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Robust Scheduling Strategy for Renewable Energy Storage Systems Considering Uncertainty

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Abstract. For multi-source joint systems containing wind solar storage, the output of wind and photovoltaic power generation is characterized by uncertainty. When the actual output of wind turbines and photovoltaic power generation does not match the power arranged in the actual scheduling plan, it will lead to a significant decrease in the economic benefits of the system. In response to the above issues, this article first establishes wind power generation models, photovoltaic power generation models, and user electricity consumption models, which have the commonality of uncertainty. Then, an energy storage model for the storage end is established, and the Seagull Optimization Algorithm is used to solve the model and obtain the optimal power storage parameters. This paper establishes a power scheduling model for the power supply side, and then optimizes the power scheduling using robust optimization strategies. Finally, to verify the feasibility of the algorithm, an IEEE 14 node model is used for validation.

Keywords: photovoltaics, seagull optimization algorithm, uncertainty, robust optimization

1 Introduction

With the intensification of global climate change and the implementation of the “dual carbon” policy, traditional fossil fuels such as coal, oil, and natural gas are no longer suitable for the development concept of low-carbon environmental protection. On the other hand, in the field of new energy, renewable energy represented by wind power and photovoltaic power generation has flourished in recent years, leading the transformation of power systems worldwide. China’s photovoltaic and wind power generation are developing rapidly. According to statistical data, as of the end of 2023, the installed capacity of solar power generation is about 660 million kilowatts, a year-on-year increase of 55%, and the installed capacity of wind power is about 460 million kilowatts, a year-on-year increase of 21.5%. At the same time, European and American countries are also vigorously developing clean and renewable energy sources, which will account for an increasingly high proportion of human energy demand in the future and become a new development direction [1].

Based on the existing experience of power grid operation, whether it is self-organized microgrids or photovoltaic and wind power generation that are connected to the overall power grid, renewable energy has a common characteristic, which is the uncertainty of power generation. Wind power generation is affected by wind volume and wind speed, while photovoltaic power generation is affected by the amount of light, that is, the electricity output of wind and photovoltaic power is fluctuating and cannot provide stable power supply. Therefore, whether it is grid connected operation or microgrid operation, as long as it includes wind and photovoltaic power generation, the uncertainty of the new energy grid must be considered.

Power dispatch is the core link of how to scientifically generate electricity, how to fully utilize renewable energy for production arrangement and distribution, and its role is like the “brain” of the entire power grid. Since the application of power data analysis, edge computing and intelligent dispatching system in power grid, today’s dispatching system can be classified as the fourth generation intelligent dispatching system. In the process of dispatching, the level of automation and intelligence of power dispatching directly determines the efficiency and accuracy of power dispatching. Therefore, the only way to improve the power dispatching capability is to

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enhance the level of automation and intelligence of dispatching, that is, the development direction of power grid dispatching. The combination of smart grid theory and existing power grid hardware systems can achieve system autonomous regulation on the one hand, and on the other hand, intelligent technology can monitor and even remotely control the operation status of the entire power grid in real time, providing data support and control basis for power grid allocation work. In addition, during power dispatching, the power grid system can fully combine the actual electricity demand of users and adopt more efficient ways to meet the power supply requirements. After the integration of photovoltaic and wind power into the power system nodes, traditional grid allocation methods cannot accurately match the rapidly developing demand for new energy electricity. The biggest feature of renewable energy is the uncertainty of power generation output. In the process of meeting the user's electricity consumption, the dispatcher must adopt the most conservative power generation plan and reserve sufficient system reserve capacity to deal with the uncertainty of renewable energy, which leads to low load rate of thermal power units, limited renewable energy consumption space and other problems [2].Therefore, this article focuses on the electricity uncertainty caused by photovoltaic and wind power generation in the power system, as well as the power dispatch problem under uncertainty. The work done is as follows:

1) Analyzed the uncertain models of photovoltaic power generation, wind power generation, and user end electricity consumption, as well as the energy storage optimization system, laying the foundation for solving the optimization strategy of the entire energy storage end.

2) In order to optimize the energy storage model, a cost minimization objective function was established, and the seagull algorithm was used to solve the objective function of the energy storage model and obtain the optimal parameters of the energy storage system.

3) On the power supply side, in order to achieve optimal power scheduling, robust optimization strategies were used to optimize the power scheduling problem, and simulation experiments were conducted using an IEEE 14 node system.

2 Related Work

Several scholars have conducted corresponding research on uncertain power supply in the power grid. Juan Li from Northeast Electric Power University [3] focuses on the accuracy of power dispatch. Firstly, a preliminary dispatch model is constructed to optimize the generation cost, determine the output efficiency of the components in the unit, and then generate wind power generation prediction results through the Monte Carlo scenario to reduce wind power uncertainty. Then, combined with the joint adjustment of active and reactive power, each unit shares the active power imbalance proportionally according to the frequency characteristic coefficient. Finally, an optimized dispatch model is established, and the model is solved through particle swarm algorithm. Finally, simulation verification is carried out at IEEE14 node.

Shunfu Lin from Shanghai Electric Power University [4] conducted research on offshore microgrids with wind power as the main source. Firstly, a third-order mixture Gaussian distribution was used to describe the prediction error and obtain a sample group. Then, based on the prediction error sample group, the conditional value at risk method was used to comprehensively consider economic, safety, and user comfort to determine the dynamic incentives for various types of users. A day ahead optimization scheduling model for islanded microgrids was established. Finally, the effectiveness and scientificity of the proposed method were validated in the wind power load temporal scenario.

Yiming Chen, also from Northeast Electric Power University, proposed a dual layer optimization strategy considering wind power prediction error and demand side response for a multi-source joint power system that includes wind power, photovoltaic power, and thermal power. In the upper layer model, the goal is to minimize the total operating cost of wind power, thermal power, and movable loads, and an improved particle swarm optimization algorithm is used to formulate the optimal scheduling strategy for thermal power and movable loads. Then, the Gibbs method is used to obtain the power shortage of each sample's upper layer power source. In the lower layer model, the goal is to minimize the total operating cost of energy storage and interruptible loads, and a linear programming method is used to hedge the power shortage of the upper layer power source, thereby formulating a dual layer model power scheduling strategy [5].

