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Research Article

A Two-Level Integrated Scheduling Strategy for Vehicle-Network Synergy considering New Energy Consumption

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With the substantial increase in the number of electric vehicles, the charging of electric vehicles without regulation and scale control will bring about problems, such as overloading of distribution transformers; the proportion of new energy power generation is also increasing year by year, and the access of new energy to the power grid will cause volatility. In order to solve the problems above, this paper proposed a coordinated and orderly scheduling strategy considering new energy consumption, which protects the interests of both users and the integrated power grid. First, a two-level vehicle-network interaction model considering both supply and demand sides was established. The upper-level model optimized the indicators on the distribution grid side, and a term of charge-discharge margin as well as grid-side load variance model was proposed. The lower-level optimization model was set based on the users' condition. The average discharge rate index was defined to evaluate the battery loss satisfaction in the scheduling strategy, which fully considered users' charging and discharging cost, and finally achieved a win-win situation between the power grid and the user. Secondly, the fast nondominated sorting genetic algorithm (NSGA-II) was used to figure out the effect of the strategy proposed in this paper, and a community is taken as an example for simulation. The results confirmed the economy and rationality of the above strategy, by rationally scheduling the charging and discharging behavior of electric vehicles, consuming new energy, restraining the fluctuation of the remaining new energy power generation, realizing the dynamic balance between the charging and discharging load and the output of new energy in a certain area, and finally effectively suppressing the fluctuation of the power grid load while improving the availability of clean energy.

1. Introduction

Electric vehicle (EV), as a new generation of green transportation, shows unique advantages and broad application prospects compared with traditional vehicles in terms of changing the energy structure, saving energy, reducing emissions, curbing global warming, and so on. As an important contributor of "peak" and "carbon neutrality," EV has been widely valued and promoted by automobile manufacturers, relevant departments, and energy companies. The load growth caused by the disorderly charging of electric vehicles, especially during the peak period, will further increase the peak-to-valley difference of the grid load, which may lead to a series of problems like voltage drop, increased network loss, overloading of the distribution network lines, and overloaded distribution of transformers [1, 2].

The traditional control method uses power generation to track load fluctuations and adjust the system operating state. The controllable load characteristics of electric vehicles will provide new solutions to this problem. Managing the load of electric vehicles to shave peaks and fill valleys can effectively reduce network losses, reducing grid operation risks, and alleviate grid peak regulation pressure. The grid-side energy storage-based dispatch strategy and the user side incentives such as time-of-use electricity prices can well solve the problem of excessive load peak-to-valley difference. Load scheduling [3] is to use load to track the change of renewable energy output. As a supplement to power generation scheduling, it helps adjust the operating state of the system. The time-of-use power price (TOU) [4] is another significant way to realize peak shaving and valley filling, which can alleviate the contradiction between supply and demand, bringing benefits in many aspects.

Through proper scheduling of electric vehicle charging, together with taking full use of its characteristics (distributed energy storage and flexible scheduling), it is possible to coordinate and optimize the scheduling of electric vehicles and new energy sources, such as wind and solar [5], and to further achieve the dynamic equilibrium between the charging load and the output of new energy in a certain area. Leveraging the advantages of flexible and adjustable electric vehicles and huge energy storage can not only restrain the fluctuation of the remaining new energy power generation, but also reduce its impact on the power grid system. It can effectively stabilize the load fluctuation of the power grid while improving the utilization of clean energy and reducing the negative impact of the two when they are connected to the grid.

2. Literature Review

In terms of orderly charging and discharging scheduling of electric vehicles, Liu [6] established a minimum model strategy for user charging and discharging costs that takes into account battery loss, but it is mainly based on the user side and lacks consideration of the demand on the grid side. Xu and Li [7] proposed an optimization strategy aiming at minimizing the peak-to-valley difference rate of power grid load, but in the optimization process, only the user's response to the peak-valley electricity price policy was analyzed, and the user's response to the scheduling strategy was not considered. Zhang et al. [8] employed the central limit theorem to calculate the distribution of the charging load of all vehicles with the goal of reducing the centralized charging under the electricity price during the valley period as much as possible and proposed a charging load calculation method based on the time-of-use electricity price. Wang [9], on the basis of user charging satisfaction and distribution network security constraints, and with the goal of optimizing operational economy, built a two-level optimization model of distribution network-charging station based on hierarchical management. Wang [10] analyzed the charging and discharging characteristics of electric vehicles from the perspective of mathematical modeling and considered the output of wind and solar power generation. However, his scheduling optimization of electric vehicles only involved the grid level and failed to notice the impact of the scheduling strategy on users and the economic analysis. Bao [11] proposed a model that achieved the mutually friendly interaction of power between electric vehicles and the power grid, which can calibrate the real-time active power demand of electric vehicles and protect the stability of power grid operation. Su et al. [12] proposed a multiobjective optimization model of dynamic TOU power price with the introduction of wind and solar, which facilitates the orderly charging of electric vehicles to achieve local consumption of new energy.

According to the above research, this paper raised a two-level vehicle-network interaction model that considers the consumption of new energy sources on both supply side and demand side comprehensively and conducted an economic research on peak shaving and valley filling and users' charging and discharging. The upper-level optimization model focused on the distribution network and was evaluated from the aspects of charge and discharge margin and load variance on the grid side so as to improve the stability of the grid operation. The lower-level optimization model fully considered the users' demand, defined the battery loss satisfaction to evaluate the battery loss cost in the V2G response process, and realized the optimal charging and discharging cost on the user side.

In addition, the coordinated optimal scheduling of electric vehicles and wind-solar, that is, the proper scheduling of the charging and discharging behavior of electric vehicles to absorb new energy and restrain the fluctuation of the remaining new energy power generation, will achieve a dynamic equilibrium between the charging and discharging load and the output of new energy in a certain area. The dynamic balance between the power grid not only effectively stabilizes the fluctuation of the grid load, but also improves the utilization of clean energy. The fast nondominated sorting genetic algorithm (NSGA-II) with elite strategy is adopted to optimize multiple objectives at the same time and find the global optimal solution. The strategy proposed in this paper is analyzed and verified by numerical example simulation, which proves that the strategy proposed in this paper can realize peak shaving and valley filling, absorbing wind, and solar power grid connection, effectively reducing the pressure on the grid. Scheduling charging and discharging behaviors also reduces user charging costs.

3. Mathematical Models (Electric Vehicle Model and New Energy Model)

3.1. Electric Vehicle Load Model. The charging behavior of electric vehicles is mainly determined by the travel needs of users and is also affected by factors such as device attributes and user habits. As far as the regional power system is concerned, it is also affected by the number and scale of electric vehicles and the perfection of charging facilities. The uncertainty and difference of user needs and behaviors will inevitably lead to randomness and dispersion of charging loads. Through the data statistics of the travel time distribution law of electric vehicles in residential areas in real life, and by normalizing the statistical graph data, the electric vehicle travel time distribution curve is fitted, and the electric vehicle load model is established. The Monte Carlo method is used to simulate the conventional load curve of the residential area [13–15], while the electric vehicle information and trip plan are obtained from the electric vehicle travel distribution model and the return distribution model.

