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Day-ahead Electric Vehicle Charging Behavior Forecasting and Schedulable Capacity Calculation for Electric Vehicle Parking Lot

Maosheng Xu^a, Shan Gao^{a,*}, Junyi Zheng^{a,b}, Xueliang Huang^a, Chuanshen Wu^c

^aSchool of Electrical Engineering, Southeast University, Xuanwu District, Nanjing 210096, China

^bWanbang Digital Energy Co., Ltd., Wujin District, Changzhou 213100, China

^cSchool of Engineering, Cardiff University, Cardiff, Wales CF24 3AA, United Kingdom

*Corresponding author. (Shan Gao)

E-mail address: shangao@seu.edu.cn

Postal address: Sipailou No.2, Nanjing, Jiangsu, China

Abstract

The Electric Vehicle Parking Lot (EVPL) aims to address the growing demand for EV charging infrastructure. EVs connected to EVPLs have extended access times compared to those at public charging stations. Consequently, EVPL owners can aggregate the schedulable capacity of connected EVs to participate in day-ahead and ancillary service markets, thereby gaining economic benefits. However, achieving this objective is hindered by the lack of accurate day-ahead forecasts of EV charging behavior. To address this issue, this paper introduces a novel day-ahead forecasting method for EV charging behavior at EVPLs, alongside a strategy for calculating EV schedulable capacity based on these forecasts. Unlike existing methods, this paper presents a day-ahead time-of-use clustering forecasting strategy, which provides more detailed and accurate predictions of EV charging behavior, eliminating the need for numerous assumptions during schedulable capacity calculations. The study demonstrates that the proposed method, validated using actual historical data, enables precise forecasting of EV charging behavior. Furthermore, the proposed day-ahead schedulable capacity calculation strategy is shown to be both effective and practical.

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Keywords: Electric vehicle; day-ahead forecasting; charging behavior; schedulable capacity; electric vehicle parking lot

1. Introduction

Nomenclature

Indices

N	Number of EV access
t	Index of time slot
n	Index of EV
i	Index of clustering input data
m	Index of TOU time period

Parameters

t_n^a	EV_n access time
t_n^d	EV_n departure time
t_n^{ad}	EV_n access duration
S_{n,t_n^a}	SoC of EV_n at t_n^a
S_{n,t_n^d}	SoC of EV_n at t_n^d
S_n^{ad}	$S_{n,t_n^d} - S_{n,t_n^a}$
U	Clustering input dataset
C_m	Typical set of EVCB in m -th period

A_n	EVSFD of EV_n
λ_t	Day-ahead electricity price at time t
p_n^{max}	Maximum power of EV_n
p_n^{min}	Minimum power of EV_n
C_n	Battery capacity of EV_n
η_n^{ch}	Charging efficiency of EV_n
η_n^{dis}	Discharge efficiency of EV_n
t^{ad}	Access duration
$p_{n,t}^{sc}$	SC of EV_n at time t
$p_{n,t}^{sc,up}$	Upper boundary of EV_n SC at time t
$p_{n,t}^{sc,down}$	Lower boundary of EV_n SC at time t
<i>Decision variables</i>	
$p_{n,t}$	Decision variable, power of EV_n at time t

With the increasing demand for energy savings and emission reductions, the adoption of Electric Vehicles (EVs) has experienced rapid growth due to their environmentally friendly characteristics [1,2]. However, the uncontrolled access of a large number of EVs has posed significant challenges for the electrical grid, including pronounced load fluctuations and operational security issues [3,4]. To address these challenges, Vehicle-to-Grid (V2G) technology has been proposed and continuously improved. Integrating numerous EVs into the electricity market through V2G technology provides the grid with substantial schedulable resources [5,6].

In recent years, the concept of Electric Vehicle Parking Lots (EVPLs) has emerged to meet the growing charging needs of EVs [7]. EVs connected to EVPLs typically exhibit longer access durations compared to those at public charging stations, thereby offering greater V2G potential. Consequently, EVPL owners can aggregate the schedulable capacities of connected EVs to participate in day-ahead markets and ancillary services market, thus deriving economic benefits.

Participation in electricity markets necessitates that EVPLs estimate the Electric Vehicle Schedulable Capacity (EVSC) in advance. For instance, forecasting Electric Vehicle Charging Behavior (EVCB) is essential for participating in the day-ahead market and for devising day-ahead charging plans based on projected tariffs [8]. Similarly, when engaging in the ancillary services market, it is imperative to report the planned curve and the corresponding EVSC based on this curve in advance [9,10]. Accurate forecasting of EVCB is thus a critical prerequisite for calculating EVSC. Therefore, precise prediction of EVCB forms the cornerstone for the effective participation of EVPLs in the electricity market, which is of paramount importance for the application and advancement of V2G technology [11].

Previous research related to EV forecasting can be divided into two main approaches.

The first is the model-driven approach, with the Monte Carlo sampling method based on probability distribution functions being the most prominent [12,13,14]. This method fits a probability density function based on historical data and samples the time distribution of EV access to charging and the distribution of miles traveled for forecasting using Monte Carlo and other methods. However, actual charging scenarios are complex, and this method often makes assumptions about EV charging targets and duration parameters, making it difficult to ensure forecasting accuracy [13,15]. Moreover, the method requires assumptions about the number of accessing EVs for day-ahead regional forecasting, but the number of EVs accessing EVPLs daily is influenced by factors such as climate, date, and owner willingness, leading to high application limitations. Some methods also consider the coupled characteristics of EVs, the traffic road network, and the distribution network, using mathematical methods such as Markov chains and travel chains to forecast the spatial and temporal load distribution of EVs [16,17,18,19]. While suitable for cases with insufficient historical data, these methods forecast the temporal and spatial distribution load under disordered charging conditions, making them unsuitable for V2G and EVSC calculation [20].

The second approach is the data-driven forecasting method. Unlike model-driven methods, these do not require a large number of variable parameters. The most dominant data-driven methods are based on machine learning algorithms [21,22,23,24,25]. These methods focus on relevant factors affecting regional EV charging load profiles, such as time, geographic location, and traffic conditions, and use algorithms to uncover the mapping relationships

between these factors and the load profile. These methods excel at fitting non-linear relationships [26]. However, existing data-driven forecasting methods have limited applications. They can only calculate load profiles for EVs charging daily in a disorderly manner or according to a fixed pattern, making it difficult for EVPL owners to base V2G plans on these forecasts. Consequently, these load profiles can only serve as references for dispatching other power resources, making it challenging to support EVPL participation in day-ahead, real-time, and ancillary services markets.

Building on existing research, to achieve accurate day-ahead EVCB forecasting and use the results for EVSC calculation and V2G, it is necessary to comprehensively address the shortcomings of the aforementioned methods and propose corresponding solutions. Firstly, EVCB needs to be modeled to analyze the behavior of EVs that may provide SC, and the forecasting target must be determined accordingly. Given that model-driven forecasting methods are limited by numerous ideal assumptions, a data-driven approach will primarily be considered for forecasting. In this approach, the forecasting target will be the EVCB rather than the load profile. Specifically, considering the significant differences in EVCB at various times within the same day, a Time-of-Use (TOU) forecasting strategy will be adopted. This strategy involves exploring EV access patterns and EVCB characteristics during different time periods based on historical data. Subsequently, machine learning, clustering, and grouping algorithms will be used to establish the EVCB forecasting model. Finally, the day-ahead EVCB forecasting process method will be established.

Based on the EVCB forecasting results, the calculation of EVSC can then be discussed. Conventional approaches apply probability functions to simulate the distribution of EV users' driving behavior and calculate EVSC based on battery physical constraints [27,28]. In addition to probabilistic models, some methods calculate EVSC based on the State of Charge (SoC) of the EV battery [29,30]. These methods often require a high number of parameter assumptions due to the lack of EVCB data [31]. These assumptions are reasonable for the household EVs. However, they do not apply to the EVPL scenario. As demonstrated in the examples and data provided in the appendix of this paper, the connection and disconnection times of EVs in EVPL, as well as their target SoCs, vary differently, exhibiting a high degree of variability. Previous methods for calculating EVSC based on the aforementioned assumptions fail to account for the characteristics of different EVCB and lack a corresponding day-ahead charging behavior forecasting method, rendering them almost inapplicable to the calculation of day-ahead schedulable capacity in EVPL scenarios.

