A Coordinated Charging Strategy for Electric Vehicles Based on Multi-objective Optimization

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***Abstract*—With the rapid growth of electric vehicles (EV), the uncoordinated charging will jeopardize the power grid. In order to reduce the impacts of the uncoordinated charging, in this paper, a multi-objective optimization algorithm based coordinated EVs charging strategy has been proposed, which considers both user level and system level benefits simultaneously. According to the actual driving pattern data of EV users, the charging demand of EVs is established by Monte Carlo method. On the basis of the difference for electrical charging cost on peak/valley of power grid, the charging patterns are refined by multi-objective optimization scheduling model. A case study also been provided on the paper to verify the effectiveness of the proposed method.**

Keywords-electric vehicles; multi-objective optimization; coordinated charging strategy; monte carlo method; CPLEX

I. INTRODUCTION

With the environmental pollution and energy crisis are continuously getting worse, the electric vehicle (EV) industry has developed rapidly in recent years. According to the 13th Five-Year Plan of Chinese government, the number of EVs will reach 5 million in 2020 [1]. EV has the advantages over traditional fuel vehicles in terms of energy saving, emission reduction, and curbing climate warming. But the charging place and charging time of electric vehicle have dispersion and randomness [2], which will exert a tremendous influence on the power grid real-time balance.

In order to reduce the adverse effects, a great deal of researches on the coordinated charging of electric vehicles were investigated. Clement-Nyns *et al*. in [3] improved the particle swarm optimization algorithm to optimize the charging of electric vehicles, but only slow charge optimization strategies of electric vehicles at night are consisted, daytime charging behaviors not informed in the paper. In [4], Xu *et al.* discussed different types of EV charging mode, then puts forward the calculation method of EV charging load, in addition, predicts and analyses future charging load of EV. But only considers continuous charging, potential intermittent charging behaviors failed to apply to the paper. An optimization model with minimum charging cost proposed in [5], and the model is solved by NSGA-II algorithm, while, this model does not consider the fluctuation of load. Wang *et al*. in [6] optimized the level of electric vehicle charging station directly, and the coordinated scheduling of wind power and electric vehicle charging is studied in this paper, however, the established model only constrains the node voltage and transmission power, no constraint considering charging time or charging capacity. Li in [7] proposed a coordinated charging strategy with reducing the loss of distribution network, and the load maximum value, minimum value is optimized, thereby reducing the peak-valley difference of load, while this model only guarantees the stable operation of the power grid without considering the economy of EV charging. In [8], Schuller *et al*. presented a charging strategy, aim at the earliest charging time, the lowest charging cost, and the periods of time-of-use price are reclassified, so as to improve the response degree of the EV users to coordinated charging, however, a large number of cars are concentrated during the price trough, may cause new load spikes, affect the safe operation of the power grid.

To solve the problems on above researches, in this paper, a multi-objective optimization based coordinated charging strategy for electric vehicles to realize optimal EV charging cost and restraining the peak-valley difference of power grid load. The paper is organized as follows: Section II researches on charging characteristics and travel habits of electric vehicle, and simulates the random charging load of electric vehicle by Monte Carlo method. Section III establishes the multi-objective optimization model and constructs the optimal objective function. Section IV puts forward a case study to verify the efficiency of the proposed strategy. Conclusion and perspectives are presented in Section V.

II. EV UNCOORDINATED CHARGING LOAD SIMULATION

A. Analysis of Charging Characteristics and Travel Habits

Charging characteristics of EV is the basis of modeling the uncoordinated charging load. To explain the analyzing process, an example case is utilized. In the case, EV charging power is set as constant power of 3.5kW, which has the rated voltage of 220V and rated current of 16A. According to the practice, the charging process of EV usually takes 5~8 hours.

