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Research on New Operation Structure and Intelligent Regulation Strategy of Distribution Grid for Diversified Energy Access

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Abstract Aiming at the characteristics of randomness and volatility of the power output of multivariate decentralized resources affected by natural conditions, this paper proposes a new type of intelligent cluster regulation and control strategy. A multivariate equivalent modeling method is designed to establish a cluster voltage control model to enhance the system's ability to dissipate decentralized resources. The krill swarm algorithm is improved, combining inverse learning and Powell's local search strategy to solve the optimization problem in dynamic reconfiguration. Simulation results show that the improved krill swarm algorithm improves the voltage of each node more than the standard krill swarm solution, and most of the node voltages can reach more than 0.95p.u. The simulation results show that the improved krill swarm algorithm can improve the voltage of each node more than the standard krill swarm solution. Comparing with the regulation strategy that does not consider the improved krill swarm algorithm for dynamic reconfiguration optimization of the distribution network and does not use the cluster voltage control model, the average wind abandonment rate, light abandonment rate, and total operating cost of this paper's regulation strategy are 4.135%, 4.315%, and 620,000 yuan, respectively, which are the best performance among the three regulation strategies.

Index Terms distribution network, multivariate equivalent modeling, cluster voltage control model, improved krill swarm algorithm, distribution scheduling

I. Introduction

Distribution network is composed of overhead lines, cables, distribution transformers, switches, reactive power offset capacitors and some other equipment, which plays a primary role in distributing electric energy in the power network [1]-[3]. With the development of society and technological progress, the electric power industry is also constantly innovating and developing [4], [5]. On the basis of traditional distribution network, new operation structure and intelligent regulation of distribution network gradually appear and are widely used [6].

The research of new operation structure and intelligent regulation strategy of distribution network is one of the current hot topics in the field of electric power system. With the promotion of the construction of energy internet and the continuous expansion of new energy access scale, the operation of traditional distribution network is facing more and more challenges and demands [7]-[10]. The application of new operation structure and intelligent regulation will provide a more flexible, efficient and secure operation mode for the distribution grid to achieve the balance of supply and demand and system optimization, which not only improves the operation efficiency and security of the power system, optimizes the allocation and management of power resources, but also enhances the user experience and service quality [11]-[14]. These advantages will promote the development of the power system in the direction of intelligence and high efficiency, and help the energy transition and the realization of sustainable development goals [15], [16].

In this paper, we first construct a multivariate equivalent model containing wind power, photovoltaic, energy storage and flexible load, and establish the objective function and constraints of the cluster voltage control model. A reverse learning mechanism is introduced to optimize the initial population diversity, and the krill swarm algorithm is improved by combining Powell's local search operator. The operation characteristics of the new structure of the distribution network are analyzed, and performance comparison experiments with typical optimization algorithms KH, PSO and CS are conducted. Based on the simulation analysis of the distribution system, the application effect of the intelligent regulation strategy in this paper is investigated.

II. New intelligent regulation strategy for distribution network based on improved krill swarm algorithm

With the acceleration of global energy transition, wind power, photovoltaic and other renewable energy sources are connected to the distribution network on a large scale, which leads to a significant increase in the uncertainty of their source and load. The unidirectional radial structure and centralized control mode of traditional distribution network can hardly cope with the problems of voltage overrun, backward transmission of power and inefficient dynamic reconfiguration caused by a high proportion of distributed energy access. At the same time, the dispersed characteristics and random fluctuations of multiple resources have put forward higher requirements for distribution network scheduling, and there is an urgent need to build an operation structure and intelligent control system adapted to the new type of power system.

II. A. New Distribution Grid Structure Design for Diversified Energy Access

With the rapid development of power grid technology and new energy technology, source and load side resources are integrated into the distribution network in the form of multiple utilization. Some of the resources in the distribution network have randomness and uncontrollability, and the random changes of source and load side resources put forward new requirements for the distribution network. Distribution network is the key infrastructure connecting the grid and users, due to the many nodes in the distribution network, the network structure is complex, and the distribution of its resources is relatively decentralized and stochastic, so it is necessary to establish the output equivalence model for multiple resources.

II. A. 1) Wind power modeling

Changes in the natural environment can directly affect the output of wind power generation, and the change in wind speed is the main factor that determines the output of wind power. In existing studies, the change of wind speed can be fitted by various probability distributions, and in probability analysis, the Weibull distribution is one of the most commonly used probability distribution models for fitting wind speed. The wind power output model can be expressed as:

$$P_{wt}=\begin{cases}0, & v<v_{in}\\ P_{wo}\dfrac{v-v_{in}}{v_o-v_{out}}, & v_{in}\le v<v_o\\ P_{wo}, & v_o\le v<v_{out}\\ 0, & v\ge v_{out}\end{cases} \tag{1}$$

where P_{wt} is the actual output power of the wind turbine, W; P_{wo} is the rated maximum power of the wind turbine, W; v is the real-time wind speed at the blades, m/s; v_{in}, v_{out}, v_o are respectively the cut-in wind speed, cut-out wind speed, rated wind speed of the fan, m/s.

