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Research on a two-stage power management system for electric vehicles

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Abstract: *The large-scale application of electric vehicles that can be connected to the grid in the future will pose new challenges to the existing theories and methods of power system planning and operation. The disorderly charging behaviour of a large number of electric vehicles may bring significant negative effects on the safety and economic operation of the power system. Free charging of a large number of electric vehicles will increase the load of the power system, and even cause the phenomenon of line congestion, so that the active distribution network cannot operate normally. Based on the two-level power management system, this paper proposes a price elasticity matrix to reflect car owners' response to charging prices of charging stations at different locations, and designs an optimal real-time charging service fee pricing scheme for multiple charging stations to guide car owners' charging behaviour. Simulation results show that the proposed blocking scheduling strategy can effectively guide car owners to make reasonable charging plans while taking into account the benefits of charging facility operators, owners' charging costs and owners' satisfaction with the way they use electricity, solve the possible distribution network congestion caused by large-scale electric vehicles' centralized charging in the network and improve the safety and economy of power grid operation.*

Keywords: *Electric vehicles; Charging station; Two level power management*

1. Introduction

The national unified electricity market framework currently under construction is a multi-level market framework that maximises social welfare on a wider scale, while ensuring that the market clearing outcomes meet the operational constraints of the grid, and is a key mechanism for synergy between the two levels of the electricity market [1].

In recent years, driven by environmental issues and the "dual carbon" strategy, renewable energy and electric vehicles EVs) have been growing on scale, which has attracted wide attention. However, the inherent intermittency of renewable energy increases the pressure of grid operation when it is connected to the grid. At the same time, the disorderly integration of large-scale electric vehicles into the smart grid for charging may increase the peak valley difference of the smart grid, increase the network loss of the distribution system, and then affect the stability and security of the smart grid. Therefore, if EVs are treated as controllable loads and their charging behaviour is effectively scheduled and managed, it can not only reduce the negative impact of EVs connected to the grid but also alleviate the instability of the grid caused by the strong volatility of renewable energy output.

There is a lot of research on power management system configuration, but optimizing the operation of the power grid to minimize the total load fluctuation of the power grid is not suitable for today's large-scale electric vehicle dispatching and management situation [2]. Therefore, this paper starts from the coordination requirements of the inter-provincial market and the intra-provincial market in China, takes the specific example as the object, analyses the characteristics of the two-level electricity market coordination mechanism through the model, and puts forward relevant suggestions for the specific situation in China.

2. Impact of grid connection of large-scale electric vehicles on distribution network

2.1 Load model of EV charging station

The charging characteristics of electric vehicle owners are uncertain in time and space, which causes the load curve of electric vehicle charging station to have strong randomness. If the electric vehicle charging station is taken as the controllable load for scheduling operation, it is necessary to establish the charging load model of the charging station to reflect this randomness [3].

The charging of electric vehicle owners has double uncertainty in time and space. Studying the charging behaviour of electric vehicle owners is the premise of establishing the load model of electric vehicle charging stations. According to the different driving characteristics of different users, EVs can be divided into taxi, bus, official car and private car categories according to their use. According to the occupation of the owner and the space, it is divided into commercial areas, residential areas, industrial areas. The charging mode of the EV battery, the battery characteristics, and the charging habits of the owner determine the load scale of the charging station. The main research object of this paper is the charging load of private cars in residential areas.

The charging mode of electric vehicles in charging stations in residential areas is ordinary charging. The activity law of residents is dynamic, random, complex and diverse, and its characteristics must be comprehensively considered when modelling the charging station load in residential areas [4]. Based on the consideration of residents' charging behaviour, the assumptions are as follows.

(1) The owner's daily mileage and the end time of the last trip are independent random variables

(2) Charging will start at the end of the owner's last trip,

(3) Each time the owner charges the battery to full power.

