Real-Time Energy Management Strategy for Parking Lot Considering Maximum Penetration of Electric Vehicles

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ABSTRACT With the rapid increase of electric vehicles (EVs), the uncoordinated charging of large-scale EVs will inevitably form a new peak of power consumption, which will put forward new requirements for the adjustment of EV charging behavior and the power supply capacity of the distribution network. However, upgrading the infrastructure of the distribution network is very expensive, so it is of great value to research on how to realize the optimal integration of EVs without infrastructure upgrading. In this paper, an intelligent grouping method is proposed considering the coupling relationship among EV travel information, battery status and other characteristics, and a charging/discharging priority model is established based on the contribution index of charging process. Finally, a smart real-time energy management strategy is formed in order to maximize the penetration level of EVs under current conditions. With the strategy proposed, the maximum penetration level of EVs is increased from 20% to 60% in the simulation. The strategy has good adaptability to the gradually growth of the base load, which can effectively delay infrastructure upgrading of the distribution network and reduce the overall operation cost of the station. It could furtherly provide a reference for the operation and upgrading of the parking lot charging station.

INDEX TERMS Intelligent grouping, coupling relationship, charging/discharging priority indicator, smart real-time energy management strategy, penetration level of electric vehicles, parking lot.

I. INTRODUCTION

With the continuous deterioration of the global environment and the exhaustion of fossil resources, energy saving and emission reduction in the transportation sector has become a severe challenge. Electric vehicles (EVs) have the advantages of reducing energy consumption and pollutant emissions, which is the main reason for the widespread promotion of EVs.

Current penetration of EVs in distribution networks is low due to high power battery prices and the shortage of charging infrastructure. However, with the promulgation of incentive policies and the improvement of charging infrastructure, the electric vehicle industry is expected to develop rapidly in the next few years, and the penetration level of electric vehicles will continue to increase [1]. When large-scale electric vehicles are connected to the power system with uncoordinated charging, it will cause great load impact on the power system, and bring serious impacts such as voltage deviation, power loss and transformer overrun [2]. Since vehicle-to-grid (V2G) integration in the power systems, the flow of power and information between EVs and power grids is bidirectional [3]. V2G technology can realize peak load shaving, frequency and voltage regulation through auxiliary service, and increasing the stability of power grid [4]–[8]. Therefore, without changing the distribution network infrastructure, the most effective way to improve the penetration level of EVs is to reasonably use smart charging strategy to coordinate the charging schedules of EVs.

In recent years, many scholars have proposed EVs charging and discharging strategy to reduce the impact of EVs on the power system [9]–[13]. The smart charging strategies deployed by parking lot charging coordinator (PLCC) can have either an economic or a technical perspective. In case
of the economic perspective, the PLCC aims to minimize charging costs and flattening load curves by setting time-of-use (TOU) price to formulate charging scheduling, charging in low-price period and discharging in high-price period. Therefore, new charging peak period and discharge peak period will be formed [14]–[17]. In case of the technical perspective, the PLCC aims to minimize peak load and flatten the load demand curve, relatively less consideration of user charging cost [9], [18]–[20].

In [14], the smart charging strategy takes minimizing the daily cost of EVs aggregator as the optimization goal, adopts charging power rate modulation and considers user preferences. In order to solve the problem of peak shaving and valley filling, a dynamic economic/emission dispatch strategy including electric vehicles is proposed, and the fuel consumption and emissions generated by different V2G loads are analyzed [9]. In [18], established an energy management system including buildings and charging facilities, and proposed a real-time intelligent charging algorithm that can effectively reduce peak demand.

In order to minimize the impact of EV charging on the grid, a smart charging strategy for workplace parking lots is proposed in [19]. A fuzzy logic-based electric vehicle charging plan formulation system is designed in [20], aiming at reducing the impact of uncoordinated charging of large-scale electric vehicles on the life loss and failure risk of distribution network transformers.

Different smart charging strategies can change the load curve of charging station or transformer by changing the charging scheduling of EVs. Therefore, when the existing infrastructure does not change, the different maximum penetration of EVs will be obtained by using different charging strategies.