II. A. 2) Modeling of photovoltaic power generation

The output power of photovoltaic (PV) power generation will be affected by the natural environment, and the intensity of solar illumination is the most important factor affecting the output power of PV power generation. Although there is a great deal of randomness in the intensity of solar illumination due to the natural environment, existing studies generally assume that it satisfies the Beta distribution, i.e., the PV output is proportional to the intensity of solar radiation in the region where it is located. The PV power output model can be expressed as:

$$P_{PV}=E\cdot S\cdot\eta \tag{2}$$

where P_{PV} is the actual output of photovoltaic; E is the intensity of solar light; S is the area of photovoltaic panels subjected to light; and η is the efficiency of solar photovoltaic conversion.

II. A. 3) Modeling of energy storage devices

With the increasing global energy demand and environmental problems, energy storage devices are receiving more and more attention. The energy storage device output model can be expressed as:

$$P_e(t)=\begin{cases}-\mu_{cd}P_{cd}(t) & Charge\\ 0 & Idle\\ \mu_{fd}P_{fd}(t) & Discharge\end{cases} \tag{3}$$

where $P_e(t)$ is the actual output power of the energy storage device at t moment; μ_{cd}, μ_{fd} are the charging and discharging efficiencies of the energy storage device, respectively; P_{cd}, P_{fd} are the charging and discharging powers of the energy storage device at t moment, respectively.

II. A. 4) Flexible load modeling

Flexible loads are loads that can be regulated up or down in a certain magnitude over a period of time, or can transfer energy between stages. According to the different characteristics of the regulated, it can be divided into leveling load, transferable load and curtailable load, in order to reduce the complexity of the model, it is assumed that the flexible loads in the distribution network include the latter two kinds, and their corresponding output models can be expressed as follows, respectively:

$$P_{l,c}(t)=\sum_{n} d_{c,n}(t)P_{c,n}(t) \tag{4}$$

$$P_{l,j}(t)=\sum_{m} d_{j,m}(t)P_{j,m}(t) \tag{5}$$

where $P_{\mathrm{l,c}}(t)$, $d_{\mathrm{c},n}(t)$ and $P_{\mathrm{c},n}(t)$ denote the power output of the transferable loads at the moment of t, the n th transferable load scheduling command and the power of the n th transferable load, respectively; $P_{\mathrm{l,j}}(t)$, $d_{\mathrm{j},m}(t)$ and $P_{\mathrm{j},m}(t)$ are denoted as the power output of the weakenable load at the t moment, the n th weakenable load scheduling instruction, and the n th weakenable load, respectively.

II. B. Cluster voltage control model

Diversified and decentralized resources have intermittent, fluctuating and uncertain characteristics affected by natural conditions, and their large-scale and decentralized access changes the unidirectional trend distribution characteristics of the distribution network, which makes the distribution network voltage overruns, power backward transmission and other problems more serious. At the same time, due to the wide range of decentralized resource access points, it greatly increases the complexity of distribution network voltage control, and puts forward new challenges to distribution network voltage management.

II. B. 1) Objective function

Existing voltage control methods are no longer able to solve the voltage overrun problem in distribution networks, so this section proposes a cluster voltage control model for distribution networks with an objective function as in equation (6):

$$F_2=F_1=\max\left\{\sum_{i=1}^{n_K^{PV}} P_{i,t}^{PV}+\sum_{i=1}^{n_K^{WT}} P_{i,t}^{WT}-\sum_{j=1}^{n_K^{ESS}} P_{j,t}^{ESS}-\sum_{ij\in\chi_K} P_{ij,t}^{loss}\right\} \tag{6}$$

where n_K^{PV}, n_K^{WT}, and n_K^{ESS} denote the number of PV, wind, and storage installations in cluster K, respectively, and χ_K denotes all lines in cluster K.

II. B. 2) Constraints

(1) Distribution network current constraints

$$u_{j,t}=u_{i,t}-2(r_{ij}P_{ij,t}+x_{ij}Q_{ij,t})+(r_{ij}^2+x_{ij}^2)L_{ij,t},\forall i,j\in\Pi_K^P \tag{7}$$

$$\begin{aligned}&P_{PV,j,t}+P_{WT,j,t}-P_{L,j,t}-P_{ESS,j,t}\\&=\sum_{l\in\Phi(j)} P_{jl,t}-\sum_{i\in\Lambda(j)}(P_{ij,t}-r_{ij}L_{ij,t}),\forall j\in\Pi_K^P\end{aligned} \tag{8}$$

$$Q_{PV,j,t}+Q_{WT,j,t}-Q_{L,j,t}=\sum_{l\in\Phi(j)} Q_{jl,t}-\sum_{i\in\Lambda(j)}(Q_{ij,t}-x_{ij}L_{ij,t}),\forall j\in\Pi_K^P \tag{9}$$

$$P_{PV,j,t}^{*}+P_{WT,j,t}^{*}-P_{L,j,t}-P_{ESS,j,t} = \sum_{l\in\Phi(j)} P_{jl,t}-\sum_{i\in\Lambda(j)}(P_{ij,t}-r_{ij}L_{ij,t}),\forall j\in\Pi_K^P \tag{10}$$

$$(U^{\min})^2\le u_{i,t}\le (U^{\max})^2,\forall j\in\Pi_K^P \tag{11}$$

$$s.t.\,(3.13)-(3.15) \tag{12}$$

where Π_K^P denotes the set of all nodes in cluster K ; $P_{PV,j,t}^{*}$, $P_{WT,j,t}^{*}$ denote the active power output of the j th PV node and the j th wind node at the moment of t , respectively, which is a constant value.

