Analysis of Optimal Bidding Strategy of Electric Vehicle Aggregators in Real-Time Energy Market

Xiumei Hou\textsuperscript{1,}, Wei Liu\textsuperscript{3}, Shiyu Chen\textsuperscript{2}, Yuenan Guo\textsuperscript{3}

\textsuperscript{1}State Grid Heilongjiang Electric Power Maintenance Co., Ltd. Harbin 150001, China
\textsuperscript{2}State Grid Heilongjiang Electric Power Co., Ltd. Electric Power Research Institute, Harbin 150001, China
\textsuperscript{3}State Grid Heilongjiang Electric Power Co., Ltd. Harbin 150001, China

*Corresponding author: houxm@hec.hl.sgcc.com.cn

Abstract. A power price control strategy is proposed for the charging of electric vehicles. Aggregation managers centrally manage the batteries of electric vehicles, and take into account the limited power supply of the grid during peak electricity consumption, and adjust the demand for charging through electricity price control. By analyzing the main body of the smart grid power market, the article constructs a multi-objective economic dispatch model, and uses Matlab to perform numerical simulation experiments on the model to verify the feasibility and effectiveness of the model.

1. Introduction
A large number of electric vehicles connected to the grid will inevitably affect the grid. First, the charging load of electric vehicles will increase the total load on the grid. Secondly, if the charging of electric vehicles is not controlled, the peak load of the power grid and power grid losses will greatly increase, which will not only cause waste of resources, but also affect the normal operation of the power grid. Therefore, the research should consider whether it can properly control the charging process of electric vehicles, smooth the load curve, reduce peak load and loss, so as to reduce the peak load and loss of the power grid, improve equipment utilization, improve power supply reliability, reduce loss, and delay investment. Based on the above analysis, this paper proposes an electricity price control strategy suitable for charging electric vehicles in smart grids [1]. This method performs coordinated control on the charging process of electric vehicles under the same distribution transformer, suppresses load fluctuations, and avoids overloading of the transformer due to the charging load of electric vehicles, which ensures operating economy and minimizes the repeated charging and discharging process to the battery. The damage caused.

2. System Model
In the smart grid, the charging scenario of electric vehicles is shown in Figure 1. The aggregate manager is the interface between electric vehicles and the grid, providing battery management and charging services. In the smart grid, an aggregation manager provides services for vehicles in a business district or a city. There is a charging pile at every parking location in the area. The charging pile is the interface between the electric vehicle and the aggregation manager, providing two-way communication and charging power. Figure 1 does not mean that vehicles must be charged at the same charging station.
Vehicles are charged in their respective parking spaces, and the aggregation manager controls the charging through two-way communication [2]. The aggregation manager aggregates the batteries of all connected vehicles in the area to form an aggregate battery. The charging demand of the aggregate battery represents the total charging demand of the connected vehicles in its coverage area.

When implementing electricity price control, the aggregate battery will adjust the charging demand according to its own power (SOC) and electricity price. However, the arrival and departure of vehicles will cause dynamic changes in the capacity and power of the aggregate battery. The mobility of electric vehicles makes it difficult for aggregate managers to predict the state of aggregate batteries, thereby affecting the effectiveness of electricity price control. In this paper, adaptive dynamic programming is adopted to obtain the optimal electricity price strategy through online learning of the mobility and charging process of electric vehicles.

3. Vehicle selection algorithm

The purpose of the vehicle selection algorithm is to make the charging and discharging power of the whole station at that moment match the order issued by the electric vehicle charging and discharging monitoring centre as much as possible, which is the key to determining the charging and discharging vehicle and power [3]. The vehicle selection algorithm must not only meet the mobility of vehicle selection, and ensure that the selected vehicle and its charge and discharge power change with the change of the charge and discharge plan of the whole station; it must also meet the stability of vehicle selection and prevent the charge and discharge power of the same vehicle. Frequent changes can damage battery performance. The objective function and constraint conditions of the vehicle selection algorithm are shown in equations (1) and (2):

\[
F_{\text{min}} = \sum_{j=1}^{m} \left( \sum_{i=1}^{n} P_{ij} - P_{ij}^{\text{opt}} \right)^2
\]

\[
I_{i\text{min}} \leq I_{ij} \leq I_{i\text{max}}
\]
In the formula: n is the number of electric vehicles in the station; \( P_{ij} \) is the charging and discharging power of the i car in j period (positive value is charging, negative value is discharging); \( P_{oj} \) is the charging and discharging command power received during j period; F is the station The square of the difference between the charging and discharging power of the entire station vehicle and the received charging and discharging command power value in m periods, the smaller F is, the better the charging and discharging plan will be executed; \( I_{ij} \) is the charging and discharging current of the i vehicle in j period (positive value Charging, negative value is discharging); \( I_{imin} \) is the discharge current limit of the i car, and \( I_{imax} \) is the charging current limit of the ith car.

