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Online Pricing Mechanism for Electric Vehicles Charging Based on Operational Condition of A Charging Station

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Abstract:
The cost and stability, in terms of stable charging load, are the main concerns of a charging station (CS). To this end, an online cost optimization algorithm is proposed by assuming that all electric vehicle (EV) users are selfless, so that they will report a real demand to the CS. However, in reality, all EV users are rational and they want to complete the energy demand in the fastest time and the lowest cost. Therefore, inspired by this characteristic of EV users, an online pricing mechanism is designed based on the online algorithm. There are three-fold benefits of the proposed pricing mechanism: giving discount to the flexibility of EV users, ensuring fairness among EV users and the individual optimal strategies of EV users jointly achieve minimizing cost of the CS. Numerical results based on real data further verify the effectiveness of the proposed online algorithm and the pricing mechanism.

Key Words: Online Pricing mechanism, online cost optimization algorithm, charging station, electric vehicles

1 Introduction

As a new-type of transportation, electric vehicles (EVs) have enormous advantages contrasted with conventional vehicles in emission reduction and energy saving, which result in the fast proliferation of EVs in recent years. As EVs surging, their charging demands are also growing enormously [1]. Charging stations (CSs) are the most common places to charge EVs, but without proper management, the heavy charging load not only poses a serious threat to power grids due to sudden and uncertain spikes [2], but also causes tremendous charging cost and unsafety to CSs, which significantly degrades the efficiency of CSs [3].

The cost and stability, in terms of stable charging load, are the main concerns of a CS. In order to lead a CS to schedule charging demand reasonably, an electricity pricing mechanism have been widely adopted by power grid operators in recent years. This pricing mechanism consists of two components: the Time-of-Use (TOU) price related to what time you use electric and critical peak price (CPP) imposed to punish the peak power over a billing cycle [4, 5]. Under this mechanism, there is a motivation for CSs to design an effective charging scheduling algorithm for reducing cost and peak power. Note that, to activate the performance of the algorithm, the response of EV users is indispensable. To this end, a reasonable pricing mechanism is needed here considering the self-interest of user. However, the charging price is generally fixed or related to the time slot at present. It is worth noting that the common drawback of the static price makes it hard to adapt the real-time load situation or its operational condition of a CS [5].

Therefore, multifarious pricing mechanisms have been proposed or adopted in recent years [6–13]. Among them, [6–9] consider the real-time electricity pricing that is defined as a quadratic function of the current load with the purpose of minimizing the total charging expense of EV users. There is a fatal weakness for [6–9] that less consider the charging expense of each EV user, which leads to EV users have no motivation to obey the scheduling. In contrast, in [10–13], the benefits of EVs have been taken into account according to different purposes when pricing for each time slot, such as minimizing the total social cost [10], avoiding network congestion [11] and filling load valley [12, 13]. However, these relevant works are designed in an offline fashion, which limits the application.

Different from above works, we propose an online pricing mechanism for EVs charging considering peak charge for CS, which is not considered in above literatures. We first introduce the cost optimization algorithm for a CS, which needs the full knowledge of charging demand information over a billing cycle, resulting in this algorithm can only run in an offline fashion. Consequently, a simple yet effective and implementable online scheduling algorithm, is proposed by transforming the offline one. After that, based on the online algorithm, we design an online pricing mechanism that can adjust the demands submitted by EV users. There are three-fold benefits of the proposed pricing mechanism: giving discount to the flexibility of EV users, ensuring fairness among EV users and the individual optimal strategies of EV users jointly achieve minimizing cost of the CS. Numerical results based on real-world data show that the proposed online algorithm and mechanism are effective and reasonable.

The rest of the paper is organized as follows. We formulate the cost optimization problem for CS and discuss its online approximate solution in Section 2. In Section 3, theoretical analysis and implementation processes of the pricing mechanism are introduced. Section 4 presents the simulation results. Finally, conclusions are drawn in Section 5.

