Siting and Sizing of Charging Infrastructure for Shared Autonomous Electric Fleets

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ABSTRACT

Business models rooted in shared economy, electrification, and automation are transforming urban mobility. Accounting for how these transformations interact is crucial if synergies are to be exploited. In this paper, we focus on how a cost-effective charging infrastructure for e-mobility can support the emergence of shared, autonomous mobility. This study addresses the problem of siting and sizing of charging stations for a fleet of shared autonomous electric vehicles (SAEVs). We develop a hybrid simulation-optimization model to find locations and numbers of chargers needed to serve charging demands. Our agent-based model provides an enhanced representation of SAEV operations allowing for smart charging and vehicle cruising when parking/charging is not available. Also, we model charging station placement as full covering optimization and solve the location-allocation problem simultaneously. Finally, we employ real-world trip data from ShareNow in Berlin to evaluate our approach for realistic demand patterns under different charging strategies and fleet sizes. The results show that charging station locations depend mostly on the spatial distribution of installation costs and charging demands. Moreover, charging strategies and fleet size affect the charging patterns and the required number of chargers as well as fleet performance.

KEYWORDS

Charging Stations; Shared Autonomous Electric Vehicles; Agent-based Simulation; Mixed-integer Linear Programming

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1 INTRODUCTION

Electric vehicles (EVs) offer an attractive alternative to internal combustion engine vehicles for their lower environmental impacts and lower operating costs. However, high initial costs and scarcity of charging infrastructure are still critical barriers to mass adoption of EVs [43]. In order to promote electric mobility, many governments and private companies invest in charging station (CS) deployment, but as EV adoption grows, the charging network must expand accordingly to cover the growing demands.

Electrification is not the only avenue toward more sustainable road transportation. Currently, most mobility demand, especially in urban areas, is satisfied by privately-owned cars, causing severe issues such as climate change, traffic jams and heavy investment for parking infrastructure [9]. Increased access to public transportation can reduce reliance on car ownership. Scheduled public transport services integrated with more flexible mobility services such as carsharing and Mobility-on-Demand offer attractive alternatives to car ownership. In fact, shared mobility services are now operating in parallel with public transportation in more than 1,000 cities worldwide [35]. Their electrification is also imminent for both economic and environmental reasons.

Autonomous vehicles (AVs) can extend shared mobility services in multiple ways. First, they eliminate human driver costs while increasing fleet utilization (i.e., available 24 hours a day, unlike taxi drivers and non-autonomous shared vehicles). Second, faster reaction time to ride requests than human drivers, as well as communication among AVs, can improve safety and reduce accident rates and traffic congestion. Last but not least, autonomy is coupled with electrification and access-based ride sharing services. It allows more efficient refueling strategies, particularly in the case of Electric Vehicles (EVs), where charging is more time consuming. AV users do not need driving licenses, do not need to pay close attention to controlling the vehicles, and are free from the need to find and pay for parking. These benefits can encourage people to use shared vehicles [36].

In the literature of charging infrastructure planning for EVs, the synergies of electrification, shared mobility and automation have been largely overlooked. The literature has mainly focused on the CS location problem for electric taxis [44]. Few studies address the challenge of charging electric shared mobility fleets; most of them are limited to station-based carsharing without integration with AVs [7]. Planning the charging infrastructure for

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shared autonomous electric (SAE) mobility services has been addressed only recently [34, 45]. We tackle this problem using a hybrid optimization-simulation approach where the operations of the fleet are modeled in the simulation environment using agent-based modeling (ABM), and the output of the simulation – charging demand – is used by the optimization model to plan the sites and sizes of CSs. ABM has been already used in both energy and mobility domains to understand the environment dynamics and robustness of decision-making strategies [13, 29]. Moreover, to calibrate the simulation parameters, we use real-world historical trip data of ShareNow in Berlin, Germany to estimate the Spatio-temporal distribution of trips. Our goal is to identify cost-optimal deployment strategies of charging infrastructure able to service the charging demand of a SAEV-based mobility service.

The rest of the paper is organized as follows. Section 2 reviews the literature on charging infrastructure development for EVs as well as the operations of SAEVs. The approach of our study is presented in Section 3. In Section 4, we apply the proposed methodology to a real-world example and discuss the results. Finally, Section 5 concludes the paper and discusses restrictions and future work.

2 LITERATURE REVIEW

Previous related works to our paper can be categorized as: (1) studies on SAEVs (2) charging infrastructure development. We separately review these areas and finally discuss their intersection in the literature.

2.1 Shared Autonomous Electric Vehicles

Several researchers have modeled SAEVs to investigate their performance and impacts on the transportation system. Some have studied related strategic and technical problems of SAEVs, many of which focused on required size of SAEV fleets to provide the same service quality as conventional transportation systems [17, 33]. Dandl and Bogenberger compare autonomous electric taxis with a current carsharing system and demonstrate that in Munich, Germany, each SAEV could replace between 2.8 and 3.7 traditional carsharing vehicles [14]. Loeb et al. study the impact of fleet size and EV type on trip response time and conclude that hybrid EVs are more profitable than battery EVs in a shared autonomous fleet [32]. Chen et al. show that fleet size is sensitive to battery recharge time and vehicle range, so larger batteries and fast charging technologies reduce the required number of vehicles [11]. He et al. address service region design for a one-way SEV system, dealing with travel behavior uncertainty and customer adoption in the planning phase, as well as repositioning and recharging in the operational phase [26].