To address these issues, this study first conducts a classification and analysis of different types of EVCBs in EVPL and constructs corresponding EV Scheduling Feasible Domain (EVSFD), considering EV energy demand and physical constraints. Subsequently, based on the proposed novel and accurate day-ahead EVCB forecasting method, EVPL participation in the day-ahead energy market within the EVSFD is enabled. Finally, EVPLs calculate the EVSC based on the day-ahead scheduling plan.

Based on the above discussion, this paper proposes methods for day-ahead electric vehicle charging behavior forecasting and schedulable capacity calculation for EV parking lot. The proposed method supports EVPL participation in V2G. The main contributions of this paper are:

- 1) A day-ahead TOU forecasting method for EVCB is proposed, considering the significant variations in EVCB at different time periods. To achieve accurate day-ahead estimation of EVCB for EVPL, neural network and K-Means++ clustering models based on historical data are established, minimizing the need for extensive assumptions.
- 2) A classification and analysis of EVCB within EVPL, combined with the physical constraints of EV charging and discharging, to construct EVSFD. The day-ahead planning curve for EVPL participation in the day-ahead energy market is developed based on the EVSFD and EVCB forecasting result.
- 3) Based on the day-ahead planning curve and EVSFD, a method for calculating the EVSC of EVPL is proposed.

The paper is organized as follows: Section 2 constructs the EVCB model. Section 3 describes the EVCB day-ahead forecasting method. The EVSC calculation strategy is introduced in Section 4. Case studies are described in Section 5. The conclusion is summarized in Section 6.

2. EV charging behavior model

The charging modes of EVs can be classified into two primary categories: fast charging and slow charging. Due to capacity constraints in the distribution grid, EVPLs typically install a large number of lower-power, slow-charging devices. EVs utilizing slow charging can remain connected for extended periods, making them suitable for participating in V2G interactions. Conversely, even if a small number of fast-charging devices are deployed, EVs in fast-charge mode require rapid energy replenishment, charge at maximum power, and result in uncontrollable charging loads, thereby eliminating their potential to provide schedulable capacity. Consequently, this paper focuses exclusively on modeling EVs in slow charging mode with extended charging durations.

EVs are considered to be enrolled in EVPL when they are accessed. For the EVPL owner, it would like to get the time and SoC of EV access as well as the time and expected SoC of pull-off in order to develop a charging plan for the EV. Therefore, the EVCB for access n -th EV can be modelled as EV_n :

$$EV_n = \{t_n^a, t_n^{ad}, S_{n,t_n^a}, S_{n,t_n^d}\} \quad (2)$$

$$t_n^{ad} = t_n^d - t_n^a; S_{n,t} = S_{n,t_n^a}, t = t_n^a; S_{n,t} \geq S_{n,t_n^d}, t = t_n^d \quad (3)$$

For EVPL, achieving accurate day-ahead forecasting of the of access number N , t_n^a , t_n^{ad} , S_{n,t_n^a} , S_{n,t_n^d} parameters for each EV are a prerequisite for the development of the day-ahead charging plan as well as for enabling day-ahead calculation of the EVSC.

3. Charging behavior day-ahead forecasting method

3.1. Overview

The proposed methodology for forecasting EVCB is structured into the following main components:

- A. Day-ahead EV Access Number TOU Forecasting Model.** This model, based on neural networks, leverages the mapping relationship between the number of EVs accessing the EVPL and various relevant known data. It maximizes the utilization of this relationship while accounting for the impact of EVCB uncertainty on the forecasting outcomes.
- B. Construction of a Typical EVCB Set Using the TOU Clustering Method.** A clustering input dataset is created from historical EVCB data, and the K-Means++ clustering algorithm is employed to perform temporal clustering. This process identifies a typical set of EVCB, enabling the determination of the EVCB distribution for each time period.
- C. Day-ahead EVCB Forecasting.** Utilizing the day-ahead forecast of EV access numbers and the typical EVCB set, the EVPL can conduct precise day-ahead EVCB forecasting.

The overall forecasting methodology flowchart is shown as Fig.1:

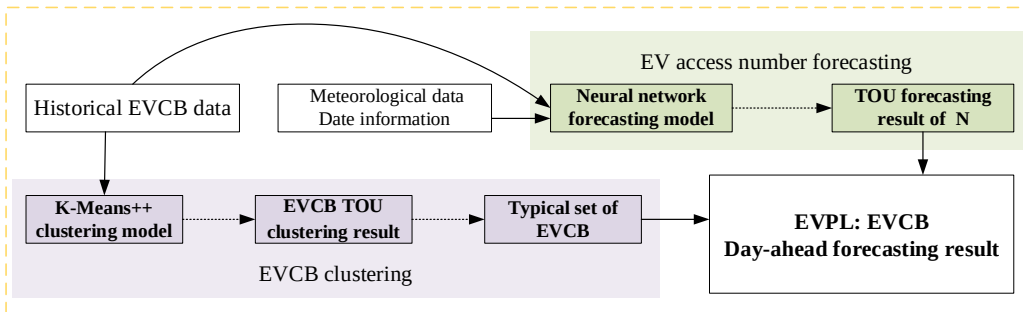


Fig. 1. Overall forecasting methodology flowchart.

3.2. Forecasting model for the number of EV access

The number of EV access for EVPL is closely related to the time period in which they occur. Therefore, the proposed method divides the day into 24 one-hour time periods. The EV is classified into the corresponding time period based on the access time t_n^a . Before the forecast day, the number of EVs access for each of the 24 time periods is forecasted.

Neural network models are commonly used in the field of forecasting and can help to account for the uncertainty of EVCB. This subsection presents a neural-network based method for day-ahead TOU forecasting of the EV accesses number, and provides detailed information on the inputs and outputs of the model. Additionally, the ADMM method is introduced as the improvement to the conventional gradient descent method for training the neural network. This helps to avoid the model from getting stuck in unfavourable results such as local optima.

3.2.1. Day-ahead TOU forecasting model

The accessed EVs number in EVPL is linked to both the date type and a range of user behaviors. To dig the impact of various uncertainties on EV access, neural network is employed to extract information from known data [32]. The data utilized in this study is presented in the following list: the day of the week the forecast date falls on (Monday to Sunday), whether it is a holiday or not, the weather conditions (sunny, cloudy, rainy, or snowy), average temperatures, and the pattern of change in the number of EV accesses over the past few days for the forecast period.

The neural network model proposed in the above discussion is structured as shown in Fig.2:

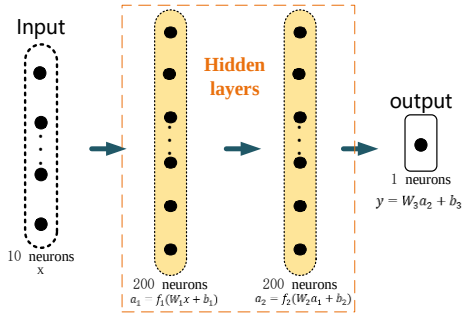


Fig. 2. Neural network model.

The input of the neural network is x and the output is y . a_1 and a_2 are the outputs of hidden layer 1 and hidden layer 2 respectively. Function f_1 and f_2 are the activation function of hidden layer 1 and hidden layer 2 respectively. W_1 and W_2 are the weight parameters of hidden layer 1 and hidden layer 2 respectively, b_1 and b_2 are the bias parameters of hidden layer 1 and hidden layer 2 respectively. The output y is the forecasting result of EV access number. The formula for calculating y is given in (4).

$$y = W_3f_2(W_2f_1(z_1 = W_1x + b_1) + b_2) + b_3 \quad (4)$$

3.2.2. Model training based on ADMM

Conventional methods for training neural networks, such as stochastic gradient descent, are susceptible to issues like vanishing gradients and the lack of global convergence [33]. To mitigate these challenges, this subsection employs the Alternating Direction Method of Multipliers (ADMM) algorithm for training the forecasting model [32,34]. This approach enhances the model's robustness and ensures more reliable convergence.