(1) The travel distribution density function of electric vehicles is

$$f_{\mu_1,\sigma_1}(td) = \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(t-\mu_1)^2}{2\sigma_1^2}}. \tag{1}$$

(2) The probability density function of the regression distribution is

$$f_{\mu_2,\sigma_2}(ta) = \frac{1}{\sqrt{2\pi}\sigma_2} e^{-\frac{(t-\mu_2)^2}{2\sigma_2^2}}. \tag{2}$$

In the formula, td is the travel time of the user, ta is the return time of the user, μ_1 and μ_2 are the expected values, and σ_1 and σ_2 are the standard deviations.

In the travel distribution, $\mu_1 = 8$, $\sigma_1 = 1.33$, while the return distribution parameter is $\mu_2 = 18.5$, $\sigma_2 = 1.99$. Whether to go out is randomly generated, and it is assumed that the total travel probability of residents is 0.8.

(3) Daily mileage

Daily mileage [16] is an important parameter of the behavior characteristics of car owners in residential areas. The daily mileage of electric vehicles is log-normal distributed, and its probability density function is shown in the following formula:

$$f_s(x) = \frac{1}{x\sigma_s\sqrt{2\pi}} e^{-\frac{(\ln x-\mu_s)^2}{2\sigma_s^2}}. \tag{3}$$

In the formula, x is the daily mileage of the electric vehicle, μ_s is the expected value, and σ_s is the standard deviation; among them, $\mu_s = 3.2$, $\sigma_s = 0.88$.

(4) Initial state of charge

According to the daily mileage of the car and the battery parameters, the initial state of charge when the vehicle starts to charge can be obtained [16], as shown in the following formula:

$$\mathrm{SOC}_{s,i} = \left(\mathrm{SOC}_{e,i} - \frac{x}{100} \times \frac{E_{100}}{B}\right) \times 100\%. \tag{4}$$

In the formula, $\mathrm{SOC}_{e,i}$ denotes the state of charge of the ith electric vehicle at the end of charging. If the power expectation is constant, the battery power of the electric vehicle when the user leaves home is the same as the user's charging expectation; $\mathrm{SOC}_{s,i}$ is the initial state of charge of the ith electric vehicle; E_{100} is the power consumption of electric vehicles per 100 kilometers, in units of kWh;B is battery capacity, in units of kWh; and$x$ is daily mileage.

The calculation of the time required by the user to charge is shown in the following formula:

$$T_{c,i} = \frac{\left(\mathrm{SOC}_{s,i} - \mathrm{SOC}_{b,i}\right)B}{P_c}. \tag{5}$$

In the formula, $T_{c,i}$ is the time required for charging; the unit is h;P_c is the charging power for electric vehicles, in units of kW.

3.2. New Energy Model

3.2.1. Wind Power Model. The relationship between the output characteristics of the wind power generation system and the wind speed is as follows [17]:

$$P_{WT} = \begin{cases} 0 & v \le v_i \text{ or } v \ge v_o \\ P_N \dfrac{v - v_i}{v_N - v_i} & v_i \le v \le v_N \\ P_N & v_N \le v \le v_o \end{cases}, \tag{6}$$

P_{WT} is the actual output power, P_N is the rated output power, v is the actual wind speed, v_i is the cut-in wind speed, v_N is the rated wind speed, and v_o is the cut-out wind speed.

3.2.2. Photovoltaic Power Generation Mathematical Model. Photovoltaic cells [17] are obviously characterized by their volatility, which is directly related to the light intensity and operating temperature. Its output power is expressed as follows:

$$P_{pv} = P_{STC}\frac{G_{ING}}{G_{STC}}\left(1 + k\left(T_c - T_r\right)\right). \tag{7}$$

P_{pv} is the actual output power; P_{STC} is the maximum output power of STC (standard test environment: irradiation intensity 1000 W/m, ambient temperature 25°C); G_{ING} is the irradiation intensity under STC, $GSTC$ is the actual irradiation intensity; k is the power temperature coefficient; T_c is the actual battery temperature; and T_r is the reference temperature.

Among them, the surface temperature of photovoltaic cell modules is not easy to measure directly, but can be estimated by empirical formula:

$$T_c = T_{et} + 0.0138 \times \left(1 + 0.0138T_{et}\right) \times (1 - 0.042v) \times G_{ING}. \tag{8}$$

In the formula, T_{et} is the ambient temperature; v is the current wind speed.

4. Vehicle-Network Interaction Optimization Model

In order to realize the distributed management of large-scale electric vehicles and guide users to charge and discharge in an orderly manner, this paper established a vehicle-network interaction optimization model. This model is composed of an upper-level optimization model of the distribution network and a lower-level optimization model of the user side. The upper one considered the charge and discharge margin and load fluctuation to optimize the safety and stability of the distribution network, while the lower layer one considered the charge and discharge of users' side. The battery loss and user costs in the process are optimized out of economic issues.

4.1. Upper-Level Optimization Model of Distribution Network

4.1.1. Charge and Discharge Margin Model. The charging margin represents the maximum charging load capacity that the grid allows the electric vehicle to bear in a certain period of time, which is represented by the optimized charging load; the discharge margin represents the maximum load absorbing capacity of the electric vehicle discharging to the grid in a certain period of time, which is represented by the optimized charging load. The discharge during the peak load period offsets the power difference between the predicted demand and the optimal load [18]. Therefore, the discharge margin model is shown in

$$P_{\text{dis}}(i) = \begin{cases} \int_{t_i}^{t_{i+1}} \left(P^*(t) - P(t)\right)\mathrm{d}t, & P^*(i) \geq P(i) \\ 0, & P^*(i) < P(i) \end{cases}, \quad (9)$$

$P_{\text{dis}}(i)$ represents the discharge margin of the i period, $P(t)$ represents the charging load after optimization at time t, $P^*(i)$ is the predicted load value of the power grid in period i.The charging margin $P(i)$ in the period i is the optimized charging load. When the predicted charging load in period i is greater than the optimized charging load, $P_{\text{dis}}(i)$ is equal to the difference integral of the two in the period ti to $ti+1$; otherwise, it is equals 0.

4.1.2. Grid-Side Load Fluctuation Model. The grid-side load consists of two parts: the basic load of the grid and the electric vehicle charging and discharging load, so it can be expressed as

$$Fc = \min \frac{1}{T} \sum \left[\left(P(t+1) + EV_{\text{load},t} + 1\right) - \left(P(t) + EV_{\text{load},t}\right)\right]^2. \quad (10)$$

In the formula, $P(t+1)$ and $P(t)$ represent the basic load during $t+1$ and t, respectively. $EV_{\text{load},t}+1$ and $EV_{\text{load},t}$ represent the load of the electric vehicle in the period t.