Analysis of EV users' travel pattern is also a necessary factor for modeling the charging load, a typical travel pattern can be described by arrival time, mileage, etc. Generally, the starting time of charging for private EV usually happen at evening in residence and during the daytime in workplace. Based on 2016 Annual Report on Traffic Development in

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Beijing[9], it is assumed that it would not travel any longer in a day if an EV starts charging in residence, after fitting the data, the arrival time can approximately meet Gaussian distribution, as shown in the Fig. 1:

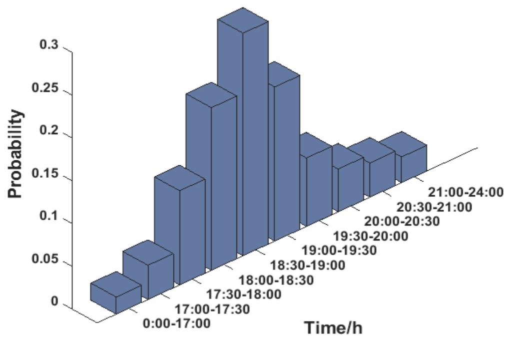

Figure 1. Probability curve of car owners home time.

The probability density function is

$$f_{1s}(x)=\begin{cases}\dfrac{1}{\sigma_{1s}\sqrt{2\pi}}exp\left[-\dfrac{(x-\mu_{1s})^2}{2\sigma_{1s}^2}\right] \\ (\mu_{1s}-12)<x\le 24 \\ \dfrac{1}{\sigma_{1s}\sqrt{2\pi}}exp\left[-\dfrac{(x+24-\mu_{1s})^2}{2\sigma_{1s}^2}\right] \\ 0<x\le(\mu_{1s}-12)\end{cases} \tag{1}$$

where μ_s =18.96, σ_s =3.1

When it comes to the condition of charging in the workplace during the daytime, the starting time, as same as the arrival time, can also be assumed to obey Gaussian distribution, as shown in the Fig. 2:

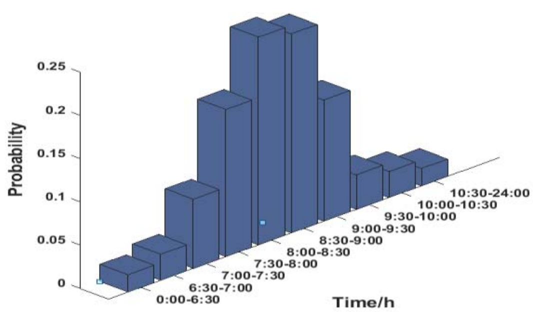

Figure 2. Probability curve of car owners arrived company time.

The probability density function is

$$f_{2s}(x)=\frac{1}{\sigma_{2s}\sqrt{2\pi}}exp\left[-\frac{(x-\mu_{2s})^2}{2\sigma_{2s}^2}\right],0<x\le 24 \tag{2}$$

where μ_{2s} =8.42, σ_{2s} =3.2

The daily travel mileage obeys log-normal distribution, and the density function can be described as

$$f_L(x)=\frac{1}{\sqrt{2\pi}\sigma_L x}exp\left[-\frac{(\ln x-\mu_L)^2}{2\sigma_L^2}\right] \tag{3}$$

where μ_L =2.98， σ_L =1.14

The simulation of EV uncoordinated charging load are carried out based on the above data.

B. Simulation of Uncoordinated Charging

The Monte Carlo method, which is a stochastic simulation method, is always used to simulate the charging load.

In order to simulate the uncoordinated charging load of EV, initial data such as charging start time and daily travel mileage are required. Through the formula (1) and (2), the charging start time can be calculated, and the daily travel mileage L can be achieved from formula (3).

When the EV is charged, the initial state of charge SOC directly affects the charging time, which can be calculated as:

$$SOC=\frac{L_{\max}-L}{L_{\max}}\times 100\% \tag{4}$$

where R_m is the max mileage that can be traveled by a battery full of electricity. After obtaining SOC, charging duration T_{ch} can be calculated as:

$$T_{ch}=\frac{(1-SOC)\cdot B}{P\cdot\eta} \tag{5}$$

where B is battery capacity of EV, P is charging power and η is charging efficiency.

