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Research Article

Optimal Day-Time Charging Strategies for Electric Vehicles considering Photovoltaic Power System and Distribution Grid Constraints

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Electric vehicles (EVs) charging stations with a photovoltaic (PV) system for day-time charging have been studied. This paper investigates the issues such as how to coordinate the EVs customers for coordinated charging, maximize photovoltaic utilization, and reduce customers cost of EVs charging and operator electricity. Firstly, an ideal charging load curve was built through using the linear programming algorithm. This optimal curve, which realized maximum photovoltaic power and minimum electricity cost, was used as the objective curve. Secondly, a customer response model was utilized, to propose an optimization method and strategy for charging service tariffs. Particle swarm optimization algorithm was used for time-of-use tariffs and peak-flat-valley time division so that the charging load after price regulation was adjusted to best fit the objective curve, and both the EVs customers and the operator benefit from this. Finally, the proposed model and method have been verified by two cases.

1. Introduction

As the global energy crisis and air pollution are getting worse, large scale application of renewable power generation and electric vehicles (EVs) becomes attractive [1–3]. Electric vehicles and plug-in hybrid electric vehicles which have zero pollution operation modes become an important method to solve environmental and atmospheric pollution problems in large and medium size cities.

The charging mode for electric vehicles and plug-in hybrid electric vehicles mainly includes night-time charging, day-time charging, and emergency charging. Night-time charging is the most widely used charging mode because it has the longest parking time during the night and uses electric load valley. Meanwhile day-time charging is another important method. Reference [4] pointed out that if the plug-in hybrid EV, which can drive up to 20 km as pure electric vehicle, is charged during the day and during the night, the fuel economy will be improved by 71%. Reference [5] mentioned that 40% of electric vehicles energy will be supplied from charging during the day in Beijing by 2020.

The connection of large scale charging infrastructure will significantly affect the stability and quality of the distribution grid. This will depend on the penetration and the charging behavior characteristic of the electric vehicles [6, 7]. Up till now, the research on electric vehicle charging load control mainly focuses on night-time charging. The main control target is to reduce the peak power, shift peak, and fill valley and maintain stable operation of the distribution grid. The main method is to control the charging power and change the charging time [8–10]. With the same operating conditions of the distribution grid, electric vehicle day-time charging will also have the same issues such as controlling the peak power of charging station and maintaining distribution grid stability. A local photovoltaic power system could be an alternative method besides control of the charging power and changing time.

Nowadays the photovoltaic power generation capacity globally installed grows explosively as the capital cost of the photovoltaic power system reduces. And almost all of the photovoltaic power system is connected to the distribution grid [11]. However, photovoltaic power generation is unstable, which is significantly affected by the weather and season; grid-connected photovoltaic power systems thus will cause issues to the distribution grid such as overvoltage and equipment overload. The methods to solve the above issues caused by the high penetration of photovoltaic power systems include control of the photovoltaic inverter output active power and reactive power. However, not all of photovoltaic energy is fed back to the grid; that is, some of it is wasted, and this is limited by the distribution grid capacity. To improve the photovoltaic power utilization, the battery energy storage system can be used to balance the differences between the photovoltaic power and load power. Compulsory measures or time-of-use tariffs can be used to adjust load power curve to satisfy the demand of maximum photovoltaic power in the meantime. However, utilization of the photovoltaic power system is poor due to the battery storage system having a short cycle life and high capital cost and a small adjustment range of conventional load.

The power demand of EV day-time charging has a large overlap with photovoltaic power generation. The EV charging time during the day is shorter than the daily average parking time [12], which is also variable. The public day-time charging infrastructure using a photovoltaic power system providing part of the energy has the following advantages:

(1) improving flexibility and economic efficiency of electric vehicles;

(2) improving local distribution grid renewable energy penetration;

(3) reducing the effect of electric vehicle and renewable power generation on the distribution grid.

Reference [13] notes commuter electric vehicles can be charged in public parking lot during the day by using photovoltaic solar panels. This reduces the dependence on fossil fuel energy sources and helps reduce electricity supply-demand unbalance. Reference [14] presents the effect of electric vehicle charging stations which can support the voltage and maintain the stability of distribution photovoltaic power systems. The plug-in electric vehicle charged by photovoltaic powered charging station in a workplace parking garage is studied in [4]. The economic and carbon emissions of a photovoltaic charging station are compared between random charging and optimal charging. In [15] the regulated and optimized charging control is studied from EV customer's perspective. This reduces the effect of charging load on the distribution grid and charging cost, which is beneficial for both the operator and EV customers. This also provides a sustainable commercial development mode and improves the adaptability of charging infrastructure.

The electric vehicle public charging stations with a photovoltaic system for day-time charging were studied in this paper. An optimized EV charging curve, which realized maximum photovoltaic power and minimum electricity cost, was built by using linear programming. An EV customer price response model was built based on load shifting ratio. Particle swarm optimization algorithm was used for time-of-use tariffs and peak-flat-valley time division so that the charging load curve after price regulation best fits aim curve, and both the EV customers and operator benefit from this.

