle time*, and waiting for public transport by 1.77 times *pt-in-vehicle time*. In accordance to the implementation in MATSim (Axhausen et al. (*4*), p.29), we therefore set

TABLE 2 Parameters from the choice model to calculate the subpopulations' parameters for the Charypar-Nagel function. c_{mode} refers to the not yet calibrated constants, β_{mode} to the value of travel time savings (VTTS), here noted as disutility, and β_{dur} indicates the value of leisure.

subpop	c_{bike}	c_{car}	c_{pt}	β_{bike}	β_{car}	β_{pt}	β_{walk}	$\beta_{lineSwitch}$	β_{dur}
1	2.55	0.85	0.14	-9.38	-12.20	-5.29	-11.06	-0.71	10.71
2	2.72	0.80	0.13	-10.50	-12.29	-5.47	-11.39	-0.75	9.34
3	2.85	0.76	0.12	-11.38	-12.36	-5.61	-11.65	-0.78	6.75
4	2.94	0.74	0.12	-11.99	-12.40	-5.70	-11.83	-0.80	9.11
5	3.04	0.71	0.12	-12.65	-12.45	-5.81	-12.03	-0.83	7.35
6	3.18	0.67	0.11	-13.53	-12.52	-5.95	-12.28	-0.86	9.99
7	3.28	0.64	0.10	-14.20	-12.57	-6.05	-12.48	-0.88	13.02
8	3.42	0.59	0.10	-15.15	-12.64	-6.20	-12.76	-0.92	7.28
9	3.66	0.52	0.09	-16.73	-12.76	-6.45	-13.23	-0.97	6.23
10	4.09	0.39	0.07	-19.58	-12.97	-6.90	-14.07	-1.08	5.92

$$\texttt{lateArrival} = 1.9 \times (\beta_{car} + \beta_{pt})/2$$
$$\texttt{waiting} = 1.83 \times \beta_{pt} + \beta_{dur}$$
$$\texttt{waitingPt} = 1.77 \times \beta_{pt} + \beta_{dur}$$

The costs for driving and owning a car follow estimations by (*24*) for average vehicles and are considered by setting `dailyMonetaryConstant` to -13.521 and `monetaryDistanceRate` to 0.00009 (0.09 EUR/km). Costs for cycling were estimated as 1 EUR/day based on (*25*). The travel costs for public transport were manually configured by averaging fares from station to station. This results in costs of 1.60 EUR/day in Vienna (0.67 EUR/day for trains) and 1.38 EUR/day (and additional 0.15 EUR/km) outside of Vienna.

The costs associated with SAEVs consist of time costs as well as fares (the latter differ across scenarios and will be specified when introducing the scenario). In line with several studies, we assume that the VTTS associated with riding a SAEV is similar to the VTTS of car passenger: whereas Lu et al. (*26*) found no differences in the VTTS between drivers and passengers of a car, Fosgerau (*27*) and Ho et al. (*28*) come to the conclusion that the VTTS for a passenger can be regarded as about 75% of the rate for car drivers. We follow in our model these latter findings.

Calibration process

The model was calibrated by the modal split per trip that was taken from "ÖU13/14". By adjusting the constants along all subpopulations (car: -1.25, bike: -8.75, pt: -5), we achieved a simulation equilibrium with a deviation of the modal split by trips of less than 1% for each mode. The modal split per kilometer also deviates only by a few percentages. This rather good fit was the result of an a priori selection of activity locations that optimally fit the activity chains and the corresponding reported travel times and distances from "ÖU13/14".

Cadyts (Flötteröd et al. (*29*)) was used simultaneously during the search for optimal constant parameters to align the simulated traffic volumes with the measured traffic counts. From the 180 count stations in our whole network, 95 are placed in Vienna. During the morning and after-

noon rush hour (6am-9am, 3pm-6pm), the sum of the normalized error at the count stations in Vienna is about 0.35, whereas the relative error is below 0.06. We ran the simulations with 500 iterations though an equilibrium was already reached after around 150 iterations. The reason for this low number of necessary iterations is mainly the intermodal *Ariadne* router which helps reducing the number reasonable alternative routes for the agent. Freight and delivery - which is estimated to have a share of 8-13% of the traffic in Vienna - is taken into account by reducing the `flowCapacityFactor` by 10% and increase the `countsScaleFactor` to 10.