4. Electricity price strategy for smart grid

Grid companies will guide electricity users to shift peak electricity consumption by changing the level of electricity prices. Common electricity price models include: instant electricity prices, electricity prices announced the day before, time-of-use electricity prices, and peak-time feedback electricity prices. This article uses the price announced by the power grid company on October 25, 2019. The unit price of its electricity price system during peak and off-peak hours is different, as shown in Table 1. This article divides the 1h electricity price into 2 periods, a total of 48 periods a day for discussion, and uses the multi-objective optimization method introduced later to do related numerical simulation and analysis.

| time | Electricity price/(cent/kW) |
|------|---------------------------|
| 1:00 | 23.53                     |
| 2:00 | 23.32                     |
| 3:00 | 22.83                     |
| 4:00 | 22.67                     |
| 5:00 | 23.33                     |
| 6:00 | 25.00                     |
| 7:00 | 22.12                     |
| 8:00 | 32.12                     |
| 9:00 | 37.04                     |
| 10:00| 36.76                     |
| 11:00| 38.36                     |
| 12:00| 40.00                     |

4.1. Target optimization

4.1.1. The utility of electric vehicles. Electric vehicle users make reservations for the nearest charging service developer through their mobile phones and select the corresponding charger number on the mobile phone, which can save the cost of electric vehicle charging, improve work efficiency, and increase the revenue of electric vehicles. Electric vehicle users receive real-time electricity price information through their mobile phones, understand the details of real-time electricity prices in time, choose a reasonable time period for charging, increase the willingness of electric vehicle users to choose independently, and improve the awareness of saving and environmental protection. And can interact with charging service developers, reflect their own charging experience, put forward some problems in the charging process, and improve the electricity efficiency of electric vehicle users [4]. The charging benefit of electric vehicle users is generally reflected by the utility function. Here, \( B(\eta, Q^r) \) is used to calculate the electricity benefit of electric vehicle users, and the charging intention of each electric vehicle user in each time period is different. The charging process of electric vehicle users is a process of psychological satisfaction. In the initial stage, the utility obtained will increase rapidly, but as time
goes by, the rising speed will slow down until the utility reaches the maximum, which is in line with the user’s psychology. Willingness. Therefore, the three-time utility function is used to quantify the benefit of charging:

\[ B(\eta, Q^r) = \eta (Q^r)^2 - \varepsilon (Q^r)^3 \]  

(3)

In the formula, \( \eta, \varepsilon \) represent the electric vehicle user’s willingness to charge and the user’s mental account, respectively, and \( Q^r \) represents the charging load.

4.1.2. Objective function. Electric vehicle users charge at real-time electricity prices, and substituting all parameters into the user utility function, the user's total utility value \( W^r (t) \) at time \( t \) can be obtained:

\[ W^r (t) = \sum_{t=0}^{24} \left( B(\eta, Q^r) - Y^r + R^r \right), 0 < Q^r < \frac{2\eta}{3\varepsilon} \]  

(4)

Through the analysis of the obtained values, within one day, we can find the time period with the greatest user benefit, and we can also find the maximum profit of the charging service developer within one day. In this paper, the optimization scheduling research comprehensively considers the profit of charging service developers and the benefits of electric vehicle users, and uses a linear weighting method to process the multi-objective optimization function and optimize the objective function [5]. Use \( a \) and \( b \) to denote the weight coefficients of charging service developers and electric vehicle users, respectively.

\[ a + b = 1 \]

\[ \max L_{\text{in}} (t) = a W^r (t) + b F^r (t) \]  

(5)

Constraints on the available capacity of electric vehicle batteries:

\[ SOC_{EV_{\text{min}}} \leq SOC (t) \leq SOC_{EV_{\text{max}}} \]  

(6)

In the formula, \( SOC (t), SOC_{EV_{\text{min}}}, SOC_{EV_{\text{max}}} \) is the battery capacity state of the electric vehicle at time \( t \), the minimum and maximum available capacity of the electric vehicle battery? Taking into account the service life of the battery, \( SOC_{EV_{\text{min}}} \) is 0.2 and \( SOC_{EV_{\text{max}}} \) is 0.85.

4.2. Electric vehicle charging strategy

Based on the above theory, a constant load value that has the same power consumption as the local load must be determined first. After the electric vehicle is connected, the total load of household \( i \) includes the base load and the charging load of the electric vehicle, namely

\[ f^i_{1, t} (t) = f^i_{1, b} (t) + f^i_{c} (t) \]  

(7)

In the formula: \( f^i_{1, t} (t) \) is the total load of family \( i \); \( f^i_{1, b} (t) \) is the base load of family \( i \); \( f^i_{c} (t) \) is the charging load of electric vehicles. First, consider the base load value of family \( i \). Suppose the constant base load value \( L_{i, b} (t) \), which has the same electric quantity as the base load value \( f^i_{1, b} (t) \) of family \( i \) in the time period \([a, b]\) is
Therefore, the charging power \( f_c^i(t) \) can be obtained within the constrained range to minimize the value of the objective function, that is, to formulate a charging strategy for household \( i \) to minimize the loss [6].

