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Full length article

A joint model of infrastructure planning and smart charging strategies for shared electric vehicles

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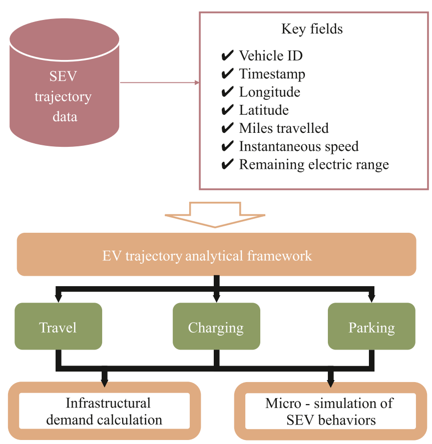
HIGHLIGHTS

- A data-driven approach to deploying infrastructure for shared electric vehicles (SEVs).
- Simulating SEVs' response to Time-of-Use (TOU) tariff and Vehicle-to-Grid (V2G).
- TOU and V2G could help save the charging cost by 17.93% and 34.97%, respectively.
- The discharging demand accounts for 42.02% of the actual charging demand under V2G.

GRAPHICAL ABSTRACT



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ABSTRACT

This paper presents a data-driven joint model designed to simultaneously deploy and operate infrastructure for shared electric vehicles (SEVs). The model takes into account two prevalent smart charging strategies: the Time-of-Use (TOU) tariff and Vehicle-to-Grid (V2G) technology. We specifically quantify infrastructural demand and simulate the travel and charging behaviors of SEV users, utilizing spatiotemporal and behavioral data extracted from a SEV trajectory dataset. Our findings indicate that the most cost-effective strategy is to deploy slow chargers exclusively at rental stations. For SEV operators, the use of TOU and V2G strategies could potentially reduce charging costs by 17.93% and 34.97% respectively. In the scenarios with V2G applied, the average discharging demand is 2.15 kWh per day per SEV, which accounts for 42.02% of the actual average charging demand of SEVs. These findings are anticipated to provide valuable insights for SEV operators and electricity companies in their infrastructure investment decisions and policy formulation.

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1. Introduction

The global push towards electrification of the transportation system has seen a rise in the adoption of Electric Vehicles (EVs), as they could bring several benefits, such as climate change mitigation [1–3], integration of renewable energy into the power grid system [4,5] and air pollution reduction [6,7]. According to the report "Global EV Outlook 2021" by IEA [8], global EV ownership reached 11.3 million in 2020, but the EV market share was only 4.6%. The uptake of EVs is hindered by several factors, including high sale price [9,10], lack of charging facilities [11–13], and long recharging time [14,15].

To address the high upfront cost of EVs, attempts have been made to introduce EVs into the carsharing system at the early stage of transportation electrification, as shared electric vehicles (SEVs) could reduce the cost of vehicle use to some extent, especially for those people with low usage rates [16,17]: Carsharing enables people to pay as you go, and thus people do not need to pay the high upfront cost. SEVs also eliminate the need for users to deal with issues related to EV usage such as battery degradation and maintenance. On the other hand, electric carsharing is also a cost-effective scheme for carsharing operators, because of the lower refueling cost and maintenance cost [18].

This study is focused on infrastructure planning and smart charging strategies for SEVs, which are of great importance and relevant to several stakeholders (e.g., SEV operators and grid companies). Specifically, the operation of SEVs heavily relies on the appropriate layout of chargers [19,20]: if chargers are not located properly, and cannot meet the charging demand of SEV users, it would be difficult for SEV operators to make a profit due to the low usage rate of SEVs [21]. For grid companies, they have two typical smart strategies to manage EV charging, Time-of-Use (TOU) tariff [22] and Vehicle-to-Grid (V2G) [23]. TOU tariff is a dynamic pricing strategy for EV charging, which tries to discourage charging with a higher charging fee during peak hours, so as to shift charging demand when the load is high and protect the grid [24]. V2G is an advanced technology that allows EVs additionally to get discharged and sell electricity back to the grid, especially during peak periods. Through V2G, EVs have the potential to integrate renewable energy into the grid and balance the electricity load for the grid [25].

Although both infrastructure planning and operation are essential for an electric carsharing system, previous studies tended to deploy and operate charging stations separately. In response, this paper will develop a joint model to deploy rental stations and chargers, and operate these facilities simultaneously. In particular, we will develop a data-driven approach to quantifying infrastructural demand and simulating SEV users' charging/discharging behaviors through smart charging strategies, including TOU tariff and V2G, with spatiotemporal and behavioral information extracted from a real-world SEV trajectory dataset in Beijing in January 2019. The outcomes would be helpful for SEV operators and grid companies in their decision-making, such as infrastructure planning (e.g., rental and charging stations), policy-making (e.g., electricity price), and technology investment (e.g., V2G technology).

The paper is organized as follows: It starts with an introduction in Section 1 which provides an overview of the research topic. Then, in Section 2, we conducted a literature review of existing charging infrastructure location models and smart charging, based on which I identified the research gaps. Next, in Section 3, we introduced the study area of Beijing, and the key SEV dataset used, as well as the analytical framework used to analyze the dataset and extract useful information for model development. In Section 4, we described the methodology in detail: we first introduced the methods used to determine the location of rental stations and further allocate chargers to the rental stations. Then, we described the process of exploring the potential of SEVs for smart charging through the chargers added. In Section 5, we set up various scenarios to explore how different charger rates and charging strategies could influence the operation of SEVs in Beijing. Finally, the paper concludes with a summary of the main findings and policy implications in Section 6.

2. Literature review

2.1. Charging infrastructure location model

The charging infrastructure location problem is an important topic in the EV studies, as several barriers to the uptake of EVs are associated with EV charging, such as the long charging time, inadequate chargers, and considerable infrastructural investment. Many attempts have been made to optimize the layout of chargers with different objectives, such as the number of EVs served, and the minimum system cost. Some of them tried to estimate charging demand, which is a key input of the charging infrastructure location model, using real-world data (e.g., GPS trajectory data). The review here will focus on how different emerging big data sources have been used in the deployment of charging infrastructure, which is relevant to one key contribution of our study. More comprehensive reviews can be found in the work by Hardman et al. [26], Das et al. [27], Funke et al. [28], Chen et al. [29], Deb et al. [30], Pagany et al. [31] and Metais et al. [32].

GPS trajectory data tended to be one of the most used data sources for deploying charging infrastructure. For example, Tu et al. [33] developed a spatial-temporal demand coverage approach for optimizing the location of charging stations for electric taxis. The estimation of public taxi service demand was based on the spatial and temporal attributes extracted from massive taxi GPS data in Shenzhen, China. Also using taxi GPS data, in Changsha, China, Yang et al. [34] presented a data-driven optimization-based approach to allocating chargers for electric taxis to minimize the investment in charging facilities. To allocate chargers in cities with a low EV ownership, Bai et al. [35] proposed a cell-based (a city was divided into several identical cells) location choice model that used GPS trajectory data to estimate the charging demand of each cell. Taking Shenzhen as a case study, the model presented a tradeoff between cost and service quality, and might provide insights into chargers' construction. Tao et al. [36] used a driving dataset of 196 battery electric vehicles (BEVs) in Wuhan to optimize the existing layout of charging facilities with a genetic algorithm-based method. Through optimization, chargers became more accessible for BEVs, which markedly reduced the over-discharge rate of BEVs and finally effectively extended the lifespan of BEVs' batteries. GSP trajectory datasets have also been used to deploy more advanced charging facilities, such as battery swap stations. For example, Yang et al. [37] proposed a model to allocate battery swap stations for SEVs, using trajectories of 514 actual SEVs in February 2019. Through various "what-if" scenarios, they identified three key parameters in the deployment, namely "the coverage rate of battery swapping demand, the service radius of a battery swap station, and the acceptable average delay time". Similarly, Wang et al. [38] tried to deploy battery swap stations for Electric Freight Vehicles (EFVs), using a one-week GPS trajectory dataset collected from 99.8% of the total Beijing EFVs (i.e., 17,716 EFVs) in 2019. The data-driven model could help figure out an optimal network of battery swap stations, which could dramatically reduce the charging time by 96.56%.

Other big data sources, such as charging transaction data, traffic flow data, and mobile phone data have also been used to deploy charging infrastructure. Pevec et al. [39] used EV charging transaction data as one of the main data sources to support the development of new chargers. Specifically, they proposed three different optimization objectives from the perspectives of different stakeholders, namely "maximizing the utilization of chargers for operators of chargers, adding chargers in unpopulated areas for government and EV owners, and making a trade-off between the former two objectives". Vazifeh et al. [40] used a four-month mobility dataset that contained location traces of about one million users in Boston to optimize charging infrastructure location, with the objective of minimizing both the number of chargers needed and the total distance to chargers. Li et al. [41] developed a model to first predict the long-term charging demand of EVs and then optimize the charger planning. The prediction was conducted by a multi-relation graph convolutional network (a deep learning technique), using traffic flow data captured by road sensors in Sydney as training data.

2.2. Smart charging

2.2.1. Time of use (TOU) tariff

Previous studies of TOU were mainly focused on two aspects: 1) the design and impact analysis of TOU and 2) consumers' willingness to adopt TOU.

In the design and impact analysis of TOU, Cao et al. [42] proposed an intelligent method to guide EV charging in response to different TOU prices. It was found that the proposed optimization was beneficial in reducing the cost and flattening the load curve during charging peak hours. The study by Said et al. [43] examined the role of TOU in minimizing peak loads on distributed feeders, through simulations that considered the real characteristics of charging at home. Simulation results showed that applying a scheduling protocol considering TOU to EV charging could reduce electricity demand during peak periods by 22% in the scenario with 50 EVs, and 42% in the scenario with 100 EVs. However, TOU was found not always effective, for example, in the study by Kucuksari et al. [44]. They analyzed two EV-specific TOU rates from the perspectives of customers and the grid: based on an optimal cost model, they designed a coordinated charging strategy that could minimize the cost of workplace charging over the entire service lifespan. The results showed that whether the EV users would get cost benefits depended on the TOU rates, and there would be no reduction in demand during peak hours. With the purpose of determining the best time for starting off-peak rates, Dubey et al. [45] conducted a study to simulate the EV charging behavior. The simulation results suggested that off-peak rates starting between 11 am and 12 am was the best, as the scheme enabled all EVs to get fully charged before 7 am and the charging events would have the least negative impact on the grid. The study by Merrington et al. [46] tried to guide the planning of solar photovoltaic (SPV) and battery storage system (BSS) for households with EVs under TOU tariff, aiming to minimize the cost of electricity. The results showed that the cost of electricity would decrease by 25.65% through the combination of EV, 10 kW SPV, BSS with 10 kWh capacity, and TOU tariff.

