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Research on EV Scheduling Optimization Strategy Based on *Monte Carlo* and *AntLion Optimizer*

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As environmental problems become more serious, the trend of "carbon peaking and carbon neutral" has become necessary. However, the disorderly entry of large-scale EVs into the grid has threatened the security of the grid. The purpose of this paper is to study the optimization strategy of EVs to improve the economy and stability of distributed energy. Firstly, the EV user behavior model is constructed to study the charging and discharging behavior influencing factors, and the EV charging and discharging loads are simulated using *Monte Carlo* simulation. Secondly, we build a hierarchical scheduling optimization strategy based on EV user satisfaction using an improved *AntLion optimizer*, finally, the load peaks of the distributed energy system are suppressed and the satisfaction of EV customers is significantly improved; in the process of EV scheduling optimization at the source storage layer, EVs fully consume renewable energy output and the comprehensive operating costs of the distributed energy system are reduced. The conclusions are verified and the system is optimized, resulting in improved user satisfaction and optimized system economy and stability.

Keywords: simulation EV user behavior, scheduling optimization, user satisfaction, Monte Carlo, antlion optimizer

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INTRODUCTION

Energy plays a pivotal role in economic development. China's energy structure is dominated by primary energy (Chen, 2021), along with a large number of carbon emissions that are extremely unfriendly to the environment. Therefore, the development of renewable energy is a necessary trend (Wu et al., 2020). However, due to the impact large-scale accessing of renewable energy from the grid will cause on the grid, the current frequent use of distributed energy in immediate consumption can solve the problem of large-scale decentralized access to the grid, and its promotion has significantly improved the utilization of energy. In summary, reasonable and optimal scheduling of EV charging and discharging loads can effectively improve the operation of distributed energy systems, and it is very important to study the problem of EV co-optimization based on economic and stability aspects (Wang et al., 2019).

Although EVs are developing vigorously everywhere, there is a lack of effective incentive mechanisms to guide EV users to charge and discharge in an orderly manner (Qilin and Qian, 2019). In addition, EVs have diversified charging needs, highway, residential buildings, and other places' charging facilities utilization rate is very high, while third and fourth-tier cities have fewer charging facilities. At the same time, there are differences in the utilization rate of charging facilities due to the charging habits of different users. Therefore, EV charging and discharging should be guided by reasonable scheduling optimization strategies, so that public charging

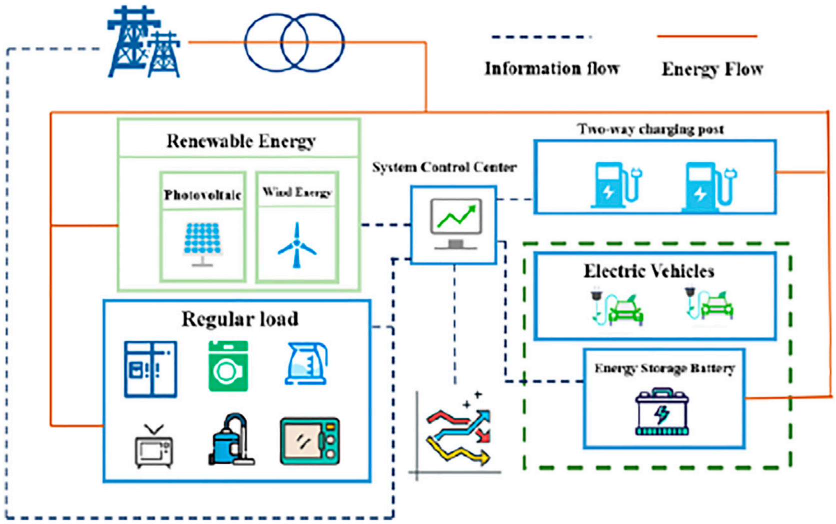

FIGURE 1 | Framework for distributed energy systems.

resources can be fully utilized while grid operation is minimized by EV charging and discharging to ensure safe and stable system operation (Hou et al., 2018; Zhao et al., 2021).

MODELING ANALYSIS OF EVS IN DISTRIBUTED ENERGY SYSTEMS

In this chapter, we construct the framework of the distributed energy system, the load capacity model of EV, and the influencing factors of EV charging and discharging load are also analyzed. These studies can provide strong support for the EV scheduling optimization strategy later in the paper.

EV Modeling Analysis

First of all, the framework of the distributed energy system is built, which includes a photovoltaic power generation system, wind turbine output system, and energy storage system (Wang et al., 2021). The framework of the distributed energy system is shown in **Figure 1**.

As a new network structure relative to the traditional grid, the distributed energy system contains RES, various types of customer loads, energy storage devices, a central control system, and a communication system. The framework of the grid-connected wind and storage distributed energy system established in this paper is shown in **Figure 1**. The roles of each module are shown as follows.

1) System control center (energy management center): an important unit for real-time control of the operation of the distributed energy system, using the information collected from the AMI as a basis to develop a reasonable optimization strategy for EV scheduling.
2) AMI (Intelligent Measurement System): is a multi-functional system that integrates the reading, sending, setting, and control of remote information by adopting different communication modes to transmit the measurement data from the user side back to the control center.
3) Bi-directional charging pile: the execution unit of EV energy conversion, which integrates charging and discharging functions and at the same time can record the charging and discharging power of EV and upload it to the system control center.
4) RES: renewable energy in the system, mainly refers to the wind and solar output units.
5) System response body: mainly refers to the energy storage lithium iron phosphate battery and EV power battery.
6) Internal tariff: In this study, internal tariff refers to a reasonable tariff mechanism.