However, the studies [9]–[20] focus mostly on the constraints of battery, user demand and charging facilities of EVs, without enough consideration of the coupling relationship between charging demands and transformer margin. The charging strategies proposed in [9]–[20] have not taken into account the adaptability of charging strategy to the growing number of EVs. In addition, in the implementation of peak shaving and valley filling strategy, it is necessary to collect EVs travel information and transformer historical information for global planning, with which the calculation amount is too large to ensure the real-time performance. In conclusion, there is no real-time charging strategies considering maximizing EVs penetration without upgrading infrastructure presented in the literature so far. The comparison of energy management in parking lots from different perspectives is summarized in Table 1.

In this paper, a smart charging strategy is proposed which incorporate a unified G2V and V2G charging framework. The main procedures and contributions of this paper are as follows:

1. An evaluation model of EV schedulable potential is established to intelligently classify the EV group, considering the coupling relationship among the current SOC, expected SOC, minimum SOC and remaining dwell time of EVs.
2. A charging/discharging priority evaluation model is established based on fuzzy control theory. This model can reflect the changes in the charging demands of EV users under the influence of multiple factors, and has high intelligence and adaptability.
3. An intelligent real-time energy management strategy is established with the maximum penetration level of EVs in the parking lot as the goal to optimize the energy flow among the EV groups. The strategy can maximize the penetration level of EVs as well as delay the upgrading of distribution network.

The rest of this paper is organized as follows. Section II explains the background and problem statement. Section III explains the modeling of EV energy demand. The proposed real-time energy management strategy for parking lot is given in Section IV. Section V introduces the case study and discusses the simulation results. Finally, Section VI gives a summary of this paper and future research directions.
Assume that all EVs are managed by the charging coordinator to make a charging schedule for each EV. When the EVs reaches the parking lot, the EV owners submit their initial information to the charging coordinator through the mobile terminal, including the initial SOC, the final SOC, the battery parameters and the leave time. Based on the information received from EV users, the operation information of charging piles and power grid, the charging coordinator uses smart charging strategy to formulate EV charging scheduling.

### B. PROBLEM STATEMENT

Figure 2 shows the typical 24-hour base load profile of the transformer and the TOU prices in the parking lot. The data are from a parking lot in Tianjin, China. It can be observed that the base load in this area varies between 63 kW and 390 kW, the power peak period is from 11:00-20:00, the power valley period is from 23:00 to 07:00 and the remaining time is the normal period.

The impact of EVs charging on power grid depends on the number and charging behavior of EVs. Figure 3 shows the collected travel information of 100 EVs. EVs have the characteristics of relatively concentrated arrival and departure time, long parking time and high occupancy rate of parking space. In order to meet the charging demands of users, it is necessary to ensure that the number of EVs and charging piles is consistent.

Immediate charging means that the EV starts charging at a constant charging power once it is connected to the grid, and finish charging when the grid is disconnected or their batteries are full [21]. Assume that the parking lot has 500 parking spaces, 100 of which are equipped with charging piles. The immediate charging simulation of 100 EVs arriving at the parking lot is carried out, and the charging load distribution is shown in Figure 4. It can be observed that if the charging behavior is not properly planned, the charging load of these EVs between 10:00-11:00 will cause severe power peak demand. This situation seriously affects the safe and stable operation of power grid.

The maximum penetration level of EVs in the parking lot represents the maximum number of charging piles allowed to work simultaneously. Therefore, it is of great value to research on how to realize the maximum penetration level of EVs without infrastructure upgrading.

### III. ELECTRIC VEHICLE ENERGY DEMAND MODELING

In order to maximize the penetration level of EVs in parking lots, it is necessary to model the overall energy demand of EVs and intelligently control and manage the charging schedule.

#### A. CHARGE END TIME AND SOC DETERMINATION

In the actual charging process, different EV users always have different charging time and demand. Therefore, PLCC needs to collect the charging time and demand of each EV in order to form an overall energy demand:

The stay time of each EV connected with the charging pile is calculated by

\[
\text{t}_{\text{stop}} = t_e - t_s
\]  

\[1\]

where \(t_s\) and \(t_e\) is the arriving and expected leaving time of EVs.