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2 Problem Formulation and Transformation

In this section, we first propose an offline cost optimization algorithm that assumes full knowledge of global charging information of EVs over a billing cycle. Although a global optimal solution can be obtained by the offline cost optimization algorithm, it is impossible to achieve in real practice but can be seem as a benchmark. Consequently, a simple yet effective and implementable online algorithm is designed that requires zero future information, which is a foundation of the proposed pricing mechanism in the next section. As simulations in Section 4 suggest, the charging cost and load profile obtained by the proposed online algorithm are close to the posterior global optimum.

2.1 Optimization Problem of A CS

Suppose that I EVs would arrive during a billing period $\mathbb{T} := \{1, 2, \ldots, T\}$, which is a discrete time horizon, and let $\mathbb{I} := \{1, 2, \ldots, I\}$ be the set of EVs. EV i randomly arrives at a CS and submits its energy demand and departure time to the CS. Assume the energy demand of EV i can be and must be fulfilled before its departure by the CS. The charging mission of an EV i can be characterized by a tuple $\pi_i := (a_i, d_i, e_i, x_i^{max})$, where a_i and d_i are the arrival and departure times, respectively, e_i is the amount of energy demand and x_i^{max} is the charging rate limit. Define x_i^t as the charging rate of EV i at time t. Since EV i can only be charged when it is at the CS, the following constraints must be satisfied:

$$\begin{aligned} & x_i^t \in [0, x_i^{max}], \quad \forall t \in [a_i, d_i], \forall i \in \mathbb{I}, \\ & x_i^t = 0, \quad \forall t \in \mathbb{T} \backslash [a_i, d_i], \forall i \in \mathbb{I}. \end{aligned} \tag{1}$$

To fulfill the charging mission of EV i before its departure, we have

$$e_i \le \sum_{t \in \mathbb{T}} x_i^t, \quad \forall i \in \mathbb{I}. \tag{2}$$

As shown in Fig. 1, all EV charging loads are supplied by a distribution transformer serving the CS. The transformer has a capacity of P which the total charging load of the CS cannot exceed at any time, i.e.,

$$\sum_{i \in \mathbb{I}} x_i^t \le P, \quad \forall t \in \mathbb{T}. \tag{3}$$

Note that if there are other loads connected to the distribution transformer, the model can be generalized such that P is time-varying.

We denote the price of electricity at time t by c^t in a billing period. The prices are external and usually set based on the grid operational conditions, i.e., high prices corresponding to heavy load hours. However, there is still the possibility of inelastic charging demand and EVs may coincide to charge simultaneously that leads to load spikes to the grid. In order to further reduce the peak load, the CS will pay a fee once over a billing period for the peak load at the unit price of α CNY/kW, which is known *a priori*. We are interested in the following problem that minimizes the total charging cost while ensuring the fulfillment of charging tasks for all EVs:

$$\min_x \quad \sum_{i \in \mathbb{I}} \sum_{t \in \mathbb{T}} c^t x_i^t + \alpha \max_{t \in \mathbb{T}} \left\{ \sum_{i \in \mathbb{I}} x_i^t \right\} \tag{4a}$$

$$\text{s.t.} \quad (1)(2)(3) \tag{4b}$$

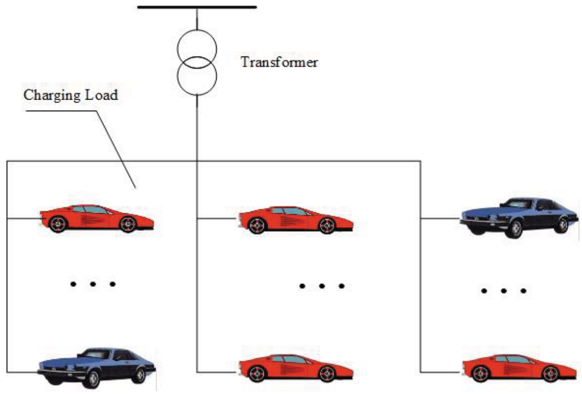


Fig. 1: Illustration of an EV CS

where $x := (x_i^t, i \in \mathbb{I}, t \in \mathbb{T})$. Suppose all EV information $(\pi_i, i \in \mathbb{I})$ and price information $(c^t, t \in \mathbb{T})$ over a billing cycle are known, solving problem (4) leads to a globally minimal total cost for the CS. As shown in the next subsection, (4) can be readily solved since it can be transformed into a linear programming easily.

