Optimal Operation Strategy of Electric Vehicle Cluster in the Electricity Spot Market Considering Scheduling Capability

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Abstract

The widespread use of electric vehicles (EV) has put a strain on the stable operation of power grid. Therefore, the potential of EV cluster power load regulation has been paid attention. In the cluster, the electric vehicle aggregator (EVA) can gather a large number of EVs and participate in the electricity spot market by optimizing the charging/discharging power. In this study, a bi-objective optimization model for V2G enabled EV cluster operation is proposed to determine the optimal load of EV cluster considering the electricity spot market. First, the scheduling capability of EVs is modelled and aggregated considering the EV user willingness. Then, the demand response and electricity spot trade for EVA are analyzed. Based on the capability

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constraints and the market rules, an optimization model is established with two objectives of maximizing EVA profits and EV user satisfaction. Finally, a case study in Beijing, China is implemented to prove the feasibility of the proposed model. The results show that the EV user willingness for orderly charging/discharging is distributed in the range of 0.26 and 0.94 with an average value of 0.85. In addition, the proposed EV cluster operation strategy can improve the EVA daily profits by 81.27% and increase the EV user satisfaction by 70% compared with normal charging strategy.

Keywords: Electric vehicle cluster, operation optimization, electricity spot market, V2G, scheduling capability.

1 Introduction

1.1 Background

In recent years, sustainable development goals and new energy markets have been continuously improved worldwide. The global demand for sustainable transportation solutions has propelled electric vehicles (EV) into the spotlight [1]. China leads this trend, contributing 40% of the 10 million global EV registrations. While this rapid EV adoption reduces carbon emissions, it strains the power grid [2]. Integrating numerous EVs escalates power demand, posing challenges for grid stability [3]. Managing the unpredictable charging patterns burdens grid operators and may lead to voltage fluctuations, imbalances, and infrastructure strain. Hence, devising strategies to optimize EV load utilization becomes vital in addressing these pressing challenges and ensuring grid reliability.

An effective approach to optimizing EV load management involves clustering vehicles and centralizing control and coordination, aligned with vehicle-to-grid (V2G) technology [4]. Grouping EV loads as clusters enables strategic control over charging and discharging based on load characteristics. Centralization enhances regulation of timing, duration, and power levels in EV activities, improving grid stability and maximizing EV efficiency while minimizing system impact. V2G technology offers opportunities for bidirectional energy flow, allowing EVs to consume electricity and serve as mobile energy storage units. This study will explore the optimal EV cluster operation strategy with the application of V2G technology, contributing to grid management knowledge and proposing strategies for successful implementation.

1.2 Literature Review

1.2.1 Research on V2G technology

V2G is a technology that connects EVs with the power network, allowing them to participate in the two-way flow of electric energy as a resource of the grid. EVs equipped with V2G technology have a high-capacity energy storage battery system for storing electrical energy and providing power. The V2G system relies on the smart grid communication and control system to enable real-time information and energy interaction between the EVs and the power grid, enabling the scheduling and control of charging and reverse energy supply.

V2G technology enables EVs to not only receive electric energy charging but also reversely output stored electric energy to the grid, supporting the balance of grid load demand [4, 5]. It can be used for energy management and power dispatching, leveraging EVs as grid resources to achieve load balancing and energy dispatching [7]. By integrating large-scale renewable energy sources like solar and wind into the power system, V2G technology can charge when there is a surplus of renewable energy and supply stored electricity back to the grid, addressing the volatility and instability of renewable energy [8, 9]. The EV's energy storage battery system can serve as a backup power source, providing emergency power supply during grid blackouts or emergencies [10]. V2G technology also enables frequency regulation and power quality control, balancing grid load fluctuations through EV charge and discharge, thereby improving power system stability and quality [11]. Moreover, V2G technology allows EVs to participate in energy markets and trading, empowering EV owners to independently decide whether to supply stored energy to the grid based on electricity prices and market demand, thereby obtaining economic returns [12, 13].

However, there are challenges associated with the application of V2G technology. Frequent charging and discharging processes may impact the battery life of electric vehicles [14]. Hence, it is crucial to research and develop optimized charging and discharging strategies for extended battery life and improved performance. The application of V2G technology involves extensive data exchange and sharing, including energy usage records and user information, necessitating enhanced data protection and cybersecurity measures to ensure privacy and security [15, 16]. Furthermore, supporting the development and application of V2G technology requires appropriate market mechanisms and regulatory norms, entailing electricity market reforms such as price policies, energy trading mechanisms, and interaction rules between electric vehicles and the grid [17]. Additionally, implementing V2G technology requires the establishment of corresponding charging facilities and communication networks, which requires a comprehensive and reliable infrastructure to support the connection and interaction between EVs and the grid [18]. In this study, it is assumed that the EVs in the cluster are all V2G enabled.

1.2.2 Research on EV cluster in electricity market

As a mobile power storage load, EVs can be charged and discharged based on the grid's demand, thereby helping to balance the supply and demand relationship. The participation of EV clusters in the electricity market provides a flexible approach to energy consumption, enabling charging and discharging activities that can mitigate the volatility of renewable energy sources and reduce the power system's operational instability [19–21]. EV clusters have the capability to adjust their charging and discharging strategies in response to market signals and incentive mechanisms, allowing them to charge and discharge based on market prices and demand [22]. This flexibility aids in optimizing and improving the efficiency of the power market. Through intelligent energy scheduling and management, EV clusters can align the storage and utilization of electrical energy with grid demands, resulting in maximized energy utilization efficiency and potential economic returns through energy trading. This optimization of energy resources contributes to overall cost savings [23, 24]. Furthermore, in situations of abnormal conditions or emergencies in the power system, EV clusters can be dynamically scheduled to provide backup power supply or load regulation capacity, thereby enhancing the stability and reliability of the power system [25, 26].

The EV clusters commonly employ market models to engage in the electricity market, including the energy market and energy dispatch market. The energy market constitutes the trading platform where EV clusters either provide or obtain electrical energy from the power system [27]. Conversely, the energy dispatch market focuses on coordinating the charging and discharging behavior of EV clusters to achieve load balance and energy optimization in accordance with supply and demand [28, 29]. EV clusters can interact with the power market through EV cluster aggregators, portable charging devices, or on-board charging devices. EV cluster aggregators act as intermediaries that negotiate transactions with the power system on behalf of a group of electric vehicles, enabling them to schedule charging and discharging based on market signals and demand, thus achieving a balance between supply and demand and optimizing energy utilization [30, 31]. Alternatively, portable charging devices or on-board charging devices facilitate direct interactions between EVs and the power system [32]. In this study, the EV aggregators are considered as the main body to gather individual EVs and participate in the electricity market.