Assuming that the EV is charging with the maximum charging power during the stay time, the battery SOC at the leaving time can be calculated by

\[
S'_{\text{fin}} = \min\{S_{\text{ini}} + (P_{\text{max}} \cdot \eta_{\text{ch}} \cdot \text{t}_{\text{stop}}) / E, S_{\text{max}}\}
\]  

\[2\]

where \(S_{\text{ini}}\) is the initial SOC of the EV, \(E\) is the battery capacity and \(S_{\text{max}}\) is the maximum SOC. \(P_{\text{max}}\) is the maximum charging power while \(\eta_{\text{ch}}\) is the charging efficiency.
According to the user’s SOC requirements, the actual SOC can be calculated by

$$S_{\text{fin}} = \begin{cases} S_{\text{expect}}, & \text{if } S_{\text{expect}} < S_{\text{fin}}' \\ S_{\text{fin}}', & \text{else} \end{cases} \quad (3)$$

where $S_{\text{expect}}$ is the SOC that EV users expect to achieve.

### B. ELECTRIC VEHICLE CHARGING PROCESS

PLCC need to consider the following constraints when planning a charging schedule for EVs connected.

1) Charging power constraint of EVs:

$$0 \leq P_{\text{ch}}^i \leq P_{\text{ch max}}^i \quad \forall t \in T \quad (4)$$

2) Discharging power constraint of EVs:

$$0 \leq P_{\text{dch}}^i \leq P_{\text{dch max}}^i \quad \forall t \in T \quad (5)$$

where $P_{\text{dch max}}^i$ is the maximum discharge power of EV.

3) The constraint that EVs cannot charge and discharge at the same time:

$$P_{\text{ch}}^i \cdot P_{\text{dch}}^i = 0 \quad \forall t \in T \quad (6)$$

4) The SOC at each time slot is calculated by:

$$S_{t+1} = S_t + \left(P_{\text{ch}}^i \cdot \eta_{\text{ch}} - P_{\text{dch}}^i / \eta_{\text{dch}} \right) \cdot \Delta t / E \quad \forall t \in T \quad (7)$$

where $\eta_{\text{dch}}$ is the discharging efficiency.

5) Battery SOC constraint of EVs:

$$S_{\text{min}}^i \leq S_t \leq S_{\text{max}}^i \quad \forall t \in T \quad (8)$$

6) The initial SOC once connected:

$$S_{\text{is}} = S_{\text{ini}} \quad (9)$$

7) The SOC required when leaving:

$$S_{\text{le}} = S_{\text{fin}} \quad (10)$$

8) The constraint of the capacity of regional grid and the transformer involved:

$$L_{\text{load}} + \sum_{i=1}^{n} P_{\text{ch}}^i + P_{\text{dch}}^i \leq T_{\text{nor}} \quad (11)$$

where $T_{\text{nor}}$ is rated capacity of the transformer, and $L_{\text{load}}$ is the regional base loads, while $n$ represents the number of charging piles connected to the EVs during the $t$-th period.

Considering the constraints listed below, the feasible range of EV charging and discharging power can be figured as shown in Figure 5. The charging schedule should be determined in order to meet the requirements of EV users. As shown in curve ②, only when the SOC is larger than the expected one does the EV have the potential to be dispatched. As shown in curve ④, if the initial SOC of the EV is less than the minimum SOC when connected to the charging pile, it needs to be charged with the maximum power immediately. After reaching the conservative SOC, a charging schedule can be determined considering the expected SOC. If the initial SOC is larger than the minimum one when connected, the charging schedule can be formed within the feasible range ensuring the final SOC equals to or is larger than the expected SOC.

### IV. REAL-TIME ENERGY MANAGEMENT STRATEGY FOR PARKING LOT

#### A. REAL-TIME ALGORITHM OPTIMIZATION RANGE

Global algorithm needs accurate EVs forecasting data when making day-ahead scheduling plan for EVs. However, great randomness exists in the time connected to the pile and the initial SOC of EVs, so the global optimization algorithm is not suitable. Real-time energy management strategy requires low accuracy of EVs prediction information, which only optimizes real-time schedulable EVs in each time period, in order to obtain the optimal charging and discharging schedule currently.

