



Article **Two-Layer Cooperative Optimization of Flexible Interconnected Distribution Networks Considering Electric Vehicle User Satisfaction Degree**

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Abstract: The scaled access of electric vehicles (EVs) exacerbates load fluctuations in distribution networks, which is not conducive to the stable and economic operation of the distribution networks. At present, user satisfaction degree is generally low. To avoid this problem, this paper proposed a twolayer cooperative optimization of flexible interconnected distribution networks considering EV user satisfaction degree. First, the EV user satisfaction degree model is established by considering EV users' charging waiting time, charging power, and other indicators. At the same time, an EV charging mode switching model is constructed based on the number of EVs entering the network and their battery charge state. On this basis, the Monte Carlo algorithm is used to generate the results of the daily distribution of EV loads taking into account the user satisfaction degree, so as to improve the load ratio of the transformer in the distribution network. Further, a two-layer cooperative optimization of flexible interconnected distribution networks considering electric vehicle user satisfaction degree is developed with the daily operating cost of each network as the optimization objective. Finally, a flexible interconnected power distribution network consisting of three power distribution networks is used as an example for validation. The results show that this method is effective in improving EV user satisfaction degree and reducing the peak-to-valley ratio of the system load while taking into account the safe and economic operation of the distribution network, which greatly improves the reliability and economy of the operation of the flexible interconnected power distribution network.

Keywords: electric vehicles; EV user satisfaction degree; flexible interconnected power distribution network; peak-to-valley ratio; reliability and economy of the operation

1. Introduction

Fuel vehicles put huge pressure on the global environment and energy. Therefore, environmentally friendly, efficient, and low-consumption new energy vehicles have become an important issue of concern to countries around the world [1,2]. At present, the development direction of new energy vehicles in China is mainly EVs. With the gradual increase in the market share of EVs, the EV charging load gradually climbs through the charging facilities' access to the distribution networks. Due to the charging characteristics of EVs, it can be used as a new type of energy storage device. However, the disorderly charging behavior of EVs will affect the load of the power grid to a certain extent, making the peak-to-valley ratio of the electric load further increase, and the disorderly charging behavior of EVs will also reduce the stability and economy of the integrated energy system operation. To avoid the occurrence of the above problems, it is necessary to optimize the current charging behavior of EVs [3,4].



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Literature Review

Currently, EV charging strategies are mainly formulated by measuring indicators such as charging time, charging power, and number of vehicles, and by using intelligent algorithms to generate EV orderly charging strategies [5]. H. G. Tran et al. in [6] provided a concise optimization method based on the Lagrange multiplier theorem and it could appropriately limit the amount of power that MG can supply to the main grid during periods of overstocking. Mostafa Rezaeimozafar et al. [7] developed a two-step scheduling model that effectively guides a large-scale EV fleet in microgrids without demanding an adynamic monetary scheme. X. Chen et al. [8] proposed an EV charging station recommendation algorithm. With a proper charging scheduling algorithm deployed, the synergy between the transportation network and the smart grid can be created. Mingyang Li et al. used Soft Opening Points (SOPs) to control the flow of lines to improve distribution network performance, better accommodate DG and EV, and optimize network loss and EV charging satisfaction targets in [9]. K. Fu et al. [10] analyzed how EV charging loads are synergized with distributed PV outputs based on a Monte Carlo algorithm simulating the travel characteristic data of different types of EVs. However, the established methods did not discuss the users' charging demand as well as their willingness, which made the users' charging time relatively concentrated and the queuing time too long, leading to the emergence of new spike loads and further exacerbating the pressure on the distribution transformers in the distribution networks [11]. In fact, EV user satisfaction is directly related to the size of the charging load in each period. Furthermore, the optimized regulation strategy of EV charging behavior and flexible interconnected distribution networks directly affects the operation effect of the distribution networks. So the optimization results need to be further improved [1,12].

In terms of EV user satisfaction degree, some scholars have carried out relevant studies. E. Wu et al. [13] divided the process of microgrid scheduling optimization into the load layer and source storage layer, and the load layer used the energy storage characteristics of EVs to suppress the load peak of microgrids under the premise of ensuring user satisfaction degree. However, its EV charging mode adopted a constant power charging model, and when the number of EVs accessed exceeds the maximum range that the microgrid can withstand, the peak load will be regenerated at another time. C. Liu et al. [14] divided the EV user group by using EV users' idle time and acceptance of discharge cutoff capacity as the classification criteria and established charging and discharging load curves for EV users with different preferences. However, this method would cause the same preference group to be too concentrated, which would lead to a long queuing time in practical scenarios, thus causing a decrease in user satisfaction. N. Bañol Arias et al. [15] proposed a two-level hierarchical optimization framework for the EV charging coordination that maximizes users' satisfaction while avoiding operational grid issues in the whole distribution system, but the paper ignored the EV travel satisfaction, which may lead to the EV battery SOC being at a low level, affecting the convenience of users' travel.