1.2.3 Research on scheduling optimization of EVs

Reducing operating costs is a crucial objective in optimizing the operations of EV clusters. One approach is to minimize energy purchase costs through smart charging and energy scheduling, leveraging power price fluctuations [33]. This involves optimizing the utilization rate of charging equipment to reduce idle time and energy waste [34, 35]. According to cluster demand and charging behaviour pattern, reasonable design and layout of charging equipment to reduce installation and maintenance costs [36]. To meet user needs, EV cluster operation optimization should also provide reliable charging services and ensure a high-quality user experience [37]. Additionally, increasing the availability and coverage of charging equipment, as well as improving charging speed and convenience, are also essential to meet the flexible charging needs of users [38, 39]. Furthermore, the collection of user needs and feedback through user participation mechanisms and feedback channels can be used to optimize charging services and operational strategies based on user input [13]. From the above literature, it is found that the economic benefits of EV cluster operator and the EV user satisfaction are vital indicators of EV cluster operation but they were not considered at the same time. In addition, the behaviours of EV cluster participating in the electricity market are not involved in the existing research.

The optimization methods for EV cluster operations include model-based optimization methods, machine learning algorithms, and intelligent control strategies. Model-based optimization methods utilize mathematical models to describe charging demand [40], power supply, and system constraints. By solving optimization problems based on these models, optimal charging scheduling schemes can be obtained. Machine learning algorithms, on the other hand, leverage historical data and patterns to provide real-time decision-making and scheduling strategies, offering adaptability and flexibility [41]. Intelligent control strategies adjust charging speed and power in real time to optimize charging behavior based on real-time power demand, electricity price signals, and user demand. Model-based optimization methods [42] are suitable for scenarios with accurate constraints and well-defined model descriptions, while machine learning algorithms and intelligent control strategies [43] are more applicable in situations that require real-time decision-making and adaptability. In this study, multiple objectives are applied and therefore the intelligent algorithms are more practical to solve the proposed problem.

1.3 Contributions

This study proposes a bi-objective operation optimization model for the V2G enabled EV cluster in the electricity spot market considering the scheduling capability. The main contributions of this paper are presented as follows.

- A scheduling capability model of V2G enabled EV cluster is proposed. First, the charging and discharging behaviour of the individual V2G enabled EV is modelled. Then, the orderly charging/discharging willingness of EV users is determined by sigmoid function and entropy weight method. Finally, the scheduling capability of EVs are aggregated considering the EV user willingness;
- A novel bi-objective operation optimization model is proposed for electric vehicle aggregator (EVA) who controls the EV cluster. In this model, the electricity spot trade is included. The objectives of maximizing EVA profits and EV user satisfaction are both considered. The scheduling capability of EV cluster is applied as constraints;
- A case study in Beijing, China is conducted to prove the feasibility of the proposed model. The Pareto front is obtained by NSGA-II algorithm. The optimal EV charging/discharging power and the DR strategy are determined. A scenario analysis is also implemented to compare the results of normal charging, orderly charging and orderly charging/discharging.

1.4 Paper Organization

The rest of the paper is organized as follows. Section 2 establishes a scheduling capability model for V2G enabled EV cluster. In Section 3, the EVA and the ways they participate in the electricity spot market are introduced. Section 4 proposes a bi-objective operation optimization model for EVA to obtain the optimal load and demand response strategies. In Section 5, a case study is implemented and different scenarios are discussed. Section 6 presents the conclusions of the paper.

2 Scheduling Capability Model of EV Cluster

In the operation optimization model of EV cluster, the large number of EVs results in a sharp increase of number of decision variables and a heavy burden

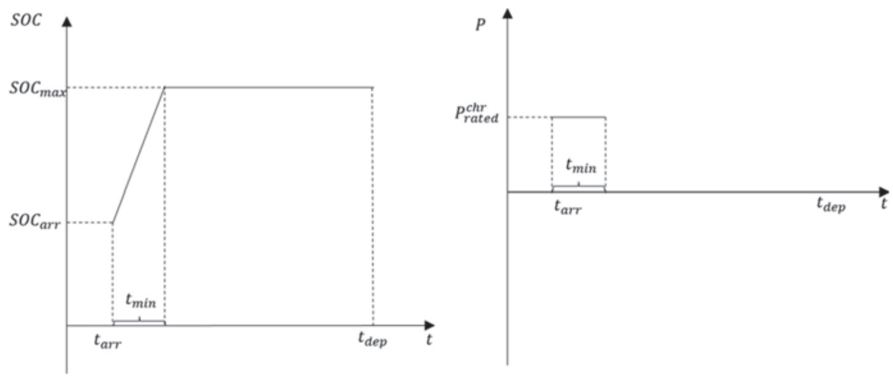

Figure 1 Charging model of EVs in normal charging.

of computation. Therefore, in this section, the scheduling potential of individual V2G enabled EVs is aggregated considering the EV user willingness. The scheduling capability, i.e., the upper and lower boundaries of power and capacity, of the EV cluster will be used as constraints in the following optimization model.

2.1 Individual EV Charging and Discharging Model

When a V2G enabled EV arrives at the charging station, the user has two options to choose: normal charging and orderly charging/discharging. If the EV user prefers normal charging, the EV will be charged immediately at the rated power. The changes of SOC and charging power during the parking time of normal charging is illustrated in Figure 1. The normal charging EVs are considered as uncontrollable load.

If the second charging option is chosen, the user can set the departure time and the expected SOC. The charging and discharging power of EV will be adjusted by EVA to smooth the load fluctuation and achieve better economic benefits. As shown in Figure 2, the SOC and charging/discharging power should be constrained within the boundaries.

