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A distributed charging strategy based on day ahead price model for PV-powered electric vehicle charging station[☆]

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HIGHLIGHTS

- A day-ahead price model based on Stackelberg Game is proposed to realize the global optimization of the PO's profit and the costs of EV users.
- To obtain the optimal price vector, the heuristic algorithm based on DE–PSO Algorithm and nonlinear constrained programming are adopted by the PO and each smart charger, respectively.
- An hourly PV energy forecast model based on BP neural network is proposed, and the similar weather days are selected as the inputs of the model.
- A real-time billing strategy is designed to deal with the error of PV energy forecast and the expected charging arrangements.

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ABSTRACT

This paper studies a distributed charging model based on day-ahead optimal internal price for PV-powered Electric Vehicle (EV) Charging Station (PVCS). Considering the feed-in-tariff of PV energy, the price of utility grid and the forecast model of PV based on back-propagation neural network (BPNN), a system operation model of PVCS is introduced, which consists of the profit model of PVCS operator (PO) and the cost model of EV users. The model proposed in this paper can be designed as a Stackelberg game model, where the PO acts as the leader and all EV users participated are regarded as the followers. An optimization strategy based on heuristic algorithm and nonlinear constrained programming are adopted by the PO and each EV user, respectively. Moreover, a real-time billing strategy is proposed to deal with the errors from the forecasted PV energy and the expected charging arrangements. Finally, through a practical case, the validity of the model is verified in terms of increasing operation profit and reducing charging cost.

1. Introduction

Electric vehicle has the incomparable advantage of traditional automobile in terms of energy saving, emission reduction, containment of global warming and oil supply safety. It has been rapidly developed under the impetus of governments, automobile manufactures and energy companies. However, with the increasing number of EV connected in power grid for charging, the load profile in distribution network will be greatly changed, which may result in the grid reliability issues due to the randomness of charging demand [1]. And the emission advantages of EVs are not obvious in the areas where power generation is dominated by coal-fired power plants [2].

As a renewable and clean energy, PV can be used to produce electricity in any place where the solar radiation resource is good, instead of the original energy supply [3]. The integration of PV with EV charging infrastructure, such as PV-powered charging station (PVCS), is a possible way to alleviate the dependence on power grid, which can effectively reduce the line loss in energy transmission, improve the utilization of local PV self-consumption, and enhance the economic benefits of renewable energy construction by directly selling the generated electricity to EVs charged during daytime with optimal charging strategies [4–7].

For the PVCS, energy generated from the integrated PV system is usually different from the energy demand of EVs, so the remaining demand must be purchased from power grid, and the surplus energy should be sold to the grid. Therefore, the most important

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concern for PVCS operator (PO) is to maximize the operating profit, which mainly consist of the electricity payment of EV users and the benefit from trading with the distribution system operator. In [8], a classification scheme of electric vehicles has been studied that can assist a PV driven charging station to reduce its total cost of energy trading with different energy entities in a smart grid network during a day. The authors establish an appropriate energy management system based on economic point of view, which can reduce energy costs of building interfaced with PV and EVs [9]. A real-time price based on automatic demand response strategy is proposed in [10] for PVCS, which intends to minimize the cost of electricity bought from power grid. In [11], a close-to-optimal algorithm based on the Lyapunov optimal is developed by controlling the price of charging service, the number of EVs, and the charging/discharging behavior of energy storage to improve the profit of charging station operator. In addition, a competition among charging stations is considered to attract EVs and maximize its revenue by setting the charging price in [12,13].

However, the overriding interest of EV user is to minimize the charging cost of entire charging process. A fuzzy logic power-flow controller was designed to limit the impact on grid and reduce charging cost for workplace parking garage equipped with PV panel in [14], which considers the energy demand by the EVs and the price of energy from utility grid. An intelligent strategy react to timer-of-use (TOU) price is proposed in [15] to control the EV charging behavior, and a heuristic method is adopted to reduce the charging cost with considering the relationship between the acceptable charging power of EV battery and the state of charge (SOC). The battery degradation cost has been taken into account by all the individual EVs to optimal their own charging behaviors in response to a common electricity price curve in [16]. The methods in integrating the degradation cost of batteries into charge of V2G-capable EVs are proposed in [17,18].

According to the studies above, most of the charging strategies only consider the interests of one party in the PO and the EV users, and the profit of one party will inevitably result in the loss of the other party. A reasonable price strategy can effectively balance the interests of energy consumers and energy suppliers, such as Time-of-use Price (TOUP), Real-time Price (RTP) and Day-ahead Price (DAP) [19,20]. However, TOUP models encourage consumers to use less electricity when peak load appears and to use more electricity when valley load appears. RTP is focused on short-term supply and demand balance, and it is difficult to obtain optimal control objectives in the whole operation cycle. In order to realize the global optimization of the PO's profit and the costs of EV users, a day-ahead optimal price model for PO among EV users is proposed, which considers the feed-in-tariff of PV energy, the price of utility grid and the forecast model of PV based on BPNN. Considering the independent decision-making ability of each participant, the Stackelberg game is usually used to design their behavior, in which PO is the leader of the game, and the EV user is a follower, and EV users are the followers. The heuristic algorithm and nonlinear constrained programming are adopted by the PO and each smart charger, respectively. Furthermore, a real-time billing strategy is designed to deal with the error of PV energy forecast and the expected charging arrangements. The cost of EV users are regulated with their utility to the actual profit of PO.

The paper is organized as follows. Section 2 provides the typical structure of PVCS and operation strategy. Section 3 presents the concrete system model which includes the cost model of EV charging and the profit mode of PO. Section 4 gives the Stackelberg game model for PVCS, and implements it through algorithm and the real-time billing strategy. Section 5 presents the effectiveness of the results in proposed strategy and compares with the results of other strategies. Finally, Section 6 give some conclusions.

2. System structure and strategy

2.1. Typical structure of PVCS

The PVCS considered in this paper is integrated between the units through DC bus, which can obtain higher efficiency than AC system. Furthermore, the DC distribution system will be a good energy solution, with the continuous increase of the DC load in the future smart grid [21]. Since the characteristics of PV power generation is only in the daytime, this paper studies a low voltage PVCS in the industrial and commercial workplace, which can provide charging services for the staff inside. The typical structure and information flows of PVCS are shown in Fig. 1.

The energy supply of PVCS is mainly composed of two parts: grid and PV generation system. PVCS is connected to the distribution network through an advanced metering infrastructure (AMI), such as smart meter, which can provide electricity price information to users. The energy conversation between grid and DC bus is realized by a bidirectional AC/DC converter which can keep DC bus voltage stability. A PV generation system that performs Maximum Power Point Tracking (MPPT) control is connected to DC bus through a DC/DC converter and a smart meter. EVs are the mainly energy consumer in the system. They purchase electricity from PVCS through chargers, which can regulate the charging power smoothly according to the inner price of PVCS and charging demand. The main responsibility of the energy management system is to collect and record the information of each unit in the system, and broadcast the inner price generated by the collected information to all the chargers.