After getting charging start time and charging duration, the charging period of each electric vehicle can be obtained, and then the charging load of electric vehicles could be simulated. One day is divided into 96 periods, each time for 15 minutes. In time period k, the total charging load is superimposed on the charging power of all electric vehicles, as follow:

$$F_{1,k}=\sum_{i=1}^{n}P_{i,k} \tag{6}$$

where $F_{1,k}$ is the total charging load of EVs in time period k, k =1,2,⋯,96; N is the total number of EVs in distribution networks, n =200 in this paper; $P_{i,k}$ is the charging power in time period k, if the car is not charged, the charging power is 0.

The total load F is equal to the charging load of EVs F_1 plus the basic load of the distribution network F_2, as follow:

$$F = F_1 + F_2 \quad (7)$$

In order to solve the adverse effects caused by the uncoordinated charging on the power grid, the corresponding coordinately charging strategy should be put forward, and establishing the optimization model of coordinated charging to optimize the disorderly charging load.

III. Optimization Model of Coordinated Charging

A. *Control Flow of Coordinately Charging Strategy*

The coordinately charging of EVs should meet the needs for both power grid and users, which means the charging strategy should not only maintain the stability of the power system, but also reduce the user's charging costs. The control strategy proposed in this paper is mainly based on time-of-use price to control user behavior, through the tariff mechanism, coordinated control into the orderly charging regulation behavior of users, and develop an electric vehicle charging plan for meeting different user needs. The flow chart of coordinately charging strategy for EVs is shown in Fig. 3.

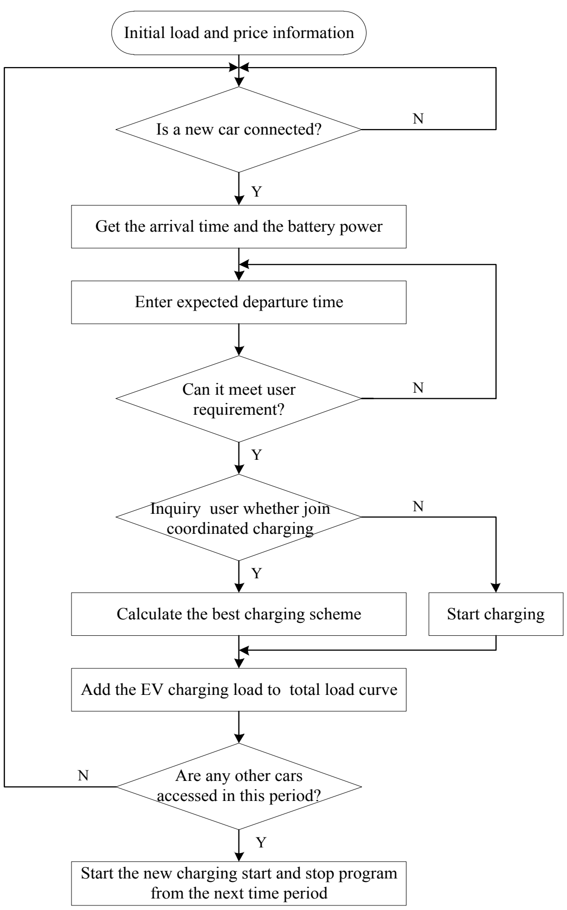

Figure 3. Flow chart of coordinately charging strategy.

When a car is connected to the charging pile, the system will automatically get the arrival time and the battery power of the electric vehicle. The EV user is then prompted to enter the expected departure time and the expected amount of charge at the end of the charging, then the system will determine whether it could meet user these requirements, and inquiries the user whether can participate in the coordinately charging adjustment program or not. If the user participate in the plan, the system would calculate the best charging scheme, and carry out the new charging start and stop plan, and begin execution at the next time period. While if the user does not participate, the electric vehicle will start charging immediately. Then the system checks if there are other electric vehicles access.

