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Two-phase operation for coordinated charging of electric vehicles in a market environment: From electric vehicle aggregators' perspective

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ABSTRACT

The increasing penetration of electric vehicles (EVs) poses challenges to the operation of existing power systems owing to the spatial and temporal randomness and dynamics of EV charging. Although substantial theoretical research efforts have been made for EV coordinated charging management, the implementation and validation in the context of a practical market mechanism in the presence of EV aggregators require further exploitation. This study develops a two-phase coordinated charging scheduling solution in the energy market environment to optimally schedule EV charging loads for profit maximization from the perspective of EV aggregators. In the first phase, EV aggregators bid for energy in the day-ahead markets, considering a wide variety of uncertainties from EV charging and electricity markets. In the second phase, EV aggregators manage the charging loads of EVs in real time using purchased energy. The proposed solution was implemented and assessed using the Guangdong energy market as a case study through extensive simulation experiments. The numerical results confirm that the proposed method can enable the actual consumed energy from EVs to match the day-ahead bidding energy well. In this regard, the charging demand of EVs can be met with proper planning, to fulfill the coordinated charging operation of EVs in power grids.

1. Introduction

1.1. Background and motivation

It is universally agreed that the large-scale deployment of electric vehicles (EVs) and distributed renewable power generation resources can effectively mitigate the dependence on fossil fuels in the transportation sector and hence reduce carbon emissions. According to a recent International Energy Agency (IEA) report, the global EV stock will reach 10 million units in 2020, a 43% increase over 2019 [1]. However, the uncertainties and randomness introduced by uncontrolled charging of numerous EVs would result in deteriorated impacts on the operation of power grids, for example, feeder and transformer overloading, and power quality degradation [2]. To avoid the significant reinforcement of existing power grids to accommodate the extra EV charging demand, coordinated charging of EVs is considered a cost-effective alternative solution to shift the EV load to load-valley periods to alleviate the power supply pressure of grids during peak hours [3].

A critical prerequisite to conducting a coordinated charging operation for EVs is the optimal charging strategy of EVs, which aims to improve the grid performance by flattening the power load profiles [4], reducing power losses [5], or enhancing voltage stability [6]. On this basis, a range of operational objectives have been developed to investigate the potential of EVs as flexible loads in the power grid, for example, minimizing the power load variance [7], minimizing the power loss [8], maximizing the load factor [9], minimizing the peak load [10], and avoiding the voltage drop [11]. Moreover, the equivalence of the three optimization objectives was investigated in Ref. [12]. The results reveal that for practical systems, load variance minimization is equivalent to power loss minimization, and load factor maximization is almost equivalent to load variance minimization. These observations indicate that the above research efforts focus on a specific target to investigate the potential benefits of using EVs as flexible resources for power grids. However, energy transactions between EV users and power grids are seldom involved, and the satisfaction or willingness of EV users to participate in coordinated charging is rarely considered.

As stated above, it is essential to develop more practical frameworks to support grid integration of large-scale EVs. In the existing literature, two operational frameworks have been widely explored and studied to coordinate the charging of EVs to avoid grid congestion. One is to

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List of acronyms

CMM	Centralized management mode
CVaR	Conditional value-at-risk
DIM	Distributed incentive mode
EV	Electric vehicle
GPEC	Guangdong power exchange center
IEA	International energy agency
PD	Price difference
SoC	State of charge
ToU	Time-of-use

Nomenclature

t	Index of hours
T	Set of hours
k	Index of time slots
K	Set of time slots
w	Index of real-time clearing scenarios
W	Set of real-time clearing scenarios
n	Index of EVs
N_1	Set of all EVs with CMM
N_2	Set of all EVs with DIM
S_k^1	Set of available EVs with CMM at k-th time slot
S_k^2	Set of available EVs with DIM at k-th time slot

Parameters

λ_t^{Day}	Day-ahead energy price at t-th hour, in CNY/kWh
$\lambda_{w,t}^{RT}$	Real-time energy price at t-th hour for scenario w, in CNY/kWh
π_w	Probability of scenario w occurrence, in p.u.
$\lambda_{n,h}^{Agr}$	Agreement price that EV aggregators sell to n-th EV with CMM at h-th hour, in CNY/kWh
θ_0	Service tariff that EV aggregators envy on EVs with DIM, in p.u.
$\varphi_{n,k}^{max}$	Allowable maximum charging energy of n-th EV at k-th time slot, in kWh
$\varphi_{n,k}$	Response coefficient of n-th EV at k-th time slot, in p.u.
ε_0	Allowable bidding deviation rate in Guangdong real-time markets, in p.u.
E_{min}^{Day}	Allowable minimum bidding energy in day-ahead markets, in kWh
E_{max}^{Day}	Allowable maximum bidding energy in day-ahead markets, in kWh
P_n^{Max}	Maximum charge power of n-th EV in kW
Δt	Length of time slots, in hour
Γ_n^c	Connection time slot of n-th EV, in p.u.
Γ_n^d	Disconnection time slot of n-th EV, in p.u.
η_n	Charger efficiency of n-th EV, in p.u.
Bat_n	Onboard battery capacity of n-th EV, in kWh
SoC_n^c	Connection battery SoC of n-th EV, in p.u.
SoC_n^d	Disconnection battery SoC of n-th EV, in p.u.
λ_i^{RT}	Actual real-time clearing energy price at i-th hour, in CNY/kWh
$\lambda_{n,j}^{Agr}$	Agreement price that EV aggregators sell to n-th EV with CMM at j-th time slot, in CNY/kWh
δ_j	Consumed energy at j-th time slot, in kWh

Variables

E_t^{Day}	Day-ahead bidding energy at t-th hour, in kWh
$\Delta E_{w,t}$	Deviation between day-ahead bids and actual energy consumption at t-th hour for scenario w, in kWh
$C_{w,t}^{Pen}$	Expected penalty costs arising from deviation $\Delta E_{w,t}$, in CNY
$E_{w,n,k}^{M_1}$	Scheduled charging quantity of n-th EV in set N_1 at k-th time slot for scenario w, in kWh
$E_{w,n,k}^{M_2}$	Determined charging quantity of user of n-th EV in set N_2 at k-th time slot for scenario w, in kWh
$E_{n,j}^{M_1}$	Actual charging quantity of n-th EV in set S_k^1 at j-th time slot, in kWh
$E_{n,j}^{M_2}$	Actual charging quantity of n-th EV in sede S_k^2 at j-th time slot, in kWh
ΔE_i	Actual deviation between day-ahead bids and EV consumed energy at i-th hour, in kWh
C_i^{Pen}	Actual penalty costs arising from deviation ΔE_i, in CNY

leverage the time-of-use (ToU) tariff policy to encourage EV users to charge during off-peak hours [13]. The implementation of ToU tariffs is easy because it only requires grid operators to broadcast price information to the EV users [14]. However, EVs, in this case, cannot offer ancillary services to power grids in the absence of a sound-charging control system. The other is to introduce EV aggregators to take charge of the EV fleet to participate in the electricity market. In this architecture, EV aggregators can remotely monitor and control the charging/discharging states of the EV batteries. As a result, EV aggregators can utilize EVs to provide a series of grid services, for example, frequency and voltage regulation, supporting the grid integration of renewable energy [15–17]. The latter was adopted in this study to investigate the charging behaviors of EVs in a market environment.

In the authors' view, the competitive electricity market creates an environment for EV-coordinated charging in its widespread practical application. Because a single EV's transaction capacity does not meet the entrance criteria for electricity markets, EV aggregators must mediate between EV users and grids and participate in the electricity market on behalf of an EV fleet [18]. EV users must contract with EV aggregators, striving for a lower charging fee. In the energy market, the clearing and pricing system depends on the power supply and demand status when considering the grid congestion level [19]. A higher electricity price signifies a shortage of energy supply, whereas a lower price reveals that there is surplus grid capacity to accommodate the extra electric load. In this sense, when EV aggregators respond to the real-time pricing system, they manage the charging time of EVs away from the grid utilities' peak hours to reduce their energy expense [20]. In the framework of electricity markets, EVs are encouraged to serve as flexible resources for providing power-balancing services through EV charging and discharging operations [21]. Recently, there has been increasing interest in exploiting the coordinated charging operation of EVs in the electricity market to promote the large-scale integration of EVs into existing power grids.

1.2. Literature review

The trading architecture of the spot electricity market includes day-ahead and real-time markets [22]. From the perspective of EV aggregators, they should bid the electricity in the day-ahead market and schedule the charging loads of EVs using the purchased electricity in real time. Consequently, the market participation processes of EV aggregators can fall into two phases: day-ahead bidding and real-time charging scheduling. In this regard, more emphasis is placed on the day-ahead bidding problem rather than the real-time scheduling operation, as EV aggregators face a variety of challenges in day-ahead markets, including, but not limited to, competition from other independent aggregators, the uncertainty of market prices, and the minimum required charging demand of EVs [23,24]. In existing studies, the focus is on optimization techniques to handle the uncertainty in the day-ahead market and make optimal bids, including stochastic programming, chance-constrained programming, and robust optimization. For instance, in Ref. [25], a stochastic programming framework was developed for EV aggregators participating in the energy and ancillary service markets, considering the impact of market price and reserve market uncertainties. In Ref. [26], a risk-constrained optimal bidding strategy was presented by incorporating demand response programs and EVs into a smart grid. In addition, a robust hierarchical optimization method was proposed to regulate the charging of EVs to make optimal decisions regarding the bidding strategy in the day-ahead market [27]. Herein, we consider the EV charging problem in a systematic manner, based on the electricity market framework.

The day-ahead bidding strategy is critical for EV aggregators to reduce their overall operating costs when participating in the electricity markets. In the day-ahead bidding problem, EV aggregators are confronted with uncertainties in two aspects: EV charging and market clearing [28]. Because of the mobility of EVs as a transportation tool, it is almost unrealistic to predict EV charging events, including the arrival/departure time and state of charge (SoC) in the following day [29]. Research efforts to cope with uncertainties in EV charging are mainly based on probabilistic modeling or scenario-based methods. For instance, in Ref. [30], the probability distribution of the charging behaviors of EV users was modeled using real-world charging data. In the simulations, the randomly generated charging data of EVs served as the input of the model for the optimal bidding strategy of the EV aggregators. The scenario-based approach was adopted in Ref. [31], where the driving distances of EVs were accurately modeled to generate scenarios of EV charging to maximize the profits of EV aggregators in the day-ahead energy trade. However, when using simulation scenarios to model the uncertainties of EVs, the driving requirements of EVs may not be satisfied if the scenarios are not properly generated [32].