(2) Upper and lower bound constraints on PV output power

$$0\le P_{PV,i,t}\le P_{PV,i,t}^{\max},\forall i\in\Pi_K^P \tag{13}$$

where $P_{PV,i,t}^{\max}$ is the upper limit of active power output by PV node i at moment t .

(3) Wind power output upper and lower limit constraints

$$0\le P_{WT,i,t}\le P_{WT,i,t}^{\max},\forall i\in\Pi_K^P \tag{14}$$

where $P_{WT,i,t}^{\max}$ is the upper limit of active power output by wind power node i at moment t .

(4) Energy storage state constraint

$$S_{OC,j}^{\min}\le S_{OC,j,t}\le S_{OC,j}^{\max}\forall i\in\Pi_K^P \tag{15}$$

$$-P_{ESS,N,i}\le P_{ESS,i,t}\le P_{ESS,N,i}\forall i\in\Pi_K^P \tag{16}$$

Compared with the traditional centralized control method, the use of cluster voltage control model can divide the decentralized resources with similar electrical characteristics into the same cluster for unified management, which can greatly reduce the search scope of the distribution network for adjustable decentralized resources and improve the search efficiency of adjustable resources. At the same time, it can make the decentralized resources similar to conventional power sources in terms of scale and regulation characteristics, improve the ability of decentralized resources to quickly respond to the voltage control of the distribution network, and enhance the ability of decentralized resources to consume.

II. C.Dynamic reconfiguration of distribution network based on improved krill swarm algorithm

Distribution network reconfiguration is the core of active distribution network operation optimization. Since the reconfiguration of distribution network is a multi-dimensional global optimization problem, and the active distribution network is larger and more complex than the traditional distribution network in terms of scale and structure, the original krill swarm algorithm in solving the dynamic reconfiguration problem of the active distribution network will be due to the fact that it has multiple types of distributed power nodes as well as the dynamic reconfiguration of the dynamic reconfiguration needs to consider the higher-dimensional objective function including switching lifetime, etc., and the original krill swarm algorithm will generate a large number of stochastic infeasible solutions when solving the dynamic reconfiguration problem of active distribution network. The original krill swarm algorithm will generate a large number of stochastic infeasible solutions when solving the dynamic reconfiguration problem of the active distribution network, and it is very prone to problems such as dimensionality catastrophe, which leads to a reduction of the algorithm efficiency. In this section, the original krill swarm algorithm is improved by considering the characteristics of the active distribution network structure and combining with the optimization characteristics of the original krill swarm algorithm, and it is applied to solve the dynamic reconfiguration problem of active distribution network.

II. C. 1) Reverse Learning Initialization

For the original krill swarm algorithm, the algorithm starts by utilizing a random and irregular way to generate initial solutions, which can lead to uncertainty in the optimality search under certain circumstances. If the generated initial solutions are all concentrated in the inferior region of the total solution set, it will cause the krill swarm algorithm to fall into the local optimum or even fail in the optimization search. To avoid this situation, a reverse learning mechanism is introduced to optimize the initial solutions, making the generated initial solutions more uniform, such that the diversity of the population in the iterative process is maintained, which is conducive to the search for the global optimal solution. Define $X=(x_1,x_2,\cdots,x_n)$ to be a point in a D-dimensional space where $(x_1,x_2,\cdots,x_n)\in R$ and $x_j\in\left[a_j,b_j\right](j=1,2,\cdots,D)$, then the inverse point of X is shown in equation (17):

$$\dot{x}_i=a_j+b_j-x_j \tag{17}$$

The population initialization process of krill swarm algorithm that introduces the principle of inverse learning is as follows: randomly generate the initial candidate population N, and calculate its corresponding initial candidate population N' through equation (17), mix the candidate populations N and N', and sort them based on the fitness value, and take the top 50 percent of them as the initial population.

II. C. 2) High-precision local optimization

In krill swarm induced movement, consider the krill swarm individual induced vector calculation method, if the krill swarm individual i is close to the optimal individual, it will produce $\left|L^{worst}-L^{best}\right|\to 0$, the induced movement inertia weights $\left|\dot{L}_u\right|\to\infty$, which makes the krill swarm individual i subject to a large induced strength, the krill swarm moving direction generates a large error, and the neighborhood of the optimal solution cannot be finely searched. Therefore, in order to solve the problems in this area, a high-precision local optimization search operator is considered for the optimization process.