Xiong Wu from Xi'an Jiaotong University proposed a multi scenario and multi time period safety constrained unit scheduling solution method that takes into account wind power uncertainty. By analyzing the actual operating situation, multiple parallel sub problems were formed. In order to ensure the feasibility of multi scenario and multi time period scheduling, consistency constraints were used to couple different sub problems. The effectiveness of the proposed method was verified through case analysis. The simulation results show that the proposed method significantly shortens the solution time compared to traditional centralized methods at acceptable accuracy [6].

Yan Liu from North China Electric Power University [7] used Kullback Leibler distance as the control condition for screening extreme wind power output scenarios, and based on this, constructed a fuzzy set as a typical wind power output scenario. On the premise of meeting relevant operational safety constraints, a distributed robust optimization model was established with maximizing the weighted load recovery as the optimization objective, and then solved using a mixed integer second-order model. During the simulation process, the IEEE 10 node model and 39 bus system of a large-scale wind farm were used for simulation, and the results showed that compared to traditional robust optimization methods, this method reduces the conservatism of the optimization results.

Fangzhao Deng from State Grid Corporation of China, in response to the continuous increase in electricity reserve caused by the large-scale grid connection of wind turbines, characterized the uncertainty of power prediction with uncertainty variance, and constructed a day ahead economic dispatch and uncertainty clearing model based on distributed robust opportunity constraint optimization. Then, he further derived the uncertainty marginal price composed of generation capacity price and transmission capacity price, which corresponds to the opportunity cost compensation for traditional units and lines, respectively. Finally, through the PJM 5-node system example, it was proved that the model can effectively cope with the prediction uncertainty in the system, ensure the safe and stable operation of the system, and the clearing price can effectively reflect the impact of uncertainty on system costs and the role of traditional units in system uncertainty balance [8].

Yanxia Ma's research aims to improve the inclusiveness of renewable energy sources such as wind power in the power grid. Therefore, she first analyzed the processing characteristics of each power supply part, and then used system operating costs and environmental costs as objective functions, with power balance, voltage constraints at each node, and line power constraints as solving constraints. Then, the integrated energy system is constructed, taking into full consideration the uncertainty of renewable energy generation. By exploring the flexibility of the integrated energy system and utilizing the coupling and coordination of various units, the uncertainty caused by the connected renewable energy output units is compensated, reducing the cost increment caused by uncertainty risks on the scheduling and operation of the integrated energy system, and achieving real-time energy supply balance. In the stage of solving the multi-objective optimization scheduling model, an improved particle swarm optimization algorithm is used to discover the optimal value by tracking oneself and the group in the multidimensional solution space [9].

Taking the above research results as a reference, this paper establishes an optimization mathematical model for the scheduling problem of power storage and supply in a remote western region, and uses intelligent algorithms to solve the optimal solution of the scheduling problem. Therefore, the composition structure of this paper is as follows:

Chapter 2 mainly introduces the relevant research results, while Chapter 3 mainly establishes uncertainty optimization models for wind and photovoltaic power generation, and then solves the models using the seagull algorithm. The fourth chapter mainly describes the robustness optimization method, the fifth chapter is the experimental simulation section, which verifies the feasibility of the method proposed in this paper, and the last part is the conclusion section, which summarizes this paper and looks forward to the future.

3 Generation End Model and Energy Storage Optimization Considering Uncertainty

The power generation equipment included in this study includes wind power generation, photovoltaic power generation, and energy storage systems. Diesel power generation is not universal and is only used in a few microgrid operations. Therefore, this article does not discuss power systems that include diesel power generation. The power generation model established in this article should have a certain degree of universality. In order to maximize the absorption of uncertain factors, the power generation section includes an energy storage optimization system, namely a battery module, as a buffer link for the overall power supply end [10]. In addition, for the overall power grid, another uncertain factor comes from the uncertainty of the user end, that is, the uncertainty of user electricity consumption. The overall structure of the power generation end is shown in Fig. 1.

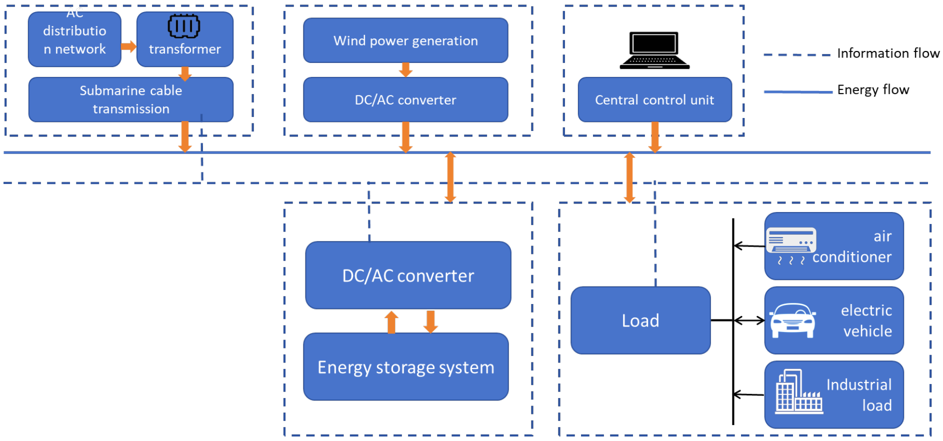

Fig. 1. The overall structure of the power generation section

3.1 Uncertain Model of Wind Power Generation

The composition of a wind turbine generally includes wind turbines, generators, grid connected controllers, and towers supporting the generator units, among which wind turbines and generators are the core structures of wind power generation. The basic principle of wind turbine power generation can be summarized into the following two stages: the first stage is that the wind drives the fan blades to rotate, and the rotating blades drive the generator to rotate through a gear transmission device for energy transfer, thereby converting wind energy into mechanical energy; The second step is for the wind turbine to drive the generator rotor to cut magnetic field lines and convert mechanical energy into electrical energy, thus completing the conversion of wind energy into electrical energy. At the same time, the control system of the generator set protects, detects, and controls the entire power generation process to ensure that the wind turbine operates within a relatively stable range. The electrical energy generated by the wind turbine is inverted by the power electronic transposition circuit, and then output to the power grid by the frequency converter and transformer [11]. The wind power generation structure is shown in Fig. 2.

