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Impacts of charging behavior on BEV charging infrastructure needs and energy use

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ABSTRACT

Battery electric vehicles (BEVs) are vital in the sustainable future of transport systems. Increased BEV adoption makes the realistic assessment of charging infrastructure demand critical. The current literature on charging infrastructure often uses outdated charging behavior assumptions such as universal access to home chargers and the "Liquid-fuel" mental model. We simulate charging infrastructure needs using a large-scale agent-based simulation of Sweden with detailed individual characteristics, including dwelling types and activity patterns. The two state-of-art archetypes of charging behaviors, "Plan-ahead" and "Event-triggered", mirror the current infrastructure built-up, suggesting 2.3–4.5 times more public chargers per BEV than the "Liquid-fuel" mental model. We also estimate roughly 30–150 BEVs served by a slow charger may be needed for non-home residential overnight charging.

1. Introduction

Electric vehicles (EVs) will play a vital role in the sustainable transformation of future transport systems. Global EV sales reached 6.75 million in 2021, doubling the sales number of 2020. The share of EVs in newly sold light-duty vehicles in 2021 reached 8.3%, most of which were battery electric vehicles (BEVs) (71%) (EV-volumes.com, 2022). European Union has passed an Executive Order that bans the sale of fossil-fuel cars by 2035 (electrive.com, 2022). Despite the need to increase the use of (electrified) public transport, biking and walking, driving private vehicles are still likely to be an important part of future travel. A future scenario of 100% BEV adoption will require careful consideration and infrastructure planning to accelerate the adoption of BEVs.

The infrastructure deployment should consider realistic charging behaviors (Chakraborty et al., 2019), which enables travelers to maximize their desired daily activities (Metais et al., 2022). When designing the location and sizing of charging infrastructure, oversimplified assumptions are typically made in the literature about charging behaviors and access to home chargers. With 100% BEV adoption, people living in all types of dwellings will demand charging. How much public charging will be needed remains a key policy question.

This study brings insights into charging infrastructure planning using state-of-the-art understanding of BEV charging & discharging dynamics, and the corresponding quantification of charging demand for BEV owners in different dwellings. The study's unique contribution is to deploy an advanced large-scale synthetic population in which we preserve realistic socioeconomic attributes and heterogeneous activity plans and implement a unique taxonomy of charging behaviors. Our results demonstrate that the spatiotemporal use patterns and the number of charging points at home, work, and other places for private BEV owners depend on the consideration of different charging strategies.

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1.1. Related work

Charging infrastructure is vital to support the diffusion of BEVs. However, deploying charging infrastructure is expensive and faces the chicken-and-egg dilemma between infrastructure operators (investment costs and profitability) and BEV consumers (charging demand) (Metais et al., 2022). Optimal locations and sizing of charging points are crucial to furthering BEV adoption and guaranteeing a good driving experience for BEV users without compromising their planned activities. The taxonomy of BEV charging options to fulfill BEV users' planned activities can be based on technology, e.g., non-contact charging, power rating, e.g., slow, intermediate, fast, and even ultra-fast charging (Suarez and Martinez, 2019), occasion, e.g., destination charging (Schmidt et al., 2020), etc.

Charging behavior is essentially a spatiotemporal concept, i.e., when and where BEV users access a specific charging point and for how long. Highlighting the behavioral aspect, we categorize the main charging options of BEV users into three groups: (1) overnight charging (slow e.g., 3–11 kW) at a home garage or non-home residential parking spot, (2) daytime charging (slow to intermediate e.g., 7–22 kW) at workplaces, and other places such as shopping malls etc., and (3) fast charging at public places (e.g., 50–150 kW), mostly along travel corridors to facilitate long-distance travel. Access to a home charger or a non-home residential parking spot leads to less dependence on public charging infrastructure. Recent studies suggest that 50%–80% of all charging events occur at home (Option 1) (Hardman et al., 2018). For daytime charging (Option 2), public charging infrastructure complements home charging only in densely populated areas (Funke et al., 2019), and workplace charging accounts for 15%–25% of BEV commuters' charging events (Hardman et al., 2018). Most of the evidence today is based on early adopters who are more likely to own detached houses with garages than the average population (Chakraborty et al., 2019). However, in places like the Netherlands with low availability of private parking space (Hardman et al., 2018), non-home residential parking spots are needed for charging at night. In a future of 100% BEV adoption, how much non-home charging is required for all dwellers remains an important policy question.

There are three broad categories of methods to determine the optimal locations and sizing of charging points: node-based, path-based, and tour-based (Deb et al., 2018). Node-based and path-based have mainly been used for planning fuel stations, but they suffer from the lack of behavior dynamics and unrealistic charging speed of BEVs equivalent to refueling an internal combustion engine car (Metais et al., 2022). Tour-based (activity-based) methods more realistically reflect driving behaviors and charging needs (Metais et al., 2022) by using data at the level of individual car trajectories. These trajectories come from detailed real-world driving records (Gnann et al., 2018) or simulated data from agent-based models (ABMs) (Zhuge and Shao, 2018; Márquez-Fernández et al., 2021).

Most studies to date do not account for realistic charging behaviors (Patil et al., 2022) and varying access to a home charger. For example, some studies locate the candidate charging stations at today's fuel stations (Zafar et al., 2021). Other studies assume that BEV users will only charge when the state of charge (SOC) drops below a certain threshold (Wang et al., 2019; Kong et al., 2019). SOC ranges between 0 and 1, indicating how full the battery is with energy (1 = fully charged). These assumptions are based on our understanding of how we refuel ICEVs despite the distinct characteristics of BEVs. For instance, BEVs need a significantly longer time than ICEVs to charge. Therefore, charging behaviors would differ in how drivers plan their charging events to anticipate planned travels (Miralinaghi et al., 2020). The lack of complexity of charging behaviors in the literature is partly due to the lack of data to make appropriate assumptions, and studies generally extrapolate from early adopters who mostly have access to home chargers (Greaves et al., 2014). Future BEV users will develop different strategies for charging, depending on their activity plans, mental models, pricing models, and willingness to pay. It remains unclear how these charging strategies affect charging demand and infrastructure. Last but not least, studies that assume all private BEV owners have access to home chargers (Pan et al., 2020) find that their need for daytime charging at work and other places is minimal (Greaves et al., 2014).

Charging infrastructure planning literature is often abstracted into an optimization problem of charge point placement and sizing. Most studies aim to find the required number and location of charge points necessary to fulfill the travel demand of today's car users.[1] The optimization goal varies, including maximized distance traveled (Shahraki et al., 2015), minimized CO2 emissions (Liu et al., 2019), and other aspects such as infrastructure costs. The optimal charging infrastructure calculated from solving spatial optimization problems is often found to be minimal, far below what is being deployed in reality. The mismatch is caused by comfort, bounded rationality, and range anxiety toward, e.g., infrequent though highly valued long-distance and weekend trips, etc. (Funke et al., 2019). This mismatch partly contributes to the chicken-and-egg dilemma. A question is worth asking to shed light on solving the dilemma: **what would be the charging demand if we provide BEV users with charge points when they *want* to, instead of *need* to, charge their cars?** The broader diffusion of BEVs calls for the sensible integration of this BEV users' perspective in quantifying charging infrastructure demand.

ABMs can bridge the gaps in the literature by simulating realistic charging strategies, heterogeneous home charger access of a large population, and integrating charging decisions from the BEV user's perspective. ABMs are suitable for this study because they capture fundamental mechanisms of individual travel behaviors, the interactions between them and the environment, and the emergence of aggregate patterns. For instance, transport energy demand is simulated in future scenarios of a varying adoption rate of EVs (Novosel et al., 2015). For these types of problems, ABMs are superior because of their complete population coverage with socioeconomic attributes and behavior characteristics such as activities that can be modified for future scenarios (Metais et al., 2022). These characteristics empower simulating future scenarios and informing policymaking for charging infrastructure planning.

[1] We should also recognize that the electrification of private cars alone is insufficient to achieve climate targets in line with the Paris Agreement (Brand et al., 2020). It is necessary to promote modal shift from private cars to electrified and decarbonized public transport, biking, and walking.

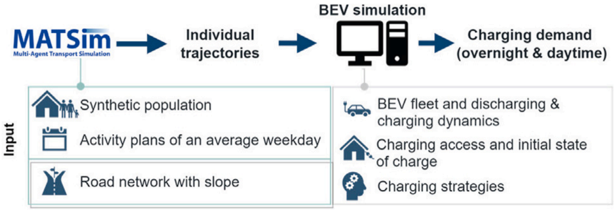

Fig. 1. Simulation flowchart for charging demand computation.

1.2. Outline of this study

This study aims to bridge the above-mentioned research gaps by applying agent-based modeling with a synthetic population of Västra Götaland, Sweden. We simulate BEV driving & charging given their planned activities for typical weekdays. We calculate the spatiotemporal patterns of charging demand considering different BEV charging strategies. We compare our results with today's charging infrastructure, highlighting the remaining infrastructure needs to support 100% BEV penetration to better inform future planning.