The flexibility and randomness of EVs are shown in the parking time, travel moment, and driving range (Junhui et al., 2021).

EV Load Capacity Model

EVs can be used as both the demand and supply side in the grid, effectively guiding and controlling EVs in order to control orderly and reasonable charging. The factors affecting the load capacity of EVs are shown in **Figure 2** (Zhang, 2020). EV charging and discharging load size is also affected by EV scale, and when large-scale EVs are charged and discharged in a disorderly manner, system operational reliability drops dramatically (Liting et al., 2020).

The total charge and discharge load of EV is

$$P_c(t) = \sum_{l=1}^{N(t)} \mu_1(t) \cdot P_{c,l}(t) \quad \mu_l(t) > 0 \tag{1}$$

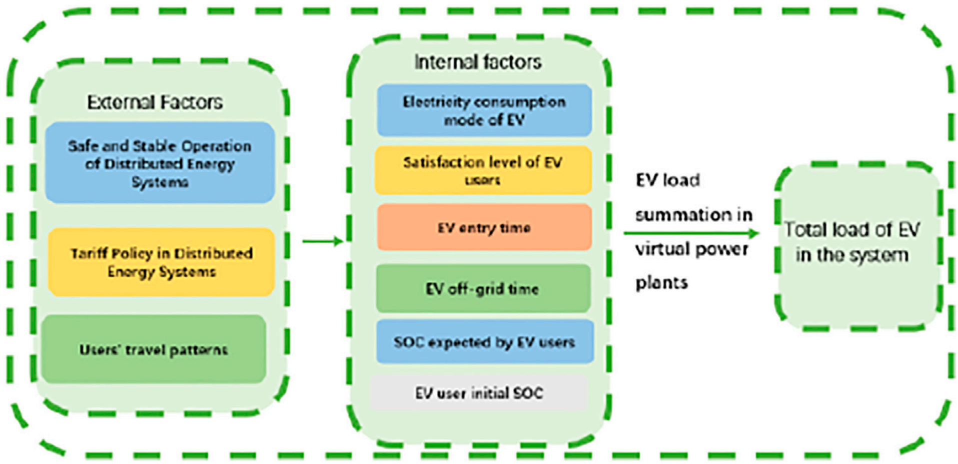

FIGURE 2 | Framework for distributed energy systems factors influencing the load capacity of EV.

$$P_d(t) = \sum_{l=1}^{N(t)} \mu_1(t) \cdot P_{d,l}(t) \quad \mu_l(t) < 0 \tag{2}$$

Where P_c, (t) is the value of charging power at time t, and $N(t)$ is the total number of EV responses at time t. $P_{d,l}$, (t) is the value of the discharging power of EV l at moment t.

User Behavior Modeling of EVs

The analysis of EV travel law is the basis for studying EV charging and discharging behavior. EV user behavior has uncertainty, so EV load distribution has randomness, mainly in the randomness of daily driving mileage.

Start Charging Moment

The main start charging time of private EVs is generally after coming home from work or on arriving at work, which is statistically strong, and the model generally obeys normal distribution, and its probability density function is

$$f_{T_{in}}(x) = \begin{cases} \dfrac{1}{\sigma_{in}\sqrt{2\pi}} \exp\left[-\dfrac{(T_{in}+24-\mu_{in})^2}{2\sigma_{in}^2}\right], 0 < T_{in} \le \mu_{in} - 12 \\ \dfrac{1}{\sigma_{in}\sqrt{2\pi}} \exp\left[-\dfrac{(T_{in}-\mu_{in})^2}{2\sigma_{in}^2}\right], \mu_{in} - 12 < T_{in} \le 24 \end{cases} \tag{3}$$

where μ_{in}, σ_{in} is taken to denote the mean and variance of the return to the system moment at the end of the EV trip (Yapeng et al., 2019), respectively.

End Charging Moment

The start moment of the day trip obeys the normal distribution, and its probability density function is

$$f_{T_{out}}(x) = \begin{cases} \dfrac{1}{\sigma_{out}\sqrt{2\pi}} \exp\left[-\dfrac{(T_{out}-\mu_{out})^2}{2\sigma_{out}^2}\right], 0 < T_{out} \le \mu_{out} + 12 \\ \dfrac{1}{\sigma_{out}\sqrt{2\pi}} \exp\left[-\dfrac{(T_{out}-24-\mu_{in})^2}{2\sigma_{out}^2}\right], \mu_{out} + 12 < T_{out} \le 24 \end{cases} \tag{4}$$

where μ_{out}, σ_{out} denotes the mean and variance of the off-grid moments of EVs, respectively.

The EV user's use habit and daily driving range determine the remaining power at the moment the EV returns home.

The probability density function of the initial SOC of the EV is

$$f_{S_0}(x) = \frac{1}{\sqrt{2\pi}\sigma_x x_a (S_E - x)} \exp\left[-\frac{(In[x_a(S_E - x)] - \mu_x)^2}{2\sigma_x^2}\right] \tag{5}$$

The probability distribution of daily mileage for EVs is shown in **Figure 3**.

