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Combining analytics and simulation methods to assess the impact of shared, autonomous electric vehicles on sustainable urban mobility

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ABSTRACT

Urban mobility is currently undergoing three fundamental transformations with the sharing economy, electrification, and autonomous vehicles changing how people and goods move across cities. In this paper, we demonstrate the valuable contribution of decision support systems that combine data-driven analytics and simulation techniques in understanding complex systems such as urban transportation. Using the city of Berlin as a case study, we show that shared, autonomous electric vehicles can substantially reduce resource investments while keeping service levels stable. Our findings inform stakeholders on the trade-off between economic and sustainability-related considerations when fostering the transition to sustainable urban mobility.

1. Introduction

Over the past decade, the *sharing economy* has fundamentally affected a variety of industry and service sectors, such as transport, finance, entertainment, and education. As a result of this ongoing transformative impact, revenues are expected to increase from USD 15 Billion in 2015 to USD 335 Billion in 2025 [1]. While the vast economic potential of the sharing economy is often proclaimed [2], its exact definition remains unclear. Lessig [3], one of the first to coin the term, describes it as an economy that “is regulated not by price, but rather by a complex set of social relations” (p. 145). Although the idea of the sharing economy that Lessig proposed can be found, for instance, in the couchsurfing or open source communities, it is less evident in the multibillion dollar behemoths that are commonly associated with the sharing economy, such as Airbnb and Uber. As a result, the notion of the *access (-based) economy* has been increasingly fostered. The key tenet of this concept is that access and ownership are separated [4]. Access to certain shared assets is facilitated through online platforms [5] as needed and, thereby, the utilization of these assets is increased [6].

A sector that exemplifies this shift from ownership to access is urban transportation with its trend toward shared mobility.[1] When planned and implemented carefully, it may unlock benefits in various areas beyond transportation such as economic development, environment, housing, and urban design.[2] In addition to ride-hailing providers like Uber and Lyft, carsharing services have experienced substantial growth in recent years [10]. Companies like Zipcar and car2go operate predominantly in densely populated areas and provide their customers with access to a vehicle on demand, fundamentally altering the transportation habits in cities around the world. Particularly free-floating carsharing (FFCS) as provided by car2go offers users a degree of flexibility that public transportation services often lack and together with a functioning public transportation network may provide a viable alternative to vehicle ownership [11,12], which seems to be specifically attractive for younger citizens [13,14].

While recent studies have begun to investigate the challenges associated with the operations of shared vehicle systems (e.g., [15–17]), the sharing economy is only one of the major transformations that are projected to fundamentally change urban mobility over the coming decades, with the others being *electrification* and *autonomous vehicles*. Electric vehicles (EVs) promise (at least locally) emission-free urban transportation, representing a powerful tool to combat air pollution that plagues urban centers around the globe [18–20]. Driverless, autonomous vehicles, on the other hand, bring the prospect of increased efficiency and safety, reduced congestion, and a further boost to urban sustainability [21–23].

Decision-makers in both public and private sectors face a range of challenges with respect to each of these developments, such as investments into charging infrastructure of EVs and ensuring demand-supply

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[1] For a comprehensive primer on shared mobility, see [7].
[2] For an overview on implementation opportunities and guidelines, see [8,9]).

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balance in shared-vehicle systems. However, these challenges should not be perceived in a vacuum. Hence, in this paper, we explore the ability of information systems that combine real-world data, analytics techniques, and simulation methods to support decision-making through an integrated analysis of these phenomena. Focusing on the concept of *shared, autonomous electric vehicles* (SAEVs), we investigate the effect of driverless vehicles on these challenges and analyze, in turn, to which degree constraints imposed by vehicle sharing and electrification shape the impact of autonomous vehicles on urban transportation.[3] For this purpose, we combine data analytics and an agent-based simulation model, leveraging real-world data on both carsharing trips and charging locations. While the analytics module enables a prediction of future demand-supply patterns, the simulation platform allows us to analyze the impact of the resulting operational decisions on the sustainability and economic feasibility of SAEVs.

The results of our analysis for the city of Berlin, Germany show that autonomous vehicles can reduce carsharing fleet size by about half. This effect is limited by usage peaks in the morning and early evening, but illustrates the potential of autonomous vehicles to solve demand-supply imbalances. The effect persists when electrification comes into play, but, more interestingly, satisfying the entire current carsharing trip demand of the investigated operator for Berlin – approximately 5700 trips per day – only requires about 30 charge points. Overall, these results emphasize the relevance of data-driven decision support systems for environmental sustainability, providing valuable insights for current discussions on sustainable urban transportation, investments into EV charging infrastructure, and shared mobility systems. For carsharing operators, our results also illustrate the trade-off between fleet size, charge point density, and service levels.

We proceed in the next section by providing an overview of relevant related work and summarizing the research gap we address, as well as our key contributions. In Section 3, we describe the data sets used in our analysis. Our methodological approach is presented in Section 4 while Section 5 contains the results of the simulation and various sensitivity analyses. We discuss the implications of our results and conclude in Section 6.

2. Related work

In recent years, the Information Systems (IS) community has renewed their interest in identifying how IS research can help to solve so-called *wicked problems* (see, for instance, [24–26]). Ketter et al. [24] describe wicked problems as those that "arise in complex sociotechnical systems where numerous social, economic, political, and technical factors interact" (p. 1057). Questions surrounding sustainability are wicked by nature as they threaten a wide range of established social, political, and economic regimes while also effecting change in individual behavior. However, in the context of cities, this wickedness is further amplified as urban areas add another layer containing multiple highly complex social and technical systems to the mix [27]. In this section, we will first outline how urban transportation as one of these subsystems at the intersection of sustainability and urban life is currently undergoing three fundamental changes. As a second step, we will discuss the contribution IS research can provide toward overcoming the resulting challenges through data-driven decision support that pairs analytics and simulation techniques.

As part of the sharing economy, **carsharing** has evolved over the past decade to become an integral element in the mobility landscape of urban areas around the globe. Between 2010 and 2016, membership numbers have increased twelve-fold from 1.2 million to 15.1 million while the number of vehicles has increased from approximately 32,000 to 157,000 [28]. Early carsharing services employed a round-trip station-based model, in which users can rent cars from designated stations and were obligated to return them to the same station. Over time, one-way station-based services developed, providing the customers the flexibility to return the vehicle to any qualified station. The emergence of one-way carsharing has also increased the operational complexity of these systems, as demand and supply vary across time and different stations. Various studies have investigated solutions to this challenge with, for instance, Nair and Miller-Hooks [29] introducing a stochastic mixed-integer program that determines vehicle redistribution plans under uncertainty. Nourinejad and Roorda [30] propose a dynamic model that combines vehicle relocation with the optimization of station inventories, while Nourinejad et al. [31] add staff considerations to the vehicle relocation problem, emphasizing the relevance of staff costs in carsharing operations. The interplay between one-way and two-way systems can be complex, with Lu et al. [16] identifying a substantial impact of internally and externally generated one-way rental demand on the operator's profit and the quality of service. The benefits of combining one-way and two-way systems to address demand-supply imbalances are also shown by Jorge et al. [32], who evaluate the concept by applying it to carsharing trips at Boston's Logan Airport.

Station-less, free-floating carsharing enables users to end the rental anywhere within the provider's business area and further exacerbates the challenges associated with balancing vehicle demand and supply. Wagner et al. [17] show that demand is driven to a large extent by specific points of interest in an area and Willing et al. [33] illustrate that the strength of these drivers varies with the time of day. Weikl and Bogenberger [34] distinguish approaches used to address the resulting vehicle relocation problem between operator-based and user-based ones. For example, He et al. [35] present an operator-based method that incorporates the temporal dependence of vehicle demand. Wagner et al. [36] propose an incentive-driven user-based strategy.

In addition to vehicle sharing, **electrification** is a second major development currently transforming personal transportation. The key challenge of EVs lies in the fact that both refueling (charging) times and the range resulting from one refueling cycle are still substantially worse than for comparable conventional vehicles [18–20]. Zhang et al. [37] propose a network flow optimization model using vehicle assignment and relays to overcome these shortcomings in one-way station-based carsharing with EVs. Kuppusamy et al. [38] show that the average distance travelled is a key determinant of whether EV adoption is advisable for a taxicab entity. Research regarding the *Green Vehicle Routing Problem* that results from this limited range commenced as early as the 1980s, when Ichimori et al. [39] investigated optimal routing under refueling and range restrictions, and continues today with the rising sales numbers of EVs (e.g., [40,41]). However, particularly in an urban setting, range anxiety is less of an issue and the use of EVs in carsharing has gained interest in both practice and research. For one-way, station-based carsharing systems with EVs, numerous recent works have contributed to the advancement of the field, e.g., on vehicle rebalancing and staff relocation [42], on combining relocation challenges and charging requirements [11], on the trade-off between relocation costs and service level [43], on fleet size and trip pricing [44], and on the placement of charging stations under stochastic demand [45]. He et al. [15] translate these challenges to the strategic level by developing a model to support carsharing providers with respect to the design of their operating area. Kahlen et al. [46] outline the potential synergies that shared EVs enable. They investigate the use of those vehicles as a virtual power plant that can support the integration of renewable energy sources.