Scenarios for SAEVs

One of our research questions is to assess the acceptance and benefits of SAEVs among different population groups. As we do not focus on one specific operation model, we analyze different pricing schemes and vary the fleet size. Next to the fix VTTS for the SAEV which is described in 3.1.6 we run simulations with different time-based fares between 0.00 EUR/min and 0.50 EUR/min. There is no minimum fare or base fare implemented. The different fleet sizes are 100, 250, 500, 1000 and 2500 vehicles. As our model is based on a `countsScaleFactor` of 10, the real fleet sizes would be ten times higher. The highest simulated drt fleet represents around 3.5% of the current fleet of private vehicles in Vienna (2019: 715 000 (*30*)), but is already more than three times higher than the current taxi fleet in the city(7500 taxis, (*31*)).

RESULTS

The SAEV rides analyzed in this section always refer to the total number of rides over the day unless otherwise stated. Though the model fits best for trips with destination or origin in Vienna during rush hours, we could observe all patterns described in the following section for all SAEV trips in the whole area and at any time.

In the first part (4.1), we describe the general usage of SAEV vehicles in the simulated scenarios. The second part (4.2) addresses the question of how agents with different socioeconomic characteristics use the SAEV vehicles.

General analysis of the scenarios

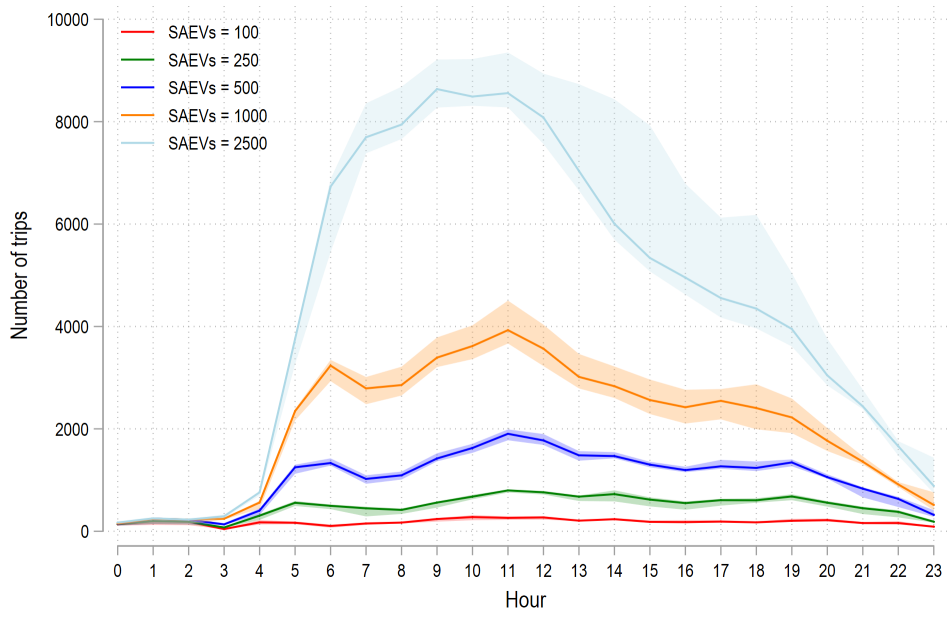
Use of SAEV vehicles

The distributions of SAEV trips over the day does not follow the typical camel function in transportation which reflects traffic peaks in the morning and afternoon rush hours. Instead, the demand usually remains stable over the day and peaks in the late morning hours (see Fig. 3). For larger fleet sizes, a higher deviation in the number of trips becomes apparent which holds true especially in the afternoon.

