Optimal Charging Strategy of Electric Vehicles in Smart Grid Considering the Characteristics of Lithium Ion Batteries

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***Abstract*—In recent years, the number of electric vehicles (EVs) in China has increased rapidly. In order to deal with the peak load and severe load fluctuation caused by large-scale EVs connected to the power grid, it is particularly important to obtain the optimal scheduling of EV demand and make the load curve flat. In this paper, Gauss distribution is used to predict the uncertain behavior of EV drivers, considering the characteristics of lithium ion batteries and the charging rate of batteries. The optimal solution of the charging target optimization model of EV in regional distribution network is obtained by improved genetic algorithm. Intelligent coordination of EV power demand improves the flexibility and security of power system, and reduces the cost of power system operation.**

***Keywords*—electric vehicle, smart grid, genetic algorithm, lithium ion battery, gauss distribution**

I. Introduction

In the traditional transportation network, the energy efficiency of diesel locomotives is only 20% [1]. With the promotion of clean energy consumption and the gradual development of EV related technologies in the world, the number of EVs is showing explosive growth [2]. In order to deal with this situation, EV charging strategy as the premise of EV entering thousands of households, is particularly important.

At present, there are four kinds of battery management technologies in the residential network, among which the smart grid-to-vehicle (G2V) load management technique as well as the smart grid-to-vehicle and vehicle-to-grid (G2V-V2G) load management technique is the focus of our research [3]. Through the optimized charging strategy, the smart grid can better realize peak load shifting.

In the current research, EV charging strategies have been gradually mature and improved, but there are still some problems. Reference [4] proposed a charging strategy based on parameter estimation, which is highly theoretical, but fails to reflect the law of users' charging behavior and lacks practicality. Reference [5] proposed a control algorithm for peak load shifting, which considers vehicle requirements and load requirements, but has certain limitations on the scale of EVs in the region. In [3], the effect of SOC (state of charging) is considered, but the EV charging state is not modeled. In [6], the randomness of EV charging is considered, but the characteristics of lithium ion batteries are not discussed too much and the charging model needs to be further optimized.

To sum up, starting from the user side and considering the randomness of EVs connected to the grid, this paper modeled the charging connection state of EV. Meanwhile, the effect of charging rate of lithium ion batteries is considered. Finally, the optimal solution of EV charging target optimization problem is given by genetic algorithm.

II. Establishment of System Model

Suppose that in a certain community, all EVs charging scheduling is realized by a programmable device connected to the residential network, and the function representing the charging situation of a specific electric vehicle connected to the grid at a certain time is as follows:

$$N_i(t) = \{0,1\} \tag{1}$$

If the i-th EV is connected to the grid for charging at time t, the function value is one, otherwise it is zero.

A. Establishment of Objective Function

This paper takes half an hour as the time interval, and the objective function uses the sum of load deviation between consecutive time periods to reflect the load fluctuation in a day, as follows:

$$F_{\mathrm{L}}(t) = \sum_{t=1}^{T} [\left| P_{\mathrm{total}}(t) - P_{\mathrm{total}}(t-1) \right|] \tag{2}$$

$$P_{\mathrm{total}}(t) = P_{\mathrm{EV}}(t) + P_{\mathrm{add}}(t) \tag{3}$$

T is the termination time, $T = 48$ in the time division of this paper. $P_{\mathrm{total}}(t)$ represents the summation of EV charging load and all other loads except EV at time t. The total electric energy demand of all EVs in the inspection area at time t can be expressed by (4):

$$P_{\mathrm{EV}}(t) = \sum_{i=1}^{I} \{[1 - SOC_{\mathrm{ini}}(i,t)] \times N_i(t)\} \tag{4}$$

I is the total number of electric vehicles. $SOC_{\mathrm{ini}}(i,t)$ represents the remaining battery power of the ith EV at time t.

In this paper, the solution of EV optimal scheduling is essentially to solve the optimization problem with inequality constraints, that is, to find the charging scheduling that makes

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$F_L(t)$ reach the minimum value, so as to achieve the minimum fluctuation of all loads in a day and better peak cut and valley filling for load curve.