4.1.3. Restrictions

(1) Fast charging and slow charging cannot be performed at the same time during the charging behavior of electric vehicles

$$\lambda_k(\theta_1) + \lambda_k(\theta_2) \leq 1. \quad (11)$$

(2) Grid-side discharge decision factor constraints

$$\omega_{ch} = \begin{cases} 1, & T_{ch} \geq \Delta T_{ch} \\ 0, & T_{ch} \leq \Delta T_{ch} \end{cases}. \quad (12)$$

In the formula, T_{ch} represents the total time for the user to connect to the grid for continuous charging and discharging, and ΔT_{ch} represents the minimum stay time for the grid company to allow electric vehicles to take discharge measures. The car interacts with the distribution network, and the SOC of the electric vehicle can still ensure the normal travel of the user when it is off the grid.

(3) Safety constraints of battery operation

$$\text{SOC}_{\min} \leq \text{SOC}_{n,t} \leq \text{SOC}_{\max}. \quad (13)$$

Among them, $\text{SOC}_{\min}$ and $\text{SOC}_{\max}$ represent the maximum and minimum values of the state of charge of the electric vehicle, respectively.

4.2. User-Side Lower-Level Optimization Model

4.2.1. Battery Depletion Model. In the actual scheduling process, users' concern about the impact of frequent charging and discharging on the battery will affect the development and promotion of the V2G project. Therefore, in order to evaluate the battery response cost in the process of implementing V2G for electric vehicles, the battery loss cost in the V2G response process needs to be fully considered, and the average discharge rate index [19] is proposed to quantify the discharge frequency:

$$\overline{\sigma} = \frac{\sum_{i=1}^{N} \sum_{k=1}^{24} \left| L_{d,k+1}^{i} - L_{d,k}^{i} \right|}{N}. \quad (14)$$

In formula (14), σ represents the average discharge rate index, which can reflect the average degree of dispatchable electric vehicles participating in the discharge. It is defined as the ratio of the discharge times in the electric vehicles participating in the dispatch strategy to the number of dispatched electric vehicles, which can intuitively express the discharge frequency.

In the application process, the excessively frequent charging and discharging behaviors in the V2G process will cause battery loss of EVs, thus affecting the interests of users. In order to improve user-side requirements and achieve optimization, this paper proposes a definition called battery loss satisfaction [20, 21]:

$$\varpi = 1 - \frac{\overline{\sigma}_k}{\overline{\sigma}_{k,\max}}. \quad (15)$$

In formula (15), is battery loss satisfaction; the larger the value, the less the discharge times of electric vehicles participating in V2G, and the smaller the battery loss is, the more satisfied the user is with the battery loss; is the average discharge rate index in the k period.

4.2.2. Charge and Discharge Cost. The orderly charging and discharging strategy of electric vehicles is not only related to the optimization of user side costs, but also involves practical problems, such as power distribution network loss and load balance. Simply controlling the variance coefficient of peak shaving and valley-filling cannot achieve the expected efficient operation mode of the power grid. Formulate the lower-level optimization model that optimizes the user's charging and discharging cost.

Considering that the user side requires more options of charging modes due to different travel purposes and travel frequencies, the power grid company can formulate various charging modes and charging prices that meet the needs of users. At the same time, as a mobile load, electric vehicles have the dual characteristics of charging and discharging and can also be used as random distributed power sources to transmit electric energy to the distribution network so that users can obtain discharge benefits and help the distribution network system run stably. The user's discharge benefits B_u can be expressed as

$$B_u = w_{u,s}(\theta) p_{EV} \eta_{u,c}(t). \tag{16}$$

In the formula, p_{EV} represents the discharge capacity of electric vehicles in residential quarters or parking lots, and its value depends on the user's expectation of electric vehicles to transmit electric power to the distribution network system; $w_{u,s}(\theta)$ is the user-side discharge decision factor, and its value is determined by whether the user chooses to allow electric vehicle charging decision; and $\eta_{u,c}(t)$ represents the time-of-use electricity price (yuan/kWh) set by the power grid company according to the system operation and revenue cost.

Combining the above factors, the charging and discharging cost of electric vehicles C_{uc} can be expressed as

$$C_{uc} = \omega_{ch} \sum_{i=1}^{N} B_u - \sum_{i=1}^{N} \sum_{j=t+1}^{J} \lambda_k(\theta_1) P_{EV,t} \rho_{v1}(t) \left(t_{\text{end}} - t_{\text{start}}\right). \tag{17}$$

In the formula, ω_{ch} represents the grid-side discharge decision factor, and its value depends on the charging and discharging time of the electric vehicle connected to the grid; $\lambda_k(\theta)$ is the charging and discharging decision variable; if the user chooses fast charging according to his travel situation, then $\lambda_k(\theta) = 1$; otherwise, $\lambda_k(\theta) = 0$; $\rho_v(t)$ is the time-of-use electricity price (yuan/kWh), which is based on the change of grid load in a day, divides a day into multiple periods such as peak period, low peak period, and peak period, and formulates different electricity prices according to the characteristics of load curves in different periods. Encourage users to choose the charging mode and charging time reasonably, which will cause the curve to cut peaks and fill valleys; $P_{EV,t}$ indicates the total charging power of the electric vehicle in the t period; and t_{start} and t_{end} represent the starting time and the leaving time of the electric vehicle user accessing the charging pile, respectively.

4.2.3. Restrictions

(1) Discharge decision factor constraints on the user side

$$\omega_{u,s}(\theta) = \begin{cases} 1, & \text{Electric vehicles are involved in discharging electricity to the grid} \\ 0, & \text{Electric vehicles do not participate in discharging to the grid} \end{cases}. \tag{18}$$

(2) Electric vehicle charging and discharging power constraints in adjacent periods

$$\left|EV_{\text{load},t+1} - EV_{\text{load},t}\right| \le \Delta EV_{p\min}. \tag{19}$$

Among them, $\Delta EV_{p\min}$ represents the maximum allowable charging power in adjacent time periods under the charging state of the electric vehicle.

(3) Electric vehicle charge and discharge capacity limitation

$$\text{SOC}_{N,t+1} = \begin{cases} \text{SOC}_{N,t} + \dfrac{\mu_{ch} P_{N,t}\left(t_{\text{end}} - t_{\text{start}}\right)}{SOC_m}, & w_{u,s}(\theta) = 0 \\ \\ \text{SOC}_{N,t} - \dfrac{\mu_{sp} P_{N,t}\left(t_{\text{end}} - t_{\text{start}}\right)}{\text{SOC}_m}, & w_{u,s}(\theta) = 1 \end{cases}. \tag{20}$$

In the formula, $\text{SOC}_{N,t}$ represents the state of charge at the end of time; μ_{ch} and μ_{sp} represent the charging and discharging efficiency of charging piles in residential areas or parking lots; $P_{N,t}$ represents the charging and discharging power provided by the user's choice of connecting to the grid mode; and SOC_m represents the battery capacity in the user's electric vehicle.