In addition to the stochastic property of EV charging, EV aggregators should deal with uncertainties from the electricity market in the day-ahead bidding process. Generally, the day-ahead settlement price cannot be acquired before market clearing. Consequently, EV aggregators need to consider potential day-ahead clearing scenarios to obtain the optimal bidding strategy. P. Afzali's study, for example, used the conditional value at risk (CVaR) to deal with uncertainty in day-ahead prices and renewable power producers for the optimal participation strategy in the day-ahead market [33]. However, the consideration of day-ahead prices for the bids of EV aggregators may not be sufficient because the real-time (or balancing) market also affects the profits of EV aggregators. More recent efforts have been devoted to the day-ahead bidding strategy while considering the possible real-time clearing scenarios, such as, in Refs. [34,35]. These studies adopt a scenario-based or risk-based approach to manage market uncertainties [36]. The scenario-based approach explicitly reveals the stochastic property of the resources and describes the probability of occurrence of real-time clearing scenarios in the day-ahead bidding model. For instance, in Ref. [37], a set of real-time clearing scenarios and their probabilities were incorporated into the stochastic optimization model to determine the optimal bidding strategy of EV aggregators in the day-ahead market. The risk-based approach introduces a risk indicator to manage potential losses when EV aggregators bid in the day-ahead market. In Ref. [38], for example, the CVaR indicator was used in the proposed model to deal with underlying uncertainties in the real-time market for risk aversion, so that the acquired bidding strategy was not too conservative or too optimistic in the energy and frequency regulation markets.

The observations show that the scenario-based approach uses the probability distribution to describe the uncertain parameters for the expected profit maximization, and the risk-based approach introduces a risk-related indicator to manage the potential risk incurred by uncertain factors in the day-ahead bidding model.

In real-time operation, EV aggregators can schedule the charging loads of EVs to decrease the deviation between the day-ahead bids and the actual energy consumption to reduce penalty costs. Owing to the short time interval for EV charging scheduling, EV aggregators require fast strategies that enable them to distribute charging/discharging commands among EVs in a timely manner, as suggested by Refs. [39,40]. In this sense, the computational complexity of the solving algorithm used for the proposed model is vital for the implementation of the real-time charging operation of EVs [41]. A very limited body of research exists regarding real-time energy management of EVs in the electricity market framework. In Ref. [42], a real-time charging-scheduling model was presented to help EV aggregators participate in the energy and regulation markets. The developed model for assigning charging points to EVs based on their charging priority was formulated as a linear program, which can be solved efficiently. In Ref. [43], a holistic methodology was presented to manage the charging of EVs in quasi-real-time for the market participation of EV aggregators, considering all aspects of restriction. The proposed method aims to minimize the penalty costs of EV aggregators incurred by the deviation between the energy bought in the market and the energy sold to EV users to increase the EV aggregators' profits. Moreover, a real-time charging strategy for EVs with vehicle-to-grid operation was performed to provide ancillary services in Ref. [44]. The computational performance and accuracy of several real-time controllers were analyzed. Extensive simulations indicate that the proposed controller can improve the accuracy of the following regulation signals and reduce battery cycling.

1.3. 1.3. Paper contributions and organizations

This study exploited the coordinated charging management of EVs in a market environment from the perspective of EV aggregators to enable the integration of EVs into the existing power grid. The day-ahead bidding process and real-time charging scheduling operations were considered to address the EV charging-scheduling problem. The former deals with the uncertainties introduced by EV charging behaviors and market clearing, and the latter dynamically adjusts the charging strategy of EVs for profit maximization. In this study, the proposed coordinated charging solution was assessed through a case study of the Guangdong electricity market. The primary technical contributions of this study are summarized as follows:

- This study bridges the gaps between theoretical research and practical applications for coordinated EV charging by introducing an electricity market framework. To apply the proposed approach to real-world situations, the agent relationship between EV aggregators and EV users is established as a premise for the EV aggregators' market participation.
- In the proposed methodology, the charging autonomy of the EV users is fully respected. In previous studies, it was assumed that EV aggregators could directly utilize the charging flexibility of EVs to participate in the electricity market. EV users have the authority to select their agent contracts with EV aggregators for EV charging management. In this context, two types of agent modes were developed to satisfy the coordinated charging requirements of EV users.
- Potential real-time clearing scenarios are incorporated into the day-ahead bidding model, which can largely reduce the risk arising from the real-time market. In addition, the real-time optimizer is designed to dynamically adjust the charging strategy of the available EVs to follow the day-ahead bidding energy profiles for the operational cost reduction of EV aggregators in the real-time market.

The remainder of this study is organized as follows. The problem regarding the coordinated charging operation of EV in a market framework is formulated to gain the optimal market participation strategy in Section 2. Subsequently, EV-related and market data for the simulations are presented in Section 3. Subsequently, a result analysis is provided in Section 4 to verify the rationality of the proposed method. Finally, Section 5 concludes this study and highlights important findings.

2. Problem formulation of coordinated EV charging in market frameworks

2.1. General description

2.1.1. Operating process of EV aggregators in markets

In this study, the coordinated charging schedule management of EVs is explored by considering the Guangdong electricity market. The Guangdong electricity market was the first batch to undertake a pilot study on the reform of power markets in China. It uses the security-constrained economic dispatch approach to produce the marginal clearing price for market-clearing. The timeline of the participation of EV aggregators in energy markets is depicted in Fig. 1. In day-ahead markets, EV aggregators need to report their power demand to the Guangdong Power Exchange Center (GPEC) before 13:00 in a day-ahead horizon. Correspondingly, power plants also need to inform the GPEC of their supply. According to the power demand and supply status of electric grids, the GPEC produces day-ahead market-clearing results before 15:30, which are released to EV aggregators. In real-time markets, the GPEC releases the real-time clearing price each hour based on the ultra-short-term load prediction (e.g., at the time scale of 15 min) and the stored bidding information from power plants and electricity retailers. In terms of the current clearing point, EV aggregators schedule the charging power of EVs from the current time period to the end of the day based on the existing clearing price.

Based on the market rules, the two-phase operating process of EV aggregators managing an EV fleet in a market environment is illustrated in Fig. 2. First, *in the day-ahead bidding phase*, EV aggregators bid electric energy for EV charging in advance in day-ahead markets. In the Guangdong spot electricity market, power plants submit priced energy supply plans to the GPEC, whereas electricity retailers (including EV aggregators) need to report non-priced energy demand bids to the GPEC. When the GPEC receives bids from all market participants, the day-ahead market is cleared by solving the security-constrained economic-dispatch problem. The day-ahead clearing price is used for the first settlement between the GPEC and EV aggregators.

In the real-time scheduling phase, EV aggregators must consider the charging demand of the current EV fleet and manage the charging scheduling of EVs based on the day-ahead bidding energy and real-time clearing price. It is worth mentioning that EV aggregators cannot bid for energy in real-time. Hence, they can only regulate the charging strategies of EVs to increase their profits. Additionally, the availability of EVs changes over time. As a result, EV aggregators must instantly update the charging information of previously connected EVs and collect the charging data of newly connected EVs for charging rescheduling in real time.

2.1.2. Charging agent modes provided for EV users

Before EV aggregators participate in electricity markets, they first need to contrast with individual EV users to procure their charging flexibility. In existing studies, EV aggregators have coordinated the charging of EVs using centralized or distributed methods [45]. In the centralized method, EV aggregators can uniformly schedule the charging of EVs to achieve a specific target. In the distributed method, the charging behavior of EVs is regulated by the price signals released by EV aggregators. This can naturally be extended to two types of agent modes provided for EV users to conduct the coordinated charging operation: centralized management mode (CMM) and distributed incentive mode (DIM).

In the CMM, EV users should hand over the charging authority of EVs to EV aggregators, and EV aggregators can utilize the charging flexibility of EVs to generate profits in the competitive electricity market. In this mode, the EV aggregators can directly control the EV charging process. In return, EV users can obtain cheaper negotiated energy to recharge their vehicles. In the DIM, EV users can reserve the charging authority of EVs and formulate the charging strategy of EVs by themselves based on real-time energy prices. In this mode, EV users must transmit their charging instructions to EV aggregators for execution [46].

A comparison between CMM and DIM in several aspects is presented in Table 1. The observations show that EVs with a CMM have no charging autonomy. Consequently, EV aggregators can completely control the charging process of these EVs. Additionally, EV users can strive for a lower price per kWh for EV charging. On the other hand, users of EVs with DIM reserve charging autonomy. Therefore, the charging flexibility of these EVs was not high. Moreover, within the DIM, the charging costs of EVs depend entirely on real-time market prices.

Once EV users plug their vehicles into the smart charging system, they can determine whether to conduct a coordinated charging operation. Either the CMM or the DIM can be selected if they are willing to provide the coordinated charging operation, and charging-related information, for example, departure time and charging demand, can be made available to EV aggregators. Otherwise, the EVs are charged in conventional charging mode.

2.2. Day-ahead bidding strategy of EV aggregators

When EV aggregators managing an EV fleet participate in energy markets, they need to bid for energy in day-ahead markets to charge EVs the next day. A day-ahead bidding strategy is critical for EV aggregators to reduce their operational costs. Herein, an optimization model is formed to help EV aggregators acquire a participation strategy in day-ahead markets by considering various uncertainties from EV charging and electricity markets.