In this paper, Powell local search is used.Powell algorithm is a conjugate search strategy in randomized mode. The method first randomly generates the initial position and then searches for the extremes along both positive and negative directions within each dimension. The method has the following advantages: the function information is utilized to solve for the minima without the need to compute the derivatives of the function, and it is considered to be one of the most effective direct search strategies.

The steps of high-precision local optimization using Powell are as follows:

(1) Choose the initial position $x^{(0)}$ and the accuracy threshold $\varepsilon>0$, and set D random initial search directions as $(u_1,u_2,\cdots,u_D)$, which are independent of each other's precedence. Let $s_j=u_j+1(j=0,1,\cdots,n-1;k=0)$.

(2) One-dimensional extreme value search to obtain λ_k such that $f\left(x^{(k)}+\lambda_k s_k\right)=\min f\left(x^{(k)}+\lambda_k s_k\right)$. Let $x^{(k+1)}=x^{(k)}+\lambda_k s_k$, if $k<D-1$, then $k=k+1$, go to (2); otherwise skip to (3).

(3) If the condition $\left|x^{(D)}-x^{(0)}\right|<\varepsilon$ is satisfied, then jump out of the loop and set $x^*\approx x^{(D)}$; otherwise take a value for $j(0\le j\le D-1)$ so that $\Delta=f\left(x^j-x^{(j+1)}\right)=\max\limits_{0\le j\le D-1}\left[f(x^{(j)})-f(x^{(j+1)})\right]$.

(4) Set $f_1=f\left(x^{(0)}\right)$, $f_2=f\left(x^{(D)}\right)$, $f_3=f\left(2x^{(D)}-x^{(0)}\right)$. If $2\Delta<f_1-2f_2+f_3$, leave $s_0,s_1,\cdots,s_{D-1}$ search direction unchanged so that $x^{(0)}=x^{(D)}$, $k=0$, return b); otherwise let $S_n=\left(x^{(D)}-x^{(0)}\right)\Big/\left|x^{(D)}-x^{(0)}\right|$, or $s_D=x^{(D)}-x^{(0)}$, $s_i=s_{i+1}$, $i=j,j+1,\cdots,D-1$, go to (5).

(5) Compute λ_n to satisfy $f\left(x^{(D)}+\lambda_D s_D\right)=\min f\left(x^{(D)}+\lambda_D s_D\right)$ to get $x^{(0)}=x^{(D)}+\lambda_D s_D$ with $k=0$, returning (2).

The main idea of Powell's strategy is to search for one-dimensional extrema in the D-dimensional orthogonal initial search direction, and update the position vector; compute the difference of the vectors, from which the difference can be derived as a search direction that is closer to the target, replacing the original search direction; and replace the original direction by using the difference of the vectors before and after the start of a new search cycle. On the basis of the above steps, the iteration is repeated until the difference between the front and back vectors is no longer generated on the iteration, and the target extreme value search is finally realized.

The wind power output also has a large volatility. In order to characterize the volatility of wind power output more intuitively, the wind power output volatility rate is introduced, which can be expressed as:

$$\eta=\left|\frac{P_W^t-P_W^{t-1}}{P_{W,N}}\right|\times 100\% \tag{18}$$

where, η - wind power output volatility, $P_{W,N}$ - rated wind power output, P_W^t, P_W^{t-1} - wind power output at t and $t-1$ moments.

III. Analysis of the effectiveness of intelligent regulation strategy of distribution network with diversified energy access

III. A. Operational characteristics of the new distribution network

III. A. 1) Randomness

The output power of wind power and photovoltaic is largely affected by the external environment and other factors, resulting in a large uncertainty in their output power. Taking wind power as an example, the distribution of daily output power of wind power in a certain place in a year is shown in Figure 1. It can be seen that the percentage of minimum and maximum output power of wind power fluctuates randomly between 0 and rated output power (100%). In addition, the wind power output in adjacent time periods also has a strong random volatility, which may have a large jump or continuous change in a small range. Photovoltaic output is easily affected by external environmental factors such as light intensity, climate, cloud cover, etc., so its output also has uncertainty and random volatility.

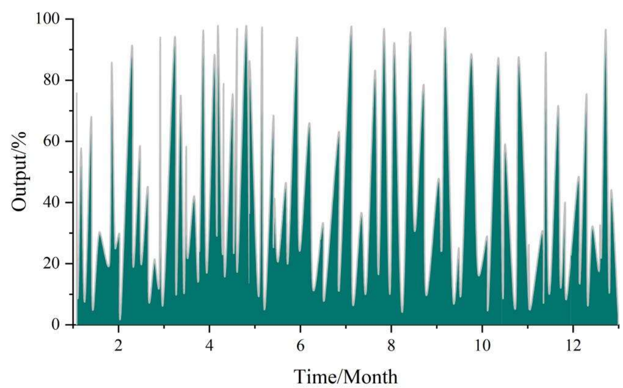


Figure 1: Annual distribution of sunrise power of a certain wind power

III. A. 2) Volatility

For the volatility of PV output, the output of a PV plant under different weather conditions is shown in Fig. 2. It can be seen that the PV output is easily affected by the weather changes, resulting in a large fluctuation. Among them, the power output is smoother on sunny days, and the maximum power output is concentrated around 12:00~13:00 in the midday. When it is cloudy and overcast, the fluctuation of output is larger because of the cloud cover, and the fluctuation in a short period of time even exceeds 50% of the capacity. In rainy and snowy weather, the overall output is maintained at a very low level, and the fluctuation of output is smaller than that in cloudy and cloudy weather.

