

A large scale simulation of the electrification effects of SAVs

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Abstract. Shared autonomous electric vehicles (SAEVs) are expected to soon revolutionize the transport system, with cheap and convenient taxi-like services. SAEVs can induce a significant modal shift from other modes of travel, with effects ranging from beneficial, like reducing private car use, to negative, like making public transport uneconomical and increasing congestion. This modal shift will also be influenced by electrification, as charging time and range limitations will influence availability of these vehicles. In this work, we expand a SAEV simulation model with mode choice to incorporate electric vehicles. In our model travelers choose between their current mode and SAEVs, which in addition to the fare, has a waiting time which depends on the real-time demand and fleet availability. We use a trip generation model based on a large person trip survey from Germany as our input data and scale-up the survey to obtain an OD matrix for the whole wider Munich area on a 1 km² mesh area and representing instances of all trips in the city. As the basis for our extension, we build on a previously published efficient and scalable simulation model. Thanks to its scalability, we are able to perform our simulation with the resulting 4.6 million trips per day over a whole week. We study the effect of electrification on modal shift considering different battery capacities and charging station numbers. We will show at what level of these three decision variables the impact of electrification is negligible compared to our previous results with (non-electric) SAVs.

Keywords: electric vehicles, autonomous vehicles, shared transport, modal shift, simulation

1 Introduction

The transport system will be soon revolutionized by shared autonomous vehicles (SAVs) or so-called robotaxis. Many companies around the globe have begun offering their service with fully driverless vehicles in pilot projects. For instance, Waymo [15] operates a driverless car service in Phoenix and Cruise has just recently launched a public waitlist for its robotaxis in San Francisco [13]. But also in Europe and Asia more and more robotaxi services will be operated in

the near future [11]. This new transport mode can revolutionize travel [14] and contribute to a more sustainable transport system: SAVs offer the same service as conventional taxis or ride-hailing services, but thanks to the driverless operation their fares are likely to be much cheaper in the long run. Due to rising energy costs, this service can also be of interest to private car owners who can no longer afford their own vehicle. In addition, the service is also attractive for public transport users as it offers more comfort and flexibility. For these reasons, demand for robotaxi services are likely to be significantly higher than for conventional taxi services with modal shifts from other modes expected.

In this paper, we study the impact of electrification of SAV fleets on modal shift under consideration of different battery capacities, charging stations numbers, as well as charging rates. These parameters influence directly the availability of vehicles and therefore various performance measures of SAEVs, such as customer waiting times. Hence, we compare internal combustion engine SAV and SAEV scenarios. We utilize a SAEV simulation model including realistic trip patterns for each mode using a statistical model trained on a large transport survey of Germany.

The work is organized as follows: in Section 2 we summarize the literature on this topic; in Section 3 we describe the simulation model used and assumptions for the case study analyzed; in Section 4 we present and discuss the results; finally in Section 5 we draw our conclusions.

2 Related work

There is a vast amount of literature in the field of SAVs. For instance, a good overview is given by a comprehensive review about SAV services presented by Narayanan et al. [12]. The authors discuss the impact of SAVs on traffic & safety, travel behavior, economy, transport supply, land-use, environment and governance and analyze several research directions as well as challenges in the context of modeling SAVs such as traffic assignment, vehicle assignment, pricing, charging and rebalancing. Another survey paper presented by Golbabaie et al. [3] deals with the impacts of SAVs on urban mobility. They highlight that lower costs and gains in time are the main drivers for the adoption of SAVs.

In order to better understand the travel behavior and economy of SAVs some researchers show how travelers shift from individual modes to shared modes [9, 4, 16]. Heilig et al. [4] utilize an agent-based microscopic travel demand model to simulate the mode choice behavior in a changing private transportation system. The author show that in a world without private cars all trips can be substituted by other modes such as SAV services, bicycles or public transport. An economic experiment to investigate the effect of autonomous vehicles on mode choice in mixed traffic flows is given by Zhang et al. [16]. Participants of the experiment were asked to choose a travel mode under both full information about the travel costs for each mode and only partial information about the travel cost of the mode they choose. Results show that participants were sensitive to cost differences in the full information case and provide insights on traffic conges-

tion and social benefits. The competition between SAVs and public transport is addressed by Mo et al. [10]. Higher profits and higher system efficiency are the results of a competitive perspective of SAV services and public transport. Modal shifts for commuting trips are analysed by [2] with a mix of revealed and stated preference data. The authors show that there are huge interactions between inertia effects and level of service variables and conclude that inertia effects are also an important influencing factor in traffic assignment models.