The EV charging load characteristics are from [16] and the photovoltaic power generation data is from a 10 kW roof PV system (annual operation) in a research institute. EV customers' price response model source data is from questionnaire among EV customers in a high education institute. The electricity price adopts general industry and commercial peak-valley tariffs in Beijing.

The structure of this paper is as follows: Section 2 covers EV day-time charging load characteristic, photovoltaic power generation characteristic, and EV customers' price response. Section 3 introduces day-time charging optimized control strategy flow-charts. Section 4 presents optimal charging aim curve from linear programming algorithm. Section 5 reports peak, flat, and valley charging service tariffs using particle swarm algorithm. Section 6 explains decision making method for base charging price which can benefit both charging station operator and EV customers. Section 7 presents the simulation results from two different cases, which validate the model and method. Section 8 draws conclusions from this paper.

2. EV and Photovoltaic Characteristics

2.1. EV Day-Time Charging Load Characteristic. Reference [15] builds the statistical probability model of EV charging demand based on the statistical data of a traditional petrol vehicle. Monte Carlo algorithm is used to obtain an EV fleet charging power curve.

Probability distribution and average of daily mileage for EV customer using day-time charging and night-time charging are identical. The probability distribution of charging start time roughly maintains the same. However, the average charging start time is totally different. The average charging start time for night-time charging is evening peak time whilst the average charging start time for day-time charging can be reasonably predicted to be morning peak time. Figure 1 shows a probability distribution model [16] and 100 EVs day-time charging curve and night-time charging curve by using Monte Carlo method. The average daily mileage is 40 km. The average start charging time is 9:00 am for day-time charging and 6:00 pm for night-time charging. EV electricity consumption is 0.15 kWh/km and power rating for on-board charger P_{charge} is 3 kW.

Where P_{ev1} and P_{ev2} notate night-time charging curve and day-time charging curve for 100 EVs, respectively, P_{pv} is a typical 100 kW photovoltaic output power curve. It can be seen from Figure 1 that the EV day-time charging curve has a good agreement with photovoltaic output power.

Methods to regulate EV charging curve include (1) control of EV charging power, (2) control of when to charge and for how long. Control of EV charging power would reduce the output efficiency of the charger. This paper therefore controls charging time whilst maintaining constant output charging power, so that high efficiency of the charger is achieved. This method needs to transform the EV charging energy demand into charging time with constant power. In the meantime, the

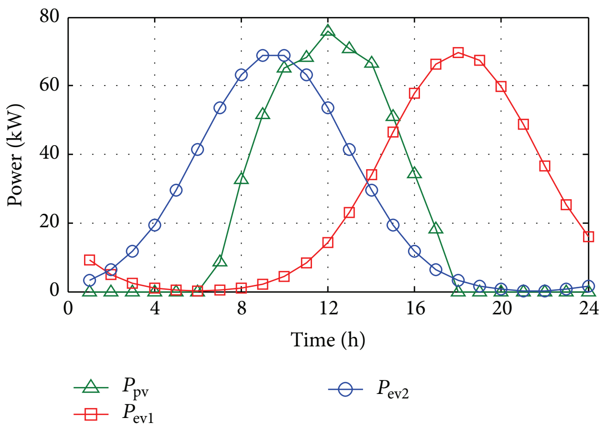

FIGURE 1: Comparison of EV charging load and photovoltaic output power.

charging process is not continuous to regulate the charging load. The charging process can be allocated into different time intervals. The EV charging power P_{charge} here is constant at 3 kW.

The day charging time (assumed from 7:00 am to 6:00 pm) is divided into n time intervals to implement charging time control and each time interval is T_s. An EV charging demand is transformed into the number of unit charging times T_s from

$$N_{ev,i} = \left\lceil \frac{S_i W}{T_s P_{charge}} \right\rceil, \tag{1}$$

where $N_{ev,i}$ is the number of unit charging time daily requirements for EV number i, S_i is the daily mileage of EV number i, and W is EV power consumption per kilometer.

The charging demands of all EVs are satisfied as long as the number of unit charging times is fulfilled during the whole charging time. Round ceiling is used for the number of unit charging times for each EV.

The number of charging EVs is $N_{ev,j}$ within time interval T_s. Adding up $N_{ev,j}$ in all the time intervals during the day gives the relationship between the total number of unit charging times and all the EVs charging demands, as shown in

$$\sum_{j=1}^{n} N_{ev,j} = \sum_{i=1}^{m} N_{ev,i} = \left\lceil \frac{Wm\overline{S}}{P_{charge} T_s} \right\rceil, \tag{2}$$

where m is the number of EVs and $\overline{S}$ is EV average daily millage.