B. EV Connection State Model

The establishment of EV connection state model needs to consider the randomness of EVs connected to the power grid. A day is divided into 48 time periods with half an hour as the interval, and the number of electric vehicles in a residential area charging at home at a certain time is counted. According to the data of [7], the peak time for EVs to get home is between 17:00 and 20:00 and the trough time is between 1:00 and 5:00. By fitting the users' charging behavior with Gaussian distribution, the following probability density distribution function can be obtained:

$$f(x)=\begin{cases}\dfrac{1}{\sigma\sqrt{2\pi}}e^{-(x-\mu)^2/2\sigma^2},(\mu-24)<x<48\\ \dfrac{1}{\sigma\sqrt{2\pi}}e^{-(x+48-\mu)^2/2\sigma^2},0<x<(\mu-24)\end{cases} \tag{5}$$

Where x is a random variable, μ is the mean value of the distribution, and σ is the standard deviation.

C. Charging Rate of Lithium Ion Batteries

As the most widely used batteries in electric vehicles, lithium ion batteries generally adopt the method of constant current first and constant voltage later, that is, when charging starts, it first enters the constant current charging mode, with constant current, constant voltage rising to the rated value, and then enters the constant voltage charging mode, with constant voltage and constant current falling to the end of battery charging [8]. In [9], the radio energy transmission mode based on LCL resonance compensation network is adopted. By adding a magnetic energy regeneration switch at the secondary side, the demand of constant current first and then constant voltage is met, and the mode switching in the charging process is more stable. The equivalent circuit diagram is as follows:

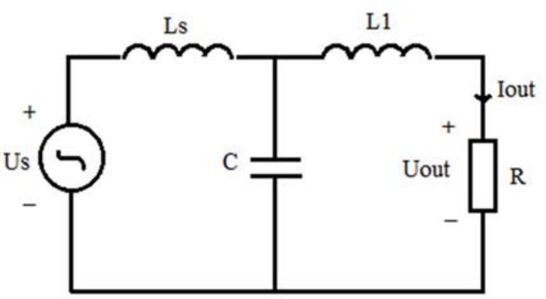

Fig. 1. Equivalent circuit diagram of radio energy transmission system

Equation (6) can be obtained from Fig. 1. When (6) is satisfied, the output current at the load end is kept constant, that is, the constant current charging mode is entered. The output current is as shown in (7):

$$\boldsymbol{Z}_{\mathrm{Ls}}+\boldsymbol{Z}_{\mathrm{C}}=\boldsymbol{Z}_{\mathrm{L1}}+\boldsymbol{Z}_{\mathrm{C}}=0 \tag{6}$$

$$\boldsymbol{I}_{\mathrm{out}}=\frac{\boldsymbol{U}_{\mathrm{s}}}{\boldsymbol{Z}_{\mathrm{C}}} \tag{7}$$

Equation (8) can be obtained from Fig. 1. When (9) is satisfied, the output voltage at the load end is kept constant, that is, the constant voltage charging mode is entered. The output voltage is as shown in (10):

$$\frac{\boldsymbol{U}_{\mathrm{out}}}{\boldsymbol{U}_{\mathrm{s}}}=\frac{\boldsymbol{Z}_{\mathrm{C}}}{\boldsymbol{Z}_{\mathrm{Ls}}+\boldsymbol{Z}_{\mathrm{C}}+\dfrac{\boldsymbol{Z}_{\mathrm{Ls}}\boldsymbol{Z}_{\mathrm{L1}}+\boldsymbol{Z}_{\mathrm{L1}}\boldsymbol{Z}_{\mathrm{C}}+\boldsymbol{Z}_{\mathrm{Ls}}\boldsymbol{Z}_{\mathrm{C}}}{R}} \tag{8}$$

$$\boldsymbol{Z}_{\mathrm{Ls}}\boldsymbol{Z}_{\mathrm{L1}}+\boldsymbol{Z}_{\mathrm{L1}}\boldsymbol{Z}_{\mathrm{C}}+\boldsymbol{Z}_{\mathrm{Ls}}\boldsymbol{Z}_{\mathrm{C}}=0 \tag{9}$$

$$\boldsymbol{U}_{\mathrm{out}}=\frac{\boldsymbol{Z}_{\mathrm{C}}}{\boldsymbol{Z}_{\mathrm{Ls}}+\boldsymbol{Z}_{\mathrm{C}}}\times\boldsymbol{U}_{\mathrm{s}} \tag{10}$$