Therefore, to avoid the low satisfaction of EV users, as well as avoiding large-scale access to electric vehicles, which is prone to causing overloading of distribution transformers in the distribution network and other issues, this paper proposes a two-layer cooperative optimization of flexible interconnected distribution networks considering electric vehicle user satisfaction degree, to guarantee the economic and safe operation of each distribution network with as high a level of user satisfaction as possible. First, it takes into account the EV users' travel probability, car charging waiting time, actual charging power, and other indicators, and an EV user satisfaction degree model is established with the maximization of EV users' travel satisfaction and cost satisfaction maximization as the objective function. Meanwhile, the EV charging mode switching model was constructed based on the state of charge (SOC) of the EV battery. On this basis, the Monte Carlo algorithm was utilized to generate EV load curves taking into account user satisfaction degree. Finally, to optimize the daily operating cost of each distribution network, a flexible interconnected distribution consisting of three distribution networks with DG and charging distribution by SOP is sim-

ulated as an example to achieve peak shaving and peak filling of loads in the distribution network, and to consume the distributed resources within the distribution network.

2. The Model with Optimizing EV User Satisfaction Degree

Two-layer cooperative optimization of flexible interconnected distribution networks considering electric vehicle user satisfaction degree in this paper is divided into an upper optimizing model called EVs charging optimization layer and a lower optimizing model called flexible interconnected distribution control layer, as shown in Figure 1.



Figure 1. Layered optimization model flow chart.

In the upper optimization model, the travel characteristics of EV users, the number of EVs, charging power, battery capacity, charging price, and other factors are taken into account to maximize the travel satisfaction and cost satisfaction of EV users, taking into account the EV user satisfaction, while being able to shave peaks and fill valleys of the system load, and alleviating the over-heavy loading of distribution transformers. In the lower optimization model, the operational safety constraints of a flexible interconnection distribution network and the constraints of the characteristics of the equipment are taken into account, with the goal of the total single-day operating costs to further reduce the operating costs of the distribution networks, to achieve the mutual benefit of each station, and to maximize the consumption of the renewable energy output.

2.1. Analysis of EV Users' Traveling Behavior

To analyze the impact of EV charging load on flexible interconnected distributions, this paper treats EV charging demand as a cluster of EVs and uses Monte Carlo simulation to

model EV charging load [16,17]. According to the vehicle travel history statistics, the user's last return moment approximately conforms to a normal distribution with the following probability density function [18]:

$$f_{\rm s}(x) = \begin{cases} \frac{1}{\sigma_{\rm S}\sqrt{2\pi}} \exp\left[-\frac{(x-\mu_{\rm s})^2}{2\sigma_{\rm S}^2}\right] & \mu_{\rm S} - 12 < x \leqslant 24\\ \frac{1}{\sigma_{\rm S}\sqrt{2\pi}} \exp\left[-\frac{(x+24-\mu_{\rm s})^2}{2\sigma_{\rm S}^2}\right] & 0 < x \leqslant \mu_{\rm S} - 12 \end{cases}$$
(1)

$$f_{\rm e}(x) = \begin{cases} \frac{1}{\sigma_{\rm e}\sqrt{2\pi}} \exp\left[-\frac{(x-24-\mu_{\rm e})^2}{2\sigma_{\rm e}^2}\right] & \mu_{\rm e} + 12 < x \leqslant 24\\ \frac{1}{\sigma_{\rm e}\sqrt{2\pi}} \exp\left[-\frac{(x-\mu_{\rm e})^2}{2\sigma_{\rm e}^2}\right] & 0 < x \leqslant \mu_{\rm e} + 12 \end{cases}$$
(2)

In Equations (1) and (2), $f_s(x)$ and $f_e(x)$ are the probability values of the electric car traveling and returning at moment x, respectively. μ_s and μ_e are the EV users' expected values of departure and arrival times. It is equivalent to the points in time at which EV users would like to depart and arrive. σ_s and σ_e are the standard deviations, which indicate the extent to which the actual departure and arrival times deviate from the expected values.

The probability density function of the distance traveled by EVs per day is:

$$f_{\rm d}(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left[\frac{-(\ln x - \mu)^2}{2\sigma^2}\right]$$
(3)

In Equation (3), $f_d(x)$ is the probability that the electric car starts charging at moment x. μ is the expected value of traveling distance. σ is the standard deviation, which indicates the degree of deviation of the actual traveling distance from the expected value.

The time constant required for EV charging which is called T_n^i can be expressed in terms of factors such as charging efficiency, SOC, and charging power:

$$T_{\rm n}^{i} = \frac{\left(S_{\rm n}^{i} - S_{\rm S}^{i}\right)E_{\rm S}^{i}}{\eta_{\rm ev,ch}P_{\rm ev,ch,i,t}} \tag{4}$$

In Equation (4), S_n^i is the starting SOC of the EVs. S_S^i is the desired SOC of the EVs. E_S^i is the battery capacity of the EVs. $\eta_{ev,ch}$ and $P_{ev,ch,i,t}$ are the charging efficiency and charging power of the EVs, respectively.

2.2. Analysis of Working Mode and Working Principle

Since the charging behavior of EVs completely follows the owner's will, to fully mobilize the user's participation, the user's travel satisfaction function and cost satisfaction function are established, respectively [19,20]. Among them, travel satisfaction refers to the degree of satisfaction of the user's charging waiting time; cost satisfaction is the degree of satisfaction of the user with the charging cost [21].