(4) Unscheduled time period constraints

$$\begin{cases} w_{u,s}(\theta) = 0 \\ \lambda_k(\theta_1) = 0 \\ \lambda_k(\theta_2) = 0 \end{cases}, \forall N, t < t_{start} or t_{en\ d}. \tag{21}$$

5. Optimization

The paper adopted one of the multiobjective optimization algorithms; NSGA-II [22] is a fast nondominated sorting genetic algorithm with elite strategy. It not only excels in simultaneously optimizing multiple objectives by using service decision variables and constraints, but also can find the global optimal solution.

NSGA-II algorithm uses a fast nondominant sorting procedure [23], an elite retention method and a parameter-free localization operator. The fast nondominant sorting process divides the target solution to generate the Pareto frontier, and the Pareto frontier level optimal solution composes the Pareto solution set. This allows the optimal solution set to find a better Pareto-optimal front; the obtained nondominant front converges better and maintains a better solution expansion.

The selection operator is achieved by combining the parental and progeny populations, while selecting the best (with regard to fitness and spread) solutions and creating mating pools. The algorithm generates a set of Pareto-optimal solutions through continuous iteration, mutation, cross selection, and other operations.

As for the fast crowded distance estimation, it makes the optimal solution set distribute in sound order. Crowding distance represents the degree of crowding among individuals and is used to calculate the distance between a unit and other units in the front end. The crowding degree distance calculation is based on the former, calculating the crowding distance of the adjacent solutions on the Pareto frontier of each level. The solution with a larger crowding distance is used as the child population and enters the cycle again so as to ensure the diversity and convergence. The specific flow of the algorithm [22] is shown in Figure 1.

6. Case Simulation

6.1. Example Description. Here is the scenario: there are 780 households in an old community, and each household owns a car. If the penetration rate of electric vehicles is 50%, the number of electric vehicles in the community will be 390, and if each electric vehicle parking space is equipped with a charging pile, there will be 390 electric vehicles correspond to 390 charging piles. The battery capacity of the electric vehicle is 40 kWh; the charging and discharging power is 7 kW.

Among them, the optimal front-end individual coefficient set by the algorithm parameters is 0.3, the population size is 100, the maximum evolutionary algebra is 200, the stopping algebra is also 200, and the fitness function value deviation is $le-100$.

The TOU power price is shown in Table 1.

Through the simulation calculation, the total charging load of electric vehicles in residential areas and the total load in residential areas can be obtained [23]. The load data of the power grid is shown in Figure 2.

6.2. Analysis of Simulation Results. The disordered charging mode refers to the mode before optimization. After optimization, the following three aspects should be considered: economic scheduling (minimum cost), stability scheduling (minimum variance), and integrated scheduling (integrated economy and grid stability and optimal). It can be seen from the algorithm convergence diagram that the Pareto front is uniformly distributed, which proves that the simulation results have good convergence.

The calculation formula of load rate is shown in the following formula:

$$g = \frac{Pav}{P\max}. \tag{22}$$

6.2.1. Analysis of Scheduling Strategy under 50% Penetration Rate. From the simulation results and Figure 3, it can be seen that the orderly scheduling strategy is generally better than the disordered charging. The reason is that it can reduce the load peaks caused by the disordered charging, fill the load valleys, and will not cause new peaks and valleys. The cost of economic scheduling is the smallest, which is 359.1 yuan, and its variance is 49575.44. The variance is the smallest during smooth scheduling, which is 1369.2, and the cost is 12329.59 yuan at this time. The scheduling results are normalized by the minimum variance and the minimum cost to obtain the optimal charge-discharge load curve. The smaller the value, the higher the satisfaction. Among them, the variance of the optimal charge-discharge curve is 21302.27, which is more obvious than the peak-cutting and valley-filling effect of the minimum-cost load curve; its corresponding cost is 785.4 yuan, which is lower than that of the minimum-variance curve. Therefore, the overall effect is the best.

From Table 2, it can be seen that in the case of 50% penetration rate (i.e., 195 vehicles are connected to the power grid), compared with disordered charging, the two-level vehicle-network interaction model on both sides of the comprehensive supply and demand is used to compare with disordered charging:

(a) . The peak value is reduced by 563.90, and the change rate is 20%; the valley value is increased by 425.40, while the change rate is −37%; the peak-valley difference is reduced by 989.30, and the change rate is 59%. It is proved that orderly charging has a sound effect on shaving peaks and filling valleys, effectively solving the problem of "adding peaks to peaks" on the grid caused by disordered charging of electric vehicles.

(b) . The standard deviation is reduced by 305.42, while the change rate is 61%, indicating that orderly charging can improve the smoothness and stability of system operation.

(c) The load rate is increased by 16%, and the change rate is −22%, which helps to reduce the network loss and improve the utilization rate of power generation equipment and the economic benefits of system operation.

6.2.2. Scheduling Strategy Analysis in the Case of Wind and Solar Access at 50% Penetration Rate. From the simulation results and Figure 4, it is known that the cost of economic scheduling is the smallest, which is 512.4 yuan, and the variance is 43055.98; the variance of stable scheduling is the smallest, which is 20086.56, and the cost is 1192.8 yuan at this time; the scheduling results are normalized by the minimum variance and the minimum cost process to obtain the optimal charge-discharge load curve. The variance of the optimal charge-discharge curve is 26318.54, which is more obvious than the peak-cutting and valley-filling effect of the minimum-cost load curve, and the system runs more smoothly; the corresponding cost is 747.6 yuan, which is