However, (4) is not implementable in practice where future EV information is not available for each current time slot and hard to determine the charging cost of each EV. Therefore, we pursue an online algorithm to solve an approximate of this global problem, which is not only simple, effective and implementable, but also makes it easy for a CS to determine the different fee of each EV that stimulates EV owner adjusting their demand to flatten the load and improve operational efficiency of a CS as shown in Section 3.

2.2 Problem Transformation

To solve the above problem (4) in an online fashion, there are two key issues. First, global information including EVs' arrival times and electricity prices in the future are unknown. Second, the posterior peak load over a billing cycle is unknown. We introduce a sliding time window mechanism to handle the first issue and the second issue is tackled by predicting locally the global peak load over a billing period.

For convenience, we define $\mathbb{I}_t$ as the set of current EVs in the CS at time t and $\mathbb{T}_t$ as the scheduling time window. Fig. 2 shows an example for better understanding of $\mathbb{I}_t$ and $\mathbb{T}_t$, where $\mathbb{I}_t = \{EV1, EV2, EV3\}$ and $\mathbb{T}_t = \{t : t_3 \le t \le t_{11}\}$. The sliding time window mechanism

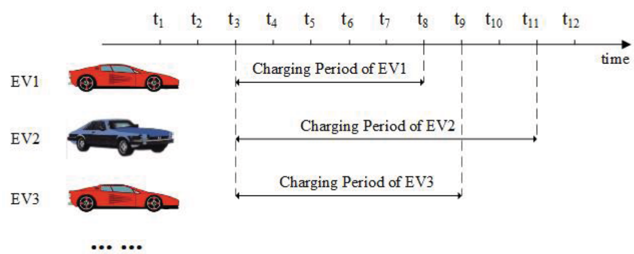


Fig. 2: Illustration of the sliding window mechanism

means that we only consider the current information of EVs in the set $\mathbb{I}_t$ and the time window $\mathbb{T}_t$. As the time window moves on, if a EV enters the CS and requests to charge then we re-solve the current local optimization problem (4) to update the charging rates to implement whenever a new EV comes to the CS or a latest electricity price is released.

Let v_{pv} be the previous peak load and v_{pd} be predicted peak load over a billing cycle. To circumvent the difficulty of characterizing the exact peak load, we instead utilize the current peak load and the predicted one from historical data.

As a result, we approximate the global problem (4) by problem (5). Since we only have the current EV information in hand, i.e., $\{\pi_i, i \in \mathbb{I}_t\}$, thus $\max_{t\in\mathbb{T}_t}\left\{\sum_{i\in\mathbb{I}} x_i^t\right\}$ can no longer represent the peak load over the whole billing cycle.

$$\min_{x,v} \quad \sum_{t\in\mathbb{T}_t}\sum_{i\in\mathbb{I}_t} c^t x_i^t + \alpha v \tag{5a}$$

$$\text{s.t.} \quad \sum_{i\in\mathbb{I}_t} x_i^t \le P, \quad \forall t \in \mathbb{T}_t \tag{5b}$$

$$e_i \le \sum_{t\in\mathbb{T}_t} x_i^t, \quad \forall i \in \mathbb{I}_t \tag{5c}$$

$$max\{\sum_{i\in\mathbb{I}_t} x_i^t, v_0\} \le v, \quad \forall t \in \mathbb{T}_t \tag{5d}$$

$$\begin{aligned} & x_i^t \in [0, x_i^{max}], \quad \forall t \in [a_i, d_i], \forall i \in \mathbb{I}_t \\ & x_i^t = 0, \quad \forall t \in \mathbb{T}_t \backslash [a_i, d_i], \forall i \in \mathbb{I}_t, \end{aligned} \tag{5e}$$

where v_0 is a constant summarizing the peak load so far and the predicted global peak load as $v_0 := max\{v_{pv}, v_{pd}\}$. We introduce an auxiliary scalar variable v to serve as a proxy for the global peak load. The advantages of this approximation are as follows:

1) (5) is a linear programming problem, which have been well studied and easy to solve.
2) The constraints (5d) and (5e) circumvent the difficulty of characterizing the exact peak load in a billing cycle. For example, if $\sum_{i\in\mathbb{I}_t} x_i^t \le v_0$, $\forall t \in \mathbb{T}_t$, it means the constraint (5d) is redundant and the second term of (5a) is constant as αv_0 and thus negligible.
3) Since the peak load in a billing cycle is relatively easy to predict compared with each EV i's information π_i, we can readily obtain v_{pd} from the historical data. It enables us to make full use of the information that are easy to obtain. Besides, the model is simple to implement in practice.

3 Pricing Mechanism

Problem (5) assumes that all EV users are completely selfless people, so that each EV user i can report the real demand information π_i to the CS. However, in reality, with a fixed predetermined price, all EV users are rational and they want to complete the energy demand in the fastest time and the lowest cost. Consequently, the scheduling space of CS will be small that leads to the optimization effect of problem (5) becomes worse and hard to adapt the real operational environment of a CS. Therefore, in this section, in order to maximize the operating efficiency of CSs and mobilize the enthusiasm of users, a pricing mechanism is designed.

3.1 Theoretical Analysis

From the above, (5), or equivalently (4), can be efficiently solved by existing algorithms or solvers. The optimal solution of (5) is denoted as (x^*, v^*). Even with the optimal scheduling at hand, it remains a critical issue how to charge EVs legitimately for the charging service.

Now that we already bear in mind the optimal peak load v^* and its corresponding cost[1], we maintain v^* as the maximum allowable peak load and replace v with v^* in (5):

$$\min_{x} \quad \sum_{i\in\mathbb{I}_t}\sum_{t\in\mathbb{T}_t} c^t x_i^t + \alpha v^* \tag{6a}$$

$$\text{s.t.} \quad e_i \le \sum_{t=a_i}^{d_i} x_i^t, \quad \forall i \in \mathbb{I}_t \tag{6b}$$

$$\begin{aligned} & x_i^t \in [0, x_i^{max}], \quad \forall t \in [a_i, d_i], \forall i \in \mathbb{I}_t \\ & x_i^t = 0, \quad \forall t \in \mathbb{T}_t \backslash [a_i, d_i], \forall i \in \mathbb{I}_t \end{aligned} \tag{6c}$$

$$\sum_{i\in\mathbb{I}_t} x_i^t \le v^*, \quad \forall t \in \mathbb{T}_t \tag{6d}$$

where the second term αv^* in the objective is constant and negligible. (6d) enforces that the aggregate charging load at any time should not exceed v^*. Note that originally EVs' concerns of energy prices and feasibility restrain the peak load from further descending, while now the peak charge is transformed to a hard constraint that binds EVs' charging rates, which, as we will show later, is more intuitive to quantify the role of each EV in limiting the peak load.

We introduce the Lagrange multipliers $\lambda := (\lambda^t, t \in \mathbb{T}_t)$ for (6d) and define the partial Lagrangian $\mathcal{L}(x, \lambda) := \sum_{i\in\mathbb{I}_t}\sum_{t\in\mathbb{T}_t} c^t x_i^t + \sum_{t\in\mathbb{T}_t} \lambda^t(\sum_{i\in\mathbb{I}_t} x_i^t - v^*)$. The corresponding dual problem for (6) can be formalized as

$$\max_{\lambda\ge 0} \min_{x:(6b)(6c)} \mathcal{L}(x, \lambda) \tag{7}$$

Since (6) is a linear programming with (6b)-(6d) all affine, the Slater's condition holds that further guarantees strong duality, i.e., $\max_{\lambda\ge0}\min_{x:(6b)(6c)} \mathcal{L}(x,\lambda) = \min_{x:(6b)(6c)}\max_{\lambda\ge0} \mathcal{L}(x,\lambda) = \min_{x:(6b)(6c)(6d)} \sum_{i\in\mathbb{I}}\sum_{t\in\mathbb{T}} c^t x_i^t$. Therefore, an optimal scheduling x^* of (7) is also an optimal solution to (6).