Some papers discuss SAEVs operations through case studies. From a service provider viewpoint, vehicle assignment strategies match vehicles with customers. Hyland and Mahmassani use vehicle status (idle, in-service, charging) to drive decision support for fleet operators [27]. Some researchers have studied the repositioning problem for both station-based and free-floating shared-vehicle systems. He et al. formulate the problem as a stochastic model considering temporal and spatial uncertainties of trip demands, obtaining optimal repositioning policies for a shared fleet [24]. Regarding electric mobility, charging decisions have a pivotal role. In addition to being time-consuming, the major difficulty is limited CS availability [5, 37]. Chen et al. claim a natural synergy between AVs and EVs as the smartness of AVs could resolve the range anxiety and charging limitations of electric fleets [11]. Most of these papers consider CS locations and sizes as fixed parameters, but performance of SAEVs depends significantly on charging infrastructure; therefore, finding optimal locations and sizes of CSs is an essential goal to fulfil.

2.2 Charging Infrastructure Development

Some researchers have investigated charging facility placement for EVs. This problem is similar to facility location problems, choosing among possible locations to add facilities to optimize an objective [38]. CS placement literature can be classified into intercity charging, where stations are located along highways, and urban charging, where stations are located in parking spots within urban areas. We are interested in the urban problem. Regarding shared mobility, Boyaci et al. use a bi-objective mixed-integer linear programming to optimize CS locations and sizes in addition to finding optimal fleet size and vehicle allocation for shared EVs [10]. He et al. focus on charging in an electric carsharing system to maximize fleet profit, integrating charging infrastructure planning with vehicle repositioning [25]. Brandstätter et al. describe an integer linear programming approach for CS placement and sizing to maximize expected value of accepted trips, as well as a heuristic solution for real-world cases [7]. Apart from shared vehicles, several papers have discussed charging infrastructure for privately owned EVs [12, 18, 23, 42], which tend to park for longer duration than shared cars [40]. Other researchers study charging locations for electric taxis [6, 39], which are similar to SAEVs since taxi drivers have flexibility for charging time and location; however, they did not consider autonomous mobility (i.e., taxi drivers are not connected, so using a central charging strategy is not achievable, and autonomous vehicles have no time and location preference for charging which removes some restrictions on CS location). There are also studies that assume EVs charge during trips, and solve the charging infrastructure placement problem accordingly [19, 31]. They use heuristic approaches and compare the results to analytical solutions. Funke et al. [19] optimize the minimum number of chargers and their locations to cover any shortest path between any two points of the network so vehicles need not detour their trips for charging events. However, these problems are different from ours since in a shared autonomous fleet vehicles do not charge while serving customers.

Another crucial issue with charging infrastructure is the additional load on the power grid. Smart charging approaches have been already proposed [20, 41]. Gerding et al. designed a novel online auction mechanism to smooth the adverse effects of EV charging demands on the distribution network [21]. Physical constraints of distribution grids must be considered when planning CS placement; optimal CS siting and sizing can significantly reduce the costs of grid expansion [22]. Physical grid constraints can be substantially relaxed if EV charging can be managed as a source of demand flexibility [28].

A few recent papers consider the intersection of SAEV operations and charging infrastructure. Zhang et al. study charging facility requirements for SAEVs [45]. They use an ABM simulation to model passenger behavior and the mobility system (e.g., driving, parking, and charging). Then given the simulation outputs (identified times and locations of charging demands) and using clustering algorithms, they find CS locations that satisfying charging demands. In this work, siting and sizing are decoupled, leading to sub-optimal solutions; also, they do not include economic factors like installation costs in the location problem, and only site CSs based on charging demands. In the most similar work to our study, Lokhandwala and Cai investigate charging infrastructure development for SAEVs using a hybrid simulation-optimization approach [34]. They simulate the transportation environment using ABM considering different adoption rates of AEVs and ride sharing to generate demand for charging facilities. They formulate the location problem as mixed-integer linear programming where the objective function is evaluated using discrete event simulation. They finally deploy a genetic algorithm to solve the optimization. They do not allocate charging demands to CSs in their mathematical model and do not address the problem using exact solutions, which therefore does not guarantee global optimal. Also, grid capacity constraints and various installation costs among different areas are not included in the optimisation model. More importantly, this work disregards the impact of fleet charging strategies on service quality and CS locations.

Clearly, charging infrastructure planning for SAEVs needs more exploration since CS placement that ignores shared autonomous mobility might lead to sub-optimal solutions in the future. We develop a methodology to simultaneously site and size the required CSs for SAEVs while considering fleet operation complexity. The major contribution of our work is a comprehensive ABM that accounts for smart charging strategies (i.e., start and interruption) based on trip demands and available vehicles, as well as allowing vehicles to cruise as an alternative to parking when parking is not available. Moreover, we model charging infrastructure deployment as a full covering problem and solve the location-allocation problem simultaneously using exact solutions, enabling us to evaluate the results for a variety of circumstances. Finally, we use real-world trip data to calibrate the simulation and evaluate our results, making it applicable for carsharing providers aiming to electrify their fleets.