Modeling of EV User Satisfaction

The user satisfaction is divided into user's travel.

(1) EV user travel satisfaction

$$\partial_l^1 = \begin{cases} 0, & 0 \le \sum_{t=1}^{T} S_l(t) < \dfrac{Q_{m,l}}{Q_{s,l}} \\ \delta, & \dfrac{Q_{m,l}}{Q_{s,l}} \le \sum_{t=1}^{T} S_l(t) < S_{E,l} \\ 1, & \sum_{t=1}^{T} S_l(t) \ge S_{E,l} \end{cases} \tag{6}$$

where $\sum T \cdot S(t)$ denotes the SOC of vehicle l at the off-grid moment and $S_{E,l} = Q_m + Q_{r,l}$, denotes the expected SOC of the user.

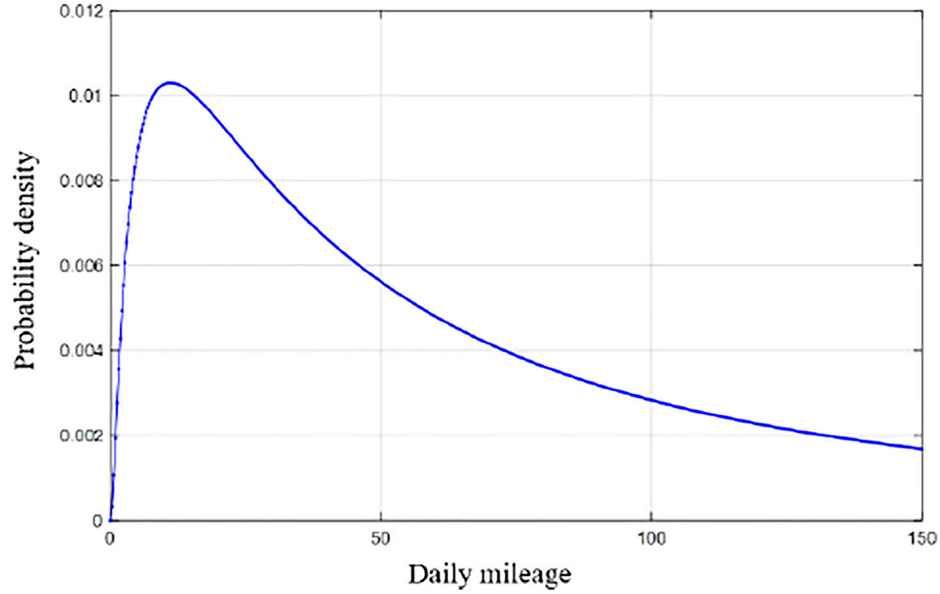

FIGURE 3 | Probability distribution of daily mileage of EVs.

(2) Cost satisfaction of EV users

$$\partial_l^2 = 1 - \frac{\left(\sum_{t=1}^{T} C_l(t) \cdot P_{C,l}(t)\right) - R_{l,sub} - C_l(t_{\min})}{C_l(t_{\max}) - C_l(t_{\min})} \tag{7}$$

where $C_l(t)$ is the tariff for electric vehicle charging at moment t. $C_l(t_{\min})$, $C_l(t_{\max})$ are the minimum and maximum costs of charging for EV l users, and $R_{l,sub}$ is the total cost of subsidies received for discharging. (Junliu et al., 2020)

The overall satisfaction of EV users can be expressed

$$\partial_l = \frac{\sum_{l=1}^{N_1}(\partial_l^1 + \partial_l^2)}{2N_1} \tag{8}$$

Monte Carlo-Based Load Calculation for EVs

EV users' charging and discharging behaviors are uncertain in both time and space, and factors such as origin, destination, and driving paths influence user behavior. In this section, the EV load is analyzed from a dual-scale perspective of time and space, and then the travel process of EV users in a day is calculated.

In this paper, the *Monte Carlo* method is used to simulate the load characteristics of EV clusters, and the specific method steps are shown below.

The *Monte Carlo* simulation method is different from the general method of calculating numerical values, it is a class of algorithms based on the theory of probability statistics. The problem for which a solution is required is sampled with random numbers, and the result will be infinitely close to the real solution after many repetitions of the sampling. The *Monte Carlo* simulation method is an excellent algorithm for events with high randomness that cannot be computed conditionally.

The *Monte Carlo* simulation method is based on the theoretical foundations of the "Theorem of Large Numbers" and "Central Limit Theorem", which establish the reference for error evaluation in the *Monte Carlo* simulation method. The steps of the *Monte Carlo* simulation method are as follows (Wuzhi et al., 2020):

1) Determine the initial EV return time, off-grid time, power battery capacity, and the total number of EVs.
2) Calculating the initial SOC of EVs by extracting the daily mileage and arrival time of EVs based on the total number of EVs.
3) Calculate the charging period of EVs from the EV return time and daily driving mileage, and superimpose the load generated by each EV at each sampling moment to obtain the total load of EVs in this time period.

