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Price-responsive early charging control based on data mining for electric vehicle online scheduling

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ABSTRACT

The uncertainty of electric vehicle (EV) behavior is deemed as a major challenge in online charging scheduling. It may lead to charging congestion to compromise the whole benefits of EV owners and aggregators. Early charging is the most efficient way to tackle the dynamic problem. However, it is very challenging for early charging to achieve the adaptive control and minimize electricity bill. In this paper, a price-responsive early charging adaptive control (PRECC) is proposed. The speedup factor is designed as a subtotal of charging demand categorized by electricity price, and it can be determined with only one offline charging optimization through a data-mining method. Due to the strong correlation with electricity price, PRECC can help online scheduling algorithms minimize early charging cost. Since it is not limited by the states of EVs, it can rapidly respond to the variations of base load and electricity price. Besides, with the independent design, it can well match online scheduling algorithms. Computer simulations are made to verify the proposed control. The results show that PRECC can improve the optimality of online scheduling by an average of 5.4%. Compared with the traditional early charging strategies, it has obvious advantages in terms of optimality, power capacity utilization, and profitability.

1. Introduction

1.1. Motivation

In response to the incentives on electric vehicles (EVs) and the restrictions on internal combustion engine vehicles, EV population has been increasing rapidly in recent years. EV charging load could lead to inefficient power system operation or even security issues [1–3]. To mitigate the negative effects of EV integration, one of the most effective ways is to deploy charging coordinated systems, where the key challenge is to develop efficient online scheduling algorithms as well as tackle the lack of future knowledge [4,5]. EV charging coordination has been extensively studied, and numerous algorithms have been developed for reducing charging cost, power loss, or voltage variance, etc. However, the uncertainties associated with coordination may greatly affect the benefits, thus relevant research has drawn a lot of attention.

The uncertainty factors, including EV mobility behavior and base load variation, will impair the effectiveness of coordination. Many research works have been conducted to power load forecasting, thus the power load uncertainty has been partially tackled. By contrast, EV mobility behavior, such as the times of arrival and departure, is more difficult to forecast due to its strong randomness [6–8]. Since online algorithms do not know the exact information of future EV arrival, they will postpone current charging to low-priced time periods as much as possible for the sake of cost saving. When a mass of vehicles unexpectedly arrive or base load suddenly increases, charging congestion may occur due to limited power capacity. That will result in a decrease in scheduling effectiveness. Such dynamic problem can become very serious in residential areas since most vehicles go back home in high-priced periods. That will compromise the benefits of both charging operators and EV owners. Since commuting usually has a daily or weekly repeated pattern, the statistical pattern of EV fleet can be revealed based on historical mobility data [8]. Nevertheless, online scheduling requires more accurate knowledge [9].

1.2. Literature review

The dynamic problem has been discussed in many studies. Wang el al. [4] investigate the uncertainty factors of charging coordination, and point out that the main uncertainty for smart grid operators is inherited from the mobility uncertainty of an EV fleet, which consists of arrival and departing times as well as the various battery status of EVs. In Ref. [10], Tang et al. present an overview of online scheduling algorithms as well as divide them into three categories: complete future knowledge (CFK), partial future knowledge (PFK), and zero future knowledge (ZFK). The CFK algorithms formulate the coordination as deterministic

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problems by setting some assumptions. For instance, in Ref. [11], it is assumed that charging stations fully know charging schemes one day ahead, i.e., all uncertainties are neglected. These algorithms need to be modified when used in practical applications. The PFK algorithms generally use probability density functions (PDFs) to describe the characteristics of EV charging demand [12,13]. In this way, the overall level of charging demand could be estimated, however the forecasting accuracy of ultra-short term (e.g., hourly) charging demand cannot meet the need of online scheduling. The ZFK algorithms prefer to use early charging strategies to mitigate the dynamic problem, i.e., charge some EVs in advance. The well-known strategies include the earliest deadline first (EDF), the least laxity first (LLF), and the lowest state-of-charge (SOC) first (LSF).

Early charging is deemed as the most effective method to tackle the dynamic problem, however it is very challenging to find a proper control factor. In Ref. [14], a speedup factor is used to speed charging rate, however this fixed factor needs to be carefully chosen by multiple offline optimizations. Apart from that, it can apply only to variable-rate charging control and does not consider the charging priority of the low-SOC EVs as well. In Ref. [15], a fixed SOC lower limit is set in the objective function, i.e., the SOC of each EV must be greater than the limit before leaving. Definitely, such limit should be very small and set separately for each individual case, otherwise it may lead to a solving failure. Qi et al. [16] add a weighting factor into the objective to prepare for the unexpected arrival of a mass of EVs, where reducing charging cost is not considered when determining this fixed factor. Hence, most of existing works use a fixed factor to control early charging, and put it in the objective function. This design comes with some obvious disadvantages. Binding to a particular scheduling algorithms greatly limits the practicality of early charging strategy. Especially, it is extremely difficult for fixed control factors to effectively response to the diversity of charging demand. Moreover, multiple iterations for determining the factor impose a heavy computational burden on online scheduling.

Another simpler method is to control early charging with a SOC threshold, i.e., to immediately charge the EVs with SOC below the threshold instead of coordinating them. To determine the proper threshold, iterative offline charging optimizations are generally required. Theoretically, the SOC threshold should be suitable for early charging control, since (1) it is very predicable due to strong correlation with total charging demand and (2) it can easily achieve the charging priority of low-SOC EVs and (3) it does not interfere with the design of scheduling algorithms. However, this control also has drawbacks. First, since it is price-independent, it may lead to high early charging cost. Second, since it is related to the SOCs, its effectiveness will be affected by EV uncertainty. Besides, for a fixed threshold, it will have the same disadvantage as the fixed factors.

In power system optimizations, electricity pricing mechanisms are crucial to reach a win-win situation between a grid operator and its customers. The correlation between power demand and electricity price is widely leveraged in demand response (DR) related studies [17–20]. Charging coordination is an important DR strategy, in which electricity price plays a decisive role to motivate EV owners to participate. Accordingly, the pattern of charging demand hidden in the optimal schemes can be revealed via a price-based data mining approach. Aiming at early charging strategy, this paper has following goals: (1) investigate the statistical pattern of charging load by exploring optimal charging schemes, and (2) develop an adaptive control of early charging based on the price mechanism.