The internal resistance of battery charging is affected by SOC, ambient temperature and charging current of battery. For convenience, this paper assumes that all EV users use the same battery, the type of lithium ion battery is ternary lithium ion battery, and the ambient temperature is 20 °C. According to [10], the change of charging internal resistance R with charging current at different SOC can be obtained, and the EV dynamic charging power P_1 can be obtained by combining the output current under constant current condition and the output voltage under constant voltage condition. From this, we can get the change of EV remaining power in the home as follows:

$$SOC_{\mathrm{ini}}(i,t+1)=SOC_{\mathrm{ini}}(i,t)+N_i(t)P_1(SOC_{\mathrm{ini}}(i,t)) \tag{11}$$

$$P_1=\begin{cases}I_{\mathrm{out}}^2R(SOC_{\mathrm{ini}}(i,t)),\text{constant current mode}\\ \dfrac{U_{\mathrm{out}}^2}{R(SOC_{\mathrm{ini}}(i,t))},\ \text{constant voltage mode}\end{cases} \tag{12}$$

D. Unequal Constraints

In this paper, when finding the optimal solution of the objective function, we need to consider that the number of EVs charging in the same time can not be greater than the number of EVs returning home, and the total power demand can not be higher than the maximum load-carrying capacity of the regional power grid, so we need to establish the related inequality constraints (13), (14):

$$I\times\int_1^t f(t)dt\geq\sum_{i=1}^{I}N_i(t) \tag{13}$$

$$P_{\mathrm{total}}(t)\leq P_{\max} \tag{14}$$

I is the total number of electric vehicles, $P_{\max}$ is the maximum carrying capacity of regional power grid.

III. Genetic algorithm

The paper chooses genetic algorithm because of its rapidity and flexibility in dealing with the optimization problems with many constraints, as well as the low requirements of this algorithm for the initial data and the randomness of the initial data generation [11].

This paper needs to obtain the optimal scheduling of electric vehicle demand and make the load curve flat, that is to say, EV charging strategies are searched through the continuous iteration of genetic algorithm to obtain the minimum value of $F_L(t)$ [12].

Firstly, input the data, initialize the charging strategy about $N_i(t)$, $P_{EV}(t)$ and calculate the F_L value of the charging strategy used in [13]. Then, the EV charged at time t is determined by $N_i(t)$ and $SOC_{ini}(t)$, and the residual electricity of EV at time (t + 1) is calculated according to (11). The F'_L under this charging strategy is calculated iteratively. F'_L is compared with F_L of the original charging strategy. If the value is larger than F_L, the charging strategy will be updated and the iterative comparison will continue. After several iterations of searching, we will get the optimal charging strategy about $N_i(t)$. This algorithm searches according to the rule of probability change and its search space is very large. Although compared with the traditional method, it has a large amount of computation and a slow speed, it avoids the situation of only getting local optimum. The specific flow chart is as follows:

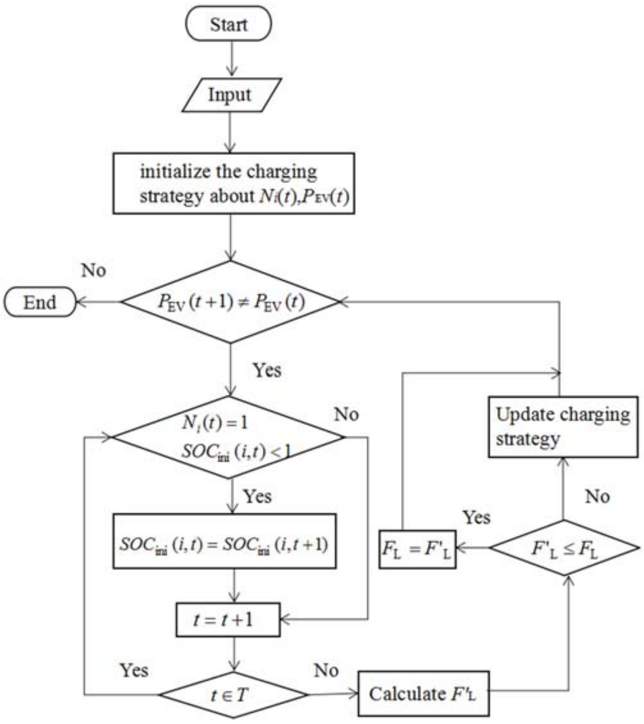

Fig. 2. Improved genetic algorithm flow chart

In the following simulation, the size of EVs is 100. The larger scale ensures the faster convergence speed of genetic algorithm, and avoids the problem of too long calculation time caused by too large initial scale [14]. In order to ensure better convergence to the global optimal, this paper sets up elite individuals in each generation of genetic algorithm, and selects a mutation rate of 50%.

IV. Simulation Result

In the process of simulation, the data of [7] are used to model the uncertainty of user behavior, and the data of [15] and [17] are used to model the residential power consumption. The transmission limit of power grid is 300kVA. EV smart load management is based on the improved genetic algorithm in this paper. It covers 100 users, and each user will connect EV to the grid as soon as they get home. The specific charging time will be controlled by the smart grid aggregator [16]. By the time you get home, the residual electricity of EV is evenly distributed between 5% and 90% [17].At the same time, in order to simplify the calculation, it is assumed that all EVs will leave the grid only after they are fully charged and each EV has a capacity of 35kWh .The power level of the charging pile is 7kW [18].

Fig. 3 compares the proportion of EVs charging in the grid in each period of the day under the traditional EV charging strategy in [3], the charging strategy in [19] and the charging optimization strategy in this paper. The peak time of EV charging in traditional charging strategy is 1:00, and the trough time is from 18:00 to 21:00, when EVs completely stop charging. Under the charging strategy in [19], EV access charging is concentrated at 5:00, and the trough time is from 18:00 to 20:00, which guarantees 5% of EVs charging in the low valley. However, in the charging strategy of this paper, EV peak charging is at 4:00, the valley charging is from 18:00 to 20:00, and the valley charging guarantees 10% of EVs charging.

Fig. 4 and Fig. 5 are respectively compared with the total load curve of the users' electric energy under the charging strategy in this paper and the curve of the other two charging strategies. Fig. 4 compares the total energy load curve of the users under the traditional EV charging strategy with the total energy load curve under the charging strategy in this paper. Fig. 5 compares the total energy load curve of the users under the charging strategy in [19] with the total energy load curve under the charging strategy in this paper. Under these three charging strategies, the total power demand is no higher than the maximum carrying capacity of the regional power grid. Finally, it is calculated that F_L under the charging strategy of this paper is 368kVA, F_L under the traditional charging strategy is 417kVA, and F_L under the charging strategy in [19] is 394kVA.It can be seen from the comparison that the F_L calculated in this paper is the smallest, and the effect of peak clipping and valley filling is more significant.