Once the coordinately charging control strategy is designed, the charging optimization model should be established to determine the specific charging plan. In the previous multi-objective optimization models, the optimization objectives were transformed into single objective functions by means of membership functions, which could result the conflicts among multi-objectives and lead to new power consumption peaks.

Thus, a two-stage optimization model proposed to avoid those issue. The first stage optimization aims at the financial improvement, minimizing the charging cost in meeting the needs of electric vehicle charging. The second stage optimization aims to fulfill the stability requirements of power grid.

B. *First Stage Optimization Model*

The first stage optimization model is based on the lowest total charge cost of EVs. In the case of time-of-use price, the lowest cost can lead to EV charging in a lower price or lower load time, so as to alleviate the pressure of power grid.

The objective function of the first stage can be expressed as:

$$min\, C = \sum_{k=1}^{T}\sum_{i=1}^{n}\left(P_{i,k} \cdot Q_k \cdot S_{i,k} \cdot t\right) \quad (8)$$

where C is the total charging cost of EVs, Q_k is the electric price in time period k, $S_{i,k}$ is the charging status of electric vehicles, which can be described as:

$$S_{i,k} = \begin{cases} 0, no\ charge \\ 1, \ charge \end{cases} \quad (9)$$

The constraints in the model are as follows:

1) Charging time constraint

$$0 \le T_{ch} \le T_d - T_a \quad (10)$$

where T_d is the expected departure time and T_a is the arrival time. The dwell time of an electric vehicle is greater than the time required for charging, and the amount of electricity in the battery can reach the desired amount of electricity. If not satisfied, it must ask the user to change the charging target power and the expected departure time, or stop the charge.

2) Charging demand constraint

$$SOC \cdot B + \sum_{k=t}^{t+T_{ch}} \left(P_{i,k} \cdot S_{i,k} \cdot \eta \cdot t \right) \leq B \tag{11}$$

At the end of the charging, the electric energy of the EV must be less than or equal to the capacity of the battery.

3) Total charge constant constraint

$$\sum_{i=1}^{n} E_i^* = \sum_{i=1}^{n} E_i = E_{sum} \tag{12}$$

where E_i^* and E_i are the daily total charge of an EV before and after charging in an orderly way, and E_{sum} is the total charge of all EVs in a day. Due to the demand for electricity in each day of the EV does not change, the total charge has not changed. The change is the charging time that will shift from the high price period to the low price period.

C. Second Stage Optimization Model

After the first stage optimization is executed, a large number of EVs will be charged during the low load period of the network, but it is possible to form new load spikes at the beginning of the low price period. In order to amend this situation, the minimum peak load difference based optimization carries out on the second stage.

The objective function of the second stage can be expressed as:

$$\min F_{p-v} = \max F - \min F \tag{13}$$

Since the second stage optimization is carried out on the basis of the first stage optimization results, the minimum total charge cost must be guaranteed when the second section is optimized. Let C^* be the minimum charge for the first stage optimization calculation, the constraint can be described as:

$$C^* = \sum_{k=1}^{T} \sum_{i=1}^{n} \left(P_{i,k} \cdot Q_k \cdot S_{i,k} \cdot t \right) \tag{14}$$

The remaining constraints of the second stage optimization are consistent with the constraints of the first stage optimization. This paper will use the MATLAB call CPLEX to solve the two-stage optimization model.

IV. Case Studies

A. Main Parameter Setting

In order to verify the effectiveness and feasibility of the proposed method, according to the actual situation of the electric vehicle, this paper makes the following settings during the simulation experiment:

1) Time-of-use price is used in electricity price, the specific price is shown in Table I.

TABLE I TIME-OF-USE CHARGING PRICE FOR EV

Time Period	Electricity price (Yuan/kWh)
0:00～7:00	0.4
7:00～10:00	0.7
10:00～15:00	1.0
15:00～18:00	0.7
18:00～21:00	1.0
21:00～0:00	0.7

2) The battery capacity of EV is 24kW · h.