According to the charging and discharging pattern in Figure 2, the individual V2G enabled EV should satisfy the following SOC boundary constraints.

$$SOC_{i,min} \leq SOC_{i,t} \leq SOC_{i,max} \quad t_{i.arr} \leq t \leq t_{i,dep} \tag{1}$$

$$P_{i,rated}^{chr}(t - t_{i,arr}) \geq (SOC_{i,t} - SOC_{i,arr})C_i \quad t_{i.arr} \leq t \leq t_{i,dep} \tag{2}$$

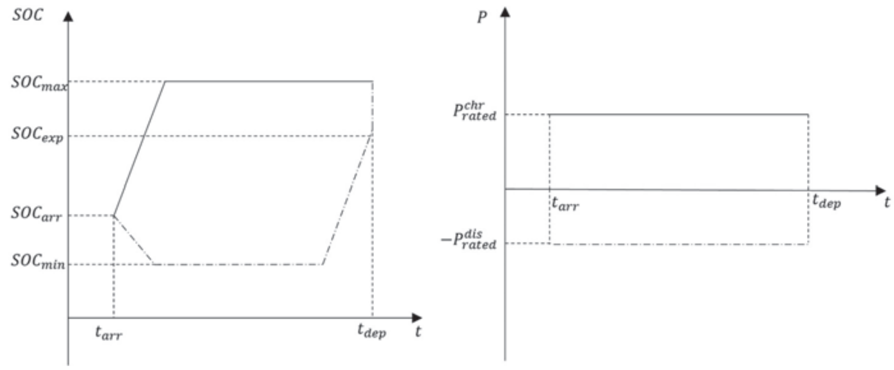

Figure 2 Charging/discharging model of EVs in orderly charging/discharging.

$$-P_{i,rated}^{dis}(t - t_{i,arr}) \leq (SOC_{i,t} - SOC_{i,arr})C_i \quad t_{i.arr} \leq t \leq t_{i,dep} \tag{3}$$

$$P_{i,rated}^{chr}(t_{i,dep} - t) \geq (SOC_{i,exp} - SOC_{i,t})C_i \quad t_{i.arr} \leq t \leq t_{i,dep} \tag{4}$$

where $SOC_{i,min}$ and $SOC_{i,max}$ are the minimum and maximum of SOC of the ith EV; $t_{i,arr}$ and $t_{i,dep}$ are the arrival and departure time of the ith EV; $P_{i,rated}^{chr}$ and $P_{i,rated}^{dis}$ are the rated charging and discharging power of the ith EV; C_i is the capacity of the battery of ith EV; $SOC_{i,exp}$ is the expected SOC of ith EV.

In the meantime, the charging/discharging power of EV should also be within the boundaries shown in Equations (5)–(6).

$$0 \leq P_{i,t}^{chr} \leq \mu_{i,t} P_{i,rated}^{chr} \quad t_{i.arr} \leq t \leq t_{i,dep} \tag{5}$$

$$0 \leq P_{i,t}^{dis} \leq (1 - \mu_{i,t}) P_{i,rated}^{dis} \quad t_{i.arr} \leq t \leq t_{i,dep} \tag{6}$$

where $\mu_{i,t}$ is the charging/charging state of ith EV. If the EV is charging, $\mu_{i,t} = 1$. Otherwise, $\mu_{i,t} = 0$.

2.2 EV User Willingness of Orderly Charging and Discharging

The EVs in the cluster are assumed to have the V2G ability and the potential to participate in the orderly charging and discharging by the control of an electric vehicle aggregator (EVA). Therefore, before calculating the scheduling capability of the EV cluster, the willingness of the users to participate in the orderly charging/discharging of EVA needs to be investigated.

2.2.1 Factors influencing EV user willingness of orderly charging and discharging

Usually, the willingness of EV users to participate in orderly charging/discharging is related with two factors: the time adequacy and the incentive satisfaction. The final decision of participation or not is the comprehensive evaluation of these two factors.

If the user chooses normal charging, the time duration to reach the expected SOC is the minimum charging time. If the parking duration of EV is longer than the minimum duration, the user will be more willing to participate in orderly charging/discharging. The time adequacy can be calculated by Equations (7)–(9).

$$T_{i,par} = T_{i,dep} - T_{i,arr} \tag{7}$$

$$T_{i,min} = \frac{(SOC_{i,exp} - SOC_{i,arr})C_i}{\eta_i P^{chr}_{i,rated}} \tag{8}$$

$$T_i = \frac{T_{i,par} - T_{i,min}}{T_{i,min}} \tag{9}$$

where $T_{i,arr}$ and $T_{i,dep}$ are the arrival and departure time of the ith EV; $T_{i,par}$ is the parking duration; η_i is the charging efficiency; $T_{i,min}$ is the minimum charging duration of ith EV.

If $T_i < 1$, the probability of the EV user participating in orderly charging/discharging is very low. Otherwise, the larger T_i is, the more willing the EV user is.

Another factor is the incentive satisfaction of EV user which is concerned with the price incentive determined by EVA and the expected incentive level of EV users. The calculation of the incentive satisfaction is presented in Equation (10).

$$I_i = \frac{I_{actual}}{I_{i,exp}} \tag{10}$$

where I_{actual} is the actual incentive given by EVA; $I_{i,exp}$ is the expected incentive level of the ith EV user. Similar to the time adequacy, if $I_i < 1$, it is not likely for the users to charge/discharge orderly. Otherwise, the larger I_i is, the more willing the EV user is.

The probability of the EV user willingness is between 0 and 1 and has a strong relationship with the time adequacy and incentive satisfaction. Therefore, the sigmoid function is employed to map the relation between two

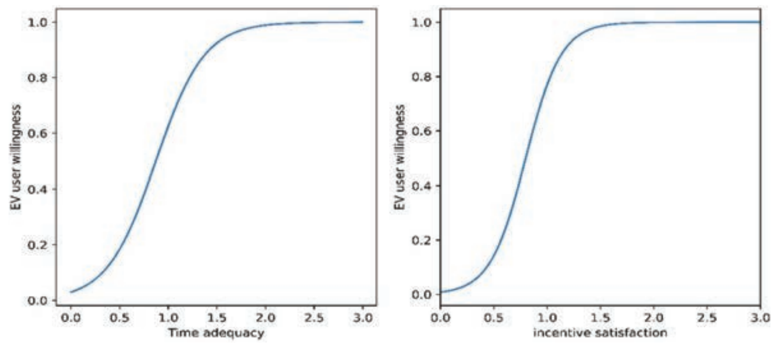

Figure 3 The sigmoid function.

factors and the probability of user willingness, shown in Equations (11)–(12).

$$p_{i,1} = \frac{1}{1 + \beta_1 e^{-\alpha_1 (T_i - 1)}} \tag{11}$$

$$p_{i,2} = \frac{1}{1 + \beta_2 e^{-\alpha_2 (I_i - 1)}} \tag{12}$$

where $p_{i,1}$ and $p_{i,2}$ are the EV user willingness under the time adequacy of T_i and the I_i respectively; α_1, α_2, β_1, β_2 are the coefficients of the function. $\alpha_1 = 4$, $\alpha_2 = 6$, $\beta_1 = 0.6$, $\beta_2 = 0.3$. The functions are illustrated in Figure 3.