In the analysis of TOU adoption, Nicolson et al. [47] used a dataset with 2020 samples in British, to explore whether people would adopt TOU and how to promote the adoption. It was found that marketing campaigns would have a significantly positive influence on people's willingness to adopt TOU of EV owners. Similarly, Sundt et al. [48] conducted a choice experiment in Germany and collected about 1,400 samples to estimate people's willingness to adopt TOU. The results showed that about 70% of respondents were likely to adopt TOU. Another study focused on the influence of attitudes on people's willingness to adopt TOU in Germany using ordered logit models [49]. Unsurprisingly, positive attitudes towards TOU would increase people's willingness to adopt TOU and negative attitudes would decrease it. However, it was also found that a higher climate change awareness would decrease the willingness as well. In addition, it remains unclear whether TOU could really bring cost reduction for EV owners. For example, Yang et al. [50] proposed a stepped tariff-tiered pricing strategy, based on which charging bills would be reduced if EVs charged less and slowly during off-peak periods. While Davis et al. [51] carried out several simulations of PHEV refueling under different TOU rates. They found that the fuel cost tended to be higher if EV owners charged during off-peak periods, which might decrease the economic benefit of TOU.

2.2.2. Vehicle-to-grid (V2G)

Previous V2G studies tended to pay more attention to technical aspects of V2G (e.g., renewable energy integration and battery degradation) than its social aspects. The study of Sovacool et al. [52] fell into the scope of V2G's social dimensions, and thus the following review will be focused on two important social aspects of V2G, i.e., willingness to use V2G, and the cost and benefit of V2G.

In terms of adoption of V2G, previous studies tended to collect data through traditional questionnaire surveys and further conduct analysis and modeling. For example, the study by Geske et al. [53] identified the two most significant factors that influenced the adoption of V2G were range anxiety and minimum range using questionnaire survey data in Germany in 2013. To promote its adoption, they suggested V2G operators design different V2G strategies for EV users with different vehicle usage demands, and develop policies to raise people's awareness of V2G. More recently, Huang et al. [54] carried out a survey in the Netherlands in 2019 and collected 148 samples, aiming to shed light on EV drivers' preference towards V2G under two different charging speeds (i.e., the current speed and a fast speed) and their concerns about V2G contract items. After analyzing the survey data using a utility function, they found EV owners were more likely to adopt V2G with a fast charging speed. Among the items of V2G contract, "discharging cycles" was the most important one. Besides, "the guaranteed minimum battery level", "monthly remuneration", and "plug-in time" also significantly influenced EV owners' willingness. Liu et al. [55] conducted a questionnaire survey on EVs and V2G in Beijing in 2019. With the survey data, they developed an agent-based model for exploring the potential market of V2G, and identifying the influence of various policies. It was found that advertisements, V2G selling price, and PHEV purchase permit had limited influence on the adoption of V2G. There are also some studies exploring the adoption of V2G through expert interviews. For instance, Noel et al. [56] interviewed 227 transportation and electricity experts across 5 European countries from 2016 to 2017. In total, experts mentioned 35 categories of barriers to V2G adoption.

In terms of cost-benefit analysis, Noel et al. [57] compared a V2G-capable electric bus against a conventional diesel school bus, using the total cost as an indicator, which considered the "bus costs", "driving behavior", "energy cost", "V2G revenue", "maintenance cost", and "health and environmental externalities". They found that V2G enabled electric buses to be more cost-effective than conventional diesel school buses. Kiaee et al. [58] simulated the charging and discharging of 5000 EVs within a power system. By comparing the two scenarios with and without V2G, they found the charging cost was decreased by 13.6%, in case the power they needed for the next journey was secured. Similarly, a study by De Los Ríos et al. [59] found that a V2G revenue could be 5%–11% of the total operating cost using another V2G simulator. Sun et al. [60] conducted a big data-based analysis using a GPS dataset containing moving trajectories of 967 SEVs. They found the amount of electricity sent back to the grid through V2G from the fleet of SEVs accounted for 2.46% of the total daily residential electricity consumption. The study by Li et al. [61] estimated the benefits of V2G for both EV users and the grid. After considering the additional cost brought by battery degradation to EV users, they found EV users could earn money if the electricity price during peak periods could triple. However, the study had negative attitudes towards the monetary benefit for the power company, as the V2G investment (e.g., developing V2G-capable chargers) always vastly surpassed the benefit.

2.3. Research gaps and aims

As discussed above, numerous efforts have been made to address the charging infrastructure location problem using a variety of models and datasets. Recently, emerging big data sources, such as GPS trajectory data, offer a promising method for estimating charging demand, which is a crucial input for charging infrastructure location models. In terms of operation, smart charging strategies, including TOU tariff and V2G, have garnered increasing attention. Previous studies have primarily focused on the development of these smart charging strategies, gauging user willingness to adopt them, and assessing their potential impacts.

For electric carsharing systems, infrastructure planning and operation are not only essential components but are also interconnected. However, previous studies on SEVs have typically treated infrastructure planning and charging strategy design separately. Consequently, these approaches have not been able to effectively plan or manage the electric carsharing system from both the users' and operators' perspectives. To address this limitation, this paper developed a data-driven micro-simulation joint model of infrastructure planning and operation for SEVs. Specifically, the proposed model can simultaneously help SEV operators select the location of rental stations, deploy charging facilities, and assess the potential impacts of smart charging strategies. Furthermore, the proposed model is data-driven: real-world SEV trip and charging information from the SEV trajectory data is used to develop the model. Such real-world datasets are expected to more accurately quantify infrastructural demand and define behavioral rules in micro-simulation models, so that the data-driven model would be more helpful for the deployment and operation of stations with smart strategies applied.

3. Study area and datasets

3.1. Study Area: Beijing

As the capital, political, and economic center of China, Beijing had put intensive efforts into transportation electrification through policy-making and charging infrastructure deployment. One of the most typical policies to stimulate New Energy Vehicle (NEV) sales is the license plate lottery policy: for example, the number of NEV license plates issued each year is 2.33 times that for conventional vehicles [62–64]. Meanwhile, the Beijing government has put considerable investments in the construction of charging facilities. As introduced by Beijing Municipal People's Government [65], the Beijing government constructed 256 thousand chargers by the end of 2021, and would strive to construct more than 700 thousand chargers by 2025. With the supportive policies and rapid development of charging infrastructure, the number of NEV owners reached 389 thousand by the end of 2020 [66]. Meanwhile, EVs were also being introduced into the carsharing system. For example, “Green Go” is one of the SEV startups in Beijing, and it established 50 rental locations operating 1,500 SEVs in 2015 [67]. Subsequently, some conventional carsharing companies (e.g., Shou Qi Group) and major vehicle manufacturers (e.g., BAIC) also joined the electric carsharing system in Beijing. According to a report by the Beijing Daily [68], in total, up to 14 thousand SEVs were operated in Beijing in 2017.

To further reduce carbon emissions and the pressure on the grid, the Beijing government advocates the integration of EVs into smart grid. As one typical smart charging strategy, the TOU tariff has already been widely applied in Beijing. As declared by the State Grid Company, all public chargers in Beijing have adopted a TOU tariff and the electricity price during the off-peak periods is only 40% of that during peak periods, since 2016 [69]. As another smart charging strategy, V2G has received considerable attention and support from the Beijing government [70], but a recent survey by Liu et al. [55] indicated that most of the citizens were not very familiar with V2G, but showed great interested in this technology.

3.2. Data source and analytical framework

The key data source of this study is a one-month GPS trajectory dataset that contained trajectory records of 514 actual SEVs in Beijing during the period from 1st February to 28th February 2019 (see Fig. 1).