3 METHOD

Our charging infrastructure development framework contains two components: (1) charging demand estimation of a SAE fleet using ABM, (2) optimal CS siting and sizing using mathematical programming. We first run the simulation for a given number of vehicles and a Spatio-temporal trip distribution to generate estimated charging demands. The generated demand is then given to the optimization model as an input to identify optimal CS sizes and locations.

3.1 Key Assumptions

To model our problem, we make several assumptions:

- Charging demand must be covered fully by installing CSs.
- Planning horizon is cyclic and we solve the optimization problem for a single period.
- All CSs and SAEVs are homogeneous.
- Grid constraints are considered as a limit on the number of chargers for each zone in the optimization part.
- Land costs and grid constraints vary across the service region
- Operational decisions (e.g., charging, relocating) are based on flexible rule-based strategies in the simulation.

3.2 Agent-based Modeling of a SAE Fleet

We develop an ABM for two purposes; first, to model fleet operations in a discrete event simulation (DES), giving us the impacts of autonomous and electric mobility on free-floating fleets. Second, we use ABM again to evaluate solutions from our optimization model. ABM has unique strengths to analyze complex system operations and behaviors, where each agent actions affect other agents [16]. They also are capable of solving wicked problems like sustainable transportation and energy systems where numerous social, economic and technical factors interact [30]. Autonomous agents have been employed to model transportation systems [8], and fit to our problem since AVs can be assumed as agents interacting with each other in an environment.

3.2.1 Simulation platform and setup. To simulate the SAE fleet, we first discretize the business area into small, fixed-sized zones over which we map trip patterns. These zones are candidates for relocation and charging stations in ABM and optimization models, respectively. The Uber H3 library[1] is applied to divide the service region into hexagons. Employing hexagons for discretization has gained popularity in spatial analyses as they fully cover the area, and the distances between centers of neighboring cells are equal. Hexagon size is chosen such that any pair of points within a hexagon can be reached at most by 5 min (driving time) – edge length is 1.22 km.

We initialize our simulation with fleet size, plus sizes and locations of CSs and parking lots. Each vehicle is represented by an agent following predefined rules. Figure 1 illustrates the simulation process, which is iterated over a certain period. It is a DES, driven by new trip requests and by vehicle state changes. Requests are added to a waiting list, sorted based on time of receipt. We determine available vehicles for each request, and using a first-in-first-serve strategy, the closest available vehicle is assigned to each request. Availability for a trip has two conditions: (1) having enough state of charge (SOC) to serve the request and be able to reach a CS afterward if necessary, (2) not being too far from the request to avoid long waiting time and inefficient vehicle assignment[2]. If there is no available vehicle for a trip, it is kept in the waiting list until a vehicle gets available. Also, we assume a waiting tolerance for customers, after which they will cancel their request and be considered as missed trips.

After serving a request, a vehicle checks its SOC, whether below a threshold or not (i.e., the charging threshold is a utility function of time, in a way that at nights when the trip demands are low this is a larger amount than peak hours). If yes, it must go to a CS to recharge the battery. We consider a charging strategy such that the vehicle is sent to the closest CS even if the CS is full and the vehicle must wait in the queue, then starts charging. In reality,

[1] Uber H3 is an open-source grid service that partitions areas of the Earth into identifiable grid cells, provided by Uber for visualizing and exploring spatial data as well as geographic information analysis. https://eng.uber.com/h3/

[2] It is not the optimal vehicle assignment strategy since we exclude currently-serving vehicles and our first-in-first-serve strategy might lead to sub-optimal solutions

it is not the optimal strategy and the charging station selection depends on many factors, including SOC, traffic, waiting time at stations, demand distribution, and fleet's state – number of available vehicles in each zone. Although there are some optimal charging strategies for more straightforward mobility systems like electric buses [4] as well as EV routing strategy assuming awareness of others' intentions [15] to minimize queue time, optimal charging decision-making for SAEVs is still an open problem and is not the goal of this paper. Often a fully charged battery is not necessary; so, we consider a charging interruption task for vehicles when there is a significant number of requests waiting for service, but inadequate available vehicles to serve them.

Once a charging session is over, or there is no need for charging, the vehicle becomes available for service. If there is no request for the vehicle, it checks the relocation task. The goal of our model's relocation strategy is to concentrate vehicles within high demand zones. Thus, relocation task of each vehicle monitors the updated status of vehicles in all zones. If the number of vehicles in its zone is more than enough and there are some zones with the lack of available vehicles; in this case, the vehicle relocates to the closest zone that needs more supply. In other words, we check relocation conditions by comparing between the number of vehicles and estimated demand for each zone.

If the SOC is sufficient, there is no request for the vehicle, and no need for relocation, the vehicle goes to a parking lot. The closest parking lot that has a free spot becomes the vehicle's destination. Our model also assumes that the vehicle can circle around for a predefined period at the end of which, if no request is assigned to it, it must park (i.e., the dilemma of parking or circling around is an interesting topic in the field of autonomous mobility which is beyond the scope of this paper). Finally, the vehicle is then available for serving requests. Notice that we count available vehicles among idle, relocating, and to-parking vehicles. In other words, if a request assigns to a vehicle while relocating or moving to parking lot, the action is interrupted and the vehicle serves the request.