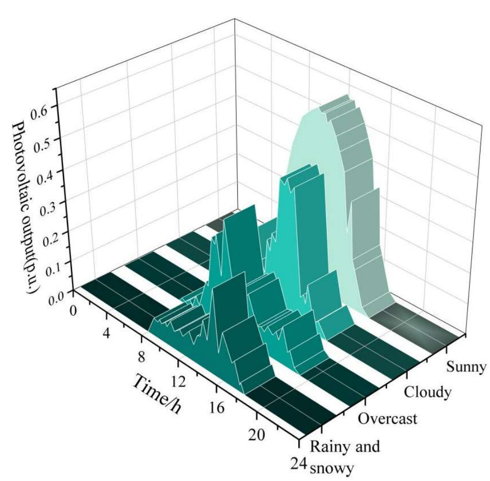


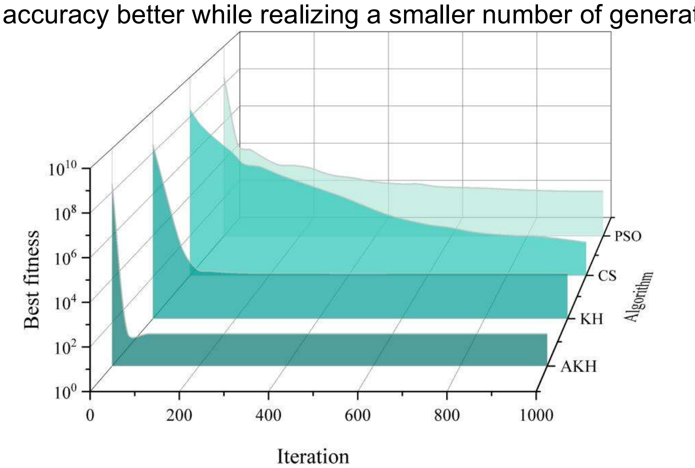
Figure 2: Sunrise power under different weather conditions

III. B. Algorithm Performance Test Comparison

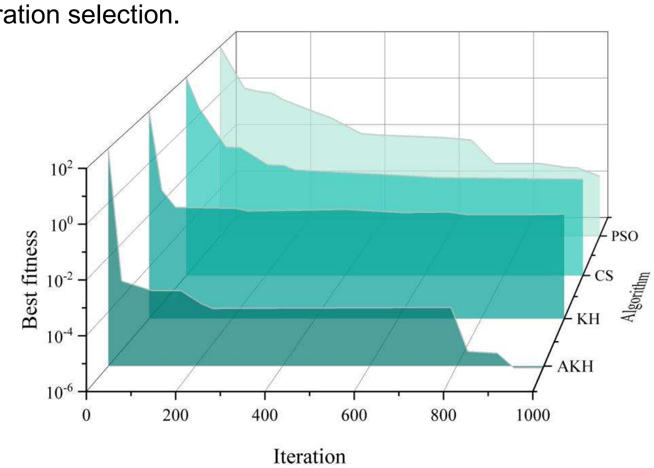
In order to verify the performance of the improved krill swarm algorithm, commonly used benchmark test functions are selected for performance comparison test In this paper, the improved krill swarm algorithm (AKH) is compared with the standard krill swarm algorithm (KH), particle swarm algorithm (PSO), and cuckoo algorithm (CS), respectively. Four test functions are selected for the experiment, where f1 to f2 are single-peak test functions and f3 to f4 are multi-peak test functions. The single-peak test function is relatively easy to find the optimization, and the development capability of the algorithm can be judged based on the test results. The multi-peak test function has multiple peaks and valleys, which makes the algorithm more difficult to find the optimal, and the multiple peaks and valleys may interfere with the algorithm to find the optimal, and appear to fall into the local optimal situation in a certain peak and valley. The multi-peak test function is suitable for better exploring the search capability of the proposed algorithm.

In this algorithm performance test comparison experiment, the operating system used is win10, 64-bit, and the integrated development environment for the experiment is Matlab (R2018b). The population size of the algorithms was set to 50, and the number of iterations was 1000. in order to ensure the fairness of the experiment, each algorithm was run on the function for 100 times, and the convergence curves of the different test functions are shown in Fig. 3(a~d), of which Fig. 3(a~b) is the result of the single-peak function test, and Fig. 3(c~d) is the result of the multi-peak function test.