Using the *Monte Carlo* method to generate the EV driving in 1 day, the charging and discharging loads of 100 EVs were simulated and averaged according to the formula, and the specific results are shown in **Figure 4**. The curves from bottom to top simulate the generated loads when 100, 200, and 400 EVs are charged in an uncontrolled manner. As we can see in the figure, if EVs are allowed to charge without control, the charging time is concentrated in the evening from 18:00 to 23:00, because 18:00 is a more concentrated time for EV users to return home, and the charging peak is reached around 19:30 at night, and the original load of the distributed energy system is also at a peak at this time, resulting in the peak of the load level in the network. The original load of the distributed energy system is also at a peak at this time, leading to a peak on top of a peak in the load level in the network, bringing impact to the stable operation of the system, and the impact will increase step by step as the number of EVs increases.

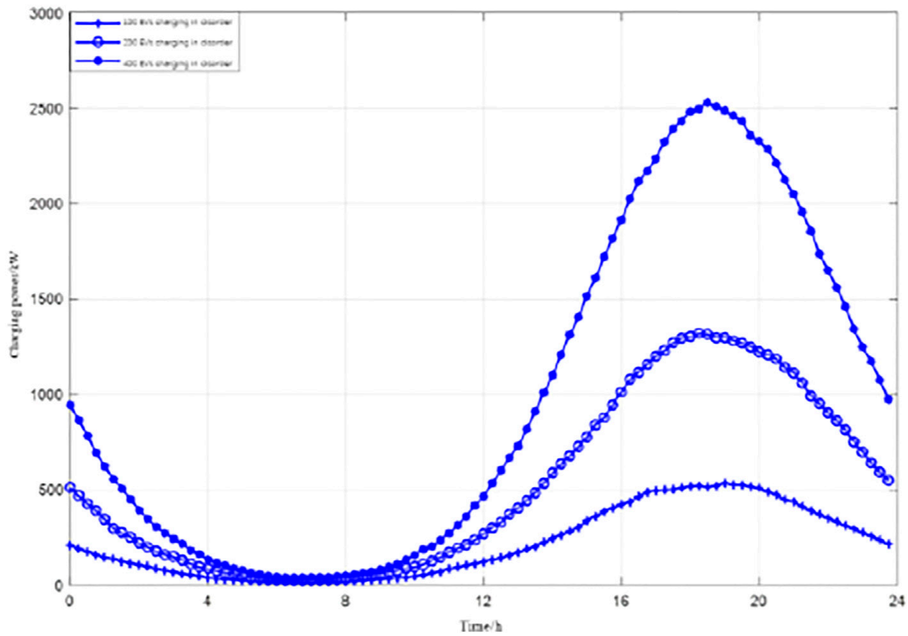

FIGURE 4 | *Monte Carlo* simulation of electric vehicle disorderly charging.

Based on the power models of wind turbines, photovoltaic units, and energy storage systems, the load characteristics of EVs are analyzed and the curve of EV load in the system for a given day is obtained based on *Monte Carlo*'s computational analysis of EV load. It provides a basis for the collaborative energy optimization of EV participation in the distributed energy system later in the paper.

OPTIMIZATION STRATEGY OF EV HIERARCHICAL DISPATCHING BASED ON USER SATISFACTION

Large-scale EVs connected to the distributed energy system can make the number of EVs accommodated by the original system increase significantly, and participation in the joint scheduling of the system is an inevitable future development trend.

Considering the comprehensive satisfaction of each EV user directly in the EV scheduling optimization process will make the problem extremely complicated and difficult to solve. Therefore, in this section, the scheduling optimization process of the distributed energy system is divided into load layer and source storage layer, and EVs with different characteristics are assigned to different layers, and their user satisfaction is considered for EVs in the load layer, and then the strategy is verified by simulating an actual scenario of the distributed energy system.

Hierarchical Scheduling Optimization Strategy

The EVs covered in this section are divided into two categories: EVs with a high degree of freedom and EVs that fully obey the management of the distributed energy system, and we only consider the user satisfaction of EVs with a high degree of freedom (Zhengfu et al., 2021).

The process of distributed energy system scheduling optimization is divided into two layers: the load layer, where EV user satisfaction is optimized while taking into account the original load peak; and the source storage layer, where further load optimization is performed on the system after optimization in the load layer (Shuai et al., 2022) so that EV load follows RES output and maximizes the absorption of RES output to reduce operating costs. The optimization strategy of hierarchical scheduling in the distributed energy system is shown in **Figure 5** below.

Load-Level Scheduling Optimization Strategy

Let the peak start moment of the original load L_B (t) of the distributed energy system be *Tstart* and the peak end moment be T_{end}. The initial state of the EV at the time of grid entry depends on the entry moment $Q_{d,l,\max}$:

$$Q_{d,l,\max} = \min\{S_{E,l} \cdot Q_{s,l} - x_l \cdot q, \gamma \cdot Q_{s,l}\} \tag{9}$$

where q denotes the power consumption per kilometer driven by EVs; γ denotes the maximum depth of discharge of the EV battery (Sheng and Jiayan, 2021).