The remainder of this paper is organized as follows. In Methods, we describe the analytic framework including the datasets, simulation modules, and the methods for calculating charging demand. In Results, we present the outcomes of the simulation in three parts: charging demand of individuals; charging infrastructure demand; and a spatial comparison with today's charge points. We discuss the results in Discussion where we also summarize the major contributions and limitations of this paper. To complement the main body of this paper, Appendix A describes the mobility patterns of the applied car agents, while Appendix B presents the sensitivity test results. The codes are available at https://github.com/TheYuanLiao/synthetic-sweden. The main data input and output are publicly available (Liao et al., 2023).

2. Methods

The simulation framework is shown in Fig. 1. We use the synthetic population and their activity plans for an average weekday from the Synthetic Sweden Mobility Model (SySMo) (Tozluoğlu et al., 2022). SySMo is an agent-based decision support framework for modeling and analyzing transport scenarios. SySMo connects agents' socioeconomic characteristics with heterogeneous daily activity plans while preserving privacy. In this study, we focus on the 1.7 million residents in the Västra Götaland (VG) region where the second largest city of Sweden, Gothenburg, is located.

We use MATSim to simulate realistic daily activity plans of the agents. MATSim is an agent-based framework that provides a microscopic description of the travel demand (W. Axhausen et al., 2016). MATSim simulates agents' movement trajectories given their activity plans by optimizing agents' utility scores, which considers activity participation as positive while being late or stuck in traffic negative. We feed the agents' daily activity plans and the road network into MATSim for replanning until they converge on a set of optimal activity plans for all agents. Next, we extract the mobility trajectories of individual agents from the MATSim simulation.

The BEV simulation is implemented on the individual agents' travel trajectories considering overnight charger access, today's car fleet composition in Sweden, road network, and BEV charging & discharging dynamics. The parking times are the charging opportunities, and we do not consider rerouting to search for charging points. If an agent cannot visit all the planned places, despite charging the BEV the whole time it is parked, we define this situation as a failure. A failure can be caused by long travel distances and short parking time windows.

In the BEV simulation, we simulate three charging strategies: (1) Liquid-fuel strategy, (2) Plan-ahead strategy, and (3) Event-triggered strategy. These charging strategies have varying SOC thresholds and conditions to start charging when the agents' BEVs are parked for more than 10 min. On the supply side, we provide three types of charging points according to the length of their parking and the SOC of their BEVs: (1) fast charger (50 kW), (2) intermediate charger (22 kW), and (3) slow charger (11 kW). We conduct extensive sensitivity analysis (see Appendix B) and summarize the results on charging demand overnight, at work, and in public spaces.

2.1. Simulating mobility trajectories

The two key inputs for MATSim to simulate the synthetic population's mobility trajectories are the car drivers with their daily activity plans, and the road network (detailed below). The configuration follows the benchmark scenario of MATSim 13.0[2] with minor modifications. The replanning strategy is a combination of BestScore (60%), TimeAllocationMutator (30%), and ReRoute

[2] https://github.com/matsim-org/matsim-libs/releases/tag/13.0

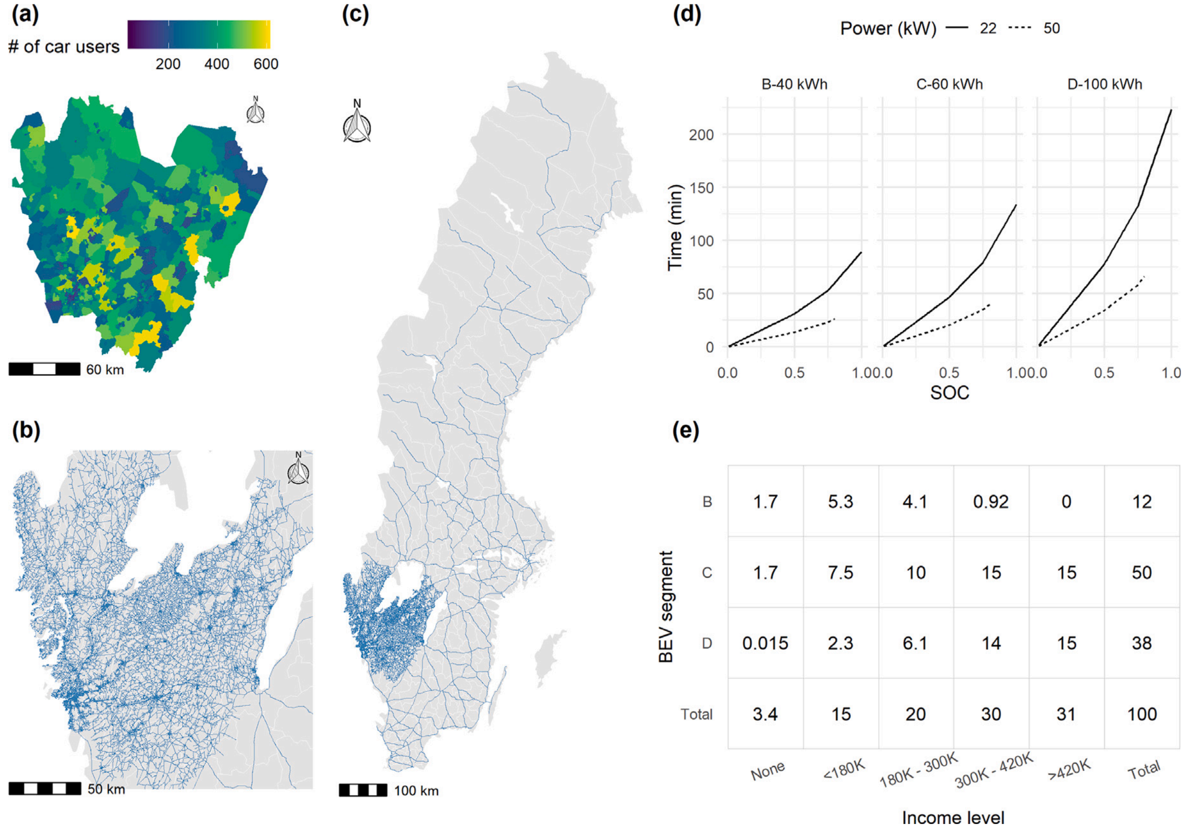

Fig. 2. Simulation inputs: agents, road network, and BEVs. (a) Car users' home distribution. (b) The road network in VG. (c) The entire road network. (d) Charging time as a function of SOC by battery size and power. For slow charging overnight (11 kW), we assume SOC will reach 1 before the start of the next day. (e) Assumed distribution (%) of BEV types by battery size and by income group. Yearly income is measured in thousand (K) Swedish krona (1K Swedish kronor is about 92 Euro).

(10%), where the percentage in the brackets indicates the share of agents who adopt these strategies.[3] After 200 iterations, we see utility scores stabilize for all agents. We take the output of the 200th iteration as the trajectories for the next module, BEV simulation. Detailed input descriptions of this module are the following.

2.1.1. Synthetic population and their activity plans

In the 1.7 million residents in VG, we use 284,000 agents who are car users. They account for 35% of all the car users and 18% of the total population (Fig. 2a). They are proportionately sampled by the demographic statistics areas (DeSO zones) (Statistikmyndigheten SCB, 2022). Each agent has a set of socioeconomic attributes such as age, gender, income level, employment status, dwelling type, etc., together with a daily activity plan covering four activities: home (H), work (W), school (S), and other (O). Most of these car users live in detached houses (62.4%) and the rest in apartments (37.6%). More car users live in suburban areas than in Gothenburg city center (Fig. 2a). Their mobility patterns in the simulation day are summarized in Appendix A.

2.1.2. Road network with slope

A road network with slope is prepared for a more accurate estimation of BEV energy consumption than assuming an average energy efficiency for BEV discharging. We download the road network from GEOFABRIK (Geofabrik GmbH and OpenStreetMap Contributors, 2022) and extract the following road segments using osmosis (osmosis, 2022): all the road segments within the VG area (Fig. 2b) and all the main road segments for the rest of Sweden (Fig. 2c). The main road segments cover motorway, trunk road, and primary, secondary, and tertiary roads.

After getting the road network, we compute the road slope for the BEV simulation. For those road links longer than 500 m, we break them down into multiple connected links to ensure all processed road links are no longer than 500 m. We get the elevation of each road link's start and end points using the European Digital Elevation Model (DEM) data (Copernicus Programme, 2022). From the elevation information, we calculate the average slope of each road link.

[3] BestScore keeps the plan scoring the highest from the previous iteration. TimeAllocationMutator shifts activity end times randomly within a range. ReRoute makes agents reroute their current route. More details can be found in W. Axhausen et al. (2016).