3.2.2 Demand generation using ABM. We deploy our ABM to generate SAEV charging demands. For this purpose, in addition to setting initial parameters including fleet size, trip demands, and parking lot locations and capacities, we assume an infinite number of chargers with the same power capacity in all zones to have unconstrained charging infrastructure in this phase of our work. Although we assume that there is an unrestricted charging network in this phase, charging rates and travel times to CSs are realistic. The simulation runs flexible charging and relocating rules for multiple iterations to smooth the impact of uncertain trip demand on final results, and charging events during the simulation time are recorded as estimated charging demands. Outputs include times and locations of charging events, as well as vehicle SOC at the start and end of charging.

3.3 Optimization of Charging Stations

Given the charging demands, distribution system topology (maximum allowable number of chargers in each zone), and land costs as known parameters, we can model the charging station placement

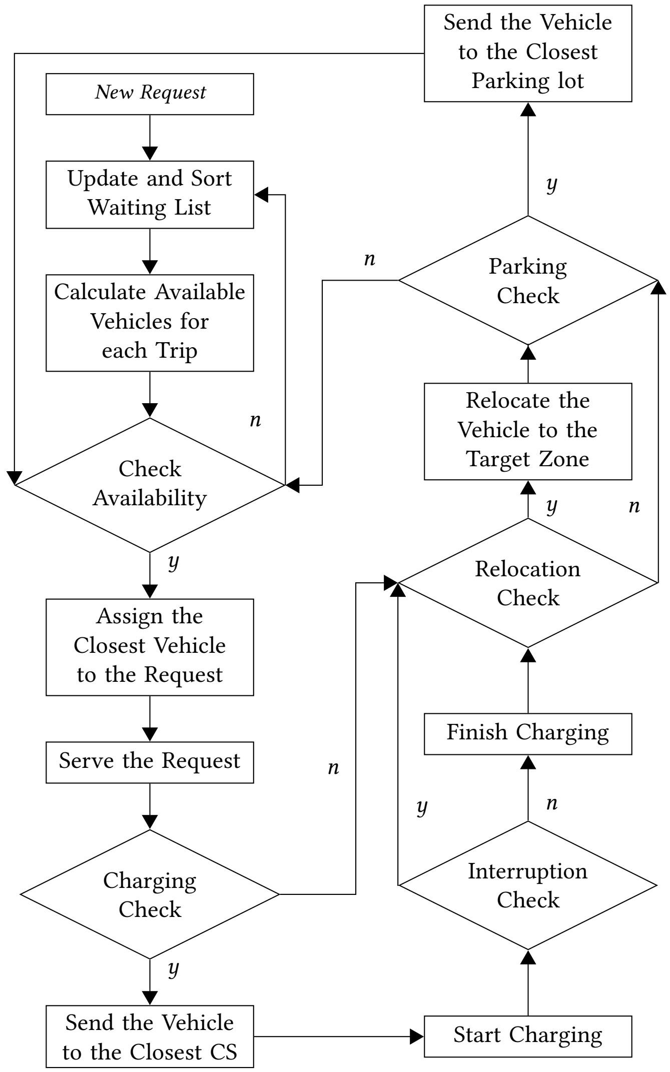

Figure 1: Agent-based simulation flowchart of SAEVs' operations

problem as mixed-integer linear programming. First, sets, parameters and variables are defined, then we formulate the optimization problem.

Sets

N: set of zones

T: set of time steps

Parameters

D_{it}: Demand in zone i at time t

L_{ij}: Distance between zones i,j per kilometer

M_i: Maximum number of chargers in zone i

C_i^{first}: Installation cost for the first charger in zone i

C_i^{add}: Installation cost of additional charger in zone i

β: Penalty rate for relocating to CSs

H: Number of weeks in the horizon time

Variables
x_i: Binary variable of installing the first charger in zone i
y_i: Integer variable of the number of installed chargers in zone i
a_{ijt}: Number of chargers in zone i allocated to the demand of zone j at time t
Objective

$$Min \sum_{i \in N} \left(\frac{x_i C_i^{first} + (y_i - 1) C_i^{add}}{H} + \beta \sum_{j \neq i \in N} \sum_{t \in T} a_{ijt} L_{ij} \right) \tag{1}$$

The optimization problem is a location-allocation model to find the optimal locations for facilities – charging stations – while allocating the charging demands to the closest CSs. Equation 1 represents the objective function minimizing the installation costs of the first and additional chargers (i.e., assuming that the first installation is as twice costly as additional chargers [34]) divided by the number of weeks in our time horizon. The second term of the objective function is a penalty on the distance between demands and allocated CSs. This term has two roles: first, installing CSs in high demand zones, second, jointly allocating vehicles to the installed chargers to minimize the summation of driving distance between vehicles and CSs.

subject to.