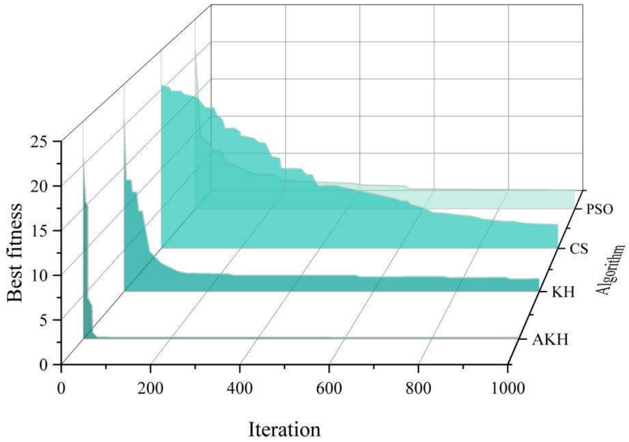
The superiority of the algorithm after improvement can be seen by comparing with the standard krill swarm algorithm. Particle swarm algorithm is one of the more commonly used intelligent optimization algorithms in recent years. Comparing the improved krill swarm algorithm with the particle swarm algorithm can well reflect the degree of performance improvement relative to the most commonly used algorithms. Cuckoo algorithm is a new type of intelligent algorithm proposed in recent years, the algorithm has a good performance in the search speed and global search ability, compared with some of the earlier algorithms has its own advantages, the improved krill swarm algorithm compared with the cuckoo algorithm can be further verified its superiority. In Figure 3(a), it can be seen that the improved krill swarm algorithm converges faster in the early stage of generation selection compared to other algorithms, and the Cuckoo algorithm has the slowest convergence speed. In Figure 3(b), the convergence curve of the improved krill swarm algorithm contains more inflection points, which indicates that the improved krill swarm algorithm has a strong global search capability, which can avoid falling into the local optimum, and the resulting solution is closer to the theoretical optimal solution. In Fig. 3(c), it can be seen that the improved krill swarm algorithm can find the minimum value with only a small number of iterations, and the minimum value is 0.1767, which is better than the optimal solution of the cuckoo algorithm of 3.0048, the optimal solution of the particle swarm algorithm of 2.4887, and the standard krill swarm algorithm of 1.5625. In Figure 3(d), the optimal solution found by the improved krill swarm algorithm is much better than the standard krill swarm algorithm, particle swarm algorithm, and cuckoo algorithm, which can show that the algorithm is able to find a better solution than the other algorithms in the optimization process. In summary, the test shows that the improved krill swarm algorithm has certain advantages over the other algorithms, and it can accelerate the convergence speed and maintain the convergence accuracy better while realizing a smaller number of generation selection.



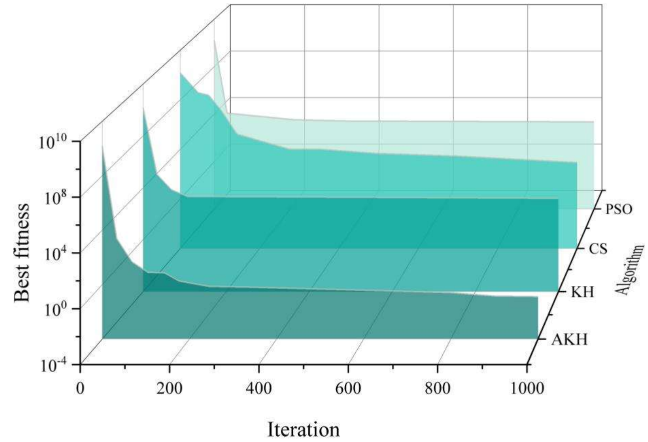
(a)f1



(b)f2



(c)f3



(d)f4

Figure 3: Convergence curves for different test functions

III. C. Analysis of application effects

Simulation analysis is carried out on a new distribution system and the voltage distribution of the system after optimization is shown in Fig. 4. As can be seen from Fig. 4, before the optimization is carried out, the voltage level is low, and the minimum value of voltage occurs at node 35 with a voltage of 0.9105 p.u.. After the standard krill swarm algorithm is performed for optimization, there is a significant increase in the voltage at all nodes, although there are still a majority of nodes with voltages below 0.95 p.u. or less. Comparing with the results after the standard krill swarm solution, it can be seen that the improved krill swarm algorithm improves each node voltage more, and most of the node voltages can reach more than 0.95p.u., and only a few of the node voltages appear to be over the limit. After optimization, the reactive load of the system is reduced, which reduces the current flowing through the distribution lines and improves the power factor of the system, and at the same time improves the quality of the node voltage and reduces the network losses.

By comparing the improved krill swarm algorithm with the optimized results of the standard krill swarm algorithm, it can be found that the improved krill swarm algorithm in this paper has better computational results, higher computational accuracy, and performs better both in terms of the maximum deviation value of the node voltage and the value of network losses. Therefore, the improved krill swarm algorithm is better than the standard krill algorithm in solving the regulation optimization problem.