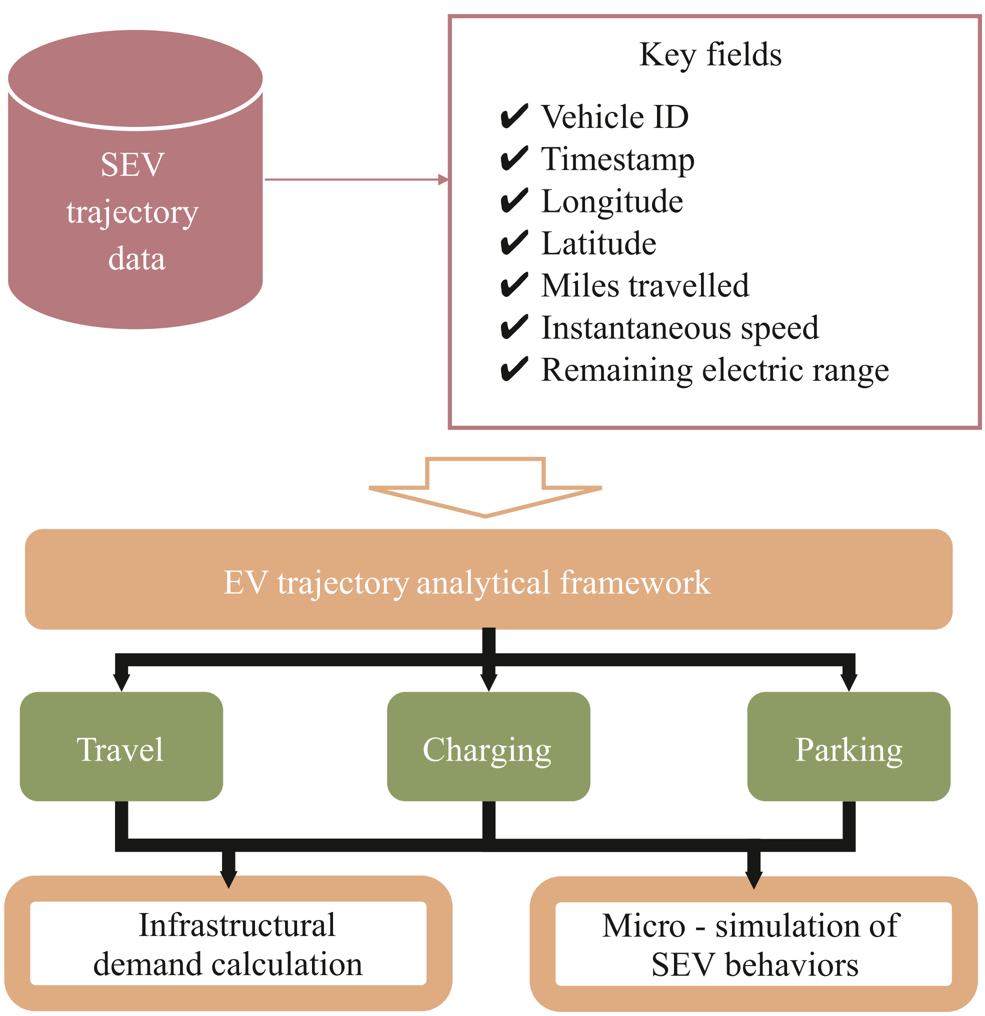

Fig. 1. SEV trajectory dataset and analytical framework.

The dataset was provided by a SEV operating company in Beijing. Its key fields include "unique vehicle ID, longitude, latitude, timestamp, miles traveled, instantaneous speed, state of charge (SOC), and remaining electric range" [37].

We first conducted spatial big data analysis using an EV trajectory data analytical framework proposed by Sun et al. [60] and Yang et al. [37], and then extracted spatiotemporal and behavioral information (e.g, travel, parking, and charging behaviors) of SEV users from the SEV trajectory dataset to quantify infrastructural demand (see Section 4.3) and simulate travel and charging behaviors of SEV users (see Section 4.4).

4. Methodology

To clarify the problem scenario and the framework of the model, we will first provide an overview of the proposed joint optimization model (Section 4.1). Then, we will introduce the methods used to determine the location of rental stations (Section 4.2) and further allocate chargers to the rental stations (Section 4.3). Next, we describe the process of exploring the potential of SEVs for smart charging (i.e., TOU and V2G) through the chargers added (Section 4.4).

4.1. Problem Statement and Model Framework

As depicted in Fig. 2(a), we proposed a data-driven optimization approach, comprising two components: data preprocessing and simulation. The data preprocessing is used to extract parking and charging events from real-world SEV trajectory data, which are used to identify rental stations through a clustering algorithm. Further, the parking and charging events, as well as the added rental stations, are used as inputs for the simulation. Specifically, the simulation consists of two sub-stages: 1) allocating chargers to each rental station, subject to the constraint of maintaining a specific service level at the rental station (for instance, charging services should not be delayed for more than 10 min); 2) assessing the impact of smart charging strategies. More specifically, as illustrated in Fig. 2(b), with the model, we could determine location of rental stations and further allocate chargers with different power rates (or charging speeds). In particular, we set up three typical scenarios (i.e., slow chargers only, fast chargers only, and both slow and fast chargers) in which we explore how smart strategies (i.e., TOU and V2G) could influence SEV users' behavior and further electricity demand and cost. The TOU strategy incentivizes SEVs to charge during off-peak periods, while

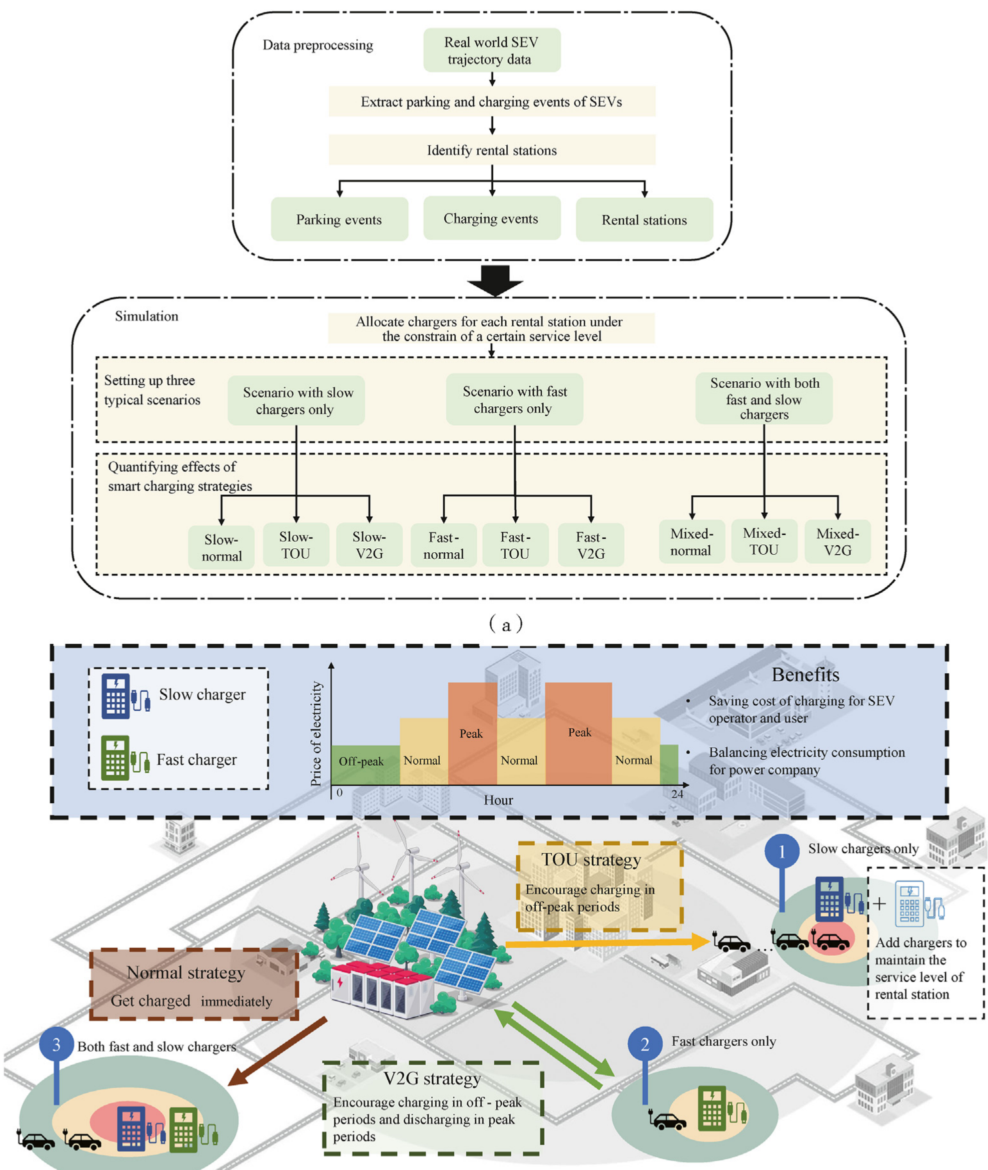

Fig. 2. Problem statement and model framework. (a) Model framework. (b) Problem illustration.

the V2G strategy encourages SEVs to charge during off-peak periods and discharge during peak periods. The effectiveness of these two strategies is evaluated by comparing cost savings and energy consumption distribution in scenarios with and without the smart charging strategies.

4.2. Determining location of rental station

Optimization model presents a typical approach to deploying transport facilities (including rental stations and EV chargers) usually with one or more objectives and several constraints, as we reviewed in Section 2.1. However, this paper used another classical approach, namely Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, to locate rental stations, and DBSCAN has also been widely used to deploy transport facilities, including charging facilities [37,71–73]. Specifically, as shown in Fig. 3, we first identified those areas with more parking events (which can be extracted from the SEV dataset) as candidate locations for rental stations through the DBSCAN algorithm (see Appendix 1.1 in Supplementary Materials). It is worth noting that DBSCAN may generate clusters that are much larger than parking lots in the real world. In response, we further check the size of candidates and split some of those candidates whose size is unrealistically large with the road network data and the data on parking lots' capacity, resulting in a final set of rental stations (see Appendix 1.2 in supplementary materials).

4.3. The approach to determining the number of chargers at a rental station

4.3.1. The approach to allocating chargers

We develop a simulation approach to figuring out the minimum number of chargers needed at each rental station, with a constraint on the minimum level of service to maintain: specifically, for any SEV, its charging service cannot be delayed over a certain time (e.g., 10 min).

The simulation approach has two versions: one is to allocate chargers with a single charging rate (either slow or fast); the other is to allocate chargers with a mixed charging rate (i.e., with both fast and slow chargers at one rental station). The latter version can be updated from the former. Therefore, we will start with an introduction to the former version.

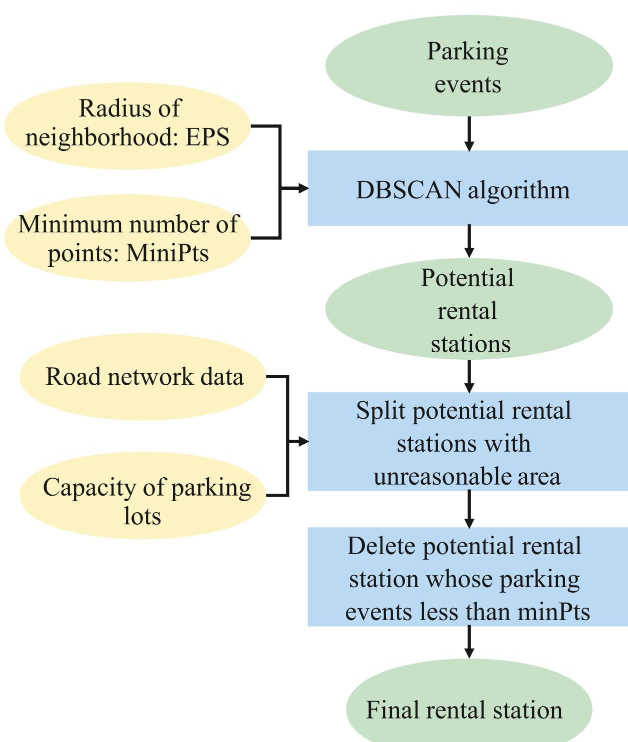

Fig. 3. The flowchart for determining the locations of rental stations.