1.3. Contribution of this paper

The main contributions and technical novelty are threefold as follows:

1) A novel price-responsive early charging control (PRECC) is proposed. It is self-adaptive and its control factor can be determined by only one offline optimization.
2) PRECC's control factor is determined with electricity price, thus it can minimize early charging cost in scheduling. Besides, unlike the SOC threshold, it is unrelated to EV states, thus it can rapidly respond to the unexpected variation of base load or electricity price.
3) PRECC is designed independently. Its control factor is estimated by data mining, without PDF construction and parameter identification. Accordingly, it can match any online scheduling algorithms very well.

1.4. Organization of the paper

The rest of this paper is organized as follows: Section 2 illustrates a two-level charging coordinated system as well as designs the online scheduling objective function. Section 3 explores the structure of optimal offline solutions, and then introduces PRECC and an improved online scheduling algorithms. In Section 4, computer simulations are made to verify the proposed work, followed by the conclusion in Section 5.

2. Problem formulation

A charging coordinated framework for parking stations is introduced as an example and shown in Fig. 1(a). The transformer supplies power to base load and EV chargers. Parking operators use the base-level controller (BLC) to schedule charging, while a power grid operator or an aggregator uses the upper-level controller (ULC) for large-scale coordination. The BLC aims to find an optimal charging scheme in a specific time period. This scheme not only has to satisfy the EV owner needs, but also must avoid power limit violations. As shown in Fig. 1(b), based on historical EV mobility behavior, the control factor of PRECC can be obtained by offline scheduling, which will be employed for early charging to improve the performance of online scheduling.

In this paper, BLC has three scheduling targets: avoiding power violation, maximizing completion rate, and minimizing electricity bill. The on-off strategy is used for charging control, i.e., an EV is charged with a constant rate and the process can be switched on/off by BLC anytime. The system time horizon is set as 24 h, equally divided into J time slots. BLC will make charging decisions at the beginning of each time slot, where the following considerations are assumed:

1) When an EV is plugged in, its initial SOC is known.
2) The base load can be measured in real time with a meter, and the BLC can obtain the base load forecasts.
3) The driver may provide the departure time when the EV is plugged in; otherwise, the BLC will estimate the time based on the historical behavior of this EV.

To realize online scheduling, the minimal known information includes: (1) power limits computed with base load forecasts and the capacity threshold, (2) estimated real-time or day-ahead electricity tariff, and (3) real-time EV data. Besides, real-time measurement of base load is needed to achieve overload control.

The power constraints for charging are denoted as

$$\mathbb{P} = [\,\chi^1 \;\; \chi^2 \;\; \cdots \;\; \chi^J\,] \tag{1}$$

where χ stands for the available power for each time slot.

The electricity prices are denoted as

$$T = [\,\theta^1 \;\; \theta^2 \;\; \cdots \;\; \theta^J\,] \tag{2}$$

where θ stands for the electricity price for each time slot.

Maximizing the utilization of power capability is the key to achieve multi-win among a power company, charging operators, and EV

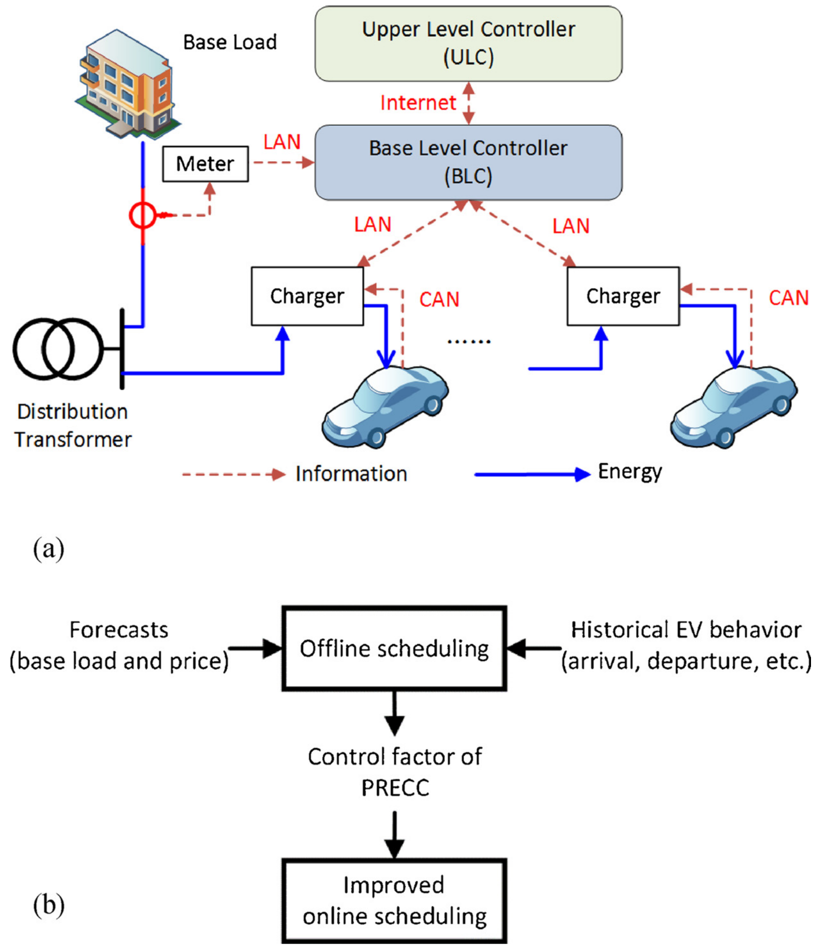

Fig. 1. Schematic illustration of a charging coordinated system: (a) topology and (b) methodology.

owners. Thus, the objective function is built in a maximization form. An integer k is defined as the index of current time slot. A group of integer sets, ψ^j, $j \in [1, J]$, are defined to store the indexes of EVs for each time slot, which will be updated with time. For an EV n, $\exists n \in \psi^j$, $\forall j \in [k, d_n]$, where d_n is the last time slot before its departure. The objective function is constructed as

$$\max \sum_{j=k}^{J} \left[\omega^j \cdot \sum_{\forall n \in \psi^j} (p_n s_n^j) \right], k = 1 \cdots J \tag{3a}$$

subject to

$$\sum_{\forall n \in \psi^j} (p_n s_n^j) \le \chi^j, \forall j \in [k, J] \tag{3b}$$

$$\gamma_n^k + \sum_{j=k}^{J} \left. \frac{\eta_n P_n s_n^j T_s}{E_n} \right|_{n \in \psi^j} \le \gamma_n^{exp}, \forall n \in \psi^k \tag{3c}$$

$$\omega^j = \frac{\theta_{\max} - \theta^j}{\theta_{\max} - \theta_{\min}} + c \tag{3d}$$

where j and n respectively denote a time slot and an EV, E_n, p_n and η_n are the battery capacity in kWh, charging power in kW, and charging efficiency lying in [0, 1] of EV n, T_s is the fixed time interval, s_n^j is the binary charging decision (i.e., 1: on and 0: off), γ_n^k and γ_n^{exp} stand for the current and expected SOC of EV n, $\theta_{\max}$ and $\theta_{\min}$ are the highest and the lowest prices, respectively, ω^j is the price preference that is linear and returns a higher value in response to a lower price and vice versa, and c is a small positive decimal such as 0.1 to set ω^j in the range of [c, $1 + c$].