With platform giants, established car manufacturers, and a cosmos of start-up companies all working on the **autonomous, driver-less car**, the implications of AVs on shared vehicle systems are emerging as a growing field of research [47]. Recently, Alonso-Mora et al. [48] have shown that driverless vehicles have the potential to magnify the benefits of ridepooling. They have simulated a network of (potentially

[3] For instance, automated charging processes for EVs require a connection between vehicle and infrastructure (V2X).

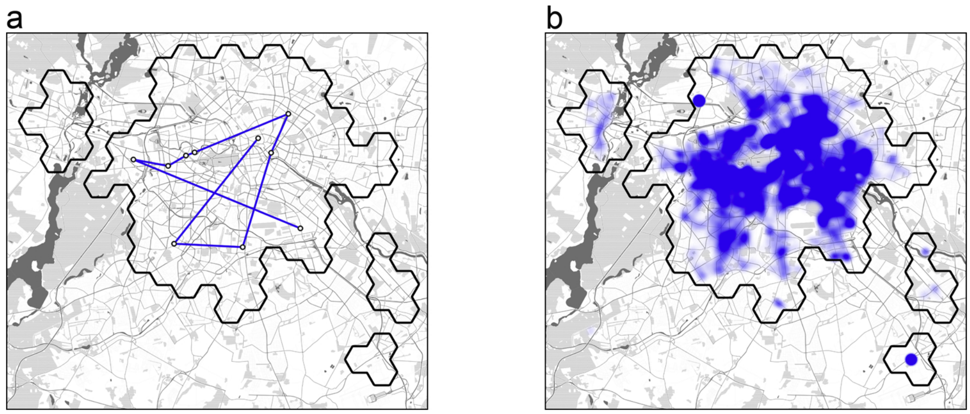

Fig. 1. (a) Exemplary vehicle trip sequence. (b) Heat map of trip starting positions.

autonomously driving) vehicles, including the option to share rides, based on trip data from New York City's taxi network. They found that 98% of all taxi demand could be served with only 23% of the fleet size if people were willing to share rides and use the full capacity of a cab (4 passengers). In that case, waiting time would average at as little as 3 min and average trip duration would be increased by only 3.5 min. However, the MERGE Greenwich [49] project shows that willingness to share rides is comparatively low for urban areas and we, therefore, focus on the case without ridepooling in this study. In a carsharing context, Chen et al. [50] and Loeb et al. [51] have been among the first to research the concept of shared, autonomous EVs. Employing a multiagent simulation in conjunction with an artificial data set of trips, they analyze the interplay of investment decisions and operations in an SAEV system.

All three of these developments pose various strategic and operational challenges that decision-makers in both business and municipal governments need to face over the coming years. They include determining appropriate fleet sizes, improving vehicle relocation techniques, and building up an urban vehicle charging infrastructure, with the last aspect in particular requiring substantial investments to make the long-term sustainability of urban transport possible. Surbakti et al. [52] discuss how IS that support such decision-making processes are increasingly becoming data-driven. In this work, we seek to further understand this transformation and **how data-driven decision support systems can aid society in tackling wicked problems**. For this purpose, we particularly focus on systems that combine data analytics and simulation techniques. The underlying theoretical motivation is that, on the one hand, leveraging large real-world data sets allows us to observe how the interactions between complex systems play out without needing to explicitly model every aspect of those systems (see, for instance, recent advances in black-box modeling reviewed in [53]). In the context of urban transportation, this relates, for instance, to carsharing and other mobility data reflecting transportation patterns in the city without needing to model people's motives for the trips. On the other hand, simulation techniques allow us to manipulate the environment – such as turning conventional vehicles into electric ones – and assess how the dynamics revealed in the real-world data react to these changes. Together, data analytics and simulation techniques can provide decision-makers with valuable insights related to the interplay of the complex systems that are at the foundation of wicked problems.

In context of urban mobility, our work **extends the current state of research** on the economic feasibility and environmental impact of shared, autonomous electric vehicle systems in several ways. First, we leverage a large real-world data set of carsharing trips to provide a realistic assessment of the impact of SAEVs on shared-vehicle systems. The data set reflects temporal and spatial patterns in carsharing use that are difficult to mimic in artificially generated data sets. We apply a prediction technique that combines spatial and temporal features to forecast future trip requests and vehicle availability. Second, we develop a highly adaptable simulation framework that utilizes this data set in conjunction with data on charge point locations to assess the impact of (electric) autonomous vehicles on carsharing operations. The framework integrates vehicle allocation to trips, vehicle relocation within the city, and charging decisions. Third, we analyze how service level, fleet size, and charging infrastructure interact within such a system of SAEVs. We particularly focus on the questions of how far historical carsharing trips can accommodate restrictions imposed by electrification, how strongly autonomous vehicles contribute to a reduction in fleet size, and how the effects of electrification and autonomy interact. From our results, we also derive policy and managerial recommendations regarding current discussions surrounding shared-vehicle systems and investments into charging infrastructure.

In the next section, we present the data set used in this study, followed by the introduction of the simulation framework in Section 4.

3. Data set and characteristics

The carsharing trip data used as input for our simulation study was collected over the course of 51 consecutive days in late 2016. It covers the entire fleet of one FFCS operator in Berlin, Germany and comprises a total of 290,000 trips over 1,104 vehicles. All of these vehicles are powered by combustion engines. For each trip the data consists of trip start and end positions (latitude and longitude), start and end timestamps, fuel level of the tank, as well as a unique vehicle identification number. An exemplary sequence of nine trips for a rental vehicle over the course of two days is depicted in Fig. 1a. Naturally – and absent operator-based relocations – each trip starting point in an FFCS system is simultaneously the end point of the previous trip. Fig. 1a also shows the honeycomb pattern we use in our simulation, which we will elaborate on in the next section. Furthermore, the black border represents the operator's business area. There are three parts of the business area that are disconnected from the main area with one of them being Schönefeld airport in the South East, at which vehicles can only be parked and picked up in a designated parking facility. The other two separated areas are Berlin-Spandau to the West and part of the Humboldt University Campus to the East, close to Schönefeld airport. The second point of heavy concentration – in addition to the one at Schönefeld – can be found in the North-West of the main area and represents a dedicated parking facility at the city's second airport, Tegel. The business area only limits customers in where they can end trips, not the route they choose. Hence, vehicles can move from any of these disjoint areas to another as long as the trip ends within one of them.

The heat map in Fig. 1b visualizes the spatial distribution of trip end points across the entire dataset. It generally shows a concentration of trips in the geographical center of the city with less activity in the outskirts. Nevertheless, levels of concentration within the city center

Table 1
Descriptive statistics of the trip data set.

	Minimum	Mean	Median	Maximum	SD
Trips per car and day	0	5.8	6	18	2.7
Idle time [min]	9	167.6	68.6	12,160	264
Trip time [min]	10	80.1	40.2	1,432	145

Table 2
Number of concurrently used vehicles and percentage of total number of vehicles.

	Minimum	Mean	Maximum	SD
Overall	130 (12%)	314 (28%)	574 (52%)	84.4
Weekdays	130 (12%)	317 (29%)	574 (52%)	81.4
Weekends	165 (15%)	307 (28%)	562 (51%)	91.2

are not homogenous. While some of the “cold” zones in the geographical center of the city can be identified as large parks or privately held parts of land, in which parking cannot occur, others arise simply due to low demand. This observation of large spatial demand variations even within small distances – the map excerpt shown covers approximately 30 × 30 km – confirms similar findings in for instance, Willing et al. [33] and Wagner et al. [17].

With the data set containing information of trip start and end times, each associated with a unique vehicle key, characteristics regarding vehicle utilization can be calculated in a straightforward manner. Table 1 summarizes the resulting descriptive statistics, further outlining high variations in demand. While some vehicles perform 18 trips on selected days, others are idle for over a week, as can be seen from the maximum idle time of 12,160 min. The minimum idle time that was observed is 9 min, which may point to a certain degree of saturation. Average utilization across all vehicles is slightly below one third because the mean idle time across vehicles is about twice as large as the mean trip time. However, this is already a substantial improvement over utilization rates of privately owned vehicles, which is generally estimated to come in at 4–5% [54]. Furthermore, operators may be required to have extra vehicle capacity to keep availability high, average distances to idle vehicles low, and customers satisfied. Nevertheless, these numbers suggest the potential of driverless vehicles to further reduce fleet size, because they could pick up customers by themselves, decreasing the required density of idle vehicles needed to guarantee a certain service level.