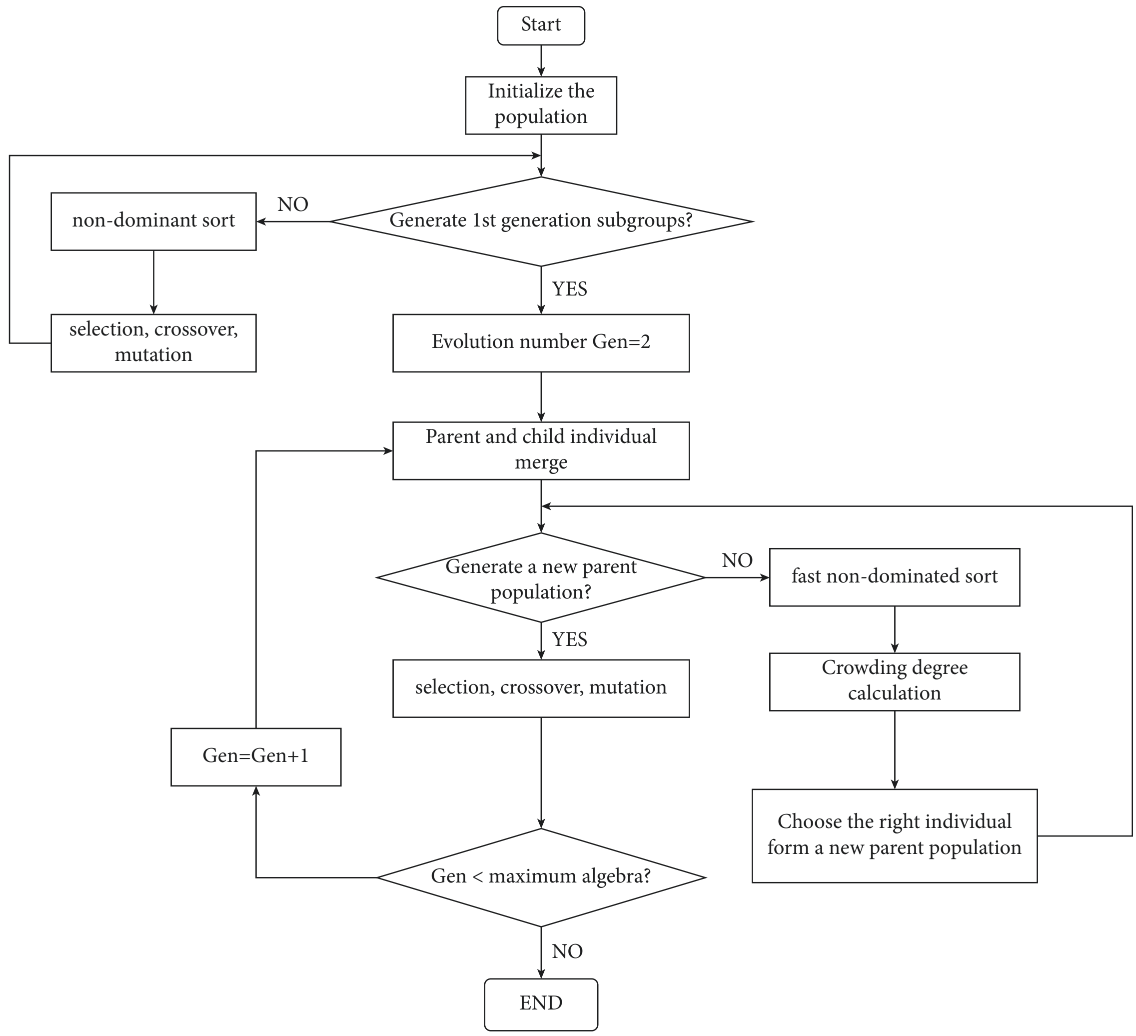

Figure 1: NSGA-II algorithm flowchart.

Table 1: Time-of-use power price parameter settings for charging and discharging.

Period	Charge and discharge electricity price (yuan·(kW·h)$^{-1}$)
Valley time (0:00–3:00, 22:00–24:00)	0.30
(3:00–7:00, 15:00–17:00)	0.60
Peak hours (7:00–15:00, 17:00–22:00)	0.90

more economical than the minimum-variance curve. Therefore, the overall effect is the best. In addition, it can be found that under the same 50% penetration rate, the introduction of new energy will increase the curve volatility, and the orderly scheduling of electric vehicles can reduce the volatility of the load curve and stabilize the load.

It can be seen from Table 3 that when the penetration rate is 50%, and when the wind and solar is introduced, the double-layer vehicle-network interaction model on both sides of the comprehensive supply and demand is compared with the disordered charging:

(a) The peak is cut by 563.90, and the rate of it was 23%; the valley is increased by 259.00, and the rate of change is −29%; peak-to-valley difference is cut by 822.00, which shows a change rate of 52%. It is proved that orderly charging can effectively reduce load peaks and fill load valleys.

(b) The standard deviation is reduced by 485.46, the change rate is 59%, and the stability of the system operation is greatly improved.

(c) The load rate is increased by 17%, and the change rate is −27%, which helps to improve the utilization rate of power resources and the operation efficiency of power distribution equipment.

6.2.3. Analysis of Scheduling Strategy under 100% Penetration Rate. As is shown in Figure 5, it can be judged that the

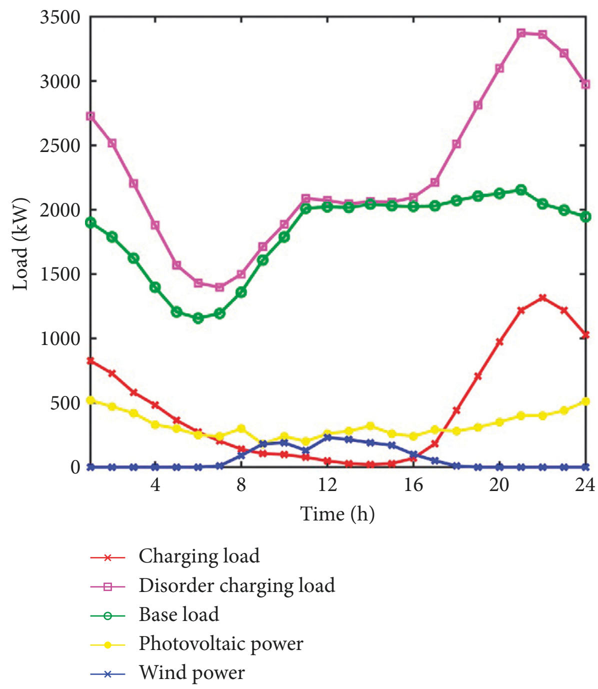

Figure 2: Microgrid base load curve.

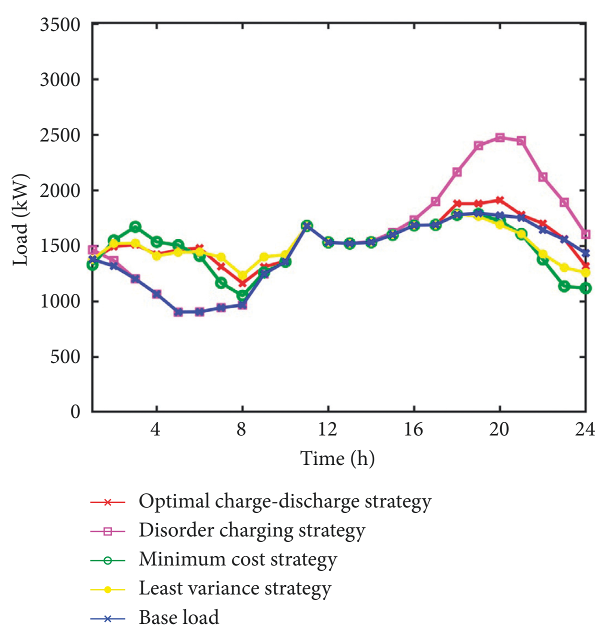

Figure 3: Load curve under the condition of 50% permeability.

Table 2: Comprehensive scheduling results of 50% penetration rate.