All the presented studies have in common that they deal with the change of transport mode choice and SAVs in general. In the context of these studies, detailed models have been developed, taking into account financial incentives among other factors. However, to the best of our knowledge, the influence of electrification of SAV services on mode choice has not yet been studied in more detail. In this work, we use our simulation model to analyze the impact of battery capacity, number of charging stations and charging rate on the system performance. Thus, it is possible to make statements about the extent to which the aforementioned parameters influence the modal shift. The city of Munich, Germany, serves as an example region. For the details of the comprehensive demand model that is required as input for our model we refer to [7, 8]. There it is described how household survey data are used to generate the detailed trip matrix for the agents in our simulation.

3 Methods

3.1 Transport simulation model

In this work we use an improved version of the model described in [6], with the addition of the mode choice logic and the clustered relocation strategy described in [8]. The simulation model is based on discretized time and space. The system service area is divided into nodes, and vehicles move between nodes to satisfy passenger requests. We assume that passenger requests start and end at the centroid of each node. As in [6], we use a subset of the nodes as destination of predictive relocation actions, so that relocation can be thought of as relocation between clusters of nodes, with the destination node the center of the cluster. The imbalance calculation is performed over departures and arrivals in all nodes belonging to a cluster, and vehicles are moved between their current node and a cluster center (relocation destination node). This allows a much higher spatial resolution with feasible computational times for relocation optimization.

We also generalize the model in [6] to specify which nodes have a charging station, rather than assuming that vehicles can charge at each node. This is more realistic for cases with a large number of nodes. Since vehicles cannot charge at all nodes, they need to actively move to a node with a charging station to charge. Vehicles move to charging stations when their state of charge drops below the minimum allowed (see Table 1) Due to asymmetry between origin and destination locations, during periods of low demand vehicles with SoC above the minimum may stay idle at nodes for long periods. To avoid this, we set a maximum idle time after which vehicles are redirected to the closest charging

station to charge. In this work we assume that vehicles charge at the maximum charging capacity as soon as connected and until they are either completely charged or are called for a trip request.

Similarly to [6], we model the vehicle status with five time-varying parameters: current vehicle destination $a_v(t)$, current distance to destination $h_v(t)$, time to destination $y_v(t)$, state of charge $q_v(t)$, and vehicle state $s_v(t)$. Vehicle state can be one of the five: 1) charging, 2) idle; 3) moving towards or with a passenger; 4) relocating empty for predictive relocation; 5) relocating empty towards a charging station.

As in [8], we implement the mode choice logic with a binary logit model. We assume that passengers have two alternatives: their mode they are currently using, and the new SAV/SAEV mode. We use this approach because passengers are unlikely to change their preference once chosen, unless there is a change such as when a new mode becomes available. More details on this method and its limitations can be found in [8]. The modes we consider in this work (in addition to SAV/SAEV) are bicycle, car, walking, and public transport. User k chooses the SAEV system with a probability defined as:

$$p_k = \frac{\exp(u_k^{SAEV})}{\exp(u_k^{SAEV}) + \exp(u_k)} \quad (1)$$

$$u_k^{SAV} = -\max(z_{min}, z d_{o_k d_k}) - (\tau_{o_k d_k}(t) + w_k) \text{VOT} \quad (2)$$

where u_k^{SAEV} and u_k are the perceived utility of SAEV and the alternative mode; z is the fare per km; z_{min} is the minimum fare; o_k and d_k are the origin and destination node of passenger k ; d_{ij} and $\tau_{ij}(t)$ are the distance and travel time (in discrete time steps) between two nodes i and j ; w_k is the waiting time offered to passenger k ; VOT is the value of time.