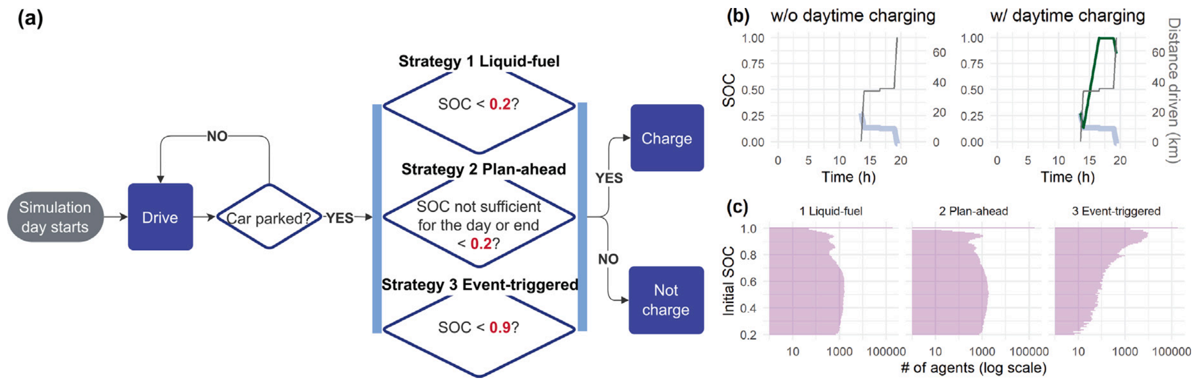

Fig. 3. Simulating three charging strategies and their SOCs. (a) Charging strategies. (b) An example of SOC time history of a selected agent. The light blue curves indicate no daytime charging. The green curve shows adopting the Plan-ahead strategy, which leads to charging during the first parking event. (c) Initial SOCs for the three charging strategies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.2. BEV simulation

The BEV simulation concerns charging infrastructure technology, battery energy density, and BEV energy consumption. We combine the current status and near-future projections in designing a future scenario of 100% BEV adoption. From this setup, one can also test different technology development scenarios.

The BEV simulation assumes the agents drive BEVs to finish the activities on the simulation day following the trajectories from the MATSim simulation. The inputs are BEV fleet and discharging & charging dynamics, charging strategies, and charging access and initial SOC. Detailed input descriptions of this module are the following.

2.2.1. BEV fleet and discharging & charging dynamics

Using the data from a previous study on future EV charging infrastructure scenarios in Sweden (Márquez-Fernández et al., 2021), we consider a BEV fleet composed of three sizes of BEVs, B- (12%), C- (50%), and D-segment (38%) reflecting today's composition, and they have battery sizes of 40, 60, and 100 kWh, respectively. Another study on charging strategies for urban private vehicles in Berlin shows a similar selection of battery sizes (Jahn et al., 2020). For discharging, each BEV segment has a lookup table of energy efficiency (kWh/km) as a function of speed (m/s) and road slope (%). For charging, the power delivered by the charge point is limited by SOC, i.e., the higher the SOC, the slower the charging (Fig. 2d). The detailed characteristics of these vehicle segments, their simulated energy efficiency maps, and SOC-dependent charging profile were generously provided by Márquez-Fernández et al. (2021).

BEVs are assigned to the agents depending on their income levels. The higher the income, the larger the assigned BEV battery sizes. The proportions of BEV assigning are randomized and heuristically determined, as illustrated in Fig. 2e.

2.2.2. Charging strategies

We abstract three charging strategies (Sprei and Kempton, 2022):

- Liquid-fuel strategy: Wait until the gauge shows low, then refill.
- Plan-ahead strategy: Plan ahead for when charging is needed. For example, when parking, think ahead to the next trip and check if BEV has enough charge for it. If not, plug in.
- Event-triggered charging: Plug in to charge whenever parking at a specific location, e.g., workplace, meal stops, sometimes without considering whether stop duration only allows a partial refill (opportunistic partial charging).

These three strategies are translated into rules for simulating the agents' charging decisions, as shown in Fig. 3a. Once an agent decides to charge, if parking time allows, the battery will be fully charged by an intermediate charger or 80% charged by a fast charger. As an example of BEV simulation outputs, Fig. 3b shows that if this agent does not use daytime charging, they will run out of battery before going to the last activity location (light blue curves). If adopting the Plan-ahead strategy, this agent will charge the battery during the first parking event (green curve) so that they are able to complete the activities of the simulation day.

2.2.3. Charging access and initial SOCs

Most public and workplace charging stations today can deliver 11 kW–22 kW (Mathieu et al., 2020). Newly installed home chargers for Tesla have a power of around 11 kW, as do most recent home chargers in Sweden and Germany, some even 22 kW. The increasing BEV adoption also comes with the expectation that the power output of workplaces and public chargers will increase in 2030 (Mathieu et al., 2020). Therefore, in this study, the charging options are (1) slow charger (11 kW) for overnight charging at a detached house or a non-home residential parking spot nearby an apartment, (2) intermediate charger (22 kW) for charging at

Table 1
Charging access.

Dwelling type	Overnight charging		Daytime charging
	Home charger	Non-home residential charger	
Detached house	Yes	No	Conditional[b]
Apartment	No	Conditional[a]	

[a]If an agent fails to finish driving or ends up with SOC below 0.2.

[b]Depending on charging strategy, parking duration, and SOC. If an agent decides to charge the car given its charging strategy, fast chargers (50 kW) for daytime charging are provided when the parking time is below 30 min and SOC below 0.8, otherwise intermediate chargers (22 kW) are provided.

workplaces and other places such as shopping malls, etc., where agents are engaged in other non-school or work activities, and (3) fast chargers (50 kW) for daytime charging depending on parking time, charging strategy, and SOC. Specifically, if an agent decides to charge the car given its charging strategy, fast chargers (50 kW) for daytime charging are provided when the parking time is below 30 min and SOC below 0.8, otherwise intermediate chargers (22 kW) are provided.

We initialize the BEV fleet SOCs according to whether the agents live in a detached house or not. For simplification, an agent living in a detached house always starts the simulation day with a fully-charged battery. This may lead to an overestimation of the overnight charging demand because people may only need to charge BEVs once every three days, according to a simple estimation (Wang et al., 2019). The SOCs of the rest of the agents are randomly drawn from a skewed normal distribution with skewness of −4 (Azzalini and Capitanio, 1999), ranging between 0.2 and 0.9. An arbitrary initial SOC distribution biases the simulation results (Hipolito et al., 2022). Therefore, we run five consecutive simulation days with the same planned activities, considering overnight charging and different daytime charging strategies. If an agent lives in an apartment and fails to finish driving or ends up with SOC below 0.2, the agent is assigned a non-home residential charger to charge the BEV overnight so that the next day will start with a fully charged battery.

Different charging strategies will lead to varying distributions of initial SOCs. For example, the Event-triggered strategy will keep SOC at a high level at the end of the simulation day and therefore a high SOC at the start of the following simulation day. After a continuous simulation spanning multiple activity days, the initial SOCs patterns stabilize and we use the fifth day's results for further analysis. In summary, we simulate charging access shown in Table 1. The three charging strategies have varying initial SOCs (Fig. 3c).

2.3. *Quantifying charging demand*

Based on the output of the BEV simulation module, we aggregate charging demand from two perspectives: individual charging patterns and spatiotemporal patterns of charging needs. We then compare the distribution of simulated charging points with today's charging infrastructure.

2.3.1. *Individual charging patterns*

We first summarize the charging demand of individual BEV users by two characteristics: whether they do daytime charging and finish all the planned activities without draining out the battery. Next, for those who use charging points at workplaces or other places, we summarize their charging behaviors in terms of charging duration, the share of charging duration of parking time, and the total energy from charging points to their BEVs.

2.3.2. *Spatiotemporal patterns of charging needs*

Charging points are provided when the agents *want* to charge their BEVs. Therefore, the required number of charging points in each DeSO zone is calculated as the maximum number of plugged-in BEVs in this area at each minute during the simulation day.

We quantify required charging points at workplaces, other places, and near apartments (non-home residential chargers) using five measures: (1) the total number of charging points, (2) the number of cars served by a charge point (the agent number divided by the number of wanted charging points), (3) the number of charging points in each DeSO zone, (4) the number of charging points per km^2, and (5) hourly power demand.

2.3.3. *Comparison with today's infrastructure*

We scale up our results from the simulation of 35% VG car users to the demand of all the VG car users. Here, we focus on the spatial disparity of daytime charging points, i.e., the value difference in the number of charging points per zone between the simulated and today's infrastructure (2022). A negative value difference indicates a region needs to build more charging points to support BEV users in VG. At the same time, a positive value suggests that today's infrastructure is sufficient for 100% BEV adoption for VG's private car owners.

Sweden currently has 14,339 public charging points (Power Circle AB, 2022). However, there are no official data on private charger deployment (Xylia and Joshi, 2022) and the statistics of charging points deviate between different data sources. Therefore, the comparison indicates the *magnitude* of the charging point deficit toward a 100% BEV adoption future and its spatial patterns. However, the absolute numbers of charging point deficits in analysis zones are less reliable due to the discrepancy between available sources. We got the data on today's infrastructure in Sweden from a free internet service that helps EV drivers find charging stations (CHARGEX AB, 2022).

Table 2
Share of agents who use daytime chargers and failure rate. HC = home charger at a detached house.

Charging strategy	Daytime charger usage (%)		Failure[a] rate (%)	
	w/o HC	w/ HC	w/o HC	w/ HC
1 - Liquid-fuel	3.59	0.35	0.96	1.17
2 - Plan-ahead	7.36	1.91	0.68	0.37
3 - Event-triggered	18.2	22.4	0.57	0.37

[a]An agent is not able to finish all the activities with the assigned BEV and initial SOC.