2.2. EV Customers' Response Model

2.2.1. Response Characteristics. There is minimum stimulation difference (difference threshold) according to consumer psychology. When the difference is lower than this threshold, customers basically have no response or tiny response (dead zone). When the difference is higher than this threshold, customers start to have response and it is related to the extent

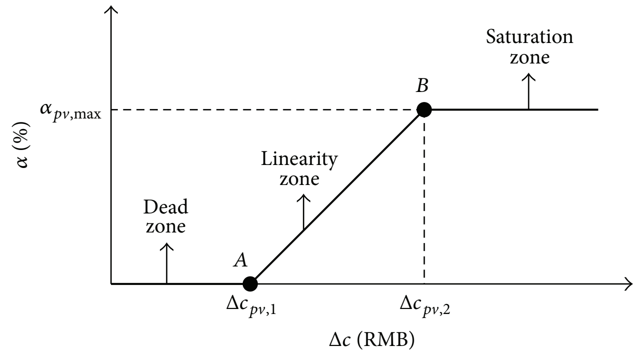

FIGURE 2: EV customers' response characteristic curve for peak-valley shifting.

of stimulation, which is called normal response (linearity zone). There is a saturation point, when the stimulation is higher than this where customers do not have any further response (saturation zone) [17, 18].

Following the definition of the load translation ratio [17], customers' response to charging service price is defined as the percentage of EV customers shifting, that is, the ratio of customers who change charging time from peak time to valley time due to time-of-use tariffs over the original peak time customers.

Daily charging service is divided into peak, flat, and valley time. Time shifting mode includes peak to valley, peak to flat, and flat to valley. The price difference for peak-valley, peak-flat, and flat-valley is notated as Δc_{pv}, Δc_{pf}, and Δc_{fv}, respectively. Peak-valley shifting is taken as an example. Figure 2 shows EV customers' response characteristic for peak-valley shifting, where the x-axis is the price difference between peak and valley time whilst the y-axis is the percentage of customers shifting from peak to valley. A and B are the turning points for dead zone and saturation zone and can be expressed as

$$\alpha = \begin{cases} 0, & 0 \le \Delta c \le \Delta c_{pv,1} \\ k_{pv} \cdot \left(\Delta c - \Delta c_{pv,1}\right), & \Delta c_{pv,1} \le \Delta c \le \Delta c_{pv,2} \\ \alpha_{pv,max}, & \Delta c \ge \Delta c_{pv,2}, \end{cases} \tag{3}$$

where $\Delta c_{pv,1}$ is the dead zone threshold, that is, price difference for peak-valley when EV customers start to respond; $\Delta c_{pv,2}$ is the saturation zone threshold, that is, price difference for peak-valley time when EV customers' response does not increase anymore; $\alpha_{pv,max}$ is the saturation value of customers' shifting percentage, that is, peak-valley EV customers responsively saturation value; and k_{pv} is the slope of linearity range and can be expressed as

$$k_{pv} = \frac{\alpha_{pv,max}}{\Delta c_{pv,2} - \Delta c_{pv,1}}. \tag{4}$$

Figure 2 shows different decisions made by EV customers with the same peak-valley price difference. Flat-valley and peak-flat EV customers' response characteristic curve is similar to Figure 2. Dead zone threshold, saturation zone threshold, and customers' shifting percentage threshold need to be confirmed to acquire each response characteristic curve.

2.2.2. Parameter Selection Analysis. Customers have a psychological price for certain products. This psychological price is a range instead of a single value. Customers will compare the actual price with the psychological price before making decision whether to purchase a product or not. Likewise, EV customers who select to charge during peak time will choose whether to change charging time when the charge service adopts use-of-time tariffs. If the price difference for the peak-valley time is within the customers' psychological price, they will not change charging time. On the contrary, customers will change charging time to a cheaper time if beneficial. The dead zone and saturation zone threshold of the customers' response characteristic in Figure 2 is decided by upper and lower limits of all EV customers' psychological price interval union.

Psychological price is developed gradually from consumption activity. Charging station refers to business electricity price when developing charging service price, as EVs are not widely used yet. Business electricity price can be used as lower limit of EV customers' psychological price. EVs are an alternative for petrol vehicles. Customers naturally will compare the cost for EVs with petrol vehicles for the same mileage. As the initial investment for EVs is high and the driving mileage range is not as good as petrol vehicles, if EVs charging cost is higher than petrol cars, it was not suitable for consumers. The cost of petrol converted into electricity price with the same mileage is taken as upper limit of the psychological price.

A price sensitivity poll for EV users in a high institute is designed in this paper. Above three core parameters will be decided by the statistical results shown in Table 1.

The customers' response characteristic parameter for peak-valley, peak-flat, and flat-valley based on Table 1 is $k_{pv} = k_{pf} = k_{fv} = 1$; $\Delta c_{pv,2} = \Delta c_{pf,2} = \Delta c_{fv,2} = 1$; $\Delta c_{pv,1} = \Delta c_{pf,1} = \Delta c_{fv,1} = 0$; $\alpha_{pv,\max} = \alpha_{fv,\max} = 100\%$.