$$y_i \leq M_i x_i \qquad \forall i \in N \tag{2}$$

$$D_{it} \leq \sum_{j \in N} a_{ijt} \qquad \forall i \in N, t \in T \tag{3}$$

$$\sum_{i \in N} a_{ijt} \leq y_i \qquad \forall j \in N, t \in T \tag{4}$$

$$x_i \in \{0, 1\} \qquad \forall i \in N \tag{5}$$

$$y_i \in Z \geq 0 \qquad \forall i \in N \tag{6}$$

$$a_{ijt} \in Z \geq 0 \qquad \forall i \in N, j \in N, t \in T \tag{7}$$

Constraint 2 places a capacity restriction on the number of ports in each zone due to distribution grid limitations or physical space restrictions (i.e., we do not have access to a real-world distribution system topology; thus for now we assign a random capacity to each zone). It also allows installing additional chargers in a zone only if a CS is placed there. Constraint 3 guarantees that installed CSs can cover the whole charging demands at all time steps. The right-hand side of the constraint is the sum of allocated ports of each installed CS at any given time, which must not be less than the demand of each zone at any time. Constraint 4 restricts the allocation of each CS at any time to the number of chargers meaning that the number of connected vehicles in each CS must not be greater than the number of ports in that CS.

4 NUMERICAL ASSESSMENT

In order to assess the proposed method's performance, we apply the model to real-world data of a free-floating carsharing fleet in Berlin, Germany. The trip dataset is used as inputs for the simulation to calibrate trip generation parameters. The data set was collected from November 2019 until February 2020, and covered the entire trip set of ShareNow, comprising 684,229 trips by 897 vehicles. Each row of the data consists of trip start and end date times, start and end locations (latitude and longitude), fuel level, and vehicle ID as well as additional information like price levels that are excluded in our study.

We discretize the business area to hexagon-shaped zones to create distinguished areas for relocation strategy in the ABM and candidates for CSs in both simulation and optimization models. To describe spatial trip patterns, we visualize trip origins using a heat map diagram (i.e., the darker zones, the higher number of trips demands) in Figure 2. Most trips start from the city center, and this pattern repeats for trip destinations as well (it is not shown here). The spatial trip characteristics are essential considerations in the simulation due to the effects on vehicle positions and charging events.

We only include hourly patterns in the simulation model (i.e., not daily, weekly, or annual periodicity). Figure 3 demonstrates that most trips occur from early morning until midnight (i.e., peak hours are between 17 and 19 p.m). It brings an opportunity for SAEVs to charge their batteries at night, when trip density is low and electricity price is inexpensive (i.e., assumed using time of use electricity tariffs). We take advantage of this temporal behavior of users in our ABM to set a relatively higher SOC threshold at low demand hours, avoiding a charging peak at high demand hours (details in Section 4.1).

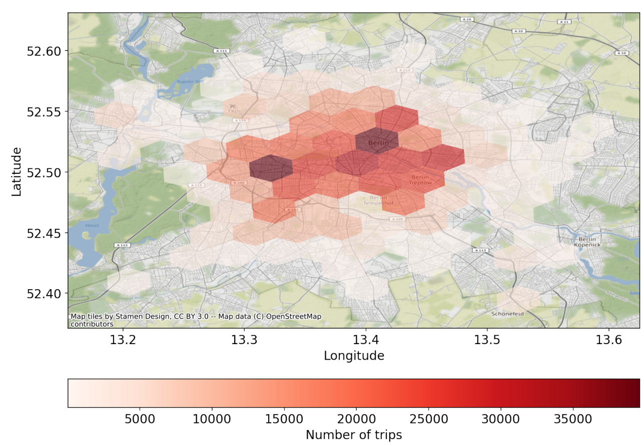

Figure 2: Heat map of trip start positions

Since there is an identified Spatio-temporal variation of trips, we need to adjust simulation parameters accordingly. First, we fit the trip data to an exponential distribution for each zone and each hour, and estimate the associated parameters to develop a trip generation in the simulation using the distribution density. This generates trip start locations. Trip destination, given the start location and time, is calculated as the probability of ending in each zone. Origin-destination patterns are modeled in the simulation to reach as close as possible to the reality.

4.1 Results

In the first step of our analysis, the simulation runs for 10 iterations (i.e., each iteration simulates seven days of fleet operation) to take the uncertainty of trip generation into account, and the average of

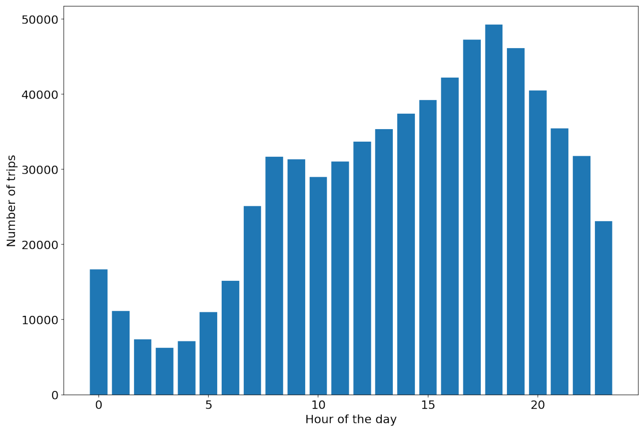

Figure 3: Hourly patterns of the number of starting trips

results is saved as generated charging demand. We assume vehicles are identical with a battery capacity of 50 kWh and fuel consumption of 15 KWh per 100 km, based on Tesla model 3 [3]. Also, the charging rate of chargers, is set to 11 kW, currently the most common capacity of charge points in Berlin [2]. A sample of outputs for one iteration are shown in Table 1, where each row represents a charging demand, giving time, location, and battery SOC.