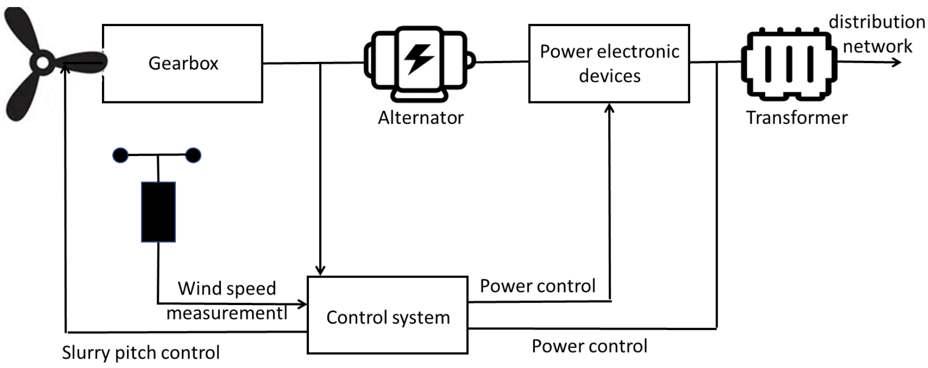

Fig. 2. Wind power generation structure model

Wind speed has the most direct impact on the power generation performance of wind turbines. Within a safe range, the higher the wind speed, the higher the blade speed of the wind turbine, and the higher the power generation efficiency and power. But when the wind speed exceeds the safety limit of the wind turbine, the safety structure inside the wind turbine will be triggered to automatically lock, causing the blades of the wind turbine to stop rotating, effectively preventing damage to the wind turbine caused by excessive speed. Due to the influence of natural climate conditions, geographical environment, and other factors on wind power, distributed wind power generation exhibits significant temporal characteristics. This article uses the Weibull [12] function to model the uncertainty of wind power. Assuming that the wind speed is a random variable containing a Weibull function.

$$f_w(v_t) = \frac{S_w}{d_w}\left(\frac{v_t}{d_w}\right)^{S_w - 1} \cdot \exp\left[-\left(\frac{v_t}{d_w}\right)^{S_w}\right] \tag{1}$$

$$S_w = \left(\frac{\sigma_t}{\overline{v_t}}\right)^{-1.086} \tag{2}$$

$$d_w = \overline{v_t} S_w^{2.667} / \left(0.184 + 0.816 S_w^{2.667}\right) \tag{3}$$

In the equation, $f_w(v_t)$ represents the probability density function, v_t is the wind speed at time t, and S_w and d_w are the shape and scale parameters of the Weibull distribution, respectively. The larger the S_w value, the higher the wind speed described by the Weibull distribution, and the larger the d_w value, the more concentrated the wind speed described by the Weibull distribution. $\overline{v_t}$ is the average measured wind speed, and σ_t is the standard deviation of the measured wind speed. The expression for wind power output is:

$$P_W(t) = KR^2 v_t^2 \tag{4}$$

In the formula, K is the fan coefficient, which is a fixed value depending on the local air density. R represents the blade radius of the fan, and v_t^2 is the square of the rotational speed of the fan. Therefore, the relationship between the output of wind turbines and wind speed can be obtained as shown in Fig. 3.

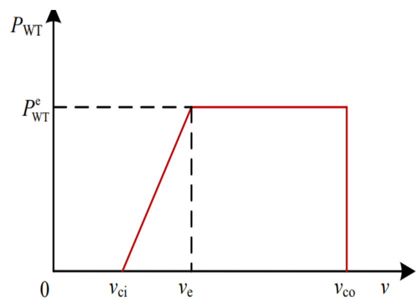

Fig. 3. Power characteristic curve between wind speed and wind power generation

3.2 Uncertainty Model of Photovoltaic Power Generation

Photovoltaic (PV) power generation system is a power generation technology that uses photovoltaic panels to generate a potential difference effect in the panel material after being exposed to sunlight, which converts light energy into electrical energy [13]. From current usage, in order to ensure the stable operation of photovoltaic power generation, the entire photovoltaic power generation system must include three main parts: photovoltaic panels, photovoltaic power generation controllers, and voltage inverters. Therefore, the biggest difference between the entire photovoltaic power generation system and wind power generation is that the entire photovoltaic power generation system is mainly a power electronic system, without mechanical parts. Therefore, the material cost of photovoltaic power generation equipment is relatively low, the installation and maintenance cost is low, and the loss is relatively slow. The structural schematic diagram is shown in Fig. 4.

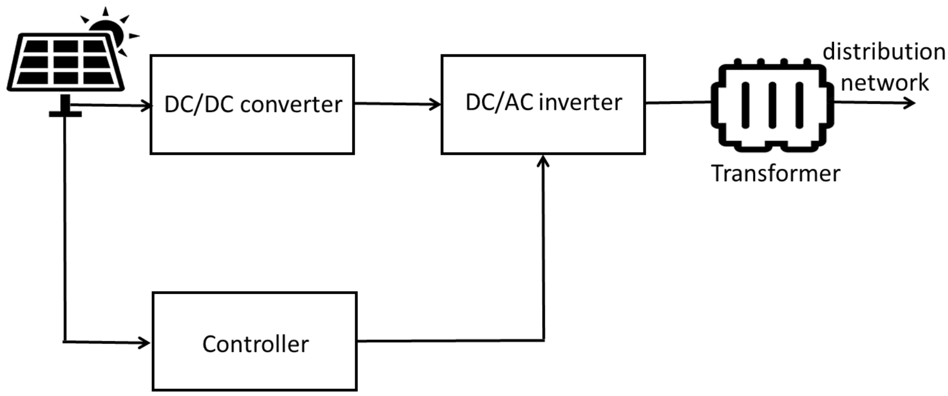

Fig. 4. Schematic diagram of photovoltaic power generation structure

This article uses the Beta [14] function to model the uncertainty of photovoltaics. The formula for calculating the uncertainty of photovoltaics is:

$$f_B\left(a_{PV}\right)=\frac{1}{\lambda A}\cdot\frac{\beta\left(x+y\right)}{\beta\left(x\right)\beta\left(y\right)}\cdot\left(\frac{a_{PV}}{a_{pv,\max}}\right)^{x-1}\cdot\left(1-\frac{a_{PV}}{a_{pv,\max}}\right)^{y-1} \quad \textbf{(5)}$$

$$x=\frac{\mu y}{1-\mu} \quad \textbf{(6)}$$

$$y=\left(1-\mu\right)\left[\frac{\mu\left(1+\mu\right)}{\sigma^2}-1\right] \quad \textbf{(7)}$$

In the formula, x and y are parameters of the Beta function distribution, A is the surface area of the photovoltaic panel, λ is the panel power generation efficiency, $f_B(a_{PV})$ is the photovoltaic output power, $\beta(\bullet)$ is the Beta function, a_{PV} is the area parameter of the photovoltaic panel, μ and σ are the mean and standard deviation. The output power of photovoltaic power generation is expressed as:

$$P_P\left(t\right)=P_P^e\cdot\eta\frac{l\left(t\right)}{l^e}\left[1+t_pT\left(t\right)\right] \quad \textbf{(8)}$$

In the formula, $P_p(t)$ is the output power of the photovoltaic power source at time t, P_p^e is the rated power of the photovoltaic power source, $l(t)$ is the illumination intensity of the photovoltaic power source at time t, l^e is the rated illumination intensity, η is the power conversion efficiency, t_p is the temperature coefficient, and $T(t)$ is the surface temperature of the photovoltaic power source at time t.