To further investigate this idea and the potential to improve overall utilization, we take a more detailed look at the number of concurrently used vehicles. Under the premise that rides are not shared and customer behavior is not altered, the maximum number of concurrent trips represents a lower bound for the fleet size needed by the SAEV operator to serve every request without significant delay. We will elaborate on our reasoning for these premises and their potential as extensions to our model in the discussion section.

Fig. 2a visualizes the fluctuation of fleet utilization over the entire observation period. Reflecting the insights from Table 1, we see that, on average, more than 70% of the fleet is idle, represented by the dotted line. This suggests that capacity is overprovided to guarantee a certain reliability of the service, but also translates into a potentially inefficient use of the operator's fleet. As summarized in detail in Table 2, the temporal variation of the utilization rate is high, with the number of concurrently used vehicles fluctuating between 130 and 574 vehicles with a mean of 314. Fig. 2a also shows that there are only four instances at which a 50% utilization rate of the fleet is reached over the entire observation period of 51 days. Fig. 2b provides a closer look at average intraday patterns, distinguishing between weekdays and weekends. We can observe that peak demand only occurs during relatively short periods of time. On weekdays, typically two phases of above-average demand arise and last for approximately 3 h in the morning and about 4 h in the evening. In between those peaks, a phase of lower demand stretches over roughly 6 h in the late morning and early afternoon. This demand suggests a potential suitability for SAEVs, since they could be recharged and relocated in these times of low demand. Weekends, however, show more of a high plateau in the afternoon with a small peak of over 2 h between 4 pm and 6 pm. This pattern could pose a larger challenge for SAEVs because it is unclear if charging in the low demand morning hours will suffice for the rest of the day.

The observable demand variations may also cause so-called *hidden demand* in free-floating carsharing systems [36]. This concept reflects the possibility that more customers would use the service if cars were available at a given location and time or if available cars would be closer to the origin of the respective customer. We investigate this issue in Section 5.3 by conducting several sensitivity analyses that consider increased demand across the city.

Regarding the potential implications of electrification on the usage patterns evident in our data set, Table 1 outlines that the average trip duration is 80 min. Even assuming that customers were to drive for the entire duration, the resulting distance is well within the range provided by today's EVs' capacities. Furthermore, particularly for longer rentals, the trip time is likely to consist of a sequence of driving and parking phases throughout the same trip. For instance, customers may stop at a store on the way to their destination without interrupting their rental to make sure that the vehicle is still there once they have finished their

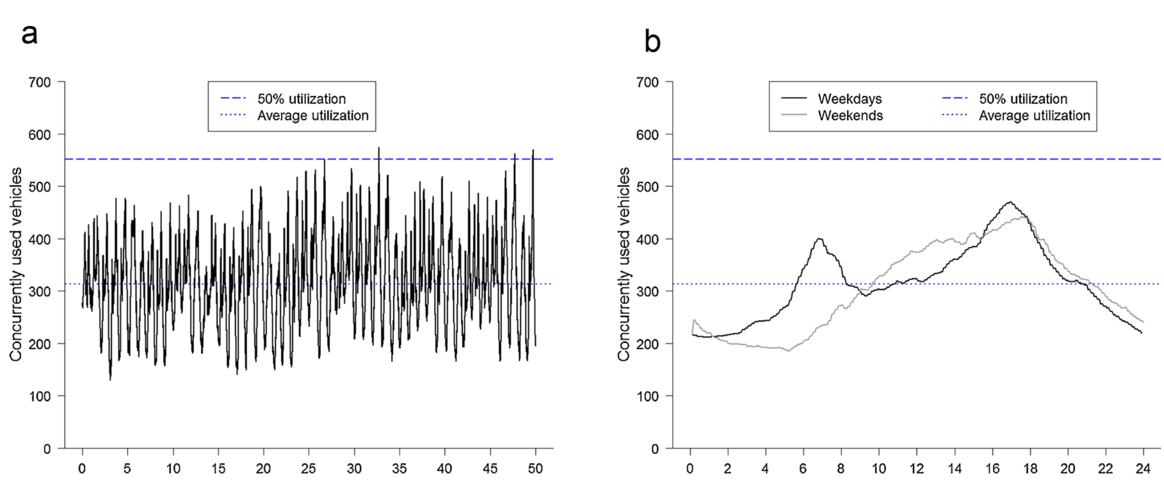

Fig. 2. (a) Utilization over observation period. (b) Average usage patterns.

errand. Such considerations become less relevant if autonomous vehicles are involved, because a (potentially different) vehicle can pick the customer up at the end of the break. Hence, we consider the distances covered within a given trip in our data set to be a relatively conservative basis for the estimated charging needs.

Nevertheless, with a decrease in fleet size resulting from autonomous cars and more densely scheduled trips for each vehicle with less idle time in-between, charging requirements may present additional constraints on fleet size and service levels that can be guaranteed. To gain a more thorough understanding of these interactions, we construct an agent-based model that leverages our real-world data set and is described in the following section.

4. Combining analytics and simulation to investigate SAEV systems

We develop an agent-based model to examine both the isolated effect of autonomously driving vehicles as well as the combined effect of electrified, autonomous vehicles on shared vehicle operations. Agent-based approaches are well-established in the literature, having a particular strength in analyzing the behavior of complex systems, in which the action of one agent affects the actions of others [55,56]. This makes them especially applicable in our context of urban transportation networks [57], because we investigate how shared vehicles interact with each other and are affected by autonomy and electrification.

There are multiple general-purpose, ready-to-use agent-based simulation platforms publicly available. The upside of broad applicability, however, comes with the caveat of a substantial amount of adaption that is required to fit them to our particular use case. Furthermore, we can only consider open-source software as commercial software is typically sold as an enclosed solution with no access to the original source code. This would prevent us from understanding all details of the model implementation. Relevant traffic-specific open-source platforms include, for instance, *Multi-Agent Transport Simulation* (https://www.matsim.org), *Simulation of Urban Mobility* (SUMO, http://sumo.dlr.de) and *Microscopic Traffic Simulation Laboratory* (https://its.mit.edu/software/mitsimlab). While all of these platforms are, in principle, capable of conducting our simulation, they were originally designed for microscopic perspectives, such as modeling lane shifts and intersection crossings. Even though they have been extended by mesoscopic and macroscopic features and have grown into powerful all-purpose solutions, the implementation of charging and relocation behavior of vehicles in particular would entail substantial additional effort. Therefore, to ensure expandability, reproducibility, and transferability to other cities and data sets, we decided to develop a Python-based agent-based simulation model specifically customized for the analysis of SAEV systems. The model is structured in a modular fashion to easily assess the impact of different algorithms or decision rules in future research.

Within the scope of this paper, the simulation leverages the data introduced in the preceding section to reflect real-world usage patterns of shared vehicles. The conducted trips from our raw data now serve as trip requests with the timestamp of the trip start becoming the timestamp of request submission. We proceed by describing the underlying logic of the model.

4.1. Model logic

For the simulation model, we first discretize the operator's business area into small zones. The resulting even honeycomb pattern that structures the area can be seen in Fig. 1a. Within the simulation runs, only those combs that overlap with the business area – represented by the dark line – are considered; the others are deactivated. The size of the combs is chosen such that any point within the comb can be reached from any other point within the same comb in at most 5 min, resulting in a diameter of 2 km.

As detailed in Section 3, the data set consists of information on conducted trips by vehicle, including start and end positions and times, from which idle times between trips can be derived. To allow the simulation to produce realistic assessments of day-to-day operations of the SAEV system, we need to include the uncertainty that is inherent to free-floating carsharing operations. As customers can take an available car on the spot and without the need to reserve ahead of time, demand is only known as it is realized. Hence, to allow for proactive relocation and charging decisions, the simulation model needs to include a predictive analytics module for demand forecasting. To enable this from the data side, we chronologically split the data set into two equally large subsets. The first of these subsets then serves as the training set and is used to predict the vehicle idle times in each comb for each hour of the day. The second subset serves as test set and contains the actual requests that come in as events during the simulation runs.

Each vehicle is represented by an agent that follows a given set of rules and instructions. When the simulation initializes, a predefined number of these agents is placed randomly within the operation area and they are set to idle. As a request comes in, the closest idle vehicle is selected to conduct the trip. The car moves to the pickup location and subsequently fulfills the requested trip. During the transfer to the pickup location and during the trip itself the vehicle is treated as locked and ignores all requests that materialize during this time. After completing a requested trip, by default the vehicle becomes idle again. However, aside from staying idle, unused vehicles can also get directions to relocate themselves to another comb or move to a charge point and recharge their battery.

