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Intelligent Equipment Scheduling Optimization Model for Transmission Lines Based on Improved BFO Algorithm

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Abstract

INTRODUCTION: In modern power systems, the optimization of intelligent equipment scheduling for transmission lines is a key task.
OBJECTIVES: To improve the effectiveness of scheduling optimization, this study introduces an intelligent equipment scheduling optimization model for transmission lines on the ground of the improved Bacterial Foraging Optimization algorithm.
METHODS: This model achieves global and local search capabilities through an improved Bacterial Foraging Optimization algorithm, maintaining the diversity of equipment states and effectively improving the optimization level of scheduling results.
RESULTS: At 3000 iterations, the model was able to reach its optimal state, and its optimization results showed excellent performance in terms of convergence and uniformity, which was very close to the optimal solution. In practical applications, the performance of the intelligent equipment scheduling optimization model for transmission lines on the ground of the improved Bacterial Foraging Optimization algorithm is also excellent. The average line usage rate of the scheduling scheme proposed by the model reached 70.69%, while the average line usage rate of the manual scheduling scheme was only 64.63%. In addition, the optimal relative error percentage of this model is less than 2.1%, while the BRE of other algorithms reaches around 10%.
CONCLUSION: The intelligent equipment scheduling optimization model for transmission lines on the ground of improved Bacterial Foraging Optimization algorithm has important practical significance for improving the operational efficiency of the power system, reducing operating costs, and making sure the stable and reliable operation of the power system.

Keywords: background foraging optimization, transmission lines, intelligent equipment, scheduling optimization model, power system

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1. Introduction

Against the backdrop of the increasingly transforming global energy structure, smart grids have become an important direction for the future development of power systems due to their efficient, reliable, green, and economical characteristics. As the main component of the power system, the scheduling optimization problem of transmission lines is crucial. However, traditional transmission line scheduling methods often suffer from low efficiency and low scheduling quality, which has a significant impact on the stable operation and economic benefits of the power system [1-2] . Therefore, how to effectively improve the scheduling optimization efficiency and quality of transmission lines is an essential issue in current power system research. Among numerous optimization algorithms, the Bacterial Foraging Optimization (BFO) algorithm is extensively utilized in various optimization problems due to its unique search strategy and optimization ability [3-4] . However, traditional BFO algorithms still face problems such as slow convergence speed (CS) and susceptibility to local optima when dealing with complex transmission line scheduling problems. Improving BFO algorithms has become a research topic that needs to be addressed. A research proposes an intelligent equipment scheduling optimization model for transmission lines on the ground of an improved BFO algorithm to solve the problems existing in traditional methods. By improving and optimizing the BFO algorithm, the CS and optimization ability have been enhanced, enabling the model to more effectively solve complex transmission line scheduling problems [5-6] . This design effectively improves the BFO algorithm and utilizes it to the optimization problem of transmission line scheduling. This is the first time that the improved BFO algorithm has been utilized to this issue, which has significant innovation. The importance of this design is that it improves the efficiency and quality of transmission line scheduling, providing guarantees for the stable operation and economic benefits of the power system. The improvement and optimization of the BFO algorithm also provide new solutions for other optimization problems. Therefore, this design has important theoretical and practical value for power system research and optimization algorithm research. The research will be conducted in four parts. The first part is an overview of the design of an intelligent equipment scheduling optimization model for transmission lines on the ground of the improved BFO algorithm. The second part is the research on the design of an intelligent equipment scheduling optimization model for transmission lines on the ground of the improved BFO algorithm. The third part is the experimental verification of the second. The fourth part is a summary and points out the demerits.

2. Related Works

With the profound transformation of the global energy structure, the efficient, reliable, green, and economical characteristics of smart grids have made them the core of the development of the power system (PS). The importance of scheduling optimization problems for transmission lines, as an important component of the PS, is self-evident. Zhu D et al. developed a simplified topology model for PSs. Three indicators were derived from three aspects to evaluate the importance of transmission lines: global topology, line operating parameters, and local line connections. The simulation outcomes showcase that this method could identify key transmission lines in the PS and test its correctness and effectiveness [7] . Geng J et al. proposed a method for predicting important nodes and transmission lines in PSs - K-means Markov chain. The simulation results have demonstrated the rationality and effectiveness of the K-M method in forecasting essential nodes and transmission lines in the PS [8] . Takeda K et al. proposed a visualization method for power transmission characteristics on the ground of WPT system decomposition analysis to solve the problem of power transmission characteristics relying on the coupling conditions of transmitter and receiver coils in traditional resonant compensation circuit design. The experimental results are significantly consistent with the intuitively estimated trend and estimated power transmission [9] . Chen Y et al. characterized a feasible set of capacity parameters under a given solar energy spill over rate. And they proposed a projection algorithm on the ground of linear programming to obtain this set, providing valuable references for system planning and policy making [10] . Wu C et al. proposed a new principle using the integral autocorrelation coefficient of fault current. The relevant outcomes showcase that the protection principle is not influenced by distributed capacitor currents. And it possesses good tolerance to fault resistance and noise interference [11] .