The end time of the last trip of the electric vehicle owner is the starting charging time. The daily driving mileage and the starting charging time of the electric vehicle owner are determined by their driving habits and travel characteristics [5]. The probability density function is shown in Equation (1), and the probability distribution diagram is shown in figure 1.

$$f_B(\mathrm{x}) = \begin{cases} \frac{1}{\delta_b\sqrt{2\pi}} exp\left[\frac{(1-\mu_b)^2}{2\delta_b^2}\right], (\mu_b - 12) < x \le 24 \\ \frac{1}{\delta_b\sqrt{2\pi}} exp\left[\frac{(x+24-\mu_b)^2}{2\delta_b^2}\right], 0 < x \le (\mu_b - 12) \end{cases} \tag{1}$$

Where, $\mu_b = 17.6, \delta_b = 3.4$

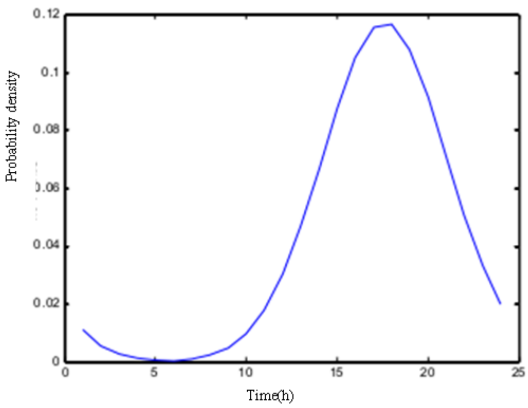

Figure 1: Electric vehicle travel end time probability distribution for the last time

The lognormal distribution can be used to approximate the daily mileage of electric vehicles, and the probability density function is shown in equation (2).

$$f_D(x) = \frac{1}{x\delta_D\sqrt{2\pi}} exp\left[-\frac{(\ln x - \mu_D)^2}{2\delta_D^2}\right] \tag{2}$$

Where, μ_D=3.2, δ_D=0.88, The probability distribution map is shown in figure 2.

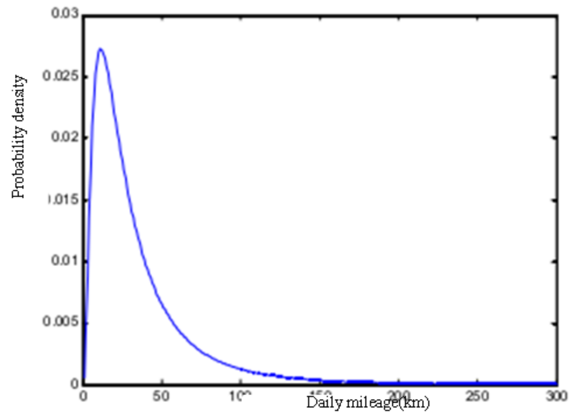

Figure 2: Electric vehicle range probability distribution

The charging time TC of electric vehicle is expressed by Equation 3,

$$T_C = \frac{SW_{100}}{100P_{ch}} \tag{3}$$

Where: S is the daily mileage (km); W_{100} is the energy consumption of 100 kilometers; P_{ch} is the charging power of the EV.

The EV charging time TC is represented by Equation (4), and the probability distribution diagram is shown in Figure 3.

$$f_{T_C}(x) = \frac{1}{x\delta_D\sqrt{2\pi}} exp\left[-\frac{\left(\ln x-\left(\mu_D+\ln\frac{W_{100}}{P_{ch}}\right)\right)^2}{2\delta_D^2}\right] \tag{4}$$

Since the above equations (1) - (4) cannot be solved analytically after being combined, the function expression of the overall power demand of the charging station cannot be determined. The Monte Carlo simulation method is used to give the power demand model of the charging station in a day. Assume that there are 1000 electric vehicles in the residential area, the number of Monte Carlo simulations is selected as 10000, the simulation step is 10min, and the expected value μ and standard deviation σ of the sample are calculated. The simulation results are shown in Figure 3.