In order to secure the next trip for EV users:

$$S_{0,l} + \frac{\left(\sum_{t=T_{in,l}}^{T_{out,l}+24} P(t) \cdot \eta_l \cdot \mu(t)\right)}{Q_{s,l}} \geq S_{E,l} \tag{10}$$

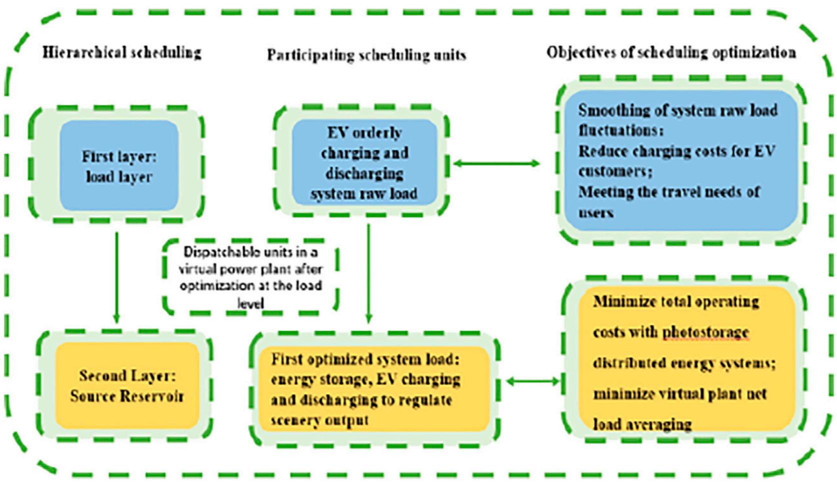

FIGURE 5 | Tiered scheduling optimization strategy for distributed energy system considering customer satisfaction.

In order to increase the cost satisfaction of EV users, certain incentives are given to EV users for discharging.

$$R_{l,sub}(t) = P_{d,l}(t) \cdot I^1_{l,sub} \tag{11}$$

Where $I^1_{l,sub}$ denotes the standard of load layer incentive cost.

Source-Storage Level Scheduling Strategy

The main objective of the source-storage layer scheduling strategy is to reduce the operating cost of the distributed energy system while allowing the EV cluster to maximize the consumption of wind and light output so that the average value of the net load of the distributed energy system is minimized (Qinshuai et al., 2019).

$$C_{BES,Loss}(t) = P_{BES}(t) \cdot \rho_{BES} \tag{12}$$

$$C_{R,op}(t) = \varphi_W \cdot P_W(t) + \varphi_{PV} \cdot P_{PV}(t) \tag{13}$$

$$C_{BES,Loss}(t) = P_{BES}(t) \cdot \rho_{BES} \tag{14}$$

$$C_{l,c}(t) = \sum_{l=1}^{N_2} P_{c,l}(t) \cdot \rho_c(t) \tag{15}$$

$$C_{RES,sub}(t) = P_W(t) \cdot I_{W,sub} + P_{PV}(t) \cdot I_{PV,sub} \tag{16}$$

$$F_2 = \min \sum_{i=1}^{F} \left(C_{R,op}(t) + C_{BES,Loss}(t) + \sum_{i=1}^{N_1} R_{l,sub}(t) + C_{l,c}(t) - C_{RES,Loss}(t) \right) \tag{17}$$

$$F_3 = \min \left\{ \frac{1}{T} \sum_{t=1}^{T} \left(L_B(t) + P_{BES}(t) + \sum_{l=1}^{N_2} P_l(t) - P_W(t) - P_{PV}(t) \right) \right\} \tag{18}$$

where $C_{R,p}(t)$ denotes the total cost of each dispatchable unit within the distributed energy system, $\varphi_W, \varphi_{PV}, \varphi_{BES}$ denotes the cost standard of wind turbine, PV and storage battery; $P_W(t), P_{PV}(t), P_{BES}(t)$ denotes the output of wind turbine, PV, and storage at the moment t, $C_{BES,Loss}(t), C_{l,c}(t), C_{RES,sub}(t)$ denotes the charging and discharging loss cost of energy storage, the benefit generated by EV charging and the subsidy cost of renewable energy generation at moment t; ρ_{BES} denotes the charging and discharging loss cost standard of the energy storage battery; $I^2_{l,sub}$ denotes the EV discharge incentive standard of the source storage layer, $\rho_C(t)$ denotes the part-time electricity price within the distributed energy system; $I_{W,sub}, I_{PV,sub}$ denotes the subsidy cost standard of wind turbine and PV generation (Yaosong et al., 2020).

EV HIERARCHICAL SCHEDULING OPTIMIZATION STRATEGY SOLVING AND RESULT ANALYSIS

Solution Method

Since the load-level scheduling optimization has the same logical framework as in Chapter 2, the optimization is performed using the *Monte Carlo* method, which is used to simulate the wind turbine, PV output, and EV load for the load tier scheduling optimization strategy (Yuying et al., 2021).

In solving the multi-objective multi-constraint optimization model for source storage layer scheduling the multi-objective optimization problem is transformed into a single-objective optimization problem using the linear weighting method.

$$F = \min \left\{ \omega_1 \frac{F_2}{F_{2\max}} + \omega_2 \frac{F_3}{F_{3\max}} \right\} \tag{19}$$

where ω_1, ω_2 are the weights corresponding to different optimization objectives (Su and Dong, 2021).

The model is then solved using the *improved AntLion Optimizer*.