We implement several decision rules to coordinate relocation procedures. First, occupying every comb with at least one idle vehicle is prioritized. In case all combs are occupied, the vehicle is sent to the comb with the lowest predicted idle time to maximize expected utilization, controlling for the time required to reach this comb. However, combs that have reached a maximum capacity of idle cars, which we set to 20, are excluded from the search. The data set does not contain information on the actual trip path but only on the overall duration as well as start and end points. We use this trip time instead of recalculating it based on the distance, because the trip might contain deliberate parking phases. All "artificial" travel durations and distances for relocations and customer pick-up are calculated by a routing server based on the Open Source Routing Machine [58]. We do not assume that vehicles themselves are proactive in the sense that they accept requests before they are idle or plan to relocate or charge before a trip has ended. The reason is that the key advantage of free-floating carsharing is flexibility and this should persist in SAEV systems. Hence, we do not assume that customers are bound by their initially chosen destination, but leave room for spontaneous extension or interruption of trips as the customer's plans change.

4.2. Simulation platform and setup

To translate this logic into an implemented simulation platform, we first discretize our observation period into T time steps of one second each. As illustrated in Fig. 3, the simulation begins to loop through each time step once the key objects of the simulation are initialized. These objects include V vehicle-agents, a predefined number of P charge points, as well as R request-events.

Every time step t follows the same sequence of tasks, each representing one aspect of the model logic previously described. These tasks are coded as independent modules, which provides the freedom to alter certain attributes of the model for sensitivity analyses on the one hand, and offer the opportunity to enhance certain aspects of the algorithm in future research on the other. Once all time steps have been completed, the results are stored and the simulation is terminated.

The first module that is called is the *Request Module*. The module considers all requests that have a timestamp within the current time step t, which are collected in the subset $R_t \subseteq R$. In their chronological

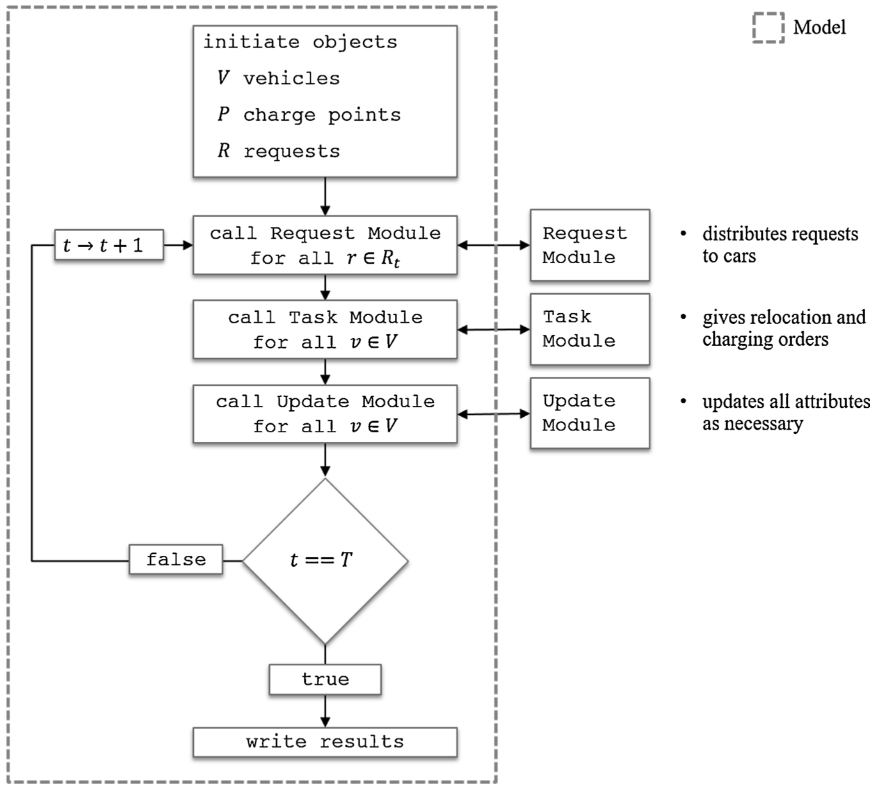

Fig. 3. Schematic representation of simulation procedure.

order, each request is then dispatched to an idle vehicle, reflecting a first-come-first-serve approach. If there is no idle car at the time of the request, the request is denied.

All tasks that are related to relocation and charging are then handled by the *Task Module*. While the module is called for each car, only cars that are in the idle mode are eligible for a new task, with the others remaining unaltered. The general intention of relocation is to position a car in such a way that it decreases the likelihood of future trips being rejected as well as next customer's waiting time. Effectively, cars are aligned with the anticipated spatial distribution of demand. As previously mentioned, we prioritize that all combs are covered with at least one idle car. If this condition is not met, a given idle car is sent to the closest uncovered comb.

Once the condition is met, demand is predicted based on the training data set using temporal and spatial features. To ensure that the prediction module can rely on a sufficient number of eligible trips, demand predictions are conducted at an hourly level and leverage a moving-average concept. For a particular hour of day, such as from 4 pm to 5 pm, all trips in the training data set that have ended between 3:30 pm and 5:30 pm are considered. The larger selection time span represents a temporal smoothing and implies that trips ending slightly before 4 pm (or after 5 pm) also have implications regarding the expected idle time for the hour in question. Based on this temporal selection, we then proxy predicted demand in a given comb by calculating the distance-weighted average idle time of trips ending within a 1000-m radius of the center of the comb. For example, if the selection contains three trips at a distance of 300, 500, and 800 m from the center with subsequent idle times of 40, 60, and 90 min, respectively, the predicted idle time would be calculated as

$$\frac{40 \times 0.7 + 60 \times 0.5 + 90 \times 0.2}{0.7 + 0.5 + 0.2} = 54.29.$$

Hence, the predicted idle time for the comb in question would be 54.29 min.

Based on these predictions, the vehicle is allocated according to the following calculation:

$$c_v = \begin{cases} \underset{c \in C}{\arg\max}\, \tau_0 - \tau_c - \mathrm{dur}_{0,c} & \text{if } \max\limits_{c \in C} \tau_0 - \tau_c - \mathrm{dur}_{0,c} \geq 120, \\ c_0 & \text{otherwise.} \end{cases} \tag{1}$$

Eq. (1) determines the comb c_v from the set of all combs C that a vehicle v is relocated to, with c_0 being the comb the vehicle is currently at. For each comb $c \subseteq C$, the difference in idle times of the current comb τ_0 and the comb under consideration τ_c is calculated. Additionally, $\mathrm{dur}_{0,c}$, the time required to cover the distance between those two combs, is subtracted. If the maximum difference that is calculated exceeds 120 min, the vehicle is assigned to the corresponding comb. This threshold is implemented to take into account the uncertainty associated with idle time predictions and to relocate only if the expected improvement is substantial. Otherwise, the vehicle stays in its current comb, c_0. To ensure clarity of the formulation, the maximum vehicle capacity of 20 is not shown in Eq. (1). If the comb that maximizes the difference in Equation (1) is already at full capacity, the next best comb is chosen if it also exceeds the threshold.

The second task that the module executes concerns charging decisions, governed by the following rule set. If an idle car is not relocated, it is given the instruction to charge if its battery status is below 50%. The closest available charge point is selected and the vehicle autonomously drives there and starts charging. For the purpose of this study, we assume that this process will not be interrupted and vehicles charge until the battery is full, turning back into idle mode afterwards. We model each charge point as having a single outlet, but naturally nearby outlets can be aggregated into a single charge point with multiple outlets in practice. However, this is unlikely to affect our simulation results. Furthermore, in case a vehicle completes a customer request and its battery status is below 25%, it will not accept any other tasks except moving to the next available charge point and charging. This prevents the vehicles from stranding during a trip. It also implies that a

Table 3
Fraction of missed requests for shared, autonomous vehicles.

Number of vehicles $\|V\|$	100	200	300	400	500	600	700
Share of missed requests	77.4%	53.1%	30.0%	12.1%	2.9%	0.2%	0.0%

shortage of charge points will not translate into vehicles stopping in the middle of a trip due to an empty battery. Rather, it will be reflected in unanswered requests as vehicles wait for charge points to become available and deny incoming trip requests.

Finally, the *Update Module* updates all cars' attributes, such as mode changes (e.g., from *locked* to *en route*), positions, and battery status. After all time slots have been simulated, a log of all relevant actions is saved and key performance indicators are recorded. The first day of the simulation does not enter into the calculation of these indicators, because initially all vehicles are randomly placed and idle. Hence, it allows for the system to self-calibrate and ensures that the results are not biased.