The model training problem can be expressed as following:

$$\min_{W_l, b_l, z_l, a_l} F(\mathbf{W}, \mathbf{b}, \mathbf{z}, \mathbf{a}) = L(z_3; y) + \sum_{l=1}^3 R_l(W_l) \quad (5)$$

$$\text{s.t. } z_1 = W_1a_0 + b_1, a_1 = f_1(z_1); z_2 = W_2a_1 + b_2, a_2 = f_2(z_2); z_3 = W_3a_2 + b_3 \quad (6)$$

where $L(z_3; y) = \frac{1}{n} \sum_{i=1}^n (z_3^i - y^i)^2$ is the loss risk function of the last layer, and $R_l(W_l)$ is the regularisation term of the l -th layer. both $L(z_3; y)$ and $R_l(W_l)$ are continuous convex functions.

Obviously, the problem is difficult to be solved directly due to the inclusion of many constraint terms, which makes it difficult to obtain the optimal model parameters. In order to simplify the problem-solving process, this method is supplemented with an ℓ_2 penalty function to reduce some of the constraints. Finally, the augmented Lagrange functional form of the problem is written as:

$$L_\rho(\mathbf{W}, \mathbf{b}, \mathbf{z}, \mathbf{a}, u) = L(z_3; y) + \sum_{l=1}^3 R_l(W_l) + \left(\frac{1}{2}v\right) \sum_{l=1}^2 (\|z_l - W_l a_{l-1} - b_l\|_2^2 + \|a_l - f_l(z_l)\|_2^2) + u^T (z_3 - W_3 a_2 - b_3) + \frac{\rho}{2} (\|z_3 - W_3 a_2 - b_3\|_2^2). \quad (7)$$

where v is a tuning parameter and satisfies the value condition of $v > 0$. u is a dyadic variable and ρ is a hyperparameter required by the ADMM algorithm and always satisfies the limiting value condition of $\rho > 0$.

The model training process involves updating parameters through multiple reciprocal iterations. The model parameters of each neural network layer are updated sequentially and then continued from back to front. The effectiveness and convergence of this training method are demonstrated in [34] and [35].

3.3. EVCB clustering method

To discern patterns in EVCB, this subsection employs the K-Means++ algorithm to cluster historical EVCB data. The clusters obtained from this process are then utilized to form a representative set of typical EVCB profiles.

3.3.1. Cluster preparation

The clustering input data U is based on the $t_i^a, t_i^d, S_{i,t_i^a}, S_{i,t_i^d}$ parameters of the EV_i model. The i -th historical clustering input data is represented by the feature vector $\mathbf{EV}_i$.

$$\mathbf{EV}_i = [t_i^a, t_i^{ad}, S_{i,t_i^a}, S_{i,t_i^d}]. \quad (8)$$

Each recorded historical EVCB data can form a piece of clustered input data $\mathbf{EV}_i$. Clustering all historical data directly is difficult. To simplify the process and improve clustering resolution, the day is divided into 24 hourly time periods. EVs accessed at different time periods exhibit a large disparity in EVCB. Therefore, this method adopts the processing idea of TOU clustering.

The proposed method first divides the EVCB into corresponding time periods based on the access time t_i^a of the EV, forming a total of 24 time periods in the clustered input dataset. The EVCB dataset is clustered separately for each time period to obtain the clustering centre. Based on the clustering result, a typical EVCB set is formed.

To expedite clustering convergence, the dataset U will undergo normalization during clustering. Normalization is applied to data from different dimensions to ensure they fall within the 0-1 interval.

3.3.2. K-Means++ clustering algorithm

The K-means clustering algorithm divides all samples into k clusters based on their attributes, and the centre of each cluster is calculated using the mean of the values contained in the cluster [36]. The basic steps are as follows:

Step 1: Randomly select K clustering centres;

Step 2: Grouping the clusters based on the distance of each EV_i from the clustering centres;

Step 3: Update to the clustering centre of each cluster by the mean value of each cluster;

Step 4: Repeat step 2 and 3, until the position of the cluster centre no longer changes.

The K-Means method is appropriate for numerical data and is straightforward to implement. However, the classification outcome of this method is influenced by the selection of initial clustering centres. Therefore, K-Means++ is proposed as an enhancement of this algorithm [37]. It improves Step 1 of the K-Means algorithm by no longer choosing the initial clustering centres completely randomly. Instead, it ensures that the initial clustering centres are as far away from each other as possible. The following steps are identical to those of K-Means. K-Means++ initializes the cluster centres deterministically, reducing the number of algorithm iterations and increasing convergence speed.

The elbow method is a technique used to determine the optimal number of clusters (K) in a dataset. It involves calculating the sum of squared distances between each data point and its assigned cluster center for different values of K. The results are then plotted on a graph, and the K value corresponding to the 'elbow' point on the graph is chosen as the optimal number of clusters.

3.3.3. TOU typical set of EVCB

Using the above method to cluster the historical data U_t for each time period, the t -th time period has a total of k_m classes of typical EVCB, and the set of clusters of typical EVCB for that time period is denoted by C_t :

$$C_t = \left\{ (t_{t,k}^a, t_{t,k}^{ad}, S_{t,k,t_{t,k}^a}, S_{t,k,t_{t,k}^{ad}}), \varphi_{t,k} \right\}, k \in [1, k_t] \quad (9)$$

φ_k is the percentage of the number of k -th typical EVCB in U_t . The typical set of EVCB is shown as C .

$$C = \{C_t, t \in [1, 24]\} \quad (10)$$

3.4. Charging behavior day-ahead forecasting process

By utilizing the aforementioned methods and models, it is possible to forecast the day-ahead EVCB F .

The model described in section 3.2 can be used to obtain the TOU access number of EVs for the forecast day. The proposed forecasting model is trained using historical data and the resulting model can forecast the number N_t of EVs accessing at t -th time period based on day-ahead known information.

Based on the forecasting result of N_t , the EVCB day-ahead forecasting result can be obtained by following steps:

(1) The number $N_{t,k}$ of each EVCB cluster $C_{t,k}$ accessed on the forecast day can be calculated as:

$$N_{t,k} = N_t * \varphi_{t,k}$$

(2) The $N_{t,k}$ EVs are considered to be all charging according to the typical EVCB $(t_{t,k}^a, t_{t,k}^{ad}, S_{t,k,t_{t,k}^a}, S_{t,k,t_{t,k}^{ad}})$ corresponding to $C_{t,k}$ and are added to the forecasting result F .

(3) For all typical EVCB clusters, Steps (1) and (2) are performed, and the final forecasting result F is obtained.

The process of EVCB day-ahead forecasting method proposed is shown in **Algorithm 1**:

Algorithm 1: Forecasting process

Input the historical EVCB, meteorological and date information

For $t=1:24$, **do**

 Load trained forecasting model for t -th period

 Load the input data

 Output the forecasting result N_t

End for

For $t=1:24$, **do**

 Load t -th EVCB typical set C_t

For $k=1: k_t$, **do**

 Calculate the number of $C_{t,k}$ base on N_t and φ_k

 Add $N_t * \varphi_k$ EVCB $(t_{t,k}^a, t_{t,k}^{ad}, S_{t,k,t_{t,k}^a}, S_{t,k,t_{t,k}^{ad}})$ to F_t

 Output the forecasting result of F_t

End for

Output $F = \{F_t, t \in [1, 24]\}$

4. Schedulable Capacity Evaluation

EVs contribute to the charging and discharging power of their on-board batteries to participate in V2G interactions, while ensuring their energy demands are met. This contributed charging and discharging power is termed the ‘schedulable capacity’ of EVs. Based on the forecasting of EVCB, EVs establish the Electric Vehicle Scheduling Feasible Domain (EVSFD) for day-ahead scheduling.

It is crucial to recognize that each state within the EVSFD at any given moment represents a potential condition that an EV can achieve during the charging and discharging process. EVs in different states at the same moment do not possess identical EVSC. Thus, to accurately calculate EVSC, it must be based on a defined state.