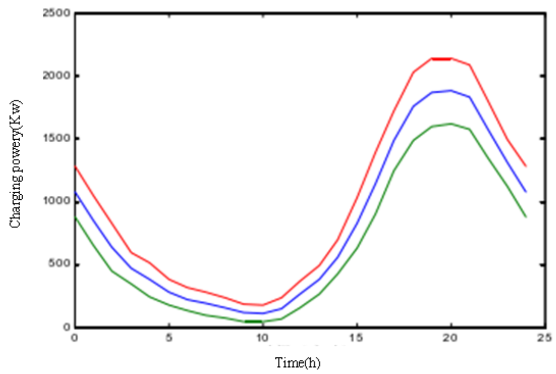

Figure 3: EVs charging disorderly charging power every moment in one day

2.2 Example analysis of the influence of disordered charging of electric vehicles on distribution network

Taking the IEEE33 distribution system as the object, this paper analyses the impact of the free charging of electric vehicles on the operating power balance and power quality of the distribution network.

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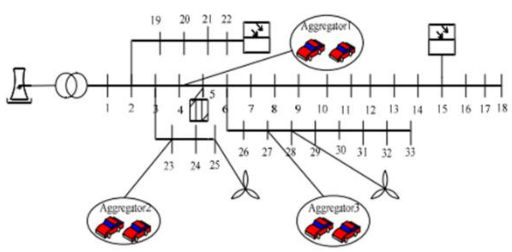

Figure 4: Modified IEEE33-bus system

As an example, the IEEE-33 node standard test system is shown in Fig. 4, where the modified system has charging stations at nodes 4, 23 and 27 and represents the EV group by the Aggregator. It is assumed that each charging station averages a fixed number of EV charges per day in the free charging mode. The number of evs in each charging station is 360/270/270. Two photovoltaic power generation systems with an installed capacity of 500kW are connected to nodes 15 and 22, and the light intensity meets the Beta distribution. A gas turbine with an installed capacity of 300kW is connected to node 5, a wind turbine with an installed capacity of 1MW is connected to node 25 and a wind turbine with an installed capacity of 500kW is connected to node 28. The wind power ou.TUPT uses a Beta distribution model based on local errors. The parameters of the electric vehicle in the example system can be obtained, and the energy consumption per 100 km is 15.19 kWh, the charging power is 4.5kW, and the battery capacity is 27.31 kWh. The generator, load and branch-related data of IEEE33 system are shown in Table 1, respectively.

Table 1 IEEE33 node data

Nodes	PL/kW	QL/kVar	Nodes	PL/kW	QL/kVar
2	100	60	18	90	40
3	90	40	19	90	40
4	120	80	20	90	40
5	60	30	21	90	40
6	60	20	22	90	40
7	200	100	23	90	50
8	200	100	24	420	200
9	60	20	25	420	200
10	60	20	26	60	25
11	45	30	27	60	25
12	60	35	28	60	20
13	60	35	29	120	70
14	120	80	30	200	600
15	60	10	31	150	70
16	60	20	32	210	100
17	60	20	33	60	40

This paper studies the probability characteristics of the driving rule of electric vehicles, establishes the charging load model of the charging station when the electric vehicle owner freely charges, and analyzes the impact of the free charging of electric vehicles on the distribution network. Combined with a specific example, through the modified IEEE33 node system, it is obtained that a large number of electric vehicles free charging will increase the load of the power system, and even make the line blocking phenomenon, so that the active distribution network can not operate normally. It is necessary to propose a strategy to solve the blocking problem of the distribution network, so that the power system can operate safely and stably.