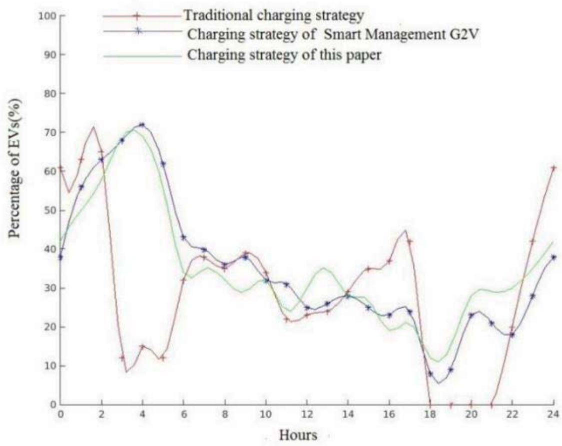

Fig. 3. Percentage of EVs charging in the grid under three charging strategies

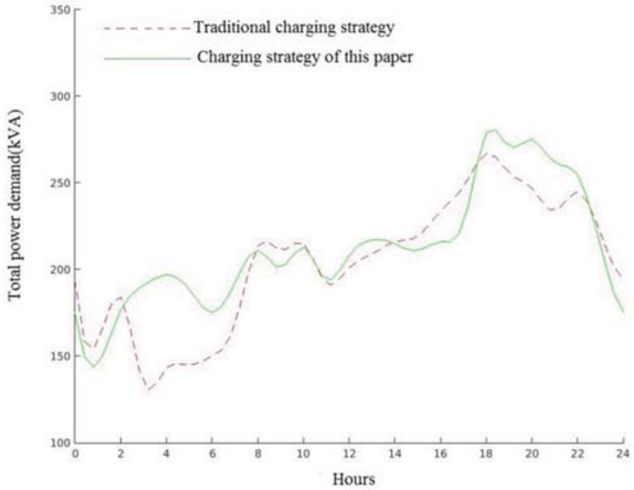

Fig. 4. Total power demand model under the charging strategy in this paper and the traditional charging strategy

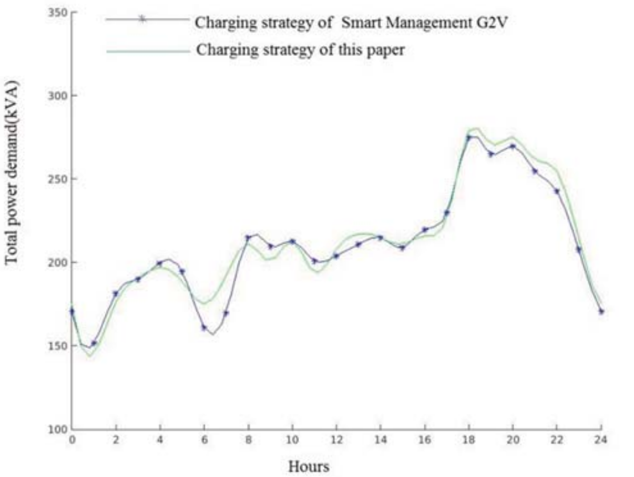

Fig. 5. Total power demand model under the charging strategy in this paper and the charging strategy in [19]

In combination with Fig. 3, Fig. 4 and Fig. 5, the advantages of this charging strategy can be summarized:

1) Compared with the traditional charging strategy, EV access charging is not completely stopped at the peak power demand time. Compared with the charging strategy in [19], it not only disperses the power demand at peak power consumption, but also increases the charging access of some EVs at peak power consumption, which is convenient for residents to travel and has a better valley filling effect.

2) Compared with the other two strategies, F_L decreases significantly, load curve is flatter, and power supply quality is improved.

3) Compared with the other two strategies, the algorithm of optimizing charging strategy in this paper not only considers the uncertainty of user behavior, but also considers the charging characteristics of the batteries. It does not simply divide the battery charging into fast and slow modes.

V. Conclusion

In this paper, based on the traditional EV optimal charging strategy, an algorithm to improve charging strategy is proposed. The users' charging behavior is fitted by Gaussian distribution to predict the drivers' uncertain behavior. At the same time, the algorithm takes into account the characteristics of lithium ion batteries, that is, the change of internal resistance with charging current at different SOC. The purpose of this genetic algorithm (GA) is to find the optimal solution of the target optimization model of EV charging, that is to update the iterative charging strategy for many times to minimize the fluctuation of the total load of users and to make the load curve most gentle, so as to improve the flexibility, safety and economy of grid operation. Compared with the charging strategies in [3] and [19], the charging strategies obtained by this algorithm are more superior. The subsequent research can further optimize the charging model based on this algorithm, and at the same time, combine economic means to reduce the adverse effect of EVs connected to the power grid for charging, so as to promote the promotion of electric vehicles.

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References

[1] R. Reisinger, A. Emadi, "Sensible transportation electrification: get rid of inefficient powertrain designs," IEEE Electrification Magazine, vol. 1, pp. 6–12, Dec. 2013.