The BFO algorithm has been widely used among numerous optimization algorithms due to its unique search strategy and optimization ability. However, when dealing with complex transmission line scheduling problems, traditional BFO algorithms have some limitations. Shaikh M S et al. proposed an optimization technique called Grey Wolf Optimization for calculating transmission line parameters. The results show that the grey wolf optimization algorithm has a significant optimization effect, which is better than the previously applied algorithms, and performs excellently in accuracy, robustness, and CS. The study also analyzed the effects of different wire bundle numbers, radii, and wire spacing on transmission lines [12]. Liu J et al. proposed a frequency dependent phase domain transmission line model on the ground of field programmable gate arrays. All software development of the model is completed using VHDL and hardware implementation is carried out using customized 48 bit floating-point data representation to improve accuracy. This FPGA based circuit model can interface with other networks for real-time simulation [13]. Kalam R et al. extracted GLCM and GLRLM features and selected them using the BFO algorithm. At last, the selected features are input into the optimized ANFIS classifier to classify tumors into meningiomas, gliomas, and pituitary tumors. In ANFIS, the optimization process is achieved by using PSO [14]. Gurrala G et al. proposed a one-step method on the ground of the characteristics of the Foster equivalent circuit, which directly fits the frequency response of the R-L equivalent circuit to the modal impedance. Then it applies the proposed model to EMTP-RV to simulate the switching transient of 400kV, 765kV, 1200kV transmission lines and an 11 bus 500kV network. Then it compares the results with the constant parameter cascade model and the general line model in EMTP-RV. The switching transient outcomes are comparable to those of the Marti model in EMTP-RV [15]. Wang et al. proposed a numerical integration method for measuring transmission line voltage using multiple D-dot electric field sensors. The research results indicate that the voltage measurement method for transmission lines on the ground of the Gaussian Kronrod integration algorithm is effective, with high measurement accuracy and an error within the range of 0.3% [16] .

In summary, the BFO algorithm has been extensively utilized to various optimization problems in current research. However, when dealing with complex transmission line scheduling problems, traditional BFO algorithms still face problems such as slow CS and susceptibility to falling into local optima. This situation clarifies the necessity of further improving the BFO algorithm and applying it to the design of transmission line scheduling optimization models. The study adopts an improved BFO algorithm to optimize the scheduling of intelligent equipment for transmission lines, and enhances the local search ability and convergence speed of the algorithm using a dynamic adaptive search step size strategy. It is expected that the exploration and research in this research direction can provide new basis for intelligent scheduling of transmission lines and open up new perspectives for the practical application of optimization algorithms.

3. Intelligent equipment scheduling optimization model for transmission lines on the ground of improved BFO algorithm

Firstly, the BFO algorithm and its improved design are introduced, followed by an analysis and model design of intelligent equipment scheduling for transmission lines. Finally, an improved BFO algorithm based optimization of intelligent equipment scheduling for transmission lines was proposed. Exploring and researching this research direction can provide new basis for intelligent scheduling of transmission lines. This can open up new perspectives for the practical application of optimization algorithms.

3.1 BFO algorithm and improved design

It is crucial to improve and design the basic structure and working mode of BFO algorithm to adapt to the complex intelligent equipment scheduling problem of transmission lines. Detailed analysis and model design enable the formalization of intelligent equipment scheduling problems for transmission lines, which can be effectively solved using improved BFO algorithms. Tendency operations are considered a crucial part of the BFO algorithm. It simulates the swimming and flipping behavior of bacteria during foraging, and optimizes and improves on this basis [17-18] . The directional operation is shown in Figure 1.