Considering these factors, the EVPL develops a day-ahead charging plan, informed by the EVSFD and physical constraints, to participate in the day-ahead energy market. Finally, the EVPL calculates its EVSC based on the day-ahead planning curve and the EVSFD. Based on the above description, Fig. 3 gives the flow of the EVSC calculation methodology.

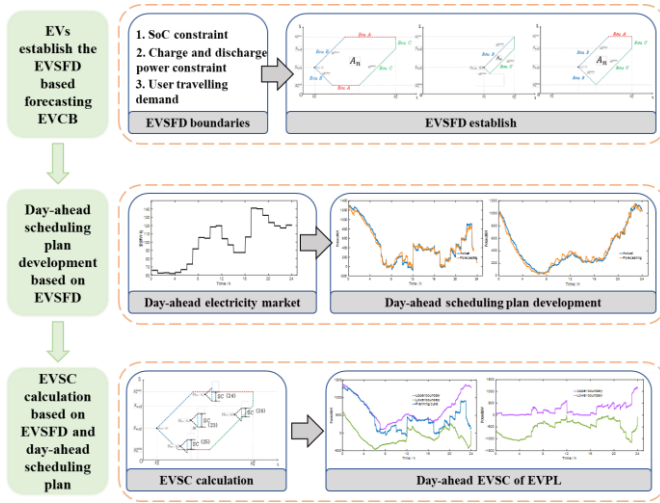


Fig. 3. The flow of EVSC calculation.

4.1. EV schedulable feasible domain (EVSFD)

For a deterministic EV_n with known access time t_n^a , departure time t_n^d , access SoC S_{n,t_n^a} , and desired minimum SoC S_{n,t_n^d} at departure time, there exist some constraints on EV_n . These constraints will construct the schedulable feasible domain A_n of EV_n . The $S_{n,t}$ of EV_n at any moment t_n should satisfy (11) when EV_n is in the access state.

$$(S_{n,t}, t_n) \in A_n \quad (11)$$

4.1.1. EVSFD boundaries

The feasible domain A_n is constructed from the following domain boundaries consisting of constraints:

A. SoC constraint boundaries

The SoC of EV_n at any time cannot exceed the set maximum value S_n^{max} and cannot be lower than the set minimum value S_n^{min} , as shown in (12):

$$S_n^{min} \leq S_{n,t} \leq S_n^{max}, \forall t \in [t_n^a, t_n^d] \quad (12)$$

B. Charge and discharge power constraint boundaries

The EV charging power at any time must not exceed the permissible value as (13):

$$p_n^{min} \leq p_{n,t} \leq p_n^{max}, \forall t \in [t_n^a, t_n^d] \quad (13)$$

The EV SoC state at the moment of access is: (S_{n,t_n^a}, t_n^a) . Therefore, at t_n^τ , the SoC can be calculated by the (14) and (15):

$$p'_{n,t} = \begin{cases} \eta_n^{ch} p_{n,t}, & p_{n,t} \geq 0 \\ \frac{p_{n,t}}{\eta_n^{dis}}, & p_{n,t} < 0 \end{cases} \quad (14)$$

$$S_{n,t_n^\tau} = S_{n,t_n^a} + \sum_{t=t_n^a}^{t_n^\tau} \frac{p'_{n,t}}{c_n} \Delta t \quad (15)$$

Depending on the charging or discharging mode, the following two boundaries exist:

Boundary B1: When an EV is connected and always charging at maximum power, the maximum SoC that the EV may reach at each timepoint can be obtained. At t_n^τ , the **Boundary B1** at maximum power is obtained:

$$S_{n,t_n^\tau} = S_{n,t_n^a} + \frac{\eta_n^{ch} p_n^{max}}{c_n} (t_n^\tau - t_n^a) \quad (16)$$

Boundary B2: When the EV is connected and always charging at the lowest power, the lowest possible SoC that the EV can reach at each timepoint is obtained. At t_n^τ , the **Boundary B2** at the lowest power is obtained:

$$S_{n,t_n^\tau} = S_{n,t_n^a} + \frac{p_n^{min}}{\eta_n^{dis} c_n} (t_n^\tau - t_n^a) \quad (17)$$

C. User travelling demand boundaries

EV travel demand exists for electric vehicle owners. Therefore, the charging and discharging process should consider the psychological impact of the user. At the charging end time t_n^d , the EV SoC should not be lower than the user's desired SoC. Therefore, there are EV user's energy demands boundary in the A_n as:

$$S_{n,t} \geq S_{n,t_n^d}, t = t_n^d \quad (18)$$

In order to satisfy the user's energy demand, the following constraints are imposed on the EV SoC at t_n^τ , taking into account the charging power limitations:

$$S_{n,t_n^\tau} \geq S_{n,t_n^d} - \frac{\eta_n^{ch} p_n^{max}}{c_n} (t_n^d - t_n^\tau) \quad (19)$$

4.1.2. A_n for different EVCB clusters

The feasible domains for EVs may vary across different EVCB clusters. This paper performs a cluster analysis of historical EV charging behaviors in EVPL using the method proposed in 3.3. The results of the cluster analysis classify all EVCB clusters into three types based on the different situations that trigger the EVSFD boundary.

A. Trigger all boundaries cluster

The EVSFD computation process in this cluster will trigger all constraint boundaries. As shown in Fig. 4, the feasible interval for this cluster of EV is the space consisting of the six boundary lines together, starting from access state.

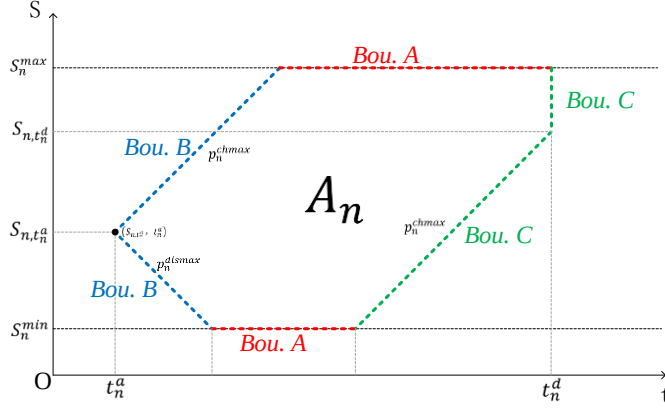


Fig. 4. EVSFD of low SoC, long time access EV

B. Trigger section of the boundaries cluster

In most cases the accessed EVs reflect the EVCB of **cluster A**. However, in a small number of cases the constraints of **Boundary A** may not be triggered. The general EVCB in this cluster is characterized by a small t_n^{ad} and a large S_n^{ad} . As shown in Fig. 5, at these cases, there are a total of four or five constraint boundaries together to form the feasible domain A_n .

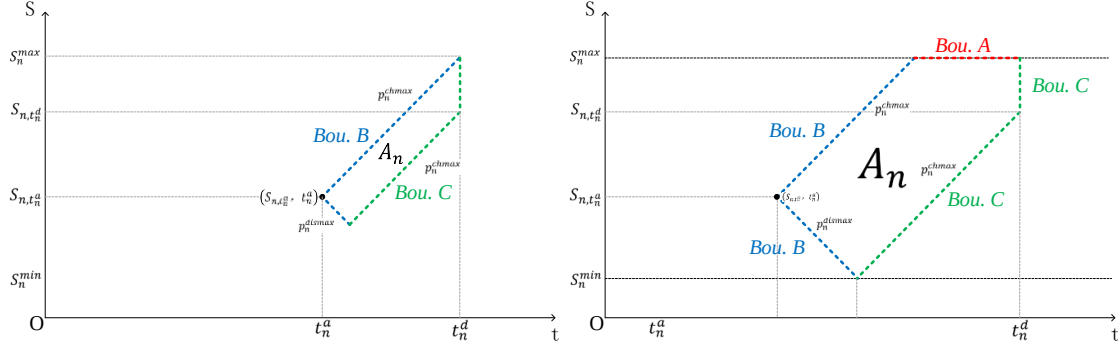


Fig. 5. EVSFD of Other cases.