To obtain the waiting time and to assign vehicles to trips we modify the algorithm in [6] with the addition of the passenger mode choice. The modified algorithm is reported in Algorithm 1. For each traveler, we first check that there are vehicles available with enough SoC to complete the trip without dropping below the minimum SoC q_{min} . If there are no vehicles available, then no trip will be offered, and we assume that passenger k will use the original mode. If vehicles are available, for each of the available vehicle for trip k , we define a cost δ_v as a function of travel time to pick-up, current SoC, and whether the vehicle is connected (Line 5). This allows to prioritize vehicles that are close to the pick-up point, and for vehicles with equal time to pick-up, it allows to choose those that are not connected and that have higher SoC.³ We select the vehicle with the lowest δ_v to offer a trip to passenger k with an estimated waiting time w_k . If passenger k accepts the trip with the estimated waiting time, then the vehicle v is assigned to trip k . Otherwise, we consider passenger k to have chosen the original mode.

³ Note that $(1 - q_v)/2 + s_v^g/2 < 1$ since we impose a minimum SoC $q_{min} > 0$

Algorithm 1 Assignment of vehicles to trip requests at time step t

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1: for each traveler  $k : t_k = t$ , in order of  $k$  do
2:    $\mathcal{V} = \left\{ v \mid q_v - \omega_d \left( h_v + d_{a_v,i} + d_{i,j} \right) > q_{min} \right\}$ 
3:   if  $|\mathcal{V}| > 0$  then
4:     for each  $v \in \mathcal{V}$  do
5:        $\delta_v = y_v + \tau_{a_v,i} + (1 - q_v)/2 + s_v^g/2$ 
6:     end for
7:     select vehicle  $v'$  with lowest  $\delta_{v'}$ 
8:      $w_k = \lfloor \delta_{v'} \rfloor$ 
9:     let  $x_k$  be a random variable with  $Pr(x_k = 1) = p_k$  calculated in (1)
10:    if  $x_k = 1$  then
11:       $h_{v'} = h_{v'} + \tau_{a_{v'},d_k}(t)$ 
12:       $a_{v'} = d_k$ 
13:    end if
14:  end if
15: end for

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Table 1. Parameters used

parameter		value unit
<i>Technical parameters</i>		
ω_d	consumption	0.15 kWh/km
B	battery capacity	50 kWh
P_c	power connection	20 kW
<i>Operational parameters</i>		
	max. idle time	5 minutes
	min. SoC	0.2 –
	max. SoC	1 –
<i>Mode choice parameters</i>		
z	SAV tariff	1 €/km
z_{min}	min. tariff	3 €
VOT	value of time	15 €/h

3.2 Case study

We use the same case study for the city of Munich described in [8]. It is based on the largest transport survey in Germany, the *Mobilität in Deutschland* (MiD), or *Mobility in Germany* study [1]. Our service area comprises 1089 square cells which represent areas with sides of 1 km, thus covering an area of 33 by 33 km centered in the city of Munich. We use the trip dataset generated from a statistical model trained on the survey. The dataset includes over 30 million trips during a week. Each trip is associated with a origin and destination node, trip starting time, and original transport mode. We also found travel time during the day considering average traffic conditions from Google Maps data. Based on the survey, we assign to each passenger a perceived utility u_k dependent on their current mode. This allows us to estimate the modal shift to SAEV with

Equation 1. For more details on the scenario and the detailed assumptions refer to [8].

4 Results

We run the simulations both with conventional internal combustion engine vehicles (ICEV) and with battery electric vehicles (BEV) with limited range. In all the simulations in this work we use 100 relocation clusters. For the base scenario, we position a charging station in each of the 100 relocation clusters (thus about 10% of nodes have charging stations). This means that relocating vehicles can connect to charge when arriving to their destination node. We test the case with a 50 kWh battery, which gives an effective range of 267 km considering the constraint on the minimum state of charge. The full list of parameters used is in Table 1. The results with fleet sizes of 2500 and 5000 vehicles are in Table 2.