As shown in Fig. 4, the algorithm starts with the number of chargers at a rental station set to 0, and then simulates the charging procedure with the given number of chargers using an EV queueing model. The model is used to simulate how EVs queue at a rental station for charging when all chargers are occupied (see Section 4.3.2 for a detailed introduction). For each iteration, we can obtain the possible delay time of each SEV caused by queueing. Here, it is defined that a charging event is delayed if the simulated parking time exceeds the real parking time extracted from the EV trajectory dataset. To maintain a certain level of service, it is further defined that all charging events should have no delay or a certain short delay time (e.g., 10 min). Otherwise, we will add one more charger to the rental station in the next iteration, which is expected to reduce the delay time and improve the level of service. It is worth noting that in some special cases, a delay is not avoidable, because the charging time needed to reach the target SOC is longer than the duration of the parking event. In such cases, no more chargers will be added.

For those scenarios where both slow and fast charging posts are needed, we can first figure out the number of fast chargers for each rental station using the algorithm in Fig. 4, and further replace fast chargers with slow ones where needed. Here, we can consider the different needs of service operators when replacing chargers, such as the cost and the level of service to maintain.

4.3.2. The EV queueing model

The EV queueing model simulates how SEVs get connected with chargers, get charged, and may queue for charging when all charging posts are occupied at a rental station, using parking events (extracted from the SEV trajectory dataset) and chargers available (from the algorithm shown in Fig. 4) as inputs. Specifically, the model is composed of six steps (see Fig. 5):

- **Step 1:** Selects SEV i (i is set to 0 when the simulation starts) from the dataset, and checks whether it is parked at a rental station at Time t (t is set to 0 when the simulation starts). If it is parked at a rental station, the algorithm will move to step 2; otherwise, the algorithm will move to step 5;
- **Step 2:** Checks the SOCs and connection status of SEV i. There are four possible cases in which different actions will be taken, as shown in Table 1;
- **Step 3:** Checks whether SEV i needs to get disconnected from the charger. If more than one SEV is queueing at the rental station or SEV i needs to leave the rental station, then it will disconnect with the charger and the algorithm will go to step 5; otherwise, the algorithm will move to step 5 directly;
- **Step 4:** Checks whether any unoccupied chargers are available at the rental station. If yes, SEV i will get charged through one of the unoccupied chargers at random and then the algorithm moves to step 5; otherwise, the algorithm will go to step 5 directly. In the scenario with both slow and fast chargers available, the algorithm will always assign slow ones first. However, if a slow charger cannot meet the charging need of a SEV (for example, a slow charger assigned may lead to a long delay time), then the SEV will choose a fast charger instead and may queue until a fast charger becomes available when all fast chargers are occupied;
- **Step 5:** Checks whether every SEV has been processed at time t. If yes, the algorithm will move to step 6; otherwise, it will continue to process the next SEV ($i = i + 1$) and move to step 1;
- **Step 6:** Checks time t. If t equals the specified end time, the simulation will end; otherwise, the algorithm will move to the next time step ($t = t + \Delta t$), and set the SEV i back to 1.

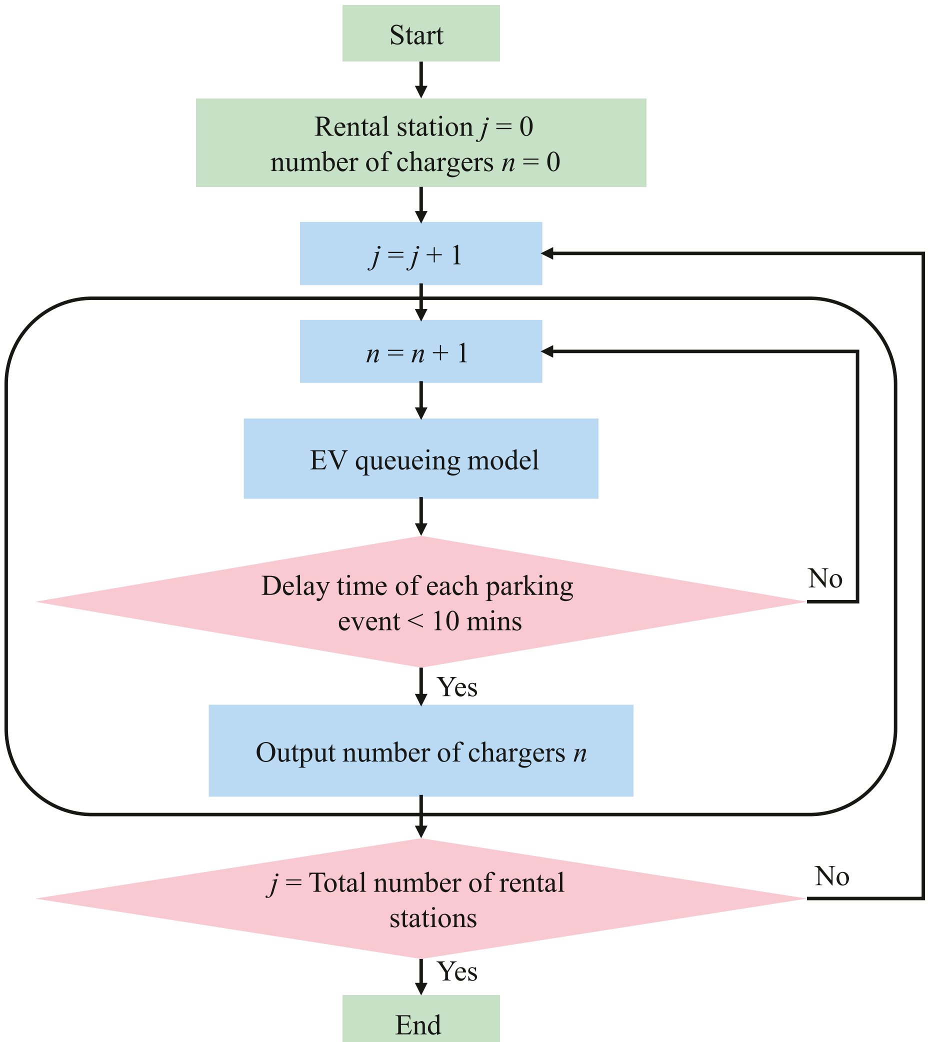

Fig. 4. The flow of allocating chargers to a rental station.

4.4. Smart charging model

After determining the layouts of rental stations and their chargers, we further develop a smart charging model to simulate charging/discharging behaviors of SEV users. The model's inputs include parking events (extracted from the trajectory data), the layout of chargers (see Section 4.3.1), and SEV plug-in time (seeSection 4.3.2). It should be noted that this joint model is developed to simulate smart charging strategies based on the layouts of rental stations and their chargers. This means that the layouts could influence smart charging strategies, but smart charging strategies would not influence the layouts. The model is comprised of eight steps (see Fig. 6):

- **Step 1:** Selects SEV i, and checks whether it is connected with a charger. If yes, the algorithm will move to Step 2; otherwise, it will move to Step 3;
- **Step 2:** Checks whether time t is the point when SEV i needs to get disconnected with the charger. If yes, SEV i will get disconnected, and the algorithm will move to Step 7; otherwise, the algorithm will move to Step 4;
- **Step 3:** Checks whether SEV i should get connected with a specific charger, according to the SEV plug-in time. If yes, SEV i will get connected with the charger, and then the algorithm will move to Step 4; otherwise, the algorithm will move to Step 7;
- **Step 4:** Calculates the remaining plug-in times during peak periods, off-peak periods, and normal periods in the current parking event at time t, based on SEV's plug-in time that records the endpoint when the SEV is connected with the charger. The result will be used to determine whether SEV i will get charged or discharged at time i in Step 6;
- **Step 5:** Checks the current and target SOCs of SEV i in the current parking event, and calculates required charging time and required discharging time, based on Eqs. (1) and (2) respectively;

$$CT(i,t) = \begin{cases} 0, & \text{if } SOC\_T(i,t) \le SOC\_C(i,t) \\ \dfrac{SOC\_T(i,t) - SOC\_C(i,t)}{v(s,t)}, & \text{if } SOC\_T(i,t) > SOC\_C(i,t) \end{cases} \tag{1}$$

$$DT(i,t) = \begin{cases} 0, & \text{if } SOC\_T(i,t) \ge SOC\_C(i,t) \\ \dfrac{SOC\_C(i,t) - SOC\_T(i,t)}{v(i,t)}, & \text{if } SOC\_T(i,t) < SOC\_C(i,t) \end{cases} \tag{2}$$

where i represents SEV i; t is time t; v is the charging speed charger, thus, $v(i,t)$ is the charging speed of the charger connected with SEV i at time t; $DT(i,t)$ is the required discharging time and $CT(i,t)$ is required charging time of SEV i at time t; $SOC\_T(i,t)$ and $SOC\_C(i,t)$ represent the target and