2.2.2 Weight determination of factors

In order to determine the degree of the EV user willingness, the influence of time adequacy and incentive satisfaction should be integrated. Therefore, the weights of two factors are calculated by the entropy weight method in this study. The process of weight determination is as follows.

(1) Data normalization. The performance of each factor needs to be normalized. In this method, it will be represented by the probability of user willingness which is a value in [0,1] and will be calculated in the following section. Consequently, the data normalization is not needed;
(2) Information entropy calculation. The information entropy of the jth factor is calculated by Equations (13)–(14);

$$r_{ij} = \frac{p_{ij}}{\sum_{i=1}^{n} p_{ij}} \tag{13}$$

$$E_j = -\ln(n)^{-1} \sum_{i=1}^{n} r_{ij} ln r_{ij} \tag{14}$$

where p_{ij} is the user willingness of the ith EV with respect to the jth factor; n is the number of EVs.

(3) Final weight calculation. After obtaining the information entropy, the final weights of two factors can be determined by Equation (15).

$$\omega_j = \frac{1 - E_j}{m - \sum_{j=1}^{m} E_j} \tag{15}$$

where m is the number of factors.

2.2.3 Comprehensive evaluation of EV user willingness

After determining the weights of two factors in Section 2.2.2, the comprehensive willingness degree of EV user can be obtained by Equation (16).

$$p_i = \omega_1 p_{i,1} + \omega_2 p_{i,2} \tag{16}$$

If the total probability is more than 0.8, it can be regarded as a clear willingness for orderly charging/discharging participation.

2.3 Aggregating EV Scheduling Capability in the Cluster

According to the statistical data of the EVs, the boundaries of SOC and power, i.e. the scheduling capability, is obtained by summing the boundaries of individual EVs. The step function $\varepsilon(t)$ is used to indicate the difference of the arriving time in the cluster. The scheduling capability of EV cluster can be modelled by Equations (17)–(21).

$$\sum_{i=1}^{n} SOC_{i,min}[\varepsilon(t_{arr,i}) - \varepsilon(t_{dep,i})] \leq SOC_t \leq \sum_{i=1}^{n} SOC_{i,max}[\varepsilon(t_{arr,i}) - \varepsilon(t_{dep,i})] \tag{17}$$

$$SOC_t \leq \sum_{i=1}^{n} \left(\frac{P_{i,rated}^{chr}(t - t_{i,arr})}{C_i} + SOC_{i,arr} \right) [\varepsilon(t_{arr,i}) - \varepsilon(t_{dep,i})] \tag{18}$$

$$SOC_t \geq \sum_{i=1}^{n} \left(\frac{-P_{i,rated}^{dis}(t - t_{i,arr})}{C_i} + SOC_{i,arr} \right) [\varepsilon(t_{arr,i}) - \varepsilon(t_{dep,i})] \tag{19}$$

$$SOC_t \geq \sum_{i=1}^{n} \left(SOC_{i,exp} - \frac{P_{i,rated}^{chr}(t_{i,dep} - t)}{C_i} \right) [\varepsilon(t_{arr,i}) - \varepsilon(t_{dep,i})] \tag{20}$$

$$\sum_{i=1}^{n} -P_{i,rated}^{dis}[\varepsilon(t_{arr,i}) - \varepsilon(t_{dep,i})] \leq P_t \leq \sum_{i=1}^{n} P_{i,rated}^{chr}[\varepsilon(t_{arr,i}) - \varepsilon(t_{dep,i})] \tag{21}$$

3 Operation Optimization Model

In this section, a bi-objective operation optimization model is established for the EVA to participate in the electricity spot market and control the power of the EV cluster so that the expectations of EVA and EV users are both satisfied. The result will be used for the EVA to report in the day-ahead electricity market.

3.1 Electric Vehicle Aggregator and Electricity Spot Market

The V2G enabled EV can be considered as a flexibly controlled and small sized energy storage system but is not able to participate in large-scale power system regulation individually. Therefore, in order to take full advantage of the scheduling capability of EVs, the electric vehicle aggregator (EVA) gathers and controls large-scale EV cluster, and then has the ability to compete in the electricity spot market. In this case, the EVA can gain economic profits from the spot market, reduce the charging cost of the EV users and smooth the fluctuations of the utility grid. In this study, the EVA is allowed to participate in the demand response trading and the electricity spot trading.

(1) Demand response trading

Demand response trading is an effective means to guide demand-side resources to cut peaks and fill valleys. It will promote the adjustment ability of power system and improve the consumption of clean energy while ensuring the system safety. The participating EVAs will also obtain economic benefits through optimizing energy use, achieving a win-win situation. In the market, the power trading center posts invitations one day before the demand response session and then the EVA responds to the invitations with the planned demand response capacity. Based on the difference of practical operation load and the base load, the EVA will obtain the corresponding economic subsidy;

(2) Electricity spot trading

The EVA can purchase and sell electricity in the electricity market transactions by integrating and optimizing the controllable EVs with advanced regulation and communication technologies. The market members report the electricity purchase and sales curves in the day-ahead market and adjust the actual operation in the real-time market.

3.2 Optimization Objectives

In the proposed optimization model, two objectives are set: the maximum of daily EVA profit and the maximum of EV user satisfaction. The decision variables are the demand response capacity and the charging/discharging power of the EV cluster in each time period.

3.2.1 Maximizing daily EVA profit

The daily EVA profit is the difference between the daily revenue and the expenses. Through the electricity spot market, the EVA can obtain the demand response subsidy and electricity sales income. Moreover, the charging fees of the EV users are another source of income for EVA. The expenses of EVA are mainly from the purchase of electricity in the market and the compensation to the EV users for EV discharging. The objective of maximizing daily EVA profit is calculated by Equations (22)–(25).

$$f_1 = max P_{EVA} = R_{DR} + R_{grid} + R_{EV} \tag{22}$$

$$R_{DR} = \sum_{t=1}^{T} S_{DR}(P_{chr}^t - P_{dis}^t - P_{base}^t)\Delta t \tag{23}$$

$$R_{grid} = \sum_{t=1}^{T} (S_{grid-s}^t P_{dis}^t - S_{grid-p}^t P_{chr}^t)\Delta t \tag{24}$$

$$R_{EV} = \sum_{t=1}^{T} (1-\varphi)(S_{EV-chr}^t P_{chr}^t - S_{EV-dis}^t P_{dis}^t)\Delta t \tag{25}$$

In the above equations, R_{DR} is the demand response subsidy, R_{grid} is the profit of exchanging electricity with electricity market and R_{EV} is the charging revenue from EV users. S_{DR}, S_{grid-s}^t, S_{grid-p}^t, S_{EV-chr}^t, S_{EV-dis}^t are the real-time unit price of demand response, electricity sales, electricity purchase, EV charging service and EV discharging cost. P^t_{chr}, P^t_{dis} are the charging and discharging power at time t from and to the market respectively. P^t_{base} is base load of EV cluster at time t. φ is the discount for EV users to participate in orderly charging/discharging.