4.3. Parameters and measures for evaluation

The simulation platform allows for various **key parameters** to be dynamically adjusted. We set the battery capacity to 50 kWh, which reflects Teslas Model 3 base version. Furthermore, we assume a fuel efficiency of 15 kWh per 100 km, which is in line with the EPA City MPG rating for current models such as Tesla's Model 3 Long Range [59], Hyundai Ioniq, and BMW i3 60 Amp-hour batteries [60]. The charging output of charge points is set to 11 kW, which is currently the most frequent version of charge points in Berlin. Based on data from Open Charge Map [61], three out of four charge points in Berlin have a power of 11 kW or higher. As previously mentioned, time steps are set to 1 s.

In Section 3, we estimated a lower bound of vehicles needed to fully satisfy peak demand – absent behavioral changes – at approximately 580 cars. To also assess the effect of lower fleet sizes on service levels, we use different values for the fleet size $|V|$, ranging from 100 to 700 in steps of 100 vehicles. A lower bound for the necessary number of charge points can be derived by comparing the distance covered through carsharing trips per day and the maximum charging output of a charge point per day. Given the maximum output of 11 kW and a fuel efficiency of 15 kWh per 100 km, a single charge point can supply at most 1760 km of travel distance per day. With an average aggregate travel distance of approximately 30,000 km per day, at least 18 charge points would be needed. Taking into account variations between days and scheduling challenges arising from using every charge point without break, we vary the number of charge points in our simulation runs, $|P|$, between 20 and 30 in steps of two. We also consider scenarios with 40, 50, 75, and 100 charge points to assess the effect of a larger charge point density on fleet sizes required to meet peak demand.

Our main **performance indicator** is the ratio of missed requests over all requests. A request is missed or denied if all vehicles are either on their way to customers, on a trip with a customer, on their way to a charge point, charging, or relocating. This ratio can be interpreted as the service level as in how many customer requests can instantaneously be answered with a dedicated vehicle and an estimated time of pickup. Naturally, the operator aims for a low share of missed requests, as it constitutes missed revenues and a decrease in service reliability and customer satisfaction.

Our second performance measure is the percentage of rides that have a waiting time of more than 10 min. We choose this timespan as a threshold because FFCS users seem to be very sensitive to waiting times. Herrmann et al. [62], for instance, surveyed FFCS customers and more than 55% of the participants stated 15 min waiting time as their acceptable maximum, with only 5% accepting waiting times of 30 min or more. Hence, to approximate a "good" service level, we choose a conservative threshold of 10 min.

5. Results

In this section, we present the simulation results, moving from a case of shared, autonomous vehicles to a case of shared, autonomous electric vehicles. Subsequently, we conduct several analyses of the sensitivity of our results to particular model parameters. We will discuss the managerial and policy implications of the results in the subsequent section. The simulations were executed on Azure DS1 v2 virtual machines and lasted on average approximately 24 h, depending on the number of vehicles, charge points, and trips.

5.1. Shared, autonomous vehicles

We first investigate the system for the case that vehicles are autonomous, but continue to be powered by combustion engines. Hence, they are not subject to any charging constraints. The time required for refueling the vehicle with gasoline is negligible, as it amounts to approximately 300 min per day for the entire fleet, assuming that a range of 500 km can be refueled in 5 min. Table 3 shows the fraction of missed requests in this scenario for various levels of $|V|$. For 600 vehicles and above, we find very little or no missed requests. This falls in line with the insights presented in Section 3, where we identified a theoretical lower bound of 574 vehicles, corresponding to a fleet size reduction of 48%. This suggests that, in the case without electrification, even relatively simple balancing and relocation strategies are sufficient to fully utilize the benefits of driverless vehicles. However, further improvements can potentially be reached through ride sharing and providing incentives to shift rides during peak hours. Furthermore, operators need to decide which service level they are willing to offer at what cost. Given that an increase in missed requests by 2.7 percentage points allows a fleet size reduction of 100 vehicles, this may be a price worth paying. While the focus of our study is on the further addition of electrification, our simulation model allows for a more detailed analysis of these relationships for any city.

5.2. Shared, autonomous electric vehicles

The results become more nuanced when electrification of vehicles is added. Table 4 summarizes the service level, represented by the fraction of missed requests, for different combinations of $|V|$ and $|P|$ values. We also provide a corresponding heat scale of the service level values for an intuitive visualization of the emerging patterns, with lighter colors representing a lower share of missed requests. When focusing on each column and considering the effect of fleet size variations, it is evident that an increase in $|V|$ always results in a better service level. The effect of an increasing number of charge points is less clear. Evidently, for fleet sizes of 100 and 200 vehicles, the availability of vehicles is the constraining factor and the service level remains unchanged across different values of $|P|$. A fleet size of 300 is the first instance for which the number of charge points creates a constraint to service provision, represented by the reduction in missed requests when moving from 20 to 22 and, to a lesser extent, from 22 to 24 charge points. This effect persists for larger fleet sizes, with an increasing number of charge points required before only the fleet size constrains the achievable service level. However, from $|P| = 28$ onward, we observe no impact from additional increases in the number of charge points and further investments into charge points do not alter the service level – as measured by the share of missed requests – across all fleet sizes considered.

Nevertheless, the relevant constellations from a practical point of view are likely to be those for which the share of missed requests does not exceed 10%. While an operator would not want to overinvest into either fleet size or charging infrastructure, it would also not be acceptable to have customers lose confidence in the availability of vehicles. The associated values for fleet size and charge point number are $500 \leq |V| \leq 700$ and $26 \leq |P| \leq 30$, respectively, which are formatted in bold font in Table 4. Starting at $|P| = 26 \wedge |V| = 700$, there are

Table 4
Fraction of missed requests for shared, autonomous electric vehicles.

Number of vehicles $\|V\|$	Number of charge points $\|P\|$: 20	22	24	26	28	30	40	50	75	100
100	79.4%	79.3%	79.2%	79.2%	79.3%	79.3%	79.3%	79.3%	79.3%	79.2%
200	57.1%	56.9%	56.8%	57.0%	57.0%	57.0%	56.9%	57.0%	56.8%	56.8%
300	42.7%	36.5%	34.9%	35.1%	35.3%	35.3%	35.1%	35.1%	35.1%	35.1%
400	41.6%	34.6%	27.2%	19.0%	16.5%	16.3%	16.4%	16.5%	16.3%	16.4%
500	39.2%	32.1%	24.5%	**15.7%**	**5.5%**	**4.7%**	4.8%	5.0%	5.0%	5.0%
600	35.2%	27.6%	18.9%	**6.6%**	**0.6%**	**0.5%**	0.5%	0.6%	0.6%	0.6%
700	31.7%	24.5%	13.6%	**0.0%**	**0.0%**	**0.0%**	0.0%	0.0%	0.0%	0.0%

absolutely no denied requests. Hence, given this minimal charging infrastructure, SAEVs would allow the operator to reduce the fleet size by at least 37% (404 of 1104 vehicles) without any measurable decrease in service level. The diagonal structures in this part of Table 4 also point to the potential trade-offs between investments into fleet size and charging infrastructure. The combinations $|P| = 26 \wedge |V| = 600$ and $|P| = 28 \wedge |V| = 500$ result in similar service levels, with around 6% of requests being missed. Hence, from the scenario with 26 charge points and 500 vehicles, the FFCS operator has the option to either invest into a larger fleet or more charge points with approximately the same impact on service level. The resulting exchange rate between cars and charge points can be estimated at around 50:1. While the optimal decision here, given market prices, would clearly be the addition of two charge points, their beneficial impact saturates at 28, as previously mentioned. A further improvement in service levels can only be achieved through an increase in fleet size.

For those trips that have been served, Table 5 summarizes our second performance measure – the percentage of rides with a waiting time of 10 min or more. We can identify a similar pattern as in Table 4, with an increase in the number of charge points beyond 20 having no effect on the instances with $|V| = 100$ and $|V| = 200$. For larger fleet sizes, the number of charge points begins to constrain the service level, but, as in Table 4, this effect saturates at $|P| = 28$ and we can see a similar exchange rate of 50:1 at the combination $|P| = 26 \wedge |V| = 500$. Figure 4 provides a closer look at the distribution of waiting times with a histogram for five different parameter setups. The distributions follow the same pattern as the other service level criteria. Scenarios with chronic shortages of vehicles and charge points ($|P| = 20 \wedge |V| = 100$) clearly display longer waiting times than cases with sufficient supply of both charge points and vehicles ($|P| = 100 \wedge |V| = 700$).

Overall, these results present a consistent picture of the interplay between fleet size and available charging infrastructure. For small fleet sizes, 20 charge points are sufficient to satisfy the charging demand and the service level is constrained by the availability of vehicles during peak times. As fleets become larger, the charging infrastructure becomes insufficient to handle the increase in kilometers driven. However, small additions to the charging network are enough to handle the additional energy demand and to improve the service level across all measurements. These results also hold for both weekdays and weekends.