An interesting phenomenon is the increasing number of trips for fleet sizes of 500, 1000 and 2500 vehicles when the SAEV fares increase (Fig. 4 a)). This is a very counter-intuitive behavior of the agents as one would expect a decreasing number of trips with SAEV for increasing fares. It is also remarkable that for fleet sizes of up to 1000 vehicles the number of trips reach its maximum at a price of 0.40 EUR/min. We found a plausible explanation for this pattern by considering the average driven distance and duration of trips with SAEVs. It is clearly visible that the average trip duration - which is highly correlated to the average trip distance – decreases for higher time-based fares. The product of these two measures represents the total usage time of SAEV vehicles and shows the expected decrease for increasing fares (Fig. 4c)).

Another conspicuousness are the results for small fleet sizes and especially for the fleet of 100

FIGURE 3 Use of SAEVs by time of day



NOTE: Dark lines show the median (50th percentile) and the bands show 10-90th percentiles for the different pricing schemes.

vehicles. Neither the total number of trips nor the average trip duration follow strictly the observed pattern of the other fleets. We therefore conclude that a density of 0.05 SAEV vehicles per 1000 agents is too low to fulfill the demand for this service.

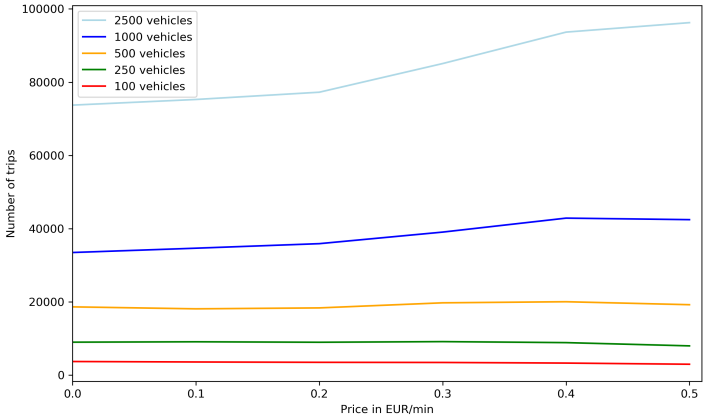
Mode switch to SAEV

The modal split of SAEV increases with a larger availability of vehicles and lower fares. While the share is still 0.5% for 100 vehicles, it grows to as much as 14% for 2500 vehicles.

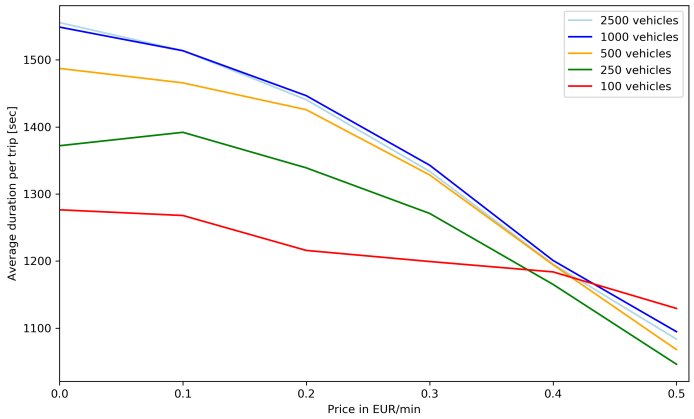
Fig. 5 shows the share of trips that switched from other modes to SAEVs as the main mode. The x-axis represents the different pricing schemes (0.00 EUR/min to 0.50 EUR/min) while the colors represent the different SAEV fleet sizes introduced on the roads. The percentage share of trips that switched to SAEVs is plotted on the y-axis. Since trips can be multi-modal in the simulation and thus consists of different modes for each leg, a main travel mode for each trip is elicited based on the hierarchy provided in "ÖU13/14". The sequence of prime modes is defined as PT > Car > Bike > Walk. For the purpose of this paper, we also assume that SAEVs trump all other modes or SAEVs > PT. Since the simulations provide unique identifiers to each trip, it is possible to compare the main modes across different experiments.