In this paper, we take EV charging power as the decision variable, the highest travel satisfaction and charging cost satisfaction as the objective function, and Equations (1)–(4) as the constraints to establish the upper layer optimization model. The objective function of the upper layer model is as follows:

$$\max f_k^2 = \sum_{i=1}^{n_k} \left(\partial_{k,i}^1 + \partial_{k,i}^2 \right) \tag{5}$$

In Equation (5),

$$f_k^{25}\ldots f_1$$

is EV user satisfaction degree. $\partial_{k,i}^1$ is EV user travel satisfaction, and $\partial_{k,i}^2$ is cost satisfaction.

There is no clear limit to how long each user will be satisfied with the wait, and when different users are satisfied with the same trip, the length of the wait varies. Therefore, this paper establishes the fuzzy subset method to model travel satisfaction, and divides the waiting time of electric vehicle users into three fuzzy subsets: "comfortable", "average", and "anxious". The membership model in this article is shown in Figure 2. The shaded part in the figure is the fuzzy boundary of the user's travel satisfaction.



Figure 2. Traveling satisfaction affiliation function.

The affiliation function for "comfort" is:

$$\mu_{\rm com} (T_{\rm wait}) = \begin{cases} 1 & T_{\rm wait} < T_{\rm com,min} \\ \frac{T_{\rm com,max} - T_{\rm wait}}{T_{\rm com,min}} & T_{\rm com,min} \leqslant T_{\rm wait} \leqslant T_{\rm com,max} \\ 0 & T_{\rm wait} > T_{\rm com,max} \end{cases}$$
(6)

In Equation (6), $\mu_{com}(T_{wait})$ is the affiliation degree of EV users who perceive the waiting time as "comfortable". T_{wait} is the actual waiting time of users. $T_{com,min}$ and $T_{com,max}$ are the lower and upper bounds of the "comfortable" affiliation degree, respectively.

The affiliation function for "normal" is:

$$\mu_{\rm nor}(T_{\rm wait}) = \begin{cases} 0.6 \times \frac{T_{\rm wait} - T_{\rm nor,min}}{T_{\rm com,max} - T_{\rm nor,min}} & T_{\rm nor,min} \leqslant T_{\rm wait} < T_{\rm com,max} \\ 0.6 & T_{\rm com,max} \leqslant T_{\rm wait} < T_{\rm anx,min} \\ 0.6 \times \frac{T_{\rm nor,max} - T_{\rm wait}}{T_{\rm nor,max} - T_{\rm anx,min}} & T_{\rm anx,min} \leqslant T_{\rm wait} \leqslant T_{\rm nor,max} \\ 0 & T_{\rm wait} < T_{\rm nor,max} > T_{\rm nor,max} \end{cases}$$
(7)

In Equation (7), $\mu_{nor}(T_{wait})$ is the affiliation degree of EV users who perceive the waiting time as "normal". $T_{nor,min}$ and $T_{com,max}$ are the lower and upper bounds, respectively, of the increasing trend of the affiliation degree of "normal". $T_{anx,min}$ and $T_{nor,max}$ are the lower and upper bounds, respectively, of the decreasing trend of "normal" affiliation.

The affiliation function for "anxiety" is:

$$\mu_{\text{anx}}(T_{\text{wait}}) = \begin{cases} 0 & T_{\text{wait}} < T_{\text{anx,min}} \\ 0.25 \times \frac{T_{\text{wait}} - T_{\text{anx,min}}}{T_{\text{anx,max}} - T_{\text{anx,min}}} & T_{\text{anx,min}} \leqslant T_{\text{wait}} \leqslant T_{\text{anx,max}} \\ 0.25 & T_{\text{wait}} > T_{\text{anx,max}} \end{cases}$$
(8)

In Equation (8), $\mu_{anx}(T_{wait})$ is the affiliation degree of EV users who perceive the waiting time as "anxiety". T_{wait} is the actual waiting time of the users. $T_{anx,min}$ and $T_{anx,max}$ are the lower and upper bounds of the "anxiety" affiliation degree, respectively.

Based on the above conditions, it is defined that the travel satisfaction of EV users $\partial_{k,i}^1$ is:

$$\partial_{k,m}^{1} = \max\{\mu_{\text{com}}(T_{\text{wait}}) \mid \mu_{\text{nor}}(T_{\text{wait}}) \mid \mu_{\text{anx}}(T_{\text{wait}})\}$$
(9)

2.2.2. Cost Satisfaction

The EV users' cost satisfaction function takes into account both the cost of charging during the scheduling period and the additional cost of the deviation component, and thus defines the cost satisfaction of the EV ∂_{ki}^2 as:

$$\partial_{k,m}^2 = 1 - \frac{\sum\limits_{t=1}^{T} C_+^t P_{\text{ev,ch},i,t} I_{k,i}^t \Delta t - cost_{k,i}^{\min}}{cost_{k,i}^{\max} - cost_{k,i}^{\min}}$$
(10)

In Equation (10), $C_{k,i}^{t}$ is the charging price cost. $cost_{k,i}^{max}$ and $cost_{k,i}^{min}$ are the highest and lowest costs for this user's current charging obtained by scheduling the *i*th EV in charging distribution *k* to charge at the extremes of the lowest and highest price periods, respectively. When the users are scheduled to charge during the low price period, the charging cost satisfaction is maximized, and $\partial_{k,i}^{2}$ is equal to 1.