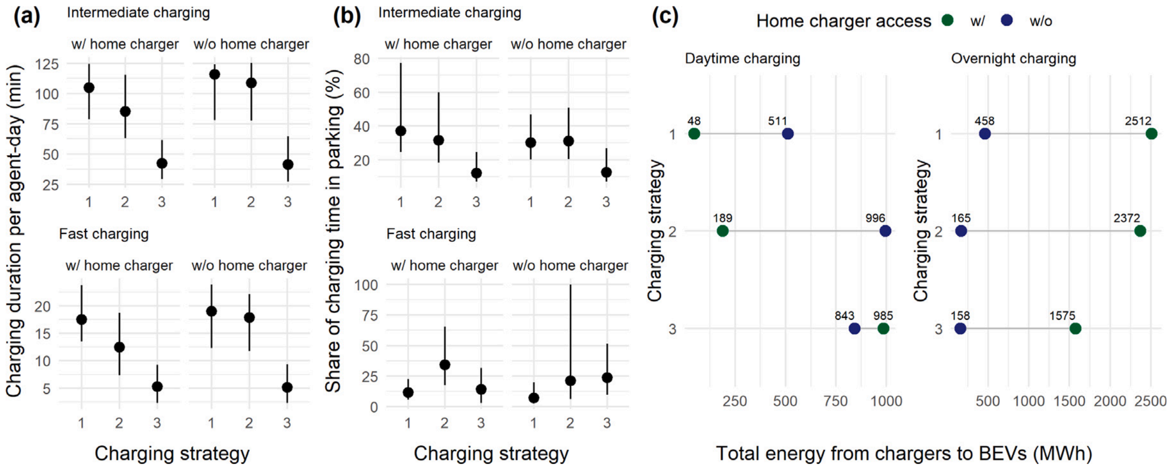

Fig. 4. Charging demand of individual agents. (a) Charging duration in minutes per agent per day. (b) Charging duration as the share of parking time per agent-day. Error bars indicate the range between the 25th-percentile and the 75th-percentile. (c) Energy flow from chargers to BEVs.

3. Results

3.1. Individual charging patterns

The share of agents who access daytime charging points is small, especially for those with access to a home charger (Table 2). Compared with the Liquid-fuel strategy, the Plan-ahead strategy significantly reduces the number of agents who fail to finish all their activities. The Event-triggered strategy further reduces the failure rate, but only slightly, compared to the Plan-ahead strategy; however, it results in considerably more charging demand for daytime charging.

Figs. 4a–b summarize the total charging duration for daytime charging. Charging times are 30–125 min for intermediate charging and 3–30 min for fast charging (Fig. 4a). For the Event-triggered strategy, the charging time is reduced due to more agents with higher SOC choosing to charge their cars. Living in an apartment without a home charger induces ~15 min longer charging time. Fig. 4b suggests that charging takes around 30% of the total parking time. Fast charging only happens when the parking time is below 30 min, but the share is rather small, especially for those with home chargers.

Figs. 4c illustrates the total energy consumption for daytime and overnight charging. Overnight charging consumes a larger amount of energy than daytime charging, especially for those with home chargers, because they always top up to 100% charged. Agents without home chargers get more energy during the day than those with home chargers, especially for Strategies 1 and 2. But the relationship is reversed for overnight charging because only a small number of apartment dwellers have access to a non-home residential charger. The Event-triggered strategy reduces the gap between the two types of dwellers and relies more on daytime charging than overnight charging.

3.2. Spatiotemporal patterns of charging needs

Table 3 summarizes the charging points required by the 284,000 car users according to the charger type, occasion, and charging strategy. The number of daytime charging points increases in the order of Strategies 1, 2, and 3, and the reverse for overnight charging. The number of charging points at workplaces is 54.6% of the number at other places for Strategy 1, 56.8% and 65.2% for Strategies 2 and 3, respectively. Regardless of the strategy, there is a smaller charging demand in terms of energy at workplaces than at other places. This is because Other activity happens more frequently than Work (Table A.1). When BEV users adopt a more conservative (and frequent) charging like Strategies 2 and 3, the demand gap between the two occasions decreases. Compared with intermediate charging points, the demand for fast charging points is minimal, especially at workplaces.

Table 3
Number of charging points for daytime charging and overnight charging (non-home residential). Inter. = intermediate.

Charging strategy	Daytime charging point					Overnight charging point (non-home residential)	
	Occasion	Inter.	Fast	# cars per inter.	# cars per fast	Slow	# cars per slow
	Other	3,471	509				
1 - Liquid-fuel	Work	1,895	8				
	Total	5,366	517	54	561	11,290	26
	Other	8,092	787				
2 - Plan-ahead	Work	4,596	30				
	Total	12,688	817	23	355	2,101	138
	Other	14,542	1,250				
3 - Event-triggered	Work	9,475	70				
	Total	24,017	1,320	12	220	1,962	148

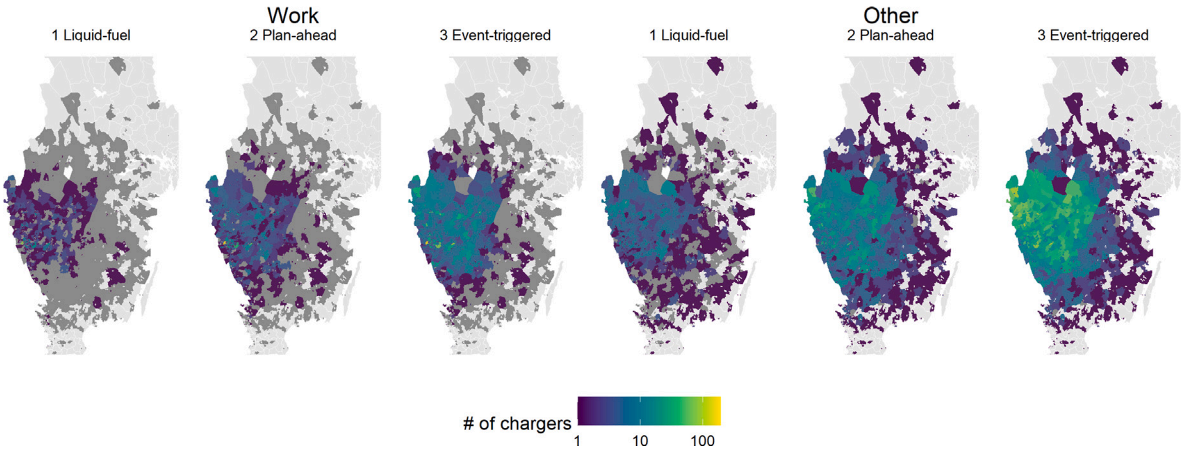

Fig. 5. Spatial distributions of charging points for daytime charging by charging strategy.

Fig. 5 shows the spatiotemporal distributions of daytime charging points. Workplace charging is concentrated in central Gothenburg, while charging points for Other activities are more spread out in southern Sweden.

From a density perspective (Fig. 6), all the charging strategies have many zones where only 1 or 2 charging points are needed. But for most zones, different charging strategies result in vastly different charging point densities seen from median and 50th-percentile and 95th-percentile values.

The temporal patterns of power demand shown in Fig. 7 suggest that the Plan-ahead strategy has a more concentrated power demand during the daytime than the Liquid-fuel strategy. The Event-triggered strategy creates ~60% more daytime power demand in MW than the Plan-ahead strategy. The three charging strategies all peak at around 8 AM but the demand for the Event-triggered strategy remains high throughout the day.

3.3. Comparison with today's infrastructure

Fig. 8 shows the difference between the simulated results and today's infrastructure. The number of zones with sufficient charging points for VG BEV users decreases in the order of Strategies 1, 2, and 3 (smaller number of blue lines). From left to right, the gap between this study's simulated required charging points and today's infrastructure becomes greater. If all agents adopt the Liquid-fuel strategy, today's charging points at central Gothenburg are sufficient for 100% BEV adoption in VG. Some surrounding cities along the coast already have enough to support all VG car users (100% BEV), despite today, only 118,400 passenger cars in Sweden are BEVs (2.2%) (Xylia and Joshi, 2022). When agents are more dependent on charging at public places and work (Strategies 2–3), more DeSO zones need to install additional charging points, not only in densely populated areas such as Gothenburg but also in its surrounding urban areas.