As shown in Fig. 1, PO provides potential users working in an industrial/commercial location with scheduled charging service. Users who schedules to charge here has the right to preemptively charge during the scheduled charging period, and the charging price is not higher than the utility grid price. They can send their charging demand information to the EMS of PVCS on the day before through the Internet, mobile terminals and other communication devices. The information sent mainly includes the arrival time, departure time, initial SOC and objective SOC of EV.

2.2. Operation strategy

After the demand information collected is completed on the day, EMS will calculate the internal electricity price for second day and the expected charging arrangement for each EV user by using day-ahead price strategy, which has considered the charging strategy of EV users to maximize PO revenue by optimizing user charging behavior, as shown in Fig. 2. The smart chargers will optimize the charging behavior of EVs during the parking period, according to the internal price and actual charging demand on the day. However, the forecast PV energy and expected charging arrangement are always different from the actual values. The smart charging piles will adjust the charging fees of EV users by using actual billing strategy in each time slot based on these differences, so as to ensure the profit of PO.

3. Model of operation strategy

3.1. Model of EV charging strategy

All the EV users scheduled charging in PVCS should be flexible, which means the size of the EV's charging power can be adjusted with time. EMS can determine that the demand of user n is flexible, while its energy demand satisfied:

$$\Delta E = \left(SOC_n^{obj} - SOC_n^a\right) \cdot Q_n < \left(t_n^d - t_n^a\right) \cdot P_n^{max} \quad (1)$$

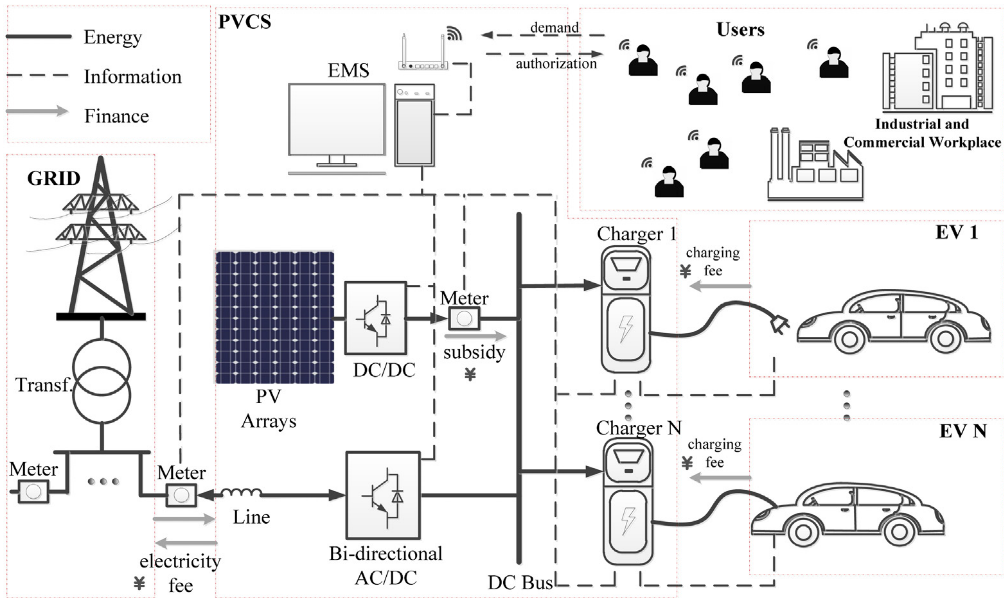

Fig. 1. Type structure of PVCS.

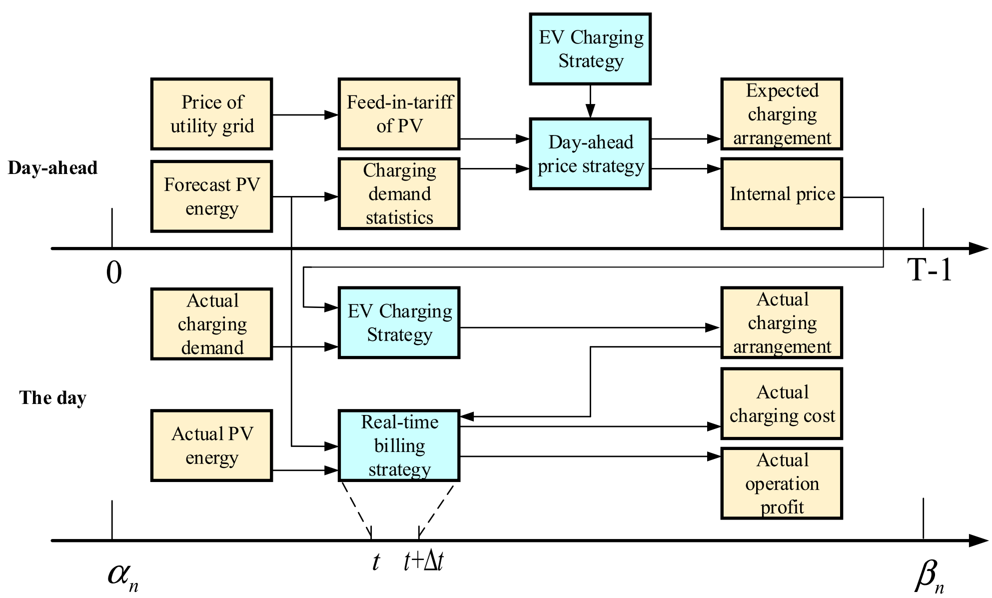

Fig. 2. Structure of operation strategy.

In this formula, SOC_n^a is the initial SOC of battery at arrival time, SOC_n^{obj} is the objective SOC that user n expects, Q_n is the capacity of EV's battery. t_n^a and t_n^d represent the arrival time and departure time of user n, respectively. P_n^{max} is the maximum charging power of EV n.

We consider the charging process of all EVs $\mathbf{T}$ over a multi-time charging interval $\mathbf{T} \triangleq \{0, \ldots, T-1\}$, and define $E_n \equiv (e_{nt}; t \in \mathbf{T})$ as the admissible strategy of EV n, with $n \in \mathbf{N}$. For the duration time $\left[t_n^a, t_n^d\right]$ of each EV, there exists a pair of $\alpha_n, \beta_n \in \mathbf{T}$ which can satisfy $\left[t_n^a, t_n^d\right] \in [\alpha_n, \beta_n]$ as the optional time range of EV n. Hence, the size of e_{nt} should be expressed as follows:

$$\begin{cases} e_{nt} \in [e_n^{min}, e_n^{max}], & t \in [\alpha_n, \beta_n] \\ e_{nt} = 0, & t \notin [\alpha_n, \beta_n] \end{cases} \tag{2}$$

$$e_n^{max} = P_n^{max} \cdot \Delta t, e_n^{min} = 0 \tag{3}$$

where $[e_n^{min}, e_n^{max}]$ is the range of e_{nt}, e_n^{min} is the minimum charging demand at period t, e_n^{max} is the maximum charging demand at period t, Δt is the time slot.