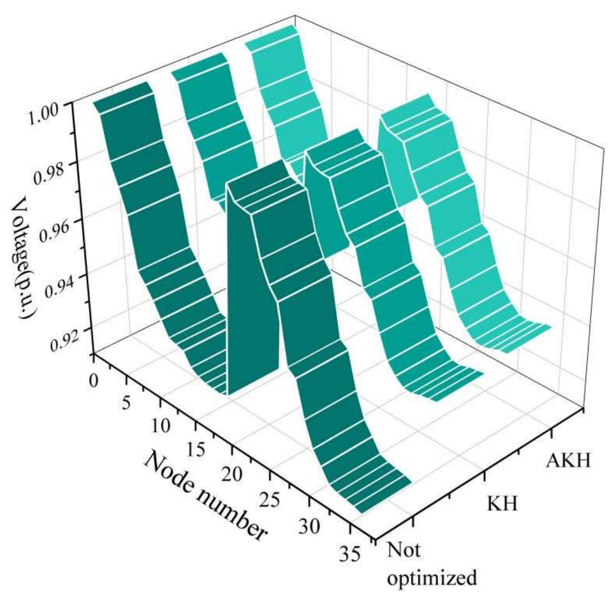


Figure 4: Voltage of each node of the system before and after optimization

The model is solved to obtain the scheduling of all the resources of the system within a day. The obtained results of day-ahead-intraday-real-time rolling optimized scheduling for 2 scenarios of positive peaking and anti-peaking of wind power within a day are taken as integer moments, and the obtained scheduling results are shown in Fig. 5. The scheduling plans for gas turbines, wind turbines, photovoltaic (PV) units, electrochemical storage plants, small pumped storage plants, and demand response resources within a day can be seen in the figure.

Analyzing the calling of each type of resources during wind power positive peaking and wind power anti-peaking, respectively, it can be found that when wind power positive peaking, the wind power high incidence period is (09:00-13:00) and (15:00-17:00) two time periods. When the wind power is anti-peaking, the high wind power occurrence time is in the early morning (1:00-7:00) and the evening (16:00-19:00).

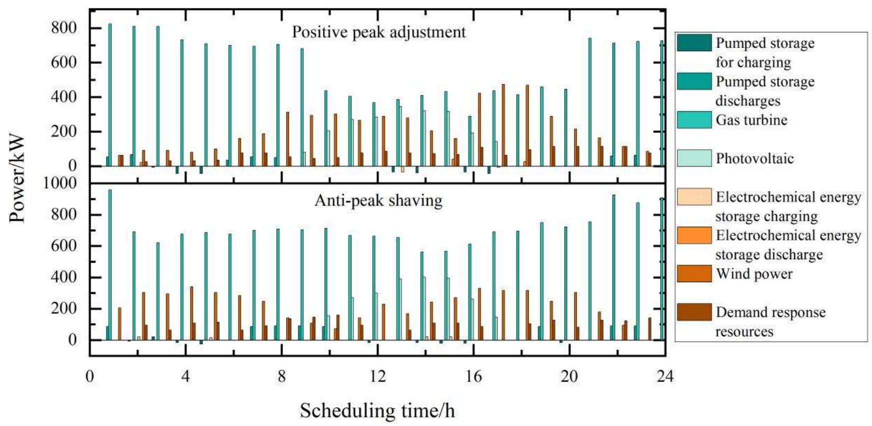


Figure 5: The invocation of various resources for wind power peak positive regulation

In order to be able to reflect the proposed regulation strategy to reduce the phenomenon of wind and light abandonment, improve the rate of wind power and photovoltaic consumption, and reduce the total operating cost of the system. Set up two kinds of control strategies to compare with this paper's program, in order to verify the effectiveness of this paper's program.

(1) Control strategy 1: using cluster voltage control model, but do not consider the improvement of krill swarm algorithm for dynamic reconfiguration optimization of the distribution network.

(2) Control strategy 2: Considering the improved krill swarm algorithm for dynamic reconfiguration optimization of the distribution network, but not using the cluster voltage control model.

Comparison of the scheduling results under three different regulation strategies is shown in Table 1. The average wind abandonment rate, light abandonment rate, and total operating cost of this paper's regulation strategy are 4.135%, 4.315%, and 620,000 yuan, respectively, which are the best performance among the three regulation strategies.

Table 1: Comparison of results from the three models

	Regulation strategy	Wind curtailment rate/%	Abandoned light rate/%	Total operating cost/tenthousand yuan
Positive peak adjustment	The proposed	3.92	4.12	60.43
	Strategy 1	15.28	16.31	73.18
	Strategy 2	14.19	16.93	69.22
Anti-peak shaving	The proposed	4.35	4.51	63.57
	Strategy 1	15.77	16.28	79.52
	Strategy 2	16.16	15.73	83.15

In summary, the intelligent regulation strategy proposed in this paper is conducive to the consumption of wind power and PV, and with low scheduling costs, it can reduce the use of higher-cost load-side demand response resources, thus reducing system operating costs. At the same time, it can better reduce the impact of uncertainty in wind power, PV, and load forecasting, reduce the increase in the rate of wind and light abandonment caused by the low accuracy of day-ahead forecasting when only day-ahead modeling is available, and reduce the total system operating costs.