4. Discussion

This study evaluates the charging infrastructure needs from the user's perspective in a future scenario of 100% BEV adoption. We take a synthetic population of Sweden for an agent-based simulation exploring the charging demand overnight and during daytime, corresponding to different charging strategies and dwelling types. The results describe individual charging patterns at a high spatial

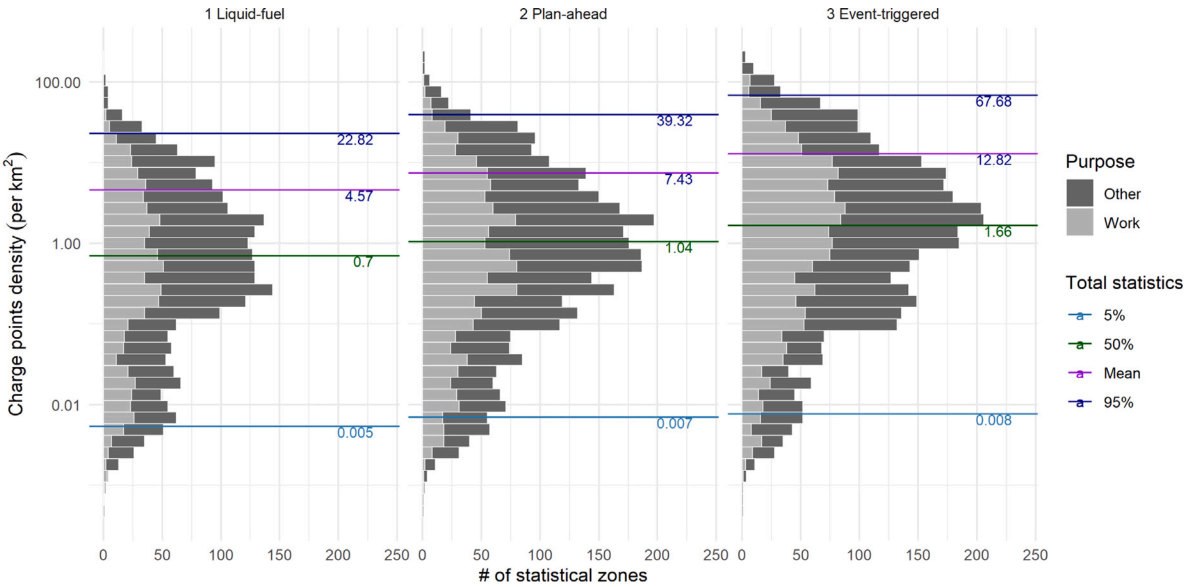

Fig. 6. Daytime charging point density by charging strategy and occasion (work or other).

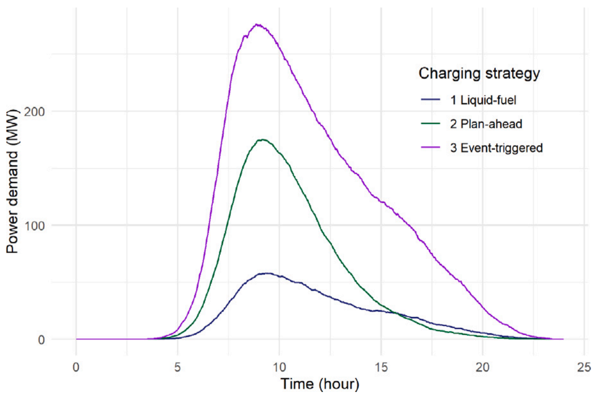

Fig. 7. Hourly power demand of all daytime charging points by charging strategy.

and temporal granularity enabling detailed and local-level explorations. We show how many intermediate and fast charging points are required when and where at work, other public places, or near home, and how the infrastructure demand varies between the three charging strategies, Liquid-fuel, Plan-ahead, and Event-triggered, and two types of dwellings, detached houses, and apartments.

The chicken-and-egg dilemma in charging infrastructure planning leads to a paradox between the perceived lack of infrastructure for a shift to BEVs and the analyses that suggest that adequate charging infrastructure is required to support BEV driving. By integrating realistic charging strategies and access to a home charger (w/ and w/o), our study contributes unique insights into this paradox of EV charging infrastructure by quantifying the charging infrastructure that BEV users *want* instead of *need*.

4.1. Feasibility of charging strategies for BEV driving

In the literature, charging strategies often refer to how charging is optimally managed to maximize the profitability or power stability (Sachan et al., 2020). In this study, we examine from BEV users' perspective by abstracting the patterns of how they charge their cars in daily life, while acknowledging the simplicity of the rules translated in Section 2.2.2. In reality, people are more likely to adopt a mix of these three strategies depending on their general preferences, timings, and occasions. However, our results provide a clear distinction between the simulated charging demand given different assumptions of charging behaviors.

The Liquid-fuel strategy, the predominant strategy assumed in the literature, is more sensible for those with fixed daily activities or secured overnight charging access. However, the assumption that BEV users will adopt this strategy might lead to more problems and less satisfaction with EVs, i.e., difficulties to adopt EVs (Sprei and Kempton, 2022). We see a much smaller share of agents with home chargers who charged their BEVs during the daytime when adopting the Liquid-fuel strategy (0.35% vs. 3.59%, Table 2). In

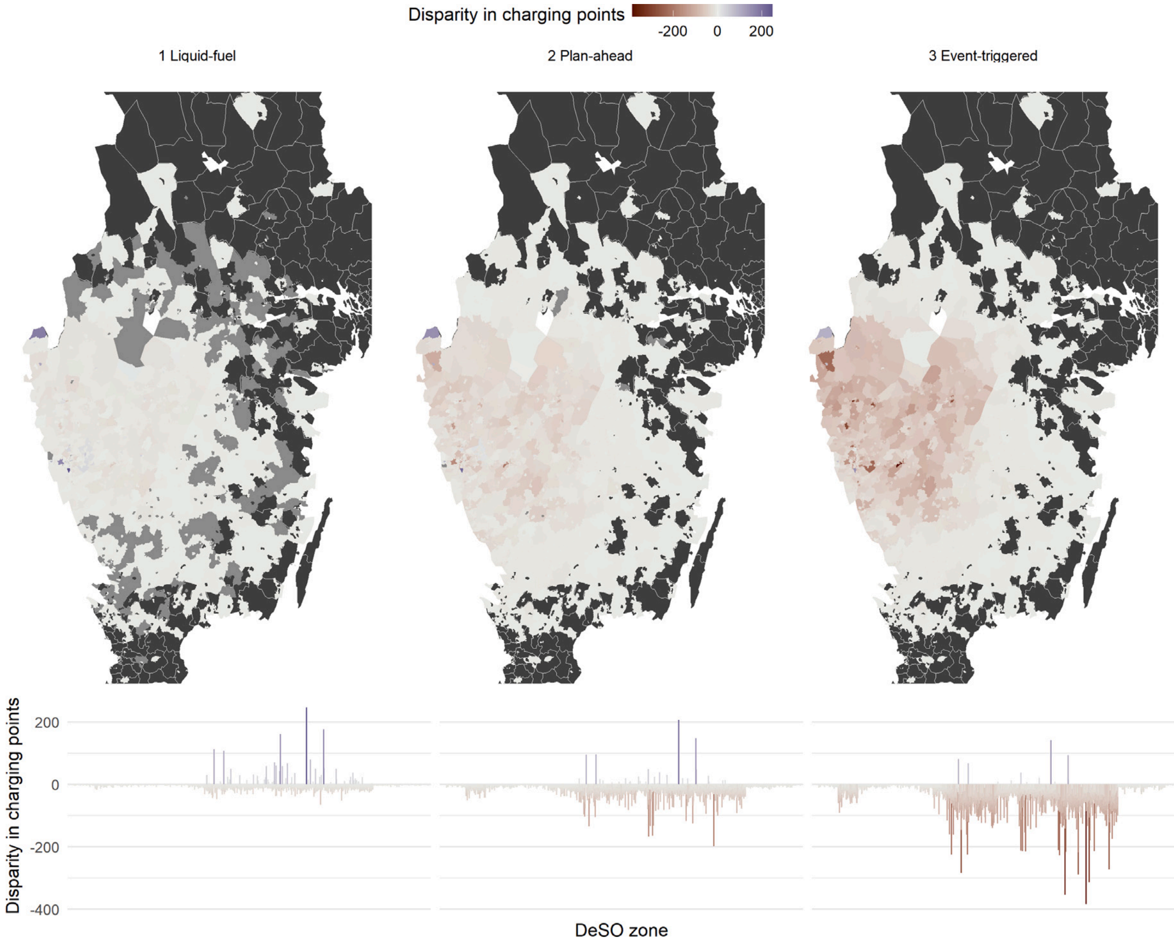

Fig. 8. Spatial disparity in charging points between simulated results and today's infrastructure: difference in the number of charging points by DeSO zone. Bottom line charts indicate the magnitude of charging points disparity where each line represents a DeSO zone.

contrast with the Liquid-fuel strategy, the Plan-ahead strategy seems more realistic and rational. It drastically reduces the failure rate for those with a home charger at their detached houses (from 1.17% to 0.37%). A more aggressive charging strategy like the Event-triggered one does not further reduce their failure rate. Despite being seemingly extreme, the Event-triggered strategy resembles the behaviors of BEV users who do not have fixed overnight charging access. They rely on public charging as finding an overnight charging point near their home maybe uncertain.

Regardless of charging strategy, 99% of BEV users can manage their weekdays by relying on charging during known parking events, provided access to charging infrastructure. However, the three charging strategies result in different numbers of charging points and how they are used. For today's Sweden (2022), we have 23 cars per charge point and 210 cars per fast charger (Power Circle AB, 2022). These numbers are close to our simulated results for the Plan-ahead and Event-triggered strategies (Table 3). Assuming that BEV users adopt the Liquid-fuel strategy leads to an underestimation of charging demand, the Event-triggered strategy results in a large number of charging points (Table 3) and shorter charging time (Fig. 4a–b), leading to potentially higher infrastructure costs.