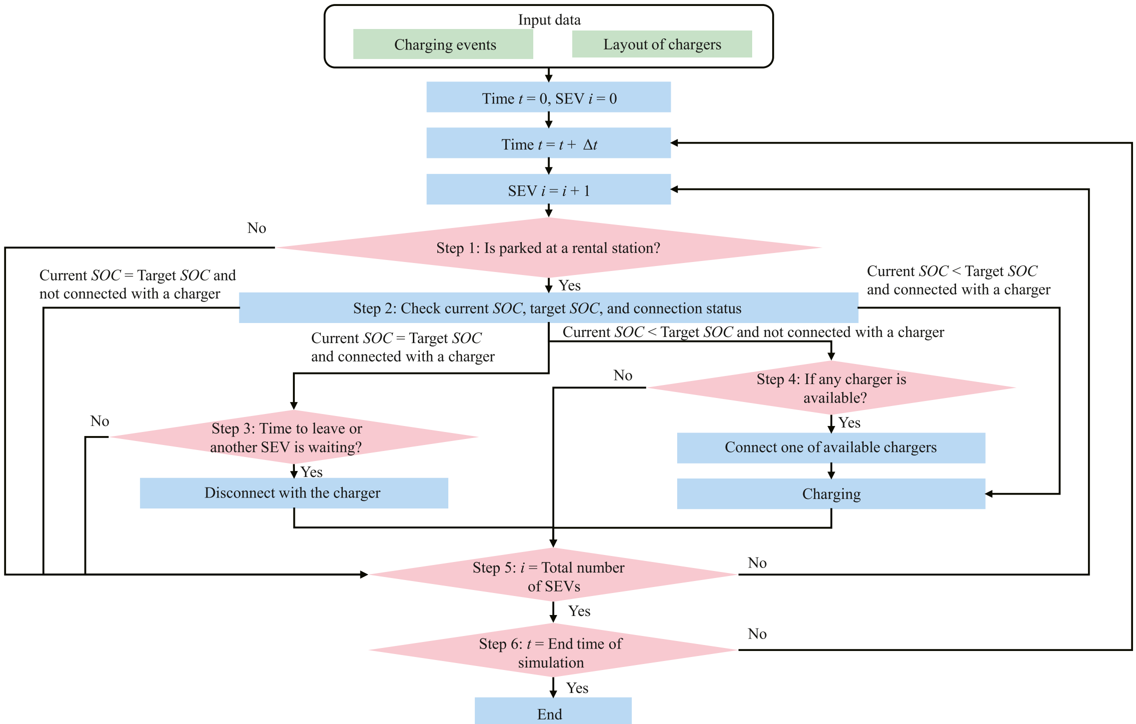

Fig. 5. The framework of the EV queuing model.

Table 1
The Actions to be taken in the four possible cases in Step 2.

	Current *SOC* is equal to the target *SOC*	Current *SOC* is NOT equal to the target *SOC*
SEV is connected with a charger	The algorithm moves to Step 3	SEV *i* continues getting charged and the algorithm moves to Step 5
SEV is NOT connected with a charger	The algorithm moves to Step 5	The algorithm moves to Step 4

current SOCs of SEV i at time t. The results of the calculation will be used to determine whether to charge or discharge SEV i in Step 6.

- **Step 6:** Determine whether to charge or discharge SEV i, under the specific charging strategy (i.e., TOU and V2G). If yes, SEV i will get charged or discharged, and the algorithm will move to Step 7; otherwise, the algorithm will move to Step 7 directly. In this model, we consider two smart charging strategies, TOU and V2G, which will be introduced in Sections 4.3.1 and 4.3.2, respectively;
- **Step 7:** Checks whether i is equal to the total number of SEVs, which means all SEVs have been checked at time t. If not, the algorithm will move to step 8; otherwise, it will continue to process the next SEV ($i = i + 1$) and move to step 1;
- **Step 8:** Checks the time t. If it is the end time of simulation, then the simulation finishes; otherwise, the algorithm will move to the next time step ($t = t + \Delta t$), and set the SEV i to 1.

4.4.1. Time-of-use (TOU) tariff

One of the most used smart charging strategies is the so-called Time-of-Use (TOU) tariff. The TOU's central idea is to apply a higher charging fee during peak periods, so as to discourage EV charging, and apply a lower charging fee during off-peak periods to encourage EV charging [60]. In our model, we divided one day into three period types according to the EV charging demand, namely 1) peak periods with a higher charging demand (and thus a higher charging fee applied); 2) off-peak periods with a lower charging demand (and thus a lower charging fee applied); and 3) normal periods with a normal charging demand (and thus a normal charging fee applied) [60].

We develop specific rules to manage charging behavior of SEVs under different TOU tariffs, with the objective of minimizing the total charging cost: in off-peak, normal, and peak periods, SEVs will get charged based on Eqs. (3)–(5), respectively.

$$TOU\_C(i,t) = \begin{cases} 1, & \text{if } CT(i,t) > 0 \\ 0, & \text{if } CT(i,t) \leq 0 \end{cases} \tag{3}$$

$$TOU\_C(i,t) = \begin{cases} 1, & \text{if } CT(i,t) > RTO(i,t) \\ 0, & \text{if } CT(i,t) \leq RTO(i,t) \end{cases} \tag{4}$$

$$TOU\_C(i,t) = \begin{cases} 1, & \text{if } CT(i,t) > RTO(i,t) + RTN(i,t) \\ 0, & \text{if } CT(i,t) \leq RTO(i,t) + RTN(i,t) \end{cases} \tag{5}$$

where, *TOU_C(i,t)* is a decision variable that determines whether SEV i will get charged at time t under TOU charging strategy: 1 means SEV i will get charged and 0 means will not. *RTO(i,t)* and *RTN(i,t)* are the remaining plug-in times of SEV i at time t in the current parking event during off-peak periods and normal periods, respectively.

4.4.2. Vehicle-to-grid (V2G) charging strategy

In the context of V2G, SEVs could not only manage to get charged with the lowest price (during off-peak periods), but also sell electricity back to the grid when the price is the highest (during peak periods), which can help SEVs to save charging costs (and even bring a profit in some cases). We use Eq. (7) to check whether a SEV in a charging event is able to participate in V2G in a parking event.

$$V(ce) = \begin{cases} 1, & \text{if } CT(i,ce0) < RTO(i,ce0) \text{ and } RTP(i,ce0) > 0 \\ 0, & \text{if } CT(i,ce0) \geq RTO(i,ce0) \text{ or } RTP(i,ce0) = 0 \end{cases} \tag{6}$$

where, *ce* is a charging event, and *V(ce)* is a decision variable: 1 means that SEV will participate in V2G during the charging event *ce*; while

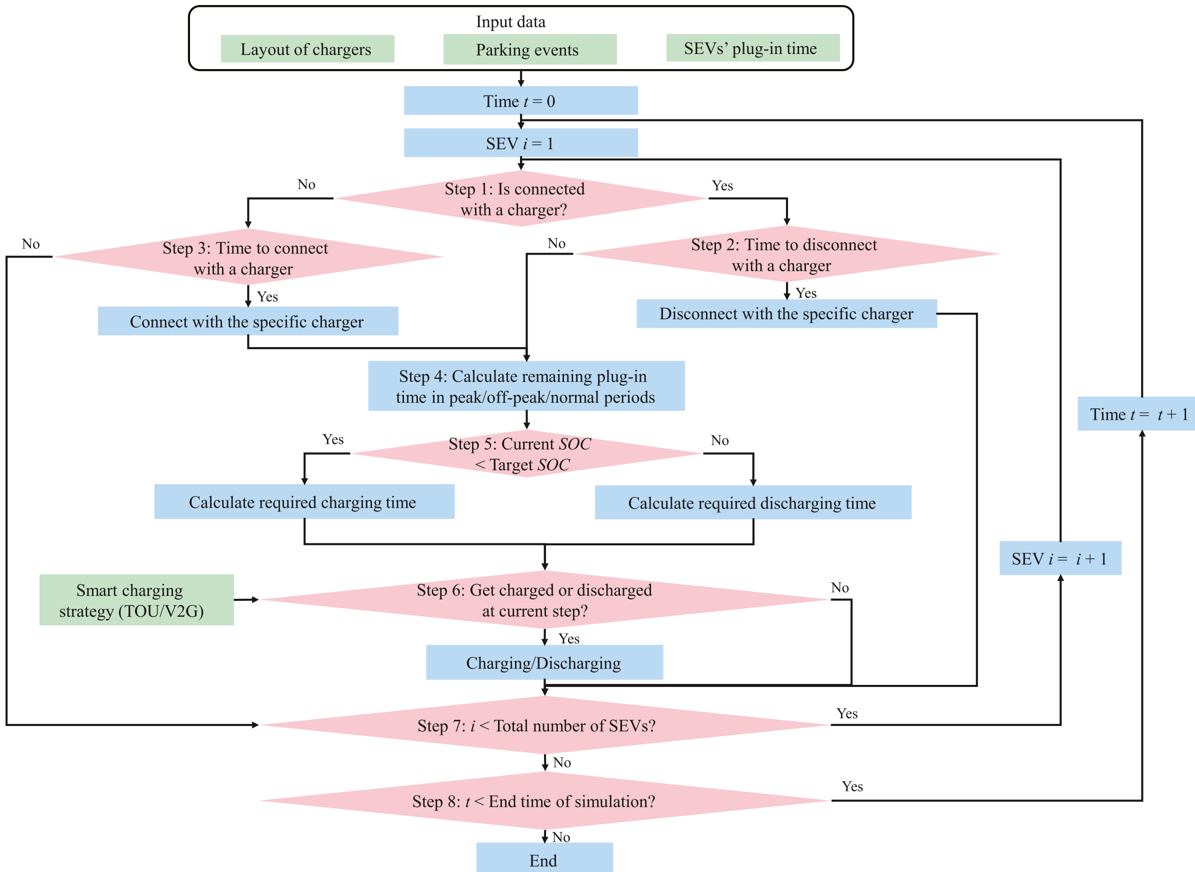

Fig. 6. The framework of the smart charging model.