As shown in Fig. 3, a one-day cycle of 24 h is considered for EV charging scheduling. In the Guangdong electricity market, the energy price was released hourly from 0:00 to 24:00. Herein, a day is divided into 24 h equally to conduct the settlement between the EV aggregators and the GPEC. However, the hourly timescale is too rough to schedule EV charging in practical applications. It is worth mentioning that if the

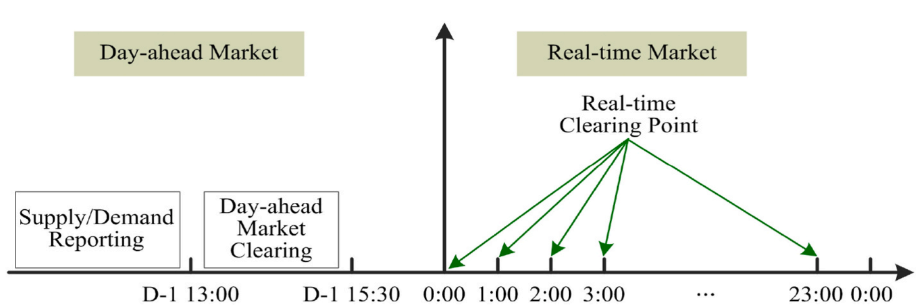

Fig. 1. Timeline of EV aggregators participating in energy markets.

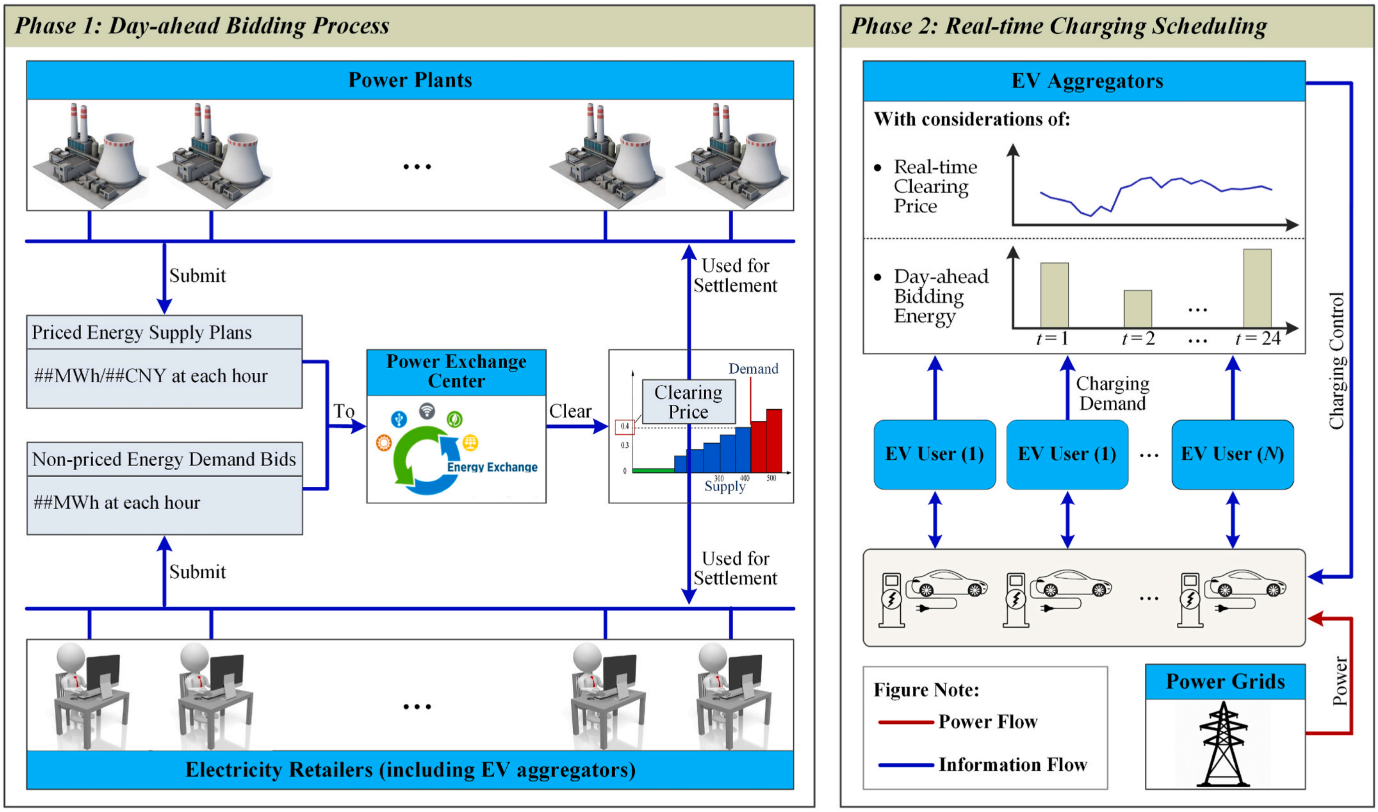

Fig. 2. Two-phase operating process of EV aggregators in market environment.

Table 1
Comparison between CMM and DIM.

Mode	CMM	DIM
Charging autonomy	No	Yes
Charging cost	Determinate	Indeterminate
Charging flexibility	High	Low
User privacy	Moderately concerned	Marginally concerned

time interval is too short, it will dramatically increase the complexity of the optimization problem and scheduling frequency in the real-time coordinated charging operation. Therefore, the 15-min-interval time scale was used for EV charging scheduling and the settlement between EV aggregators and EV users. In addition, different time discretization scales for the EV charging schedule are compared in Table 2.

To calculate the operational costs of the EV aggregators, we define t to represent the serial number of hours during a day and $t \in T (T = [1, 24])$. Hence, the bidding costs of EV aggregators in day-ahead markets can be expressed as

$$C_1 = \sum_{t \in T} \lambda_t^{Day} E_t^{Day} \tag{1}$$

where

λ_t^{Day} denotes the day-ahead energy price at the t-th hour, in CNY/kWh;

E_t^{Day} denotes the amount of day-ahead bidding energy at the t-th hour, in kWh.

It should be noted that the potential clearing scenarios in real-time markets should be integrated in the day-ahead bidding model, as extra penalty costs are incurred when the imbalance quantity in real-time markets exceeds tolerance. In Guangdong real-time markets, because of the imbalance quantity, the potential costs of EV aggregators can be expressed as

$$C_2 = \sum_{w \in W} \pi_w \sum_{t \in T} \left(\lambda_{w,t}^{RT} \cdot \Delta E_{w,t} + C_{w,t}^{Pen} \right) \tag{2}$$

where

w, denotes the index of potential real-time clearing scenarios, in p.u.;

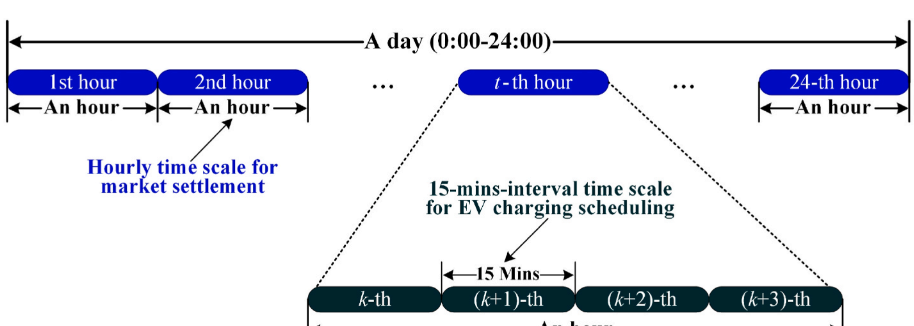

Fig. 3. One-day cycle and time scales adopted for EV charging scheduling.

Table 2
Time scales for EV charging scheduling in existing studies.

Reference	Length of each time slot	Scheduling accuracy for load smoothing	Computation cost for optimal solution
[47]	1 Hour	Low	Low
[48,49]]	0.5 Hour	Moderate	Moderate
[3,10,50, 51]	15 Minutes	High	High
[52]	10 Minutes	Extremely high	Extremely high

π_w, denotes the probability of the scenario w occurrence, in p.u.;

$\lambda^{RT}_{w,t}$, denotes the real-time price at the t-th hour for the scenario w, in CNY/kWh;

$\Delta E_{w,t}$, denotes the deviation between the day-ahead bidding energy and the energy consumed by EVs at the t-th hour for the scenario w, in kWh;

$C^{Pen}_{w,t}$, denotes penalty costs arising from the deviation at the t-th hour for the scenario w in CNY.

In Eq. (2), $\Delta E_{w,t}$ can be calculated by:

$$\Delta E_{w,t} = E^{RT}_{w,t} - E^{Day}_t \tag{3}$$

where $E^{RT}_{w,t}$ denotes the energy consumed at the tth hour for scenario w. In addition, $C^{Pen}_{w,t}$ can be calculated by

$$C^{Pen}_{\omega,t} = \begin{cases} \left[E^{Day}_t - (1+\varepsilon_0)E^{RT}_{\omega,t}\right]\left(\lambda^{RT}_{\omega,t} - \lambda^{Day}_t\right), E^{Day}_t > (1+\varepsilon_0)E^{RT}_{\omega,t} \text{ and } \lambda^{RT}_{\omega,t} > \lambda^{Day}_t \\ \left[(1-\varepsilon_0)E^{RT}_{\omega,t} - E^{Day}_t\right]\left(\lambda^{Day}_t - \lambda^{RT}_{\omega,t}\right), E^{Day}_t < (1-\varepsilon_0)E^{RT}_{\omega,t} \text{ and } \lambda^{RT}_{\omega,t} < \lambda^{Day}_t \\ 0, otherwise \end{cases} \tag{4}$$

where ε_0 denotes the allowable bidding deviation rate in Guangdong real-time markets.

As stated above, the total costs of EV aggregators can be given by:

$$C = C_1 + C_2 \tag{5}$$

where the formation of C_1 andC_2 refer to Eqs. (1) and (2), respectively.

In energy markets, EV aggregators can sell energy to users for revenue. To obtain the optimal charging strategy for EVs, each hour is divided into 4 units equally, and there are a total of 96 time slots during the day, as illustrated in Fig. 3. Let k denote the serial number of the time slots and kÎK ($K = [1, 96]$). As indicated above, two types of agent modes are provided for EV users to conduct coordinated charging: CMM and DIM. Let N_1 denote the set of EVs with CMM. For EVs with CMM, the charging costs rely on the negotiated price of EV users with EV aggregators. Hence, the expected revenue that EV aggregators can obtain from EVs with the CMM can be calculated by

$$R_1 = \sum_{w\in W}\pi_w \sum_{k\in K}\left(\sum_{n\in N_1}\lambda^{Agr}_{n,h}\cdot E^{M_1}_{w,n,k}\right), \text{where } h = \text{int}((k-1)/4)+1 \tag{6}$$

where

$E^{M_1}_{w,n,k}$ denotes the charging quantity of the n-th EV in the set N_1 at the k-th time slot for the scenario w, in kWh;

$\lambda^{Agr}_{n,h}$ denotes the agreement price that EV aggregators sell to the n-th EV in the set N_1 at the h-th hour, in CNY/kWh.