A major simplification of simulating charging behaviors in the current work is the lack of charging costs including electricity price and parking fee. This simplification is made to separate the demand and supply sides providing a perspective on what BEV users want, free of other constraints. The literature indicates that consumers can be price sensitive and modify their charging behaviors accordingly (Yang et al., 2021). Chakraborty et al. (2019) show that plug-in electric vehicle drivers use workplace charging when the electricity cost is higher at home, and more so when charging at work is free. In our study, due to more activities in public places than work activities, there are more charging points wanted at Other occasions than at workplaces (Table 3). In reality, the difference may be smaller due to a better charging price at workplaces.

The current results regarding the three simplified charging strategies can work as a starting point to further building other scenarios, e.g., a more realistic representation of charging behaviors by integrating different supply-side pricing options and seeing how the charging cost affects charging demand. With 100% BEV adoption, the grid will need to significantly expand in capacity (Powell et al., 2022), and pricing can provide incentives to make BEV users adapt to more grid-friendly charging behavior.

4.2. Role of charging access at work, public places, and near home

Overnight charging contributes more energy than daytime charging at work and other public places for an average weekday (Fig. 4). The relationship between these two sources of energy depends on dwellings. For all the detached house dwellers (62.4%) of VG car users, overnight charging provides the energy of 1500–2600 MWh, about 1.5–54 times the energy supplied by daytime chargers (48–985 MWh). For all the apartment dwellers (37.6%), this number is around 0.2–0.9 (150–460 vs. 511–996 MWh). Early adopters have predominantly access to home chargers (Hardman et al., 2018) but the demand of those who do not have home chargers in a future scenario remains unclear. Our study shows a distinct difference in charging infrastructure needs and charging demand between the two types of dwellers. Policymakers should be aware of such a difference to efficiently plan charging infrastructure for wider BEV adoption, especially to encourage those living in other types of housing than detached houses. The role of overnight charging also depends on the charging strategies for daytime charging. The more aggressively batteries are topped up during daytime, the less dependence on overnight charging there is (Table 3).

This study also reveals the spatiotemporal distribution of the charging needs at work and other places desired by BEV users with different charging strategies. When adopting the Plan-ahead strategy, agents think about planned activities before the first parking event, leading to early charging (Fig. 7). On the other hand, the Liquid-fuel strategy prolongs the time between starting the day and the first charging because people wait until batteries run low.

Compared with today's infrastructure in the study area (Fig. 8), significantly more charging points are needed for 100% BEV adoption according to the Plan-ahead and the Event-triggered strategies. A previous study (Funke et al., 2019) suggests that "public charging infrastructure as an alternative to home charging is only needed in some densely populated areas". However, our results show that, first, not all future BEV users will have stable access to home charging, which leads to a distinct demand split between overnight charging and daytime charging (mostly in public spaces). Second, to meet local BEV users' charging demand, additional 11–220 charging points per zone can be needed in many cities and surrounding areas, in addition to a few densely populated areas. Our synthetic population will be open source and available publicly. Others can, for example, use our work to look at the storage capacity available for vehicle-to-grid systems (Hipolito et al., 2022) or other applications.

4.3. Daytime charging demand and grid perspective

The overall daytime charging demand for 100% BEV adoption is high regardless of charging strategies. The peak demand in Gothenburg is 250 MW (Svenska Kräfnät, 2022), ca. 750 MW in Västra Götaland, considering its population is three times that of Gothenburg. Our results indicate that the peak demand of daytime charging corresponds to roughly 6%–33% of today's grid capacity. This is related to the simulation assumptions. First, we assume a charging point is placed when an agent wants to charge the car. This is different from many previous studies, where the number of charging points is optimized according to various targets, e.g., minimized infrastructure cost. Based on this distinct simulation design of this work, the results highlight what BEV users *want* instead of *need*. Second, the three charging strategies are abstracted and simplified from real-world behaviors. In reality, electricity prices will affect BEV users' charging decisions. Given these assumptions, this study provides a baseline from a charging behavior point of view.

In general, charging infrastructure will affect the electricity grid. For example, a recent study suggests that the peak net electricity demand would increase by 50% in full electrification in the US (Powell et al., 2022). The study also indicates that daytime charging can be essential in reducing the load on the electric grid. Moreover, smart pricing incentives for demand shift and vehicle-to-grid strategies will significantly reduce the grid impact (Barthel et al., 2021; Tuchnitz et al., 2021). The daytime power demand according to different charging strategies given by the current study can contribute insights to designing good daytime charging experience from a user's perspective.

4.4. Limitations and future work

The first limitation is the lack of charging cost from the user's and the infrastructure's perspectives (as discussed in Section 4.1). Future directions include having more realistic charging strategies integrating charging cost models and minimizing charging infrastructure costs. The second limitation is the lack of feasibility constraints regarding land use and grid. We assume a charging point can be installed where the agents park and decide to charge their BEVs. However, in reality, the feasibility of a charging point placement is constrained by many factors such as zoning constraints, business models, etc. A more detailed depiction will better guide planning practice. The third limitation concerns using today's population and travel patterns for a future scenario. Our future work will incorporate changes in the population, including sociodemographic and behavioral changes, e.g., the share of car users, etc. We will in particularly consider interactions between driving and a shift to more sustainable modes of transport such as cycling and public transit, thus further reducing the need for parking and charging stations. By varying assumptions of travel demand such as trip distances, we could also explore the impacts of behavioral changes on charging travel demand in the future.

Moreover, we currently simulate an average weekday (Mon-Fri) and not an average day of the week (any day); thus, long-distance driving is under-represented, and so is the need for fast-charging, particularly along travel corridors. This study reveals that the need for fast charging to facilitate daily driving is small. One future direction would be to extrapolate one average weekday to multiple-day (Mon-Sun) travel distances and test the robustness of the model.

Table A.1
Activity statistics. Except for the share of activities, the rest of indicators are median values of all car agents.

Activity	Share (%)	Frequency per day	Duration per activity	Duration per day
Home	57	2.2	7.1	15.1
Other	30	1.7	1.7	2.5
School	2	1.1	8.2	8.4
Work	11	1.1	8.7	8.9

Table A.2
Top 10 activity plans of car agents.

Activity sequence	Share (%)	Cumulative share (%)
H-O-H	26.9	26.9
H-W-H	23.4	50.4
H-O-H-O-H	7.5	57.8
H-O-O-H	7.1	64.9
H-S-H	6.2	71.1
H-O-O-O-H	5.9	77.0
H-W-O-H	3.8	80.8
H-W-H-O-H	2.9	83.7
H-W-O-W-H	2.0	85.6
H-O-O-H-O-H	1.9	87.5

Table A.3
Car trip statistics.

Indicator	Travel time per trip (min)	Travel distance per trip (km)	Daily travel distance (km)
Median	17.6	11.0	32.9
5th percentile	3.0	1.4	4.1
95th percentile	145.7	71.1	189.4
Maximum	690.0	658.5	1140.2

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Mobility patterns of simulated car agents

We summarize the mobility patterns of the agents in the simulation day in two aspects: activities and car trips. Table A.1 shows the share, frequency, and durations per day and per activity of all the involved car agents. More than half of the activities are staying home, followed by Other, Work, and School.

Table A.2 shows the top 10 daily activity plans. Half of the agents have simple daily plans, H-O-H or H-W-H. Besides these two typical plans, the rest of the activity plans suggest that Other activities happen frequently, and Work often comes with some secondary Other activities.

Fig. A.1 shows overall hourly activity participation (a) and activity duration when the BEVs are parked (b).

Table A.3 shows the statistics of all the simulated car trips regarding travel time and distance, and daily travel distance (also visualized in Fig. A.2).

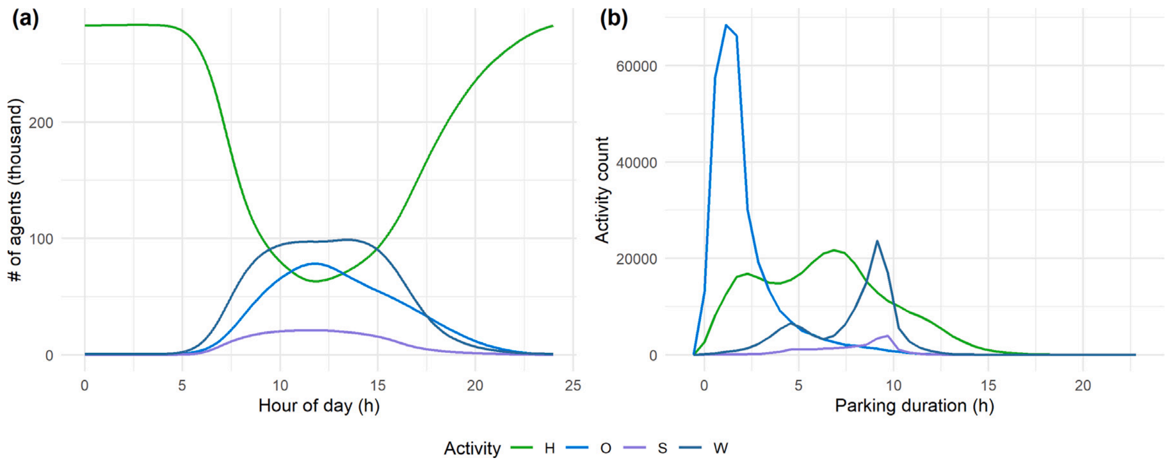

Fig. A.1. Activity patterns. (a) Temporal profiles. (b) Distribution of parking duration for the activities reached by car.