3. Coordinated planning method for distribution system and EV charging network

3.1 Maximizing traffic flow intercepted by fast charging stations

To improve the efficiency of investment and facilitate the rapid development of the EV industry, it is often hoped that a network of fast charging stations will provide convenient fast charging services for more EV vehicles. In view of this, this chapter considers the annual intercepted traffic flow at the fast charging station as another target for the coordinated planning model of the distribution system and the EV charging network. In this way, investors can make a trade-off between the sum of annual investment cost and system network loss cost and the annual intercepted traffic flow of fast charging stations to

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develop a more reasonable planning scheme. The interception location model can be described as follows.

$$Max\ f_2 = \sum_{r\in N^T}\sum_{S\in N^T}\sum_{q\in Q_{rs}} T^{rs}_{q,annual}\tau^{rs}_q \tag{5}$$

$$\text{s.t}\quad \sum_{k\in\Omega^K_q} \geq \tau^{rs}_q \tag{6}$$

$$T^{rs}_{q,annual} = d^{annual}\sum_{t\in T} f^{rs}_{q.t} \tag{7}$$

In Equations (5) -(7) : $N^T$is the node set of the transportation network; $Q_{rs}$is the path set connecting the Origin r and the destinations s(Origin destination pair rs, hereinafter referred to as OD pair rs) of passenger car travel. $T^{rs}_{q,annual}$ is the annual traffic flow carried by path q connecting OD pair rs. τ^{rs}_q is the decision variable whether the traffic flow on the path q connecting OD pair rs can be intercepted or not. $\tau^{rs}_q = 1$and $\tau^{rs}_q = 0$ indicate that the traffic flow on the path can/cannot be intercepted, respectively. Ω^K_q is the set of fast charging stations that can intercept the traffic flow on path $f^{rs}_{q.t}$ is the traffic flow during the period of time on the path connecting OD to rs. In this model, the physical meaning expressed by the objective function equation (5) is to maximize the annual intercepted traffic flow of the fast charging station. Constraint equation (6) indicates that only if there is at least one fast charging station on path q, its traffic flow can be intercepted. The constraint equation (7) gives the mathematical definition of $T^{rs}_{q,annual}$, where the parameter $f^{rs}_{q.t}$ should be obtained by solving the traffic allocation model based on user balance shown in Equations (8) - (11) each time period.

$$\text{Min}\ \ \text{f(x)} = \sum_{(mn)\in\Omega^{TL}}\int_0^{x_{mn}} P_{nm}(\omega)\,d\omega \tag{8}$$

$$\text{st.}\quad \sum_{q\in\delta_{rs}} f^{rs}_q = q_{rs} \tag{9}$$

$$x_{mn} = \sum_{r\in N^T}\sum_{s\in N^T}\sum_{q\in Q_{rs}} f^{rs}_q\delta^{rs}_{mn,q} \tag{10}$$

$$f^{rs}_q \geq 0 \tag{11}$$

In equations (8) - (11) : Ω^{TL} is the set of roads in the traffic network; x_{mn} is the traffic flow on the road segment; $P_{nm}(.)$ is the section impedance function; f^{rs}_q is the traffic flow on the path connecting the pair; q_{rs} is the traffic flow between the OD pair rs; $\delta^{rs}_{mn,q}$ is the flag variable whether the path q connecting OD pair rs contains road segment mn. In this model, the objective function equation (8) is to minimize the integral of the impedance function of all road sections, which itself has no intuitive physical meaning and is only used to obtain the equilibrium solution of the model. The impedance function of a road section can usually be described as a numerical relationship between the travel time and the traffic flow carried by the section.

3.2 Example analysis

After implementing the real-time charging and changing service charge policy, the charging and changing service charge of evs is adjusted, and the corresponding charging power distribution of each charging station is shown in Fig. 5. The load rate changes of each line before and after adjustment related to the charging power of charging station nodes are shown in Fig.6.