3.1.1. Cost model of EV charging

The cost considered by each user is mainly composed of the cost of battery degradation related to real-time charging power and the electricity cost associated with internal price $P_b \equiv \left(p_b^t; t \in \mathbf{T}\right)$. The cost function of each EV in period t can be described as:

$$C_n^t(e_{nt}) = f_n(e_{nt}) + p_b^t e_{nt} \tag{4}$$

$$f_n(e_{nt}) = a_n e_{nt}^2 + b_n e_{nt} + c_n \tag{5}$$

where $C_n^t(e_{nt})$ is the cost function of EV n during period t. $f_n(e_{nt})$ is the battery degradation cost function, which is a quadratic function about e_{nt}. a_n, b_n and c_n are the battery parameters of EV n, and are all larger than zero; the charging cost of EV n during the whole charging process can be expressed as:

$$C_n = \sum_{t=\alpha_n}^{\beta_n} C_n^t(e_{nt}) \tag{6}$$

3.1.2. The objective of EV charging strategy

According to the formulas (4)–(6), it is noted that, for a fixed internal price sets P_b, the objective of each EV user is to minimize the total charging cost, which can be modeled as a nonlinear programming problem with equality and inequality constraints.

$$\begin{aligned} \min_{e_{nt}} \quad & C_n = \sum_{t=\alpha_n}^{\beta_n} C_n^t(e_{nt}) \\ \text{s.t.} \quad & \sum_{t=\alpha_n}^{\beta_n} e_{nt} = \Delta E, e_n^{min} \le e_{nt} \le e_n^{max} \end{aligned} \tag{7}$$

The second derivative of EV user's objective function is

$$\frac{\partial^2 C_n}{\partial e_{nt}^2} = 2a_n > 0 \tag{8}$$

Therefore, C_n is strictly convex with respect to e_{nt}, and there exits an unique optimal solution. The problem of formula (7) can be transformed into a convex optimization problem. The problem (7) can be reformulated by the θ-logarithmic barrier and the Lagrange multiplier λ [22], and translated into an unconstrained nonlinear programming problem as follows.

$$\begin{aligned} \min_{e_{nt}} C'_n = & \sum_{t=\alpha_n}^{\beta_n} C_n^t(e_{nt}) - \theta \sum_{t=\alpha_n}^{\beta_n} \left(\ln(e_{nt}) + \ln(e_n^{max} - e_{nt})\right) \\ & + \lambda \left(\Delta E_n - \sum_{t=\alpha_n}^{\beta_n} e_{nt}\right) \end{aligned} \tag{9}$$

3.2. Forecast model of PV output

In order to realize the global optimization of PO profit and EVs charging cost, PV power generation needs to be predicted day-ahead. A prediction method based on BPNN is proposed, which has good abilities of nonlinear mapping, learning and self-adaptive, and the similar weather days in the past three months are selected as the inputs of the predicted model. The Prediction accuracy is influenced by meteorological factors such as temperature and humidity, which are chosen as basic elements of feature vector to obtain similar days, and coefficient of similarity can be expressed as:

$$\zeta_h = \left| x_f - x_h \right| \tag{10}$$

where x_f is the feature vector of the forecast day, that composed of the highest, lowest, and average values of temperature and humidity. x_h is the feature vector of the historical day. The smaller the value of ζ_h, the higher the similarity between the corresponding historical PV power generation data and the forecast day. The K historical days with the smallest similarity coefficient will be selected as the training input of the BPNN, where K is the size of input data.

3.2.1. The training structure of BPNN

The BPNN selected in the paper has three layers, including the input layer, the hidden layer and the output layer, as shown in Fig. 3.

The number of input nodes is 25, of which 13 nodes are the hourly PV energy output of the similar day that has the minimum coefficient, and the other 12 nodes are the elements of characteristic vectors of similar days and the forecast day. The number

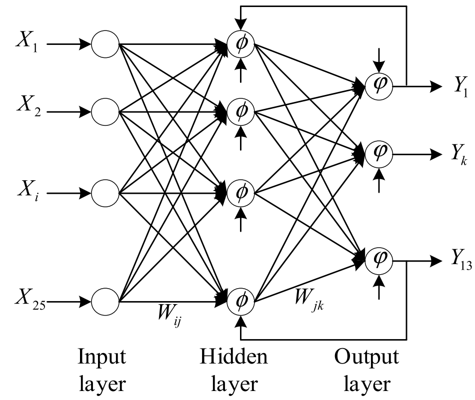

Fig. 3. Training structure of BPNN.

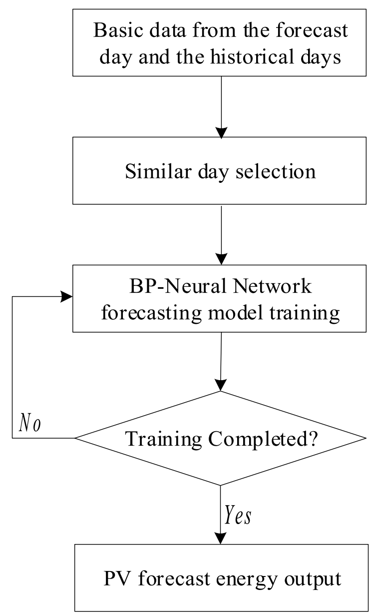

Fig. 4. Forecasting process of PV output.

of output nodes is 13, indicating the output energy of 13 h in the forecast day. The tangent sigmoid-function and the purelin-function are adopted as the activation functions of hidden layer and output layer, respectively.

3.2.2. Forecasting process

As shown in Fig. 4, the BPNN is trained by the historical data of similar days. The day-ahead hourly PV output energy will be predicted through the trained BPNN and the forecast meteorological data, while the training is completed.

In order to evaluate the accuracy of the prediction, the forecast error is defined as follow:

$$\varepsilon_f = \sum |e_{pv}^{at} - e_{pv}^{ft}| / \sum e_{pv}^{at} \tag{11}$$

where e_{pv}^{at} is the actual output energy of PV, and e_{pv}^{ft} is the forecast PV output energy.

3.3. Model of day-ahead price strategy

3.3.1. Net energy of PVCS

In each time slot, the energy generated by PV system may not be equal to the energy demand of all EVs, the net energy of PVCS in specific period can be describe as:

$$e_g^t = e_{net}^t = e_{pv}^t - \sum_{n \in N} e_{nt} \tag{12}$$

In (12), while $e_g^t \geq 0$, it can be considered that the energy generated by PV system can supply the charging demand of EVs, and the excess energy will be send to utility grid; while $e_g^t < 0$, it means that PO should buy electricity from grid to meet users' demand.