Table 1: A sample of generated charging demands

Time	*Longitude, Latitude*	*SOC*
2020-01-01 03:22:22	13.32, 52.43	39.78
2020-01-01 04:54:12	13.46, 52.51	36.86
2020-01-01 05:43:44	13.42, 52.49	35.70
.	.	.
.	.	.
.	.	.
2020-01-07 23:18:36	13.28, 52.35	40.69

We aggregate the generated demands from ABM by zones and hourly time buckets to reshape it as input for our optimization model. The charging demands represent the number of EVs in each zone that need charging at any time. Also, since we do not have access to grid topology and land prices to calculate the grid restrictions and installation costs of CSs for each zone, we generate them randomly. It is assumed that the grid restricts each zone to have at most 5-10 chargers. Installation and operational costs for the first charger in each zone are randomly generated between 10000 and 15000 Euros (we assume costs of high demand areas are higher than the other zones) [1], and the additional cost for adding another charger is assumed to be half of the first one.

The location-allocation problem is solved for the above-stated assumptions, and the results are pointed in Figure 4. The heat map highlights the spatial distribution of generated charging demands among zones, where the darker zones have more demand, following trip demand patterns. The optimal locations of CSs, as well as the associated sizes, are illustrated in the figure. The outcomes heavily rely on installation costs, penalties on driving distances, and charging demand distribution. As a result, some CSs are installed in the city center due to the high charging demand while others are located in the suburbs where installation costs are lower.

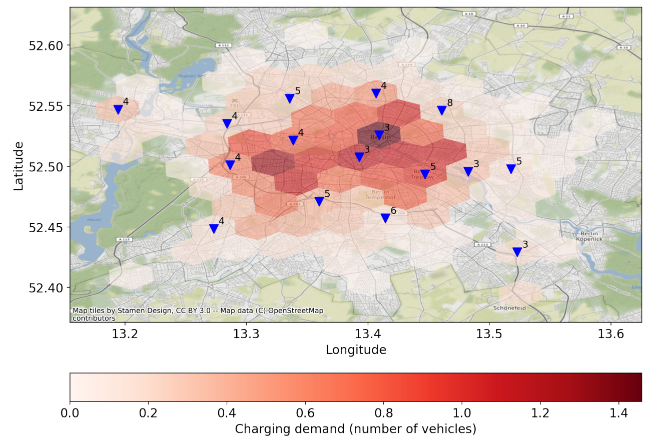

Figure 4: Heat map of generated charging demands and optimal sites and sizes of CSs

Since we solve the optimization problem using offline generated charging demands for an unconstrained charging network, we need to compare the initial charging demands with charging demands generated by updated charging infrastructure both spatially and temporally. If the charging results between infinite capacity network and restricted network are different, we need to iteratively solve the simulation and optimization to achieve converged solutions. The comparison is shown using a box-plot in Figure 5, where each box presents differences between the charging demands for all zones at any hour of the day. Apart from outliers, each box's mean is relatively close to zero ,with a low standard deviation. Additionally, we applied a t-test on the estimated charging demands, and a p-value of 0.58 shows that there is no such a significant difference between their averages.

Integrating the optimization outputs into the simulation, we test CS and fleet performance for the updated charging infrastructure. Figure 6 displays the fluctuation of CSs utilization over the entire planning time. On average, only around 40% of the chargers are being used by vehicles, and the maximum utilization is around 70%. This relatively low utilization is caused by the full-coverage optimization model as our primary goal is to serve the entire charging demand and guarantee a high quality mobility service. Also, excluding the beginning of simulation time, when vehicles are fully charged, the other parts of the graph have a cyclic pattern indicating that charging demands follow an approximate daily pattern. The principal source of this pattern are trip temporal distribution as well as hourly charging strategies.

To reveal the importance of charging strategies, we assess the simulation using two different charging strategies:

(1) The simple strategy that sends vehicles to CSs if their SOC is below a fixed threshold (e.g., 30% of the battery capacity). This strategy is used in most SAE fleet ABMs in the literature [16, 33].