The scheduling denoted by (3) is a binary integer programming (BIP) problem, which can be solved by proper algorithms such as the branch and cut (B&C). The solution can be expressed as a binary decision matrix $\mathbb{S}$, and only the current decisions, s_n^k, $\forall n \in \psi^k$, will be performed. The current decisions can be denoted as $\mathbb{S}^{(k)}$. For the past system time horizon, an online solution can be obtained by

$$\mathbb{S} = \bigcup_{j=1}^{J} \mathbb{S}^{(j)} \tag{4}$$

where $\cup$ is the union operator. That is, the online solution is a binary matrix consisting of the performed charging decisions of J time slots. In the next section, the proposed early charging control will be discussed in detail, where the scheduling problem of (3) will be leveraged for illustration.

3. Improved online scheduling algorithms

3.1. Structure analysis of optimal offline solutions

Due to the strong randomness, it is impossible to accurately predict the times of EV arrival and departure. Especially, the accuracy of ultra-short term forecasting of charging demand should be very poor. In contrast, it is more practical to forecast total charging demand in the system time horizon by exploring optimal offline solutions [10]. Unlike the random arrivals, an optimal charging scheme has much better regularity since it has been well reorganized. That is, its charging demand has clearer patterns and a more stable structure. For instance, low-priced electricity will be always consumed first by EVs due to the cost-saving goal [4].

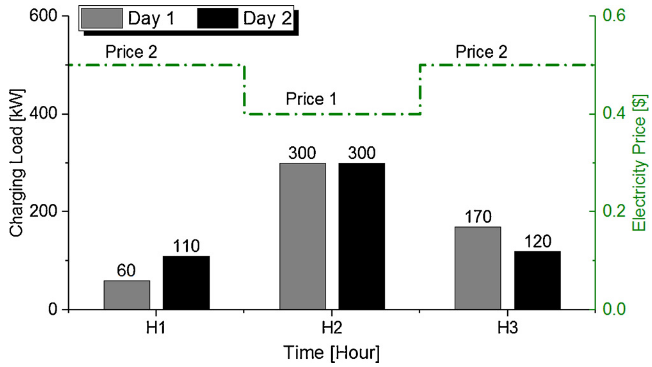

Fig. 2. Schematic of charging loads based on the optimal solutions.

The schematic of optimal charging loads of two days, Day 1 and Day 2, has been shown in Fig. 2, where three assumptions are considered for ease of explanation:

1) Only three hours and two prices are set in the system time horizon.
2) Daily charging demand is set as a fixed value of 530 kWh.
3) The power constraint is set as a fixed value of 300 kW in the system time horizon.

As shown in Fig. 2, the load level of H2 is very stable, since low-priced electricity will be consumed first. On the contrary, the high-priced load of H1 or H3 may have a large deviation for the following reasons:

1) In a system time horizon, two different time slots may have the same price, e.g., H1 and H3, thus the scheduling algorithms may give different solutions with the same electricity bill. Since the low-priced power is consumed first, the differences among the solutions are mainly reflected in high-priced periods, e.g., the charging loads of Day 1 and Day 2.
2) High-priced load is more susceptible to the uncertainty of EVs, since high-priced electricity has low priority in consuming.

Consequently, it is still very difficult to accurately forecast ultra-short term high-priced charging demand. Logically, the charging demand within a specific time period should have an expected value since EV fleet mobility has a stable statistical pattern. Thus, the total charging load of a day can be denoted as a random variable:

$$A = \sum_{h=H1}^{H3} (\mu_h + \Delta_h) \tag{5}$$

where μ_h is the mean and Δ_h is a random variable that stands for the deviation of charging load in time period h. According to the charging loads of Day 1 and Day 2, μ_{H1}, μ_{H2}, and μ_{H3} are computed as 85 kW (i.e., the average of 60 kW and 110 kW), 300 kW, and 145 kW, respectively. Δ_{H1}, Δ_{H2}, and Δ_{H3} are respectively −25 kW (i.e., the result of 60 kW minus 85 kW), 0 kW, and 25 kW for Day 1, while 25 kW, 0 kW, −25 kW for Day 2. Evidently, the deviations of high-priced loads are still very large.

Since the daily charging demand is assumed to be constant, according to (5), the total deviation is equal to zero, i.e., $\sum_{h=H1}^{H3} \Delta_h = 0$. As aforementioned, low-priced electricity will be consumed first, therefore Δ_{H2} is approximately equal to zero, as shown in Fig. 2. The deviations should satisfy

$$\begin{cases} \Delta_{H2} = 0 \\ \Delta_{H1} + \Delta_{H3} = 0 \end{cases} \tag{6}$$

According to (6), EV randomness hardly affects the total low-priced and high-priced charging loads unless the total charging demand significantly changes. For a multilevel electricity tariff, the charging power consumption can be divided by a specified price θ^t into two parts:

$$A = \sum_{\substack{j=1 \\ \theta^j < \theta^t}}^{J} a_j + \sum_{\substack{j=1 \\ \theta^j \geq \theta^t}}^{J} a_j \tag{7}$$

where a_j represents the power consumption of EV charging during a time slot j.

The summations in the right of (7) are much more predicable for following reasons:

1) Aggregating multiple time slots broadens the time horizon of forecasting, reducing the errors caused by the uncertainty of EV arrival, departure, and parking duration.
2) Aggregating by electricity price can leverage the objective of cost saving to further reduce forecast error. The lower the price of θ^t, the more accurate the forecast.
3) Although the forecast deviation can increase with θ^t, it is still smaller than directly forecasting a single time slot due to the first reason.