C. Clusters without scheduling feasible domain

For this cluster of EVCB, due to the uncertainty of the EVCB and the user expects a high target SoC throughout the access period, some EVs may not be able to meet the energy demand even with full maximum power charging. The EVSFDs of such EVs are all a line charging at maximum power, and the EVSCs are all zero. This type of EV is not capable of providing schedulable capacity.

It is important to mention that several feasible domains in cluster B are actually partial special cases of the cluster A feasible domains.

The day-ahead scheduling plan can be developed for clusters A and B based on their EVSFD A_n .

4.2. Day-ahead scheduling plan development based on A_n

Based on the constructed EVSFD and physical constraints, EVPL can participate in the day-ahead energy market and develop the day-ahead scheduling plan.

EVPL represents the interests of all access EVs to participate in the day-ahead peaking energy market, and develops the day-ahead optimal charging schedule curve based on day-ahead energy tariffs, with the objective of minimizing charging consumption. The following day-ahead EVPL charging and discharging scheduling optimization model is established as (20) and (21):

$$\min_{p_{n,t}} f_{EVA} = \sum_{t=1}^T \sum_{n=1}^N \lambda_t p_{n,t} \quad (20)$$

$$\text{s.t. } p_n^{\min} \leq p_{n,t} \leq p_n^{\max}, \forall t \in [t_n^a, t_n^d]; p_{n,t} = 0, \forall t \notin [t_n^a, t_n^d]$$

$$S_{n,t+1} = \begin{cases} S_{n,t} + \frac{\eta_n^{ch} p_{n,t}}{C_n} \Delta t, p_{n,t} \geq 0 \\ S_{n,t} + \frac{p_{n,t}}{\eta_n^{dis} C_n} \Delta t, p_{n,t} < 0 \end{cases}, (t, S_{n,t}) \in A_n, \forall t \in [t_n^a, t_n^d] \quad (21)$$

4.3. EVSC calculation based on A_n and day-ahead scheduling plan

When the EV_n is in the determined state $(S_{n,t}, t_n)$, its possible SoC states to be reached after Δt are $S_{n,(t_n+\Delta t)}$:

$$S_{n,t_n} + \frac{p_n^{\min}}{\eta_n^{dis} C_n} \Delta t \leq S_{n,(t_n+\Delta t)} \leq S_{n,t_n} + \frac{\eta_n^{ch} p_n^{\max}}{C_n} \Delta t \quad (22)$$

EV's SoC is constrained by the feasible domain A_n . In most cases, the EV's charging and discharging behavior will not cross the constraints, e.g., (23), as shown in Fig. 6. In this case, the schedulable capacity $p_{n,t}^{sc}$ of the EV in this state is:

$$p_{n,t}^{sc} = [p_{n,t} - p_n^{\min}, p_n^{\max} - p_{n,t}] \quad (23)$$

In some cases, there may be travelling SoC crossings, e.g., (24) (25) (26), as shown in Fig. 6. The EVSC of the EV_n in these cases are respectively:

$$p_{n,t}^{sc} = [p_n^{\min} - p_{n,t}, \frac{(S_n^{\max} - S_{n,t}) C_n}{\eta_n^{ch} \Delta t} - p_{n,t}], p_{n,t}^{sc,up} = \frac{(S_n^{\max} - S_{n,t}) C_n}{\eta_n^{ch} \Delta t} - p_{n,t}, p_{n,t}^{sc,down} = p_n^{\min} - p_{n,t} \quad (24)$$

$$p_{n,t}^{sc} = [\frac{(S_n^{\min} - S_{n,t}) \eta_n^{dis} C_n}{\Delta t} - p_{n,t}, p_n^{\max} - p_{n,t}], p_{n,t}^{sc,up} = p_n^{\max} - p_{n,t}, p_{n,t}^{sc,down} = [\frac{(S_n^{\min} - S_{n,t}) \eta_n^{dis} C_n}{\Delta t} - p_{n,t} \quad (25)$$

$$p_{n,t}^{sc} = [\frac{(S_{n,t_n^d} - \frac{\eta_n^{ch} p_n^{\max}}{C_n} (t_n^d - (t + \Delta t)) - S_{n,t}) \eta_n^{dis} C_n}{\Delta t} - p_{n,t}, p_n^{\max} - p_{n,t}], p_{n,t}^{sc,up} = p_n^{\max} - p_{n,t},$$

$$p_{n,t}^{sc,down} = \frac{(S_{n,t_n^d} - \frac{\eta_n^{ch} p_n^{\max}}{C_n} (t_n^d - (t + \Delta t)) - S_{n,t}) \eta_n^{dis} C_n}{\Delta t} - p_{n,t} \quad (26)$$

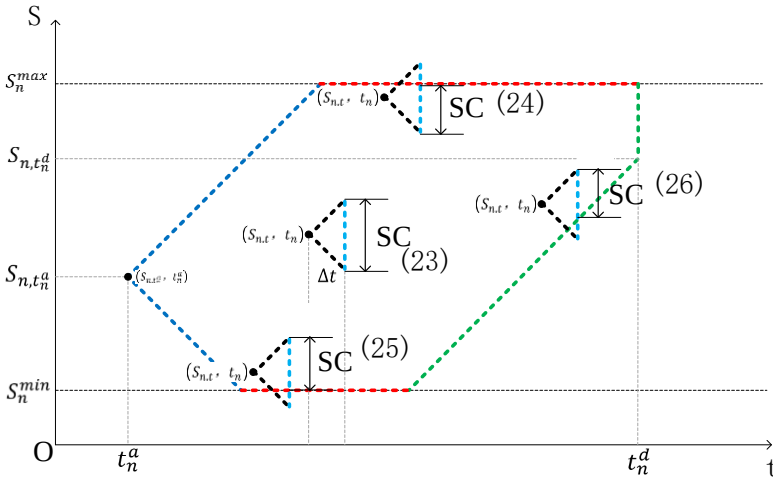


Fig. 6. SC of different state of EV_n .

For a defined EV_n charging and discharging schedule curve, the dispatchable capacity of the entire EV_n charging and discharging process can be calculated based on (27):

$$SC_n = \{p_{n,t}^{sc}, t \in [t_n^a, t_n^d]\} \quad (27)$$

For an EVPL with N EVs accessed in a day, its EVSC is the superposition of the SC of all EVs. This yields the scheduling EVSC of EVPL:

$$EVSC = \{\sum_{n=1}^N p_{n,t}^{sc}, t \in [0, 24h]\} \quad (28)$$

5. Case Studies

5.1. Dataset and parameter setting

This paper uses dataset on EV charging behavior recorded in January 2022 in Suzhou city, China. The dataset comprises historical EVCB data from EVPLs. In Appendix A, we provide more details about this dataset, including some of actual history EVCB data. In addition, meteorological information used for the forecasting is obtained from the publicly available meteorological websites.

In following case studies, the EV's battery capacity is set to 48kWh, with maximum charging and discharging power are both at 7kW, and the charging/discharging efficiency $\eta_n^{ch} / \eta_n^{dis}$ both are 0.98. The minimum scheduling interval is set to 3 minutes.

5.2. Comparison and analysis of EVCB day-ahead clustering forecasting result

The dataset is split into a training set and a test set. The test set includes data from the recordings on 29 January, referred to as the forecast day, ranging from 0 to 24 hours. More detailed information about the training and test datasets is provided in Appendix A.

Case1, Case2 and Case3 are established to verify the proposed method's forecasting ability.

Case1: Comparison of forecasting result of EV access number

The proposed forecasting model is used for the forecasting of EV access number per hour on 29 January. The comparison of forecasting result and actual data is shown in Fig. 7. The average forecasting accuracy is 88.5%. From the result, it can be seen that the forecast values are basically consistent with the actual values, and the forecasting model has a high average accuracy. In addition, the conventional Monte Carlo method requires knowledge of the total number of EVs in order to make forecasting. However, the number of EVs connected to charging in EVPL on one day is influenced by many factors and is not fixed. Therefore, the Monte Carlo method cannot achieve the forecasting. The methodology proposed is theoretically and conclusively superior.