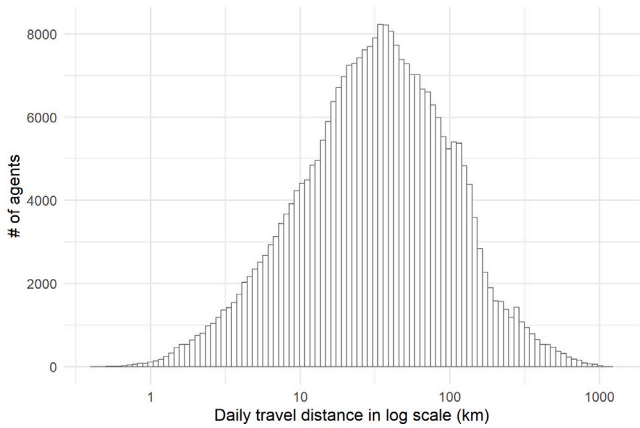

Fig. A.2. Distribution of daily travel distance by car.

Appendix B. Sensitivity test results

The sensitivity test aims to reveal how the simulation results change corresponding to different SOC thresholds of the three charging strategies and fast charging powers. We ran seven additional simulations using a SOC threshold of 0.3 for Strategies 1 and 2 and the fast charging power of 150 kW. There are ten scenarios (Table B.1), where the main body of the manuscript presents scenarios No. 1–3, and the sensitivity test covers additional scenarios No. 4–10. We present the sensitivity test results in this section, complementary to the manuscript's main body.

B.1. Individual charging patterns

As an addition to Table 2, Table B.2 shows the sensitivity results of individual charging behaviors. Higher power for fast charging does not affect the share of agents using daytime chargers and the agents' failure rate. A higher SOC threshold of commencing daytime charging induces greater charging demand and a slightly lower failure rate for those without a home charger.

Table B.3 summarizes the median values of individuals' total daytime charging duration and charging time ratio and their total energy consumption for daytime and overnight charging (in addition to Fig. 4). Higher fast charging power does not affect intermediate charging due to its small share but reduces the number of fast charging points and the required fast charging time. A greater SOC threshold leads to increased daytime charging and decreased overnight charging.

Table B.1
Scenarios of charging strategies and fast charging powers.

No. of scenario	Charging strategy (SOC threshold)	Fast charging power (kW)
1	1 (0.2)	50
2	2 (0.2)	50
3	3 (0.9)	50
4	1 (0.2)	150
5	2 (0.2)	150
6	3 (0.9)	150
7	1 (0.3)	50
8	2 (0.3)	50
9	1 (0.3)	150
10	2 (0.3)	150

Table B.2
Daytime charger usage and failure rate. HC = home charger at a detached house.

Charging strategy (SOC threshold)	Fast charging power (kW)	Daytime charger usage (%)		Failure[a] rate (%)	
		w/o HC	w/ HC	w/o HC	w/ HC
1 (0.2)	50	3.59	0.35	0.96	1.17
1 (0.2)	150	3.60	0.35	0.94	1.17
1 (0.3)	50	6.70	0.63	0.80	0.99
1 (0.3)	150	6.66	0.63	0.79	0.98
2 (0.2)	50	7.36	1.91	0.68	0.37
2 (0.2)	150	7.29	1.91	0.67	0.37
2 (0.3)	50	8.17	2.53	0.60	0.37
2 (0.3)	150	8.05	2.53	0.60	0.37
3 (0.9)	50	18.21	22.44	0.57	0.37
3 (0.9)	150	18.23	22.44	0.57	0.37

[a]An agent is not able to finish all the activities by the assigned BEV and initial SOC.

Table B.3
Charging demand of individual agents. HC = home charger at a detached house.

Charging strategy (SOC threshold)	Fast charging power (kW)	Fast charging time (min)		Inter. charging time (min)		Fast charging time ratio		Inter. charging time ratio		Total daytime energy (MWh)		Total overnight energy (MWh)	
		w/o	w/ HC	w/o	w/ HC	w/o	w/ HC	w/o	w/ HC	w/o	w/ HC	w/o	w/ HC
1 (0.2)	50	19	18	116	105	7	11	30	37	511	48	458	2,512
1 (0.2)	150	16	14	116	105	6	7	30	37	514	48	459	2,512
1 (0.3)	50	19	20	108	101	10	10	30	33	901	82	335	2,478
1 (0.3)	150	15	15	108	101	8	8	30	33	906	83	332	2,477
2 (0.2)	50	18	12	109	85	21	34	31	31	996	189	165	2,372
2 (0.2)	150	13	8	109	85	16	29	31	31	991	189	163	2,371
2 (0.3)	50	17	11	102	80	22	34	29	29	999	231	160	2,329
2 (0.3)	150	12	7	102	80	16	28	29	29	991	231	159	2,329
3 (0.9)	50	5	5	41	42	24	14	12	12	843	985	158	1,575
3 (0.9)	150	2	2	41	42	10	11	12	12	845	986	156	1,574

B.2. Spatiotemporal patterns of charging

As an addition to Table 3, we show the sensitivity results of required charging points in Table B.4. Higher power for fast charging sometimes leads to more fast charging points (SOC=0.2 for Strategies 1–2) but a reduced number of fast charging points in the other scenarios. We see more fast charging points required for Strategies 1–2 when the agents decide to charge on a low battery (SOC=0.2) because, in these scenarios, they are more likely to have short parking events with the battery SOC below 0.8, triggering the need for fast chargers. On the other hand, when the agents have a more conservative charging strategy (SOC=0.3 for Strategies 1–2 or Event-triggered strategy), we see a declined demand for fast charging. However, a higher fast charging power always goes with a slightly smaller number of intermediate charging points. A higher SOC threshold of commencing daytime charging means more daytime charging points and fewer overnight charging points for apartment dwellers.

Fig. B.1 shows the temporal profile of daytime charging power demand of the ten scenarios. Higher fast charging power has minimal impact because most wanted charging points are intermediate (Table B.4). A greater SOC threshold induces higher power demand in both Strategies 1 and 2, especially the Liquid-fuel strategy.

Table B.4
Number of charging points by scenario. Inter. = intermediate.

Charging strategy (SOC threshold)	Fast charging power (kW)	Occasion	Daytime charging				Overnight charging	
			Inter.	Fast	# cars per inter.	# cars per fast	Slow	# cars per slow
1 (0.2)	50	Other	3,471	509				
		Work	1,895	8				
		Total	5,366	517	54	561	11,290	26
1 (0.2)	150	Other	3,457	540				
		Work	1,855	8				
		Total	5,312	548	55	529	11,348	26
1 (0.3)	50	Other	5,352	754				
		Work	3,762	19				
		Total	9,114	773	32	375	5,051	57
1 (0.3)	150	Other	5,335	739				
		Work	3,757	14				
		Total	9,092	753	32	385	4,983	58
2 (0.2)	50	Other	8,092	787				
		Work	4,596	30				
		Total	12,688	817	23	355	2,101	138
2 (0.2)	150	Other	8,065	800				
		Work	4,516	32				
		Total	12,581	832	23	349	2,060	141
2 (0.3)	50	Other	8,807	899				
		Work	4,955	43				
		Total	13,762	942	21	308	2,001	145
2 (0.3)	150	Other	8,825	842				
		Work	4,842	37				
		Total	13,667	879	21	330	1,969	147
3 (0.9)	50	Other	14,542	1,250				
		Work	9,475	70				
		Total	24,017	1,320	12	220	1,962	148
3 (0.9)	150	Other	14,526	1,121				
		Work	9,465	68				
		Total	23,991	1,189	12	244	1,905	152

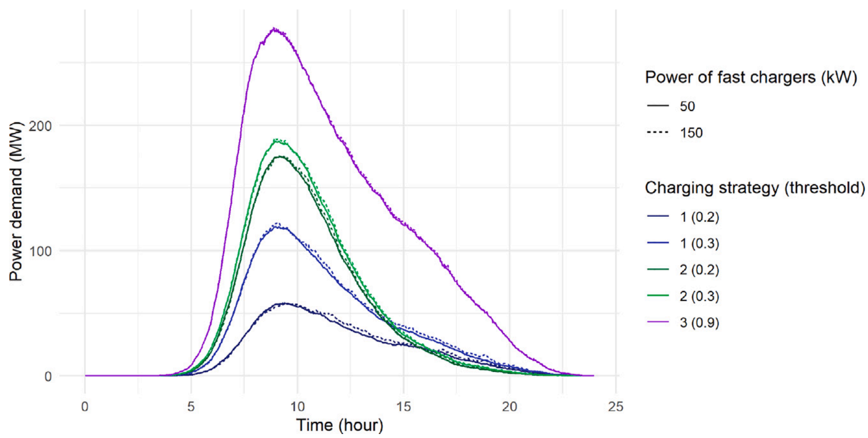

Fig. B.1. Hourly power demand for daytime charging by scenario.

B.3. Comparison with today's infrastructure

Table B.5 suggests higher fast charging power only slightly reduces the demand for charging points. More conservative charging (higher SOC threshold) requires more additional charging points for Strategy 1 Liquid-fuel but is not significantly different in Strategy 2 Plan-ahead.