3.3.2. Profit model of PO

The profit of PO consists of the revenue from EV users, subsidy of distributed PV generation from government, income of selling electricity to utility grid, and expenditure of buying electricity from utility grid. The profit function could be formulated as:

$$U^t = \sum_{n \in F} p_b^t e_{nt} + \tau e_{pv}^t + g_s^t \max(e_g^t, 0) + g_b^t \min(e_g^t, 0) \tag{13}$$

$$U_{po} = \sum_{t=0}^{T-1} U^t \tag{14}$$

where R is the set of rigid EV, F is the set of flexible EV, τ is the price of subsidy, g_s^t is the selling price of utility grid, g_b^t is the buying price of grid.

3.3.3. The target of day-ahead price strategy

To achieve the maximum operational profits, PO can optimize the user's charging behavior by adjusting the internal price. It can be reduced properly to encourage EV users buy more energy in the period of PV power is sufficient. On the contrary, raising the price aptly while the PV power is not enough. The operation target of PO can be expressed as:

$$\begin{aligned} \max \quad & U_{po} = \sum_{t=0}^{T-1} U^t \\ \text{s.t.} \quad & g_s^t \leq p_b^t \leq g_b^t \end{aligned} \tag{15}$$

It is known from expression (15) that the maximum profit of PO is related to the electricity price strategy and the EV price response strategy which aims at minimizing the cost. The interest problem between PO and EV constitutes the Stackelberg game. The day-ahead price strategy can be realized by solving the equilibrium solution of the game.

4. Game approach for PVCS and strategy implementation

4.1. Noncooperative Stackelberg game

A Stackelberg game formally studies the multilevel decision-making processes of a number of decision makers (followers) in response to the decision taken by the leading players (leaders) of the game [23,24]. In this paper, the trade problem in PVCS is formulated as a noncooperative Stackelberg game, where the PO is the leader that sets the internal prices for EV charging with Day-ahead Price Strategy, and the EV users are the followers who respond to the prices by using the Intraday Charging Strategy. Therefore, the game between the PO and the EV users can be formally defined by its strategic form as:

$$\Gamma = \left\{ (N \cup \{PO\}), \{E_n\}_{n \in N}, \{P_b\}, \{C_n\}_{n \in N}, U_{po} \right\} \tag{16}$$

which consists of the following components.

(1) The users in set N act as followers and choose their strategies in response to the price set by PO, who is the leader of the game.
(2) E_n is the set of strategies of each user in N.
(3) P_b is the set of strategies set by PO, which is the vector of the internal price p_b^t.
(4) C_n is the cost function of user n, as explained in (6), that captures the total cost of user from buying energy e_{nt}.
(5) The utility function U_{po} of PO captures the benefit from the selling energy e_{nt} of all users, trading energy with main grid and subsidy of PV generation from government.

One feasible solution for the proposed game in (16) is the Stackelberg equilibrium (SE) at which the leader obtains its optimal price with the best responses of followers. At the SE, neither the leader nor any follower can benefit, in term of total cost and utility, respectively, by unilaterally changing strategies [25]. Therefore, the SE of Game Γ can be defined as follows:

Definition. In the game defined as (16), where C_n and U_{po} are determined by (6) and (14), respectively. A set of strategy $\left(E_n^*, P_b^*\right)$ constitutes an SE of this game, if and only it satisfies the following set of inequalities:

$$\begin{aligned} & C_n\left(E_n^*, P_b^*\right) \leq C_n(e_n, e_{-n}^*, P_b^*), \forall n \in N, \forall e_n \in E_n \\ & U_{po}\left(E_n^*, P_b^*\right) \geq U_{po}(E_n^*, P_b) \end{aligned} \tag{17}$$

where $e_{-n}^* = [e_1^*, \ldots, e_{n-1}^*, e_{n+1}^*, \ldots, e_N^*]$, and $E_n^* = [e_n^*, e_{-n}^*]$.

Therefore, when all the players in $(N \cup \{PO\})$ reach the SE, the PO cannot improve its utility by adjusting internal price from SE price P_b^*. As the same, no user can reduce their cost by making other strategies different fromE_n^*.

Proof. The optimal solution of problem (7) is defined as $e_n^* = [e_{n\alpha_n}^*, \ldots, e_{n\beta_n}^*]$. Therefore, for any time slot t, there exists a first derivative equal to a certain constant satisfying the optimal solution condition, such as

$$\frac{\partial C_n'}{e_{nt}} = 2a_n e_{nt} + p_b^t + b_n = \xi_n \tag{18}$$

and hence

$$e_{nt} = \frac{\xi_n - p_b^t - b_n}{2a_n} \tag{19}$$

By replacing e_{nt} in (12) and (13) with expression (19), there exits two situations, i.e., $e_g^t > 0$ and $e_g^t < 0$. As the space constraints, here we only discuss the previous situation. Then expression (13) can be rewritten as

$$U^t = \sum_{n \in N} p_b^t \frac{\xi_n - p_b^t - b_n}{2a_n} + \tau e_{pv} + g_s^t(e_{pv}^t - \sum_{n \in N} \frac{\xi - p_b^t - b_n}{2a_n}) \tag{20}$$

The derivatives of (20) with respect to p_b^t is

$$U^t = \sum_{n \in N} \frac{\xi_n - b_n + g_s - 2p_b^t}{2a_n} \tag{21}$$

Setting the above derivative equal to zero, we can get

$$p_b^t = \frac{\xi_n - b_n + g_s}{2} \tag{22}$$

The second derivative of U^t is given by

$$\frac{\partial^2 U^t}{\partial {p_b^t}^2} = \sum_{n \in N} -\frac{1}{a_n} < 0 \tag{23}$$

and therefore, U^t is strictly concave with respect to p_b^t. Hence the PO would be able to find an optimal price set P_b^* for selling its energy to EV users based on their strategies. Therefore, there exits a unique SE in the proposed game, and thus, the Definition is proved.

4.2. The implementation of EV charging strategy

Considering that problem (9) belong to unconstrained non-linear programming problem, the objective of the strategy can be solved by Steepest descent method, which can approach the optimal solution by recursive iteration, such as

$$e_{nt}(m+1) = e_{nt}(m) + \gamma_t \| - \nabla C_n'(m) \| \tag{24}$$

where m is the number of iteration, γ_t is the iterative coefficient. And the specific implementation methods are shown in Algorithm 1.

Algorithm 1: Solution Method of EV Charging power

Steepest Descent Method

1: **procedure**

2: Initial parameter m = 1, γ_t, ε_n

3: **repeat** /* Approximately minimize C_n' */

4: $t = \alpha_n$;

5: **repeat**/* Computing e_{nt} of all periods */

6: $e_{nt}(m+1) = e_{nt}(m) + \gamma_t \| -\nabla C_n'(m) \|$;

7: $t = \alpha_n + \Delta T$;

8: **until** $t = \beta_n$

9: **until** $\| -\nabla C_n'(m) \| \leq \varepsilon_n$

10: **return** E_n^*

11: **end procedure**

4.3. The implementation of day-ahead price strategy

With the consideration of the strategy adopted by EV users, the game is essentially a nonlinear bilevel programming problem, and it is difficult to directly obtain the optimal solution with the conventional mathematical methods [23]. Heuristic optimization algorithms are usually adopted to solve such problems, such as Particle Swarm Optimization (PSO) and Differential Evolution (DE). Although PSO has fast convergence, it is easy to fall into the local optimal solution in solving the high dimension problem, and the optimization result is greatly influenced by setting parameters. However, DE has strong global convergence and low parameter sensitivity. In this paper, a DE–PSO algorithm mentioned in [26] is adopted to optimize the internal price set by PO.