2.3. Photovoltaic Forecast. Photovoltaic power generation forecast is from measured data of a 10 kW power system in a research institute. Photovoltaic power generation on a clear day is selected as typical data. This data can be enlarged proportionally to different power ratings. An enlarged 100 kW photovoltaic power system is shown in Figure 1.

Photovoltaic power is converted into the number of charging EVs for charging load time control as follows:

$$N_{\mathrm{pv},j} = \left[\frac{P_{\mathrm{pv},j}}{P_{\mathrm{charge}}} \right], \tag{5}$$

where $P_{\mathrm{pv},j}$ is the photovoltaic output power in time interval $j$and $N_{\mathrm{pv},j}$ is the corresponding number of charging EVs in time interval j.

2.4. Electricity Price. Beijing general industrial and commercial use-of-time electricity tariffs are used to calculate the cost for electricity purchase besides photovoltaic power. The price for peak, flat, and valley time is notated as t_p, t_f, and t_v, as shown in Table 2.

3. Charging Service Optimization Strategy

Use-of-time charging tariffs are used by a charging station operator to regulate EV customers charging behavior. Overall, EVs charging load would move towards the target of maximum photovoltaic power utilization and minimum electricity cost for the charging station operator. The charging cost of EV customers after charging station operator regulation is lower than previous random charging, so that both charging station operator and EV customers benefit from this. The process of use-of-time tariffs includes two aspects: daily optimal charging load objective curve and daily charging service price.

Firstly, the charging station operator needs to estimate the daily photovoltaic maximum power output curve before charging starts. On the basis of the probability of EV customers' daily driving mileage and the probability distribution of charging start time, daily natural charging curve is estimated. The natural charging curve is referred to as a charging process which starts when it becomes continuous. Based on the constraints of the distribution network capacity, the objective of optimized charging load curve is maximum utilization of photovoltaic power and minimum electricity cost.

Secondly, with the EV customers charging behavior price model, the charging price difference for each time interval is optimized based on an optimal charging load objective curve. The actual charging load after price regulation is enforced to best fit optimal charging load objective curve. Charging station operator will divide the profit by predetermined ratio between EV customers and themselves. Charging base price is determined by daily electricity cost and ratio of profit. Use-of-time tariffs are achieved with the charging base price and price difference for each time. EV customers can book the charging time length and when to charge according to charging price and vehicle charging demand. The operator will control the correspondent charging post according to customers booking information.

The following sections in this paper are based on the following assumptions.

(1) The power rating for the on-board charger is constant at 3 kW.

(2) Each vehicle has an independent parking lot and charging post.

(3) The total charging load maintains the same before and after charging service price regulation.

(4) Use-of-time tariffs are divided into peak, flat, and valley charging service price, similar to electricity tariffs.

Table 1: Poll statistical table.

Question	Result
Usage (multichoice)	Commute (49.0%), Business (13.1%), Pregnant women and children (24.8%), Food and entertainment (31.7%), others (12.4%)
Price difference for peak-valley (CNY/kWh)	0 (0%); 0.25 (39.4%); 0.5 (50%); 0.75 (71%); 1 (100%)

4. EV Day-Time Charging Load Objective Curve

4.1. Objective Function. In each interval, the difference between optimal charging load objective $N^*_{\mathrm{ev},j}$ and photovoltaic output power estimation is

$$d_j = N^*_{\mathrm{ev},j} - N_{\mathrm{pv},j} \quad (j = 1, 2, \ldots, n), \tag{6}$$

where $N_{\mathrm{pv},j}$ is the number of charging EVs corresponding to photovoltaic power generation in time interval j; $N^*_{\mathrm{ev},j}$ is the optimal number of charging EVs in time interval j, which also satisfy the constraint condition of (2). The total numbers of EVs charging in all time intervals daily equal EV overall numbers of unit time charging demands.

Energy absorbed from the grid and photovoltaic discard in each time interval thus can be expressed as

$$\begin{aligned} u_j &= \frac{\left(\left|d_j\right| + d_j\right)}{2} \quad (j = 1, 2, \ldots, n), \\ v_j &= \frac{\left(\left|d_j\right| - d_j\right)}{2} \quad (j = 1, 2, \ldots, n), \end{aligned} \tag{7}$$

where u_j is the energy from grid in time interval j and v_j is the photovoltaic discard energy in time interval j. The energy from grid and photovoltaic discard energy cannot be positive at the same time in time interval j, which is true for practical situation:

$$u_j v_j = 0 \quad (j = 1, 2, \ldots, n). \tag{8}$$

To reduce customer charging price and operator electricity cost and reduce the effect of photovoltaic power system on the distribution grid, photovoltaic power will be used in priority in every time interval. If EV charging demand is higher than photovoltaic energy in certain time interval, this extra charging load will be tried to shift to grid valley time. Optimized objective should include the following two aspects: minimizing daily photovoltaic discard energy and purchasing electricity at valley time. The expressions of objective function and constraints are shown as follows:

$$\min_{N_{\mathrm{ref},j}} z_1 = \sum_{j=1}^{n} \alpha_j v_j \tag{9}$$

s.t.