3.3 Energy Storage Model

Load also has randomness, and normal distribution is usually used to describe the uncertainty of load [15]. The probability density function of the load is:

$$f_F\left(p\right)=\frac{k}{\sigma}\exp\left(\frac{\left(p-\mu_p\right)^2}{2\sigma_p^2}\right) \tag{9}$$

3.4 Electricity Consumption Load Model

As an optimization process, the energy storage system stores the remaining electricity of the entire power grid during low electricity consumption periods, and releases the stored electricity during high electricity consumption periods when the power supply of the grid is insufficient [16], so as to maintain balance between power supply and consumption at the terminal stage and compensate for the uncertainty of power generation after adding wind and photovoltaic power generation. The core component of the energy storage system is generally a lithium battery, and the circuit model of the lithium battery is shown in Fig. 5.

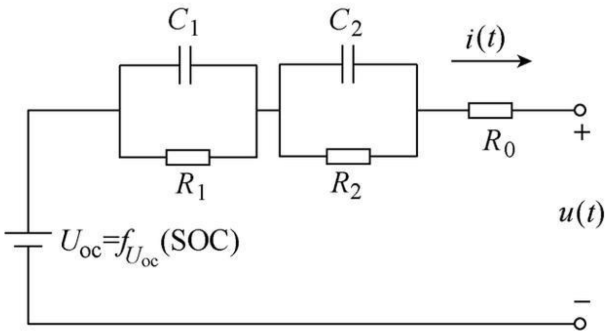

Fig. 5. Battery model

The relationship between the open circuit voltage U_k of the battery and its state SOC of charge can be expressed using the following formula:

$$U_k=\lambda_0-\frac{\lambda_1}{SOC}-\lambda_2 SOC+\lambda_3\ln\left(SOC\right)+\lambda_4\ln\left(1-SOC\right) \tag{10}$$

In the formula, λ_1, λ_2, λ_3, λ_4 is the fitting coefficient, and the model parameter identification method can obtain the set of fitting coefficients for different battery types.

The internal resistance characteristics of batteries include polarization internal resistance caused by concentration polarization and electrochemical polarization, as well as Ohmic internal resistance characteristics caused by resistance polarization. Two RC parallel circuits connected in series with Ohmic internal resistance can jointly simulate the internal resistance characteristics of batteries.

Obtain charging response information such as battery voltage or current, SOC, temperature, etc. through simulation calculations [17]. The expression SOC of a battery in the discrete time domain is:

$$SOC_k=SOC_{k-1}+\frac{1}{R}\lambda_{SOC}\lambda_T\eta I_{R(k-1)}\Delta t \tag{11}$$

From the above model, it can be seen that energy storage systems, as both power generation units and load units, have timeliness and controllability. When the output of renewable energy exceeds the load demand, the energy storage system absorbs energy as a load. When the output of renewable energy does not meet the load demand, the energy storage system releases energy to supply power to the system.

3.5 Energy Storage Optimization System

Energy storage system (ESS) [18], as an important energy buffering unit in microgrids, can not only suppress the fluctuations of distributed energy and load in microgrids, but also play a role in peak shaving and valley filling. The operating cost of ESS is expressed as:

$$C_E = \sum_{t=1}^{t=n} \left[\varphi_E \cdot P_{E,c}(t) + \phi_E \cdot P_{E,f}(t) \right] \tag{12}$$

C_E is the operating and maintenance cost of the energy storage device during the charging and discharging process, φ_E and ϕ_E are the operating and maintenance cost coefficients of the energy storage system during the charging and discharging process, $P_{E,c}$ and $P_{E,f}$ are the charging and discharging power of the energy storage system during the t-th period, respectively. Further constraints are imposed on the upper and lower limits of the charging and discharging power of the external energy storage system, as well as the internal battery state of charge of the energy storage system.

$$\begin{cases} H_E(t) = H_E(t-1) + \dfrac{\omega(t)\eta_c P_{E,c}(t)\Delta t}{E} - \dfrac{(1-\omega(t))P_{E,f}(t)\Delta t}{\eta_f E} \\ H_E^{\min}(t) \le H_E(t) \le H_E^{\max}(t) \end{cases} \tag{13}$$

In the formula, $H_E(t)$ represents the state of charge of the energy storage system during the t period, η_c and η_f represent the charging and discharging efficiency of the energy storage system, and E represents the energy storage capacity. $H_E^{\min}(t)$ and $H_E^{\max}(t)$ are the maximum and minimum allowable states of charge for energy storage facilities, respectively.

In summary, models for wind power generation, photovoltaic power generation, user electricity consumption, and energy storage optimization system with energy storage batteries as the core were established to address the uncertain factors at the power supply end, and model parameters for each power supply end were established.

4 Energy Storage System Optimization and Power Supply Scheduling Optimization

For the optimization of energy storage systems, this article uses an improved seagull algorithm to solve the optimal solution of the energy storage system. Therefore, this article first establishes an optimization objective model. For power dispatch strategies, robust optimization methods are used for optimization.