[2] J. Han, L. Kong, and H. Wang, "Review on the planning of charging facilities for electric vehicles," Proceedings of the CSU-EPSA, vol.28, pp. 63–67, Dec. 2016.

[3] M. Alonso, H. Amaris, J. G. Germain, and J. M. Galan, "Optimal charging scheduling of electric vehicles in smart grids by heuristic algorithms," Energies, vol. 7, pp. 2449–2475, Jul. 2014.

[4] H. Hou, H. Fan, and J. Xie, "The optimal charging strategy of EV rational user based on TOU power price," Electric Power, vol.28, pp. 171–178, Oct. 2018.

[5] Z. Wang, S. Wang, "Grid Power Peak Shaving and Valley Filling Using Vehicle-to-Grid Systems," IEEE Trans. Power Deliv., vol.28, pp. 1822–1829, Jun. 2013.

[6] J. Yao, T. Han, W. Lu, Q. Yan, C. Liu, and Z. Yang, "Electric Vehicle Charging Strategy for Smart Grid Considering Uncertainties in User Behaviors," Proceedings of the CSU-EPSA, vol.11, pp. 84–89, Mar. 2019.

[7] S. E. Galus. (2018, Sep.). Energy National Laboratory User Data. Lawrence Berkeley National Laboratory, San Francisco, CA. [Online]. Available: http://v2gsim.lbl.gov/case-studies/grid-impacts.

[8] R. Mai, Y. Chen, and Y. Liu, "Compensation capacitor alteration based IPT battery charging application with constant current and constant voltage control," Proceedings of the CSEE, vol.36, pp. 5816–5821, Dec. 2016.

[9] L. Ji, L. Wang, C. Liao, and S. Li, "Research and Design of Automatic Alteration between Constant Current Mode and Constant Voltage Mode at the Secondary Side Based on LCL Compensation Network in Wireless Power Transfer Systems," Transactions of China Electrotechnical Society, vol.33, pp. 34–40, May 2018.

[10] W. Sun, "Research on Charging Properties and Control technology Optimization of Lithium-ion Power Batteries," Ph.D. dissertation, Univ.Jilin, China. Changchun, 2018.

[11] H. Hou, H. Fan, and J. Xie, "Computational intelligence-based energy management for a large-scale PHEV/PEV enabled municipal parking deck," Appl. Energy, vol.96, pp. 171–182, Feb. 2012.

[12] J. Zheng, X. Wang, K. Men, C. Zhu, and S. Zhu, " Aggregation model-based optimization for electric vehicle charging strategy," IEEE Trans. on Smart Grid, vol.4, pp. 1058–1066, Mar. 2013.

[13] F. Ju, C. Yang, X. Xu, J. Zhang, and Y. Liu, "A charging strategy for electric vehicles based on spatiotemporal restriction," Power System and Clean Energy, vol.32, pp. 96–101, Mar. 2016.

[14] M. Alonso, H. Amaris, "Integration of renewable energy sources in smart grids by means of evolutionary optimization algorithms," Expert Syst. Appl., vol.39, pp. 5513–5522, Jun. 2012.

[15] P. Stanley. (2013, Nov.). Load profiles and their use in electricity settlement. Elexon, London, UK. [Online]. Available: https://www.docin.com/p-1400640503.html.

[16] Ch. Peng, J. Zou, L. Lian, and L. Li, "An optimal dispatching strategy for V2G aggregator participating in supplementary frequency regulation considering EV driving demand and aggregator's benefits," Appl. Energy, vol. 190, pp. 591-599, Sep. 2017.

[17] W. Bush. (2020, Jan.). Independent Electricity System Operator Power Data. IESO, Toronto, ON. [Online]. Available: http://www.ieso.ca/Pages/Power-Data/default.aspx.

[18] B. Lane. (2019, Sep.). Connector selector. Next Green Car Ltd., Bristol, UK. [Online]. Available: http://www.zap-map.com.

[19] M. R. Mozafar, M. H. Amini, M. H. Moradi, and J. M. Galan, "Innovative appraisement of smart grid operation considering large-scale integration of electric vehicles enabling V2G and G2V systems," Electric Power Systems Research, vol. 154, pp. 245–256, Sep. 2018.