2.2.3. Charging Mode Switching Model Construction of Charging Distribution

EVs are both a consumer and a store of electric energy, and usually, the grid entry duration of EVs is much longer than the minimum charging duration required. Based on this characteristic of EVs, the charging distributions can flexibly regulate the charging process of grid-entry EVs, so that it can fully participate in the operation of the distribution. Based on the charging mode switching technology, the EV can interact with the charging distribution to adjust the charging mode of the EV in the process of entering the network. During the interaction process, the charging distribution operator then guides the owner's charging behavior through certain incentives and measures.

In this paper, we detect the status of the SOC of the accessed EVs and select the charging mode corresponding to the charging distribution. When the EV SOC is low, fast charging or super-fast charging mode could be selected, and when the SOC increases to a certain level, it is switched to slow charging mode thus reducing the EV charging load and alleviating the overloading of the distribution transformer in the distribution networks. The formula is as follows:

$$P_{\text{ev,ch},i,t} = \begin{cases} P_{\text{ev,ch},i,t,f} & 0 \le SOC_{ev,i} < 0.4 \\ P_{\text{ev,ch},i,t,m} & 0.4 \le SOC_{ev,i} < 0.7 \\ P_{\text{ev,ch},i,t,s} & 0.7 \le SOC_{ev,i} < 1 \end{cases}$$
(11)

In Equation (11), $P_{ev,ch,i,t}$ is the actual charging power of the electric car at moment *i*. $P_{ev,ch,i,t,f}$, $P_{ev,ch,i,t,m}$, and $P_{ev,ch,i,t,s}$ are the super-fast charging power, fast charging power, and slow charging power, respectively.

3. Optimization Model of Flexible Interconnected Distribution Operation for Lower Tier Counting and Electric Vehicle User Satisfaction Degree

This chapter introduces the operation optimization model of a flexible interconnected distribution network that takes into account the satisfaction of electric vehicle users. Firstly, the charging load of the electric vehicle is superimposed with the base load of the original distribution network based on the results obtained from the upper optimization. Secondly, the single-day operation cost of the flexible interconnected distribution network is taken as the optimization target, and the internal equipment characteristics and operation safety of the distribution network are the constraints. Finally, the CPLEX solver is called based on the Matlab distribution network.

3.1. Objective Function

In this paper, the lower optimization objective function of the two-layer optimization model is established with SOP transmission power, power transaction from the grid by the distribution networks, wind turbine, and photovoltaic output power, and energy storage charging and discharging power, etc., as the decision variables, and with the optimization objective of reducing the single-day operation cost of the system as the optimization objective, as follows:

$$\min F = C_{\rm sop} + C_{\rm grid} + C_{\rm pv} + C_{\rm wind} + C_{\rm ess}$$
(12)

In Equation (12), *F* is the comprehensive loss of the system in a single day. C_{sop} is the cost of SOP operation. C_{grid} is the cost of purchasing and selling electricity in a single day in the distribution. C_{pv} is the cost of the PV operation. C_{wind} is the cost of wind operation. C_{ess} is the cost of the energy storage operation. C_{ev} is the charging cost of EVs, which is calculated by the following formulas:

$$\begin{cases}
C_{\text{sop}} = \eta_{\text{sop}} S_{\text{sop}} \\
C_{\text{grid}} = \sum_{t=1}^{T} (C_{+}^{t} P_{\text{buy},i,t} + C_{-}^{t} P_{\text{sell},i,t}) \\
C_{\text{pv}} = \alpha \times \sum P_{\text{pv},i,t} \\
C_{\text{wind}} = \beta \times \sum P_{\text{wind},i,t} \\
C_{\text{ess}} = \gamma \times \sum (P_{\text{ess},\text{dch},i,t} + \sum P_{\text{ess},\text{ch},i,t})
\end{cases}$$
(13)

In Equation (13), η_{sop} is the modulus of the SOP operation, and S_{sop} is the actual capacity used by the SOP. $P_{buy,i,t}$ and $P_{sell,i,t}$ are the purchased and sold power of the distribution to the larger grid. α is the operational cost factor of the PV. $P_{pv,i,t}$ is the actual output power of the PV. β is the operational cost factor of the wind. $P_{wind,i,t}$ is the actual output power of the wind power; and γ is the operational cost factor of the energy storage. $P_{ess,dch,i,t}$ and $P_{ess,ch,i,t}$ are the charging power and the discharging power of the energy storage, respectively.

3.2. Constraints

The constraints of the lower-level optimization objective function include the distribution equipment characteristic constraints as well as the operational safety constraints, which are modeled as follows.