The biggest switches happen from biking and public transport (PT). The introduction of SAEVs strongly impacts trips with walking (Fig. 5a) and biking (Fig. 5b) as the main modes. The higher the price and the larger the fleet, the more likely is it that agents switch from bike or walk to SAEV. This result is not surprising as we have revealed that trip distances and durations decrease for higher fares. These trips are more typically done by using bike or walk as main mode. The strong cannibalization of PT trips can be explained by a missing car availability of agents. By

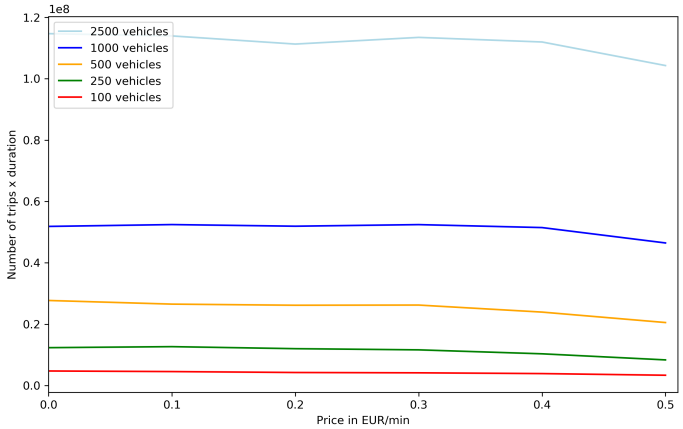
FIGURE 4 Number of trips, average duration and total usage time of drt vehicles