3.2. Price-responsive early charging control (PRECC)

For early charging, the key is to determine which EVs should be immediately charged rather than participate in coordination. For an optimal offline solution, each price should match a proper power consumption. Consequently, more power consumption in high-priced periods will increase charging cost, while less power consumption in high-priced periods may aggravate the dynamic problem. The proper consumption is named as the charging load expectation (CLE) and will be employed as the control factor of early charging. Evidently, the CLE should be obtained by exploring optimal offline solutions.

Using historical EV data, the arrival and departure times in the past system time horizon are completely known. The optimal offline solution is then denoted as:

$$\hat{\mathbb{S}} = \arg \mathscr{O}(\mathbb{P}, \mathbb{T}, \hat{\mathbb{Q}}) \tag{8}$$

where $\hat{\mathbb{Q}}$ denotes historical EV data, and $\mathscr{O}$ is the scheduling algorithm (e.g., solving the problem of (3) with B&C).

A real-valued set ξ is defined to save the CLEs, where ξ^t is the CLE with respect to a time slot t. According to (3) and (8), the element ξ^t is computed as

$$\xi^t = \sum_{\substack{j=1 \\ \theta^j \geq \theta^t}}^{J} \sum_{n \in \psi^j} (p_n \hat{s}_n^j T_s), \forall\, t \in [1, J], \hat{s} \in \hat{\mathbb{S}} \tag{9}$$

where ψ is derived from $\hat{\mathbb{Q}}$ and it is completely known.

According to (9), the CLE ξ^t is a subtotal of charging loads during the time slots with equal or higher prices than θ^t. In early charging, a specific strategy will be employed to select EVs to charge in advance until ξ^k or χ^k is less than the minimal charging rate of participated EVs. According to the optimal solution of Day 1 or Day 2 in Fig. 2, a sample of the CLE set can be obtained and shown in Fig. 3, which is denoted as [230, 530, 230]. The number of 230, which is the subtotal of charging loads with respect to the two hours of H1 and H3 (i.e., the result of 60 kW plus 170 kW for Day 1, or the result of 110 kW plus 120 kW for Day 2), represents the expected charging load at the price equal to or higher than the price 2, while the number of 530 stands for the expected charging load at the price equal to or higher than the price 1 (i.e., 530 corresponds to the three hours of H1, H2, and H3). This sample only has three elements, and the actual length of ξ depends on the number of prices. The real-valued set ξ can be described with only a few hundreds of bytes (e.g., pricing at an interval of 15 min) as well as computed only once for a system time horizon, therefore PRECC comes

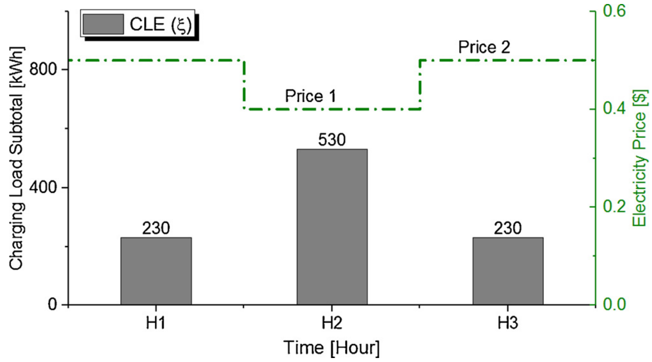

Fig. 3. A sample of the CLE set: $[\xi^1, \xi^2, \xi^3]$ = [230, 530, 230] kWh.

with low communication overhead.

To sum up, the steps of computing CLE are as follows:

1) For the coming day, update electricity prices of $\mathbb{T}$, and compute power limits of $\mathbb{P}$ with base load forecasts and the capacity threshold.
2) Update $\hat{\mathbb{Q}}$ with the historical EV data of the last same-type day.
3) Obtain the optimal scheme by scheduling algorithms according to (8).
4) Compute the CLEs according to (9).

Based on multiple-day historical EV data, multiple optimal offline solutions can be obtained according to the above steps, therefore the CLE averages can be computed to further improve the PRECC's stability.

3.3. Improved online scheduling using the PRECC

At the beginning of the **current** time slot k, PRECC will be performed before running scheduling algorithms, where the LSF strategy is employed for EV selection. The steps are as follows:

1) Update power limits and electricity prices for the coming system time horizon with the forecasts.
2) Solve the objective function of (3) to obtain the optimal offline solutions based on multiple-day historical EV data.
3) Compute the CLEs according to (9), and then obtain the averages.
4) Update ψ^j, $j \in [k, J]$ with the information of participated EVs, and save ψ^k as a new set ϕ. Initialize s_i^k to be 0, $\forall i \in \psi^k$. Update χ^k with real-time base load.
5) Select an EV n with the **lowest** SOC from ϕ (i.e., LSF).
6) If $p_n \le \xi^k$ and $p_n \le \chi^k$, set s_n^k to be 1 and remove EV n from ϕ, and modify the constraints by the following equations:

$$\begin{cases} \chi^k = \chi^k - p_n \\ \xi^t = \xi^t - p_n, \ \forall\ t \in [1, J] \end{cases} \tag{10}$$

1) If no EV is in ϕ or no EV meets the conditions of $p_n \le \xi^k$ and $p_n \le \chi^k$, then go to Step 8; otherwise, go to Step 5 to select the next EV.
2) Save early charging decisions as an integer array $\mathbb{S}_E^{(k)}$, $s_i^k \in \mathbb{S}_E^{(k)}$, $\forall i \in \psi^k$.
3) Solve the problem of (3), and then obtain the solution:

$$\tilde{\mathbb{S}} = \arg\mathscr{O}(\tilde{\mathbb{P}}, \mathbb{T}, \tilde{\mathbb{Q}}) \tag{11}$$

where $\tilde{\mathbb{P}}$ denotes the modified power limits, and $\tilde{\mathbb{Q}}$ denotes the modified charging demand considering early charging. The final decisions at current time slot k is

$$\mathbb{S}^{(k)} = \tilde{\mathbb{S}}^{(k)} \cup \mathbb{S}_E^{(k)} \tag{12}$$

At last, perform the decisions $\mathbb{S}^{(k)}$, and wait for the next time slot, i.e., $k = k + 1$. The first three steps can be performed at the beginning of system time, or at the beginning of each time slot in response to real-time variation of power load or electricity price. When J time slots are all completed, the performed decisions can be combined into an optimal online solution by (4).

It should be noted that the overload control works independently at a short interval such as 15 s to real-time protect power systems. The chargers will be turned off in a SOC descending order until no power violation occurs, i.e., the EV with the largest SOC will be suspended first.