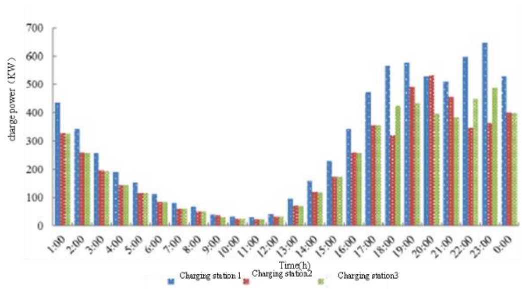

Figure 5: Charging power distribution of each charging station after adjustment for charging service

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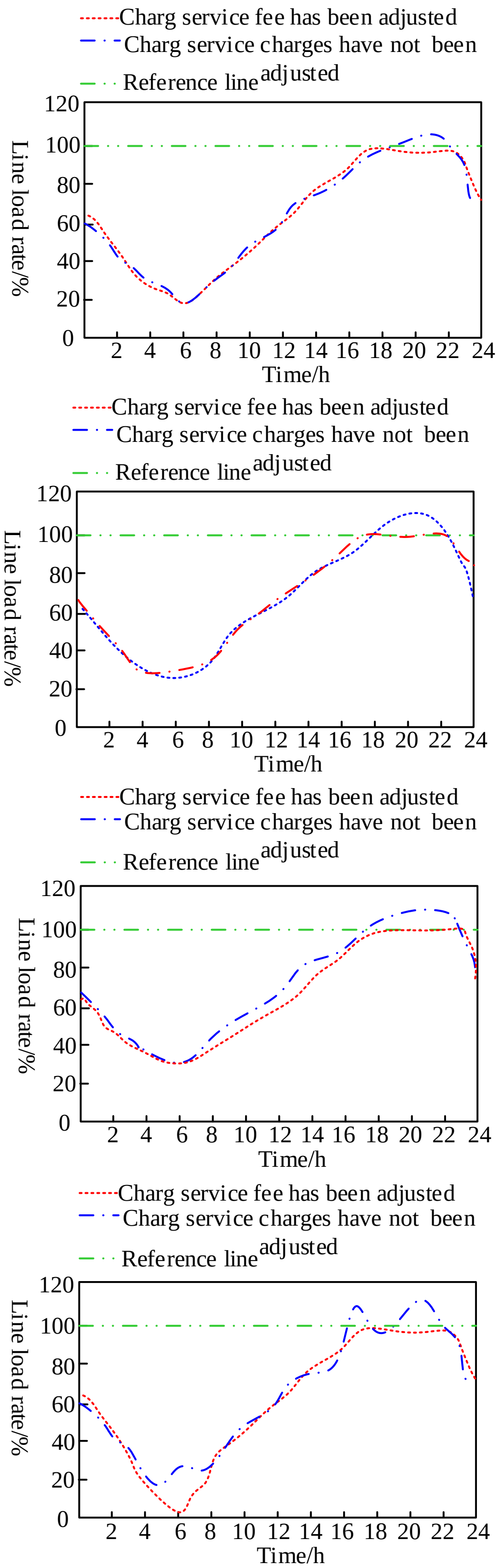

Figure 6: Line load rate of the congestion lines comparison before and after adjustment for charging service fee

From the comparison results of the charging power of each charging station in one day before and after the implementation of the real-time charging service charge policy, it can be seen that the sum of the charging power of each charging station in one day changes before and after the charging charge adjustment, while the sum of the charging power of each charging station in the whole day remains unchanged, indicating that there is power flow between the three charging stations in the region. Real-

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time charging and changing service charges at charging stations in different locations have different levels of appeal for car owners. Some car owners change their charging habits and transfer between charging stations, which realizes the guidance of spatial factors.

4. Conclusion

This paper proposes a time-space scheduling model of distribution network guided by charging service fees of electric vehicles. The model uses the price elasticity matrix to reflect the response degree of owners to the charging prices of charging stations at different locations. The example verification shows that the proposed blocking scheduling strategy can effectively guide the owners to formulate a reasonable charging plan while taking into account the revenue of the charging facility operator, the charging cost of the owners and the satisfaction of the owners with the electricity consumption mode, solve the problem of distribution network congestion caused by large-scale electric vehicle centralized charging in the network, and improve the security and economy of power grid operation.

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