IV. Conclusion

In this paper, a new operation structure of distribution network with diversified energy access is constructed, an improved krill swarm algorithm is proposed for intelligent regulation of distribution network, and its effectiveness is explored through simulation experiments.

In the single-peak test function f1, the improved krill swarm algorithm converges faster in the early stage to select generations, and the cuckoo algorithm has the slowest convergence speed. In the single-peak test function f2, the convergence curve of the improved krill swarm algorithm contains more inflection points, and the resulting solution is closer to the theoretical optimal solution. In the multi-peak test function f3, the improved krill swarm algorithm needs very few iterations to find the minimum value, which is 0.1767, which is superior to the optimal solution of the cuckoo algorithm of 3.0048, the optimal solution of the particle swarm algorithm of 2.4887, and the standard krill swarm algorithm of 1.5625. In the multi-peak test function f4, the improved krill swarm algorithm can find a better solution than other algorithms in the optimization search process. In summary, the test shows that the improved krill swarm algorithm has certain advantages over other algorithms, and can accelerate the convergence speed and better maintain the convergence accuracy while realizing a smaller number of generation selection. Simulation analysis on a power distribution system, compared with the results of the standard krill swarm solution, the improved krill swarm algorithm makes each node voltage enhancement more, most of the node voltage can reach more than 0.95 p.u..

Compared with the regulation strategy that does not consider the improved krill swarm algorithm for dynamic reconfiguration optimization of the distribution network and does not use the regulation strategy that does not use the cluster voltage control model, the average wind abandonment rate, the light abandonment rate, and the total operating cost of this paper's regulation strategy are 4.135%, 4.315%, and 620,000 yuan, respectively, which is the best performance among the three regulation strategies.

References

[1] Mangiaracina, R., Song, G., & Perego, A. (2015). Distribution network design: a literature review and a research agenda. International Journal of Physical Distribution & Logistics Management, 45(5), 506-531.
[2] Mishra, S., Das, D., & Paul, S. (2017). A comprehensive review on power distribution network reconfiguration. Energy Systems, 8, 227-284.
[3] Ehsan, A., & Yang, Q. (2018). Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques. Applied energy, 210, 44-59.
[4] Shyam, A. K., & von Rosing, M. (2025). Innovation in the power industry. In The Sustainability Handbook, Volume 1 (pp. 245-253). Elsevier.
[5] Grafström, J., & Lindman, Å. (2017). Invention, innovation and diffusion in the European wind power sector. Technological Forecasting and Social Change, 114, 179-191.
[6] Gouin, V., Alvarez-Hérault, M. C., & Raison, B. (2017). Innovative planning method for the construction of electrical distribution network master plans. Sustainable Energy, Grids and Networks, 10, 84-91.
[7] Evangelopoulos, V. A., Georgilakis, P. S., & Hatziargyriou, N. D. (2016). Optimal operation of smart distribution networks: A review of models, methods and future research. Electric Power Systems Research, 140, 95-106.
[8] Zhichao, L., & Yuping, Z. (2018, September). Research on distribution network operation and control technology based on big data analysis. In 2018 China International Conference on Electricity Distribution (CICED) (pp. 1158-1161). IEEE.
[9] Kazmi, S. A. A., Shahzad, M. K., Khan, A. Z., & Shin, D. R. (2017). Smart distribution networks: A review of modern distribution concepts from a planning perspective. Energies, 10(4), 501.
[10] Ruiz-Romero, S., Colmenar-Santos, A., Mur-Pérez, F., & López-Rey, Á. (2014). Integration of distributed generation in the power distribution network: The need for smart grid control systems, communication and equipment for a smart city—Use cases. Renewable and sustainable energy reviews, 38, 223-234.
[11] Haddadian, H., & Noroozian, R. (2017). Multi-microgrids approach for design and operation of future distribution networks based on novel technical indices. Applied energy, 185, 650-663.
[12] Al-Jaafreh, M. A., & Mokryani, G. (2019). Planning and operation of LV distribution networks: a comprehensive review. IET Energy Systems Integration, 1(3), 133-146.
[13] Wang, Y., Mao, M., Chang, L., & Hatziargyriou, N. D. (2022). Intelligent voltage control method in active distribution networks based on averaged weighted double deep Q-network algorithm. Journal of Modern Power Systems and Clean Energy, 11(1), 132-143.
[14] Liu, X., Wu, Q., Sun, J., Xu, X., & Wen, Y. (2019, March). Research on self-healing technology for faults of intelligent distribution network communication system. In 2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC) (pp. 1404-1408). IEEE.
[15] Biagini, V., Subasic, M., Oudalov, A., & Kreusel, J. (2020). The autonomous grid: Automation, intelligence and the future of power systems. Energy Research & Social Science, 65, 101460.
[16] Pandey, U., Pathak, A., Kumar, A., & Mondal, S. (2023). Applications of artificial intelligence in power system operation, control and planning: a review. Clean Energy, 7(6), 1199-1218.