With the real-time strategy, EVs send information to PLCC when they connect or disconnect charging piles. After figuring out the optimized schedules it will publish them to each EV correspondingly. As shown in Figure 6, the whole range of the schedulable charging time of EVs is all under optimization process.

The schedulable time of the EV at the time interval $t$ is calculated by

$$H_i^l = t_i^l - t \quad (12)$$

The optimization time range of PLCC is calculated by

$$W_i = \max \{\cup H_i^{l}, i \in N'\} \quad (13)$$

where $N'$ represents the total number of connected EVs for time period $t$.

When PLCC detects a new EV connection, the optimization ranges are all needed to redefine.

#### B. GROUPING METHOD BASED ON THE SCHEDULABLE POTENTIAL OF EVS

Due to the large number of EVs, the charging and discharging characteristics of each EV are different. In order to reduce the random factors in the optimization process, a grouping method based on the dispatchable potential of EVs is proposed considering several characteristics of parking time, remaining charging energy, etc.
In order to meet the travel needs of EV users, the SOC limit for each time interval is calculated, which is marked as $SOC_{\text{min}}^t$, according to the information of the remaining parking time, expected SOC, maximum charging power, etc.

$$SOC_{\text{min}}^t = \min\{SO_{\text{exp}}^t - (P_{\text{max}} \cdot H_{\text{left}}^i / E), SOC_{\text{min}}\}$$

(14)

Only when SOC is larger than $SOC_{\text{min}}^t$ in each time period, do the EV have the potential to be dispatched and to meet the travel needs before departure time.

The charging schedulable index $a$ is defined to indicate the ability to be dispatched according to the relations among $SOC_{\text{now}}$, $SOC_{\text{min}}^t$, $t_{\text{now}}$ and $t_e$.

$$a = \text{sign}\left(\frac{SOC_{\text{now}} - SOC_{\text{min}}^t}{t_e - t_{\text{now}}}\right)$$

(15)

where $t_{\text{now}}$ and $SOC_{\text{now}}$ represent the current time and SOC respectively.

When $a = 0$, the charging demand is flexible, which can be changed considering the operating status of the station. When $a < 0$, the charging demand is rigid, which is needed to be meet with the maximum charging power.

In order to ensure the service quality of EVs, the discharge service can only be carried out after meeting the charging demand of EVs. The discharging schedulable index $b$ is defined to indicate the ability to discharge to the station according to the relations among $SOC_{\text{now}}$, $SOC_{\text{exp}}$, $t_{\text{now}}$, and $t_e$.

$$b = \text{sign}\left(\frac{SOC_{\text{now}} - SOC_{\text{exp}}}{t_e - t_{\text{now}}}\right)$$

(16)

When $b > 0$, the EV has the ability to discharge power to the station, which can be controlled according to the operating status. When $b = 0$, the EV is not able to discharge.

Comprehensively considering the coupling relationship between the charging schedulable index $a$ and the discharging schedulable index $b$, the grouping criterion is obtained:

$$EV_n = \begin{cases} 
\text{group 1}, & \text{if } a + b < 0 \\
\text{group 2}, & \text{if } a + b = 0 \\
\text{group 3}, & \text{if } a + b > 0 
\end{cases}$$

(17)

Group 1 is a rigid group, and the EVs in it are needed to be charged at the maximum charging power. Group 2 is a flexible group, in which the charging power can be adjusted appropriately. Group 3 is a discharge group, which has the ability to discharge to the station.

The specific process is as shown in Figure 7.

In order to reflect the changes in the charging needs of EV users under the influence of many factors, and to improve the intelligence and adaptability of the charging priority model, a charging priority evaluation model based on fuzzy control is established. Fuzzy control can design control rules according to the users’ objective and subjective conditions. In the case of abundant EV load and driving data can be obtained in the future, different fuzzy rules can be designed according to different input parameters to improve the accuracy of the algorithm.