3.2.2 Maximizing EV user satisfaction

The EV users who have a contract with the EVA to participate in the orderly charging and discharging usually have two requirements: reaching the expected charging capacity and reducing the charging cost as much as possible. When the EVA responds to the demand response invitations and transact electricity, the second objective is to maximize the EV user satisfaction. The difference between the cost of normal charging and orderly charging/discharging is one of the most important factors to improve the user satisfaction. Another factor is the charging capacity expectation. When the EVs leave the charging station, the best off-grid SOC is 100%. However, in the orderly charging/discharging mode, he EV users usually agree on a minimum off-grid SOC expectation with the EVA to guarantee the flexibility. The closer the off-grid SOC gets to 100%, the more satisfied the users are. Therefore, the second objective is calculated by Equation (26).

$$f_2 = maxC_{user} = 0.5 \times \frac{\sum_{t=1}^{T}(S^t_{EV-chr}P^t_{base}\Delta t - R_{EV})}{\sum_{t=1}^{T}(S^t_{EV-chr}P^t_{base}\Delta t - R^{expected}_{EV})} + 0.5 \times \frac{\sum_{t=1}^{T}(P^t_{chr} - P^t_{dis})\Delta t}{\sum_{i=1}^{n}(100\% - SOC^i_{arrive})C_i} \tag{26}$$

where $R^{expected}_{EV}$ is the expected EV service fee for users. SOC^i_{arrive} is the SOC of the ith EV when it arrives the charging facility.

3.3 Constraints

(1) The charging/discharging power constraint

According to the model in Section 2, the charging and discharging power of EV cluster should be within the scheduling capability. In addition, the EV cluster cannot charge and discharge at the same time. The power constraints are shown in Equations (27)–(29)

$$P^{min}_{chr} \le P^t_{chr} \le P^{max}_{chr} \tag{27}$$

$$P_{dis}^{min} \leq P_{dis}^{t} \leq P_{dis}^{max} \tag{28}$$

$$P_{chr}^{t} P_{dis}^{t} = 0 \tag{29}$$

where P_{chr}^{min} and P_{chr}^{max} are the minimum and maximum charging power of EV cluster; P_{dis}^{min} and P_{dis}^{max} are the minimum and maximum discharging power;

(2) The EV energy storage capacity constraint

The energy storage capacity of EV cluster should satisfy the following constraints.

$$E_{t+1} = E_t + P_{chr}^{t} \eta_{chr} - P_{dis}^{t} \eta_{dis} + E_{arr}^{t} - E_{dep}^{t} \tag{30}$$

$$E_t^{min} \leq E_t \leq E_t^{max} \tag{31}$$

where E_t^{min} and E_t^{max} are the minimum and maximum capacity of EV cluster. E_{arr} and E_{dep}^{t} are the initial capacity of EVs which arrive at time t and the capacity of EVs which depart at time t.

3.4 Optimization Algorithm

In this study, the proposed bi-objective optimization is solved by Non-dominated Sorting Genetic Algorithm II (NSGA-II) which is a widely-applied multi-objective optimization algorithm. In this algorithm, the solutions in each generation are grouped into multiple layers based on the dominated relationship and individuals in the same layer are ranked by the crowding distance. The individuals which do not satisfy the constraints will have a penalty on the objective functions. After the iteration, the Parato front where all solutions are non-dominated is obtained.

Based on NSGA-II algorithm, the process of solving the proposed model is as follows, illustrated in Figure 4.

Step 1. Input the driving patterns of the EV cluster including the distribution of arrival time, departure time, arrival SOC, expected SOC and expected incentive level.

Step 2. Based on the input data, calculate the base load of EV cluster and the limits of charging power and SOC (scheduling capability) according to the model in Section 2.1.

Step 3. Calculate the willingness of EV users in the cluster. First calculate the time adequacy and incentive satisfaction. Then determine the weights of

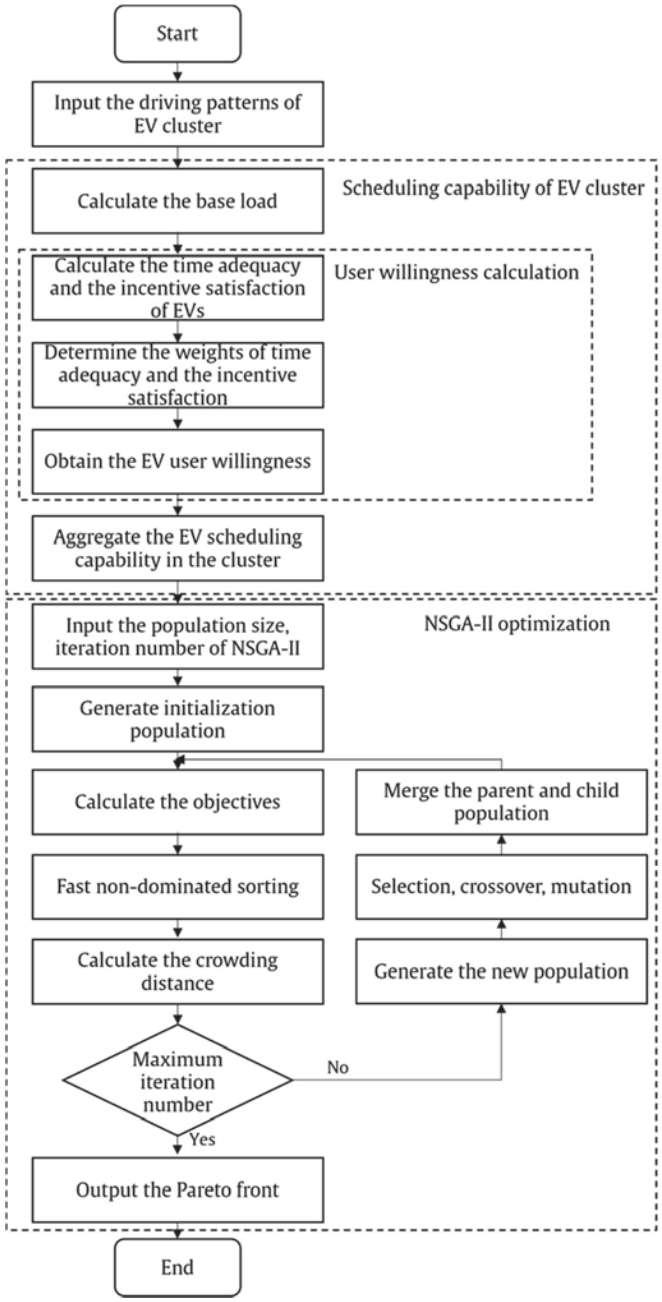

Figure 4 The process of proposed model.

these two factors based on entropy weight method. Finally, aggregate the performance of two factors and obtain the final user willingness.