(1) SOP constraints, including SOP port power balance constraints and SOP capacity constraints.

$$\begin{cases} P_{s1} + P_{s2} + P_{s3} = 0\\ S_{sop} \le S_{sop,max} \end{cases}$$
(14)

In Equation (14), P_{s1} , P_{s2} , and P_{s3} denote the active power at the 1st, 2nd, and 3rd ports of the SOP, respectively. $S_{sop,max}$ is the maximum capacity of the flexible interconnection device.

(2) PV plant output power constraints:

$$0 \le P_{\mathsf{pv},i,t} \le P_{\mathsf{pv},i,t}^{\max} \tag{15}$$

In Equation (15), $P_{pv,i,t}^{max}$ is the upper limit of the power output of the PV.

(3) Wind power plant output power constraints:

$$0 \le P_{\text{wind},i,t} \le P_{\text{wind},i,t}^{\max} \tag{16}$$

In Equation (16), $P_{\text{wind},i,t}^{\max}$ is the upper limit of the power output of the wind power distribution.

(4) Energy storage plant constraints:

$$u_{\mathrm{dch},i,t} + u_{\mathrm{ch},i,t} = 0 \tag{17}$$

$$S_{\text{ess},i,start} = S_{\text{ess},i,end} \tag{18}$$

$$S_i^{\min} \le S_{i,t} \le S_i^{\max} \tag{19}$$

$$P_{\text{ess,dch},i,t} \le u_{\text{dch},i,t} P_{\text{ess,dch},i}^{\text{max}}$$
(20)

$$P_{\text{ess,ch},i,t} \le u_{\text{dch},i,t} P_{\text{ess,ch},i}^{\max}$$
(21)

$$S_{\text{ess},i,t+1} = S_{\text{ess},i,t} + \eta_{\text{ch}} P_{\text{ess},\text{ch},i,t} - \frac{1}{\eta_{\text{dch}}} P_{\text{ess},\text{dch},i,t}$$
(22)

In Equations (17)–(22), $u_{dch,i,t}$ and $u_{ch,i,t}$ are 0–1 variables indicating the charging and discharging identifiers of the energy storage plant. $S_{ess,i,start}$ and $S_{ess,i,end}$ are the charging start and end states of the energy storage plant, respectively. S_i^{min} and S_i^{max} are the upper and lower limits of the capacity of the energy storage plant, respectively. $S_{i,t}$ is the SOC of the energy storage plant at the moment *i*. $P_{ess,ch,i}^{max}$ and $P_{ess,dch,i}^{min}$ are the upper limits of the charging power of the energy storage plant, respectively. $S_{ess,i,t}$ is the capacity of the energy storage plant, respectively. $S_{ess,i,t}$ is the capacity of the energy storage plant, respectively. $S_{ess,i,t}$ is the capacity of the energy storage plant.

(5) EV capacity constraints.

$$S_{\text{ev},i,t+1} = S_{\text{ev},i,t} + \eta_{\text{ev},\text{ch}} P_{\text{ev},\text{ch},i,t} I_{k,i}^t$$
(23)

In Equation (23), $S_{\text{ev},i,t}$ is the EV battery SOC, $\eta_{\text{ev},\text{ch}}$ is the EV charging efficiency, $P_{\text{ev},\text{ch},i,t}$ is the EV charging power, $I_{k,i}^t$ is a 0–1 variable, and it denotes the EV charging identification.

4. Calculation Example Analysis

In this paper, the validity of the model and methodology is verified using a flexible interconnected distribution network test system consisting of three distribution networks, all of which are 17 km \times 17 km in size, and are equipped with electric vehicle charging distributions and energy storage distributions. Among them, there is a wind power plant in distribution network 1 and photovoltaic power plants in distribution network 2 and 3. The topology of this flexible interconnected distribution network is shown in Figure 3.



Figure 3. Flexible interconnected distribution topology.

4.1. Simulation Scenarios and Parameter Settings

It is assumed that the number of EVs under the jurisdiction of each distribution is 100, 70, and 50, respectively, in this paper. The general car-using habits of car owners are to

leave the car early and return home late, and most of them concentrate on charging at night. Therefore, the scheduling cycle is selected as from 0:00 of the current day to 0:00 of the next day, and setting up a dispatch schedule for 15 min dispatches. The user's demanded power is calculated from his daily driving mileage. The probability density function is utilized to randomly generate user information to obtain the charging load under the random charging scenario, thus providing a basis for performing charging scheduling. The parameters of the facilities within the distribution are shown in Table 1. The bidirectional time-sharing purchase and sale of electricity between the distribution network and the main grid are shown in Figures 4 and 5. The data used in the paper are from [22].

Table 1. Parameterization of	the algorithm.
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Parameters	Values	Parameters	Values
Numbers of EV	[100, 70, 50]	Operational cost factor of the wind	0.2
EV battery capacity (kWh/vehicle)	60	Wind farm capacity (MW)	3.4
EV charging power (kW)	[20, 70, 110]	Operational cost factor of PV	0.192
Transformer capacity (MVA)	[6.3, 7, 9]	Photovoltaic power plant 1 and 2 capacity (MW)	[4, 6.96]
SOP loss factor	0.02	Operational cost factor of the energy storage	0.23
SOP port capacity (MVA)	25	Energy storage power Distribution 1, 2, and 3 capacity (MW)	[4, 4, 2]



Figure 4. Distribution 1 load data and its electric price.