1) FUZZY LOGIC CONTROLLER

The control rules of the fuzzy logic controller are based on the description of fuzzy conditions. The design includes the following aspects:

(1) Determination: Determine the input and output variable of the fuzzy controller, which are used as the control variables.

(2) Fuzzification: Select the input quantity of the fuzzy controller and convert it into which can be recognized by the system, including the following three steps:

First, the input is to be processed to meet the requirements of fuzzy control;

Second, the input quantity is to be scaled;

Third, the fuzzy language value of each input and the corresponding membership function are to be determined.

(3) Rule base: A fuzzy rule library is established based on the experience of experts, which contains many control rules.

(4) Fuzzy reasoning: Knowledge-based reasoning and decision-making are mainly realized.
Deblurring: The main function is to convert the control quantity obtained by reasoning into control output. The specific process is as shown in Figure 8.

![FIGURE 8. Fuzzy control process.](image)

2) CONTRIBUTION DEGREES
Considering that the phenomenon of charging interruption occurs during the charging process in order to avoid the transformer overrun or to meet the charging needs of EV users, as shown in the of Figure 5, which contributes to the safe and stable operation of the parking lot. Define the user’s contribution degree as:

\[ w_n = \frac{t_{\text{break}}}{t_e - t_s} + Z_n \]  

where \( Z_n \) is used to indicates the times of pauses in charging process:

\[ Z_n = t_{\text{on} \rightarrow \text{off}} \]  

\( t_{\text{break}} \) is used to indicate the time period of charging pauses:

\[ t_{\text{break}} = t_{\text{on} \rightarrow \text{off}} - t_{\text{off} \rightarrow \text{on}} \]

3) PRIORITY CALCULATION MODEL
The input of the fuzzy controller is the EVs’ remaining energy demand \( L_D \), the remaining charging time \( H_{\text{left}} \) and the contribution degree \( w \), while the output is the charging priority. The basic range of the input indexes are respectively \([0, L_{D,\text{max}}]\), \([0, H_{\text{left},\text{max}}]\) and \([0, w_{\text{max}}]\), while the basic domain of fuzzy controller response output is \([0, 1]\). \( C'_{EV} \) and \( D'_{EV} \) indicates the charging and discharging priority.

The selected word sets of input and output variables are \{small (S), medium (M), large (H)\}, and the membership functions are established by Gbellmf functions. The design of fuzzy rules follows the criteria as: when any of the factors including the contribution degree, dwell time or energy demand is at a high level, the EV has the priority to charge; when none of the three factors are at a high level, the priority can be defined by investigation into users’ psychology and experience. The membership function and priority fuzzy calculation results are shown in Figure 9.

![FIGURE 9. Membership functions and priority fuzzy calculation results.](image)

D. ENERGY MANAGEMENT STRATEGY BASED ON GROUPING AND PRIORITY OF EVS
In every time interval \( t \), according to the transformer rated capacity \( T_{\text{nor}} \) and the base load \( L_{\text{load}} \), the remaining available capacity of the transformer is calculated by

\[ T_{\text{res}} = T_{\text{nor}} - L_{\text{load}} \]  

According to the charging power required by the EVs connected to the piles in the \( t \)-th time slot, the energy margin that the parking lot can provide for EV charging is calculated by

\[ I_{CS} = \frac{P_{CS,\text{demand}}}{T_{\text{res}}} \]  

The proportion of the overall charging demand in the power margin the station can supply would indicate the tension between energy supply and demand. When \( I_{CS} < 1 \), the remaining power margin is sufficient and there is no need to adjust the EV charging schedules, while when \( I_{CS} > 1 \), the latter need to be adjusted.

According to the power margin and the energy demand of each group, the flow of energy and information among the grid, base loads, and EV groups is shown in Figure 10.