The dual problem is shown in below and let λ^* be its optimal solution. Then the inner problem $\min_{x:(6b)(6c)} \mathcal{L}(x, \lambda^*)$ is separable among all EVs, i.e.,

Individual scheduling subproblem:

$$\begin{aligned} \min_{x_i} \quad & \sum_{t=a_i}^{d_i} (c^t + \lambda^{t*}) x_i^t \\ \text{s.t.} \quad & \text{(6b)(6c)} \end{aligned} \tag{8}$$

where $x_i := (x_i^t, t \in \mathbb{T}_t)$. This indicates that given the time-varying pricing scheme $(c^t + \lambda^{t*}, t \in \mathbb{T}_t)$, it could be guaranteed that EVs individually charging strategies are the optimum but still jointly achieve the optimal peak load v^* as well as the optimal scheduling x^*, i.e., the cost of the station is minimized.

Note that (6) can be efficiently solved by existing algorithms like dual simplex algorithm or solvers like CVX[14], hence λ^* can be easily obtained. Therefore, the cost of each EV can be determined legitimately.

The benefits of our proposed pricing mechanism are as fellows:

[1]Without energy expenditure, v^* would be the biggest value of the previous maximum peak load over a billing v_{pv} and the predicted peak load over a billing cycle v_{pd}.

1) **Economically Efficiency**: As explained above, the mechanism is also economically efficient in terms of achieving social optimum.
2) **Fairness**: Note that the loads at time slots with high added values $\lambda^{t*} > 0$ should reach v^*, λ^{t*} is therefore set to induce some EVs to shift loads to other slots such that peak loads exceeding v^* can be avoided. Since the prices are uniformly imposed on all EVs, the scheme $(c^t + \lambda^{t*}, t \in \mathbb{T}_t)$ is fair as an EV i is charged $\sum_{t=a_i}^{d_i}(c^t + \lambda^{t*})x_i^{t*}$ that minimizes individual cost.
3) **Discount for flexibility**: Intuitively, if an EV i postpones its departure time d_i, more scheduling flexibility is available for the station to lower the cost. Therefore, EV i ought to enjoy a discount as reward, i.e., the expense of an EV i should be non-increasing w.r.t d_i. However, the challenge here is that d_i is a parameter in the problem whose effect on the expense of EV i is implicit through (4) first and then (6).

3.2 Implementation of Pricing Mechanism

Here is a sketch of the implementation of our proposed pricing mechanism. Note that there are three possible cases about the Lagrange multipliers $\lambda := (\lambda^t, t \in \mathbb{T}_t)$ for (6d) of problem (6):

1) (6) is feasible and $\forall \lambda^{t*} = 0, t \in \mathbb{T}_t$. This case demonstrates that there is no tense time slot. Therefore, we do not need to adjust the price to change the EV user's demand.
2) (6) is feasible and $\exists \lambda^{t*} > 0, t \in \mathbb{T}_t$. This case indicates that there are some emergency time slots, where the load is heavy but the price is low and need to raise the price, i.e. let the price equal to $c^t + \lambda^{t*}, t \in \mathbb{T}_t$, so that EV users have the reason to submit demands that can avoid high-load slots.
3) (6) is infeasible, $\exists \lambda^{t*} = \infty, t \in \mathbb{T}_t$. Some EV users are urgent to complete the charging demand. Compared to the cost, they care about the charging time. They tend to submit an exigent charge mission to the CS, which will break the constraint (6d) . If we are in the condition of ensuring the transformer capacity limit P not exceed, i.e., $v^* < v_{pv} < P$, the exigent charge mission is acceptable, If not, reject the request. Consequently, if we accept the exigent charge mission, v^* in (6) will change according to $v^* := max\{v^*, v_{pv}\}$. Note that v^* obtained by the analysis of historical data and equivalents to v^{pd} mentioned in the previous section.