(a) Number of trips with SAEV



(b) Average duration of SAEV trips

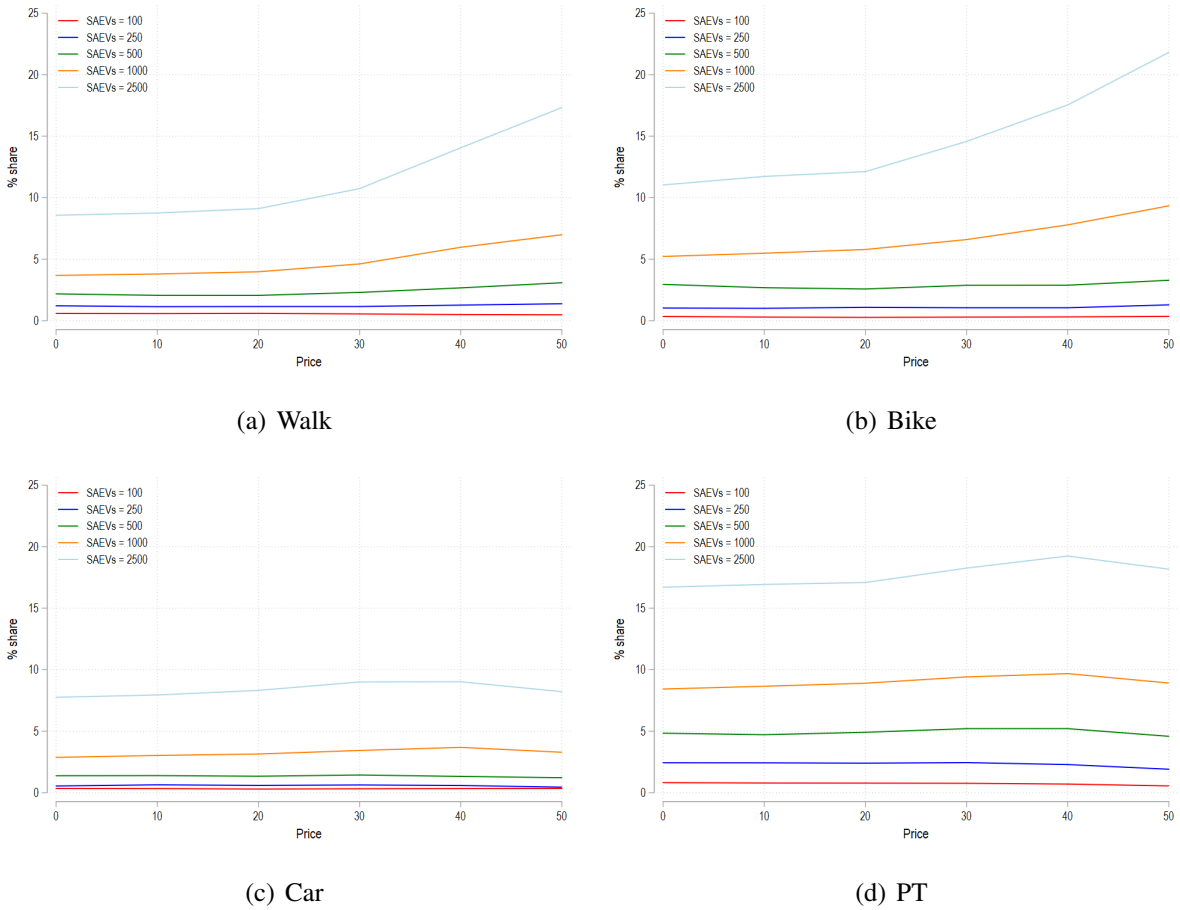


(c) Number of SAEV trips $\times$ average duration of SAEV trips

providing a new mode opportunity, travel time savings become very likely for those people. We will have a closer look at car availability in 4.2.1.

Cars travelers have the lowest response to the introduction of SAEVs with less than 10% switching even with 2500 SAEVs on the road. Both car and PT trips are sensitive to prices changes and show a reduction in demand for SAEVs at the highest price level.

FIGURE 5 Share of trips that switch to SAEVs by main mode



(a) Walk (b) Bike

(c) Car (d) PT

SAEV as ridesharing service

An essential characteristic of SAEV vehicles is the option for ridesharing. Agents do not necessarily take the direct way to their next activity but accept a bearable detour on their trip if another agent requests to share the ride. This detour factor compares the rate of the actual taken route with the most direct connection that the agent would have taken if it would not share the vehicle. Duration detour factors are naturally higher because the routed duration is taken as reference which does not consider congestion or other delays. This number therefore cannot be considered as factor to compare SAEV trip durations to car trip durations.

The analysis of the detour factors for the trip distances show no remarkable change for the different fleet sizes. They mostly remain between 1.11 and 1.16. Higher prices result in higher distance detour factors. This holds also for detour factors of the trip duration. In contrast to

the distance detour, this measure increases for larger fleets (up to 2.20 for 2500 vehicles, 0.50 EUR/min). We expect that these results originate from the shorter distances of trips. As described in 3.1.5, the agent's trip duration is increased by one minute for boarding and alighting the vehicle. Other passengers in the vehicle will be affected by this rule. For shorter trips, this setting becomes more visible in the duration detour factor.

The occupancy rate of vehicles shows a clear pattern over all scenarios. It is higher for lower prices, and higher for larger fleet sizes. For a SAEV fleet of 100 vehicles, it ranges between 1.55 (0.00 EUR/min) and 1.49 (0.50 EUR/min), whereas is drops from 1.78 to 1.58 in the scenarios with 2,500 SAEV vehicles. This measure is calculated as average of the occupancy rates of vehicles which is observed every 5 minutes. Therefore, the results reflect the higher attractiveness of SAEVs if the price is lower.

Another interesting figure is the share of vehicles that is not driving. For scenarios with a fleet size of up to 500 vehicles, this share increases for higher fares (from 58% to 66%). For large fleet size, this share remains similar over all prices (1000: 64%, 2500: 70%). A similar pattern occurs for the average kilometer driven by a SAEV. In scenarios with 100, 250 or 500 vehicles, the average distance drops from around 295 km/veh (0.00 EUR/min) to 230 km/vehicle (0.50 EUR/min). The larger the fleet size, the smaller the is the difference among all pricing schemes. For 1000 vehicles, the average is between 250 and 243 km/veh and for 2500 vehicles between 202 and 198 km/vehicle These numbers are similar, though slightly lower than reported average trip distances of taxis in urban areas (e.g. New York: 290 km/shift (*32*), Hangzhou is 336 km/day (*33*)).