Step 4. Based on the user willingness, divide the base load into uncontrollable and controllable loads. Aggregate the scheduling capability of the controllable EVs.

Step 5. Start the optimization iteration. Input the population size n and maximum iteration number. Set $t = 0$. Initialize the population.

Step 6. Calculate the objective functions of each solution in the population. Fast non-dominate sort the population and calculate the crowding distance of each solution.

Step 7. If the iteration number reaches the maximum, go to step 9. Otherwise, go to step 8.

Step 8. Select the top n solutions and generate the new population as the parent population. Perform the selection, crossover and mutation operators. Generate the child population and merge the parent and child population. Go to step 6.

Step 9. Output the Pareto front. The optimal charging and discharging power and the demand response capacity are obtained.

4 Case Study

4.1 Problem Description

An EVA in Beijing, China have aggregated a large number of EVs in a region which have potential to participate in the orderly charging and discharging. The EVA make strategies of the demand response and electricity purchase/sales in electricity spot market one day ahead by scheduling the charging and discharging power of EV cluster within the constraints. The EVs in the cluster have two patterns of power utilization, shown in Table 1. The arrival and departure time follow the normal distribution and the arrival SOC conforms to the uniform distribution. The predicted electricity price

Table 1 The patterns of EV cluster

	Arrival Time	Departure Time	Arrival SOC	Number of EV
Cluster 1	N(19,2)	N(8,2)	U(0.2,0.5)	1500
Cluster 2	N(9,2)	N(17,3)	U(0.3,0.5)	500

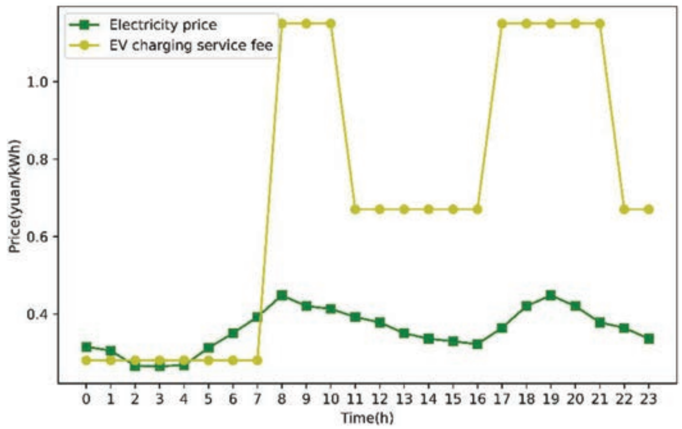

Figure 5 The predicted electricity price.

in the next day is presented in Figure 5. The peak clipping time duration is 9:00–11:00, 15:00–17:00 and 18:00–20:00, and the compensation price is 2.0 yuan/kWh. The valley filling time duration is 3:00–5:00 and 11:00–13:00, and the incentive price is 1.2 yuan/kWh. If the EV user agrees to orderly charging and discharging, they will have a 15% discount on the total service fee. In NSGA-II, the population size is 50. The iteration number is 2000. The mutation rate is 0.5.

4.2 Result Analysis

According to the patterns of EV cluster, the time adequacy and incentive satisfaction of each EV can be simulated. For calculation simplicity, the incentive expectation is expressed as a uniform distribution U(0.65,0.9). Based on the entropy method, the weights of time adequacy and incentive satisfaction are obtained as $\{0.53,0.47\}$. The user willingness function can be illustrated in Figure 6. The user willingness is distributed in the range of 0.26 and 0.94. The average value is 0.85, which means the user willingness of orderly charging and discharging is relatively high.

The base load of EV cluster is calculated by Monte Carlo simulation, as shown in Figure 7. The load of EVs which do not participate in demand response cannot be adjusted, illustrated as fixed load in Figure 7. The other load is controllable since the users agree to the orderly charging and discharging. In this study, only the controllable load is used to finish the following calculation. According to the aggregation method of EV load in

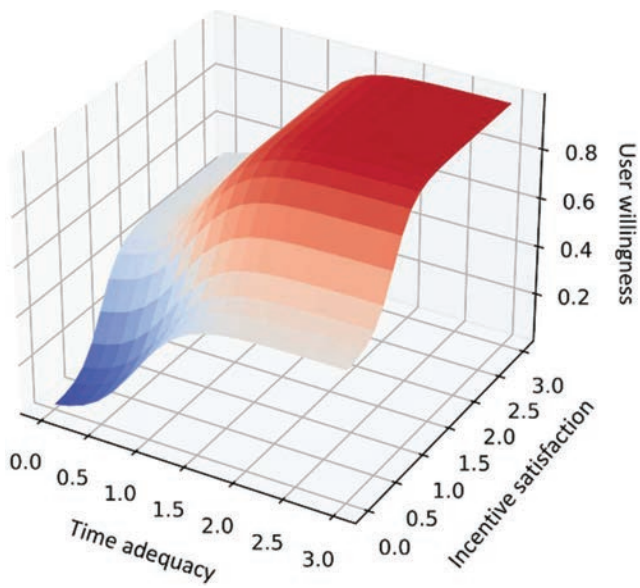

Figure 6 The user willingness function.

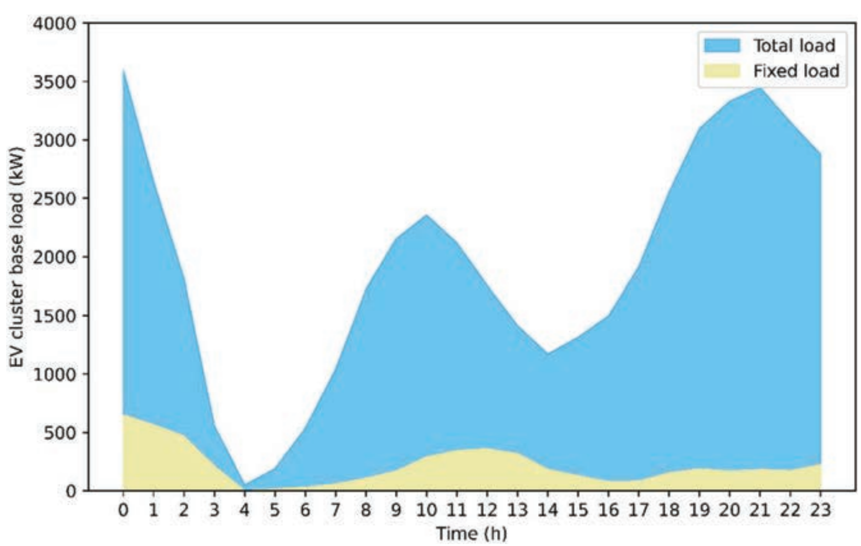

Figure 7 The base load of EV cluster.