3.4. The properties of PRECC

As with the widely-used SOC-threshold strategy, PRECC's control factor is strongly related to total charging demand. Accordingly, its control accuracy can be ensured due to the stability of total demand. Furthermore, PRECC has unique advantages:

1) PRECC is an adaptive control. The control factor is determined by only one offline charging optimization, and its resolution can be very high (e.g., 0.1 kW).
2) Each CLE is a subtotal of power consumptions above a specified price in the system time horizon, instead of a fixed SOC threshold, i.e., it is not tied with the states of participated EVs. As a result, PRECC can rapidly respond to unexpected variations of base load and price. For instance, a drop in base load will increase the available power capacity. In this case, PRECC can start more charging tasks to well prepare the future massive arrivals, while the SOC-threshold control can hardly do this.
3) CLE is categorized with electricity price, therefore PRECC can minimize early charging cost while addressing the dynamic problem.
4) Due to the independent design, PRECC can flexibly match scheduling algorithms.

Like other strategies, PRECC may be affected by some uncertainties:

1) Once EV population changes, PRECC can follow it by computing CLEs based on recent EV mobility data. However, its accuracy may decrease, and that will be discussed in the next section.
2) The forecast error of base load or electricity price can affect PRECC in a complex way. It is actually a common problem for online scheduling algorithms, which can be tackled by existing mature methods [21–25]. The specific impact will be tested by simulation.
3) For a special day such as an annual holiday, the historical data of EV behavior one year ago might be required for computing CLEs, however EV population may have changed significantly. Therefore, historical data should be proportionally modified according to current EV population.

4. Computer simulations

4.1. Simulation settings

As shown in Fig. 4, 44-**Monday** load data, from January 2 to October 30, 2017, is extracted from RTE-France [26], including 30-min average power values and forecasts. The load forecasts will be used to determine power constraints, while the actual load data is used for overload control. The load data is converted by a fixed ratio to fit a power distribution system. The electricity prices in Fig. 5 are acquired from EPEX-SPOT [27], which will be used as day-ahead prices in following simulations.

The system time horizon and the time interval are set as 24 h and 30 min, respectively. A coordinated system as shown in Fig. 1 is deployed in a residential parking station, and the capacity threshold of the distribution transformer is set to be 1 MW. The number of participated EVs on every day, M, is assumed to follow a normal distribution:

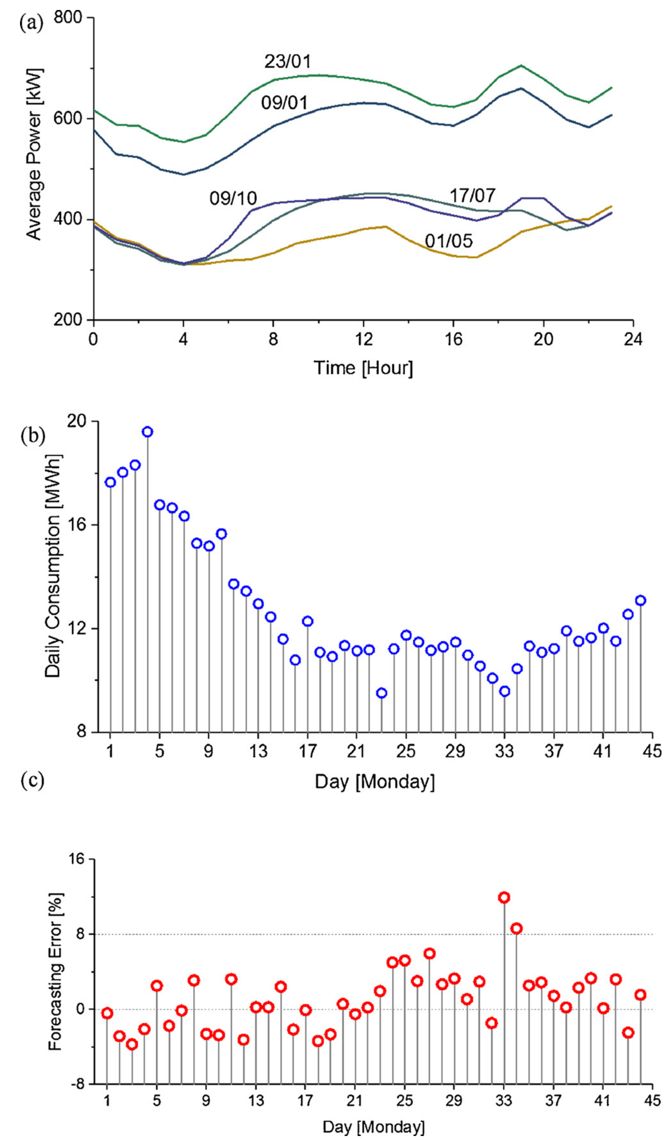

Fig. 4. The load data from RTF-France: (a) partial load profiles, (b) daily consumptions, and (c) forecasting errors of daily consumptions.

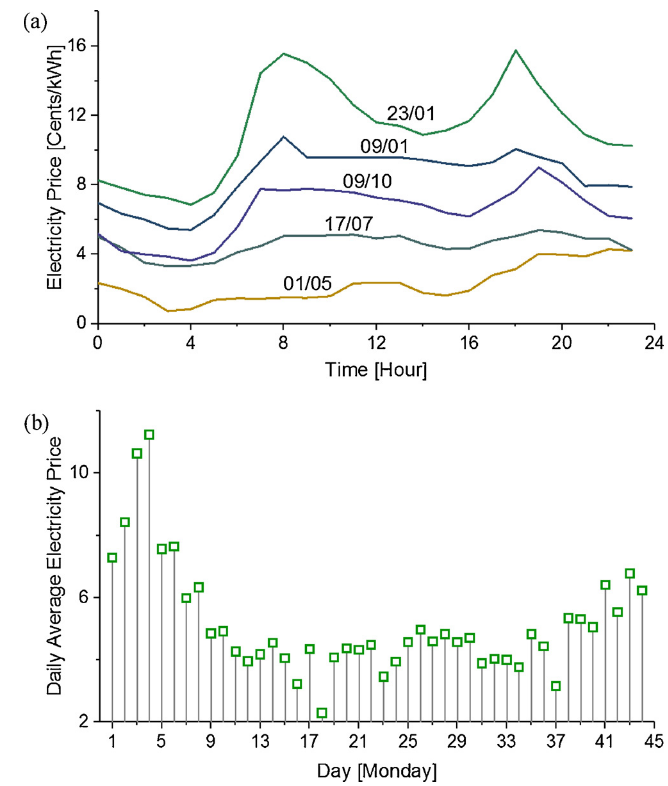

Fig. 5. The day-ahead electricity prices from EPEX-SPOT: (a) partial price profiles and (b) daily average prices.