The DE–PSO which consists of alternating phase of DE and PSO is designed so as to preserve the strengths of both algorithms. The general implementation processes of the model executed by EMS are shown in Algorithm 2. The operations used in DE–PSO algorithm are derived from reference [26], and shown in Table 1.

Algorithm 2: Solution of Day-ahead price vector

DE-PSO

1: Initial parameter

$F = 0.5; CR = 0.5; \omega = 0.5; c_1 = 2; c_2 = 2;$
$r_1 = rand[0,1]; r_2 = rand[0,1];$

2: Produce the first internal price population

$P_{bK,g} \equiv (P_{bk,g}; k \in K)$ randomly;

3: Calculate U_{po} with E_n^* calculated by Algorithm 1;

4: Perform mutation operation;

5: Perform crossover operations;

6: Generate offspring internal price set $P_{bk,g+1}^{de}$;

7: Execute step 3 with $p_{bk,g+1}^{de} \in P_{bk,g+1}^{de}$;

8: **if** $U_{po}(p_{bk,g+1}^{de}) > U_{po}(p_{bk,g})$

9: $p_{bk,g+1} = p_{bk,g+1}^{de}$;

10: **else**

11: generate $p_{bk,g+1}^{pso}$ by PSO algorithm

12: executing step 3 with $p_{bk,g+1}^{pso}$;

13: **if** $U_{po}(p_{bk,g+1}^{pso}) > U_{po}(p_{bk,g})$ then

14: $p_{bk,g+1} = p_{bk,g+1}^{pso}$;

15: **else**

16: $p_{bk,g+1} = p_{bk,g}$;

17: **end if**

18: **end if**

19: **repeat**

20: step4-step18;

21: **until** (16) is satisfied

22: **return** P_b^*;

4.4. The implementation of real-time billing strategy

According to the expression (13), the profit of PO is affected by the forecasted output of PV and the scheduled demand from EV users, and the cost of user n is related to its own scheduled demand. Because the errors of forecasting and scheduling are always existed in each time slot, the actual profit of the PO and the costs of EV users

Table 1

Differential evolution
$v_{id} = x_{R_1 d} + F\left(x_{R_2 d} - x_{R_3 d}\right)$ $u_{id} = \begin{cases} v_{id} & if \quad rand\,[0,1] \le CR \quad or \quad i = i\_rand \\ x_{id} & if \quad rand\,[0,1] > CR \quad or \quad i \neq i\_rand \end{cases}$
Particle swarm optimization
$v_{id} = \omega v_{id} + c_1 r_1 (p_{best} - x_{id}) + c_2 r_2 (g_{best} - x_{id}) x_{id} = x_{id} + v_{id}$

may have some differences from their expectations. In this paper, a real-time billing strategy based on the utility of errors is proposed to deal with these errors.

The energy deviation of EV user n in a specific period t can be defined as the difference between expected energy demand and actual energy demand

$$\sigma_n^t = e_{nt}^a - e_{nt}^* \tag{25}$$

$$\sigma^t = \sum_{n \in N} \sigma_n^t \tag{26}$$

where e_{nt}^a is the actual energy demand of user n in period t, e_{nt}^* is the expected energy demand of user n in period t, σ^t is the total energy demand of EV users. Similarly, the energy deviation of PV output will be

$$\sigma_{pv}^t = e_{pv}^{at} - e_{pv}^{ft} \tag{27}$$

where e_{pv}^{ft} is the forecast PV energy, and the net energy of PVCS in period t could be expressed as:

$$e_{net}^{at} = e_{pv}^{ft} + \sigma_{pv}^t - \sum_{n \in N} e_{nt}^* - \sigma^t \tag{28}$$

From (13), the actual profit of PO with deviations exists two situations, i.e., $e_{net}^{at} > 0$ and $e_{net}^{at} < 0$. For the former situation, the actual profit of PO is:

$$\begin{aligned} U^{at} &= \sum_{n \in N} p_b^t (e_{nt}^* + \sigma_n^t) + \tau (e_{pv}^{ft} + \sigma_{pv}^t) \\ &\quad + g_s^t (e_{pv}^{ft} + \sigma_{pv}^t - \sum_{n \in N} e_{nt}^* - \sigma^t) \\ &= U^{*t} + (p_b^t - g_s^t)\sigma^t + (\tau + g_s^t)\sigma_{pv}^t \end{aligned} \tag{29}$$

It is known from expression (29) that

(1) while$\sigma_n^t < 0$, the utility to the profit of PO by user n can be regarded as negative, due to $(p_b^t - g_s^t)\sigma_n^t \le 0$. There is a penalty for the lack of buying energy from PVCS

$$V_n^t = e_{nt}^a p_b^t - \sigma_n^t (g_b^t - p_b^t) \tag{30}$$

(2) while $\sigma_n^t > 0$, it means that the utility to the profit of PO by user n is positive with $(p_b^t - g_s^t)\sigma_n^t \le 0$. Thus, the user n could buy the energy with the price p_b^t, and without any penalty

$$V_n^t = e_{nt}^a p_b^t \tag{31}$$

However, for the latter situation, the actual profit of PO is:

$$\begin{aligned} U^{at} &= \sum_{n \in N} p_b^t (e_{nt}^* + \sigma_n^t) + \theta (e_{pv}^{ft} + \sigma_{pv}^t) \\ &\quad + g_b^t (e_{pv}^{ft} + \sigma_{pv}^t - \sum_{n \in N} e_{nt}^* - \sigma^t) \\ &= U^{*t} + (p_b^t - g_b^t)\sigma^t + (\theta + g_b^t)\sigma_{pv}^t \end{aligned} \tag{32}$$

In the same way, there will be two cases:

(1) while $\sigma_n^t < 0$, the utility to the profit of PO by user n can be regarded as positive, due to $(p_b^t - g_s^t)\sigma_n^t \ge 0$. Thus, the user n will buy the energy with the price p_b^t, and without any penalty

$$V_n^t = e_{nt}^a p_b^t \tag{33}$$

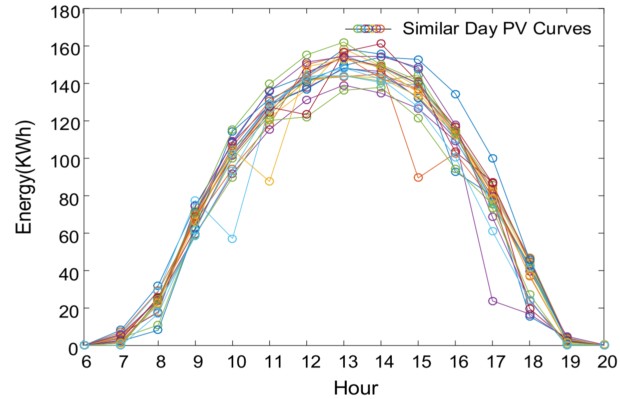

Fig. 5. Twenty PV curves of similar days.