	Disorder charging	Comprehensive scheduling	Difference before and after optimization	Rate of change before and after optimization (%)
Peak (kW)	2847.60	2283.70	563.90	20
Valley value (kW)	1157.30	1582.70	−425.40	−37
Peak-to-valley difference (kW)	1690.30	701.00	989.30	59
Load standard deviation (kW)	497.87	192.45	305.42	61
Load average (kW)	1976.50	1940.30	36.20	2
Load rate	69%	85%	−16%	−22

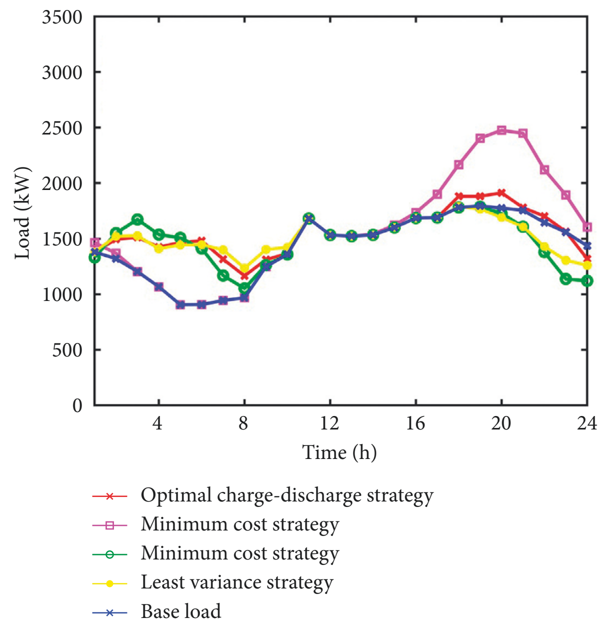

Figure 4: Load curve under the condition of new energy access (50% penetration rate).

Table 3: 50% penetration rate wind-solar access integrated scheduling results.

	Disorder charging	Comprehensive scheduling	Difference before and after optimization	Rate of change before and after optimization (%)
Peak (kW)	2475.70	1912.70	563.90	23
Valley value (kW)	905.70	1164.70	−259.00	−29
Peak-to-valley difference (kW)	1570.00	748.00	822.00	52
Load standard deviation (kW)	485.46	197.26	288.20	59
Load average (kW)	1586.70	1550.00	36.70	2
Load rate	64%	81%	−17%	−27

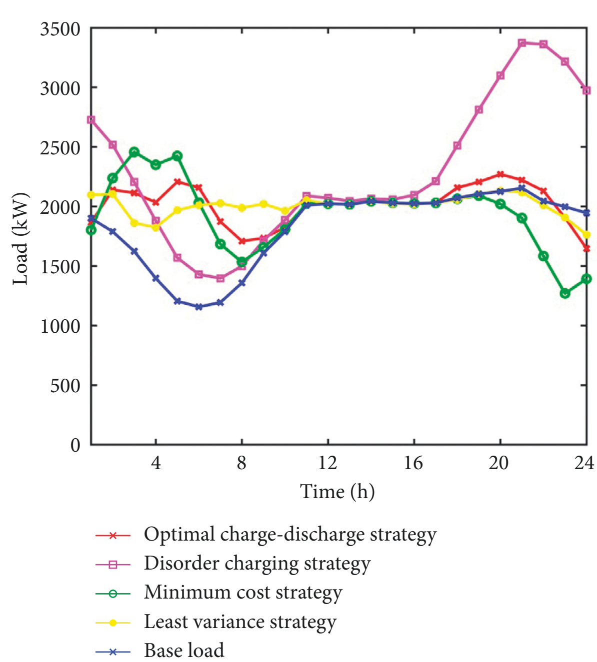

Figure 5: Load curve under the condition of 100% penetration rate.

Table 4: Comprehensive scheduling results of 100% penetration rate.

	Disorder charging	Comprehensive scheduling	Difference before and after optimization	Rate of change before and after optimization (%)
Peak (kW)	3372.60	2140.60	1232.00	37
Valley value (kW)	1397.10	1526.70	−129.60	−9
Peak-to-valley difference (kW)	1975.50	613.90	1361.60	69
Load standard deviation (kW)	608.30	164.67	443.63	73
Load average (kW)	2283.60	1940.90	342.70	15
Load factor	68%	91%	−23%	−34

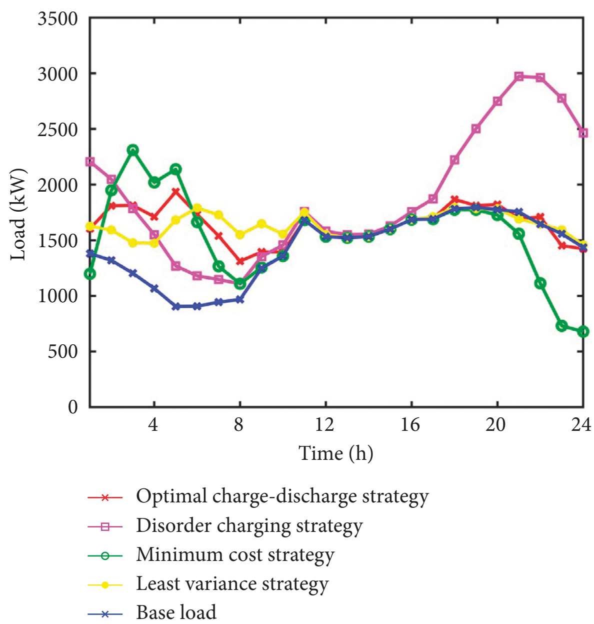

Figure 6: Load curve under the condition of new energy access (100% penetration rate).

Table 5: 100% penetration rate wind-solar access integrated scheduling results.

	Disorder charging	Comprehensive scheduling	Difference before and after optimization	Rate of change before and after optimization (%)
Peak (kW)	2972.60	1934.70	1037.90	35
Valley value (kW)	1108.73	1311.70	−202.97	−18
Peak-to-valley difference (kW)	1863.90	623.00	1240.90	67
Load standard deviation (kW)	584.63	167.85	416.79	71
Load average (kW)	1893.80	1636.60	257.20	14
Load rate	64%	85%	−21%	−33

charging cost is the smallest, which is 1354.5 yuan during economic scheduling; the variance is 144574.5 at this time; the variance is the smallest in smooth scheduling, which is 20040.4, and the cost is 3301.2 yuan at this time; the scheduling results are normalized by the minimum variance and the minimum cost process to obtain the optimal charge-discharge load curve. The variance of the optimal charge-discharge curve is 52779.85, which is more obvious than the peak-shaving and valley-filling effect of the minimum-cost load curve, and the system runs more smoothly; the corresponding cost is 2030.7 yuan, which is more economical than the minimum-variance curve. Therefore, the overall effect is the best. In addition, it can be found that the higher the penetration rate, the better the smoothness.