$$\min_{N_{\mathrm{ref},j}} z_2 = \sum_{j=1}^{n} T_s P_{\mathrm{charge}} t_j \beta_j u_j, \tag{10}$$

$$\sum_{j=1}^{n} N^*_{\mathrm{ev},j} = \sum_{i=1}^{m} N_{\mathrm{ev},i}, \tag{11}$$

$$0 \le N^*_{\mathrm{ev},j} \le m \quad (j = 1, 2, \ldots, n), \tag{12}$$

$$\frac{\left|N^*_{\mathrm{ev},j+1} - N^*_{\mathrm{ev},j}\right|}{N^*_{\mathrm{ev},j+1}} \le e\% \quad (j = 1, 2, \ldots, n), \tag{13}$$

where α_j and β_j are weight coefficient, which is 1 in this paper; z_1 is the photovoltaic discard energy in a day; z_2 is electricity cost in a day; t_j is electricity use-of-time tariffs in time interval j, and its value is shown in Table 2, and e is charging load peak fluctuation ratio.

In constraint conditions, (11) means that the total numbers of EVs charging equal EV overall numbers of unit time charging demands in a day for optimal charging objective. Equation (12) indicates that the number of unit power modules obtained from optimal charging objective should be higher or equal to zero and lower or equal to number of EVs in time interval j. Equation (13) means that the optimal charging load should satisfy the requirement of the load fluctuation ratio for the distribution grid; that is, the difference for load in time interval j and $(j-1)$ should be lower than a certain percentage of loads in time interval j. 50% is selected in this paper.

4.2. Optimization Method. The above objective functions are multiobjective functions and have to change into single objective functions before solving. Based on the relationship between the total charging load and total photovoltaic power generation in (8), the objective functions will be divided into three situations and discussed, respectively, so that multiobjective functions can be changed into single objective functions.

(1) If the total charging load is higher than the total photovoltaic power, objective functions and constraints can be simplified as

$$\min_{u_j} z_2 = \left\{ \sum_{j=1}^{n} T_s P_{\mathrm{charge}} t_j \beta_j u_j \right\} \tag{14}$$

Table 2: Beijing general industrial and commercial use-of-time electricity tariffs.

	Time division	Price (CNY)
t_p	10:00–15:00, 18:00–21:00	1.0853
t_f	7:00–10:00, 15:00–18:00, 21:00–23:00	0.6725
t_v	23:00–7:00	0.2833

s.t.

$$\begin{gathered}\sum_{j=1}^{n}\left(u_j-v_j\right)=\operatorname{sum}N-\sum_{j=1}^{n}N_{\mathrm{pv},j},\\ N_{\mathrm{pv},j}-m\le\left(-u_j+v_j\right)\le N_{\mathrm{pv},j}\quad(j=1,2,\ldots,n),\\ -e\%\le\frac{\left(u_j-v_j\right)+N_{\mathrm{pv},j}-\left(u_{j-1}-v_{j-1}\right)-N_{\mathrm{pv},j-1}}{\left(u_j-v_j\right)+N_{\mathrm{pv},j-1}}\le e\%\\ (j=1,2,\ldots,n),\\ u_j\ge 0\quad(j=1,2,\ldots,n),\\ v_j=0\quad(j=1,2,\ldots,n).\end{gathered}\tag{15}$$

(2) If the total charging load is lower than the total photovoltaic power, objective functions and constraints can be simplified as

$$\min_{v_j} z_1=\left\{\sum_{j=1}^{n}\alpha_j v_j\right\}\tag{16}$$

s.t.

$$\begin{gathered}\sum_{j=1}^{n}\left(u_j-v_j\right)=\operatorname{sum}N-\sum_{j=1}^{n}N_{\mathrm{pv},j},\\ N_{\mathrm{pv},j}-m\le\left(-u_j+v_j\right)\le N_{\mathrm{pv},j}\quad(j=1,2,\ldots,n),\\ -e\%\le\frac{\left(u_j-v_j\right)+N_{\mathrm{pv},j}-\left(u_{j-1}-v_{j-1}\right)-N_{\mathrm{pv},j-1}}{\left(u_j-v_j\right)+N_{\mathrm{pv},j}}\le e\%\\ (j=1,2,\ldots,n),\\ u_j=0\quad(j=1,2,\ldots,n),\\ v_j\ge 0\quad(j=1,2,\ldots,n).\end{gathered}\tag{17}$$

(3) If the total charging load equals the total photovoltaic power, optimization is not necessary and the result is

$$N_{\mathrm{ev},j}^{*}=N_{\mathrm{pv},j}\quad(j=1,2,\ldots,n).\tag{18}$$

Linear algorithm or Lagrange optimization algorithm is generally used for the above optimization problems [19, 20]. The linear algorithm is used here in this paper for the following cases.

5. Charging Service Price Optimization

The optimal charging load objective curve was acquired in Section 4; the optimization objective is the actual charging load after the charging service regulation best fits the optimal charging load objective curve. The charging service price optimization function is built and shown as follows.