(2) while $\sigma_n^t > 0$, it means that the utility to the profit of PO by user n is negative with $(p_b^t - g_s^t)\sigma_n^t \le 0$. There is an added penalty for buying extra energy from PVCS

$$V_n^t = e_{nt}^a p_b^t + \sigma_n^t g_b^t \tag{34}$$

According to the formulas from (30) to (34), EV users need to pay an additional penalty fee when the EV charging demand error has negative impact on the profit of PO. Therefore, the revenue from EV users in PO's profit function should be changed, and it can be expressed as

$$V^t = \sum_{n \in N} V_n^t \tag{35}$$

In addition, other benefits of PO also need to be calculated by actual value, including the subsidy of distributed PV generation from government, the income of selling electricity to utility grid, and expenditure of buying electricity from utility grid. Thus, the actual profit of PO in each time slot can be updated as

$$U^{at} = \sum_{n \in N} V_n^t + \tau e_{pv}^{at} + g_s^t \max(e_g^{at}, 0) + g_b^t \min(e_g^{at}, 0) \tag{36}$$

And, the profit of PO during the entire operation period is

$$U_{po}^a = \sum_{t=0}^{T-1} U^{at} \tag{37}$$

5. Case study

5.1. Basic data

This paper mainly considers the operation of PVCS located in an industrial/commercial workplace on sunny days. The data of PV output power was collected from an actual PV power generation system, and the rated capacity of the PV system is 180 kW. Twenty historical days with the smallest similarity coefficient in past three months are selected as the training input of the BPNN, as shown in Fig. 5.

The scheduled values of start time and end time of 48 EVs are obtained from an actual parking lot, shown in Fig. 6(a), and the actual values of end time are assumed to be the same as the scheduled values. A random error ranged from −0.5 h to 0.5 h are introduce to the scheduled start time as the actual values. The scheduled initial SOC of EVs are generated randomly from 0.2 to 0.5, and it is supposed that the actual SOC values are generated by introducing a random error between −0.2 and 0.2 in the scheduled values. The objective SOC of all the EVs are set as 0.85 in this paper. All of the SOC data are shown in Fig. 6(b). The parameters of all EV batteries are assumed the same, as listed in Table 2.

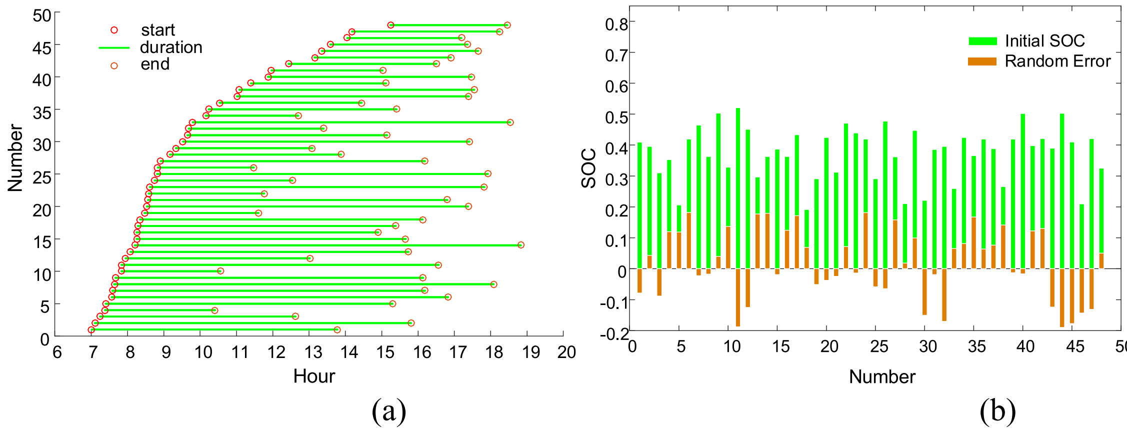

Fig. 6. Charging demand information: (a) Start time, end time and charging duration of 48 EVs; (b) Initial SOC of 48EVs with random error.

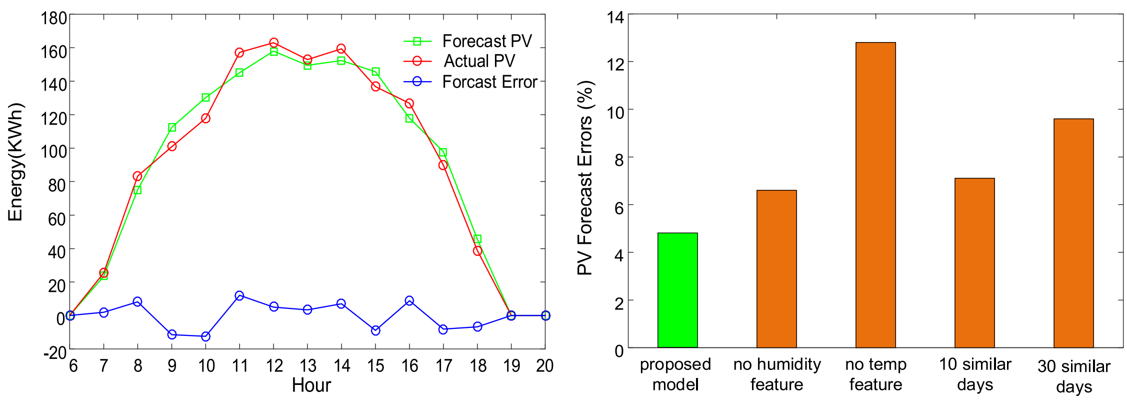

Fig. 7. (a) Result of forecast PV and actual PV; (b) forecast error under different situation.

Table 2

Parameters of battery

Parameters of battery	
Rated capacity	60 kWh
Maximum charging ratio	0.3C
a_n	0.022
b_n	0.14
c_n	0.005

The buying prices of grid use the time-of-use (TOU) prices adopted in most areas of China, and the selling prices are set up as the electricity price of the local coal-fired unit. The price of subside from government is 0.42 RMB/kWh in this paper. The simulation runs from 7:00 to 19:00 in the daytime and the length of each time slot is 1 h.