4.1 Establishment of Energy Storage Objective Function

Establish a distribution network model that includes wind power, photovoltaic power, electricity consumption, and energy storage batteries [19]. As a supplementary link in the entire uncertain distribution network, energy storage batteries require the least number of charge and discharge cycles, indicating that the energy storage optimization system needs to optimize the entire power grid the least. That is, the power grid can fluctuate the least number of times on its own. The minimum number of battery arrangements indicates that the entire power grid has the least cost in terms of batteries. Therefore, a model is established based on the number of battery charge and discharge cycles, and the model is represented as follows:

$$\min D_{cf} = \begin{cases} n_{c,\min} & \begin{aligned} & a_1 \sum_{n=1}^{N} f_B\left(a_{PV}\right) \cdot P_P\left(t\right) + a_2 \sum_{n=1}^{N} f_w\left(v_t\right) \cdot P_W\left(t\right) \\ & -a_3 \sum_{n=1}^{N} f_F\left(p\right) P_{out} \geq 0 \end{aligned} \\ n_{f,\min} & \begin{aligned} & a_1 \sum_{n=1}^{N} f_B\left(a_{PV}\right) \cdot P_P\left(t\right) + a_2 \sum_{n=1}^{N} f_w\left(v_t\right) \cdot P_W\left(t\right) \\ & -a_3 \sum_{n=1}^{N} f_F\left(p\right) P_{out} \leq 0 \end{aligned} \end{cases} \tag{14}$$

4.2 Finding the Optimal Solution for Energy Storage System Operation

This article uses the Seagull Optimization Algorithm (SOA) [20] to solve the optimal solution of the model. The Seagull Algorithm is an optimization algorithm that simulates the migration and predation behavior of seagulls, proposed by Gaurav Dhiman et al. in 2019. This algorithm is based on the natural behavior of seagulls, such as migration and attacking prey, and simulates these behaviors to find the optimal solution to the problem. The main steps of the seagull optimization algorithm include initializing parameters, initializing population positions, calculating fitness values and retaining the global optimal position, and simulating seagull migration behavior for global search. Specifically, seagulls avoid colliding with other seagulls during migration and move towards the optimal position by calculating a new position that does not collide with adjacent seagulls and determining the direction of the optimal position. In traditional seagull algorithms, a pseudo-random number generator is typically used to generate the initial population. The results of pseudo-random number generators in low dimensional space can be considered random, but in the high-dimensional solution space of complex problems, the limitations of pseudo-random number generators begin to emerge. The initial population generated by them is unevenly distributed in high-dimensional space, which affects the diversity of the population and may reduce the search performance of the algorithm. This article uses a nonlinear search method to search for the optimal solution, with the following formula:

$$C_s = f - f \sin\left(\frac{i}{I} \cdot \pi / 2\right) \tag{15}$$

C_s is the movement coefficient of individual seagulls in a given space, f is the control coefficient, i is the current iteration number, and I is the maximum iteration number.

The SOA algorithm requires a global search of the solution space during its initial iteration, while in the later stages, it needs to fully explore the solution space to obtain a compromise solution that is closer to the true Pareto front. In order to further enhance the algorithm's local convergence and mining capabilities, a local convergence mining operator is introduced.

$$\begin{cases} w = 1 - \left(i / I\right)^{1/a} \\ P_{wj} = \left(\dfrac{P_{wj}^{\max} - P_{wj}^{\min}}{I}\right) \cdot i + P_{wj}^{\min} \end{cases} \tag{16}$$

$$\vec{A}_i^n = \begin{cases} \vec{A}_{zy}^n + \omega \times r_c \times \left(U^n - L^n\right) + L^n, r_b < 0.5 \cap r_a \leq P_{wj} \\ \vec{A}_{zy}^n - \omega \times r_c \times \left(U^n - L^n\right) + L^n, r_b \geq 0.5 \cap r_a < P_{wj} \end{cases} \tag{17}$$

In the formula, $\vec{A}_i^n$ and $\vec{A}_{zy}^n$ are the n-th dimensional variables of the current seagull individual and the optimal seagull individual, U^n and L^n are the upper and lower limits of the n-th dimensional variable, r_a, r_b, r_c are random numbers with a range of [0,1], ω is the nonlinear weight, and P_{wj} is the local convergence mining probability, which increases linearly during the convergence process. a is the mining accuracy. The larger the value of a, the faster the migration behavior transitions from global search to local mining, and the higher the mining accuracy. In this paper, $a = 7$ and $P_{wj}^{\max}$ are set as the maximum values of local convergence mining probability, and $P_{wj}^{\min}$ is set as the minimum value of local convergence mining probability.

The algorithm flow is shown in Fig. 6:

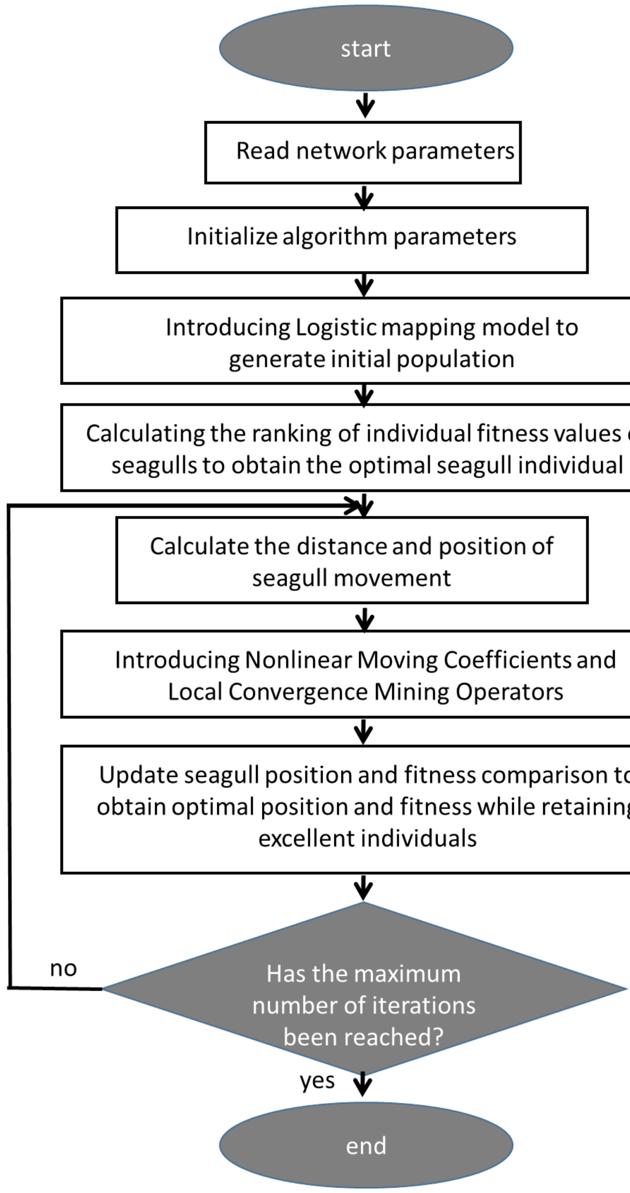

Fig. 6. Algorithm flow chart

4.3 Robust Optimization Strategy for Power Dispatching

In power dispatch problems, the uncertainty of renewable energy output is the main source of uncertainty, while photovoltaic output is mainly determined by solar radiation intensity, and is also affected by factors such as cloud cover and temperature. The accuracy of photovoltaic output prediction is closely related to weather conditions. When the cloud cover is large, the root mean square error of ultra short term photovoltaic output prediction can reach more than 20%. In addition, factors such as ground temperature can also affect the prediction error of photovoltaic power generation output. The regulating ability of energy storage systems is greatly affected by usage losses and temperature. The loss of lithium batteries is irreversible and changes relatively slowly, but it is strongly affected by temperature. In cold weather, the storage capacity of lithium batteries is about two-thirds of the normal level.