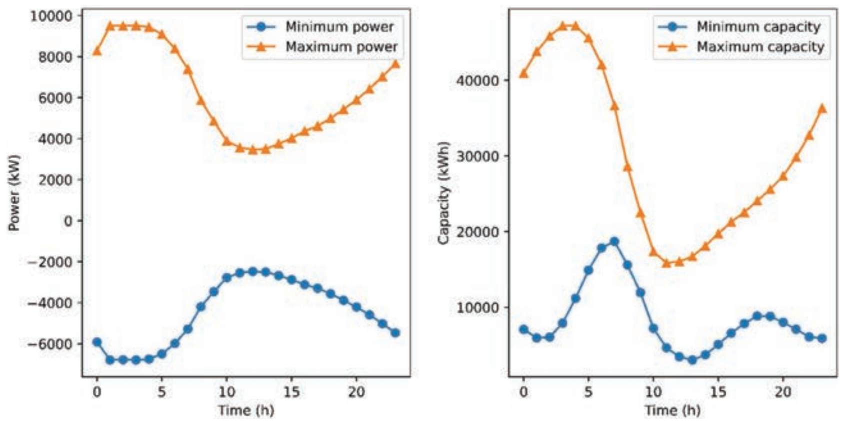

Figure 8 The scheduling capacity of EV cluster.

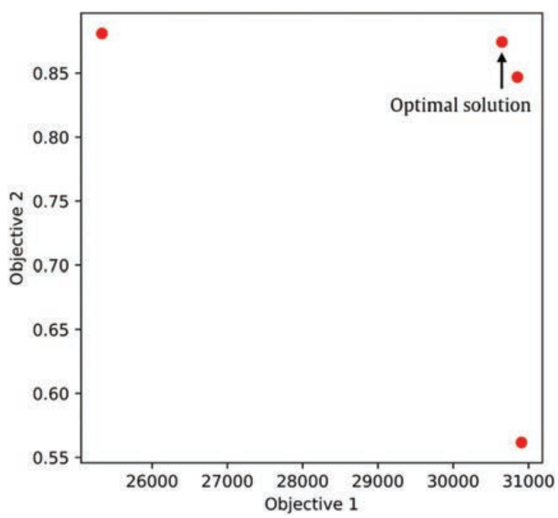

Figure 9 The Pareto front.

the cluster, the EV cluster scheduling capability can be presented in Figure 8. The maximum and minimum values of the charging/discharging power and current capacity are considered as constraints in the optimization model.

After 2000 times of iteration, the non-dominated Pareto solutions are obtained, as shown in Figure 9. In the Pareto front, 4 solutions are generated, in which the one with the largest crowding distance is selected as the final optimal solution.

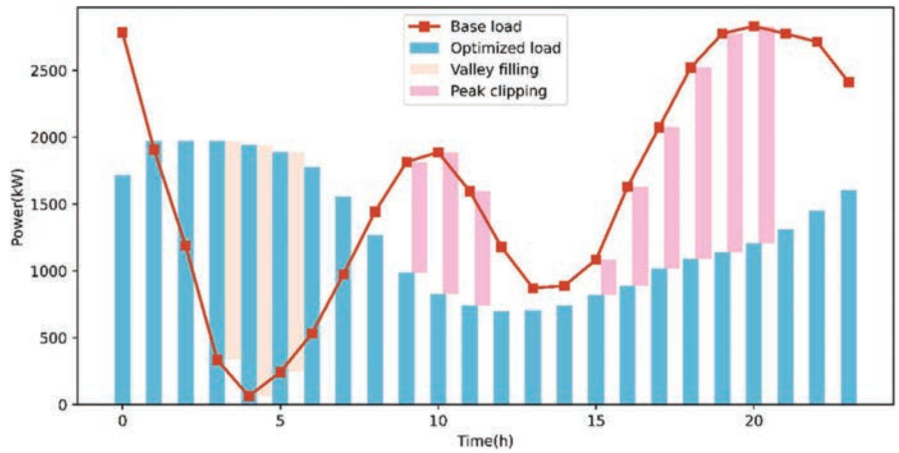

Figure 10 The optimal charging and discharging power of EV cluster.

The result shows that the optimal daily profit of EVA reaches 30853.34 yuan. The profits from EV charging service are 16533.77 yuan and the DR profits are 25194.26 yuan. The costs of purchasing electricity from the market are 10874.69 yuan. For the EV users, the optimal user satisfaction is 0.88 with the cost satisfaction of 0.95 and the time satisfaction of 0.81. The EV users in the cluster can save the cost of 14853.54 yuan compared with normal charging. In addition, the charging expectations can also be satisfied.

The optimal charging and discharging power of EV cluster is shown in Figure 10. During the valley filling and peak clipping time period, the demand response capacity is 5166.58 kWh and 9497.18 kWh respectively, shown in Figure 10. The amount of electricity purchased in the market is 31310.59 kWh. It is obvious that the load during peak hours is transferred to the valley hours and then the optimal charging power is smoother than the base scenario.

4.3 Discussion

In the proposed model, it is assumed that the V2G technology can be used by each EV and the EVs which participate in demand response can be charged or discharged orderly. The following scenarios are set to explore the superiority of V2G technology and orderly charging and discharging.

Case 1: normal charging.
Case 2: orderly charging.
Case 3: orderly charging and discharging (base scenario).

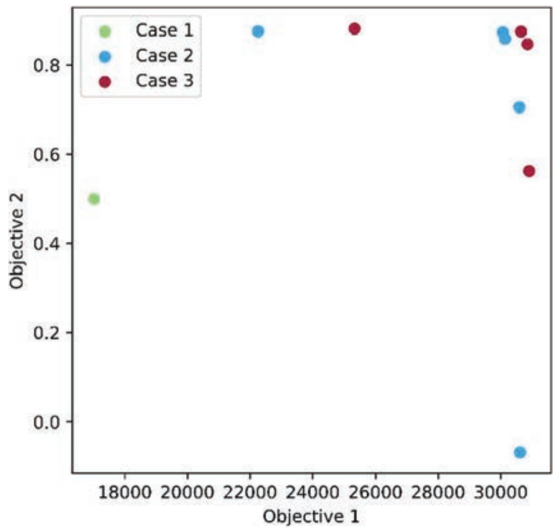

Figure 11 The results of Case 1 to 3.