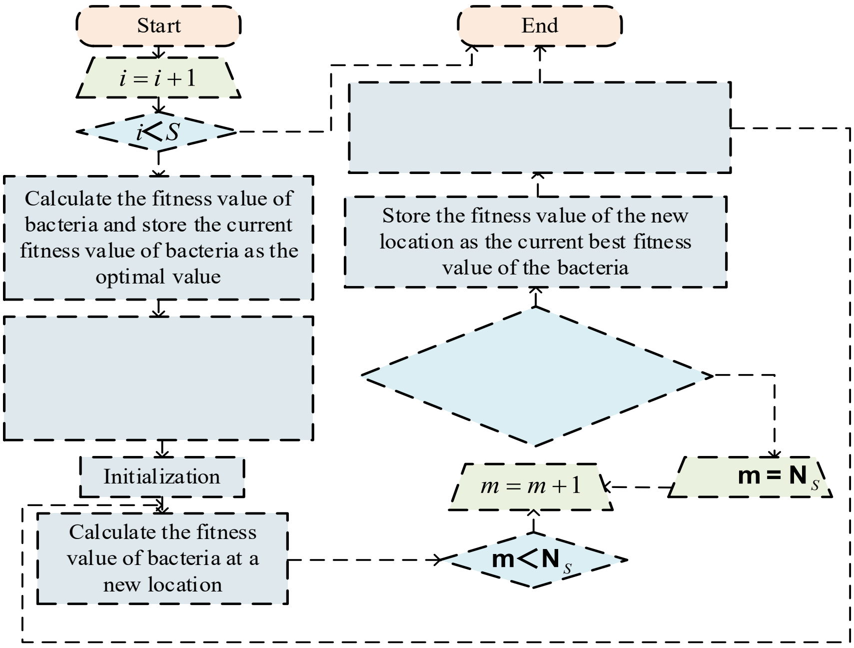

Fig.1 Trend based operation process

In Figure 1, in a food rich environment, bacteria will swim in the same direction and reduce the change in search direction. When the food density is high, it will prolong the swimming time and increase the distance of movement. When food is scarce or the environment is acid-base imbalanced, bacteria will randomly change their direction of movement. In the BFO algorithm, bacterial individuals first move in a random direction, and if the fitness value of the new position is low, they will randomly change direction. If the fitness value is high, keep moving forward in the current direction. When the maximum of operations is achieved, the operation terminates.

The mathematical model of bacterial i in the trend operation is shown in equation (1).

$$\begin{cases} \theta(j+1,k,l)=\theta(j,k,l)+C(i)\varphi(i) \\ \varphi(i)=\dfrac{\Delta(i)}{\sqrt{\Delta(i)^{\Gamma}\Delta(i)}} \end{cases} \quad (1)$$

In equation (1), $\theta(j+1,k,l)$ represents the position of bacterial i, j serves as the tendency operation cycle algebra, and k serves as the replication operation cycle algebra. l is the migration operation loop algebra, $C(i)$ is the unit of forward walk step size, $\varphi(i)$ is the random angle generated after flipping, and $\Delta(i)$ is the unit vector on the random angle. This study uses BFO algorithms to simulate the scheduling process of intelligent equipment on transmission lines. In the model, the position, orientation, replication, and migration of bacteria are key parameters, including the cycle algebra, swimming step units, flipped random angles, and unit vectors. The aggregation behavior and quorum sensing mechanism of bacteria provide new solutions in solving optimization problems. The expression for the aggregation behavior between bacteria is shown in equation (2).

$$J_{cc}\left(\theta,\theta^{i}(j,k,l)\right)=\sum_{i=1}^{S}\left[-d_{attract\tan t}\exp\left(-\omega_{attract\tan t}\sum_{m=1}^{D}\left(\theta_m-\theta_i^m\right)^2\right)\right]+\sum_{i=1}^{S}\left[-h_{repellant}\exp\left(-\omega_{repellant}\sum_{m=1}^{D}\left(\theta_m-\theta_i^m\right)^2\right)\right] \quad (2)$$

In equation (2), $d_{attract\tan t}$ serves as the depth of gravity, $\omega_{attract\tan t}$ serves as its width, $h_{repellant}$ serves as the height of repulsion, and $\omega_{repellant}$ serves as its width. θ_i^m represents the proportion of bacteria, and θ_m represents the proportion of other bacteria in the entire microbial community. The laws of biological evolution, namely the survival of the fittest, have a significant impact on the foraging process of bacteria. Bacteria with strong foraging ability and located in areas with abundant food will be retained, while bacteria with poor foraging environment or weak foraging ability will be eliminated. The preserved bacteria maintain population size through division and replication, simulating natural laws. After the trend operation is completed, half of the bacteria with poor health are eliminated on the ground of their health level, while the healthy ones replicate themselves. Bacteria may migrate to new areas due to environmental changes, which may disrupt directional behavior but is beneficial for long-term rapid foraging. The main structure of the BFO algorithm is the migration operation, replication operation, and chemotaxis operation, which are nested within each other. The overall workflow is showcased in Figure 2.