5.1. Objective Function. The EV customers day-time charging has been divided into n time intervals; peak-flat-valley time interval vector identified for the peak-valley use-of-time tariffs is defined as $\mathrm{lab}=[\mathrm{lab}_1,\mathrm{lab}_2,\ldots,\mathrm{lab}_n]$. Time interval j is the peak time of the charging service when $\mathrm{lab}_j=3$. Time interval j is the flat time of the charging service when $\mathrm{lab}_j=2$. Time interval i is the valley time of the charging service when $\mathrm{lab}_i=1$.

According to EV customers' price response model, EV customers will respond as to whether to shift charge time under the condition of peak-valley use-of-time tariffs. The load at peak and flat time will be allocated to flat and valley time. The actual charging load after peak-valley charging service price regulation can be approximated by curve-fitting and is expressed as

$$N'_{\mathrm{ev},j}=\begin{cases}N_{\mathrm{ev},j}-\dfrac{\left[\left(k_{pf}\cdot\Delta c_{pf}\cdot L_{p,\mathrm{all}}\right)\right]}{T_p}\\ \quad-\dfrac{\left[\left(k_{pv}\cdot\Delta c_{pv}\cdot L_{p,\mathrm{all}}\right)\right]}{T_p}, & \mathrm{lab}_j=3\\ N_{\mathrm{ev},j}+\dfrac{\left[\left(k_{pf}\cdot\Delta c_{pf}\cdot L_{p,\mathrm{all}}\right)\right]}{T_f}\\ \quad-\dfrac{\left[\left(k_{fv}\cdot\Delta c_{fv}\cdot L_{f,\mathrm{all}}\right)\right]}{T_f}, & \mathrm{lab}_j=2\\ N_{\mathrm{ev},j}+\dfrac{\left[\left(k_{pv}\cdot\Delta c_{pv}\cdot L_{p,\mathrm{all}}\right)\right]}{T_v}\\ \quad+\dfrac{\left[\left(k_{fv}\cdot\Delta c_{fv}\cdot L_{f,\mathrm{all}}\right)\right]}{T_v}, & \mathrm{lab}_j=1\\ 0, & \mathrm{lab}_j=0,\end{cases}\tag{19}$$

where $N_{\mathrm{ev},j}$ is the number of charging vehicles before use-of-time tariffs in time interval j; $N'_{\mathrm{ev},j}$ is the number of charging vehicles after use-of-time tariffs in time interval j; $L_{p,\mathrm{all}}$ and $L_{f,\mathrm{all}}$ notate the total number of charging vehicles at peak time and flat time, respectively, under the condition that the charging service is divided into peak, flat, and valley; Δc_{pv}, Δc_{pf}, and Δc_{fv} are the price difference for peak-valley, peak-flat, and flat-valley, respectively. k_{pv}, k_{pf}, and k_{fv} are the slope of customers' response characteristic for peak-valley, peak-flat, and flat-valley, respectively. T_p, T_f, and T_v are the length of time for peak, flat, and valley, respectively.

Based on the above assumptions and EV customers' price response characteristic, the actual charging load curve is guided to best fit the optimal charging load curve. The objective function expression is

$$\min\sum_{j=1}^{n}\left(N'_{\mathrm{ev},j}-N_{\mathrm{ev},j}^{*}\right)^2\tag{20}$$

s.t.

$$0 \leq \Delta c_{pv} \leq 1, \tag{21}$$

$$0 \leq \Delta c_{pf} \leq 1, \tag{22}$$

$$0 \leq \Delta c_{fv} \leq 1, \tag{23}$$

$$\Delta c_{fv} = \Delta c_{pv} - \Delta c_{pf}, \tag{24}$$

$$\text{lab}_j \in \{1, 2, 3\}, \quad (j = 1, 2, \ldots, n), \tag{25}$$

where $N'_{\text{ev},j}$ is the number of charging vehicles in time interval j after charging service price regulation; Δc_{pv}, Δc_{pf}, and Δc_{fv} are the price difference for peak-valley, peak-flat, and flat-valley, respectively.

Equations (21), (22), and (23) signify the price differences constrained within the acceptance of EV customers, which are acquired by the poll from Table 1. Equation (24) is constraints for the price differences. Equation (25) restrains that the charging service only has peak, flat, and valley tariffs.

5.2. Optimization Methodology. Combining (19) with (20), the control variable is the price difference of peak-valley Δc_{pv}, flat-valley Δc_{fv}, peak-flat Δc_{pf}, and the charging service peak-valley time division scalar lab $= [\text{lab}_1, \text{lab}_2, \ldots, \text{lab}_n]$.

Dr. Eberhart and Dr. Kennedy proposed particle swarm optimization in 1995, which is an evolved computing technology based on iterations. Particle swarm optimization has the following advantages: simple structure, being easy to apply, and having good performance on function optimization and neural network weight estimation [21, 22]. This paper utilized particle swarm optimization to solve the above optimization problems and acquire optimized charging service price.