The objective values of Case 1 and Pareto fronts of Case 2 and 3 are shown in Figure 11. It is shown that the best solution in Case 3 can dominate all the solutions in Case 1 and Case 2. The optimal EVA daily profits of Case 1 to 3 are 17020.83 yuan, 29354.40 yuan and 30853.34 yuan respectively. With respect to the objective 2, the optimal EV user satisfaction degrees of Case 1 to 3 are 0.5, 0.87 and 0.88. It can be seen that the orderly charging and discharging can help EVA achieve the highest economic benefits. If the EVA participates in DR, with or without V2G technology, the EV user satisfaction is almost equally good, which means the demand response can significantly improve the user satisfaction.

The comparison of economic benefits among Case 1, 2 and 3 is illustrated in Figure 12. The EV service fees in Case 1 to 3 are 31387.31 yuan, 16865.66 yuan and 16533.77 yuan respectively. Therefore, the EV users can reduce the charging cost significantly by participating in orderly charging and discharging. The EVA can also make the highest profits by orderly charging and discharging because the cost of purchasing electricity from the market is the lowest and more DR profits can be obtained. The result shows the orderly charging and discharging can improve the EVA daily profits by 81.27% and 5.1% respectively compared with Case 1 and 2.

As illustrated in Figure 13, the total charging amount of electricity in Case 3 is the lowest compared to Case 1 and 2 because the optimal control

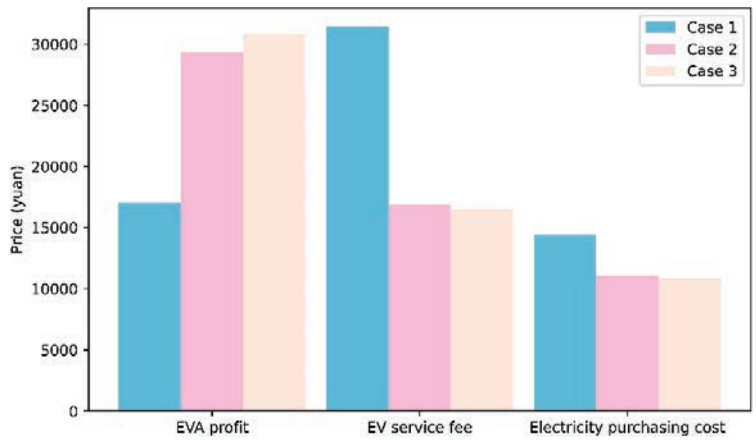

Figure 12 The comparison of economic benefits in Case 1 to 3.

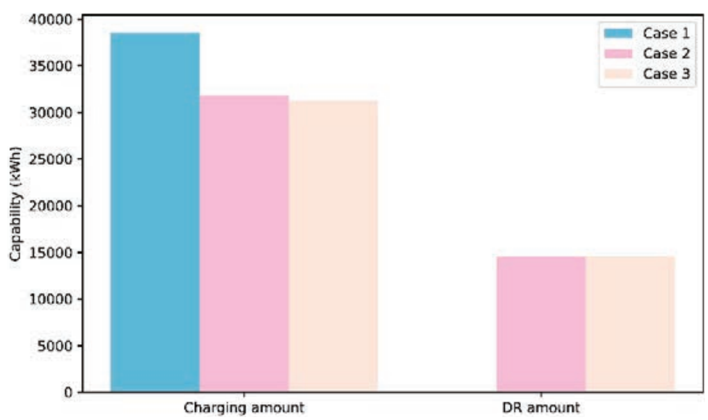

Figure 13 The comparison of total charging amount and DR amount in Case 1 to 3.

of EV load sacrifices the need of fully charging and the application of V2G technology also reduces the lower limit of SOC. The amount of DR electricity of Case 3 is slightly higher than that in Case 2, which can help the EVA gain more DR profits.

In summary, compared to normal charging, the orderly power scheduling of EV cluster can help both the EVA and the EV users gain more economic benefits in the electricity market with the charging expectation of EV users satisfied. Moreover, compared to the normal charging, the utilization of V2G technology can improve the EVA profits and the EV user satisfaction.

5 Conclusions

Nowadays, the V2G enabled EV cluster controlled by EVA can participate in the electricity spot market and can be optimized to obtain higher benefits. This study proposed a scheduling capacity model for V2G enabled EV cluster and established a bi-objective operation optimization model for EVA considering the electricity spot trade. The main conclusions are given as follows.

(1) The scheduling capability of V2G enabled EVs is modelled and aggregated considering the EV user willingness. The EV user willingness is determined by two factors: time adequacy and incentive satisfaction whose weights were obtained as $\{0.53, 0.47\}$. In the case study, the result shows that the user willingness was distributed in the range of 0.26 and 0.94 with an average value of 0.85. Based on the user willingness values, the limits of charging/discharging power and capacity for EV cluster were obtained;
(2) A bi-objective operation optimization model for EV cluster in the electricity spot market was proposed. In this model, the objectives of maximizing EVA daily profits and EV user satisfaction were both considered. The scheduling capability of EV cluster was utilized as constraints. Based on NSGA-II algorithm, the optimal EV cluster operation and demand response strategy were determined;
(3) A case study in Beijing, China was implemented. Based on the charging patterns and orderly charging/discharging willingness of EVs in this region, the EV load was divided into fixed load and controllable load. The scheduling capability of the controllable load was calculated as constraints. After 2000 times of iteration, 4 Pareto solutions were generated. The optimal solution shows that EVA can make a daily profit of 30853.34 yuan and the EV user satisfaction reaches 0.88. The EV users can save the charging cost of 14853.54 yuan compared to normal charging;
(4) The result of scenario analysis shows that the orderly charging and discharging scenario (the proposed model) improves the EVA daily profits by 81.27% and 5.1%, compared with normal charging and orderly charging. In the base scenario, The EV users can also have the best satisfaction degree. Moreover, the EV service fee and the electricity purchasing cost of the base scenario were also the lowest.

The proposed model can be employed in the day-ahead market for EVA. In the future, the real-time operation optimization model will be investigated. Moreover, the optimization algorithm will be improved for better efficiency.

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