Table 1
Assumptions of EV proportion and specifications.

Type	E^{cap} [kWh]	p [kW]	γ^{max}	η	Proportion
1	24	3.3	1.00	0.9	50%
2	30	6.0	1.00	0.9	30%
3	48	9.0	1.00	0.9	20%

$\mathcal{N}(300, 10^2)$, and every EV can be charged upon arrival. Both commuting and random EVs are considered, and the ratio is set as 7:3. For commuting EVs, both arrival and departure times have stable expectations, thus the normal distribution has been widely used in simulation [8,9,15,16]. Here, the times are set to follow normal distributions: $\mathcal{N}(18, 2^2)$ and $\mathcal{N}(6, 1^2)$, respectively. For random EVs, the arrival and departure times are uniformly distributed within the system time horizon. The initial SOC is described by a lognormal distribution: $\ln\mathcal{N}(5.0, 0.78^2)$ used in Ref. [28]. The specifications of EVs are assumed in Table 1 as well.

4.2. Scheduling algorithms

In simulations, (3) is used as the objective function, and the CPLEX [29] is employed as the solver. A SOC threshold, γ^e, is defined as the speedup factor, i.e., each EV with less SOC than γ^e will be immediately charged rather than participating in scheduling until its SOC reaches γ^e.

Six algorithms are implemented for comparisons: (1) first come first serve strategy with overload control (FCFS), (2) online (dynamic) scheduling by B&C algorithms (LP-D), (3) LP-D with early charging using a fixed SOC threshold of $\gamma^e = 0.6$ (LP-E), (4) LP-D with early charging using an adaptive SOC threshold (LP-A), (5) LP-D with PRECC (PRECC), and (6) offline (static) scheduling by B&C (LP-S).

Here, LP-A is implemented with an enumeration method determining a proper γ^e automatically. The ratio of objective function values is employed as the basis of selection, computed as

$$\mathbb{B}_i = \frac{f(\hat{\mathbb{S}})}{f(\mathbb{S}_i)} \tag{13a}$$

$$\gamma_i^e = 0.1 \cdot i,\ i = 0 \ldots 10 \tag{13b}$$

$$f(\mathbb{S}) = \sum_{j=1}^{J} \left[\omega^j \cdot \sum_{\forall n \in \psi^j} (p_n s_n^j) \right] \tag{13c}$$

where $\hat{\mathbb{S}}$ is the optimal offline solution obtained through LP-S based on the completely known information, and $\mathbb{S}_i$ denotes the optimal online solution using γ_i^e to realize early charging. The proper γ^e for the coming system time horizon is then determined by

$$\underset{\gamma^e\ i=0\ldots10}{\arg\max}\, \mathbb{B}_i \tag{14}$$

All algorithms are achieved via CPLEX 12.6. A personal computer, with Intel Core i7-6700 CPU @3.4 GHz and 16-GB RAM, is used as the hardware platform. Besides, the CPLEX's gap tolerance and time limit are set to be 0.0005 and 60 s.

EV behavior data of last ten days is used to determine the control factors for LP-A and PRECC. In this case, LP-A needs 110 optimizations

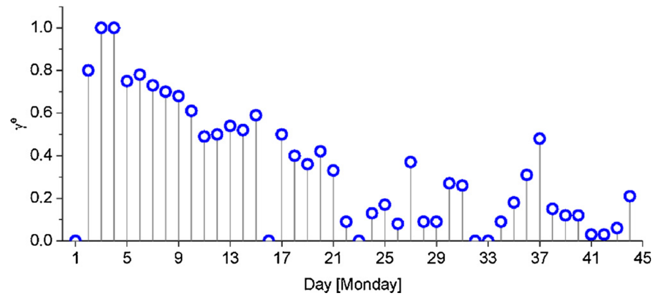

Fig. 6. Results of the adaptive speedup factor γ^e of LP-A.

to find the proper SOC threshold for a day, while PRECC needs only 10 optimizations. LP-A's speedup factors for 44 days are identified and presented in Fig. 6. In scheduling, the threshold SOC will be fixed during a system time horizon. As can be seen, the factor approximately follows the fluctuation of daily power consumption shown in Fig. 4(b). Note that, the proper value of a speedup factor is also affected by electricity price profiles.

ORCHARD in Ref. [14] achieves early charging with a speedup factor of charging rate, where the power capacity is not constrained. Like a SOC threshold, this speedup factor is also related to the EV's state, i.e., charging rate. If it can be determined for every day, ORCHARD should be close to LP-A in terms of optimality and factor identification cost.

4.3. Optimality comparison

Competitive ratio (CR) is usually employed to evaluate the optimality [10]. Here, the LP-S is used as the benchmark. For the maximization problem of (3), the CR in the worst case can be obtained by

$$\mathbb{R}_X = \max_{d=1:L} \frac{f(\hat{\mathbb{S}})}{f(\mathbb{S}_X)},\ X = \text{FCFS, LP-D/-E/-A, or PRECC} \tag{15}$$

where **max** is to evaluate the **worst-case** performance, L is the number of days, and $\mathbb{S}_X$ stands for the optimal online solution obtained through the algorithms X.

The CR results have been shown in Fig. 7, where the closer the CR is to 1 the better the optimality. Note that, since no historical EV data is available for the first day, early charging for LP-A and PRECC is effective for the rest 43 days. The $\mathbb{R}$ results of FCFS, LP-D, LP-E, LP-A, and PRECC are 2.090, 1.179, 1.215, 1.093, and 1.039, respectively. The averages are 1.384, 1.070, 1.095, 1.038, and 1.007, respectively. Moreover, PRECC achieves the best for 40 out of 43 days. For 33 days, its CRs are less than 1.01. That is, in most cases, the gap between PRECC and LP-S is less than 1%. Consequently, PRECC improves the performance of online scheduling to an approximate level of offline one.

Compared with LP-D, PRECC improves the optimality by a maximum of 15.2% and an average of 5.4%. Compared with LP-A, PRECC has higher accuracy due to the high resolution of the control factor, as well as better flexibility due to independence from the EV's states. Its optimality is improved by a maximum of 8.2% and an average of 2.9%.