Herein, the function 'int ()' rounds a number down to the nearest integer. The expression in Eq. (6) aims to convert the energy price at the k-th time slot to the energy price at the t-th hour.

Let N_2 denote the set of EVs with DIM. For EVs with DIM, the charging costs depend on the real-time market price. As a result, the revenue that EV aggregators can obtain from EVs with the DIM can be calculated by

$$R_2 = \sum_{w\in W}\pi_w \sum_{k\in K}\left((1+\theta_0)\lambda^{RT}_{w,h}\cdot \sum_{n\in N_2}E^{M_2}_{w,n,k}\right), \text{where } h = \text{int}((k-1)/4)+1 \tag{7}$$

where

$E^{M_2}_{w,n,k}$ denotes the charging quantity of the n-th EV in the set N_2 at the k-th time slot for the scenario w, in kWh;

$\lambda^{RT}_{w,h}$ denotes the real-time price at the h-th hour for the scenario w, in CNY/kWh;

θ_0 denotes the service tariff that EV aggregators envy on the EVs with the DIM, in p.u.

Herein, the value of $E^{M_2}_{w,n,k}$ is determined by the EV users. In the demand response program, EV users decrease their charging amount for a higher energy price. In addition, when the energy price reaches an unacceptable level, they tend to terminate EV charging to reduce charging costs. Based on this principle, the value of$E^{M_2}_{w,n,k}$ can be formulated as

$$E^{M_2}_{w,n,k} = \begin{cases} \varphi^{max}_{n,k} - \varphi_{n,k}\lambda^{RT}_{\omega,h}, \lambda^{RT}_{\omega,h} \le \varphi^{max}_{n,k}\big/\varphi_{n,k} \\ 0 \quad, \lambda^{RT}_{\omega,h} > \varphi^{max}_{n,k}\big/\varphi_{n,k} \end{cases}, \forall\omega, n\in N_2, k \tag{8}$$

where $\varphi^{max}_{n,k}$ indicates the maximum allowable charging energy of the n-th EV in the set N_2 at the k-th time slot, $\varphi_{n,k}$ denotes the response coefficient of the n-th EV at the k-th time slot, *and h* is defined as the same in Eq. (6).

Thus, the total revenue of EV aggregators can be calculated as:

$$R = R_1 + R_2 \tag{9}$$

where the formation of R_1 andR_2 can be referred to in Eq. (6) and Eq. (7).

Consequently, the expected net profits of EV aggregators in the day-ahead bidding model can be expressed as

$$P = R - C \tag{10}$$

In combination with Eqs. (1)–(9), the objective function can be formulated as

$$\begin{aligned} \max \sum_{w\in W}\pi_w\sum_{k\in K}\left(\sum_{n\in N_1}\lambda^{Agr}_{n,h}\cdot E^{M_1}_{w,n,k}\right) + \sum_{w\in W}\pi_w\sum_{k\in K}\left((1+\theta_0)\lambda^{RT}_{w,h}\cdot\sum_{n\in N_2}E^{M_2}_{w,n,k}\right) \\ -\left(\sum_{t\in T}\lambda^{Day}_t E^{Day}_t + \sum_{w\in W}\pi_w\sum_{t\in T}\left(\lambda^{RT}_{w,t}\cdot\Delta E_{w,t} + C^{Pen}_{w,t}\right)\right) \end{aligned} \tag{11}$$

where the mathematical expressions for h and $C^{Pen}_{\omega,t}$ are expressed in Eq. (4) and Eq. (6), and

$$\Delta E_{w,t} = E^{RT}_{w,t} - E^{Day}_t, \text{where} E^{RT}_{w,t} = \sum_{n\in N_1}\sum_{k=4t-3}^{4t}E^{M_1}_{w,n,k} + \sum_{n\in N_2}\sum_{k=4t-3}^{4t}E^{M_2}_{w,n,k} \tag{12}$$

subject to:

$$E^{Day}_{min} \le \sum_{t\in I}E^{Day}_t \le E^{Day}_{max} \tag{13}$$

$$E^{M_1}_{\omega,n,t} \le P^{Max}_n \quad \Delta t, \forall n\in N_1 \tag{14}$$

$$\sum_{t\in\left[\Gamma^c_n,\Gamma^d_n\right]} E^{M_1}_{\omega,n,t}\cdot\frac{\eta_n}{Bat_n} = SoC^d_n - SoC^c_n, \forall\omega, n\in N_1 \tag{15}$$

$$E^{M_1}_{\omega,n,t} \ge 0, \forall\omega, n\in N_1, t \tag{16}$$

where

E^{Day}_{min} denotes the minimum bidding energy in day-ahead markets, in kWh;

E^{Day}_{max} denotes the maximum bidding energy in day-ahead markets, in kWh;

P_n^{Max} denotes the maximum charge power of the n-th EV in the set N_1, in kW;

Δt denotes the length of time slots, in hour;

Γ_n^c denotes the connection time slot of the n-th EV in the set N_1, in p.u.;

Γ_n^d denotes the disconnection time slot of the n-th EV in the set N_1, in p.u.;

η_n denotes the charger efficiency of the n-th EV in the set N_1, in p.u.;

Bat_n denotes the onboard battery capacity of the n-th EV in the set N_1, in kWh;

SoC_n^d denotes the disconnection battery SoC of the n-th EV in the set N_1, in p.u.;

SoC_n^c denotes the connection battery SoC of the n-th EV in the set N_1, in p.u.

Herein, Eq. (13) denotes the total day-ahead bidding energy that should be limited between the minimum and maximum transaction capacities. (14) represents the charging power of each EV, which cannot exceed the maximum charging power of its charger during the charging process. (15) reveals the charging demands of EV users that must be satisfied before EVs are disconnected from the power grids, and Eq. (16) indicates that the discharging process of the EVs is not considered.

2.3. Real-time charging scheduling of EVs

In real-time operation, EV aggregators need to make the utmost of the purchased energy for EV charging to avoid unnecessary penalty costs. The charging flexibility of EVs should be fully utilized to reduce the total operational costs of EV aggregators in real-time markets.

Fig. 4 depicts the real-time charging scheduling process of EVs on a time-rolling horizon. In the k-th time slot, EV aggregators need to judge whether to adjust the existing charging strategy of EVs through three types of triggering events: 1) Do the real-time clearing prices change? 2) Are there new EVs connected to power grids? 3) Are there current EVs expectedly disconnected from grids? If any triggering event occurs, EV aggregators need to reschedule the charging strategy of EVs; otherwise, they will maintain the existing operating strategy for EVs. Before rescheduling the charging of EVs, EV aggregators should collect the charging data of EVs as the input of the proposed model. Also, the real-time clearing prices and the day-ahead bidding strategy are served as inputs of the real-time optimizer for the charging rescheduling strategy of EVs. After the k-th time slot, the charging data of EVs disconnected from power grids will be removed from the charging scheduling system, and the remaining day-ahead bidding energy of EV aggregators will be updated for EV charging scheduling in the next time slot.

Herein, Model (k) is introduced to obtain the optimal charging strategy of EVs for the kth time slot at the tth hour for EV charging rescheduling. We define S_k^1 to denote the set of available EVs with the CMM at the k-th time slot and define S_k^2 to denote the set of available EVs with the DIM at the k-th time slot. Let λ_i^{RT} indicate the released real-time clearing price at the i-th hour ($i \geq t$). For the time periods after the k-th time slot, the expected revenue that EV aggregators can obtain from EVs with these two modes in real-time markets can be written as

$$R_{RT} = \sum_{j=k}^{96} \left(\sum_{n \in S_k^1} \lambda_{n,j}^{Agr} \cdot E_{n,j}^{M_1} \right) + \sum_{j=k}^{96} \left((1+\theta_0)\lambda_h^{RT} \cdot \sum_{n \in S_i^2} E_{n,j}^{M_2} \right), \text{where} h = \text{int}((k-1)/4)+1 \tag{17}$$