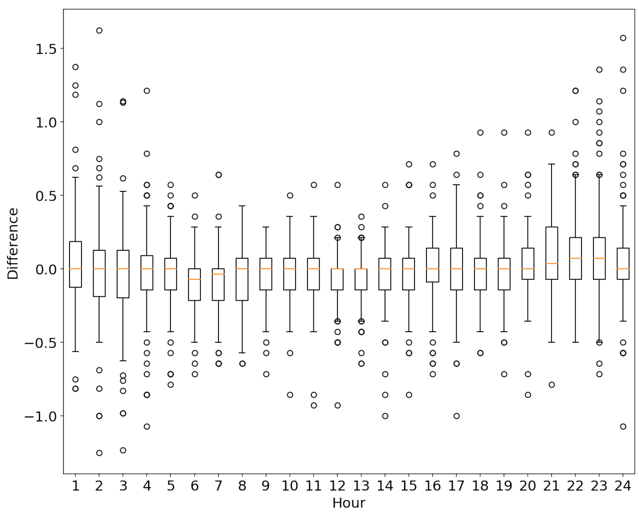

Figure 5: Charging demands difference for initial and updated charging network

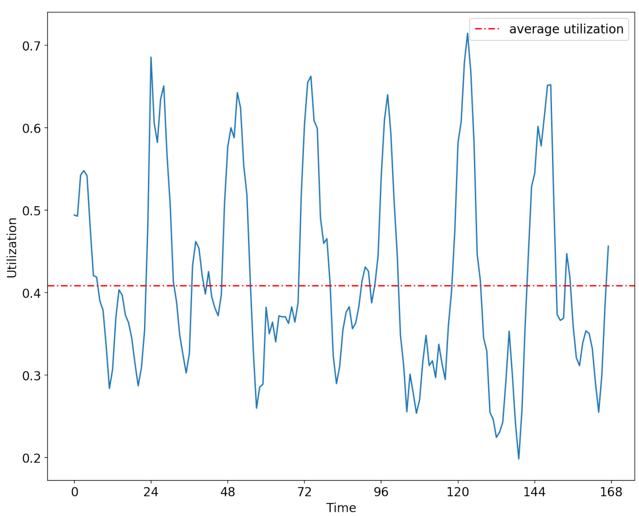

Figure 6: Charging infrastructure utilization over the planning time

(2) A smarter version of the first strategy where the SOC threshold is a function of time, adjusted by trip demands (e.g., in this example, the threshold is between 20% and 60%).

Figure 7 compares these strategies. The solid graph represents charging distribution of the first strategy over 24 hours, and the dashed graph represents the second one. With a fixed strategy, charging demand follows trip patterns due to the fixed SOC threshold. On the other hand, the smart charging strategy's goal is to charge more during low demand hours – night hours – to keep vehicles available during the peak time. It shifts the peak from late evening to the midnight while the amount of peak does not increase significantly. Although the smart strategy brings benefits of charging often at off-peak hours (i.e., regarding traffic congestion, mobility demand and electricity consumption), these results only show that charging strategies affect the fleet performance and CS placement; finding an optimal charging strategy for other specific goals is beyond the scope of this paper.

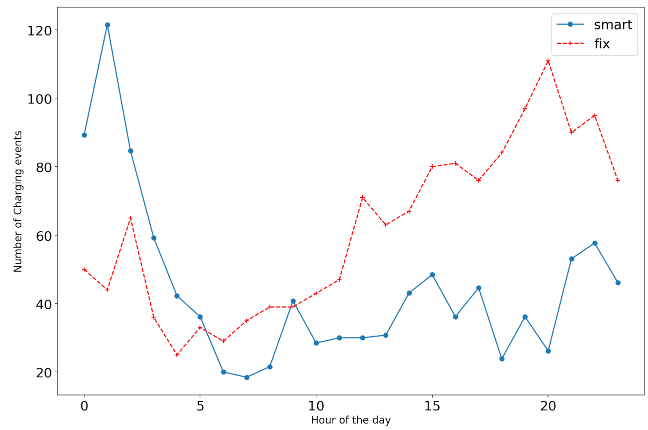

Figure 7: Distribution of the number of charging events for two different charging strategies

We evaluate our method across a range of fleet size scenarios. Table 2 summarizes charging infrastructure and fleet's performance under a variety of fleet sizes. The most remarkable result is that reducing the fleet size (FS) increases the required number of chargers (NoC) (i.e., fleet size reduction increases the fleet utilization (FU) leading to higher charging demands during peak demand periods and therefore a need for additional chargers). The findings of charging infrastructure utilization (CIU) need to be interpreted with caution. Although reducing the fleet size increases the number of chargers, there is no significant difference among charger utilization as the additional chargers are used by more charging demands. Regarding the fleet's performance, as anticipated, fewer vehicles leads to lower service quality – more waiting time (WT). Note that waiting time is in minutes and as we do not take traffic delays into account, these results might be optimistic. Apart from that, the important measurement for our analysis is the difference between scenarios, not the absolute numbers. Moreover, we test the outputs for the smart and fixed charging strategies, and report the missed trip percentages in the two last columns of Table 2 – denoted by MT1 and MT2, respectively. There is a considerable difference between these strategies concerning missed trips since the smart strategy forces vehicles to charge mostly at night, leading to more available vehicles during peak hours.

Our final results can be compared with a naive strategy in the demand generation section where there is an infinite number of chargers (i.e. 50 chargers in each zone and 4450 chargers in total). Although the optimal number of chargers reduces dramatically nearly by 98%, the fleet performance remains approximately the same. Trips are rarely missed with fewer CSs using the smart charging strategy, and waiting time is increased by less than 5% on average compared to the infinite setting.