6. Base Price Calculation

The charging service use-of-time tariffs peak-valley time division and price differences are achieved by optimization. Besides, the operator needs to calculate the base price for the charging service, that is, valley price. Overall charging service use-of-time tariff c_j is obtained using the base price plus price difference for each time interval. The base price should consider the satisfaction of both the EV customers and the operator. The EV customers charging cost and the operator electricity expenses after charge service price regulation would be reduced. The reduction of electricity expenses will be divided by 1 : 1 to the EV customers and the operator so that both of them are satisfied. The base charging service price is calculated by

$$\sum_{j=1}^{n} \left(t_j N_{\text{ev},j} - c_j N'_{\text{ev},j} \right) P_{\text{charge}} T_s = 0.5 \Delta P_{\text{grid}}, \tag{26}$$

where t_j is the electricity price in time interval j, c_j is the charging service price in time interval j, and ΔP_{grid} is the reduction of electricity cost after charging service price regulation.

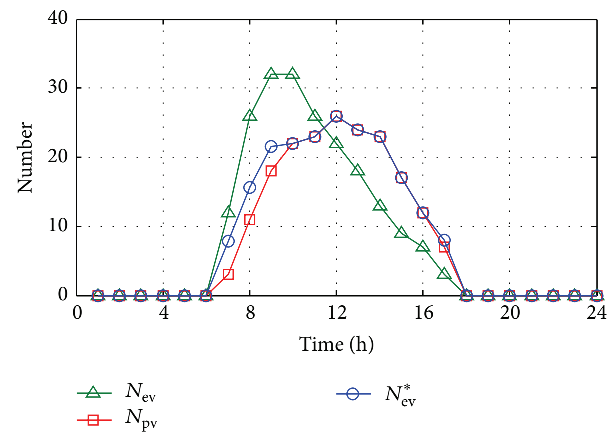

FIGURE 3: Optimized charging load curve comparison for case 1.

TABLE 3: Optimized charging load comparison for case 1.

	Original	Optimized
PV discard energy (kWh)	111	0
Operator electricity cost (CNY)	118.99	28.25

7. Case Analysis

Multiple objective functions have been changed into single objective functions in Section 4. Two cases are simulated and the results are compared.

7.1. Case 1. The charging station is assumed to provide day-time charging service for 100 EVs and the photovoltaic capacity is 100 kW. The EV charging load, photovoltaic output power curve, and peak-valley tariffs were shown in Section 2. The total charging energy is higher than the photovoltaic energy according to (2). The optimized charging load objective function, therefore, is (14). Linear programming algorithm is used in this paper to solve the objective function and the obtained optimal charging load curve is shown in Figure 3.

In Figure 3, N_{ev} is the number of charging EVs along the day before price regulation. N_{pv} is the number of charging EVs correspondent to 100 kW photovoltaic power estimation. N^*_{ev} is the optimized ideal number of charging EVs along the day. The photovoltaic discard energy is zero after linear programming optimization, and the electricity cost is 28.25 CNY. It can be seen from Figure 3 that linear programming optimization maximizes photovoltaic energy utilization. The charging time is arranged to valley time when the charging load is higher than the photovoltaic power. The results for the original and optimized charging load are compared in Table 3.

The optimal charging load curve is used as the guidance objective for charging load price. EV charging service price strategy is by obtained by combining (19) and (20), with the particle swarm optimization method. Between 7:00 and 18:00 during the day, the results of optimization are as follows: charging service peak time is 7:00~12:00, flat time is 14:00~

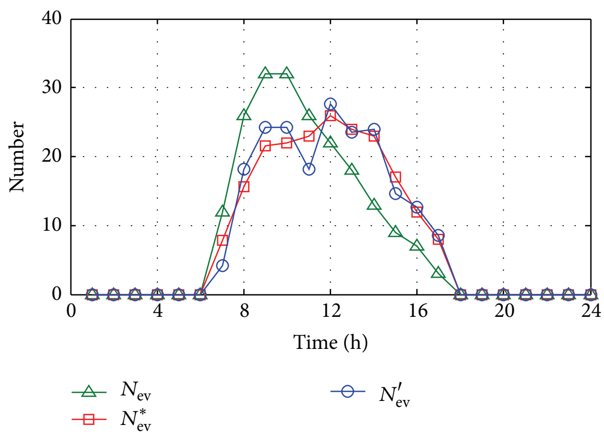

Figure 4: Charging load curve comparison after regulation for case 1.

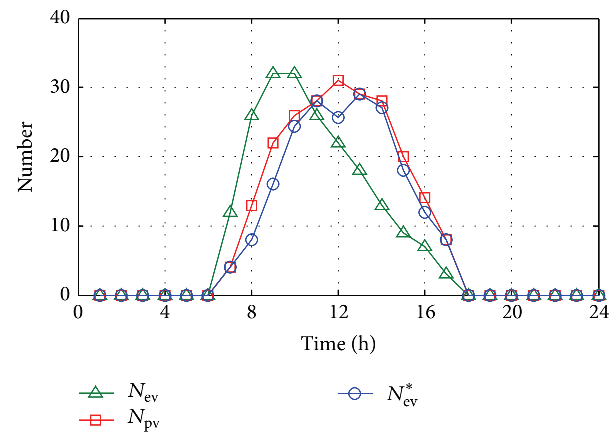

Figure 5: Optimized charging load curve comparison for case 2.