Use of SAEV in different socioeconomic groups

While describing the general use of SAEVs in 4.1, we will now look closer of how agents with specific socio-demographic characteristics use SAEVs. The distinction of subpopulations as described in 3.1.4 is a convenient way to implement the various mode choice behavior of people. However, the interpretation of the results under the consideration of subpopulations remains difficult. A main issue is the characterization of the subpopulations which does not follow standardized social milieus. Therefore, we will present the analysis of the scenarios along common socioeconomic characteristics to facilitate the understanding and transferability of the results.

In the beginning, we have a closer look at two variables that might influence different use of SAEVs: gender and car availability in the household. To reveal differences in the usage behavior of the agents, we will redo some of the previous analysis in 4.1 by separating the data sets according to the social characteristic. After that, we will additionally look at the age distribution of SAEV users. Finally, we will use a scenario as an example to describe which agents benefit from the introduction of a SAEV service.

Gender and car availability

Separating the number of SAEV trips by gender does not reveal significant differences in the general pattern (Fig. 6a)). It is however apparent that women use this service slightly more often than men. This difference becomes more pronounced with higher fares and larger fleet size. The analysis of trip durations reveal that female agents do in average shorter trips with SAEV vehicles in all scenarios.

The availability of a car in the household is an interesting characteristic to look at as SAEV bears the chance to eventually reduce car ownership. In the scenarios with no or low fares for SAEVs,

there are significantly less SAEV trips done by agents that have no car available in their household (around 20-25% less). However, this difference disappears with higher pricing schemes. The SAEV trips of agents with no car in their household are in average a bit shorter in scenarios with low pricing schemes (Fig. 6b)). These numbers are becoming more similar for higher fares.
Fig. 6c) shows the average age of agents that used SAEV vehicles. There is a clear gap between the group of agents who have a car available and those who do not. Agents with access to a private car are in some scenarios in average more than six years older. This phenomenon may occur since agents without a car in their household are younger on average. In terms of gender, we see a difference of three to four years in average age. Across all scenarios, women who use the SAEV service are older than men.

Benefits of SAEV for socioeconomic groups
In this last section we leave the method of scenario comparison and instead take one example scenario as an experiment for our analyses. We are interested to which extent certain population groups benefit from the introduction of SAEVs in the market. For this purpose, we focus on travel time savings as a success indicator.

As benchmark experiment we consider the scenario with 1000 vehicles and a fare of 0.30 EUR/min. Table 3 provides a summary of travel time savings by different socioeconomic groups resulting from the introduction of SAEVs. The first two columns show the average travel times per trip over all trips in the experiment. Column 3 indicates the share of trips that switched to SAEVs which can be regarded as the modal split of SAEVs in this particular population group. The last two columns show the average travel time of those trips that were made in the experiment with a SAEV.

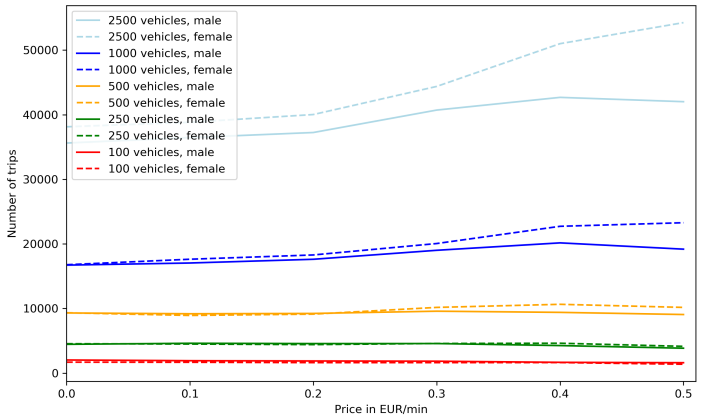
It is no surprise that the overall effect of SAEV on travel time savings is not remarkable. For the specific trip, however, the agent saves on average more than 12 minutes. The strongest drop is observed of those with no car availability in their household. This also explains the high attractiveness of the service which results in the highest modal split of SAEV among all population groups. Also agents with age over 35 years and those who live in urban areas are more likely to take the SAEV vehicles than other ones. Agents in rural areas make below-average use of the service which clearly results from the comparable low travel time savings.