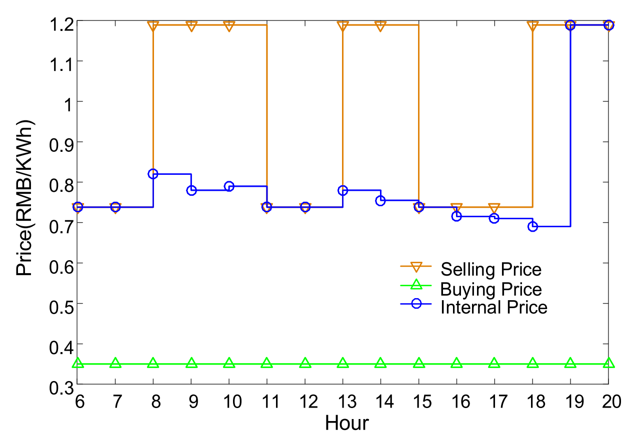

Fig. 8. Prices of power grid and PO.

5.2. Results of simulation

5.2.1. PV energy output forecast

The result of forecast energy of PV output and actual energy are shown in Fig. 7(a), and the forecast error under different situations are shown in Fig. 7(b), including the proposed model, the forecast model without considering humidity feature, the forecast model without considering temperature feature, the forecast model with 10 similar days and the forecast model with 30 similar days. It is obvious that the prediction error of the proposed model is lower than that of the other four cases.

5.2.2. Internal price

According to the prediction and scheduled demand, algorithm II is used to reach the SE, and the internal price curve of daytime can be obtained, as shown in Fig. 8. Before time slot 7 and after time slot 19, the irradiance of sunshine is close to zero, there is no PV energy can be used to charge EVs, therefore the internal price should be the selling price of power grid. In time slots 7–16, as shown in Fig. 7(a), the number of EV charged at PVCS continues to increase, and the total charging demand is relatively larger than the other periods. To sell more PV energy to EV users, the internal price changes between the peak price and flat price of grid. In time slots 16–19, there are no more EVs coming to charge here, and the total charging demand begins to decline. The internal price falls below the flat price of grid, but still higher than the buying price of power grid.

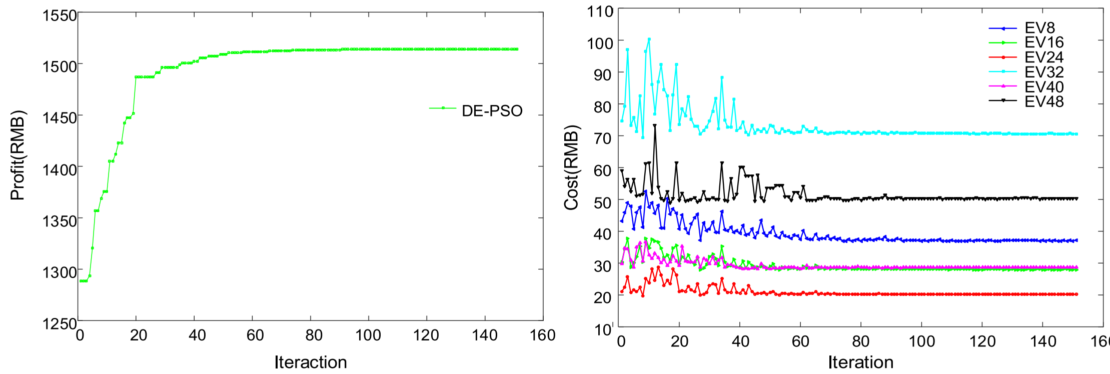

Fig. 9. Iterative process: (a) Profit of PO with different algorithm; (b) costs of six sampling EV with DE–PSO algorithm.

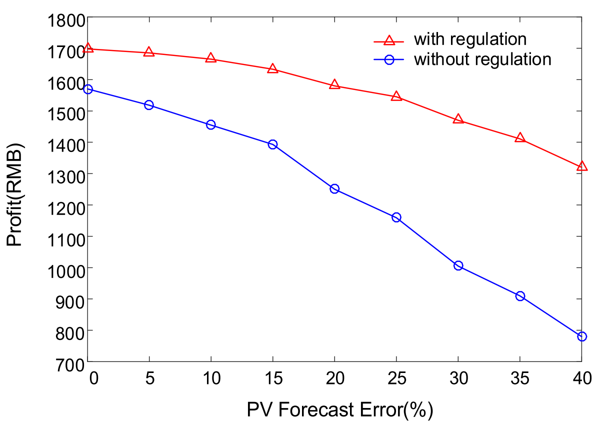

Fig. 10. Profit curves with PV forecast error.

5.2.3. Expected profit and expected cost

The optimization iterative processes of PO profit is shown in Fig. 9(a). It can be noted that the curve based on DE–PSO algorithm tend to converge after about 80 iterations. Six sampling EV users' cost curves are shown in Fig. 9(b), which decrease as the number of interactions increases until it converges. As the objective of Algorithm 2 is to optimize the profit of PO, who is the leader of game. The profit of PO will continue to grow in the process of iteration. However, the EVs users are the followers of the game, who will response to the prices generated by Algorithm 2. The cost cannot be gradually reduced with the change of internal prices, and the fluctuations shown that the costs of EV users are sensitive to the internal price strategy.

5.3. Analysis of real-time billing strategy

5.3.1. Profit with PV forecast error

The accuracy of PV energy output forecast has a direct impact on the profit of PO, even with the real-time billing strategy, as shown in Fig. 10. An error ranged from 0 to 40% is introduced to the actual PV output energy as forecast PV. It assumed that the initial SOC of EV user has no scheduled error, the profit will be changed without regulated as the blue curve. Otherwise, if the scheduled error exists, the profit will be regulated with real-time billing strategy, whose values are higher than the first curve. Obviously, the values of both curves will be reduced with the increase of PV forecast error.

5.3.2. Real-time billing with initial SOC error

The real-time billing strategy proposed in this paper is used to treat the errors from scheduled charging demand. To further illustrate the necessity of the strategy, the profit of PO and the charging cost of EV8 are chosen as the objects to analysis. It is assumed that the initial SOC error of all the EV users are ranged from −0.2 to 0.2. The profits of PO considering with the error are shown in Fig. 11(a), and the charging costs of EV8 are shown in Fig. 11(b).

From Fig. 11(a), it is obvious that the profit of PO without regulation will be reduced with the change of initial SOC, no matter it is positive or negative. However, the profit with regulation will be greatly improved when the charging demand increases, and maintained when the demand reduces. In Fig. 11(b), the penalty for EV8 increases with the increase of initial SOC error, and it indicates that users who wants to reduce the charging cost should exactly estimate the scheduled initial SOC.

5.4. Comparison with different strategies

To better discuss the advantages of proposed strategy, three comparative cases are considered as the follows:

Case 1: The electricity price of utility grid is taken by PO as the sale price. In addition, EV users adopt uncontrolled charging strategy, and EVs are charged with maximum power as soon as they arrive until the SOCs reach the target values.

Case 2: PO uses the electricity price of utility grid as the sale price, and the EV users still adopt algorithm I as the minimum cost charging strategy, respectively.