Figure 5. Distribution 3 load data and its electric price.

4.2. Analysis of Simulation Results

To compare the effects of different charging and discharging modes of electric vehicles on the economy of flexible interconnected distribution networks, the following three strategies are adopted for simulation.

Scenario 1: The EV charging strategy in the operational optimization model is a random charging mode, which serves as a blank control group;

Scenario 2: The EV charging strategy in the optimization model is the ordered charging regulation strategy without considering the EV user satisfaction degree. It is the traditional ordered charging regulation strategy. This method is derived from [23].

Scenario 3: The EV charging strategy in the optimization model is the ordered charging regulation strategy considering EV user satisfaction. It is the optimized regulation strategy in this paper.

4.2.1. Electric Vehicle Charging Strategy Analysis

Using the optimization method in this paper, the net load curves of the distribution network before and after charging scheduling are obtained as shown in Figures 6 and 7, taking Distribution 1 and Distribution 3 as examples. As can be seen from the figure, under the random charging scenario (users arrive at the charging distribution that is to start charging until full), the charging load is superimposed on the load peak, while the charging load is less during the valley time, the load peak–valley difference becomes larger, and the load fluctuation is aggravated. By adopting this paper's two-layer optimization method for EV charging scheduling, under both the traditional orderly charging regulation strategy and this paper's optimized regulation strategy, EV charging is rarely arranged during the original peak load hours, and the charging load can be distributed more evenly and reasonably during the scheduling hours, thus effectively reducing the load fluctuations of the distribution network.



Figure 6. Load profile before and after charging optimization for Distribution 1.



Figure 7. Load profile before and after charging optimization for Distribution 3.

In addition, under the consideration of the EV user satisfaction, for the sake of the operation safety and stability of the distribution network, the charging mode switching is utilized to improve the new peak loads that appear under the traditional orderly charging strategy scenario. Taking Distribution 1 and Distribution 3 as the example. In Distribution 1, the load peak-to-valley difference rate of the proposed scheme in this paper is 22.9% less than that of unordered charging and 13.5% less than that of traditional ordered charging. In Distribution 3, the load peak-to-valley difference rate of the proposed scheme in this paper is 15.62% less than that of unordered charging and 8.47% less than that of traditional ordered charging.

Considering that the pressure on the distribution transformer is also different after different proportions of EVs are connected to the distribution, the response before and after EV orderly charging considering charging mode switching (Scenario 2 and Scenario 3) is analyzed for Distribution 3 as an example, and Figures 8 and 9 and Table 2 show the response of EVs with different proportions of EVs connecting to the distribution under Scenario 2 and Scenario 3, respectively. The simulation results show that in the EV sequential charging strategy without considering charging mode switching, the load peak-to-valley difference increases with the increase in the proportion of EV access, which is very likely to cause transformer overloading. In the case of the orderly charging strategy considering charging mode switching, the load peak-to-valley difference decreases with the increase in the proportion of EV access, which can better reduce the peak-to-valley difference rate of the load in the distribution network, effectively preventing the large-scale EVs from generating new peak loads when charging in the low price hours, and thus avoiding the occurrence of the over-heavy-loading situation of the distribution transformer.



Figure 8. Sequential charging strategy for electric vehicles without considering charging mode switching.



Figure 9. Sequential charging strategy for electric vehicles considering charging mode switching.

Scenario 2		Scenario 3				
Ratio	Maximum Load Value (MW)	Minimum Load Value (MW)	Load Peak-to-Valley Ratio (%)	Maximum Load Value (MW)	Minimum Load Value (MW)	Load Peak-to-Valley Ratio (%)
200	3	6.7	55%	3.7	6.2	40%
300	3.1	7.2	56%	4.1	6.4	36%
400	3.1	8.4	63%	4.2	6.6	36%
500	3.1	9.3	67%	4.5	6.6	31%
600	3.2	10.2	69%	5.2	6.9	25%

Table 2. Influence of electric vehicles with different proportions on load peak-valley difference in distribution network.

Table 3 shows the results of user satisfaction for different scenarios, and it can be found that in terms of trip satisfaction, the present solution improves by 15.64% over the ordered charging strategy without considering user satisfaction. In terms of cost satisfaction, the present invention improves 76.94% over the unorganized charging scenario, which is the same as in the ordered charging scenario without considering user satisfaction. In terms of overall satisfaction, the present invention scheme is 42.45% higher than the unorganized charging and 15.64% higher than the conventional strategy.

Table 3. User satisfaction results in different scenarios.

	Traveling Satisfaction	Cost Satisfaction	
Scenario	Distribution Network [1, 2, 3]		
Scenario 1 Scenario 2 Scenario 3	[1, 1, 1] [0.715, 0.578, 0.179] [0.9263, 0.1912, 0.8479]	[0.1132, 0.0257, 0.0127] [0.9768, 0.686, 0.821] [0.9768, 0.7456, 0.7374]	

Therefore, in the electric vehicle charging strategy optimization model involved in the present invention, user satisfaction and intelligent switching of charging modes are considered in the comprehensive loss optimization portion of the system, which can effectively reduce the peak-to-valley difference rate of the system load and improve the user satisfaction of the electric vehicle.