In the case of uneven illumination, uncontrollable human factors, and a complex detection environment, the results predicted by the algorithm calculation performed by the general algorithm may have problems such as inaccurate data evaluation. In this case, it is necessary to improve the accuracy of

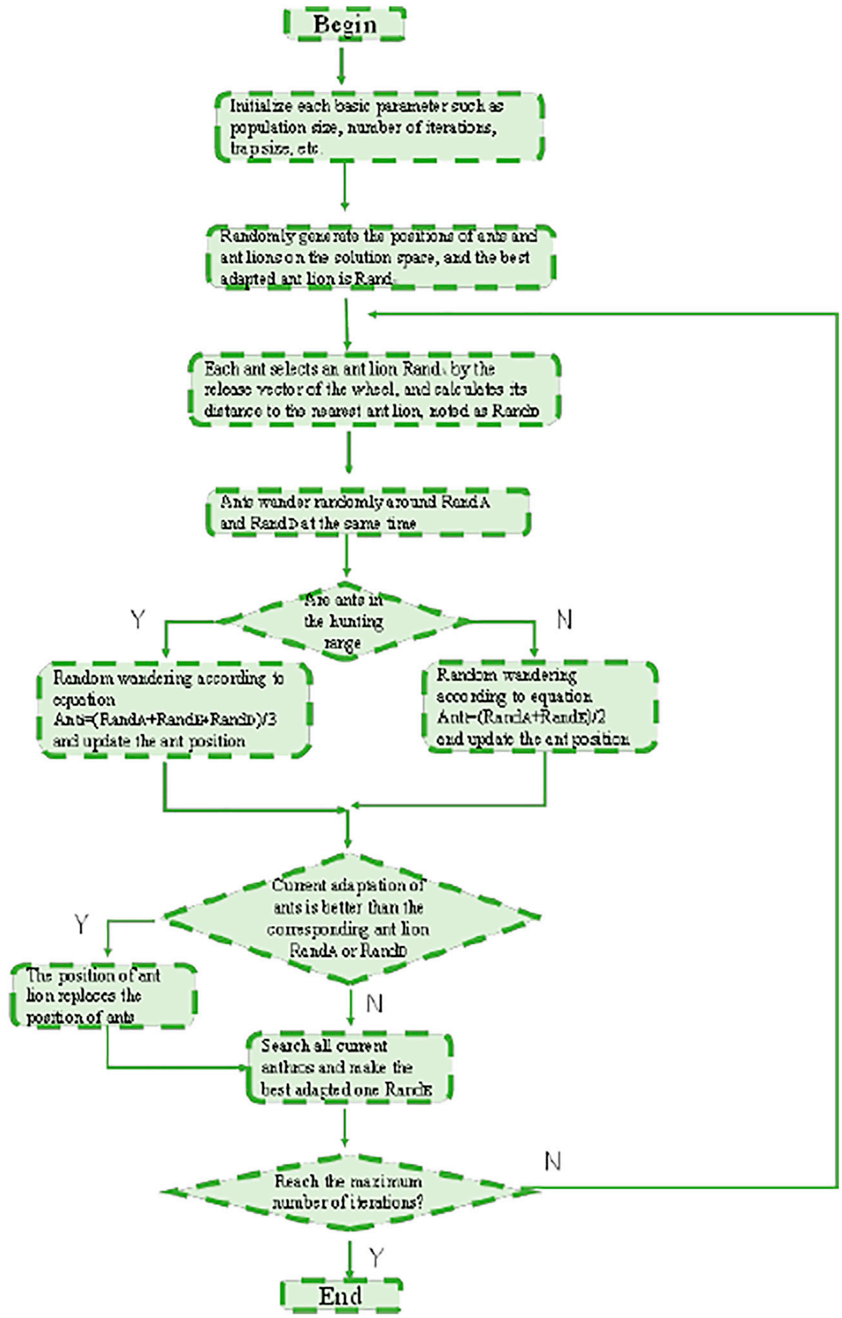

FIGURE 6 | Flow chart of improved ALO algorithm.

the operation to achieve accurate prediction. For the hyperparameter optimization problem, Grid Search is too computationally intensive; the Bayesian optimization technique requires a priori sample design, difficult kernel function selection, and long evaluation time, and EV scheduling optimization needs a lot of data support, so *AntLion Optimizer* is finally decided.

The algorithm steps are shown in **Figure 6**.

The methodological framework is useful for policymakers to improve the appropriate charging strategy to achieve an optimal balance between charging and discharging in the face of a large number of EVs charging in a disorderly manner.

Algorithm Parameter Settings

In this section, to re-simulate a specific distributed energy system scenario, the system contains wind turbines, photovoltaic units, a lithium iron phosphate battery storage system, and a certain scale of private car EVs; the system contains a 400kW photovoltaic battery and 400 kW of wind turbines, plus the capacity of 300 kW