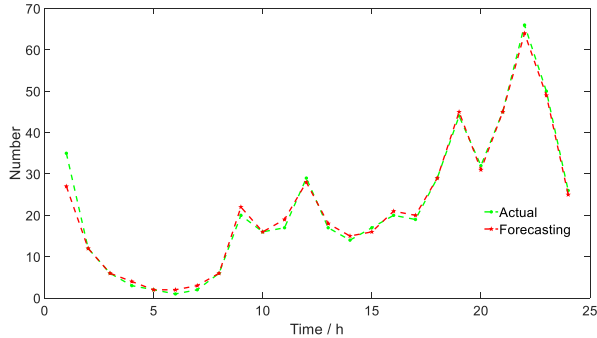


Fig. 7. Forecasting result comparison of EV access number.

Case2: Analysis of EVCB clustering result

The total number of historical EVCBs for each time period and the number of typical EVCB classes obtained are shown in Table 1. A total of 376 clusters of typical EVCB are obtained. The clustering result shows that the largest

number of EV accesses and the richest cluster of EVCB are found in the evening to late night. As can be seen in Table 1, there is a large gap and a wide variety of EVCB among different EVs.

Table 1

The total number of historical EVCB number for each time period and the number of typical EVCB classes obtained.

Time/h	[0,1)	[1,2)	[2,3)	[3,4)	[4,5)	[5,6)	[6,7)	[7,8)	[8,9)	[9,10)	[10,11)	[11,12)
EV number	939	296	160	95	67	66	118	330	649	511	545	610
Clusters	20	7	7	6	5	5	8	11	14	13	10	15

Time/h	[12,13)	[13,14)	[14,15)	[15,16)	[16,17)	[17,18)	[18,19)	[19,20)	[20,21)	[21,22)	[22,23)	[23,24)
EV number	606	566	547	519	699	943	1251	1167	1327	2150	1340	839
Clusters	14	16	16	16	17	20	25	25	28	32	26	20

The distribution of t^{ad} and expected S^{ad} for each cluster of typical EVCB is analyzed and the result is shown in Table 2 and Table 3. It can be seen that most of the typical EVCBs are accessed for more than 2 hours and have the ability to provide EVSC. In addition, most clusters of EVs would like to have access to at least 40% of S^{ad} .

Table 2

Distribution of access duration t^{ad} .

t^{ad}	>2 h	>4 h	>6 h
Percentage	76.3%	46.3%	32.2%

Table 3

Distribution of expected charge volume S^{ad} .

S^{ad}	>40%	>60%	>80%
Percentage	67.6%	35.9%	9.8%

Case3: Analysis of EVCB day-ahead forecasting result

Case3 is set up to verify the accuracy of the EVCB forecasting result. EVCB can be forecasted based on the forecasting result of EV access number and EVCB clustering result.

The number of EVs on the forecasting day is large and EVCB ($\{t^a, t^{ad}, S^a, S^d\}$, $t^d = t^a + t^{ad}$) are four-dimensional data. It is difficult to directly show the comparison result between the forecasting and actual EVCB. The EVCB forecasting result includes access time (t^a, t^d) and SoC (S^a, S^d). Hence, this case chooses $\{t^a, t^d\}$ and $\{S^a, S^d\}$ to draw the comparison chart of access time and SoC forecasting result respectively to show the comparison result more intuitively. The result is shown in Fig. 8 and Fig. 9. In addition, the validity of the forecasting method is also verified by comparing the distribution of parameters t^d , S^a and S^d (the distribution of t^a is the same as the distribution (Fig. 7) of the EV access number). The result is shown in Fig. 10 and Table 4. The forecasting result is closed to the actual value. It can be seen that the proposed method has a high forecasting accuracy.

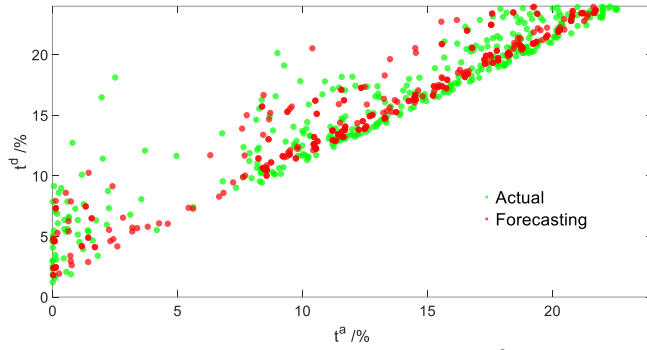


Fig. 8. Comparison of actual and forecasting $\{t^a, t^d\}$.

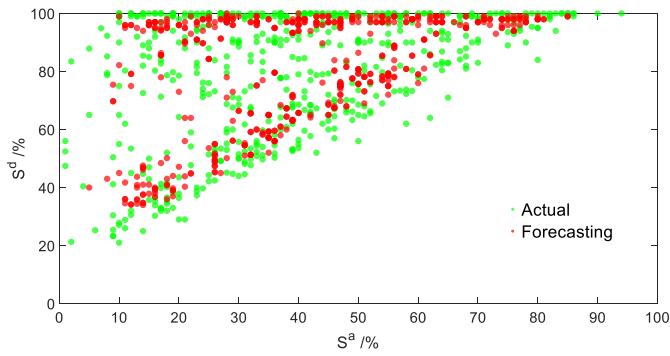


Fig. 9. Comparison of actual and forecasting $\{S^a, S^d\}$.

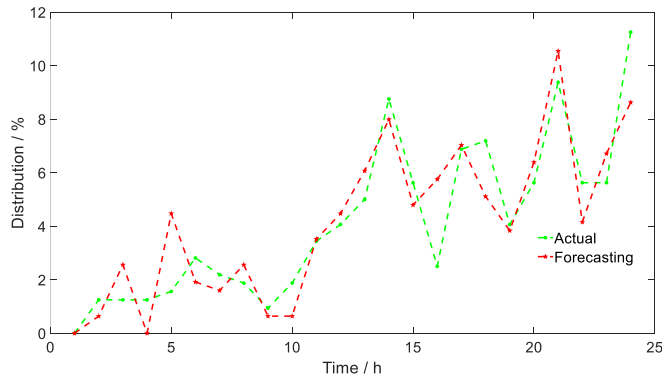


Fig. 10. Comparison of actual and forecasting distribution of t^d .

Table 4

Actual and forecasting distribution of S^a and S^d .

SoC/%	[0,20]		(20,40]		(40,60]		(60,80]		(80,100]	
	S^a	S^d	S^a	S^d	S^a	S^d	S^a	S^d	S^a	S^d
actual	21.0%	0%	35.6%	1.5%	26.9%	4.7%	13.3%	5.9%	3.2%	87.9%
forecasting	16.9%	0%	35.4%	1.2%	32.0%	3.4%	14.7%	7%	1.0%	88.4%

5.3. Comparison and analysis of EVSC day-ahead calculation result

Case4 calculates the day-ahead scheduling plan curve, and the disordered charging curves are calculated for comparison. **Case5** calculates the EVSC of EVPL, while **Case6** compares the contribution of EVs with different t_n^{ad} to the EVSC of EVPL. Meanwhile, **Case5** and **Case6** compare the EVSC calculation results based on forecasting and actual EVCB to further validate the superiority of the proposed method.

Case4: Result of charging plan curve in the day-ahead market of participation.

In order to achieve a higher economic benefit, the EVPL will participate in the day-ahead market and develop day-ahead charging plan. It is necessary to accurately forecast the EVCB of the accessed EVs. The proposed method addresses this forecasting challenge well. In order to verify the superiority of the proposed method, the following case is designed: all EVs participate in the day-ahead market based on the rule of 4.2 and develop day-ahead charging plan. The tariff is based on the day-ahead hourly tariff from the PJM electricity market as of 29 January 2022, and the detailed tariff are shown in Fig. 11. Considering the existence of charging of EVs accessed on the day before forecast day that continues until forecast day, the day-ahead charging schedule curves of EVPL developed based on the actual EVCB and the day-ahead EVCB forecasting result are plotted respectively, as shown in Fig. 12. In addition, to compare ordered and unordered charging strategies, load profiles of EVs involved in disordered charging are calculated based on the EVCB, as shown in Fig. 13.