Robust Optimization (RO) [21] is a method for handling optimization problems with uncertain parameters. RO assumes that the uncertain parameters take values in an uncertainty set, with the goal of finding a solution that satisfies constraints for any uncertain parameter value and minimizes the worst-case cost. Due to the extremely low probability of the worst-case scenario and the fact that most uncertain predictions are around the expected value, in order to improve the conservatism of traditional two-stage robustness, this paper adopts a two-stage robust model based on expected scenarios to solve the optimal solution for microgrid scheduling under expected scenarios, and the optimal solution can adapt to the uncertainty under the worst conditions.

1) Robust optimization fully considers the uncertainty of each link in the modeling process and expresses each uncertainty factor in the form of a set. Therefore, robust optimization does not require a distribution model of uncertain parameters or fuzzy membership functions of uncertain parameters [22].

2) In robust optimization, as long as the uncertain parameters belong to the uncertain set, the solutions obtained can satisfy the constraint conditions. The optimization model has strong robustness, and the optimal solution has low sensitivity to parameter changes.

The robust optimization model itself is a semi infinite optimization problem that is difficult to solve directly, and the computational results of robust optimization are limited by the different uncertainty sets. The above model can be represented in the form of a compact matrix as follows:

$$\begin{cases} \min\limits_{\alpha,\beta,\gamma}\left(A^T\alpha + B^T\beta + C^T\gamma\right) \\ E\alpha \ge F \\ G\alpha + H\beta + I\mu \le \omega \\ O\alpha + M\beta + N\gamma = \mu \end{cases} \tag{18}$$

A, B, C, D, E, G, H, I, O, M, N is the coefficient matrix of the objective function or constraint conditions, F, ω, μ are the constant column vectors of the constraint conditions, and α, β, γ are the decision variables. The uncertainty set consists of an allowed range of uncertainty, which limits uncertainty and makes optimization problems practical. Based on this, taking into account the uncertainty of wind and solar power output, improvements are made using formulas 4 and 8 as the basis:

$$\begin{cases} U_W(t) = \left\{ KR^2 v_t^2 : \lim_W^l \le \frac{1}{t}\sum\limits_{t\in n} KR^2 v_t^2 \le \lim_W^u \right\} \\ U_P(t) = \left\{ P_P^e \cdot \eta \frac{I(t)}{I^e}\left[1 + t_p T(t)\right] : \lim_P^l \le \frac{1}{t}\sum\limits_{t\in n} P_P^e \cdot \eta \frac{I(t)}{I^e}\left[1 + t_p T(t)\right] \le \lim_P^u \right\} \end{cases} \tag{19}$$

In addition, for each set of uncertain variables, the upper and lower limits of uncertainty defined as $\lim^u$ and $\lim^l$ represent the possible intervals of different uncertainties throughout the day. Setting the upper and lower limits as 90% and 110% respectively, the size of the uncertainty set will increase, and the final optimization solution will be more conservative. Comparing the advantages and disadvantages of solving algorithms and selecting a more suitable one, there are particle swarm optimization and ant colony algorithm in evolutionary algorithms. Among them, ant colony algorithm simulates the way ants search for food, and ants find the optimal route through their secreted pheromones. Therefore, the setting of pheromones is crucial in the solving process. At the same time, in terms of search method, ant colony uses probability search strategy [23]. Moreover, ant colony search algorithm has a larger volume relative to the model, higher performance requirements for the system, and lower solving efficiency, which leads to the final convergence result taking a long time to stabilize. Most importantly, ant colony algorithm may fall into local optimal solutions. Compared with ant colony algorithm, particle swarm algorithm is computationally simple, easy to operate, and has fast convergence speed. At the same time, through effective parameter settings, it can effectively avoid getting stuck in the foot optimal solution. Therefore, this article chooses particle swarm algorithm, and does not take up space to demonstrate the simulation process of the two algorithms.

The algorithm flowchart is shown in Fig. 7.