Table 4: Before and after charging service price regulation comparison for case 1.

	Before regulation	After regulation
PV discard energy (kWh)	111	22.8
EVs customer cost (CNY)	540.96	506.23
Operator electricity cost (CNY)	118.99	84.26
Peak load power (kW)	96	82.8

15:00, and valley time is 12:00~14:00 and 15:00~18:00. The price difference between peak and valley time is 0.2 CNY, between peak and flat time 0.1 CNY, and between flat and valley time 0.1 CNY. Curve-fitting for the EVs charging load after price regulation is shown in Figure 4. N'_{ev} represents the number of charging EVs along the day after regulation.

The valley charging service price is 0.74 CNY from (26), so the flat price is 0.84 CNY and the peak price is 0.94 CNY. The total cost of EV customers and operator before and after charging service price regulation is presented in Table 4.

7.2. Case 2. In order to simulate the situation that total charging load is lower than the photovoltaic output power, the maximum photovoltaic output power is enlarged to 120 kW. The number of EVs is still N_{ev} and the electricity price remains the same. The total charging energy is lower than the photovoltaic energy according to (2), and the optimized charging load objective function therefore is presented in (16). Linear programming algorithm is used in this paper to solve the objective function and the obtained optimal charging load curve is shown in Figure 5.

In Figure 5, N_{ev} is the number of charging EVs along the day before price regulation. N_{pv2} is the number of charging EVs corresponding to 120 kW photovoltaic power estimation. N_{ev}^* is the optimized ideal number of charging EVs along the day. The photovoltaic discard energy is 69 kWh after linear programming optimization, and the electricity cost is 0 CNY. The results for the original and optimized charging load are compared in Table 5.

Table 5: Optimized charging load comparison for case 2.

	Original	Optimized
PV discard energy (kWh)	180	69
Operator electricity cost (CNY)	82.08	0

Table 6: Before and after charging service price regulation comparison for case 2.

	Before regulation	After regulation
PV discard energy (kWh)	180	89.7
EVs customer cost (CNY)	540.96	505.92
Operator electricity cost (CNY)	82.08	47.04
Peak load power (kW)	96	79.50

The optimal charging load curve is used as the guidance objective for charging load price. EV charging service price strategy is obtained combining (19) and (20), with the particle swarm optimization method. Between 7:00 and 18:00 during the day, the results of optimization are as follows: charging service peak time is 7:00~11:00, flat time is 11:00~13:00, and valley time is 13:00~18:00. The price difference between peak and valley time is 0.3 CNY, between peak and flat time 0.1 CNY, and between flat and valley time 0.2 CNY. Curve-fitting for the EV charging load after price regulation is shown in Figure 6. N'_{ev} represents the number of charging EVs along the day after regulation.

The valley charging service price is 0.7 CNY from (26), so the flat price is 0.9 CNY and the peak price is 1.0 CNY. The total cost of EV customers and operator before and after charging service price regulation is presented in Table 6.

8. Conclusions

This paper proposed an effective price response model for electric vehicle customers and optimized charging service tariffs, which serves electric vehicle day-time charging station integrated with a photovoltaic power system. A reasonable use-of-time tariff for charging service was recommended. EV

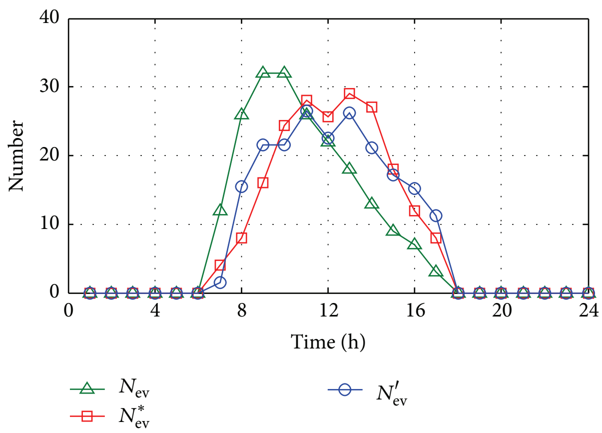

FIGURE 6: Charging load curve comparison after regulation for case 2.

customers' charging behavior would be regulated by charging service use-of-time tariffs to improve the electric vehicle charging load curve. Maximum photovoltaic utilization and minimum electricity cost have been achieved. This method has been used in two cases and proved that it can reduce the customers charging price and the operator electricity cost, so that both the customers and the operator benefit from this. Furthermore, the demand on grid capacity is reduced, which improves the versatility of charging station infrastructure.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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