Furthermore, PRECC shows good stability. Its CR changes in a very narrow range. On the contrary, larger deviations can be observed in the results of other algorithms. For the first ten days, due to the insufficient power capacity, the dynamic problem is serious, hence LP-D presents worse results than other algorithms except FCFS. For the last dozen days, when power capacity is sufficient, LP-E is the second worst since its fixed factor leads to high cost in early charging.

It should be noted that, for the 34th days, PRECC gives a worse result than LP-D and LP-A. On this day, the load forecast error reaches 8.6%, i.e., the dynamic problem is over-estimated, and the number of participated EVs is 281, i.e., 19 less than the mean of 300. For LP-D, LP-E, and LP-A, the decrease of participated EVs can bring the same effect as real-time reducing the SOC threshold. Evidently, that leads to the curtailment of early charging load and the decrease of charging cost, so that the optimality is improved.

4.4. Completion rate comparison

Charging completion rate (CCR) is the ratio of charging load to charging demand, which actually denotes the power capacity utilization. CCR can be computed by the following equations:

$$\mathbb{C}_X = \frac{g(\mathbb{S}_X)}{\mathscr{D}(\hat{\mathbb{Q}})},\ X = \text{FCFS, LP-D/-E/-A, or PRECC} \tag{16a}$$

$$g(\mathbb{S}) = \sum_{j=1}^{J} \sum_{\forall n \in \psi^j} (p_n s_n^j) \cdot T_s \tag{16b}$$

$$\mathscr{D}(\hat{\mathbb{Q}}) = \sum_{n=1}^{N} \frac{E_n(\gamma_n^{exp} - \gamma_n^0)}{\eta_n} \tag{16c}$$

where $\mathscr{D}$ represents the charging demand, N is the total number of EVs corresponding to $\hat{\mathbb{Q}}$, and γ_n^0 and γ_n^{exp} are the initial and the expected SOCs, respectively.

The CCR results are shown in Fig. 8, where PRECC achieves the highest CCR for 40 out of 43 days. For the 10th day, PRECC gives the result of 0.969 while LP-A gives 0.984, and the charging load profiles the CLEs are shown in Fig. 9. PRECC gives an almost coincident charging load profile with LP-S, while LP-A guides EVs to consume much more high-priced electricity. PRECC prefers to restrain charging during high-priced periods, and this may lead to a slight loss of capacity utilization when a large positive forecast error occurs. Nevertheless, PRECC gives a better CR result than LP-A for the 10th day.

4.5. Earning capacity comparison

The BLC should be the main entity using the PRECC, thus earning

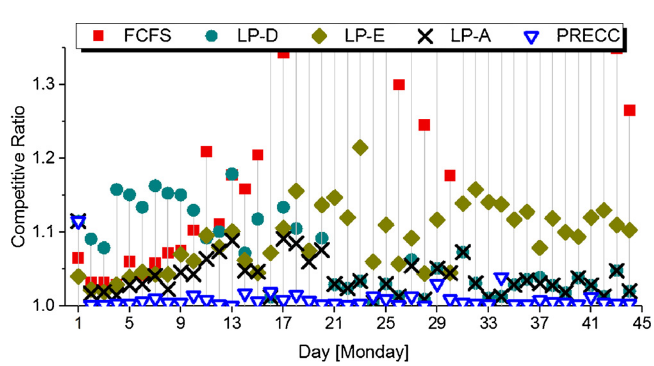

Fig. 7. Comparison of CR results.

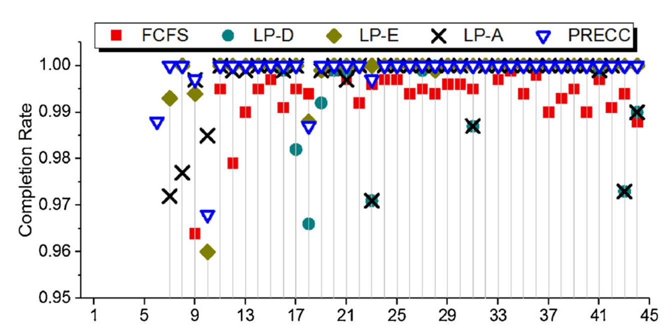

Fig. 8. Comparison of CCR results.

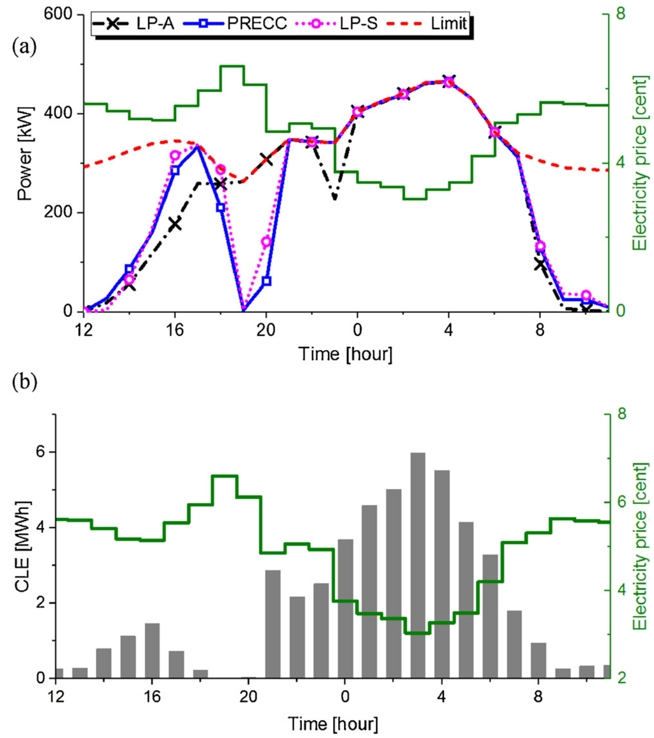

Fig. 9. Simulation results of the 10th day (March 6, 2017): (a) the charging load profiles of LP-A, PRECC and LP-S and (b) the CLEs.

capacity (EC) will be evaluated from the perspective of a charging operator, where the operator offers charging service at a fixed price of 20 cents/kWh that includes electricity price. FCFS is employed as the benchmark, and the EC is then described by a percentage:

$$EC = \frac{\mathscr{P}_X - \mathscr{P}_{FCFS}}{\mathscr{P}_{FCFS}} \times 100, X = \text{LP-D/-E/-A/-S, or PRECC} \tag{17a}$$

$$\mathscr{P} = \sum_{j=1}^{J} \left[\left(\rho - \theta^j \right) \cdot \sum\nolimits_{\forall n \in \psi^j} (p_n s_n^j) \cdot T_s \right] \tag{17b}$$

where $\mathscr{P}$ stands for charging profits, and ρ denotes the fixed service price.