0 means that it will not. *ce*0 is the start time of charging event *ce*. Thus, *CT*(*i*,*ce*0) denotes the required charging time of SEV *i* in the charging event *ce*, which can be calculated by Eq. (1). *RTO*(*i*,*t*) and *RTP*(*i*,*t*) denote, during the current parking event, the remaining plug-in times during off-peak periods and peak periods of SEV *i* at time *t*. Thus, *RTO*(*i*,*ce*0) and *RTP*(*i*,*ce*0) denote the remaining plug-in times of SEV *i* at the start time of the charging event *ce* during off-peak periods and peak periods, which are also the total plug-in times during off-peak and peak periods of the charging event *ce*.

In those charging events where SEVs participate in V2G, they will get charged during off-peak periods and get discharged during peak periods, so as to make a profit. It is worth noting that we do not consider any charging or discharging behavior during normal periods for charging events where SEVs participate in V2G. This is mainly because the battery degradation cost brought inevitably by V2G offsets the profits partially, which makes the benefits that involve charging or discharging behavior during normal periods negligible and may not even cover its consumption (in the Beijing case, the net profit from selling 1 kWh of electricity is only 0.04 RMB). For those charging events with no V2G involving, SEVs will get charged through the TOU charging strategy (see Section 4.4.1). We use Eqs. (7) and (8) to determine whether a SEV *i* in a charging event participating in V2G will get charged and discharged at a specific time *t* in off-peak periods and peak periods, respectively.

$$V2G\_C(i,t) = \begin{cases} 1, & \text{if } SOC\_C(i,t) < 1 \text{ and } DT(i,t) < RTP(i,t) \\ 0, & \text{if } SOC\_C(i,t) = 1 \text{ or } DT(i,t) \geq RTP(i,t) \end{cases} \tag{7}$$

$$V2G\_D(i,t) = \begin{cases} 1, & \text{if } SOC\_C(i,t) > 0 \text{ and } CT(i,t) < RTO(i,t) \\ 0, & \text{if } SOC\_C(i,t) = 0 \text{ or } CT(i,t) \geq RTO(i,t) \end{cases} \tag{8}$$

where *V2G_C*(*i*,*t*) and *V2G_D*(*i*,*t*) are decision variables that determine whether SEV *i* will get charged and discharged at time *t*: 1 means SEV *i* will and 0 means it will not. As defined as former, *SOC_T*(*i*,*t*) and *SOC_C*(*i*,*t*) represent the target and current SOCs of SEV *i* at time *t*; *DT*(*i*,*t*) is the required discharging time and *CT*(*i*,*t*) is required charging time of SEV *i* at time *t*; *RTO*(*i*,*t*) and *RTP*(*i*,*t*) denote, during the current parking event, the remaining plug-in times during off-peak periods and peak periods of SEV *i* at time *t*.

5. Results

5.1. Scenario description

We set up three groups of scenarios (see Table 2) to explore how different charger rates and charging strategies could influence the

Table 2
"What-if" scenarios.

Scenario group	Scenario type	Charger type	Smart charging strategy
Reference scenario	Ref-slow	Slow	No
	Ref-fast	Fast	No
	Ref-mixed	Mixed	No
TOU scenario	TOU-slow	Slow	TOU
	TOU-fast	Fast	TOU
	TOU-mixed	Mixed	TOU
V2G scenario	V2G-slow	Slow	V2G
	V2G-fast	Fast	V2G
	V2G-mixed	Mixed	V2G

operation of SEVs in Beijing. Specifically, within the Reference Scenario group, we first investigate how different charger types could influence the operation given that no smart charging strategy is applied. Here, we consider two charger types, i.e., slow charger with a power of 7 kW and fast charger with a power of 60 kW. Within the TOU and V2G scenarios, we further explore how TOU and V2G might influence the operation, compared to the Reference scenarios.

5.2. Locations of rental stations

We use the DBSCAN algorithm (see Section 4.2) to determine the locations of rental stations using the SEVs' parking events as inputs that are extracted from the SEV trajectory dataset. Fig. 7(a) shows the spatial distribution of 30,832 SEVs' parking events. It can be found that most parking events occur in the central area of Beijing, with a small portion of them located in the outer districts. Eventually, we generated 195 rental stations in those areas with a high density of parking events (see Fig. 7(b)), covering 16,143 parking events (i.e., 52.36% of the total parking events).

5.3. Results of reference scenario

In terms of quantity of chargers (see Fig. 8), RefSc-slow needs the most chargers (i.e., 244 chargers) to maintain a specific level of service (i.e., none of charging events would be delayed over 10 min), for the lowest charging speed of 7 kW chargers (which is set to 0.117 kWh per minute). In RefSc-fast and RefSc-mixed, 188 (fast chargers) and 192 chargers (53 slow chargers plus 139 fast ones) are needed to meet the same level of service, respectively. For the scenarios, 9 rental stations do not need any chargers, as there are no charging events at the stations. In RefSc-slow, 146 out of 195 rental stations (74.8%) can maintain the specific level of service with only 1 charger, while the proportions in RefSc-fast and RefSc-mixed raise to 94.3% and 93.3%, respectively. This is because these two scenarios have fast chargers, which can get SEVs recharged at a much higher rate and reduce the number of chargers needed. In addition, 14 rental stations in RefSc-slow need over 2 chargers; while no rental stations in Scenario-fast or Scenario-mixed need more than 2 chargers.

As shown in Table 3, the total investment costs in RefSc-slow, RefSc-fast, and RefSc-mixed are about 0.512 million, 7.52 million, and 5.67 million RMB respectively, indicating that RefSc-slow needs the least cost, which is 6.80% and 9.04% of the total costs of RefSc-fast and RefSc-mixed, respectively. However, the charging events in RefSc-slow will be delayed for 4.90 min on average, which is much longer than the delayed times in RefSc-fast and RefSc-mixed (which are both only 0.05 min). This suggests that RefSc-mixed would be more competitive than RefSc-fast, as its cost could be much lower with the same level of service. However, if the SEV operator allows for a lower level of service (e.g., an average delay time of 5 min), RefSc-slow could become a better alternative, as the total cost could be significantly lower. More details on the usage of chargers in RefSc can be found in Appendix 2.1 of the Supplementary Materials.

5.4. Results of TOU (time-of-use) scenario

Within the TOU scenarios (see Table 2 above), we explore how TOU may influence the operation of SEVs, compared to the reference scenarios. The current TOU tariff in Beijing divides 24 h of a day into three different groups with different electricity prices applied. We use the light blue bars in Fig. 9 to show the electricity prices over 24 h. Through the TOU charging strategy, SEV operators can reduce the total charging cost per day by 311.82 RMB (i.e., 19.39%) in TOUSc-slow, 277.5 RMB (i.e., 17.08%) in TOUSc-fast, and 280.67 RMB (i.e., 17.32%) in TOUSc-mixed, on average (see Fig. 9(a)). Fig. 9(b) shows the distribution of saving per charging event. 47.45% of charging events in TOUSc-slow can have a lower charging cost through the TOU charging strategy, while the proportions drop to 35.8% and 37.7% in TOUSc-fast and TOUSc-mixed, respectively. This indicates that TOU could be more effective in those scenarios with more slow chargers, likely because the average plug-in time of charging events in these scenarios (e.g., Scenario-slow) is longer and TOU-based charging events can be scheduled more easily.

Fig. 10 compares the 24-h distributions of charging demands in TOU and Reference scenarios to explore the extent to which TOU may shift charging demand of SEVs. It can be found that in RefSc, the average electricity consumption in peak periods is 914 kWh per day, while it sharply drops to 451 kWh in TOUSc. This suggests that 50.66% of charging demand during peak periods has been shifted towards the normal and off-peak periods when the charging fees are lower. Furthermore, TOU can also influence electricity load during off-peak periods significantly: the amount of electricity consumed per day during off-peak periods in TOUSc is 7.05 times higher than that in RefSc, on average.

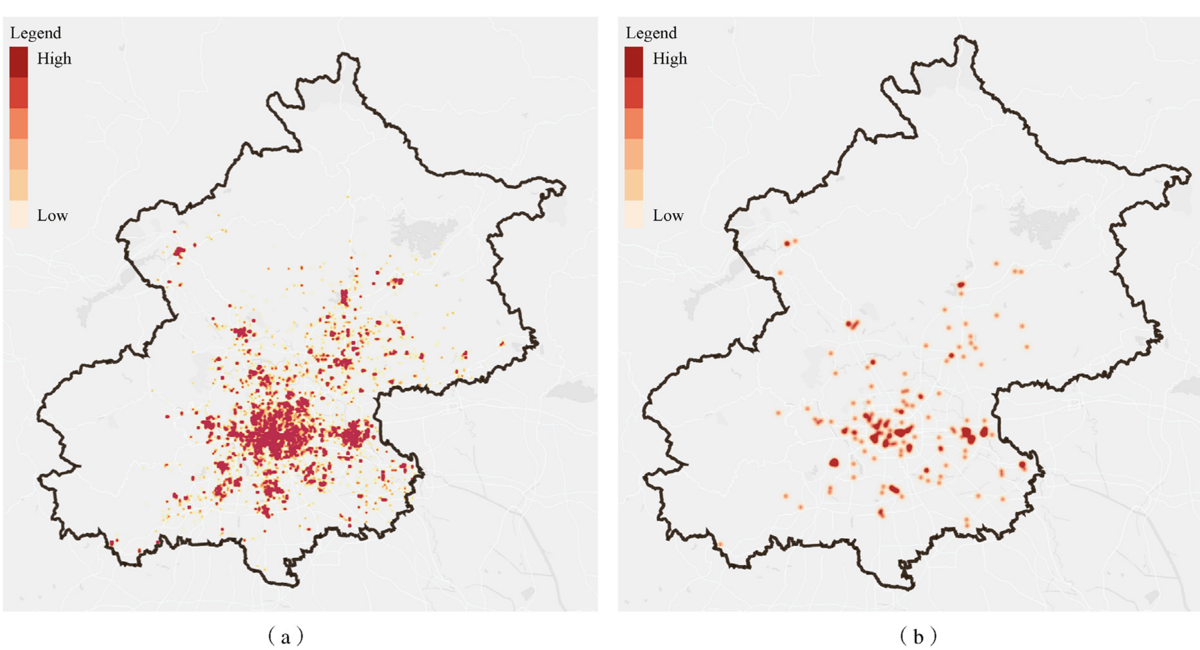

Fig. 7. Spatial distribution of SEVs' parking events and rental stations. (a) SEVs' parking events. (b) SEVs' rental stations.