DISCUSSION

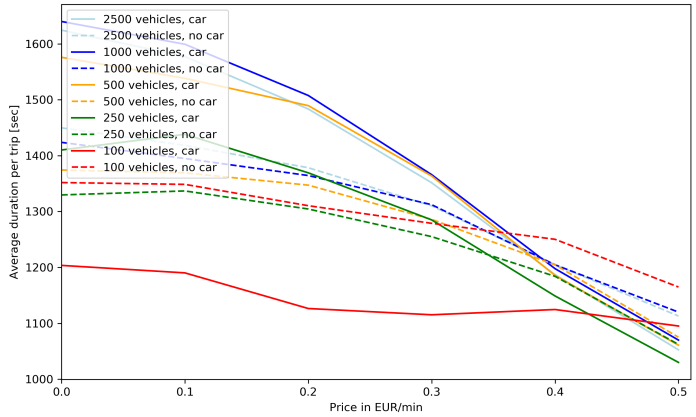
In this paper, we described the preparation of a MATSim model for Vienna and added a new service of shared autonomous electric vehicles as transportation mode to it. While impacts of SAEV fleets have often been described in literature under the aspect of spatial heterogeneity, we focus in our work on the socioeconomic heterogeneity. Our MATSim model takes different behavioral patterns of people into account by splitting the population in subpopulations based on socioeconomic characteristics. We discuss different scenarios which vary in the number of SAEV vehicles and the time-based price that is charged. These settings are considered as different policy options, so that the results of this paper can also be taken as guidance for policy makers in promoting or restricting the operation of this service in future.

Before describing the main findings of our study, we want to consider the limitations of our approach. A very general aspect that a MATSim model cannot reflect is the varying demand for mobility needs. Travel time savings as consequence of SAEV services will therefore always be beneficial for the system, though there have been various studies on the phenomenon of in-

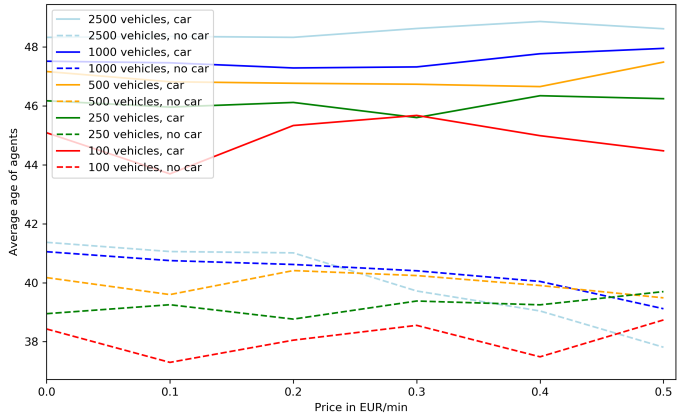
FIGURE 6 Number of trips separated by gender, average duration for SAEV trips separated by car availability and average age of agents separated by car availability.



(a) Number of trips with SAEV separated by gender



(b) Average duration of SAEV trips separated by car availability



(c) Duration

TABLE 3 Socioeconomic variables and travel time savings with SAEVs for the scenario with fleet size 1000 vehicles and a fare of 0.30 EUR/min (=Experiment). Columns 1–2 show the average travel time per trip in minutes. Column 3 lists the share of trips that switched to SAEV as the main mode. Columns 4–5 consider only the trips that switched to SAEVs.