For cases 1) and 2), the price is clear, i.e., $c^t + \lambda^{t*}, t \in \mathbb{T}_t$. The cost of EV user i is

$$\sum_{t \in \mathbb{T}_t} (c^t + \lambda^{t*})x_i^t, \quad \forall t \in \mathbb{T}_t. \tag{9}$$

For case 3), to make problem (6) feasible, we drop the constraint (6d) from problem (6) then solve it, we can obtain the total profile $p^t, t \in \mathbb{T}_t$ then let $p^m = \max\{p^t, t \in \mathbb{T}_t\}$. If $p^m > P$, reject the request. If $p^m < P$ then let $\overline{c}^t = \max\{c^t, t \in \mathbb{T}\}$ when $p^t > v^*$, otherwise, $\overline{c}^t = c^t$. Note that $v^{pv} = p^m$. The cost of EV user i as shown in (10), in addition to energy costs, a tariff imposed to charge peak power increment, i.e. $v^{pv} - v^*$, should be charged.

$$\sum_{t \in \mathbb{T}_t} \overline{c}^t x_i^t + \gamma(v^{pv} - v^*), \quad \forall t \in \mathbb{T}_t. \tag{10}$$

where γ is a constant, which is a penalty coefficient to EV user i for raising the value of v^*. The energy demand e_i of EV i is updated as follows:

$$e_i = \begin{cases} 0, & if\ EV\ i\ finishes\ charging \\ e_i, & if\ EV\ i\ arrives \\ e^i - x_i^t, & otherwise. \end{cases} \tag{11}$$

The pricing mechanism is summarized in Algorithm 1.

Algorithm 1 Pricing Mechanism

Input: c^t, P, v^*,π_i.
Output: The cost list of EV user i .

```
for t = 1 to T do
    Set a_i = t for EV i currently in the CS.
    if an EV i, or more than one, arrives and submits an
        energy demand e_i then
        Calculate The shortest charging time slots ∇t.
        for t' = a_i + ∇t to a_i + ∇t + 4 hours do
            Assume d_i = t' and determine I_t, T_t based on
            time t'.
            Solve problem (6) to obtain x then according to
            different cases (9) and (10), we can obtain the
            charging cost of EV i corresponding d_i.
        end for
        Give the cost list corresponding departure time to EV
        user i and then let EV user i chooses a departure time
        or rejects to charge.
    end if
    if x is not empty then
        Update {e_i, i ∈ I_t} according to (11).
    end if
end for
```

4 Simulation Results

We use the real-world charging data from January 2016 to March 2018 provided by the South China Charging Technology Co., Ltd to evaluate the performance of our proposed online algorithm and pricing mechanism.

As shown in Fig. 3, TOU electricity prices are divided into three categories: the off-peak price 0.36 CNY/kWh, shoulder price 0.73 CNY/kWh and on-peak price 1.08 CNY/kWh, while the CPP is 44 CNY/kW. For convenience, we consider a day of 24 h as a billing period, where each time slot lasts 15 minutes. The CPP is then correspondingly transformed from 44 CNY/kW to 1.446 CNY/kW by assuming that there are 30 days in a month, i.e., α=44/30=1.446 CNY/kW. The peak load over a billing cycle is predicted by calculating the average of the historical peak loads. All the convex optimization problems are solved by CVX with Matlab 2016b on a computer with 3.4GHz Intel Core i5-7500 CPU and 8 GB memory.