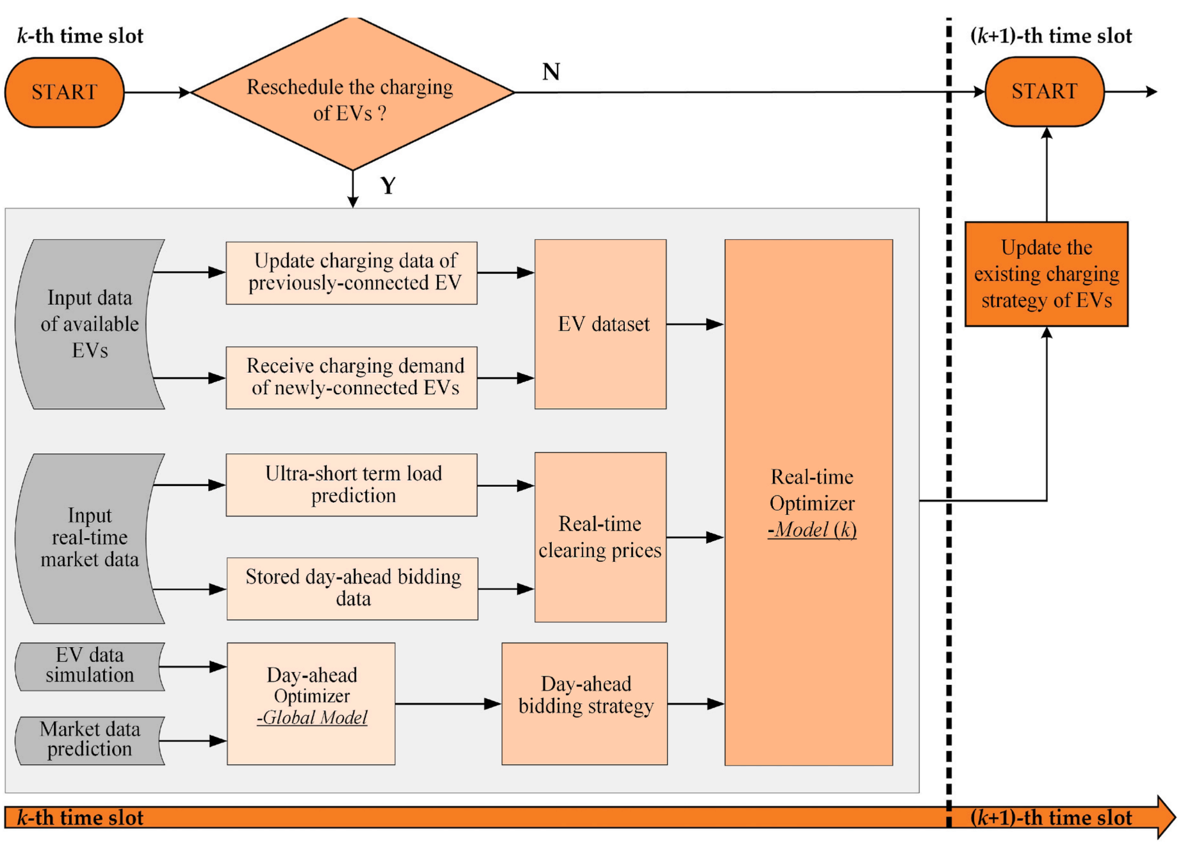

Fig. 4. EV real-time charging scheduling schematic diagram.

where

$\lambda_{n,j}^{Agr}$ denotes the agreement price that EV aggregators sell to the n-th EV in the set S_k^1 at the j-th time slot, in CNY/kWh;

$E_{n,j}^{M_1}$ denotes the charging quantity of the n-th EV in the set S_k^1 at the j-th time slot, in kWh;

λ_h^{RT} denotes the released real-time clearing price at the h-th time slot, in CNY/kWh;

$E_{n,j}^{M_2}$ denotes the charging quantity of the n-th EV in the set S_k^2 at the j-th time slot, in kWh.

Correspondingly, the expected costs that EV aggregators should pay for the time periods after the k-th time slot at the t-th hour in real-time markets can be calculated by:

$$C_{RT} = \sum_{i=t}^{24} \left(\lambda_i^{RT} \cdot \Delta E_i + C_i^{Pen} \right) \tag{18}$$

where

$$\Delta E_i = E_i^{RT} - E_i^{Day} \tag{19}$$

$$E_i^{RT} = \begin{cases} \sum_{j=4k-3}^{k-1} \delta_j + \sum_{n \in N_1} \sum_{j=k}^{4k} E_{n,j}^{M_1} + \sum_{n \in N_2} \sum_{j=k}^{4k} E_{n,j}^{M_2}, i = t \\ \sum_{n \in N_1} \sum_{j=4i-3}^{4i} E_{n,j}^{M_1} + \sum_{n \in N_2} \sum_{j=4i-3}^{4i} E_{n,j}^{M_2}, i > t \end{cases} \tag{20}$$

$$C_i^{Pen} = \begin{cases} \left[E_i^{Day} - (1+\varepsilon_0) E_i^{RT} \right] \left(\lambda_i^{RT} - \lambda_i^{Day} \right), E_i^{Day} > (1+\varepsilon_0) E_i^{RT} \ \ and \ \ \lambda_i^{RT} > \lambda_i^{Day} \\ \left[(1-\varepsilon_0) E_i^{RT} - E_i^{Day} \right] \left(\lambda_i^{Day} - \lambda_i^{RT} \right), E_i^{Day} < (1-\varepsilon_0) E_i^{RT} \ \ and \ \ \lambda_i^{RT} < \lambda_i^{Day} \\ 0, otherwise \end{cases} \tag{21}$$

where

ΔE_i denotes the deviation between the day-ahead bidding energy and the consumed energy at the i-th hour, in kWh;

δ_j denotes the consumed energy at the j-th time slot, in kWh;

C_i^{Pen} denotes the penalty costs arising from the deviation at the i-th hour, in CNY.

Therefore, the objective function with the target of maximizing the profits of the EV aggregators in Model (k) can be formulated as:

$$\max \sum_{j=k}^{96} \left(\sum_{n \in S_k^1} \lambda_{n,j}^{Agr} \cdot E_{n,j}^{M_1} \right) + \sum_{j=k}^{96} \left((1+\theta_0) \lambda_h^{RT} \cdot \sum_{n \in S_k^2} E_{n,j}^{M_2} \right) - \sum_{i=t}^{24} \left(\lambda_i^{RT} \cdot \Delta E_i + C_i^{Pen} \right) \tag{22}$$

subject to:

$$\sum_{j \in [k, \Gamma_n^d]} E_{n,j}^{M_1} \cdot \frac{\eta_n}{Bat_n} = SoC_n^d - SoC_n^c, \forall n \in S_k^1 \tag{23}$$

$$E_{n,j}^{M_1} \le P_n^{Max} \ \ \Delta t, \forall j \ge k, n \in S_k^1 \tag{24}$$

$$E_{n,j}^{M_1} \ge 0, \forall j \ge k, n \in S_k^1 \tag{25}$$

where Eqs. 23–25 indicate that the charging requirements of EVs should be satisfied before they are disconnected from the grids, and that the charging power of EVs should be limited to the maximum value of the charger, as in the day-ahead bidding model. In addition, the charging quantity $E_{n,j}^{M_2}$ of EVs in the set S_k^2 was simulated using Eq. (8).

The aforementioned model can obtain the optimal EV charging strategy at the kth time slot. In real-time energy management, if there are variations in real-time clearing prices, if there is any new EV being plugged into the system, or if there is any existing EV being disconnected from power grids, the model will be triggered as per the updated inputs. Once the EV aggregators obtain the optimal EV charging strategy, co-ordinated charging instructions are delivered to the charging piles for implementation.

3. Data preparation for simulations

3.1. EV charging data

In the day-ahead bidding model of EV aggregators, it is extremely difficult to predict the charging behavior of EVs because of their mobility as transportation tools. To address the impact of EV charging uncertainties on the bidding strategy of EV aggregators in this study, charging data for EVs were generated using stochastic simulations as the model's input.

In general, an overwhelming majority of EVs employ either daytime charging in the workplace or overnight charging at home for energy replenishment. In the simulations, it was assumed that the charging events of EVs with overnight and daytime charging accounted for approximately 75% and 25%, respectively. According to Ref. [53], rough distribution functions can be acquired to describe the charging behavior of EVs. The data generation methods for EVs with daytime and overnight charging are summarized in Table 3.

When EV users charge overnight at home, they plug their vehicles into charging piles in the evening and disconnect them from charging piles in the morning to drive to the destination. Therefore, it is assumed that the plug-in time of EVs with overnight charging is mainly distributed in the evening, at approximately 8:00 p.m., and the plug-out time of EVs is mainly distributed in the morning, at approximately 7:30 a.m. The plug-in time of EVs follows a normal distribution with a mean of 20:00 and a standard variation of 2 h. The plug-out time of EVs is always the morning of the next day. The plug-out time of EVs can be described by a normal distribution with a mean of 7:30 and a standard variation of 1.5 h. For the charging schedule of EVs on the target day, the charging ending time of EVs was set to 24:00. The battery SoC of EVs at 24:00 for overnight charging is a variable determined by the expected SoC of EVs and the EV connection time. The plug-in SoC of the EVs can be described by a uniform distribution between 0.2 and 0.5. Finally, the maximum operating power of the charger is set to be 3.52 kW (level 1:16A/220 V).

However, when home charging facilities are unavailable, EV users tend to charge their vehicles in the workplace as a primary alternative to home charging. In such a scenario, EVs will go through daytime charging in most cases, in which EV users plug their vehicles into the charging piles after they arrive at the workplace and disconnect them from the charging piles in the evening to drive home. Therefore, it is assumed that the plug-in time of EVs with daytime charging is mainly distributed in the morning at approximately 8:00 a.m., and the plug-out time of EVs is mainly distributed in the morning at approximately 7:30

Table 3
Creation methods for EV-related data.

Charge Type	Proportion	Plug-in time	Plug-out time	Plug-in SoC	Plug-out SoC	Charging level
Overnight charging	75%	N (20, 2)	N (7.5, 1.5)	U (0.2, 0.5)	Variable	Level 1: 16A/220 V
Daytime charging	25%	N (8, 1.5)	N (17.5, 2)	U (0.2, 0.5)	Variable	Level 2: 32A/220 V

p.m. The plug-in time of EVs can be described by a normal distribution with a mean of 8:00 and a standard variation of 1.5 h, and the plug-out time of EVs can be described by a normal distribution with a mean of 19:30 and a standard variation of 2 h. In addition, the battery SoC of EVs is low when plugged into charging piles, and EV users usually expect to charge their vehicles to a high level. In this study, the plug-in SoC of EVs is assumed to follow a uniform distribution between 0.2 and 0.5, and the plug-out SoC of EVs is assumed to be 80% of the maximum SoC that can be charged in the connection time. In addition, the maximum operating power of the charger is set to be 7.04 kW (level 2:32A/220 V).

3.2. Market data

In this study, the proposed solution is implemented in the context of the Guangdong electricity market to investigate EV charging behaviors. Guangdong Province is the most developed region in China and has adopted a series of strong policies to promote the adoption of EVs. The large-scale adoption of EVs will challenge distribution networks. On the other hand, the Guangdong Province is one of the first to conduct the reform of power markets in China. This provides an opportunity to investigate EV charging behavior in a market environment. In the day-ahead bidding model, EV aggregators should combine the day-ahead clearing prices with potential real-time clearing scenarios to create the optimal bidding strategy. It is noteworthy that both day-ahead and real-time clearing prices are unknown in advance. In general, day-ahead clearing prices can be accurately predicted because daily day-ahead price profiles show a certain regularity. Nonetheless, there are extremely high uncertainties in the real-time clearing prices associated with the real-time status of grid supply and demand. Consequently, several potential real-time clearing scenarios were considered to handle price uncertainties in real-time markets.