From Fig. 12, it can be seen that the charging schedule curves developed based on the forecasting EVCB are very close to the charging schedule curves developed based on the actual EVCB, reflecting the superiority of the proposed method in terms of accuracy. Compared with the disordered charging curve in Fig. 13, the day ahead planning curve can charge when the electricity price is low and discharge when the electricity price is high on the premise of meeting the demands of EVs, which reduces the charging cost. Based on actual data calculations, EVPL's participation in day-ahead market resulted in an overall reduction of 15.3% in charging costs compared to disordered charging.

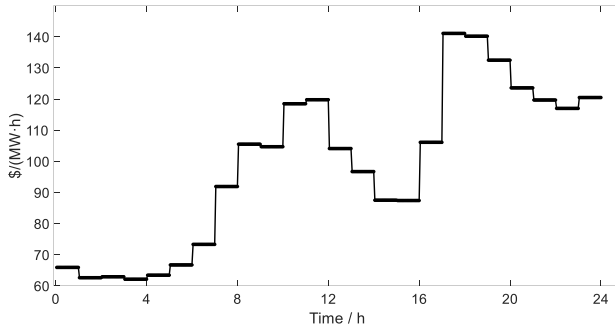


Fig. 11. The day-ahead hourly tariff of PJM electricity market as of 29 January 2022.

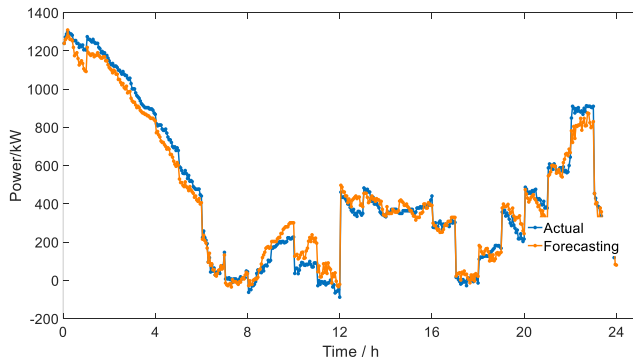


Fig. 12. Comparison for the day-ahead charging plan curves of regional EVPL developed based on the result of the actual EVCB and the day-ahead EVCB forecasting result. (Considering EVs accessed on the day before the forecast day that continues until the forecast day)

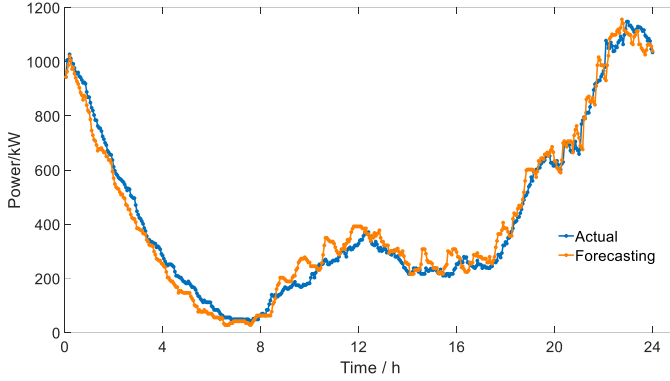


Fig. 13. Comparison of actual and forecasting values of load profiles during disordered charging of EVPL in the forecast day. (Considered EVs accessed the day before the forecast day continue to charge until the forecast day)

Case5: EVSC calculation of EVPL

Based on the EVCB data, EV charging and discharging parameters, the EVSC will be calculated using the method proposed. In addition to the charging load for the forecast day, a portion of the EVs that were accessed the previous day are still accessed on the forecast day. Therefore, the EVSC that can be provided by this part of EVs is superimposed to get the result of the calculation of EVSC of EVPL. Calculate the EVSC based on the actual situation and forecast result, respectively. The results are shown in Fig. 14. The EVSC of EVPL that can be scheduled upward or downward relative to the day-ahead schedule curve is shown in Figure 15.

From Fig. 14 and Fig. 15, during periods of cheaper electricity price, e.g., 0-8 p.m. and 12-16 p.m., the EV is supplemented with electricity at maximum power. The EV in this state provides basically min upward SC, but can provide a large amount of downward SC. On the contrary, in the hours of 9-12 and 17-24 when electricity is more expensive, the EV tries to minimize the replenishment power and considers selling electricity to the grid for economic benefits. At this time EVs can provide larger SC based on ancillary services, real-time market demand. In addition, it can be seen that the EVSC calculated based on the forecasting EVCB and the actual EVCB are closer, which also reflects the superiority of the proposed day-ahead EVCB forecasting method.

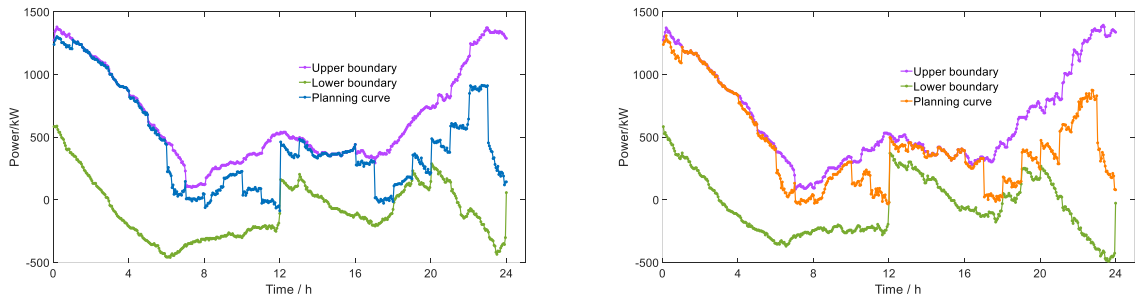


Fig. 14. EVSC of regional EVPL. (The first figure is based on actual EVCB calculations and the second figure is based on forecasting EVCB calculations)

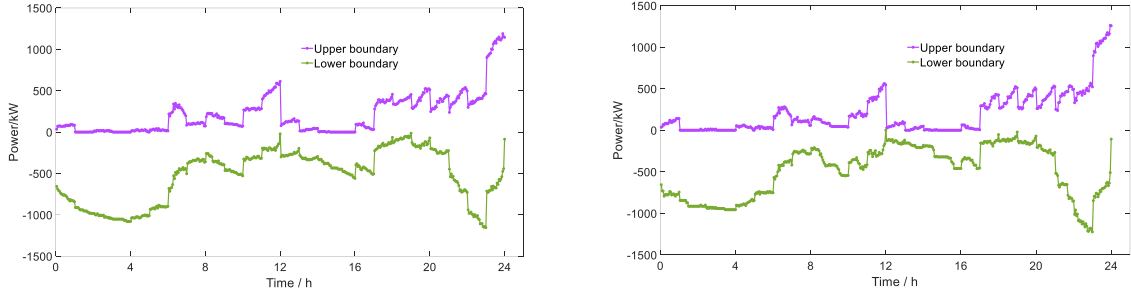


Fig. 15. EVSC for regional EVPL relative to the day-ahead plan curve. (The first figure is based on actual EVCB calculations and the second figure is based on forecasting EVCB calculations)

Case6: EVSC comparison of EVPL with different levels of t^{ad}

The longer the duration of the access, the more SC that the EV can provide. Therefore, the t^{ad} of EV access is analyzed firstly. The forecasting and actual distribution of access duration for EVs accessed on the forecast day is shown in Table 5.

Table 5

Actual and forecasting distribution of access t^{ad} .

t^{ad}	>2 h	>4 h	>6 h
actual	68.2%	41.8%	25.0%
forecasting	73.2%	40.8%	23.3%

As can be seen from the Table 5, the forecasting result are closer to the actual situation, and this proves that the high accuracy of the proposed forecasting method while there is a huge uncertainty in the EVCB. More critically, it can be found that the access duration of most EVs is less than 6 hours. The percentage of EVs with longer t^{ad} that have greater SC is not significant.