Table 2. Results for different fleet sizes for ICEVs and BEVs

Case	Fleet	Modal shift (%)					Fleet results			
		Total	Bicycle	Car	Foot	PT	VT	VKT	RV	eVKT
ICEV	2500	5.37	0.39	1.68	15.46	7.29	80.7	630	437	15.78
ICEV	5000	11.19	1.11	4.97	26.38	17.63	83.6	526	411	11.96
BEV	2500	4.57	0.77	2.11	11.92	5.80	71.9	537	313	32.58
BEV	5000	9.19	1.48	4.79	21.25	13.14	71.4	474	305	28.31

*VT= vehicle-trips; VKT= vehicle-km traveled; RV= revenue per vehicle (€); eVKT= empty VKT share (%).

All quantities are per day averages.

As expected, the introduction of electrification reduces the modal shift due to the lower availability of vehicles. Interestingly, while the shift is significantly reduced from public transport users and from walking trips, the shift from car trips is similar (with 5,000 vehicles) or higher (for the case with 2,500 vehicles). This may be due to the different availability of electric vehicles during the day. Availability tends to drop significantly in the evening as batteries get more and more depleted, especially for smaller batteries (see Fig.1b). This also creates extreme inefficiencies, as vehicles spend most of their time moving between serving passengers and charging. This can be avoided by specifying a minimum amount of charging time before vehicles disconnect (as in [5]) or a minimum SoC for the vehicle to become available again when connected. This inefficiency is the main reason for the much higher empty vehicle-km traveled for electric vehicles.

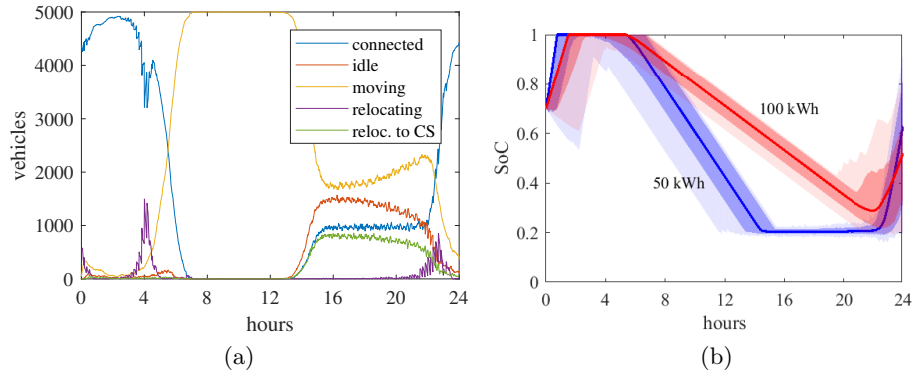


Fig. 1. a) State of vehicles during one day of simulation for the case with 50 kWh battery; b) State of charge of vehicles during one day: comparison between 50 and 100 kWh batteries. The lightly shaded area represents the total range within the fleet; the darker shaded area are SoC between percentiles 2.5 and 97.5; the solid line is the median SoC of the fleet. The very narrow band of SoC seen when average SoC levels are low is the result of our assignment algorithm: we prioritize vehicles with the highest charge to respond to requests. This effectively ensures that vehicles cannot have much higher SoC than the minimum when the system is charge-constrained.

4.1 Sensitivity analysis

To study the effect of charging stations number, in addition to the results shown above with 100 charging stations we also ran simulations with 20 and 50 charging stations. For these and the following simulations we only use the first day of the week (Monday) which has average trip numbers, to reduce the computational time. We select the k cluster centers with charging stations using the k-medoids clustering method on the nodes, using the travel time as metric. Results for these scenarios are in Fig. 3a. The number of charging stations does not significantly affect the results in terms of modal shift, with the shift only decreasing slightly with lower number of CS. The results may be significantly different in the case where charging stations are positioned in a less efficient way.

We also test the case for these additional battery sizes: 40 kWh (effective range: 213 km), 70 kWh (373 km), and 100 kWh (533 km). The results are in Fig. 3b. This has a much more significant effect on modal shift. This is because below about 100 kWh, the vehicle range is not enough to cover the average daily vehicle distance, thus a charge during the day is needed. Larger batteries also reduce inefficiency inherent in the premature disconnection of vehicles and associated extra trips to charging stations.