As suggested in Ref. [23], the potential real-time clearing scenarios can be classified into four categories by using a multi-class support vector machine to analyze the historical market clearing data: low, medium, high, and extra high, as illustrated in Fig. 5. It can be observed that these four real-time clearing price curves show the same variation trend. In each potential clearing scenario, a high price usually occurs from 9:00 to 11:00, from 15:00 to 17:00, and from 20:00 to 23:00. Low prices appear at 13:00, 19:00, and 0:00 to 8:00. In addition, in the extra-high real-time clearing scenario, the lowest clearing price in a day is 0.410 CNY/kWh, whereas the highest clearing price can reach 1.236 CNY/kWh. However, for the low real-time clearing scenario, the clearing prices vary from 0.268 CNY/kWh to 0.759 CNY/kWh. These four potential clearing scenarios were integrated into the model using a probability function.

From the perspective of EV aggregators, the day-ahead clearing price

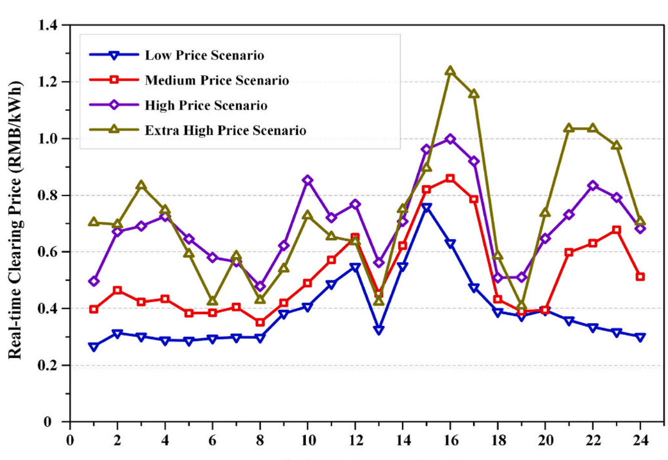

Fig. 5. Four types of potential real-time clearing scenarios.

must be predicted by adopting advanced prediction algorithms for bidding (e.g. Refs. [54,55]), which is beyond the scope of this study. The actual clearing data in the day-ahead markets listed in Table 4 was used to validate the proposed method. In addition, regarding the actual real-time clearing prices, there is a high level of uncertainty and fluctuation. In this study, real-time clearing prices are generated by a normal distribution to schedule the charging of EVs in a real-time fashion.

4. Case study and numerical results

4.1. Simulation setting

In the case study, the details of the necessary parameters for the simulations are provided in Table 5. Contracts between EV aggregators and EV users have significant impacts on EV aggregators' profits. Herein, the agreement price $\lambda_{n,h}^{Agr}$ that EV aggregators sell to EVs with the CMM is set as 0.5 CNY/kWh, and the service tariffθ_0 that EV aggregators charge to EVs with the DIM is set to 0.25. The following section investigates the profits of EV aggregators for different values of$\lambda_{n,h}^{Agr}$ andθ_0 involved. In addition, the allowable tolerance for the penalty due to the imbalance in energy in real-time markets is set as 0.05 based on the rules of Guangdong electricity markets [23]. The day-ahead bidding energy for EV charging was not lower than 1000 kWh and higher than 10,000 kWh. Moreover, the response coefficient for the coordinated charging of EVs with the DIM was set to 2.86, and the charging efficiency of EVs was set to 0.95.

4.2. Result analysis for day-ahead strategy

First, the number of EVs managed by the EV aggregators was set to 2000. EVs with CMM and DIM accounted for 50% of EVs, respectively. The charging events of the EVs were generated according to the method presented in Section 3.1. The number of EVs connected to the power grids for charging scheduling in each time slot is shown in Fig. 6. The number of available EVs at each time slot varied from 251 to 753. The minimum available EVs occurred at the 49th time slot, and the maximum available EVs appeared at the 96th time slot. In addition, more EVs are available for charging scheduling during the time periods from the 1st time slot to the 32nd time slot (i.e., from 0:00 to 8:00), and from the 80th time slot to the 96th time slot (i.e., from 20:00 to 24:00). Currently, most EV users prefer to charge their vehicles at night. Therefore, the simulated charging data of EVs is consistent with real-life situations regarding EV charging behavior.

In the day-ahead time horizon, EV aggregators bid energy for EV charging. The simulation results reveal that the day-ahead bidding strategy of the EV aggregators is not merely dependent on the day-ahead energy price, as illustrated in Fig. 7. In fact, the day-ahead bidding strategy of EV aggregators is determined by the day-ahead and real-time markets. When the real-time clearing price is higher than the day-ahead clearing price, it is profitable for EV aggregators to bid more energy in day-ahead markets without the punishment mechanism. However, given the disparity in energy costs, EV aggregators should implement an appropriate bidding strategy in day-ahead markets to reduce operational costs. Overall, the price difference (PD) between the real-time and day-ahead markets can significantly impact the day-ahead bidding strategy of the EV aggregators. Fig. 8 presents the relevance between the day-ahead bidding strategy and PD when considering four types of potential real-time clearing scenarios. PD was larger than 0 in all potential clearing scenarios at 9, 11, 12, 14, 15, 16, 17, 18, and 19 h. Nonetheless, EV aggregators bid for the maximum allowable energy only at 9, 12, 16, 17, and 19 h. This is because EV aggregators can obtain enough revenue by purchasing cheaper electricity in day-ahead markets and selling it in real-time markets to offset the penalty costs caused by the energy imbalance.

When EV aggregators submit the day-ahead bidding strategy to the

Table 4
Day-ahead energy price at each hour in a day.

Serial Number of Hours	1	2	3	4	5	6	7	8	9	10	11	12
Energy Price (CNY/kWh)	0.594	0.560	0.479	0.584	0.571	0.467	0.444	0.345	0.311	0.454	0.405	0.439
Serial Number of Hours	13	14	15	16	17	18	19	20	21	22	23	24
Energy Price (CNY/kWh)	0.431	0.409	0.557	0.527	0.444	0.341	0.300	0.395	0.392	0.420	0.502	0.526

Table 5
Values of necessary parameters for simulations.

Parameter	$\lambda_{n,h}^{Agr}$ (CNY/kWh)	θ_0 (pu)	ε_0 (p.u.)	E_{min}^{Day} (kWh)	E_{max}^{Day} (kwh)	$\varphi_{n,k}$ (p.u.)	η_n (p.u.)
Value	0.5	0.25	0.05	1000	10,000	2.86	0.95

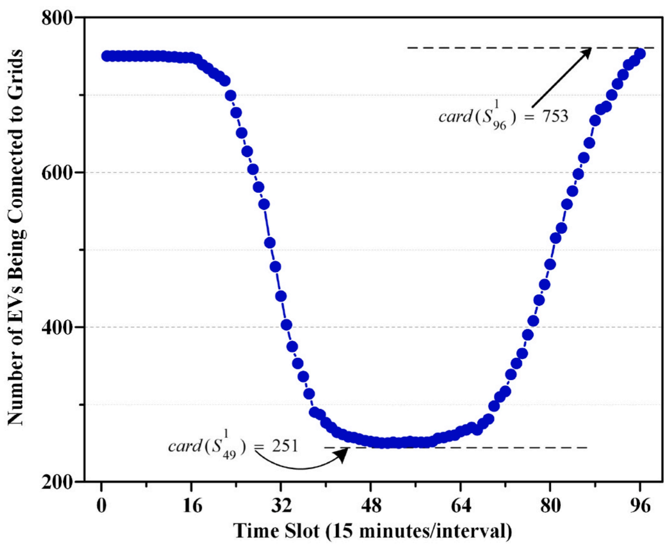

Fig. 6. Number of available EVs for charging scheduling at each time slot.

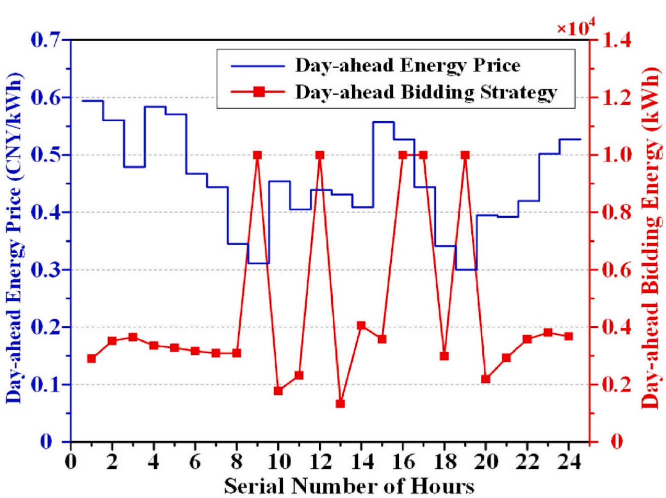

Fig. 7. Day-ahead bidding strategy of EV aggregators associated with day-ahead energy prices.

energy exchange center, the purchasing costs and expected penalty costs of the EV aggregators can be calculated, as shown in Fig. 9. It can be seen that the purchasing costs in day-ahead markets are mostly located between 1000 CNY and 2000 CNY. Higher purchasing costs appear at the hours of 9, 12, 16, 17, and 19, more than 3000 CNY. During these hours, EV aggregators pay the highest fee (roughly 5000 CNY) at hour 16. The higher purchasing costs are due to the extremely large volume of purchased energy and high energy price. Lower purchasing costs occur at hours 10, 11, 13, and 20, which are less than 1000 CNY. In addition, the expected penalty costs are less than 500 CNY during most hours. Despite this, the expected penalty costs exceeded 1500 CNY at 11, 12, 15, 16, and 17 h. This is because the day-ahead bidding energy is extremely high, whereas the energy used for charging EVs is very limited.