Case 3: PO charges the EV users by electricity tariff of grid, and uses a centralized strategy to management the charging behavior of all the EV users. The optimization goal of this strategy is to maximize the revenue of PO.

5.4.1. EV charging energy and net energy

The comparison results of the EVs charging energy and the net energy of PVCS users are shown in Fig. 12. It is obvious that the charge energy curve of EVs in case 1 and case 2 in Fig. 12(a) fluctuates greatly, and the photovoltaic energy is not fully utilized. Therefore, there will be a lot of energy transactions between PVCS and the grid, which can be observed through the net load energy curve of case 1 and case 2 in Fig. 12(b). On the contrary, the EV charge energy curve of case 3 and the proposed model has the characteristics of tracking the photovoltaic energy curve effectively, as shown in Fig. 12(a). Obviously, the energy transaction between PVCS and the grid is greatly reduced than the previous two situations in Fig. 12(b), which is beneficial to the improvement of the profits of PVCS operator.

5.4.2. Profit and costs

The comparison results of the profit of PO and costs of six EV users are shown in Fig. 13. Obviously, the profit of PO in case 1 and case 2 is much lower than the other two cases, although the

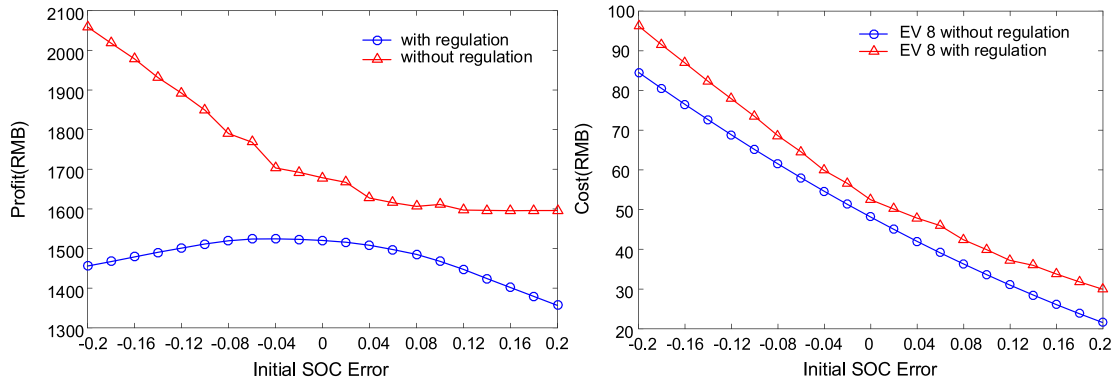

Fig. 11. Comparisons of profit and cost: (a) profit of PO; (b) cost of sampling EV8.

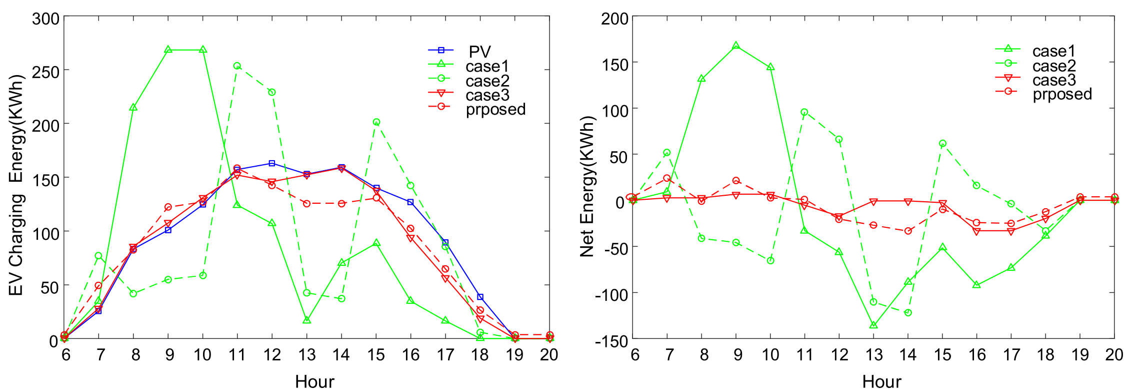

Fig. 12. Energy comparison results: (a) EV charging energy; (b) Net energy of PVCS.

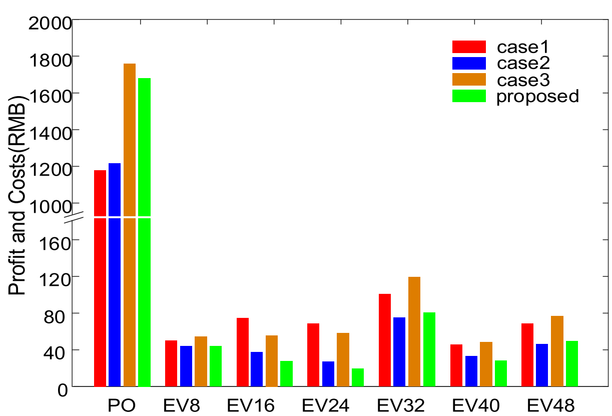

Fig. 13. Comparison results of the profits of PO and the costs of six EV users.

charging cost of six EV users in case 2 is lower than that of other cases. The revenue of the proposed model is very close to the value of case 3, which has the highest profit. The charging costs of the EV users in the proposed model are also very low, and there are even some EVs' charging costs lower than those in case 2, such as EV16, EV24 and EV40. That is because the internal price of PVCS is lower than the grid price in some periods. Therefore, it can be considered that the strategy proposed in this paper can effectively reduce the costs of EV users while maximizing PO's profit.

6. Conclusions

This paper proposed a day-ahead optimal internal price model for PVCS. The profits model of PO is proposed with considering the electricity payment of EV users, the benefit from trading with the distribution system operator and the subside of PV energy from government. The cost model of EV user is build, which consists of the cost of electricity and the cost of battery degradation. To capture the interactions between PO and EV users, a distribution algorithm based on Stackelberg game is proposed. Furthermore, PO is the leader of the game, who interests to gain more profits by adjusting the internal price, and a heuristic algorithm based on DE–PSO is adopted to achieve the goal. EV users are the followers of the game, who respond to the internal price and model the problem of minimize charging cost as a nonlinear constrained programming. The internal price is no more than the price of power grid, especially in the peak period of TOU, which is attractive to the users who expect to reduce charging cost. Comparing with the directly trading with the price of utility grid and feed-in-tariff of PV energy, the utility of PO could be enhanced. The cost of EV user has greatly reduced, contrasted to the centralized strategy of maximizing the profit of PO. Finally, a real-time billing strategy is studied to deal with the deviation of PO's profits caused by the forecast error of PV energy based on BPNN and the error of scheduled charging demand.

Present works mainly solved the problem of conflict interests between the profit of PO and costs of EV users under EVs charging from PV and grid. The situation of EVs participated in vehicle-to-grid (V2G) and vehicle-to-vehicle (V2V) should be further considered.

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