One of the key parameters in bacterial trend manipulation is the swimming step size, and traditional fixed search steps cannot meet the dual requirements of search accuracy and CS. Large step size can quickly move towards the target, but it may lead to insufficient convergence accuracy. Small step sizes can perform precise searches, but may reduce computational efficiency. Therefore, this article introduces a dynamic adaptive search step strategy, which integrates the dynamic adaptive search step strategy from the artificial fish swarm algorithm into the BFO algorithm. This is to solve the problem of getting stuck in local optima. By using a large step size for coarse search in the initial stage of the algorithm and a small step size for precise search in the later stage, the local search ability was improved, and the CS and accuracy were improved. The search step size is shown in equation (4).

$$\begin{cases} C(i)=C_{\max}\times a+C_{\min} \\ a=\exp\left[-30\times\left(\dfrac{t}{T_{\max}}\right)^{s}\right] \end{cases} \quad (4)$$

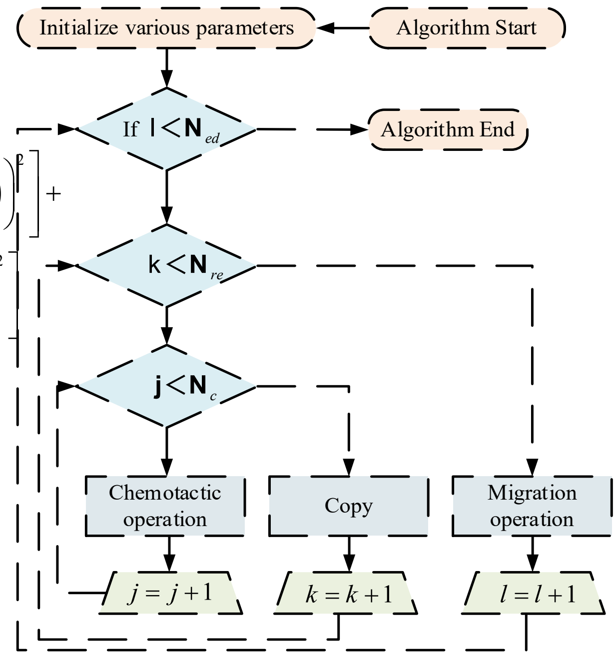

Fig. 2 Overall workflow of BFO algorithm

In equation (4), $T_{\max}$ serves as the maximum iteration number, t serves as the current iteration number, $C_{\max}$ is the initial step size, and $C_{\min}$ serves as the step size at the end of the iteration cycle. s serves as an integer greater than 1.

3.2 Analysis and model design of intelligent equipment scheduling for transmission lines

This study is on the ground of BFO algorithms, with a focus on the intelligent equipment scheduling problem of transmission lines. As a crucial part of the PS, the scheduling decisions of transmission lines directly affect the stability and efficiency of the system. Therefore, it is necessary to design an effective scheduling model tailored to the characteristics of intelligent equipment on transmission lines. For scheduling models, they are not simple single threaded or sequential logic programs, but have a unique loop structure that processes device status and executes scheduling logic in each loop. An effective scheduling model needs to consider the characteristics of multithreading, event driven, and state management. Through reasonable design and implementation, a high-performance scheduling model can be constructed. This can achieve stable and reliable scheduling operations [19-20] . The basic process of the scheduling model is shown in Figure 3.