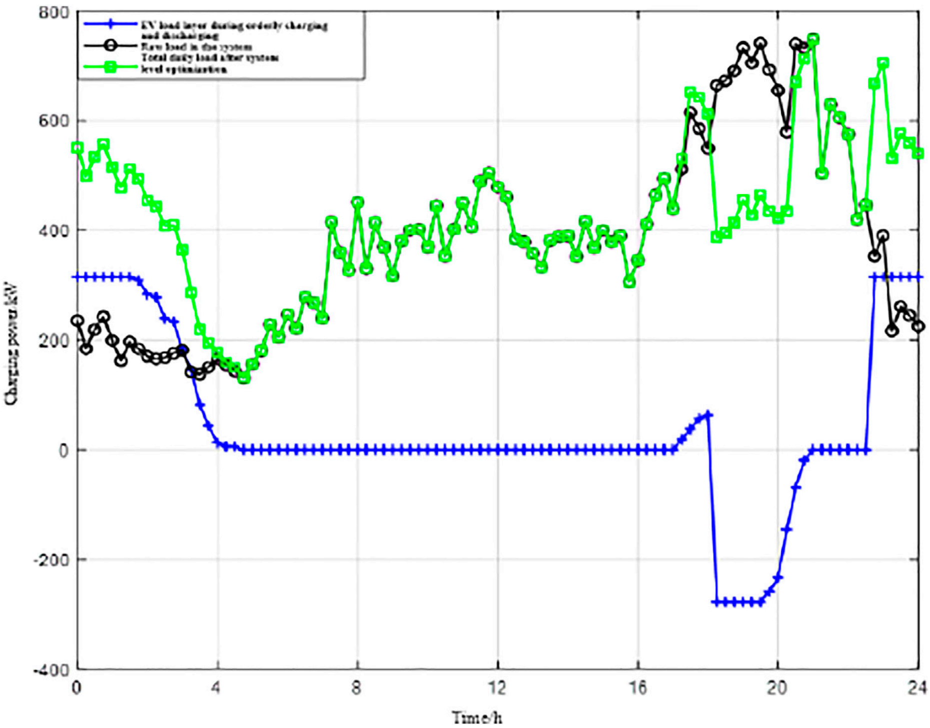

FIGURE 7 | Total daily load curve after optimization.

lithium iron phosphate as energy storage units, electrochemical energy storage losses converted to The cost is $\rho_{BES} = 0.2 Yuan/kWh$, the standard of operation and maintenance cost of wind. and light is $\varphi_W = 0.03 Yuan/kWh$, $\varphi_{PV} = 0.01 Yuan/kWh$, and the standard of subsidy cost is as follows: $I^1_{l,sub} = 1.2 Yuan/kWh$, $I^2_{l,sub} = 0.8 Yuan/kWh$, $I_{W,sub} = I_{PV,sub} = 0.01 Yuan/kWh$. The initial parameters of the improved ALO algorithms are set as follows: the initial ant number is 50, and the maximum number of iterations is 200.

The proposed model is programmed, analyzed and its simulation results are calculated in MATLAB R2018a.

Analysis of the Results

(1) Results of the load level optimization

According to the management strategy for EVs, the peak load of the distributed energy system can be reduced, and the obtained results are shown in **Figure 7**.

As seen in **Figure 7** A large number of EVs return to the distributed energy system one after another after 17:00 but do not charge directly, while the main charging period is concentrated between 22:00 on the first day and 4:00 on the second day, charging until the SOC automatically quit charging and maintained a static state. The average net load value changed from 170.4769 to 147.1115 kW, the load-level scheduling strategy played a role in suppressing load peaks and increasing the operational stability and reliability of the system.

The EV users who participate in peak discharge will get the incentive fee, and according to **Eq. (18)**, the comprehensive satisfaction of EV users before and after the optimization of the distributed energy system in the scheduling optimization process of the load layer is 0.38 and 0.79, respectively. Its value is significantly improved. The details are shown in **Table 1**.

(2) Results of source reservoir optimization

The daily total load optimization results of the load layer are substituted into the optimization model of the source reservoir, and the model is solved by using the improved *ALO* algorithm (Qiu et al., 2021), and the output of each dispatchable unit of the source reservoir is shown in **Figure 8**.

The response curve is shown as the cyan curve in **Figure 8**, and the trend of the response curve is almost the same as the trend of the background output curve. In addition, the graph shows that the response body starts charging when the background output is at a high level (i.e., from 8:00 a.m. to 16:00 p.m.), and stays mostly discharged for the rest of the time.

In the scheduling optimization of the source storage layer, all EVs have the substitution role of energy storage units, so the power fluctuation of energy storage units is relatively small.

(3) Comparative analysis

The simulation indexes (including cost, net load average, and EV user satisfaction) in the case of EV unordered charging are compared and analyzed with the indexes of EV stratified ordered charging and discharging, and the details are shown in **Table 2**.

TABLE 1 | Before and after load comparison analysis.

Project	Load fluctuation level/kW	EV discharge bonus/yuan	EV charging cost/yuan
Raw load optimized by load layer	170.47 147.11	0 1114.90	1348.20 813.25