5. Example simulation

5.1. Simulation parameter setting
In order to verify the effectiveness of the algorithm in this paper, a simulation program was developed in the Matlab 2013 environment. Without loss of generality, suppose a cell is powered by a transformer with a rated capacity of 160kVA. There are 50 electric vehicles in the cell, the model is Chevy Volt (20 vehicles, serial number 1-20), Nissan LEAF (20 vehicles, Serial number 21-40) and Tesla Roadster (10 vehicles, serial number 41-50). The scheduling interval is from 17:00 to 7:00 the next day, a total of 14h, which is divided into 70 time slots with a single length of 0.2h. The transformer load management system predicts the total load in the district except the electric vehicle charging load as shown in Figure 2.

![Figure 2. Predicted cell load without electric vehicle charging power.](image)

5.2. Simulation results and analysis
Under the control of the collaborative charging optimization scheduling algorithm, the total load curve of the cell including the electric vehicle charging load in the scheduling interval is shown in Figure 3. For the convenience of comparison, the total load curve of each electric vehicle optimized separately is also given in the figure. As shown in Figure 3, no matter under the control of the algorithm in this paper or the independent optimization scheduling algorithm, users tend to charge electric vehicles during the time when the electricity price is the lowest in order to minimize the user's charging fee. However, if the user's charging behaviour is not coordinated control, a huge load peak will be formed during the low electricity price period. The load peak when optimized independently in Figure 3 is 300.82kW, which
is 1.88 times the rated capacity of the transformer, causing serious overload and acceleration. The aging of the transformer threatens the stable operation of the power system. The maximum load of 160kW under the control of the algorithm in this paper can effectively avoid the overload of transformer load and enhance the stability of the power system [7].

![Figure 3. Total cell load curve in the dispatching interval.](image)

At the end of the simulation, the actual SOC values of all 50 electric vehicles under the control of the algorithm in this paper have reached the user's set value, while under the control of the over-limit issuing DR signal method, only 19 electric vehicles' SOC reached the set value; and, if the same electric vehicle can reach the SOC value set by the user in these two modes, the user's charging fee under the control of this algorithm is lower than the charging fee in the mode of over-limit issuing DR signal. Under the two control methods, the average charging cost of electric vehicles who’s final SOC reaches the user's set value is 7.36 yuan under the control of the algorithm in this paper, and 7.55 yuan under the over-limit release DR signal mode.

6. Conclusion
It can be seen from the simulation that the battery replacement station achieves its own economical optimization by responding to the different electricity prices issued by the grid, and at the same time indirectly realizes the response to the grid peak shaving strategy; on this basis, the battery health is used as an indicator, through Gradient utilization makes reasonable use of batteries on the basis of ensuring battery health, ensuring the health of the batteries in the station to the greatest extent, and prolonging the service life of the batteries; and the user satisfaction of different periods is considered in the constraint conditions to achieve overall optimization. The optimal feasible solution can be obtained after the number of handovers is reduced to a certain extent.

References
[1] Sarikprueck, P., Lee, W. J., Kulvanitchaiyanunt, A., Chen, V. C., & Rosenberger, J. M. Bounds for optimal control of a regional plug-in electric vehicle charging station system. IEEE Transactions on Industry Applications, 54(2) (2017) 977-986.
[2] Ahmad, A., Khan, Z. A., Saad Alam, M., & Khateeb, S. A review of the electric vehicle charging techniques, standards, progression and evolution of EV technologies in Germany. Smart Science, 6(1) (2018) 36-53.
[3] Pagany, R., Ramírez Camargo, L., & Dorner, W. A review of spatial localization methodologies for the electric vehicle charging infrastructure. International Journal of Sustainable Transportation, 13(6) (2019) 433-449.
[4] Vagropoulos, S. I., Balaskas, G. A., & Bakirtzis, A. G. An investigation of plug-in electric vehic
le charging impact on power systems scheduling and energy costs. IEEE Transactions on power systems, 32(3) (2016) 1902-1912.

[5] Hassoune, A., Khafallah, M., Mesbahi, A., & Bouragba, T. Power management strategies of electric vehicle charging station-based grid tied PV-battery system. International Journal of Renewable Energy Research, 8(2) (2018) 1-10.

[6] Muratori, M. Impact of uncoordinated plug-in electric vehicle charging on residential power demand. Nature Energy, 3(3) (2018) 193-201.

[7] Sarker, M. R., Pandžić, H., Sun, K., & Ortega-Vazquez, M. A. Optimal operation of aggregated electric vehicle charging stations coupled with energy storage. IET Generation, Transmission & Distribution, 12(5) (2017) 1127-1136.