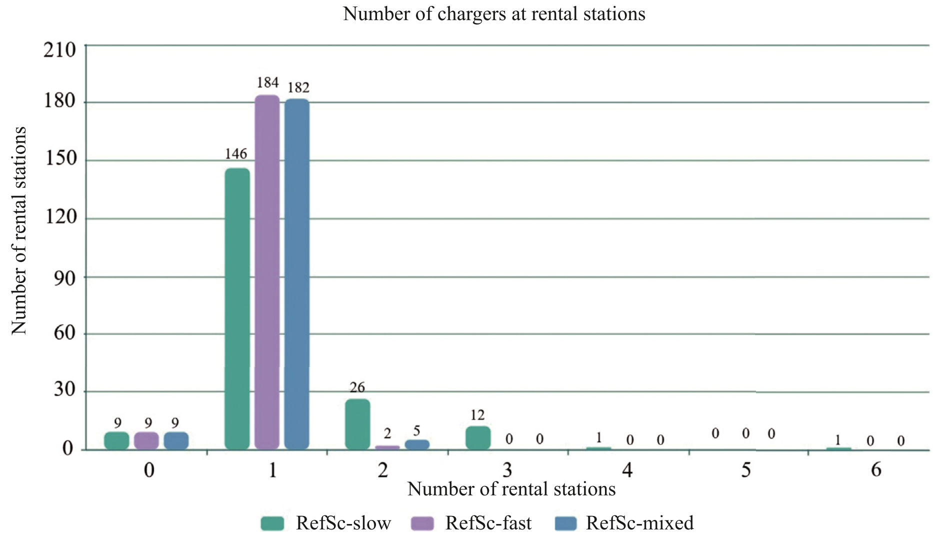

Fig. 8. Number of chargers at rental stations in the group of reference scenarios.

Table 3
Trade-off between investment cost and the level of service in RefSc

Scenario	Total number of chargers	Total cost (RMB)	Average delay time for charging event (Min)
RefSc-slow	244	0.512 million	4.90
RefSc-fast	188	7.52 million	0.05
RefSc-mixed	192	5.666 million	0.05

Note: the prices of slow and fast chargers were set to 2,000 and 40,000 RMB respectively, according to star charger, one of the most used chargers in China [74].

5.5. Results of vehicle-to-grid (V2G) scenario

In quantifying the benefit of V2G, we consider the cost of a SEV battery and the acceleration of battery degradation caused by V2G. Specifically, given that the price of a lithium battery is 720 RMB/kWh (equivalent to 111 dollars/kWh) in China [75], the cost of a SEV's battery of 30.4 kWh is 21,888 RMB. Also, we consider the cost of battery degradation caused by charging/discharging in the estimation, which is set to 0.36 RMB/kWh in V2G scenarios, given that the battery will be retired after 2,000 charging/discharging cycles (the life cycle of Lithium Iron Phosphate battery) [76].

As shown in Fig. 11(a), the charging cost is reduced significantly through V2G, with an average saving of 566 RMB for SEV operators per day. Among the three scenarios, V2GSc-slow has the most significant saving (38.94%), with the total cost decreasing from 1,608 RMB to 982 RMB per day; while the savings in V2GSc-fast and V2GSc-mixed account for 32.72% and 33.25% of total costs, respectively. As shown in Fig. 11(b), the proportions of charging events that can obtain savings in V2GSc and TOUSc are the same, but the average saving per charging event raises to 4.38 RMB in V2GSc-slow, 3.72 RMB in V2GSc-fast, and 3.77 RMB in V2GSc-mixed, respectively. Furthermore, 605 (15.13%), 491 (12.28%), and 489 (12.23%) charging events in V2G-slow, V2G-fast, and V2G-mixed obtain relatively higher savings which can completely cover their charging cost.

Fig. 12 compares electricity consumption by hour in RefSc and V2GSc, so as to evaluate the influence of V2G on the grid. The results suggest that V2G could significantly influence the electricity load. Specifically, in V2GSc, it can be found that several peak hours (i.e., 10:00–15:00 and 18:00–21:00 in V2GSc-slow; 10:00–11:00, 14:00–15:00, and 18:00–21:00 in V2GSc-fast; 10:00–11:00, 13:00–15:00, and 18:00–21:00 in V2GSc-mixed) witness the amount of electricity consumed below 0 kWh, indicating that the electricity stored in the SEVs' battery not only meet users' travel demand, but also can be sold back to the grid for peak shaving. On average, the amounts of electricity sold back to the grid per day per SEV are 2.49 kWh in V2GSc-slow, 1.98 kWh in V2GSc-fast, and 1.99 kWh in V2GSc-mixed, respectively. This indicates that those V2G scenarios with slower chargers would contribute more to the grid, likely because the SEVs in these scenarios tend to have a longer plug-in time. More details on the charging and discharging demands in V2GSc can be found in Appendix 2.2 of the Supplementary Materials.

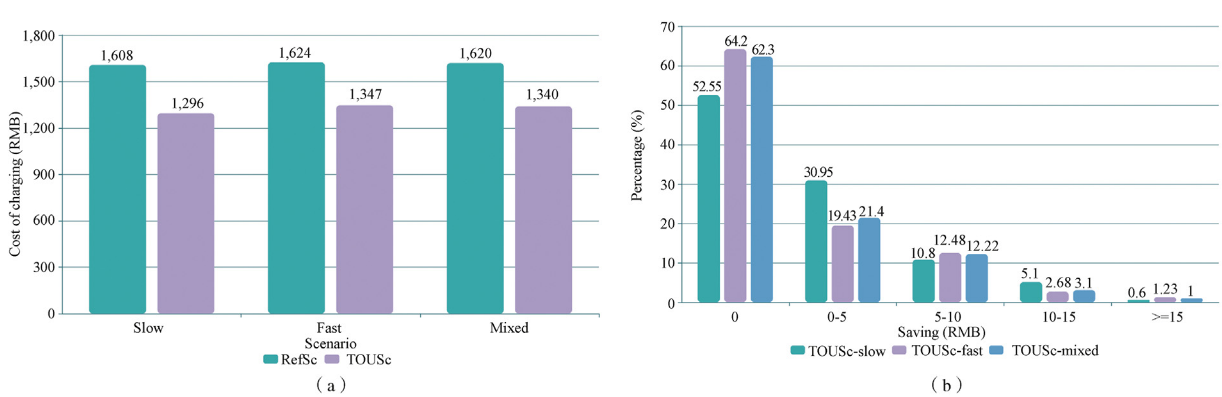

Fig. 9. Charging cost saved through TOU. (a) Total charging cost per day. (b) Savings for charging events.

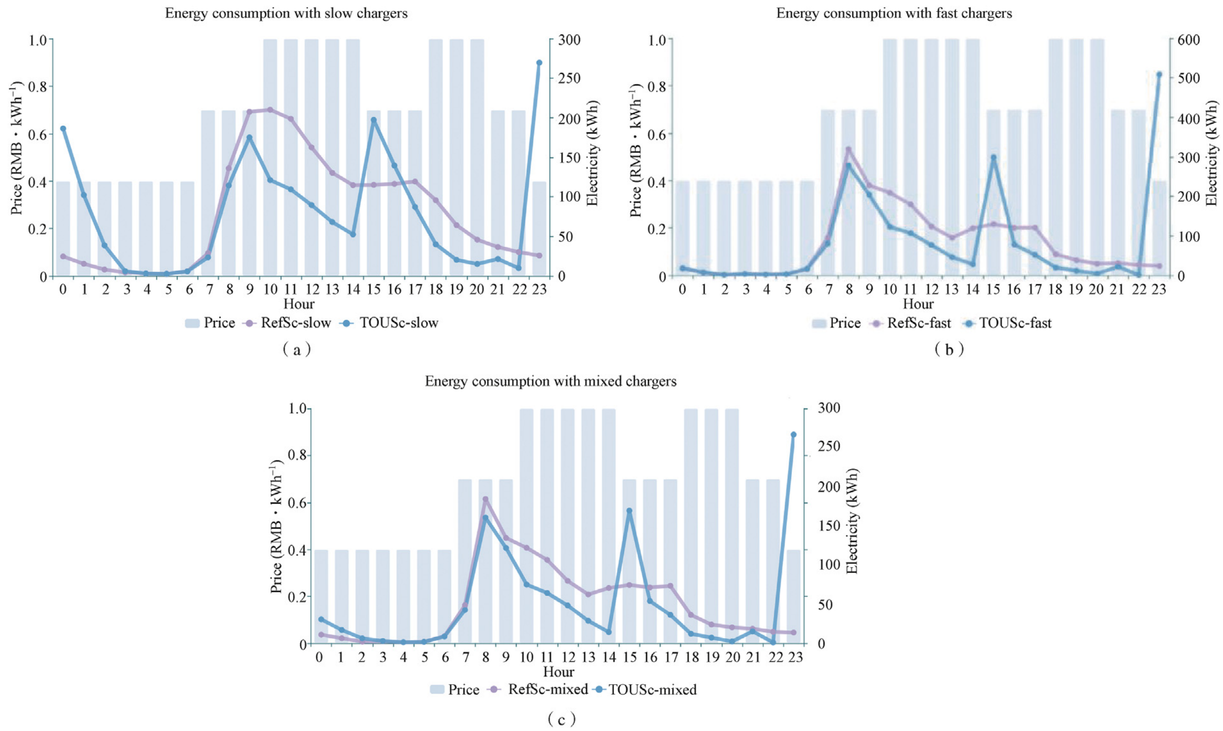

Fig. 10. The TOU's impact on the 24-h distribution of SEVs' charging demand. (a) Scenarios with slow chargers. (b) Scenarios with fast chargers. (c) Scenarios with mixed chargers.