4.1 Online Algorithm Performance

We demonstrate the performance of our proposed online cost optimization algorithm by comparing with the following different scheduling strategies:

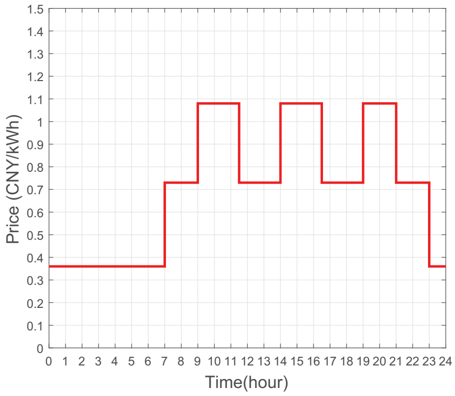


Fig. 3: TOU electricity prices

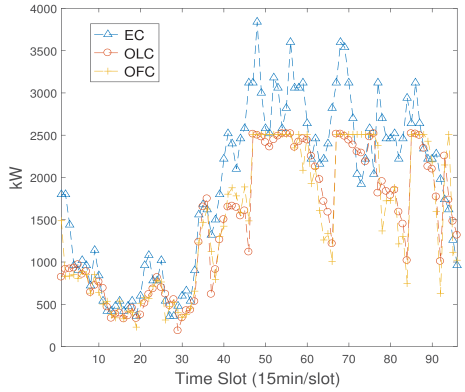


Fig. 5: Charging power trajectories over a day under different algorithms

1) **EC**: Eagerly charging strategy, which means EV i is charged at the maximum charging rate until the charging task is completed.
2) **OFC**: offline optimal charging strategy (4), which achieves the globally minimal total cost by assuming full knowledge of future information.
3) **OLC**: online optimal charging strategy (5) with predicting the peak load v_{pd} over a billing cycle.

The corresponding normalized costs for different strategies are shown in Fig. 4, where the charging costs are normalized with respect to the benchmark of OFC. EC has much higher charging cost due to the lack of scheduling. $0.4\%-3.23\%$ difference in cost is shown with different numbers of EVs between OLC and OFC.

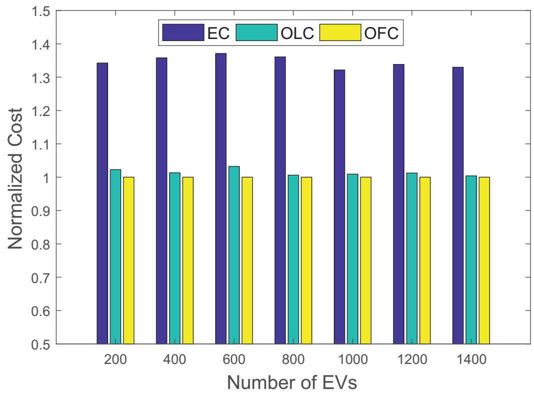


Fig. 4: Charging costs of different algorithms

Fig. 5 shows the charging power trajectories over a day under different algorithms. Seen from the figure, the load profile of OFC is quite similar to that of OLC.

4.2 Simulation Analysis of Pricing Mechanism

To briefly illustrate the feasibility of the proposed pricing mechanism, we do not consider the possible case 3) mentioned in the subsection 3.2. While γ can be set according to market circumstances by a CS. For the other two possible cases, we assume that an EV user i submits a charging demand of 60 kW to the CS and the maximum charging rate r_i^{max} of this EV is $r_i^{max} = 60kW/h$. The CS needs to give a tariff corresponding to departure time of EV user i. In the simulations, v^* is equal to 2500 kW which is obtained by calculating the average of the historical peak loads. The two cases are as follows:

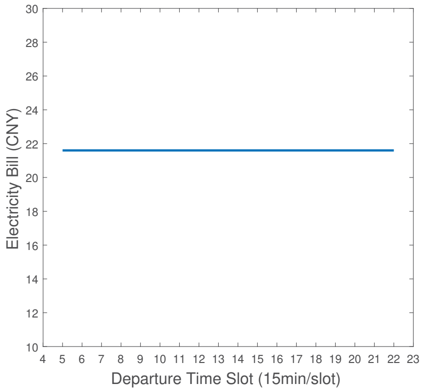
1) Case 1: the charging load is not heavy. We assume that the EVs are charging in the CS at time slot 1 as shown in Fig. 5, where the charging load is not heavy.
2) Case 2: the charging load is heavy. We assume that the EVs are charging in the CS in the time slot 55, where the charging load is heavy.