3) There are 1000 households in the distribution network, the average tenure of 1 vehicle. The penetration rate of EV is 20%, or 200 electric vehicles.

B. Simulation Result

According to the proposed method, the charging load of EVs is simulated, then add it to the base load of the grid, so as to obtain the total load curve, as shown in the Fig. 4.

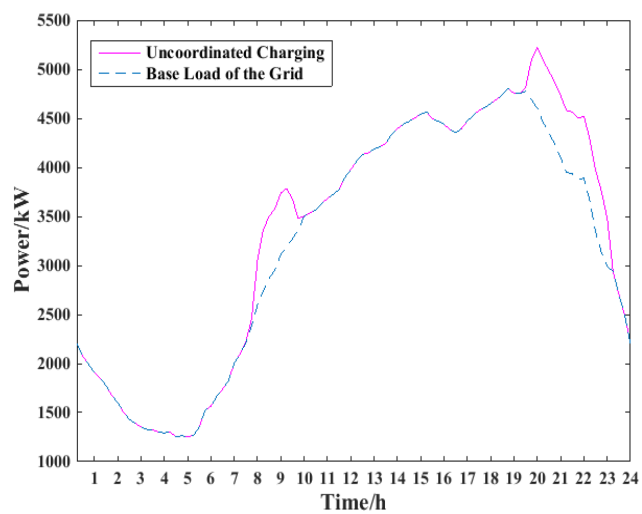

Figure 4. Load curve of EV slow charging.

In the figure, it can be found that at about 8 p.m. is the peak period of the power grid or the peak period of EV charging. The two peak phases coincide, leading to peak load increase in the overall load, and the new charge spike generated by uncoordinated charging reaches 5220.9kW, and the peak-valley difference is 3968.7kW, which will cause great burden on the power grid. However, during the low load period of the grid, few EVs charge.

After the first stage optimization of the EV charging, the load curve is shown in Fig. 5.

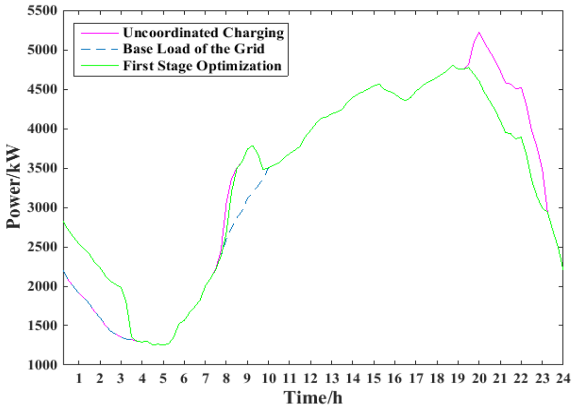

Figure 5. Load curve after the first stage optimization.

Through the simulation results, it can be seen that after the first stage optimization, the disordered charging load from 7 to 10 p.m. is transferred to the charging at late night, which mitigates the impact of the daytime charging load on the grid. Because the charging cost between 7 and 10 p.m. is much higher than the late night, the charging cost will be reduced obviously, which is in line with the optimization target of the first stage. However, after the transfer, the load is concentrated in the initial period of the valley price, charging to form a new peak of local load. When the total load of the grid reaches the minimum, almost no electric vehicle is in charge, and the effect of "filling valley" is a problem.

Additionally, in 8 to 10 a.m., the optimization result of the first stage is not obvious, because from 10 a.m. the price rises for peak, until 3 p.m. was restored. Therefore, the second stage is needed to optimize the charging load of EVs.