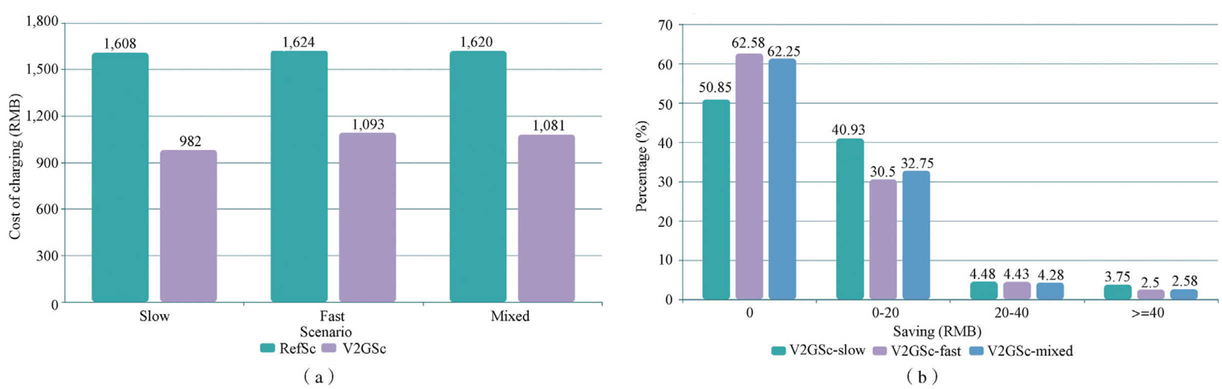

Fig. 11. Charging cost saved through V2G. (a) Total charging cost per day. (b) Saving for charging events.

6. Policy implications and conclusions

6.1. Policy implications

The key findings of "what-if" scenarios are summarized in Table 4, and the findings would be helpful for different EV-related stakeholders, including SEV operators and power grid companies.

For SEV operators, firstly, deploying slow chargers only at rental stations tended to be the most economical option, as this would require the lowest investment and have the most savings obtained through TOU and V2G, compared to the development of fast chargers only or mixed charger types (i.e., both slow and fast chargers). Secondly, operators may need to make a trade-off between the desired level of service and infrastructural investment cost (i.e., different types of chargers used), as different charger types (with different powers or charging speeds) would significantly influence the level of service (see Table 3). In the Beijing scenario, the average delay time of charging events is 4.90 min if only slow chargers are deployed; while the delay time sharply drops to 0.05 min if fast chargers are used. Thirdly, both smart charging strategies (i.e., TOU and V2G) can offer significant cost reductions for SEV operators: on average, 17.93% and 34.97% of the cost could be reduced through TOU and V2G in the Beijing scenario, respectively. In addition, both charging strategies performed best in those scenarios only with slow chargers available. This might be because these scenarios tended to have more chargers, and thus SEVs had a higher probability of getting connected with chargers. Therefore, SEV operators are encouraged to apply these smart charging strategies as far as possible.

For power grid companies, smart charging presents a promising approach to managing the grid system by integrating EVs. Specifically, in the V2G context, each EV becomes a mobile storage device, and can sell electricity back to the grid when needed (especially during the peak periods when the electricity consumption in the residential sector peaks). In our V2G scenarios, the contribution of V2G is substantial. Specifically, on average, the charging demand during peak periods dropped by 1,553.67 kWh; and the discharging demand is 2.15 kWh per day per SEV, accounting for 42.02% of the actual average charging demand. Furthermore,

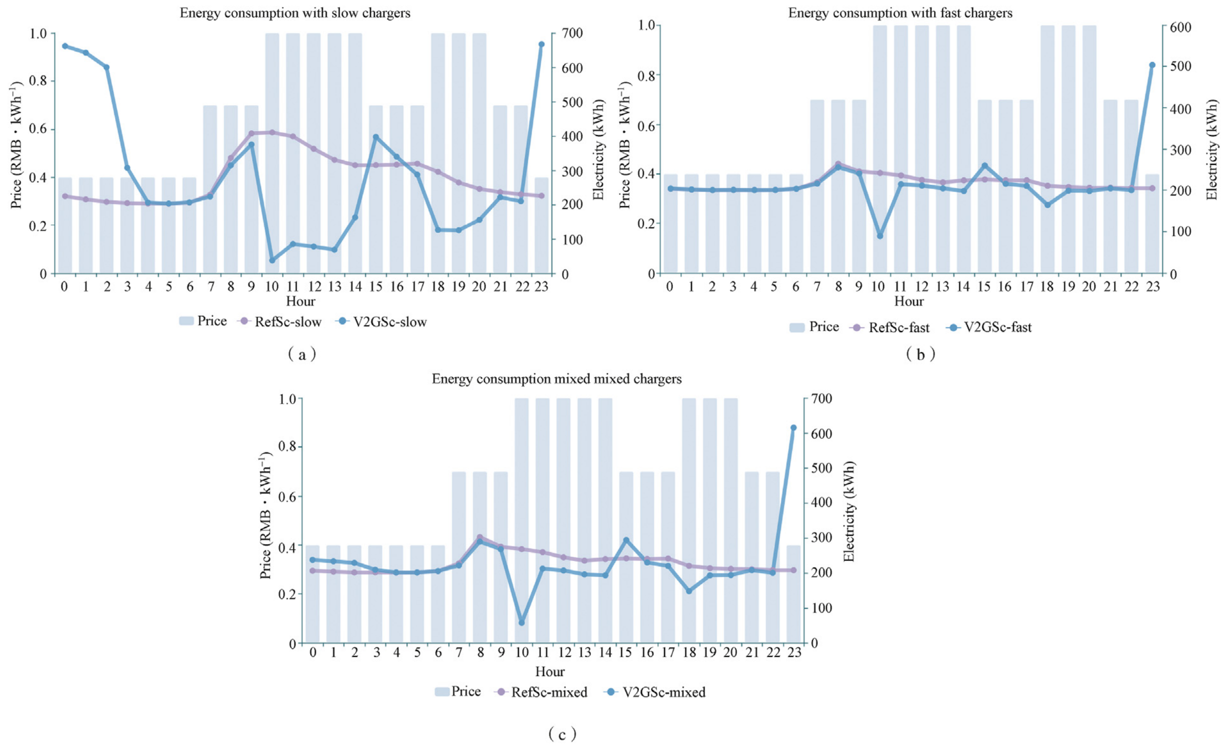

Fig. 12. The V2G's Impact on the 24-h Distribution of SEVs' Charging and Discharging Demands (Note: a negative value for electricity consumption indicates discharging). (a) Scenarios with slow chargers. (b) Scenarios with fast chargers. (c) Scenarios with mixed chargers.

Table 4
A summary of the key results from the "what-if" scenarios.

Scenario	Cost of charger (Million RMB)	Charging fee (RMB·Day^{-1})	Saving (RMB·Day^{-1})	The difference between charging and discharging demands[a] during peak periods (kWh·Day^{-1})
RefSc-slow	0.51	1,608	–	1,022
RefSc-fast	7.52	1,624	–	848
RefSc-mixed	5.67	1,620	–	840
TOUSc-slow	0.51	1,296	312	516
TOUSc-fast	7.52	1,347	277	416
TOUSc-mixed	5.67	1,340	280	405
V2GSc-slow	0.51	982	626	−763
V2GSc-fast	7.52	1,093	531	−605
V2GSc-mixed	5.67	1,081	539	−583

[a] Note: a negative figure means discharging demand is greater than charging demand during these periods.

power grid companies are suggested to design a reasonable V2G pricing strategy, as it would influence EV users' willingness to participate. For example, we find the current pricing strategy in Beijing cannot provide SEV operators with attractive monetary benefits to encourage discharging during normal periods, considering the battery degradation cost. As another smart charging strategy, TOU is also a promising approach to peak load shifting. For example, in our Beijing scenario, we find that 50.66% of charging demand in peak periods has been shifted towards the normal and off-peak periods when the charging fees are lower.

6.2. Conclusion

This paper proposed a data-driven joint model to deploy rental stations and chargers for SEVs and further develop smart charging strategies, including time-of-use (TOU) tariff and vehicle-to-grid (V2G). We consider three infrastructure planning scenarios, in which only fast chargers, only slow chargers, and mixed fast and slow chargers can be installed at rental stations. Key findings are summarized as follows: first, the level of service and the total cost vary across scenarios. Among the three scenarios, the mixed one seems to be the most suitable, because it can maintain the same level of service as the scenario with only fast chargers deployed, but at a lower cost. Second, on average, 59.68% of charging events can be rescheduled to make use of the TOU charging strategy. Consequently, the total charging cost decreases by 17.93% and 50.66% of charging demand during peak periods can be shifted to off-peak and normal periods. Third, the V2G strategy can bring even more remarkable benefits than the TOU strategy. Specifically, the total cost could decrease by 34.97% which is almost twice the cost reduction with TOU. Furthermore, discharging events occur most of the time in peak periods (accounting for 79.12%), and thus would potentially help relieve pressure on the grid load.

The future work will be focused on the two aspects below: first, 52.36% of parking events in the current scenario do not have charging events associated, indicating that these parked SEVs could also get recharged, for example, through more chargers deployed or introducing autonomous vehicles into carsharing system. Specifically, we could further explore the potential of autonomous SEVs which could automatically drive to rental stations with chargers available and get recharged by themselves. Second, the micro-simulation approach could be further improved by considering SEV users' heterogeneous preferences and needs. Different SEV users might have different preferences towards charging cost and time, which might vary across activity types (e.g., shopping and leisure) that they would perform. Such detailed behavioral rules could be incorporated into the micro-simulation approach, so as to improve model realism.

Data availability statement

The data that has been used is confidential.

CRediT authorship contribution statement

Junbei Liu: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Xiong Yang:** Writing – review & editing, Validation, Methodology. **Chengxiang Zhuge:** Methodology, Conceptualization, Funding acquisition, Validation, Writing – review & editing.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.geits.2024.100168.

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