As shown in Fig. 10, for the first ten days, affected by the dynamic problem, LP-D presents worse profitability even than FCFS. After the 21st day, due to the sufficient power, the online scheduling algorithms all achieve better profitability. For 39 out of 43 days, PRECC is better than the other online algorithms. The EC averages of LP-D, LP-E, LP-A, PRECC, and LP-S are 1.33%, 4.01%, 4.75%, 5.87%, and 6.15%, respectively. The gap between PRECC and LP-S is only 0.28%, therefore PRECC is very close to LP-S in terms of earning capacity.

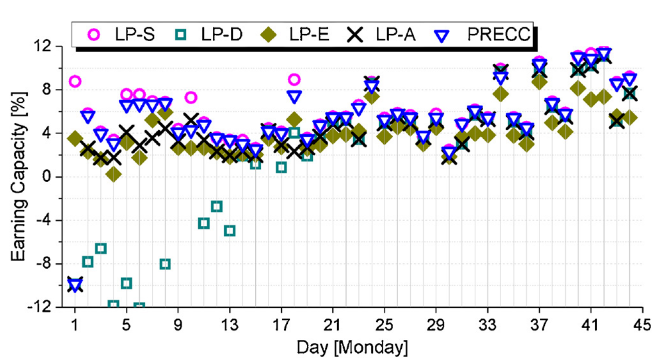

Fig. 10. Comparison of EC results.

Table 2
Simulation results when forecast absolute error exceeding 3%.

Day	Forecast error [%]	*M*	Competitive ratio		Completion rate	
			LP-A	PRECC	LP-A	PRECC
3	−3.70	297	1.019	1.001	0.761	0.787
8	3.11	302	1.023	1.004	0.977	1.000
11	3.24	294	1.064	1.008	1.000	1.000
12	−3.23	306	1.074	1.002	0.999	1.000
18	−3.36	293	1.085	1.015	0.943	0.987
24	5.02	287	1.005	1.013	1.000	1.000
25	5.23	306	1.030	1.009	1.000	1.000
26	3.02	291	1.013	1.001	1.000	1.000
27	5.96	306	1.055	1.013	1.000	1.000
29	3.31	291	1.051	1.030	1.000	1.000
33	11.93	305	1.011	1.002	1.000	1.000
34	8.64	281	1.013	1.039	1.000	1.000
40	3.34	310	1.038	1.002	1.000	1.000
42	3.22	301	1.013	1.004	1.000	1.000

4.6. Discussion

EC can reflect the commercial value of charging coordination, while CCR represents service capability of a charging operator, asset utilization of a power company, and even satisfaction of EV owners. According to the objective function denoted by (3), as long as charging service price is higher than electricity price, the indexes of CR, CCR, and EC are coincident when power capacity is sufficient. They may show minor differences when power capacity is not sufficient. Overall, PRECC has obvious advantages over LP-A in all indexes for following reasons: (1) PRECC considers price preference in early charging to further narrow the gap to LP-S; (2) PRECC is more effective when coping with base load variations; (3) CLE has a higher resolution than a SOC threshold. Besides, no iterative optimization is required to determine CLE, thus PRECC does not cause a computational burden on online scheduling. This is very meaningful for reducing the overall costs of a charging coordinated system.

Table 2 presents the comparison results for the days with load forecast absolute error exceeding 3%. The results show that the impact of load forecast deviation on PRECC is very limited. As aforementioned, a large drop of EV population may bring an advantage for SOC-threshold algorithms. However, that occurs only if base load forecast has a large positive deviation at the same time. In most cases, PRECC is much better.

Moreover, two simulation settings should be explained:

1) The purpose to select Mondays in the simulations is to emphasize that CLE should be separately computed with a day type. According to (8), as long as the pattern of EV behavior is stable and the forecasts are accurate enough, PRECC can guarantee the optimality for any specific day type.
2) PRECC is not affected by the complexity of EV mobility pattern, since it depends on the pattern's stability. That is, the pattern setting does not affect PRECC, unless the pattern is not repeated for the same day type.

PRECC's effectiveness may be reduced on weekends due to the strong randomness of base load variation. To evaluate such impact, a simulation for 30 Sundays from January 1 to July 23, 2017 is also made, with the largest load forecast error of more than 26%. EV mobility pattern is the same as the previous simulation. PRECC outputs the best CRs for 26 Sundays, and the comparison is presented in Table 3 as well. Obviously, PRECC is much better than the other algorithms, although the optimality gap increases by 1.3% in average and 2.5% in the worst case.

Table 3
Comparison of CR results for Mondays and Sundays.

Algorithms	CR of the Mondays		CR of the Sundays	
	Worst-case	Average	Worst-case	Average
FCFS	2.090	1.384	1.909	1.473
LP-D	1.179	1.070	1.171	1.059
LP-E	1.215	1.095	1.199	1.103
LP-A	1.093	1.038	1.084	1.043
PRECC	1.039	1.007	1.065	1.020

5. Conclusion

The strong randomness of EV mobility behavior is one of the most important issues in online scheduling. Early charging is regarded as the most effective strategy to tackle the dynamic problem caused by the uncertainties. It is very challenging for early charging to achieve self-adaptive control and reduce electricity bill. Most existing strategies require iterative optimizations to determine a proper control factor. That is computationally costly. Moreover, those price-independent factors cannot minimize the electricity bill for early charging.

The proposed PRECC employs the subtotal charging demand categorized by electricity prices for early charging control. First, it is a self-adaptive control, and only one offline optimization is needed to obtain the control factor. Second, by using the price-responsive factor, it can help online scheduling algorithms to minimize early charging cost. Third, it is more flexible and more robust than the existing strategies since its control factor is not constrained by the SOCs of participated EVs. Last, PRECC is designed independently, therefore it can work for any online scheduling algorithms to improve the effectiveness and profitability. The simulation results show that the gap between PRECC and the offline optimization is only 0.7% in average and 3.9% in the worst case.

For a distributed charging network, additional objectives including minimizing voltage fluctuation and power loss should be considered in coordination. One of future works is to establish a multiple-objective factor playing the role of electricity price, so that PRECC can be applied to more scenarios.

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