From Table 4, it can be seen that in the case of 100% penetration rate, compared with disordered charging, the

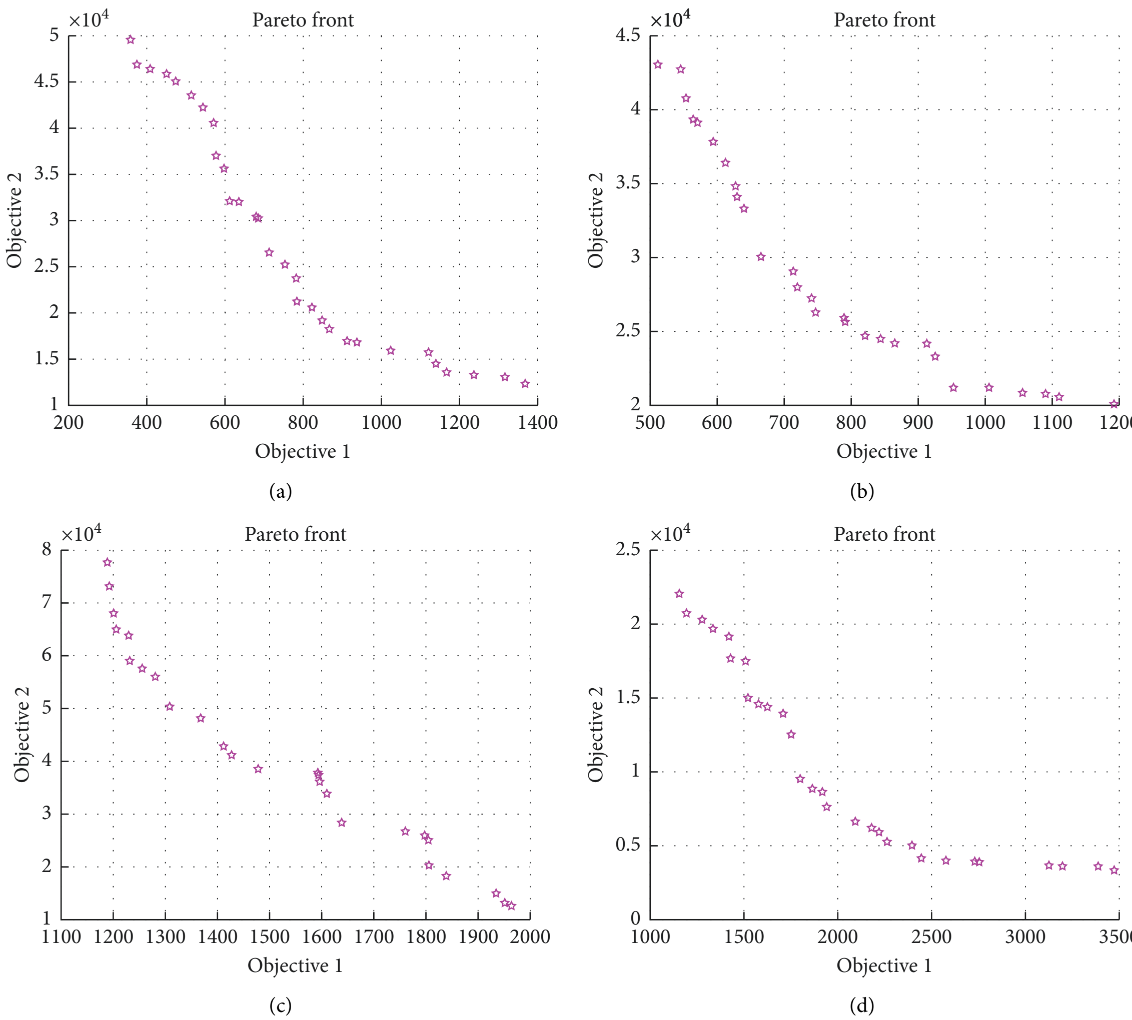

Figure 7: Algorithm convergence graph. (a) 50% penetration Pareto frontier. (b) Introducing the scenery, 50% penetration Pareto frontier. (c) 100% permeability Pareto frontier. (d) Introducing the scenery, 50% penetration Pareto frontier.

double-layer vehicle-network interaction model on both sides of the comprehensive supply and demand is compared with disordered charging:

(a) The peak value is reduced by 1232.00, and the rate of change is 37%; the valley value is increased by 129.60, whose change rate is −9%; the difference between peak and valley is reduced by 1361.60, and its rate of change is 69%. It is proved that orderly charging has a good effect of shaving peaks and filling valleys and effectively solves the problem of "adding peaks to peaks" on the grid caused by disordered charging of electric vehicles.

(b) The standard deviation is reduced by 443.63, and the change rate is 73%, indicating that orderly charging can improve the smoothness and stability of system operation.

(c) The load rate is increased by 23%, and the change rate is −34%, which helps to reduce network losses and improve the utilization rate of power generation equipment and the economic benefits of system operation.

6.2.4. Scheduling Strategy Analysis in the Case of Wind and Solar Access with 100% Penetration Rate. As is shown in Figure 6, compared with the disordered charging curve, the ordered charging curve can effectively cut peaks and fill valleys. The cost of economic dispatch is the smallest, which is 1150.8 yuan, and its variance is 221197.6; variance is the smallest during smooth scheduling, which is 33799.68, and its cost is 3473.4 yuan. The scheduling results are normalized by the minimum variance and the minimum cost, and the optimal charge-discharge load curve is obtained. The variance of the optimal charge-discharge curve is 76823.1, which is more obvious than the peak-cutting and valley-filling effect of the minimum cost load curve, and the system runs more smoothly at this time. Its corresponding cost is 1938.3 yuan, which is more economical than the minimum variance curve. Therefore, the overall effect is the best. In addition, it can be found that the introduction of new energy sources such as wind and solar will bring volatility, but stability will improve as the penetration rate increases.

From Table 5, it can be seen that in the case of 100% penetration rate (introducing scenery), compared with disordered charging, the double-layer vehicle-network interaction model on both sides of the comprehensive supply and demand is adopted.

(a) The peak value is reduced by 1037.90, and the change rate is 35%; the valley value is increased by 202.97, and the change rate is −18%; the peak-valley difference is reduced by 1240.90, and the change rate is 67%. It is proved that orderly charging has a good effect of shaving peaks and filling valleys and effectively solves the problem of "adding peaks to peaks" on the grid caused by disordered charging of electric vehicles.

(b) The standard deviation is reduced by 416.79, and the change rate is 71%, indicating that orderly charging can improve the smoothness and stability of system operation.

(c) The load rate is increased by 21%, and the change rate is −33%, which helps to improve the utilization rate of power generation equipment and the economic benefits of system operation.

6.2.5. Results' Comparison and Analysis. By comparing the optimization results under different permeability conditions, we can find in Figure 7 that the comprehensive scheduling mode after optimization is compared with that before optimization:

(a) The load rate has been significantly improved, which not only helps to reduce network losses, but also improves the economic benefits of system operation.

(b) The introduction of new energy will bring volatility; that is to say, the load variance will become larger when the penetration rate is the same.

(c) The cost is reduced, and the economy of the system operation is improved.