For this reason, this case compares EVSC contributed by EVs of different t^{ad} . On the basis of the day-ahead schedule, this case calculates the EVSC contributed by EVs that are at different access durations based on actual EVCB. The result is shown in Fig. 16. Also, this case calculates the EVSC distribution based on EVCB forecasting result to show the superiority of the proposed forecasting model. The result is shown in Fig. 17. This case focuses in the discussion of the contribution of EV clusters with different t^{ad} to the SC. Therefore, EVs accessed before the forecast day are considered. The comparison of EV number and EVSC contribution of different t^{ad} is shown in Table 6.

From above results, the number of EVs with t^{ad} greater than 6 hours is only 25% of the total, yet it provides more than half of the EVSC. EVs with less than 2 hours of access time, which accounted for about 30% of the total, provided less than 7% of the EVSC. It can be seen that the EVSC of EVPL is mainly derived from EVs with longer access times. This result inspires V2G policymakers to consider directing EVs to provide longer access hours, and thus larger EVSC, when developing incentive strategies.

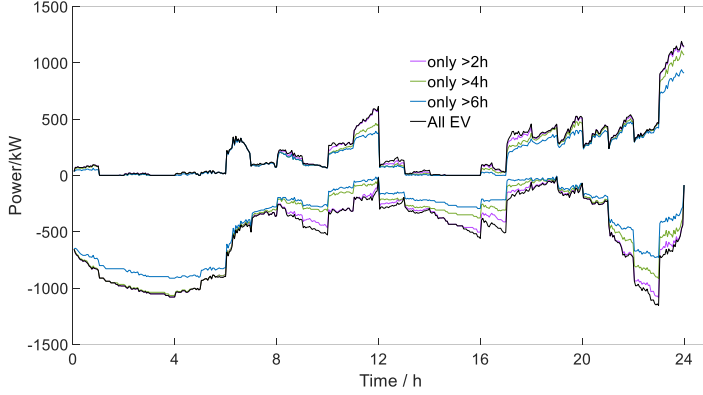


Fig. 16. EVSC contributed by EVs that are at different access durations based on actual EVCB.

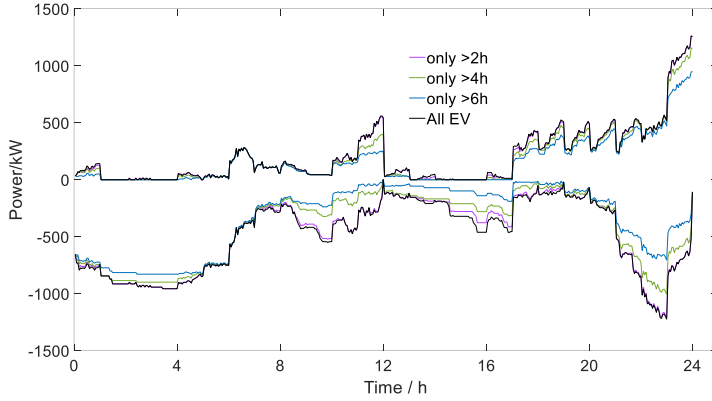


Fig. 17. EVSC contributed by EVs that are at different access durations based on forecasting EVCB.

Table 6

Comparison of EV number and EVSC contribution of different t^{ad} .

t^{ad}		>2 h	>4 h	>6 h
actual	number	68.2%	41.8%	25.0%
	capacity	93.0%	75.7%	56.2%
forecasting	number	73.2%	40.8%	23.3%
	capacity	93.8%	69.0%	43.2%

6. Conclusion

Accurate forecasting of electric vehicle charging behavior is essential for calculating schedulable capacity and is a prerequisite for enabling EV Parking Lots to participate in Vehicle-to-Grid interactions and electricity markets. Existing methods fail to provide accurate day-ahead forecasts of EV charging behavior for EVPLs and do not adequately support the calculation of schedulable capacity necessary for participation in V2G and electricity markets. This paper presents a novel method for day-ahead forecasting of EV charging behavior and calculating schedulable capacity for EVPLs, with the following methodological contributions:

- 1) A day-ahead Time-of-Use forecasting method for EV charging behavior is introduced, considering the significant variations in EVCB across different time periods. This method employs a neural network and K-Means++ clustering model based on historical data to achieve accurate day-ahead estimation of EVCB for EVPLs, minimizing the need for extensive assumptions.

- 2) A classification and analysis of EVCB within EVPL, combined with the physical constraints of EV charging and discharging, to construct EVSFD. Subsequently, a day-ahead planning curve for EVs participating in the day-ahead energy market is developed based on the EVSFD and EVCB forecasting result.
- 3) Utilizing the day-ahead planning curve and EVSFD, a method for calculating the EVSC for re-schedulable EVs is proposed.

Case studies demonstrate that the proposed method accurately forecasts EVCB. The multi-scenario load profiles and EVSC, derived from the forecasted EVCB, closely align with those calculated from actual EVCB. Additionally, the arithmetic case analysis highlights the contribution of schedulable capacity from EVs with varying access durations. The proposed method effectively addresses the challenges associated with EVPL participation in V2G and electricity markets.

Future research, based on the research in this paper, the impact of real-time scheduling strategy on the result of schedulable capacity calculation can be analyzed. Further research will be carried out on EVSC mining in different scenarios for different clusters of EVs in EVPL.

CRedit authorship contribution statement

Maosheng Xu: Conceptualization, Methodology, Software, Visualization, Writing - original draft. **Shan Gao:** Conceptualization, Supervision, Validation, Resources, Writing - review & editing. **Junyi Zheng:** Data curation, Formal analysis, Validation. **Xueliang Huang:** Funding acquisition, Investigation, Project administration, Supervision. **Chuanshen Wu:** Writing - review & editing, Formal analysis.

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

The data that has been used is confidential.

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Appendix A. Supplementary data and information.

This appendix adds some data and information relevant to this paper.

A.1. History dataset

The EVCB dataset used in this paper is derived from actual historical EV charging behavior data obtained from China's National Monitoring and Management Platform for New Energy Vehicles (NMMV). All data were recorded within January 2022 in Suzhou city, China. The dataset includes various types of EV charging behaviors, such as t^a , t^d , S^a and S^d . The dataset comprises over 10 thousand historical EVCB data from EVPLs. Table A1 provides some examples of EVCB. In addition, history meteorological information of Suzhou used for the forecasting is obtained from the publicly available meteorological websites. Meteorological dataset includes the weather conditions (sunny, cloudy, rainy, or snowy) and average temperatures. Table A2 provides some examples of meteorological data segments.

Table A1

Examples of EV charging behavior data.

EVCB ID	1	2	3	4	5	6	7	8
t^a /hour:min:sec	00:32:28	06:47:05	09:54:44	12:10:31	15:17:47	17:36:59	18:48:45	20:00:33
t^d /hour:min:sec	05:22:58	13:30:20	17:48:16	13:58:31	18:52:34	23:08:33	23:49:45	23:48:23
S^a /%	37	10	43	18	67	54	54	69
S^d /%	99	55	100	32	99	97	98	99

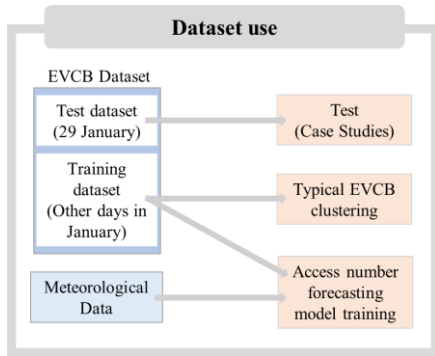
Table A2

Examples of meteorological data.

Days	1	2	3	4	5	6	7	8
weather	sunny	cloudy	cloudy	rainy	rainy	cloudy	cloudy	cloudy
min temperature	2°C	2°C	3°C	8°C	5°C	3°C	2°C	5°C
max temperature	11°C	11°C	14°C	12°C	9°C	8°C	10°C	8°C

A.2. Training and testing datasets

The historical dataset is numerical and normalized and can be used for the training and test process of the proposed method in this paper. The test dataset includes data from the history dataset on 29 January, containing 528 data. The other data constitute the training dataset, containing more than 10 thousand data. Meteorological data are used during the training and testing of the EV access number forecasting model, matching the EVCB recording time. The use of the dataset is shown in Fig. A1.

**Fig. A1.** The use of the dataset.

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