![FIGURE 10. Energy flow paths between different EV groups.](image)
The specific power distribution is as follows:

Case1: When charging demand index of group1 $In_{group1}^t < 1$, the charging demand of the rigid group can be met without any adjustments in the charging schedule. The remaining power can be allocated to the EVs in group2 and group3 according to the charging priority:

$$P_{EV,i, ch}^t = \frac{C_{EV,i}^t}{\sum_{i} N_{group2,3} C_{EV,i}^t} \cdot (T_{res}^t - P_{group1, demand}^t) \quad (23)$$

Case2: When $In_{group1}^t > 1$, the charging demand of the rigid group cannot be met. At this time, it is necessary to take actions after comparing the remaining energy ($T_{res}^t - P_{group1, demand}^t$) and the discharge capacity $P_{group3, dis}^t$ of group3.

1. If $P_{group3, dis}^t > T_{res}^t - P_{group1, demand}^t$, the discharge capacity of group3 can afford the unsatisfied charging demand of group1, so the charging schedule of group1 does not need to be changed. And the power remaining of group3 can be supplied to charge EVs in group2:

$$P_{EV,i, ch}^t = \frac{C_{EV,i}^t}{\sum_{i} N_{group2,3} C_{EV,i}^t} \cdot (P_{group3, dis}^t - (T_{res}^t - P_{group1, demand}^t)) \quad (24)$$

The actual energy provided by each EV in group 3 can be calculated by the actual power consumption of group 1 and group 2

$$P_{EV,i, dis}^t = \frac{D_{EV,i}^t}{\sum_{i} N_{group3} D_{EV,i}^t} \cdot (P_{group1, demand}^t + P_{group2, demand}^t) \quad (25)$$

2. If $P_{group3, dis}^t < T_{res}^t - P_{group1, demand}^t$, the discharge capacity of group3 cannot meet the unsatisfied demand of group1. In this situation, the discharge capacity of group3 is all provided to group1, and the charging demand and schedule of group2 can be adjusted to meet the demand of group1. The specific power distribution is as follows:

$$P_{EV,i, ch}^t = \frac{C_{EV,i}^t}{\sum_{i} N_{group1} C_{EV,i}^t} \cdot (T_{res}^t + P_{group3, dis}^t) \quad (26)$$

At this time, if the charging demand of group1 should be met compulsorily, the transformer will overrun. Therefore, this method can be used to determine the maximum penetration level of EVs in the parking lot.

### E. CALCULATION OF THE PARKING LOT’S OPERATION COSTS

The daily operating cost of the parking lot can be expressed as:

$$F = F_1 + F_2 \quad (27)$$

$F_1$ represents the charging cost of EVs:

$$F_1 = \sum_{t=1}^{T} \sum_{i=1}^{N} \Delta t \cdot \left( (P_{ch}^t \cdot \alpha_t - P_{dch}^t \cdot \beta_t) \right) \quad (28)$$

$F_2$ represents the punishment cost of transformer overrun:

$$F_2 = \sum_{t=1}^{T} \left\{ \sum_{n=1}^{N} \Delta t \cdot \left( P_{ch}^t - P_{dch}^t \right) \right\} + L_{load} - T_{nor} \cdot \delta \quad (29)$$

where $\Delta t$ is the time interval, $P_{ch}^t$ and $\alpha_t$ are the charging amount and charging price at time $t$, while $P_{dch}^t$ and $\beta_t$ are the discharging amount and discharging price at time $t$. $\delta$ is used to represent of the punishment price of overrun.

### F. CHARGING STRATEGY

For each time interval $t$, the following steps need to be performed:

1. **Step 1**: As long as the EV arrives at the parking lot, begin to charge it and calculate the charging demand $P_{CS, demand}^t$ and $In_{CS}^t$ according to (22). If $In_{CS}^t < 1$, there is no need to adjust the charging schedule, and the process can be skipped to Step 5. If $In_{CS}^t > 1$, the schedule should be adjusted through Step 2 to 4.

2. **Step 2**: Calculate the dispatchable potential of EVs, and divide them into groups based on the grouping method. Calculate the charging demand and discharge capacity of each group.

3. **Step 3**: Calculate the charging or discharging priority of EVs in each group and rank them accordingly.

4. **Step 4**: Distribute power according to the power margin and the schedulable potential of each group.