4.3. Result analysis for real-time operation

In real-time operation, EV aggregators desire to adjust the charging power of available EVs for more profits based on the real-time market-clearing result and day-ahead bidding strategy. A comparison between the day-ahead bidding energy and the energy consumed by the EVs is shown in Fig. 10. The energy consumed by EVs can coincide with the day-ahead bidding energy for most hours of the day. This indicates that the charging tasks of EVs are scheduled to achieve coordinated energy management. Note that there are large deviations between the day-ahead bidding energy and the energy consumed by the EVs at 9, 12, 16, 17, and 19 h. This is because EV aggregators bid for the maximum allowable electric energy, but there are no sufficient EVs available to consume the bidding energy. Overall, the EV aggregators schedule the charging of EVs to match the day-ahead bidding energy profiles to reduce their penalty costs. The relationship between the energy consumed by EVs and PD with the actual real-time clearing price is shown in Fig. 11. When PD is less than 0, the day-ahead price is higher than the real-time price. This indicates that EV aggregators bid for electric energy at a higher price in the day-ahead markets. As a result, in real-time operation, they will consume energy for EV charging to avoid more operational costs. The numerical results revealed that the energy consumed by EV charging is at a comparatively high level when the PD is less than 0, for example, at hours 2, 3, and 22. In contrast, when the PD is greater than 0, the real-time price is larger than the day-ahead price. This implies that EV aggregators bid for energy at a lower price in day-ahead markets. Therefore, they can reduce the utilization of energy to obtain more revenue in real-time markets, for example, at 1, 4, 5, 6, 20, 21, 23, and 24 h. Hence, the real-time charging strategy of EVs largely depends on the difference between the actual real-time clearing price and day-ahead price, in addition to the day-ahead bidding strategy.

The cost-benefit analysis of EV aggregators participating in real-time markets is presented in Fig. 12. To obtain revenue, EV aggregators can sell energy to individual EVs for charging. In addition, they need to pay the penalty costs for the imbalanced energy in real-time markets, and the settlement for the imbalanced energy also needs to be conducted. The revenue of the EV aggregators over a day is illustrated in Fig. 12 (*a*), indicating that the overall variation trend of revenue from EVs with the CMM is consistent with that from EVs with the DIM. When the PD is less than 0, EV aggregators obtain more revenue from EVs with both the CMM and DIM, as shown in Figs. 11 and 12. However, the curve fluctuation of revenue from EVs with DIM is much larger than that from EVs with CMM. The costs of the EV aggregators are illustrated in Fig. 12 (b). Because the energy consumed by EVs fits the day-ahead bidding strategy well, there are very low penalty costs incurred in real-time markets, except at 9, 12, 16, 17, and 19 h, under the condition that the EV aggregators bid the maximum allowable energy. Only at hours 9, 12, 16,

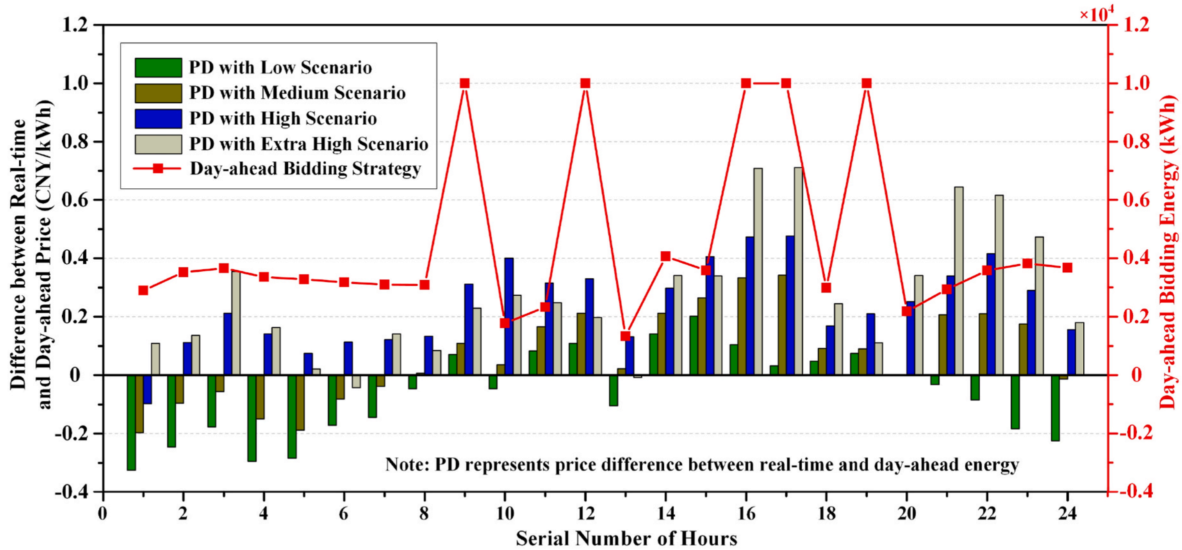

Fig. 8. Day-ahead bidding strategy of EV aggregators considering potential real-time clearing scenarios.

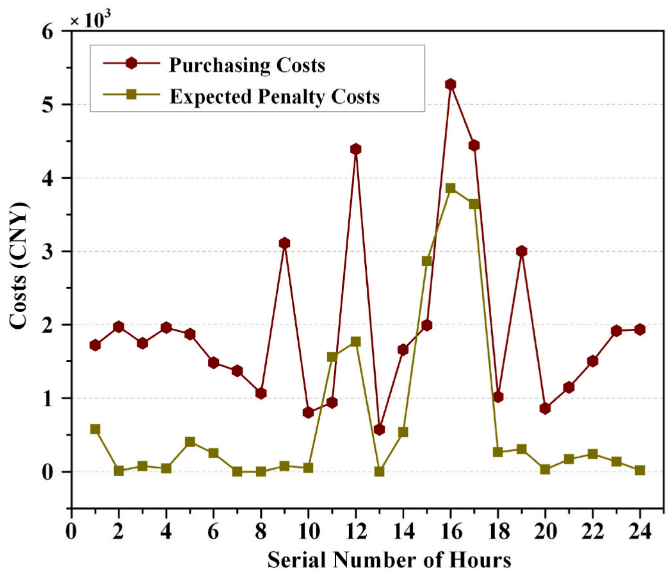

Fig. 9. Purchasing costs and expected penalty costs of EV aggregators in day-ahead markets.

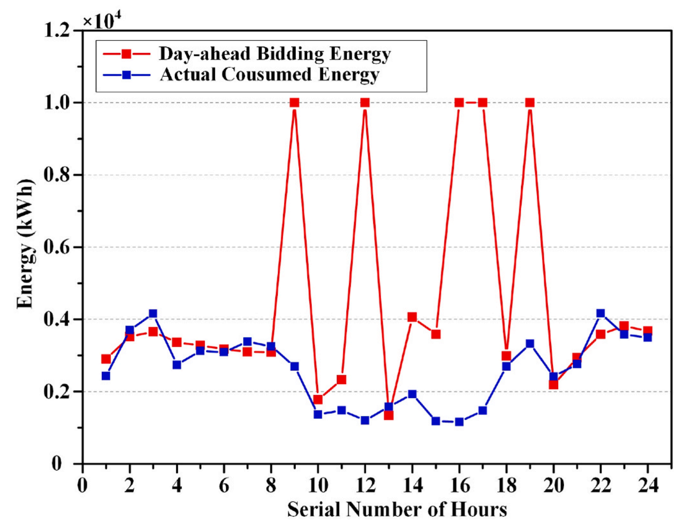

Fig. 10. Comparison between day-ahead bids and energy consumed by EVs.

17 and 19, there are huge deviations, resulting in high penalty costs for the EV aggregators. Despite all these factors, the massive surplus day-ahead purchased energy can be traded in real-time markets for the second settlement. It can be observed that at 9, 12, 16, 17, and 19 h, the revenue obtained by trading the imbalance energy is greater than the penalty cost of the imbalance quantity.

Finally, other case studies with different agreement prices and service tariff rates are considered, as illustrated in Table 6. For the worst scenario (i.e., Case 1 with the lowest agreement price and service tariffing), EV aggregators can obtain a net profit of 20901.07 CNY. Nevertheless, in the best scenario (i.e., Case 9 with the highest agreement price and service tariffing), EV aggregators can obtain a net profit of 30385.22 CNY. It can be observed that EV aggregators can employ the flexibility of EV charging to make a considerable profit under various conditions. This indicates that there are huge business opportunities for EV aggregators to coordinate the charging of EVs in energy markets while helping EV users reduce their charging costs.

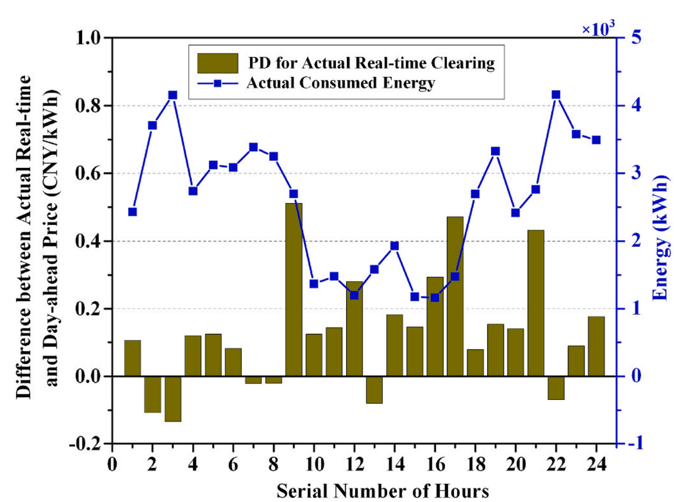

Fig. 11. Consumed energy by EVs associated with PD for actual real-time clearing results.