Lastly, in Section 3, we outlined that current carsharing vehicles in our data set are idle for about two-thirds of the day – which is already a substantial improvement over the 5% utilization rate of individually owned cars. As shown in Table 6, the utilization rate is further improved in the case of SAEVs. Naturally, idle times are very low for small fleet sizes because vehicles are hard-pressed to keep up with demand. As fleet size increases, the share of idle time increases. However, compared to the raw data, we now have six different modes that cars can be in instead of two. In addition to *idle* and *active*, cars can now also be *en route to customer*, *en route to charging*, *charging*, or *relocating*. The effect is particularly noteworthy in the bottom left corner of Table 6, which shows a substantial reduction in idle time as the number of charge points increases for large fleet sizes. This confirms that for low $|P|$-values, vehicles are often waiting to be charged and unable to fulfill requests during this time. While a drop in idle time does not directly translate into an equal increase in utilization, the share that is taken by the additional modes is small. For instance, for every 100 min on a trip, the average time spent on relocation is below 1 min across all cases. Taking the case of $|P| = 28 \wedge |V| = 600$ as an example, every vehicle needs to drive 50 km per day to meet the average daily travel demand

Table 5
Share of rides with waiting time above 10 min for shared, autonomous electric vehicles.

Number of vehicles $\|V\|$	Number of charge points $\|P\|$: 20	22	24	26	28	30	40	50	75	100
100	28.5%	28.7%	26.7%	28.1%	28.4%	28.3%	26.6%	29.0%	26.5%	29.0%
200	19.3%	19.2%	17.6%	19.1%	19.0%	19.1%	17.7%	19.2%	17.7%	19.4%
300	15.8%	14.4%	13.0%	14.0%	14.2%	14.1%	12.8%	13.9%	12.9%	14.0%
400	15.2%	13.8%	11.3%	10.0%	9.3%	9.3%	8.5%	9.2%	8.6%	9.4%
500	14.0%	12.6%	10.2%	**8.6%**	**5.3%**	**4.8%**	4.6%	4.9%	4.5%	4.9%
600	12.0%	10.4%	8.0%	**4.8%**	**1.8%**	**1.7%**	1.6%	1.9%	1.7%	1.9%
700	10.6%	9.3%	6.0%	**0.4%**	**0.3%**	**0.3%**	0.3%	0.4%	0.3%	0.3%

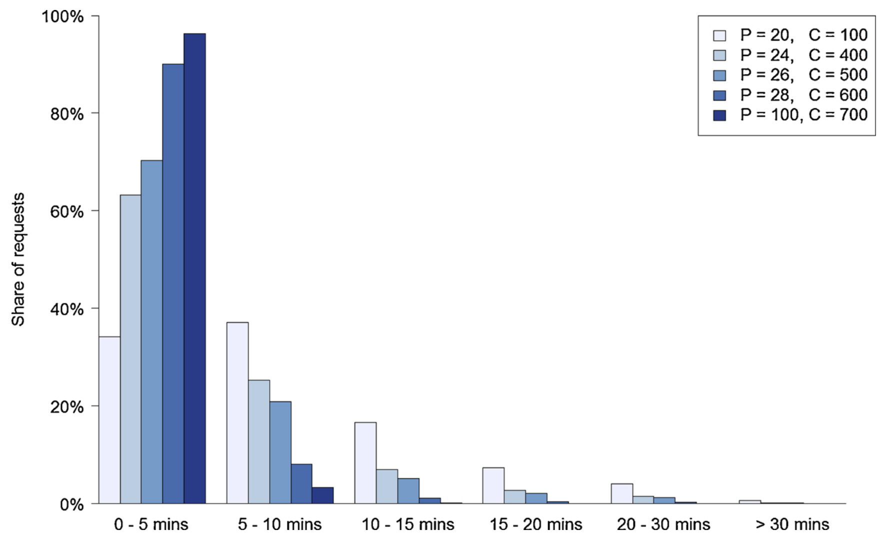

Fig. 4. Waiting time distribution.

of 30,000 km. This translates in 41 min of charging time or 2.8% of the day. Hence, this case exhibits a utilization rate of vehicles of more than 55%, illustrating the impact on resource efficiency enabled by shared, autonomous EVs.

5.3. Sensitivity Analysis

We used the simulation platform to analyze the impact of changes to several parameters on our results. The cases that were considered are summarized in Table 7 and, for each case, we investigated a corresponding set of $|V|$ and $|P|$-values as in the benchmark case from the preceding subsection.

As a first adjustment, we chose to investigate the influence of charge point positioning on our results. In the benchmark case, the existing network of charge points in Berlin was taken and $|P|$ of these charge points were randomly selected. A more strategic placement of charge points could lead to a lower number of charge points required to satisfy charging demand. For the sensitivity analysis, we position charge points strategically according to the energy demand incurred in a comb as derived from the training data set. Specifically, for each comb $c \subseteq C$, we calculate the aggregate energy consumption E_c of all trips $R_c \subseteq R$ ending in c as $E_c = \sum_{r \in R_c} e_r$ with e_r as the energy required to complete trip r.

Subsequently, the total energy consumption over the entire business area, E, is $E = \Sigma_{c \in C} E_c$. When placing $|P|$ charge points, each charge point is assumed to be able to supply an amount of energy equal to $\frac{E}{|P|}$ for all demand to be served. We then place all $|P|$ charge points sequentially into the comb with the highest unserved demand. For example, if $E = 10$, we place ten charge points, and $E_c = 2$ is the highest demand of any comb, the charge point is placed in comb c and E_c is updated to 1. If there is no comb $c' \neq c$ with $E_{c'} > 1$, the second charge point would also be placed in comb c; otherwise in the other comb c' with the highest unsatisfied demand. The exact position within the comb is chosen randomly. Fig. 5a and b shows the different charge point placements for $|P| = 100$. We see that strategically placed charge points are more uniformly scattered across the business area and less dense in hot spots. On the other hand, they appear to serve the city's two airports better. These two distributions clearly differ and they represent two fundamentally different approaches of positioning. Nevertheless, the simulation results are highly similar to the benchmark case, as evident in Table 8. While similar patterns emerge, we can see that, for a given fleet size, strategic placement of charge points can reduce the share of missed requests by up to 1.5%. The exception is the scenario $|P| = 26 \wedge |V| = 600$, as strategic placement improves the service level by 4.7 percentage points, making 26 strategically placed charge points almost equal to 28 randomly placed charge points.

Given the current rise of vehicle electrification, we also test the impact of more powerful charge points on the simulation outcome in the *Accelerated charging* case. Moreover, assuming that driverless cars make shared vehicles more appealing to customers, we investigate cases of increased demand. As shown in Table 7, we expand the volume of demand to 2.5, 5, 7.5, and 10 times its original size through resampling,

Table 6
Share of idle time for shared, autonomous electric vehicles.

	Number of charge points $\lvert P \rvert$									
Number of vehicles $\lvert V \rvert$	20	22	24	26	28	30	40	50	75	100
100	5.9%	5.9%	6.0%	6.0%	5.9%	5.9%	6.0%	5.9%	6.0%	5.9%
200	8.1%	8.2%	8.4%	8.4%	8.4%	8.4%	8.4%	8.4%	8.4%	8.5%
300	20.8%	14.0%	12.4%	12.3%	12.5%	12.7%	12.9%	12.9%	13.0%	13.0%
400	39.3%	33.3%	27.4%	21.0%	19.1%	19.0%	19.7%	19.6%	19.8%	19.8%
500	49.5%	44.9%	40.0%	**34.7%**	**29.3%**	**29.0%**	29.3%	29.4%	29.6%	29.6%
600	56.0%	51.9%	47.5%	**41.7%**	**39.8%**	**39.7%**	39.9%	39.9%	40.1%	40.1%
700	60.9%	57.6%	53.1%	**48.9%**	**49.0%**	**49.0%**	49.1%	49.2%	49.2%	49.3%

Table 7
Overview of simulation cases.