Electricity bill changes over EV user i's departure time and changes in electricity price for the two cases are shown in Fig. 6. Since in the slot 1 the charging load is not heavy, the pricing mechanism will not change the electricity bill of EV user i, even if EV user provides later departure time as shown in Fig. 6(a)(b). On the contrary, in the time slot 55 to 60, the charging load is heavy and the load may exceed v^* as shown in Fig. 5. However, The price of electricity in the time slot 55 and 56 are relatively small compare to the time slot 57 to 66. Therefore, under the effect of our proposed pricing mechanism, the electricity prices of the time slot 55 and 56 increase as shown in Fig. 6(d). We can see from Fig. 6(c), that the electricity bill of EV user i will decrease about 30% if his departure time is after the time slot 71. Since EV i avoids the rush charging hours and high-priced slots, the electricity bill reduction is produced.

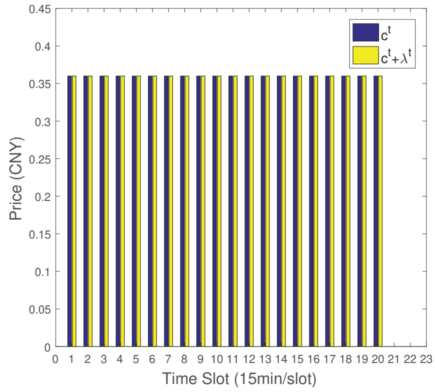
5 Conclusion

In the context of a current electricity tariff mechanism, which additionally charges for peak power, we present an offline cost optimization algorithm of a CS but cannot implement in practice. Then, a simple yet effective and implementable online algorithm is proposed by assuming all EV users will submit a real charging demand. However, EV user tends to make decisions that beneficial for himself without considering CS. To this end, an online pricing mechanism is designed to guide EV users to make decisions that also minimize the total charging cost of a CS.

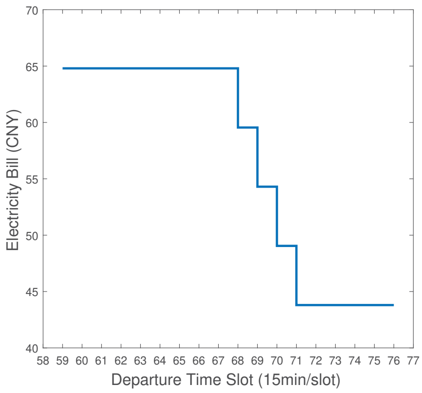
The proposed pricing mechanism has three main advantages. First, it could be guaranteed that EVs individually charging strategies are the optimum but still jointly achieve the optimal scheduling of the station. Second, it can assure the fairness between EV users. Third, it gives a discount to the flexibility, i.e., the departure time of EV users. Numerical results based on real-world data show that our proposed



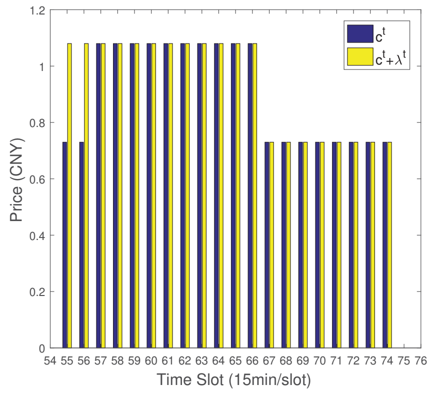
(a) Case 1: electricity bill changes over departure time



(b) Case 1: changes in price of each time slot



(c) Case 2: electricity bill changes over departure time



(d) Case 2: changes in price of each time slot

Fig. 6: Electricity bill changes over EV user's departure time and changes in price of each time slot

online algorithm can achieve a very close charging cost to optimal offline solution and our price mechanism can provide a tariff to EV users so that they can submit a reasonable demand and departure time to the CS, reducing the charging cost and smoothing the power trajectory.

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