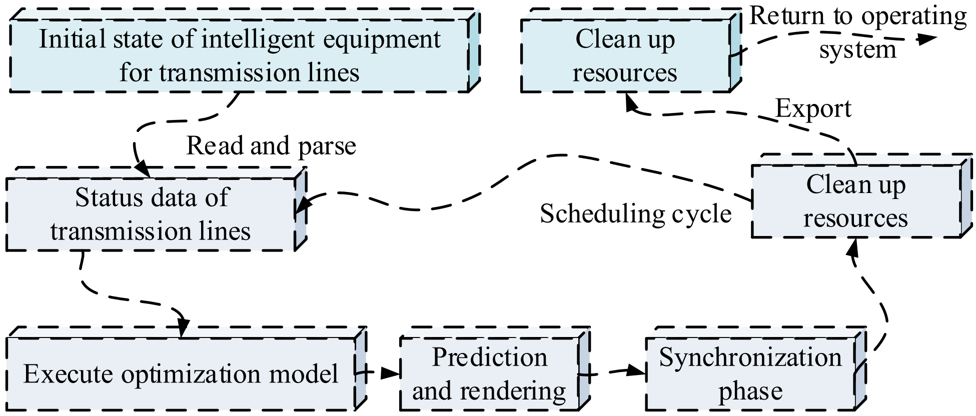

Fig. 3 Basic process of scheduling model

In Figure 3, the initialization process is executed first, and then the scheduling loop is entered to read the device status. Afterwards is the core program of scheduling, which is to execute scheduling logic. This step reflects the scheduling rules and enters the next cycle, where each cycle of the scheduling main cycle needs to be synchronized and controlled. Afterwards, it returns to the schedule to continue the next cycle. The implementation of the main loop structure aims to manage the status of multiple devices. Here, a stack based state machine approach will be adopted to manage device status. This method abstracts each state as a class, and describes the relevant variables of each state attribute as data members of the class. When the device is in a running state and receives a command to pause the device, the device enters a pause state as shown in Figure 4.

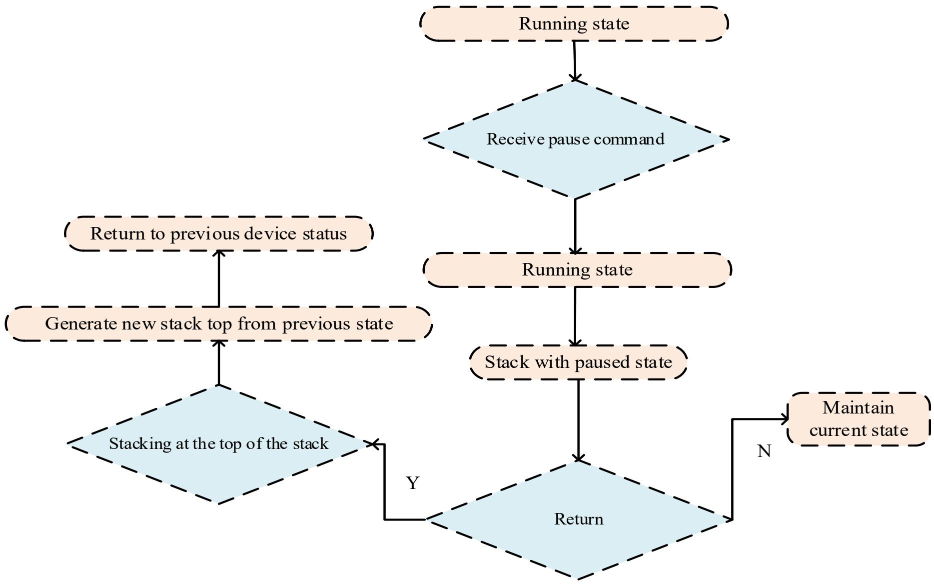

Fig. 4 Schematic diagram of intelligent equipment scheduling method based on stack

In Figure 4, exiting the current state can be simply achieved by popping up the top element of the stack. This will make the next element the new top of the stack, representing the new device state. For the paused state, the paused state object can be pushed onto the stack. When restoring to the previous state, it can be achieved by popping the top element of the stack. In this way, the previous state object will become the new top of the stack and return to the previous device state. The Hourglass algorithm was used in the study to design characters and combined with pose calculation as shown in equation (5).

$$S_{i,j}^{*}(p) = e^{(\frac{-\|p-x_{i,j}\|^2}{\sigma^2})} \quad (5)$$

In equation (5), $x_{i,j}$ represents the various parts of the intelligent equipment for transmission lines, and p represents the equipment status. When there is a significant deviation between the equipment state and the ideal operating state, the optimization level of scheduling is lower. And there is a relationship between equipment status and scheduling instructions, so the scheduling priority of equipment status is shown in equation (6).

$$A_f(p) = \begin{cases} 1\ , & \text{P On the limb} \\ 0\ , & \text{P is not on the limb} \end{cases} \quad (6)$$