4.2.2. Analysis of Optimization and Regulation Strategies for Flexible Interconnected Distributions

Table 4 shows the comparison results of the system's single-day operation cost under the three scenarios, from which it can be seen that this paper's regulation strategy can effectively reduce the system's single-day operation cost by 12.75% compared to the unorganized charging strategy, and the EV single-day charging cost is reduced by 39.84%. The regulation strategy in this paper can effectively reduce the system's single-day operation cost by 6.2% and the electric vehicle's single-day charging cost by 22.74% compared with the ordered charging strategy without considering user satisfaction. This shows that compared with the traditional regulation strategy, the regulation strategy in this paper can further reduce the comprehensive loss of the system.

Table 4. Comparison of system operating costs per day.

Scenario	Single-Day Running Cost of the System/CNY	Electric Vehicle Single Day Charging Costs/CNY
Scenario 1	80,710	3439.9
Scenario 2	75,069	2678.6
Scenario 3	70,418	2069.3



The optimized flexible interconnected distribution response diagrams are shown in Figures 10-13.

Figure 10. Wind and PV power.



Figure 11. Energy storage system's state of charge (SOC).



Figure 12. Active power transmission of SOPs.



Figure 13. Power interaction diagram of each distribution network with the grid.

At 00:00~04:00, the load demand of Distribution 1 is relatively higher than that of Distribution 3, but at this time, the price of Distribution 1 is at a high level, and the prices of Distribution 2 and Distribution 3 are in the peak–valley stage, so at this time, Distribution 2 and Distribution 3 purchase power from the large grid, and after satisfying their load demand, they transmit the remaining power to Distribution 1 is discharging, and wind generator output can also be supplied to Distribution 1 load demand, at the time of satisfying the load demand of Distribution 1, the wind generator output can also supply to Distribution 1 load demand. Since the energy storage distribution inside Distribution inside Distribution 1 is discharging, the wind generator output can also be supplied to the load demand of Distribution 1, so the excess power is returned to the power grid to gain revenue while satisfying the load demand of Distribution 1.

From 8:00 to 12:00, the load demand of Distribution 2 and Distribution 3 rises, and the corresponding price level is at a higher stage, while the load demand and price level of Distribution 1 fall, so that Distribution 1 purchases electricity from the main grid during this time, and the output of the wind power plant within Distribution 1 can satisfy the load demand of Distribution 1, and Distribution 1 transmits the electricity through the SOP to Distribution 2 and Distribution 3. at this time, the wind generator within Distribution 2 and Distribution 3 can also supply the load demand of Distribution 1, so that excess electricity can be returned to the main grid while satisfying the load demand of Distribution 1, thus obtaining revenue. At this time, the output of the photovoltaic power plants inside Distribution 2 and Distribution 3 is high, so Distribution 2 and Distribution 3 return the remaining power to the power grid to generate revenue.

5. Conclusions

Aiming at the problem that the large number of EVs accessing the distribution produces the scale effect of entering the network, which is not conducive to the stable economic operation of the distribution, this paper proposes a two-layer cooperative optimization of flexible interconnected distribution networks considering electric vehicle user satisfaction degree, and obtains the following conclusions through the analysis of the calculation examples:

(1) In the EV charging load optimization, the load peak-to-valley difference rate of the proposed scheme in this paper is 22.9% less than that of unordered charging and 13.5% less than that of traditional ordered charging in Distribution 1. The load peak-to-valley difference rate of the proposed scheme in this paper is 15.62% less than that of unordered charging and 8.47% less than that of traditional ordered charging in Distribution 3. And in the case of the orderly charging strategy considering charging mode switching, the load peak-to-valley difference decreases with the increase in the proportion of EV access, which can better reduce the peak-to-valley difference rate of the load in the distribution network.

It is effectively preventing the large-scale EVs from generating new peak loads when charging in the low price hours, and thus avoiding the occurrence of the over-heavy-loading situation of the distribution transformer.

- (2) Compared with the EV charging strategy that only takes into account the customer cost satisfaction of time-sharing prices, the ordered charging strategy by introducing the fuzzy subset-based customer travel satisfaction model and charging mode switching can improve EV user satisfaction by 15.64%, and compared with the disordered charging strategy, the EV user satisfaction is improved by 42.45%. Meanwhile, the load peak-valley difference in this paper's strategy is reduced by 15.62% compared to disordered charging and 8.47% compared to the traditional strategy. Therefore, this paper's strategy can effectively improve the EV user satisfaction while reducing the system load peak-to-valley difference.
- The method in this paper takes into account the safe and economic operation of the (3) distribution network as well as the good experience of electric vehicle users, which can effectively reduce the system's single-day operating cost by 9% compared with the unordered charging strategy, and the single-day charging cost of electric vehicles is reduced by 39.84%. Compared to the unorganized charging strategy, which does not take user satisfaction into account, the ordered charging strategy can effectively reduce the system's single-day operation cost by 6.2%, and the EV's single-day charging cost is reduced by 22.74%. It further improves the operational reliability and economy of flexible interconnected distribution network, which are of practical significance for the operation optimization and control of distributions.