Case	Positioning of charge points	Charging power	Scaling factor	Fuel consumption
Benchmark case	Random	11 kW	1.0	15 kWh/100 km
Strategic positioning	Strategic	11 kW	1.0	15 kWh/100 km
Accelerated charging	Random	24 kW	1.0	15 kWh/100 km
Demand expansion	Random	11 kW	2.5; 5.0; 7.5; 10.0	15 kWh/100 km
Elevated consumption	Random	11 kW	1.0	20 kWh/100 km

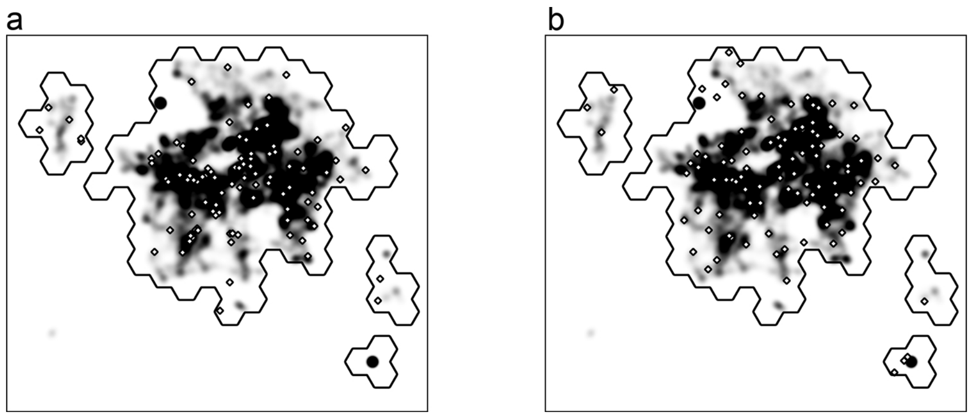

Fig. 5. (a) Random draw of 100 charge points. (b) Strategic placement of 100 charge points.

to preserve the daily demand patterns. Finally, we test the system's sensitivity to an increase in fuel consumption per 100 km by 5 kWh to 20 kWh in the *Elevated consumption* case. The simulation results for these cases can be found in the Appendix. For the cases with increased demand (Tables 10–13), we have scaled $|P|$ and $|V|$ by the corresponding factor. For the cases with accelerated charging (Table 9) and elevated consumption (Table 14), we have similarly adjusted the values of $|P|$ in proportion to the increased power output or power consumption, respectively. Once these corrections are taken into account, patterns similar to the benchmark case emerge. This emphasizes on the one hand that an SAEV system requires an appropriate fleet size and a minimal charging infrastructure to function. On the other hand, it suggests that the required number of vehicles is substantially driven by peak demand, a notion that we will elaborate on in the next section.

6. Discussion and conclusion

In this section, we will first reflect on the simulation results and discuss managerial and policy implications. We will then conclude by outlining potential paths for further research that build on the simulation platform developed for this work as well as on the results we presented.

6.1. Managerial and policy implication

Urban transportation is one of the *wicked problems* society is currently facing and our findings support policy makers and managers alike in giving quantitative arguments for their decisions regarding investment in technology, fleet size, and charging infrastructure. Our results show that a system of shared, autonomous EVs can enable sustainable, zero-emission urban mobility with a substantially reduced fleet size – resulting in a higher resource utilization – while satisfying current service level requirements. What is particularly noteworthy is the low number of charge points required to make such a system work. Recalling that a single charge point can supply 264 kWh of energy per day, which translates into 1760 km driven, the 28 charge points identified as the infrastructure threshold would run at a utilization rate of 61% to satisfy daily travel demand of 30,000 km. This illustrates not

Table 8
Strategic positioning results in a fraction of missed requests.

Number of vehicles $\lvert V\rvert$	Number of charge points $\lvert P\rvert$: 20	22	24	26	28	30	40	50	75	100
100	79.4%	79.3%	79.3%	79.3%	79.3%	79.3%	79.4%	79.2%	79.3%	79.3%
200	57.0%	57.0%	57.2%	56.8%	56.8%	57.0%	57.0%	56.8%	56.9%	56.9%
300	42.3%	36.3%	35.0%	34.9%	35.3%	35.3%	35.3%	35.0%	35.1%	35.2%
400	41.0%	33.9%	26.7%	18.1%	16.3%	16.2%	16.3%	16.3%	16.5%	16.3%
500	38.8%	31.2%	24.3%	13.9%	5.3%	4.6%	4.8%	4.9%	4.9%	5.0%
600	34.8%	27.2%	18.8%	1.9%	0.5%	0.5%	0.6%	0.6%	0.6%	0.6%
700	31.2%	23.6%	13.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

just a very efficient use of vehicle capacity, but also of infrastructure capital enabled by SAEV systems. While our showcase analyzed data from the city of Berlin, Germany, the approach is easily transferable and extendable to other cities through the openly accessible simulation platform.

For a **carsharing operator** in a city like Berlin, the *autonomy* aspect of SAEVs enables a fleet size reduction of approximately 400 vehicles without compromising on service levels or reducing revenues. Assuming leasing rates of approximately 200 USD per month, this translates into an effective cost reduction of 960,000 USD per year just from the smaller fleet size. While this is a substantial amount and does not include carsharing staff salaries, the cost drivers of autonomous vehicles, such as a coordinating management staff as well as the actual technology, are harder to anticipate. Nevertheless, our simulation platform provides operators with a valuable tool to support decision-making in the coming decades, as electrification and driverless technology become increasingly prevalent and advanced. Particularly nuanced decisions between fleet size increases and investments into additional chargers, as illustrated for the $|P| = 26 \wedge |V| = 500$ case, become more transparent.

From a **policy perspective**, our work provides on the one hand a clearer picture of the effects of SAEVs on resource efficiency and insights on zero-emission urban mobility that are based on real-world data. This is particularly relevant in the ongoing discussion about investments into charging infrastructure, both from the public sector as well as businesses. Our carsharing data set contains approximately 5700 trips per day, which can be served by 28 charge points. Clearly, this is only a small fraction of all trips in Berlin, a city of more than three million inhabitants. However, our sensitivity analyses suggest that this relationship scales linearly, with a 10-fold increase in trips being served by 280 charge points. The city of Berlin estimates that 88.4% of the resident population (3.4 million) is mobile, conducting 3.4 journeys per day, of which 32% are done by “private motorized transport” and 1.3 passengers per car [63]. If all of these trips were to be performed by SAEVs, this would translate into a 440-fold increase compared to our benchmark case. Assuming a linear scaling factor, the entire motorized travel demand in Berlin could be satisfied by 264,000 SAEVs powered by 12,320 charge points. Although this is a rough approximation, these numbers contain a powerful message. On the one hand, there were an estimated 1.15 million cars on the road in Berlin in 2012, implying a possible reduction of 77%. On the other hand, it also illustrates that investments into charge points – often considered a chicken-egg problem with low EV adoption rates – present a clear path toward zero-emission urban mobility. With Berlin moving toward 1000 charge points within the city just to “ignite” EV adoption, our results show that a further increase by one magnitude is sufficient to transfer the entire urban motorized mobility demand to SAEVs, particularly if fast-charging options are used.

6.2. Implications for research

As we have argued in Section 2, data-driven decision support systems that combine analytics and simulation techniques can become a powerful tool, as we seek to overcome the wicked problems our societies are facing – not just in the context of climate change and sustainability, but also with respect to other challenges, such as poverty and urban crime. In the case of urban mobility, we show that such a data-driven approach enables us to investigate the interplay between three major, transformative developments – the sharing economy, autonomous vehicles, and electrification. Thereby, we contribute to the growing body of literature researching these aspects and are among the first to consider an integrated perspective.

Both, the simulation platform we developed and the results we presented, offer several promising paths for further research. One of those paths is the **extension of the data foundation**. This includes on the one hand the analysis of carsharing data sets from other cities. As we have previously mentioned, the lower bound of the fleet size is determined by peak demand and it would be interesting to see how temporal and spatial demand patterns from other cities affect the implications related to fleet size and charging infrastructure. On the other hand, carsharing data is just one data type that reflects urban mobility patterns and a combination with individual trajectory data from public transport or ride-hailing services could provide a more precise reflection of those dynamics. However, the overall impact of autonomous vehicles on public mass transit is difficult to predict. While it is possible that mass transit services such as metros and buses remain critical components of urban transportation systems [64], mobility-on-demand services enabled by autonomous driving may lead to a shift toward smaller, more flexible vehicles instead of larger buses and trains.

As the focus of our research was on the system perspective, we employed relatively straightforward decision algorithms in the request and task modules. Our results illustrate that even these simple, assumption-free algorithms can leverage a large share of the theoretical limit with respect to fleet size reduction and minimizing the required number of charge points. Nevertheless, these modules can be further refined by **leveraging** more **advanced methods**. First, this relates to the prediction of idle times. In our work, the predictive analytics module focuses on temporal and spatial autocorrelation by taking historical averages. This approach can be extended by, for instance, including event and weather data, as well as applying more advanced machine learning methods. In addition to the prediction method, sophisticated optimization algorithms that take into account expected incoming requests may generate better relocation decisions. Second, queuing of customer requests could provide the means to further increase utilization and optimize vehicle assignment and routing. As shown by Hermann et al. [62], customers are in principle willing to disclose their final destination at the time of the trip request. Another path would be the optimization of vehicle waiting times at charge points as proposed by García-Magariño et al. [65] or the recharging policies, as introduced by Sweda et al. [66]. For instance, in times of peak demand, interrupting charging processes might free critical resources on short notice, enabling further utilization increases for both vehicles and charging infrastructure. The impact for the benchmark case is likely limited, but for scenarios with substantially larger demand levels, this can further reduce the number of required charge points. In addition, an extension of the *accelerated charging case* in line with modern superchargers of 50 kW or even 175 kW will likely strengthen our findings and further decrease the number of required charging points. However, with supercharging, the nonlinearity of charging functions becomes more relevant and needs to be considered when conducting the respective simulations.