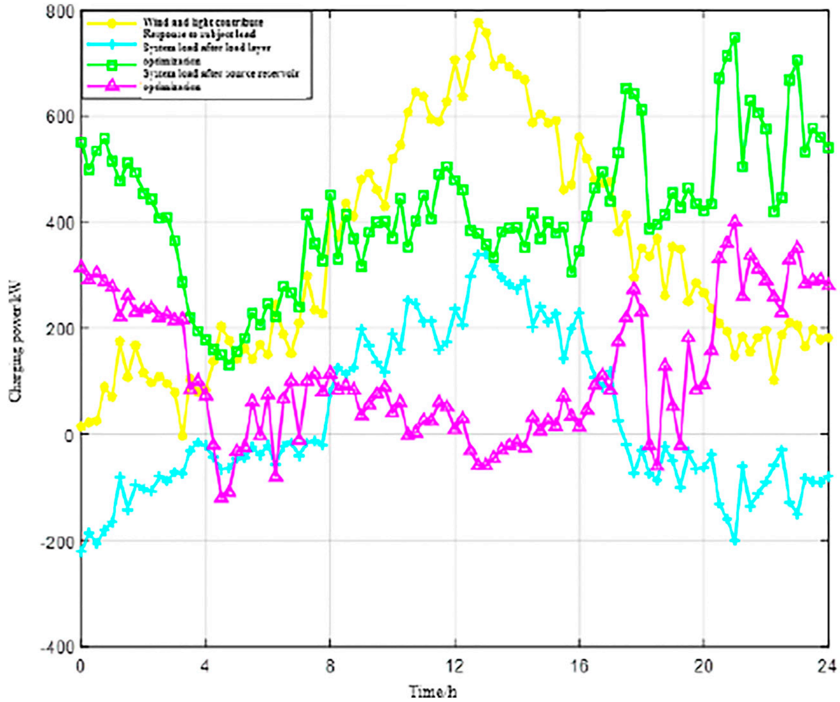

FIGURE 8 | Optimized load curve of the source reservoir.

TABLE 2 | Comparison of the results of disordered charging and hierarchically ordered charging and discharging of EVs.

Project	EV discharge incentive/yuan	Total running cost/yuan
Disorderly charging Layered orderly charging and discharging	0 1415	2426.21 1507.33
Project	Net load average value/kW	Satisfaction of EV users
Disorderly charging Layered orderly charging and discharging	319.20 137.58	0.38 0.79

Integrating the load level optimization and source reservoir optimization experimental data, the data in the following table contains the hierarchical ordered charging and discharging of EVs for two different scenarios.

As seen in **Table 2**, from the operator's point of view, the hierarchical ordered charging and discharging strategy relative to disordered charging has more EV discharging incentives for this expenditure, but even though the cost of the distributed energy system increases by one, the final total system operating cost decreases by $919 and gets optimized, while the average net load in the system decreases by 57% and the satisfaction of EV users increases by 107%.

The proposed hierarchical scheduling optimization strategy considering EV user satisfaction has a good effect on improving the economy and stability of distributed energy system operation (Ye et al., 2021). From the results of the analysis of the calculation cases, it can be seen that in the process of EV dispatch optimization in the load layer, the net load mean value of the distributed energy system is effectively reduced, and the satisfaction of EV users is significantly improved, which realizes the sustainability of the economic dispatch optimization strategy of the distributed energy system proposed in this paper; in the process of EV dispatch optimization in the source storage layer, the EV load fully consumes the renewable energy. In the process of EV scheduling optimization at the source storage layer, the EV load fully consumes the renewable energy output and the storage output is less, which makes the comprehensive operation cost of the distributed energy system reduced, thus forming a win-win situation for all parties in a real sense.

CONCLUSION

As EVs enter the network on a large scale, they are facing two problems: how to make large-scale EVs enter the network in an orderly manner and optimize the scheduling strategy to achieve better results, and how to set the charging facilities and charging mode to make the highest utilization rate. In this paper, we analyze the charging and discharging behavior of EV users in a distributed energy system scenario, and use time-of-use tariffs to guide EV users, so as to solve the problem of large-scale EVs entering the grid in an orderly manner and improve the RES utilization rate and achieve peak and valley reduction effects.

For the first problem, in the distributed energy system, we analyze EV users' charging and discharging behavior, use time-of-use tariffs to guide EV users solve the problem of large-scale EVs entering the grid in a disorderly manner, improve RES utilization, and achieve peak and valley reduction effects.

For the second problem, we establish a *Monte Carlo* simulation-based EV disorderly charging model to verify that large-scale EV disorderly access will add peaks to the system load, seriously threatening the reliability and stability of system operation; a hierarchical scheduling optimization model based on EV user satisfaction is developed and solved; a hierarchical scheduling optimization strategy for distributed energy systems considering EV customer satisfaction is proposed. From the results of the analysis of the calculation case, it can be seen that in the process of load-level EV dispatch optimization, the load peak is suppressed, customer satisfaction is greatly improved, and the sustainable development of the economic dispatch optimization strategy for distributed energy systems is realized; in the process of EV scheduling optimization at the source storage layer, EVs fully consume renewable energy output and the comprehensive operating costs of distributed energy systems are reduced, thus forming a mutually beneficial win-win situation for multiple parties in a real sense.

With the development of Internet technology and the continuous iteration and upgrading of the semiconductor industry, there is no big problem in software and hardware, then the key of the problem becomes how to arrange a scheduling optimization strategy for EVs to achieve better results, and this paper carries out scheduling optimization to solve the problem.

With the influence of national policies in recent years, the popularity of EVs in China has been quite high, and the rapid development of EVs in China is staggering. However, the real situation is that EVs in China are only promoted and used in areas such as Beijing Shanghai, and Guangzhou, and the popularity of EVs in third and fourth-tier cities and towns is still very limited, and the construction of public charging facilities in cities is relatively small, which is not enough to support the free use of EVs by EV users. But the times are progressing, and we hope that our country will have its own core competitiveness in both EV and semiconductor-related technologies. In the future, the rapid development of artificial intelligence will also make the two problems raised in the previous article no longer exist, and all the scheduling strategies and charging and discharging behaviors will be executed very intelligently and efficiently, while our power workers may also face more technical challenges, so it will be a great test for us all.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

CL, DP, HZ, and SY contributed to conception and design of the study. CL EF the first draft of the manuscript. DP, HZ, and SY wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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