In equation (6), when the improved BFO algorithm is selected for intelligent equipment scheduling of transmission lines, each part of the equipment has a corresponding scheduling priority. The scheduling priority calculation between two different parts is shown in equation (7).

$$E_c = \int A_c(p(u)) \frac{X_{j2} - X_{j1}}{\left\| X_{j2} - X_{j1} \right\|} du \quad (7)$$

In equation (7), with the increase of scheduling optimization, the operating status of the equipment tends to be consistent, and the overall operating efficiency also improves. After obtaining a large amount of device status data, an improved BFO algorithm was used for optimization scheduling through data processing and analysis. When there is a state sequence L of intelligent equipment for transmission lines, the sequence is shown in equation (8).

$$\begin{cases} L = \{l_1, l_2, l_3, \ldots l_M\} \\ Y = \{y_1, y_2, y_3, \cdots y_N\} \\ \hat{Y} = f(x_1, x_2, x_3, \cdots x_T) \end{cases} \quad (8)$$

In equation (8), $\hat{Y} = \{\hat{y}_1, \hat{y}_2, \hat{y}_3, \cdots \hat{y}_N\}$ is the output result of scheduling. For ease of calculation, it is assumed that the state sequence and scheduling instruction sequence are consistent. That is to say, there is a certain correlation between the data and scheduling instructions in a given state sequence, and their relationship is interdependent. Due to the adoption of an improved BFO algorithm, the number of optimization parameters is utilized to increase the possibility of global optimization. The scheduling algorithm for processing a certain moment is shown in equation (9).

$$F(t) = (X * f_d)(t) = \sum_{i=0}^{k-1} f(i) \cdot x_{t-d \cdot i} \quad (9)$$

In equation (9), d is the search step size, k serves as the quantity of searches, and $t - d \cdot i$ serves as the size of the scheduled time window. It improves the scheduling accuracy of intelligent equipment for transmission lines, obtains equipment status through real-time monitoring, and optimizes scheduling. It collects the original device status, removes redundancy through an improved BFO algorithm, and combines operating parameters for obtaining the optimal operating status of the device. It utilizes a layered abstraction strategy to detect and schedule each device, simplifying the process of establishing and implementing scheduling models. The established intelligent equipment scheduling model for transmission lines is shown in Figure 5.

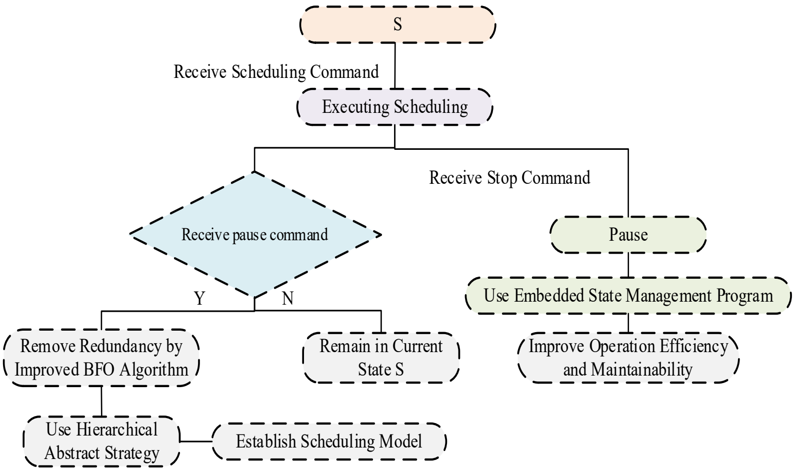

Fig. 5 Transmission Line Intelligent Equipment Scheduling Model

In Figure 5, during the initial startup, the standing state is S. If a scheduling command is received, the state will switch to executing scheduling J. Similarly, receiving a stop command will cause the state to switch to pausing D. Embedded state management programs can directly utilize the properties and other data of the managed object for state transitions, thereby improving operational efficiency and maintainability. In the scheduling of intelligent equipment for transmission lines, the use of embedded state management tools can effectively manage the status of equipment.

3.3 Optimization of intelligent equipment scheduling for transmission lines on the ground of improved BFO algorithm

On the ground of the improved BFO algorithm, the scheduling optimization model of intelligent transmission line equipment starts from a group of initial intelligent transmission line equipment to find the optimal scheduling solution. When the initial state of intelligent equipment for transmission lines has good diversity, this algorithm can optimize search in local and global ranges and obtain good results. The flowchart of this algorithm is shown in Figure 6.