	All trips			SAEV as main mode	
	(1) Baseline	(2) Experiment	(3) % switch	(4) Baseline	(5) Experiment
Overall	30:57	30:21	5.89	34:58	22:22
Male	32:10	31:30	6.08	36:25	23:40
Female	29:52	29:20	5.71	33:36	21:09
Rural	33:04	33:11	3.72	29:45	21:00
Urban	30:15	29:25	6.60	35:56	22:38
Single: No	31:12	30:40	5.68	34:50	22:40
Single: Yes	30:03	29:15	6.62	35:24	21:29
Age ≤ 35	31:42	31:05	5.62	36:14	23:31
Age > 35	28:47	28:14	6.64	31:53	19:35
Car: No	31:44	30:29	7.10	39:06	21:52
Car: Yes	30:31	30:17	5.21	31:53	22:45
Employed: No	28:22	27:47	5.63	32:36	19:44
Employed: Yes	33:26	32:50	6.13	37:05	24:44
Income high: No	31:48	31:02	6.29	36:53	22:42
Income high: Yes	29:51	29:28	5.36	32:03	21:53

duced traffic (*34*). Apart from these general issues, scholar might argue that the chosen number of subpopulations seems arbitrary and not well motivated in our approach. We admit that this granularity of distinction was a first assumption that we pursued further, since the parameters for the utility functions showed a plausible ratio of variability. Future research on the effects of different numbers of subpopulations may help to solve this open issue.

Another critical point is that we currently do not focus on underlying business models. We assume instead that costs are covered for the provider, and the fleet provider would not be able to increase its profits by reducing the fleet size.

The MATSim model allows a more precise formulation of the business models. Not only can time and distance dependent price tariffs be selected, but also different service models can be chosen. In addition to the door-to-door service simulated by us, the business area can be limited to a section of the simulation area, or only certain stops can be selected as pick-up and drop-off stations. An option not yet used in our simulations is the iterative adjustment of the SAEV distribution. In the presented version of the scenarios, the vehicles are placed at the initially selected locations in each iteration. This can optionally be controlled in such a way that the locations of the last drop-offs from the previous iteration are selected. Thus, the SAEV distribution will be adapted to the needs of the agents throughout the iterations and another important insight for operators and planners can be gained from the model. Likewise, the frequency of vehicle reallocation (currently 30 min) is variable.

CONCLUSION

One main finding of our paper is that the number of SAEV trips does not decrease if the fares are higher. Our simulation shows that up to a certain price – in our case 0.40 EUR/min – people will use the service even more. However, the average trip duration decreases when the service gets more expensive.

A positive effect of SAEVs is the better accessibility of places. Travel time savings for the trip that a SAEV was chosen for are about 10 to 12 minutes on average. A particularly large reduction in travel time is achieved by people who do not have a car in their household. SAEVs are far better accepted in urban than in rural areas. We conclude that there are other policy interventions necessary to promote SAEVs in the suburbs. Occupancy rates range from 1.5 to 1.7 and are hence above the average of 1.15 to 1.3 for private cars in Austria (*35*). The time that a vehicle is not in use (max. 70%) is also far lower than for private vehicles. A spatial optimized distribution of vehicles will be even more beneficial.

The fact that shorter trips are preferred for higher SAEV fares also results in a high mode switch from pedestrians and cyclists to SAEVs, especially for higher fares. Public transport is highly cannibalized by the new service regardless of the price, whereas SAEVs would always replace no more than 10% of car trips. As the common goals for policy makers is to promote active mobility, it remains a challenge to formulate appropriate policies that have the desired effect of bringing car drivers to SAEVs and other environmentally friendly mobility modes.

Further information about the AIT's MATSim model Vienna can be found in the corresponding github repository (`https://github.com/ait-energy/matsim-model-vienna`). The MATSim software is openly available at `https://github.com/matsim-org/matsim/releases`.

AUTHORS CONTRIBUTION

The authors confirm contribution to the paper as follows:
study conception and design: Müller, Naqvi, Peer, Richter, Rudloff, Straub;
data collection: Müller, Peer, Richter, Rudloff, Straub;
analysis and interpretation of results: Müller, Naqvi
draft manuscript preparation: Müller, Naqvi, Peer, Richter, Rudloff, Straub;
All authors reviewed the results and approved the final version of the manuscript.

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