A difference of autonomous vehicles from conventional vehicles in the CS placement problem is that the travel distance to the CSs

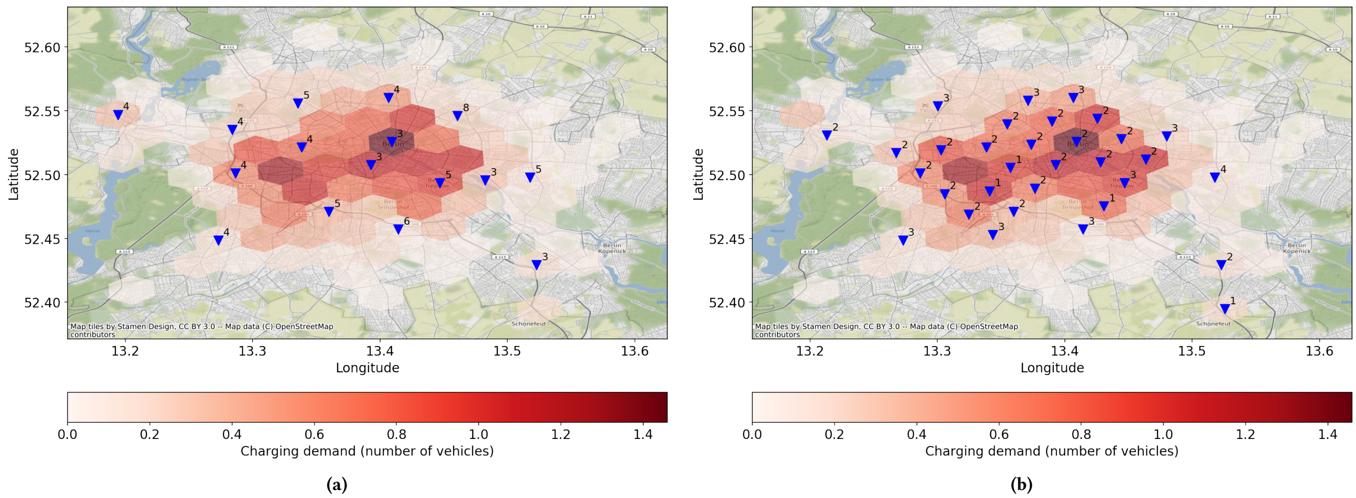

Figure 8: Optimal CS sites and sizes for 900 fleet size with (a) low (b) high driving distance penalties

Table 2: Results of CS and fleet performance for different fleet sizes

FS	*NoC*	*CIU*	*FU*	*WT*	*MT1*	*MT2*
900	70	0.41	0.11	6.67	0.00	0.00
800	72	0.42	0.13	7.20	0.00	0.06
700	78	0.39	0.14	7.80	0.00	0.08
600	79	0.41	0.16	11.27	0.06	0.11

is less costly as there is no need for operators to relocate vehicles to CSs because they automatically relocate to charge their batteries. To clarify, we solve the optimization problem with higher penalty factor for driving distance – the case of conventional vehicles – and the comparison is shown in Figure 8. Although the total number of required chargers is the same for both cases, the higher penalty for driving distance leads to more stations with smaller sizes to distribute more evenly across the landscape.

5 CONCLUSION AND FUTURE WORK

This paper gives an account of charging infrastructure planning for a fleet of SAEVs, a likely feature of future road transportation systems. We devise a viable methodology, optimally siting and sizing CSs to cover fleet charging demands while minimizing installation and operational costs. To estimate charging demands, we employ ABM to model mobility system complexities – vehicle assignment, relocation and charging strategies. The generated demands are then used to solve the location-allocation problem, using mixed-integer linear programming to find the ideal charging infrastructure.

We apply this method to real-world data and evaluate our results under various scenarios. Our initial finding indicates that optimal CS location hinges on spatial distribution of charging demands plus installation costs. Optimal CSs are located in both central areas where demand is high, and suburbs where installation costs are lower. Moreover, a comparison across a range of fleet sizes indicates that the number of vehicles affects the size of charging infrastructure. With a smaller fleet size, vehicles utilization slightly increases, which leads to higher peaks of charging demands and more need of chargers. Our analysis also underlines the importance of fleet charging strategies. In addition to a fixed rule, we tested our ABM for a smart strategy – SOC threshold as a function of time – that improved fleet performance. Finally, to study the significance of autonomous mobility, we solve the optimization model for different driving distance penalties. For conventional vehicles where the driving costs are higher, the number of stations rises to have a more spread charging network while the total number of chargers remains the same.

Despite improving charging infrastructure planning for a SAE fleet, this study contains some limitations. First, siting and sizing of CS is solved in an optimization model while unrestricted charging demands are generated in the simulation part without taking the constraints of charging infrastructure into account. Connecting simulation and optimization parts could yield more realistic results. Second, operational decisions in our ABM are made based on flexible and straightforward rules, which may not be optimal. Developing a more nearly-optimal decision support system for fleet management could improve performance and avoid sub-optimal solutions. One possible approach is to distribute the decision-making to the vehicles, perhaps by having them bid in a synthetic market for trips, charging sessions, and perhaps parking. The third shortcoming is that we have not considered different types of chargers; some areas might benefit from fast chargers based on their time-sensitive charging demands. Finally, this study solves the charging station placement problem for a SAE fleet, but the charging demands of a diverse EVs population (e.g., private EVs, electric public transportation, and electric delivery fleets) would likely be more complex. A more holistic approach to charging infrastructure planning for heterogeneous electric fleets could increase efficiency and utilization and lower overall cost.

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