5. **Step 5**: Update the information of the EVs to determine whether the charging demands are satisfied. Determine whether the current time interval is the end time, if yes, the procedure ends; otherwise, return to step 1, and optimize the charging schedule for the next time interval according to the updated EVs information. Figure 11 shows the flowchart of the smart charging strategy proposed.

### V. CASE STUDY AND RESULT

In this section, the smart charging strategy proposed is applied to the charging stations in the parking lots of workplace mentioned in section II to achieve the optimal integration of EVs. It is assumed that there are 500 stalls in the lot, and the penetration of EVs is divided into 10 levels.

### A. CASE STUDIES DEFINITION

In order to prove the effectiveness of the strategy proposed, several cases are set as follows, and another two charging strategies are simulated for comparison, including Strategy A: immediate charging with which the EVs can begin to charge as long as plugging in to minimize charging time, Strategy B: economic charging based on (27) in order to reduce the charging cost, and last but not least, Strategy C which is proposed in the paper.
The successful operating times of different strategies are shown in Table 2 where the maximum possible EV penetration levels for Strategy A, B and C are 10%, 10%, and 60%, based on the premise that all 30-timesuccessful operations.

| Penetration Level of EVs | Charging Strategy A | Charging Strategy B | Charging Strategy C |
|-------------------------|---------------------|---------------------|---------------------|
| 10%                     | 30                  | 30                  | 30                  |
| 20%                     | 11                  | 24                  | 30                  |
| 30%                     | 0                   | 10                  | 30                  |
| 40%                     | 0                   | 0                   | 30                  |
| 50%                     | 0                   | 0                   | 30                  |
| 60%                     | 0                   | 0                   | 30                  |
| 70%                     | 0                   | 0                   | 15                  |
| 80%                     | 0                   | 0                   | 10                  |
| 90%                     | 0                   | 0                   | 0                   |
| 100%                    | 0                   | 0                   | 0                   |

Figure 12, Figure 14, and Figure 16 show the transformer load distribution under strategy A, B and C correspondingly at different EV penetration levels. It can be seen that when the EV penetration levels of strategy A, B and C are 10%, 10% and 60%, the peak load of the transformer will exceed the limit of 500KVA.

![Figure 12. Strategy A load curve under different EVs penetrations.](image)

![Figure 13. Charging power and battery SOC spectra of strategy A.](image)
Figure 15 illustrate the range of charging power and battery SOC of a typical EV selected from the case presented in Figure 14. With Strategy B, the EVs would be arranged to charge when the electricity price is low and to discharge when the price is high, which would cause a significant change in the power spectrum. However, with the increasing number of EVs, new peak of charge and discharge peak periods will be formed.

![Figure 14. Strategy B load curve under different EVs penetrations.](image)

![Figure 15. Charging power and battery SOC spectra of strategy B.](image)

Figure 17-18 illustrate the range of charging power and battery SOC of two typical EVs selected from the case presented in Figure 16. The charging time of EV1 is adjusted according to the power margin of the charging station to reach the expected SOC before departure. And EV2 begins to charge to the maximum SOC 0.9 when the power margin is large. In addition, EV2 would discharge to the station, helping provide enough power margin in order to afford the expected SOC of other EVs when the power margin of the station is small.

![Figure 16. Strategy C load curve under different EVs penetrations.](image)

![Figure 17. Charging power and battery SOC spectra of EV1.](image)

![Figure 18. Charging power and battery SOC spectra of EV2.](image)

It can be seen from the Figure 12-18 that the total load curves of the station with the three strategies are essentially different. A new load peak will appear when adopting Strategy A, which lets EVs begin to charge as long as arrival disorderly; Strategy B, which optimizes charging economically according to the electricity price issued by the charging station, lets EVs charge when the price is low and discharge when the price is high, but it will generate a new peak and valley on the load curve; Strategy C proposed in the paper is a smartly-controlled charging strategy following the guidance of charge and discharge priority indicator, which can eventually achieve the most reasonable use of the energy storage features of EVs and optimize it in real time, bringing highly-feasible real-time performance. Compared with the existing strategy of overall optimization, it reduces the influence of uncertain factors such as travel behaviors and conventional load fluctuations. The strategy proposed in this paper can effectively increase the penetration level of EVs while greatly reducing the operation time.
2) THE DAILY OPERATING COST OF THE PARKING LOT; PAR AND THE PEAK-TO-VALLEY DIFFERENCE