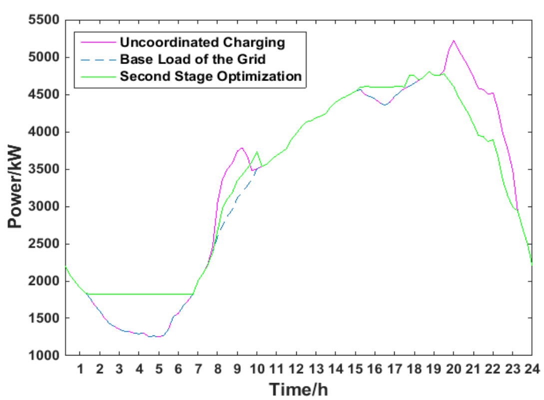

Figure 6. Load curve after the second stage optimization.

As shown in the Fig. 6, after the second stage of optimization applied, the coordinated charging load curve has been significantly improved. First of all, the "filling valley" effect is obvious, the minimum load from the original 1251.3kW to 1819.1kW, the peak valley difference from the original 3968.7kW down to 2985.8kW, 28.2% less than before optimization, greatly improving the stability of power system. Secondly, the load curve during night is more stable, which is conducive to the operation of power grids, but also can promote the consumption of new energy at night.

After optimization, the daily charge cost of 200 electric vehicles from 2473.7 yuan fell to 1409.5 yuan, a decrease of 43%.

Therefore, if the EV users fully respond to coordinated charging strategy, the two-stage optimization can effectively solve the problems caused by the disorder charging, it can also significantly reduce the charging cost of EVs at the same time.

V. Conclusion

This paper mainly researches a coordinated charging strategy for EVs based on multi-objective optimization. Through time-of-use electricity price mechanism, taking advantage of the adjustment of EV charging load in space and time to promote the coordinated charging of EV users. The two-stage optimization can both satisfy the needs of EV charging and make full use of the low load period. The simulation results show that this strategy is ideal for EV charging control, and can greatly reduce the cost of EV charging.

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References

[1] Z. C. Hu, Y. H. Song, Z. W. Xu, Z.W. Luo, K.Q. Zhan, and L.Jia, “Impacts and utilization of electric vehicles integration into power systems,” Proceedings of the CSEE, vol. 32, pp. 1-10, Feb.2012.

[2] R.C. Leou, C.L. Su, and C.N. Lu, “Stochastic analyses of electric vehicle charging impacts on distribution network,” IEEE Transactions On Power System, vol. 29, no. 3, pp. 1055-1063, May. 2014.

[3] K. Clement-Nyns, E. Haesen, and J. Driesen, “The Impact of Charging Plug-In Hybrid Electric Vehicles on a Residential Distribution Grid,” IEEE Transactions On Power System, vol. 25, pp. 371-380, Feb.2010.

[4] Z. W. Xu, W. C. Su, Z. C. Hu, Y. H. Song, and H. C. Zhang, “A Hierarchical Framework for Coordinated Charging of Plug-In Electric Vehicles in China,” IEEE Transactions On Smart Grid, vol. 7, pp. 428-438, Jan.2016.

[5] P.Richardson, D. Flynn, and A. Keane, “Optimal charging of electric vehicles in low-voltage distribution systems,” IEEE Transactions On Smart Grid, vol. 27, pp. 268-279, Feb.2012.

[6] X. X. Wang, J. Q. Zhao, K.Wang, J. G. Zhao, S. C. Yang, and S. M. Feng, “Multi-objective Bi-level Electric Vehicle Charging Optimization Considering User Satisfaction Degree and Distribution Grid Security,” Power System Technology, vol. 41, pp. 2165-2172, Jul.2017.

[7] Q. S. Li, X. N. Xiao, J. Guo, and L. Lin, “Research on Scheme for Ordered Charging of Electric Vehicles,” Power System Technology, vol. 36, pp. 32-38, Dec.2012.

[8] A. Schuller, B. Dietz, C.M. Flath and C. Weinhardt, “Charging strategies for battery electric vehicles: economic benchmark and V2G potential,” IEEE Transactions On Power System, vol. 29, pp. 2014-2022, Sep.2014.

[9] Beijing Transport Institute, “2016 Annual Report on Traffic Development in Beijing,” 2016.