The user satisfaction study in this paper does not consider the weighting of travel satisfaction and cost satisfaction. There is no study of what the difference in weighting would result in. In the future, we will develop further synergistic optimization of new energy consumption with EV loads to better integrate EV loads into new energy consumption.

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Nomenclature

Definitions

 $f_{\rm s}(x), f_{\rm e}(x)$ Probability values of the electric car traveling and returning at moment *x* EV users' expected values of departure and arrival times Probability that the electric car starts charging at moment xExpected value of traveling distance Standard deviation which indicates the degree of deviation of the actual traveling distance from the expected value The time constant required for EV charging Starting SOC of the EVs Desired SOC of the EVs Battery capacity of the EVs Charging efficiency

 $\mu_{\rm s}, \mu_{\rm e}$ $f_d(x)$ μ σ

 $\begin{array}{c} T_n^i\\ S_n^i\\ S_S^i\\ E_S^i\end{array}$

 $\eta_{\rm ev,ch}$

Parameters

P _{ev.ch.i.t}	Charging power of the EVs
f_k^2	User satisfaction
∂_{k}^{1}	EV user travel satisfaction
$\partial_{L}^{2,i}$	Cost satisfaction
K_{i}	Affiliation degree of EV users who perceive the waiting time as "comfortable"
	Actual waiting time of users
$T \rightarrow T$	Lower and upper bounds of the "comfortable" affiliation degree
$1 \operatorname{com}, \min (T \operatorname{com}, \max (T \operatorname{com}, $	Affiliation degree of FV users who perceive the waiting time as "normal"
$T \cdot T$	Lower and upper bounds, respectively, of the increasing trend of the affiliation degree of "normal"
T = 1 nor,min / T = 0 com,max	Lower and upper bounds, respectively, of the decreasing trend of the annaholi degree of normal
1 anx,min, 1 nor,max	Affiliation degree of EV users who perceive the waiting time as "anviety"
$\mu_{anx}(1 \text{ wait})$	Lower and upper bounds of the "anviety" officiation degree
anx,min, ¹ anx,max מ בו	Travel estisfaction of EV users
$\sigma_{k,i}$	
$\partial_{\vec{k},i}$	Cost satisfaction
C^{ι}_{+}	Charging price cost
costmax, costmin	The highest and lowest costs for this user's current charging obtained by scheduling the ith EV in
$k_{k,l}$	charging distribution k to charge at the extremes of the lowest and highest price periods
P _{ev,ch,<i>i</i>,<i>t</i>}	Actual charging power of the electric car at moment i
$P_{\text{ev,ch},i,t,f}, P_{\text{ev,ch},i,t,m}, P_{\text{ev,ch},i,t,s}$	The super-fast charging power, fast charging power, and slow charging power
C _{sop}	Cost of SOP operation
C _{grid}	Cost of purchasing and selling electricity in a single day in the distribution network
C _{pv}	Cost of the PV operation
C _{wind}	Cost of wind operation
C _{ess}	Cost of the energy storage operation
C _{ev}	Charging cost of EVs
η_{sop}	Modulus of the SOP operation
S _{sop}	Actual capacity used by the SOP
P _{buvit} , P _{sellit}	Purchased and sold power of the distribution to the larger grid
α	Operational cost factor of the PV
P _{pvit}	Actual output power of the PV
β	operational cost factor of the Wind
Pwind it	Actual output power of the wind power
γ	Operational cost factor of the energy storage
Pess deh i t, Pess ch i t	Charging power and the discharging power of the energy storage
P_{s1}, P_{s2}, P_{s3}	Active power at the 1st, 2nd, and 3rd ports of the SOP
Ssop max	The maximum capacity of the flexible interconnection device
P ^{max} ,	Upper limit of the power output of the PV
⁻ pv, <i>t</i> , <i>t</i> pmax	Upper limit of the power output of the wind power distribution
wind, <i>i</i> , <i>t</i>	0.1 variables indicating the charging and discharging identifiers of the energy storage
$u_{\text{dch},i,t}, u_{\text{ch},i,t}$	0-1 variables indicating the charging and discharging identifiers of the energy storage
Sess, <i>i</i> ,start, Sess, <i>i</i> ,end	Use and leave limits of the same site of the same stars of an
S_i , S_i	Copper and lower limits of the capacity of the energy storage
$S_{i,t}$	SOC of the energy storage plant at the moment 1
Pess,ch,i [,] Pess,dch,i	Upper limits or the charging and discharging power of the energy storage
S _{ev,<i>i</i>,<i>t</i>}	EV battery SOC
$\eta_{\rm ev,ch}$	EV charging efficiency
Pev,ch, <i>i</i> , <i>t</i>	EV charging power
$I_{k,i}^{\iota}$	0–1 variable, and it denotes the EV charging identification

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