It can be seen from Table 3 and Figure 19-21 that with the increasing penetration level of EVs, the performance in charging cost, PAR and peak-to-valley difference differs among using the three strategies. From the perspective of charging costs, as the penetration level of EVs continues to increase, charging costs are increasing. Compared with Strategy C, operating with A and B should consider the punishment price of transformer overrun, which leads to higher costs. The PAR of Strategy A and B has been increasing, Strategy C starts to decline from 30% penetration level, it shows that after adding EVs charging demand, the load curve of the distribution network becomes more stable. The peak-to-valley difference values of Strategy A and B are increasing, Strategy C reaches the highest value at 20% penetration level and remains unchanged. Therefore, PLCC can choose reasonable operation strategy according to different operating goals.

**C. CASE STUDY 2**

This case evaluates the performance of different charging strategies with the index of maximum penetration level of EVs in the next few years. Assuming that the conventional load in the distribution network would increase at an annual rate of 0.63% in average [22], other conditions are set as in Case Study 1.

As shown in Table 2, the maximum EVs penetration level of Strategy A, B and C are separately 10%, 10% and 60% in the current year. Figure 22 indicates that different strategies will result in different penetration level in future without infrastructure upgrading, and shows a decrease tendency in the next 15 years. In the 6th year after, the maximum EV penetration level of Strategy C would decrease from 60% to 50%, while in the 10th year, it of Strategy A would decrease from 10% to 0% as well. Therefore, the 6th and 10th year are defined as critical years.

**VI. CONCLUSION**

This paper proposes a smart charging strategy based on charging and discharging indicators, combined with G2V and V2G charging technology, in order to maximize the EV penetration level in the parking lot without changing the distribution network infrastructure. Two cases are set up to simulate with three optimization strategies for comparison. The research results are analyzed from both the economic and technical aspects, which shows that the charging cost with the strategy proposed in this paper is lower than the other two strategies, and the maximum EV penetration level is the highest one to be achieved.

### TABLE 3. Performance comparison of different charging strategies.

| Penetration Level of EVs | Charging Strategy | Cost (¥) | PAR | Peak-to-valley Difference |
|--------------------------|------------------|---------|-----|---------------------------|
| 10%                      | A                | 1.7428  | 1.221 | 146.798                   |
|                         | B                | 1.8281  | 1.281 | 136.850                   |
|                         | C                | 1.9778  | 1.378 | 124.074                   |
| 20%                      | A                | 2.2939  | 1.378 | 179.719                   |
|                         | B                | 2.0408  | 1.378 | 184.808                   |
|                         | C                | 1.9147  | 1.378 | 196.171                   |
| 30%                      | A                | 2.3922  | 1.378 | 196.171                   |
|                         | B                | 1.809   | 1.378 | 196.171                   |
|                         | C                | 1.2614  | 1.378 | 196.171                   |
| 40%                      | A                | 2.6870  | 1.378 | 196.171                   |
|                         | B                | 2.3930  | 1.378 | 196.171                   |
|                         | C                | 1.6951  | 1.378 | 196.171                   |
| 50%                      | A                | 3.1972  | 1.378 | 196.171                   |
|                         | B                | 2.7672  | 1.378 | 196.171                   |
|                         | C                | 2.6782  | 1.378 | 196.171                   |
| 60%                      | A                | 3.3306  | 1.378 | 196.171                   |
|                         | B                | 2.7138  | 1.378 | 196.171                   |
|                         | C                | 2.1898  | 1.378 | 196.171                   |

**FIGURE 20. The PAR of different strategies under different penetration levels.**

**FIGURE 21. The peak-to-valley difference of different strategies under different penetration levels.**

**FIGURE 22. Maximum possible PEV penetration obtained in upcoming years with different charging strategies.**
The strategy has good adaptability to the gradually growth of the base load, which could furtherly provide a reference for the operation and upgrading of the parking lot charging station.

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