In our study, we have also purposely disregarded potential **behavioral changes** of customers to enable us to work with real-world data and to keep the complexity of the simulation tractable. Nevertheless, behavioral changes – such as ridepooling or shifting traveling times – are the clearest way to reducing peak demand and, thereby, fleet size. As Agatz et al. [67] point out, the feasibility of ridepooling algorithms depends fundamentally on the willingness of customers to share the vehicle with a potential stranger. Our platform may be used to evaluate to which degree ridepooling improves system performance if it is sufficiently incentivized, such as through fee reductions and similar pricing strategies.

Lastly, our work provides a starting point to investigate how urban personal transportation systems **intersect with other systems**. The “elephant in the room” in this context is the energy system. Kahlen et al. [46] point out how shared EVs can be used as a virtual power plant to balance volatile renewable energy generation in power grids. If the entire motorized vehicle transport in Berlin is moved to SAEVs and the energy required to satisfy 30,000 km per day is multiplied by 440, the power system needs to be able to supply gigawatt-hours of additional energy per day. Research on the integration of SAEV usage patterns into the energy system is clearly needed to make this transition possible.

However, a city is first and foremost a social system and mobility is a key enabler of participation in social life. The approach presented in our study can serve as a foundation to investigate how the transition to SAEVs affects access to mobility across different social groups. While SAEVs represent, in principle, simply a new mode of transportation, it is critical to see whether access to this mode is affordable and people in different parts of the city and different age groups benefit equally – particularly in case SAEVs compete with more established forms of public transportation.

On a broader scale, our research emphasizes that fundamental transformations like the energy transition, the sharing economy, or autonomous driving can rarely be conclusively perceived in a vacuum. We illustrate that in the case of urban mobility these three major developments jointly transform this sector in the years to come. Nevertheless, this integrated perspective is increasingly taken across the board, with, for instance, research and the public discussion on accommodation sharing and Airbnb integrating perspectives on gentrification, urbanization, and an aging society.

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Appendix A. Sensitivity analyses

The following tables show the simulation results for the remaining cases from the sensitivity analysis table. Values marked with an asterisk (*) are accompanied by the corresponding values from the benchmark case in parentheses.

Table 9
Accelerated charging case results in a fraction of missed requests.

Number of vehicles $\lvert V\rvert$	Number of charge points $\lvert P\rvert$*: 8 (18)	10 (22)	12 (26)	14 (31)	16 (35)	18 (39)	22 (48)	26 (57)	30 (65)	40 (87)
100	78.4%	78.6%	78.5%	78.4%	78.5%	78.3%	78.3%	78.4%	78.3%	78.2%
200	57.8%	55.0%	55.2%	55.2%	55.2%	55.2%	55.0%	55.0%	55.0%	54.9%
300	56.8%	43.6%	33.0%	32.7%	32.8%	32.7%	32.6%	32.6%	32.6%	32.5%
400	55.1%	42.1%	28.8%	15.0%	14.1%	14.2%	14.2%	14.3%	14.3%	14.1%
500	53.1%	39.8%	25.9%	5.2%	3.7%	3.8%	3.8%	3.9%	3.9%	3.8%
600	49.5%	35.8%	21.2%	0.4%	0.3%	0.4%	0.4%	0.4%	0.4%	0.4%
700	46.2%	32.3%	16.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table 10
Expansion case (2.5-fold) results in a fraction of missed requests.

Number of vehicles $\lvert V\rvert$*	Number of charge points $\lvert P\rvert$*: 50 (20)	55 (22)	60 (24)	65 (26)	70 (28)	75 (30)	100 (40)	125 (50)	187 (75)	250 (100)
250 (100)	77.1%	77.1%	77.2%	77.0%	77.1%	77.2%	77.1%	77.0%	77.1%	77.0%
500 (200)	56.0%	55.0%	54.5%	54.1%	54.2%	54.2%	54.0%	53.7%	54.0%	54.1%
750 (300)	52.7%	46.2%	38.4%	33.0%	32.2%	32.0%	31.5%	31.3%	31.7%	31.6%
1000 (400)	50.6%	43.6%	35.8%	25.0%	14.1%	12.8%	12.4%	12.3%	12.5%	12.5%
1250 (500)	46.6%	39.5%	30.1%	16.6%	3.0%	2.6%	2.7%	2.6%	2.7%	2.7%
1500 (600)	41.8%	33.8%	23.5%	0.3%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
1750 (700)	37.7%	28.3%	12.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table 11
Expansion case (5-fold) results in a fraction of missed requests.

Number of vehicles $\lvert V\rvert$*	Number of charge points $\lvert P\rvert$* 100 (20)	110 (22)	120 (24)	130 (26)	140 (28)	150 (30)	200 (40)	250 (50)	375 (75)	500 (100)
500 (100)	77.2%	77.2%	77.1%	77.1%	77.3%	77.0%	77.2%	77.1%	77.0%	77.0%
1000 (200)	56.9%	55.3%	54.7%	54.5%	54.4%	54.2%	53.9%	53.9%	53.7%	53.9%
1500 (300)	55.0%	49.4%	43.0%	36.3%	33.5%	32.8%	31.4%	31.0%	30.5%	30.8%
2000 (400)	53.2%	47.4%	40.8%	32.9%	20.1%	13.8%	11.3%	11.0%	10.7%	11.0%
2500 (500)	48.4%	41.8%	33.9%	21.8%	2.5%	2.0%	1.9%	1.9%	1.8%	1.9%
3000 (600)	42.7%	35.5%	23.9%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3500 (700)	38.4%	27.5%	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table 12
Expansion case (7.5-fold) results in a fraction of missed requests.

Number of vehicles $\lvert V\rvert$*	Number of charge points $\lvert P\rvert$* 150 (20)	165 (22)	180 (24)	195 (26)	210 (28)	225 (30)	300 (40)	375 (50)	561 (75)	750 (100)
750 (100)	77.1%	77%	77.1%	77.0%	77.1%	77.1%	77.1%	77.0%	77.1%	77.1%
1500 (200)	56.7%	55.3%	54.8%	54.3%	54.3%	54.2%	53.9%	53.7%	53.8%	53.8%
2250 (300)	55.3%	49.7%	43.7%	36.5%	34.0%	32.7%	31.4%	31.0%	30.7%	30.9%
3000 (400)	53.5%	47.8%	41.7%	33.6%	21.4%	14.6%	11.1%	10.7%	10.7%	10.7%
3750 (500)	48.4%	41.9%	34.3%	20.3%	2.3%	1.9%	1.7%	1.7%	1.7%	1.7%
4500 (600)	42.2%	35.0%	21.8%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5250 (700)	37.5%	25.4%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table 13
Expansion case (10-fold) results in a fraction of missed requests.

Number of vehicles $\lvert V\rvert$*	Number of charge points $\lvert P\rvert$* 200 (20)	220 (22)	240 (24)	260 (26)	280 (28)	300 (30)	400 (40)	500 (50)	750 (75)	1000 (100)
1000 (100)	77.2%	77.3%	77.3%	77.1%	77.3%	77.1%	77.2%	77.3%	77.2%	77.2%
2000 (200)	56.6%	55.2%	54.7%	54.3%	54.5%	54.2%	54.1%	54.0%	54.0%	53.9%
3000 (300)	54.9%	49.3%	43.1%	36.3%	33.8%	32.9%	31.6%	31.1%	30.9%	30.8%
4000 (400)	52.9%	47.5%	41.3%	33.4%	20.7%	15.0%	11.3%	10.8%	10.7%	10.7%
5000 (500)	47.9%	41.7%	34.3%	20.8%	2.2%	1.8%	1.6%	1.6%	1.6%	1.6%
6000 (600)	40.8%	33.1%	14.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7000 (700)	36.1%	23.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table 14
Elevated consumption case results in a fraction of missed requests.

		Number of charge points $\|P\|$*			
		35 (26)	37 (28)	40 (30)	53 (40)
Number of vehicles $\|V\|$	500	18.7%	9.8%	5.9%	5.7%
	600	14.3%	1.1%	0.7%	0.8%
	700	0.1%	0.0%	0.0%	0.0%

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