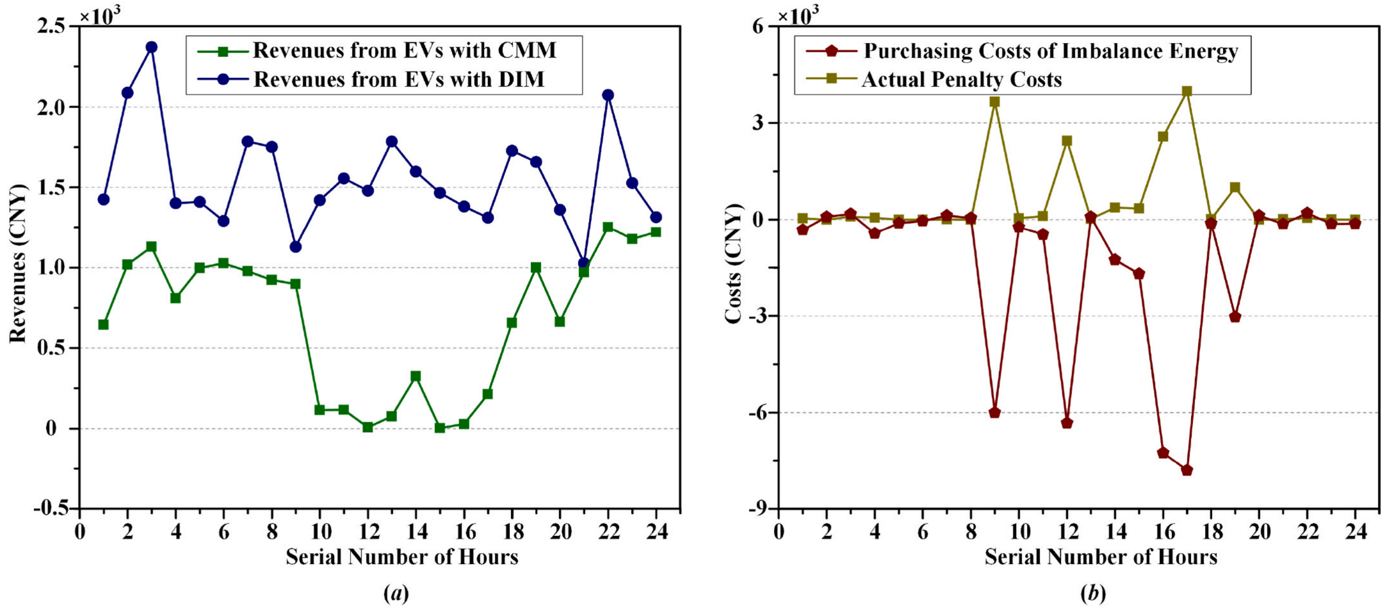

Fig. 12. Revenue and cost of EV aggregators in real-time markets over a day: (*a*) revenue; (*b*) cost.

Table 6
Profit analysis of EV aggregators for different agreement prices and service tariffing rates.

Case	Agreement Price for EVs with CMM (CNY/kWh)	Service Tariffing for EVs with DIM (p.u.)	Net Profit (CNY)
1	0.4	0.20	20901.07
2	0.4	0.25	22394.58
3	0.4	0.30	23888.08
4	0.5	0.20	24149.64
5	0.5	0.25	25643.15
6	0.5	0.30	27136.65
7	0.6	0.20	27398.21
8	0.6	0.25	28891.71
9	0.6	0.30	30385.22

4.4. Comparison of different cases

The effectiveness of the proposed solution was evaluated in a large-scale EV deployment scenario. It is assumed that EV aggregators manage 4000 EVs (2000 EVs with the CMM and 2000 EVs with the DIM) in the energy markets. In addition, a more general day-ahead price curve is considered, wherein the day-ahead price at each hour is not lower than the price with a low real-time clearing scenario and not higher than the price with an extra high real-time clearing scenario. Unlike the case in Section 4.2, EV aggregators do not bid for the maximum allowable energy under such a condition. Fig. 13 illustrates the charging schedule results for a given day-ahead price curve. The EV aggregators bid for energy between 1000 kWh and 8000 kWh. It can also be observed that there is a minor deviation between the bidding energy and the actual consumed energy from EVs; hence, EVs can be charged as planned based on the proposed method to achieve coordinated charging.

In this study, the potential real-time clearing scenarios are narrowed down to four categories to obtain the optimal bidding strategy of EV aggregators in a short time. It should be noted that when completely considering all possible real-time clearing scenarios, EV aggregators can obtain a more satisfactory solution for bidding. Nevertheless, it consumes a significant amount of computational time for the solution, particularly when EV aggregators managing large-scale EVs are

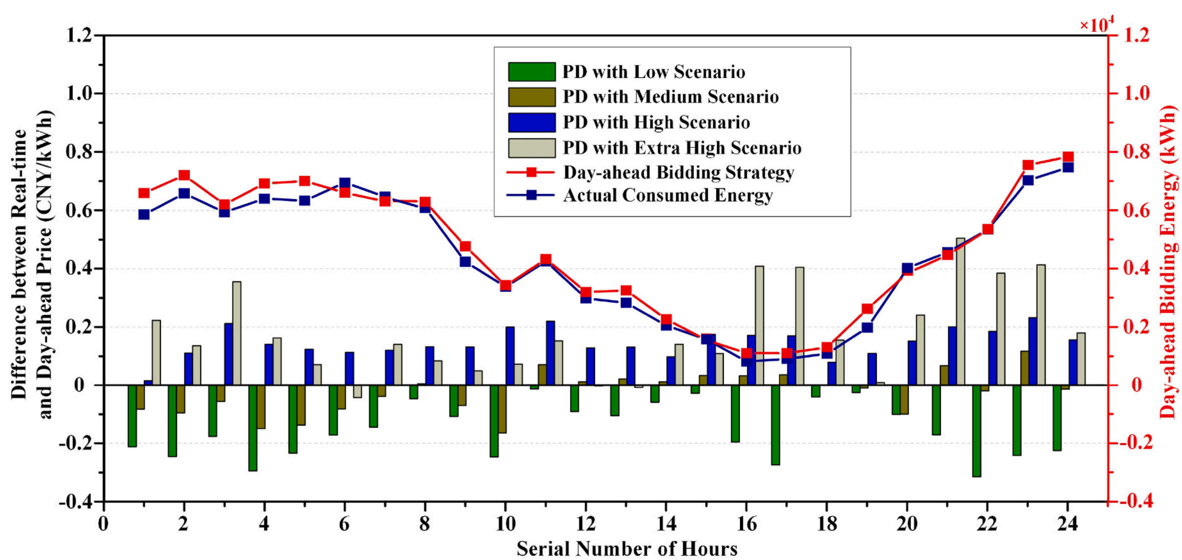

Fig. 13. Coordinated charging scheduling results with a large scale of EVs involved.

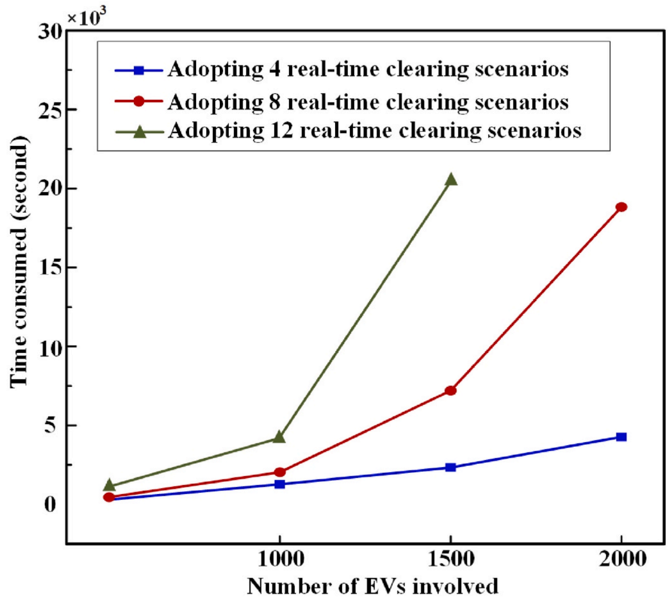

Fig. 14. Comparison of time consumed considering different numbers of real-time clearing scenarios.

involved. The model was run on a 64-bit PC equipped with an i5-10400 processor and 16 GB of RAM, and an interface of Lingo 18.0 × 64 was employed for solving. Fig. 14 visually presents a comparison of the time consumed for adopting different numbers of real-time clearing scenarios to obtain the bidding strategy. There were minor differences in the computational time when the EV number was small (e.g., 500 and 1000). However, when the EV number becomes large (e.g., 1000 and 1500), it requires several times the computing time for the model to adopt 8 real-time clearing scenarios than that to adopt 4 real-time clearing scenarios. This demonstrates that the proposed strategy can significantly reduce the time complexity of the bidding problem.

5. Conclusion and remarks

This study explored the optimal charging scheduling operation of EVs in a competitive electricity market environment from the perspective of EV aggregators. To this end, a two-phase energy management framework for EV charging scheduling was developed based on the market rules. In the day-ahead bidding phase, EV aggregators consider a wide variety of uncertainties arising from EV charging and markets when making optimal bidding decisions. In the real-time scheduling phase, EV aggregators dynamically adjust the charging strategy of the available EVs to follow the day-ahead bidding energy profile to reduce their operational costs. In broad terms, the proposed method enables the total charging load profile of the EVs to coincide with the bidding energy profile.

Three important findings are based on this case study. First, the bidding strategy of EV aggregators is associated with the grid connection time of EVs and the clearing prices. Numerical results indicate that EV aggregators bid more electricity in the night than in the daytime, as there are more EV charging demands owing to the charging preference of EV users. Second, the day-ahead bidding strategy of EV aggregators depends largely on the difference between the day-ahead clearing prices and real-time clearing prices. If the day-ahead price at an hour is lower than the price in all potential real-time clearing scenarios, EV aggregators are likely to bid the maximum allowable energy in day-ahead markets (e.g., at 9, 12, 16, 17, and 19 h in the case study presented in Section 4.2). Third, and most importantly, EV aggregators can employ the proposed method to schedule the charging loads of EVs to match the day-ahead bidding energy to reduce their operational costs. In addition, the simulation results show that the model using four real-time clearing scenarios for optimal bids is more efficient than the model that considers massive historical real-time clearing scenarios.

This study investigates the coordinated charging strategy of EVs in the energy market. It should be noted that EVs can also provide ancillary services for power grids, e.g., frequency regulation. Consequently, the charging scheduling strategy of EVs in both the energy and ancillary service markets needs to be further exploited.

Credit author statement

Yanchong Zheng: Conceptualization, Methodology, Data curation, Writing – original draft. Yubin Wang: Visualization, Writing – reviewing and editing. Qiang Yang: Supervision, Funding acquisition, Writing – reviewing and editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Qiang Yang reports financial support was provided by National Natural Science Foundation of China.

Data availability

The authors do not have permission to share data.

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