5 Conclusions

In this work we aimed to investigate the effect of electrification on the demand for shared autonomous vehicles, and in particular on how this would change

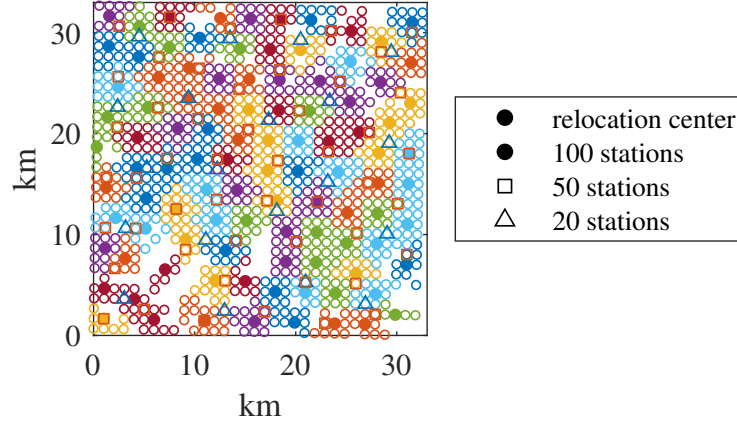


Fig. 2. Map of nodes. Relocation cluster centers highlighted with a filled circle. These also correspond to charging station positions for the case with 100 stations. Triangles and squares represent the position of the stations in the case with 20 and 50 stations, respectively.

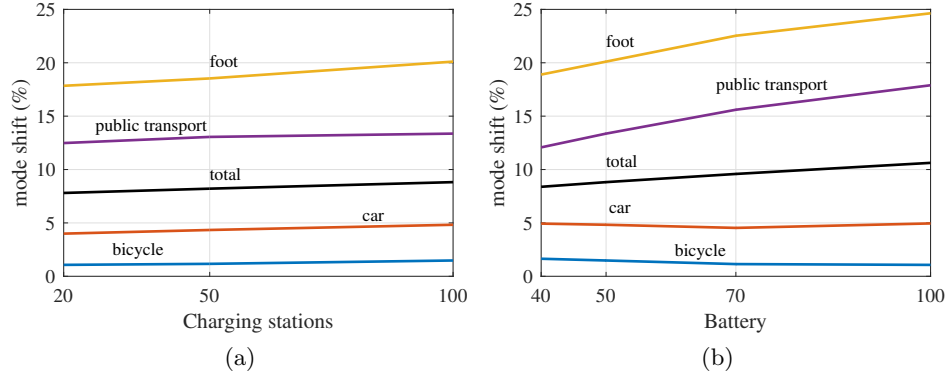


Fig. 3. Modal shift sensitivity to: a) charging station numbers; b) battery capacity.

the modal shift from current modes. We expanded a SAEV simulation model with the addition of mode choice, as well as other improvements. For our case study, we use a trip generation model based on a large person trip survey from Germany, resulting in a dataset with over 30 million trips during a week.

Our results show that electrification somewhat reduces the modal shift, but its effects are relatively minor overall. However, the effects are not the same across the different modes, with significant decreases in shift from walking and PT trips, and negligible decreases or even increases for car and bicycle trips. This is likely caused by the different trip patterns of passengers using these modes. We also show that charging station numbers does not have a significant effect on the results, while battery size (and therefore range) is a more significant factor.

There are several aspects of this work that can be improved. A better management of charging vehicles is needed to avoid inefficiencies related to repeated connections and disconnections. Charging speed also has an influence on the performance, and its effects could be investigated in future work. Moreover, limitations in charging station sizes could be included for more realistic results, as this is likely a significant factor in the availability of vehicles. Our charging station positioning method minimizes the average travel time to each charging station from each node. However, as noted before, in reality charging station positioning needs to take into account several constraints related to land availability and cost. For example, large charging stations are more likely to be positioned in the outskirts of the city rather than in the city center, thus increasing the travel time to charge for vehicles. We plan to study this aspect in future work. In the future we also plan to investigate the case where the charging of the vehicles is optimized according to real time prices or carbon emissions from the power grid. This could be a promising approach to better integrate electrified transport as well as intermittent renewable energy sources.

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