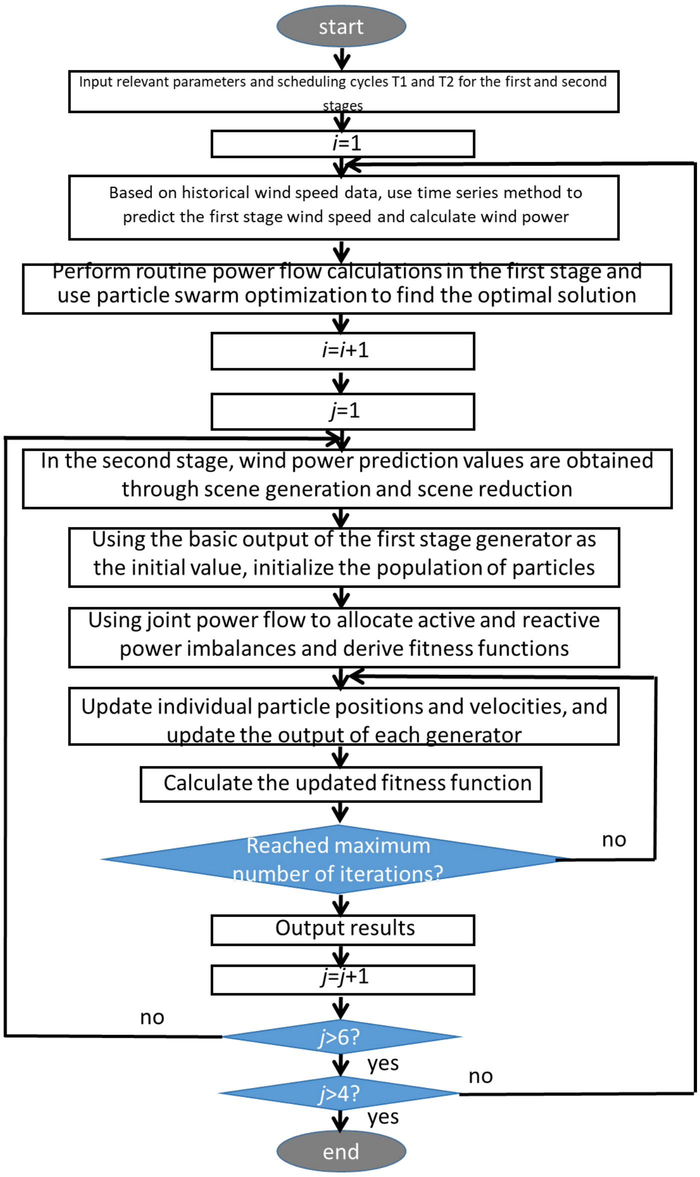

Fig. 7. Robust optimization process

The basic idea is to randomly generate several sets of solutions, namely power allocation schemes for each unit. Calculate the objective function obtained from each existing allocation scheme, and select the group of allocation schemes with the lowest objective function as the current optimal scheme. The remaining power allocation schemes are calculated through transformation, continuously approaching and iterating towards the current optimal scheme, and taking the set of schemes with the smallest objective function after each iteration as the current local optimal scheme. The position and speed of particles are updated through each iteration. After the iteration, the group of allocation schemes with the smallest scheduling objective function is the global unit optimal power allocation scheme. The objective function is the fitness function, so when substituting the allocation scheme into the fitness function, the smaller its value, the better its fitness. The current position of the particle is the local optimum, and its velocity is the iterative convergence velocity. Therefore, the velocity of the particle at the next moment is determined by the current velocity, its local optimum, and the global optimum. The particle moves from the current position to a new position at an iteratively updated velocity. As the iteration progresses, the entire particle population gradually completes the search for the optimal allocation scheme in the decision space.

5 Case Analysis and Simulation

This article uses the IEEE 14 node system for simulation analysis [24]. The IEEE14 system is shown in Fig. 8. The Weibull parameter is set to number $k = 0.23$, the scale parameter $c = 0.98$, and the beta function parameters are set to $\mu = 5.4$ and $\sigma = 0.4$. The node model is shown in Fig. 8.

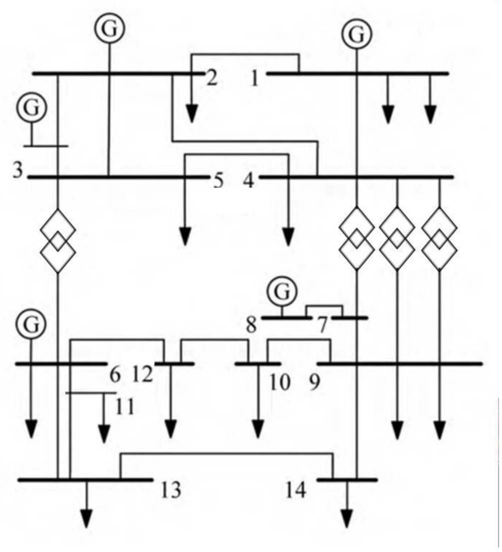

Fig. 8. IEEE 14 node system

5.1 Robust Optimization Strategy for Power Dispatching

The optimal position during the migration of seagulls corresponds to the optimal solution of the objective function, and the angle and velocity of seagull attack behavior correspond to the capacity of the energy storage system configuration. Under the same node network model, energy storage system configuration cases were set up at different locations and solved using SOA algorithm. The configuration results of the cases are shown in Fig. 9.

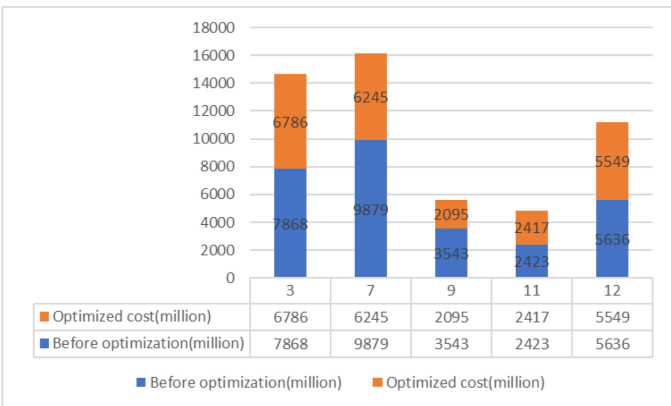

Fig. 9. Cost comparison of optimized energy storage batteries

According to the algorithm solution, it can be concluded that connecting wind and photovoltaic power generation at nodes 3, 7, 9, 11, 12, and 5 can ensure optimal energy storage in the system. After optimization, the battery usage cost at each location and the optimized usage cost are shown in the figure. The maximum decrease is 40.86%, which indicates that the configuration of the energy storage system can effectively improve the flexibility of the distribution network.

5.2 Robust Optimization Method for Solving the Optimal Solution of Power Dispatching

1) Phase One Optimization

The optimized scheduling result is shown in Fig. 10, which is the first stage decision. After scheduling, the electricity consumption will be expanded from 13:00 to 15:00, and the load during peak hours will be transferred and shifted. In addition, the electricity consumption from 02:00 to 05:00 is expected to be higher as the output of photovoltaic and wind power is sufficient. On the other hand, from 17:00 to 20:00, there is insufficient photovoltaic and wind power, and the purchase price of electricity from the large grid is relatively high. Transferring, shifting, and reducing the load can reduce customer demand.