Table B.5
Statistics of charging point disparity between simulated results and today's infrastructure by scenario.

Charging strategy (SOC threshold)	Fast charging power (kW)	Zones needing additional charging points (%)	# of additional charging points	
			Max	Median
1 (0.2)	50	93.6	65	6
1 (0.2)	150	93.4	59	6
1 (0.3)	50	96.9	156	9
1 (0.3)	150	97.2	151	9
2 (0.2)	50	97.9	199	11
2 (0.2)	150	98.0	185	11
2 (0.3)	50	98.3	193	11
2 (0.3)	150	98.5	216	11
3 (0.9)	50	99.4	379	20
3 (0.9)	150	99.4	376	20

References

Azzalini, A., Capitanio, A., 1999. Statistical applications of the multivariate skew normal distribution. J. R. Stat. Soc. Ser. B Stat. Methodol. 61 (3), 579–602.

Barthel, V., Schlund, J., Landes, P., Brandmeier, V., Pruckner, M., 2021. Analyzing the charging flexibility potential of different electric vehicle fleets using real-world charging data. Energies 14 (16), 4961.

Brand, C., Anable, J., Ketsopoulou, I., Watson, J., 2020. Road to zero or road to nowhere? Disrupting transport and energy in a zero carbon world. Energy Policy 139, 111334.

Chakraborty, D., Bunch, D.S., Lee, J.H., Tal, G., 2019. Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. Transp. Res. D 76, 255–272.

CHARGEX AB, 2022. URL https://uppladdning.nu/.

Copernicus Programme, 2022. European digital elevation model (DEM) data. URL https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1.

Deb, S., Tammi, K., Kalita, K., Mahanta, P., 2018. Review of recent trends in charging infrastructure planning for electric vehicles. Wiley Interdiscip. Rev. Energy Environ. 7 (6), e306.

electrive.com, 2022. EU council confirms ICE ban for cars and vans by 2035. electrive.com. URL https://www.electrive.com/2022/06/29/eu-council-decides-on-100-co2-reductions-for-cars-and-vans-by-2035/.

EV-volumes.com, 2022. The electric vehicle world sales database. URL https://www.ev-volumes.com/.

Funke, S.Á., Sprei, F., Gnann, T., Plötz, P., 2019. How much charging infrastructure do electric vehicles need? A review of the evidence and international comparison. Transp. Res. D 77, 224–242.

Geofabrik GmbH and OpenStreetMap Contributors, 2022. OpenStreetMap data extracts. URL http://download.geofabrik.de/.

Gnann, T., Funke, S., Jakobsson, N., Plötz, P., Sprei, F., Bennehag, A., 2018. Fast charging infrastructure for electric vehicles: Today's situation and future needs. Transp. Res. D 62, 314–329.

Greaves, S., Backman, H., Ellison, A.B., 2014. An empirical assessment of the feasibility of battery electric vehicles for day-to-day driving. Transp. Res. A 66, 226–237.

Hardman, S., Jenn, A., Tal, G., Axsen, J., Beard, G., Daina, N., Figenbaum, E., Jakobsson, N., Jochem, P., Kinnear, N., et al., 2018. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transp. Res. D 62, 508–523.

Hipolito, F., Vandet, C., Rich, J., 2022. Charging, steady-state SoC and energy storage distributions for EV fleets. Appl. Energy 317, 119065.

Jahn, R.M., Syré, A., Grahle, A., Schlenther, T., Göhlich, D., 2020. Methodology for determining charging strategies for urban private vehicles based on traffic simulation results. Procedia Comput. Sci. 170, 751–756.

Kong, W., Luo, Y., Feng, G., Li, K., Peng, H., 2019. Optimal location planning method of fast charging station for electric vehicles considering operators, drivers, vehicles, traffic flow and power grid. Energy 186, 115826.

Liao, Y., Tozluoğlu, Ç., Sprei, F., Yeh, S., Dhamal, S., 2023. Open Synthetic Data on Travel and Charging Demand of Battery Electric Cars: An Agent-Based Simulation on Three Charging Behavior Archetypes. Zenodo, http://dx.doi.org/10.5281/zenodo.7549847.

Liu, Q., Liu, J., Le, W., Guo, Z., He, Z., 2019. Data-driven intelligent location of public charging stations for electric vehicles. J. Clean. Prod. 232, 531–541.

Márquez-Fernández, F.J., Bischoff, J., Domingues-Olavarría, G., Alaküla, M., 2021. Assessment of future EV charging infrastructure scenarios for long-distance transport in Sweden. IEEE Trans. Transp. Electr. 8 (1), 615–626.

Mathieu, L., Poliscanova, J., Ambel, C., Muzi, N., Alexandridou, S., 2020. Recharge EU: How many charge points will Europe and its Member states need in the 2020s. TE Instrastructure Report, European Federation for Transport and Environment.

Metais, M.-O., Jouini, O., Perez, Y., Berrada, J., Suomalainen, E., 2022. Too much or not enough? Planning electric vehicle charging infrastructure: A review of modeling options. Renew. Sustain. Energy Rev. 153, 111719.

Miralinaghi, M., de Almeida Correia, G.H., Seilabi, S.E., Labi, S., 2020. Designing a network of electric charging stations to mitigate vehicle emissions. In: 2020 Forum on Integrated and Sustainable Transportation Systems. FISTS, IEEE, pp. 95–100.

Novosel, T., Perković, L., Ban, M., Keko, H., Pukšec, T., Krajačić, G., Duić, N., 2015. Agent based modelling and energy planning–Utilization of MATSim for transport energy demand modelling. Energy 92, 466–475.

osmosis, 2022. Osmosis: a command line java application for processing OSM data. URL https://wiki.openstreetmap.org/wiki/Osmosis.

Pan, L., Yao, E., Yang, Y., Zhang, R., 2020. A location model for electric vehicle (EV) public charging stations based on drivers' existing activities. Sustainable Cities Soc. 59, 102192.

Patil, P., Kazemzadeh, K., Bansal, P., 2022. Integration of charging behavior into infrastructure planning and management of electric vehicles: A systematic review and framework. Sustainable Cities Soc. 104265.

Powell, S., Cezar, G.V., Min, L., Azevedo, I.M., Rajagopal, R., 2022. Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption. Nat. Energy 7 (10), 932–945.

Power Circle AB, 2022. URL https://www.elbilsstatistik.se/laddinfrastatistik.

Sachan, S., Deb, S., Singh, S.N., 2020. Different charging infrastructures along with smart charging strategies for electric vehicles. Sustainable Cities Soc. 60, 102238.

Schmidt, M., Staudt, P., Weinhardt, C., 2020. Evaluating the importance and impact of user behavior on public destination charging of electric vehicles. Appl. Energy 258, 114061.

Shahraki, N., Cai, H., Turkay, M., Xu, M., 2015. Optimal locations of electric public charging stations using real world vehicle travel patterns. Transp. Res. D 41, 165–176.

Sprei, F., Kempton, W., 2022. Electric vehicle adoption limited by liquid fuel mental models (under review).

Statistikmyndigheten SCB, 2022. DeSO – Demografiska statistikområden. URL https://www.scb.se/hitta-statistik/regional-statistik-och-kartor/regionala-indelningar/deso---demografiska-statistikomraden/.

Suarez, C., Martinez, W., 2019. Fast and ultra-fast charging for battery electric vehicles–a review. In: 2019 IEEE Energy Conversion Congress and Exposition. ECCE, IEEE, pp. 569–575.

Svenska Kräfnät, 2022. URL https://www.svk.se/.

Tozluoğlu, Ç., Dhamal, S., Liao, Y., Yeh, S., Sprei, F., Dubhashi, D., Marathe, M., Barrett, C., 2022. Synthetic Sweden mobility (SySMo) model documentation. URL https://research.chalmers.se/en/publication/531094.

Tuchnitz, F., Ebell, N., Schlund, J., Pruckner, M., 2021. Development and evaluation of a smart charging strategy for an electric vehicle fleet based on reinforcement learning. Appl. Energy 285, 116382.

W. Axhausen, K., Horni, A., Nagel, K., 2016. the Multi-Agent Transport Simulation MATSim. Ubiquity Press.

Wang, H., Zhao, D., Meng, Q., Ong, G.P., Lee, D.-H., 2019. A four-step method for electric-vehicle charging facility deployment in a dense city: An empirical study in Singapore. Transp. Res. A 119, 224–237.

Xylia, M., Joshi, S., 2022. A Three-Dimensional View of Charging Infrastructure Equity. SEI: Stockholm Environment Institute.

Yang, D., Sarma, N.J., Hyland, M.F., Jayakrishnan, R., 2021. Dynamic modeling and real-time management of a system of EV fast-charging stations. Transp. Res. C 128, 103186.

Zafar, U., Bayram, I.S., Bayhan, S., 2021. A GIS-based optimal facility location framework for fast electric vehicle charging stations. In: 2021 IEEE 30th International Symposium on Industrial Electronics. ISIE, IEEE, pp. 1–5.

Zhuge, C., Shao, C., 2018. Agent-based modelling of locating public transport facilities for conventional and electric vehicles. Netw. Spat. Econ. 18 (4), 875–908.