(d) The system peak-valley difference is reduced, giving full play to the peak-shaving and valley-filling effect of the electric vehicle charging load, effectively solving the problem of "peaks over peaks" of the grid caused by disordered charging of electric vehicles, and the utilization and distribution of power resources. The operating efficiency of electrical equipment is significantly increased.

(e) The peak level of the system is significantly reduced, and the valley value has greatly improved, which is conducive to reducing the times of starts and stops, improving the safety of system operation, and saving costs.

(f) The load variance is reduced, and the stability of the system operation is greatly improved. The reduced load variance of the distribution network also means that the degree of stability is improved. With the improvement of the responsiveness, it is more and more stable, and economy grows better as well.

7. Conclusion

Under the background of the large-scale application of electric vehicles and the increase of new energy power generation year by year, this paper proposed a coordinated optimal scheduling strategy for electric vehicles and wind-solar synergy. By rationally scheduling the charging and discharging behavior of electric vehicles, the dynamic balance between the charging and discharging load and the output of new energy in a certain area can be achieved, and the intermittent load of renewable energy can be effectively stabilized, while the load fluctuation can be stabilized, and the peaks and valleys can be cut. This paper also built a two-level vehicle-network interaction optimization model that takes into account the interests of both the user side and the grid side so as to achieve a win-win situation. Since there are multiple optimization objectives in the analysis process, the fast nondominant sorting genetic algorithm NSGA-II with elite strategy was adopted, and a series of "approximate optimal solutions" were obtained by weighing each objective function to generate the Pareto solution set. Finally, the strategy proposed in this paper was analyzed and affirmed by numerical example simulation, which proved that orderly charging of electric vehicles can cut peaks and fill valleys, improve the utilization rate of power generation equipment, increase the reliability of power supply, and improve the efficiency and reliability of power grid operation.

This paper only considers the time-disordered scheduling of private vehicles and does not discuss the long-term scheduling strategy of electric vehicles. In reality, the charging rules of EVs vary greatly with factors such as seasons, weather, and policies, and it is difficult to ensure the accuracy of load forecasting. Therefore, the analysis and prediction of the actual charging behavior of electric vehicles in combination with the actual scene still need further research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] L. Tang, F. Wang, and X. Y. Liu, "Research on the influence of electric vehicle charging load on the life loss of distribution transformers," *Electrotechnical Application*, vol. 37, no. 12, pp. 80–88, 2018.

[2] X. Y. Duan, C. Yan, G. Zizhen, C. Xi, D. Ning, and Z. Yang, "Optimal charging and discharging strategy for electric vehicles in large timescales," *Power Technology*, vol. 42, no. 12, pp. 4037–4044, 2018.

[3] S. Y. Kuai, "EV charging load dispatching benefit and potential research," *Electronic Measurement Technology*, vol. 42, no. 14, pp. 37–42, 2019.
[4] G. H. Yu, "Order charging method research of electrical vehicle based on dynamic distributed time electricity cost need answer," *Rural Electrification*, vol. 08, pp. 57–60, 2021.
[5] J. D. Duan, "Coordinated charging control for EV charging stations considering wind power accommodation," *Energy Storage Science and Technology*, vol. 10, no. 2, pp. 630–637, 2021.
[6] L. B. Liu, "Orderly charging and discharging strategy optimization for electric vehicles considering dynamic battery-wear model," *Automation of Electric Power Systems*, vol. 40, no. 5, pp. 83–90, 2016.
[7] S. Xu and Y. Li, "An optimization model of peak-valley price time interval for guiding the orderly charging and discharging of electric vehicles," *Power Demand Side Management*, vol. 20, no. 5, pp. 11–15, 2018.
[8] Z. Zhang, X. Huang, Y. Cao, H. Yang, and B. Xiao, "Charging load calculation considering TOU for electric vehicles," *Electric Power Automation Equipment*, vol. 34, no. 2, pp. 24–29, 2014.
[9] X. X. Wang, "Multi-objective Bi-level electric vehicle charging optimization considering user satisfaction degree and distribution grid security," *Power System Technology*, vol. 41, no. 7, pp. 2165–2172, 2017.
[10] X. Wang, "Research on Optimal Scheduling Strategy of Electric Vehicle Charging and Discharging in V2G mode," Master Diseertation, North China Electric Power University, Beijing, China, 2021.
[11] Z. D. Bao, "Research on Charging and Discharge Technology Control Method of Electric Vehicles Based on V2G mode," Master Dissertation, Ningxia University, Ningxia, China, Ningxia University, 2021 .
[12] S. W. Su, "Research on coordinated charging for electric vehicles considering new energy accommodation," *Journal of China Three Gorges University*, vol. 41, no. 5, pp. 84–89, 2019.
[13] S. N. Wang and S. B. Yang, "Strategies for orderly control of electric vehicle charging load in residential areas," *Automation of Electric Power Systems*, vol. 40, no. 4, pp. 71–77, 2016.
[14] Z. W. Xu, Z. Hu, Y. Song, H. Zhang, and X. Chen, "Coordinated charging strategy for PEV charging stations based on dynamic time-of-use tariffs," *Proceedings of the CSEE*, vol. 34, no. 22, pp. 3638–3646, 2014.
[15] P. Chen, Q. H. Meng, and Y. J. Zhao, "The electric vehicle charging load calculation based on the Monte Carlo method," *Journal of Electrical Engineering*, vol. 11, no. 11, pp. 40–46, 2016.
[16] Y. Ao, "Research on orderly control strategy of electric vehicle charging in residential areas," Nanchang University, Master Dissertation, 2021.
[17] J. Y. Zhu, "Research on Microgrid Economic Dispatch Considering the Response of Electronic Users," Master Dissertation, Hebei University of Technology, Tianjin, China, 2017.
[18] Y. Wang, "Sequential charge-discharge guidance strategy for electric vehicles based on time-sharing charging-discharging margin," *Power System Technology*, vol. 43, no. 12, pp. 4353–4361, 2019.
[19] Y. R. Li, "Charging and discharging scheduling strategy of EVs considering demands of supply side and demand side under V2G mode," *Electric Power Automation Equipment*, vol. 41, no. 03, pp. 129–135+143, 2021.
[20] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: nsga-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.
[21] M. Wang, "Three-dimensional MultiUAV cooperative path planning based onan improved NSGAII algorithm," *Machinery & Electronics*, vol. 39, no. 11, pp. 73–80, 2021.
[22] X. Jin, H. Tang, X. Wang, G. Qi, X. Jin, and D. Li, "Design of nuclear reactor power LQG controller based on NSGA- II algorithm," *Atomic Energy Science and Technology*, pp. 1–11, 2022, http://kns.cnki.net/kcms/detail/11.2044.TL.20220218.1150.006.html.
[23] R. F. Shi, Z. H. Liang, and Y. Ma, "TOPSIS method based orderly charging strategy for electric vehicles in residential area," *Automation of Electric Power Systems*, vol. 42, no. 21, pp. 104–110+159, 2018.