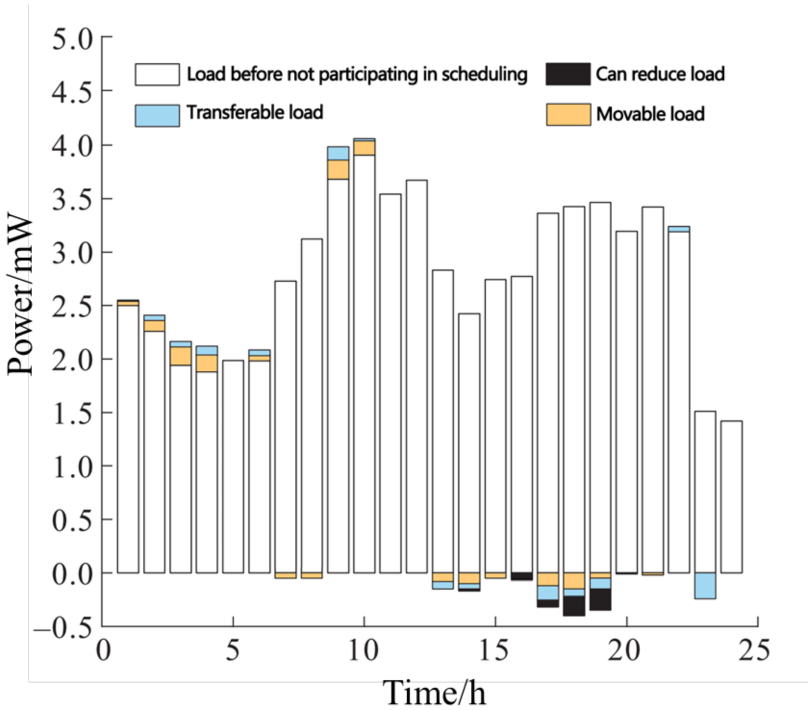

Fig. 10. Optimized power supply strategy after scheduling

2) Second stage optimization

In the second stage, it is possible to accurately predict the output and load demand of renewable energy generation based on short-term levels. In order to achieve precise real-time wind speed prediction, this paper reduces 1000 wind power sample scenarios by minimizing the probability scenario distance to obtain 5 sets of scenarios. The probability distribution of wind power output is shown in Fig. 11, where the vertical axis represents probability data and the horizontal axis represents the number of scenarios.

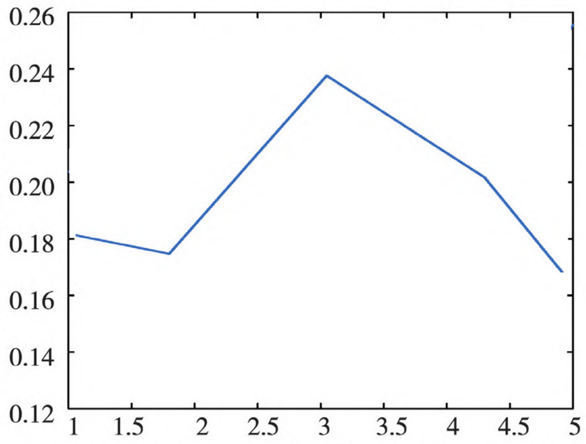

Fig. 11. Probability distribution diagram of wind power output

During the peak discharge period and the valley storage period, sharing energy storage can effectively reduce the amount of electricity purchased by microgrids from the large grid, thereby achieving the goal of reducing the operating costs of microgrids.

6 Conclusion

The large-scale use and grid connected operation of wind and photovoltaic power generation have brought undeniable impacts on the optimization of power system operation. On the one hand, the uncertainty of wind and photovoltaic power generation makes traditional decision-making schemes too conservative, resulting in the inability to absorb the remaining electricity generated by wind and photovoltaic power generation. Therefore, it is necessary to include it in the formulation of decision-making plans after analyzing the characteristics of wind and photovoltaic power generation. On the other hand, the development of battery energy storage technology has introduced new solutions to improve the consumption of surplus electricity from wind and photovoltaic power, and ensure the economic and stable operation of the power system. In response to the above issues, this article proposes a wind solar storage joint system scheduling model and method based on traditional decision-making schemes, taking into account the uncertainty of wind and photovoltaic output, and combining with energy storage system regulation optimization, to achieve coordinated and optimized operation of the power system. The work completed in this article is as follows:

(1) Based on the Weibull distribution of wind speed and the beta distribution of light intensity, model functions for wind turbine output and photovoltaic output were derived. In addition, the distribution function of user electricity load was introduced. On this basis, the probability distribution functions of the three uncertain factors of wind power output, photovoltaic output, and load are discretized. Then, based on the obtained sequences of the three uncertain factors, the joint probability sequence of the three is obtained to obtain the output optimization parameters of the wind turbine, photovoltaic, and load joint system.

(2) A robust power dispatch strategy considering the uncertainty of wind and solar power was introduced, with the optimization objective of minimizing the number of charge and discharge cycles. The particle swarm algorithm was used for solving the problem, and finally, the effectiveness and correctness of the method were verified through case analysis.

(3) In the verification process of the calculation example, this article used the IEEE14 node model for validation, and calculated that the optimal location for connecting wind and photovoltaic power generation can ensure the optimal energy storage of the system. After optimization, the battery usage cost and optimized usage cost at each location were reduced, and the power generation cost and scheduling cost were reduced.

This article studies a series of planning and operation optimization problems for new energy photovoltaic and wind power generation systems. Due to time and condition limitations, there are still many shortcomings in current research. In future research, further studies will be conducted on the following two aspects.

1) More uncertainty factors that can affect wind and photovoltaic power generation should be considered. In

this study, only the uncertainty factors such as wind speed, light intensity, and light intensity that directly affect renewable energy output were considered. At the same time, in the calculation of user side electricity consumption, only traditional electricity consumption was considered. With the widespread popularity of new energy vehicles, the charging of new energy vehicles has a significant impact on power scheduling. Therefore, it is necessary to explore the construction method of boundary adjustable uncertainty sets that are suitable for integrating multiple uncertainties, as well as the establishment method of optimization models after introducing this uncertainty set.

2) Combining mathematical optimization methods with artificial intelligence algorithms to improve the computational efficiency of the algorithm. The main algorithms used in this paper are mathematical optimization methods, heuristic algorithms, and nonlinear solving methods. With the increasing uncertainty factors to be considered in the future, the currently used algorithms will not be able to meet the computational requirements of the optimization model. In the process of solving the optimal solutions for various models, how to use a reasonable and lightweight solution method will also become an important research topic. In future research, artificial intelligence algorithms will be combined to improve the calculation speed and accuracy of optimization algorithms.

3) As the number of charge and discharge cycles increases, the energy storage system will experience battery loss, which is an unavoidable process. At the same time, the energy storage system with lithium batteries as the core is greatly affected by temperature. Therefore, the energy storage system needs to further consider loss and temperature factors, improve the accuracy of the energy storage optimization system model, and establish aging cost and temperature related objective functions and constraints based on discharge depth in subsequent work. The computational efficiency of the distributed robust optimization scheduling model for wind storage joint systems based on the comprehensive norm is still affected by the amount of data, and more efficient computational strategies should be sought.

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