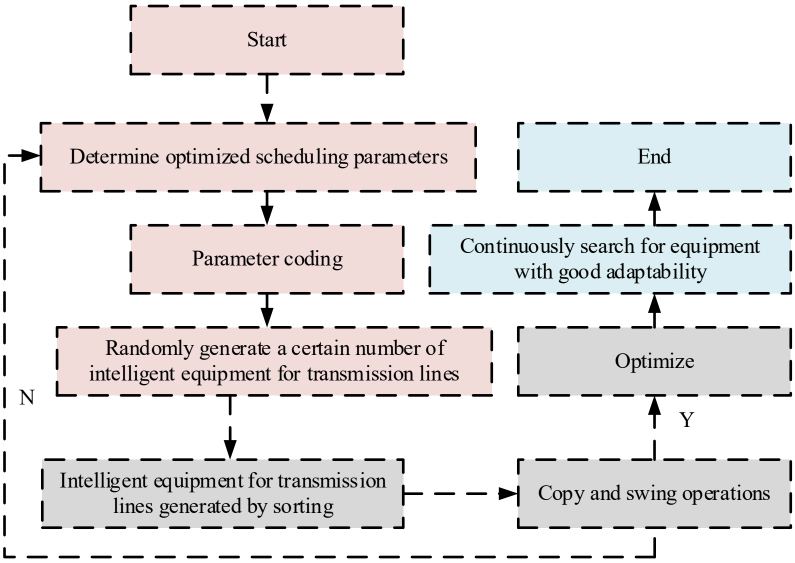

Fig. 6 Flowchart of Improved BFO Algorithm

In Figure 6, first it determines the scheduling parameters that need to be optimized, and then encodes the parameters that need to be optimized. Next, it randomly generates a certain number of intelligent transmission line equipment and selects an appropriate fitness function (FF). Then it sorts the intelligent equipment of the transmission line on the ground of the size of the function value, eliminates equipment with lower fitness values, and retains elite equipment. Then, it replicates and swings the remaining elite equipment to generate new equipment, and optimizes it again until the maximum of iterations is achieved or the average deviation between equipment is less than a certain value. The essence of optimizing on the ground of the improved BFO algorithm is on the ground of the fitness of intelligent transmission line equipment, and through repeated iterations such as copying and swinging, it continuously searches for equipment with better fitness, and finally obtains the optimal solution to the issue. The FF is the standard for evaluating the quality of intelligent equipment on transmission lines and the only basis for simulating natural selection. This study establishes a mapping relationship that minimizes the objective function as shown in equation (10).

$$F(x)=\begin{cases} C_{\max}-f(x), & f(x)<C_{\max} \\ 0, & f(x)\geq C_{\max} \end{cases} \quad (10)$$

In equation (10), $C_{\max}$ can be either a specific scheduling state or the theoretically optimal state of intelligent equipment for transmission lines. $f(x)$ is the objective function, $F(x)$ is the FF, and the process from scheduling state to optimal state is the optimization process. Similarly, the problem of maximizing the objective function establishes a mapping relationship, as shown in equation (11).

$$F(x)=\begin{cases} f(x)-C_{\min}, & f(x)>C_{\min} \\ 0, & f(x)\leq C_{\min} \end{cases} \quad (11)$$

In equation (11), $C_{\min}$ can be either a specific scheduling state or the optimal state among all current algebras or the K-th generation. Each device has a selection probability, which depends on its fitness and distribution. The selection rate of its computing device and the probability of being selected are shown in equation (12).

$$P(V_i)=\frac{c_i}{\sum_{i=1}^{pop,size} c_i}, i=1,2,\ldots, pop\_size \quad (12)$$

In equation (12), V represents a single device and c_i represents fitness. The improved BFO algorithm simulates bacterial reproduction and foraging through replication and swaying operations, generating and optimizing new device states. The replication operation is to copy the state of one device to another device to generate a new state, enhancing the optimization ability of the algorithm. The swing operation performs a small random change in the device state, simulating bacterial foraging. The swinging operation has two main functions: firstly, it provides local random search ability to accelerate the convergence of the optimal solution; The second is to maintain diversity in equipment status.

4. Intelligent equipment scheduling optimization model for transmission lines on the ground of improved BFO algorithm

The study uses convergence, proximity to the optimal solution, resource utilization, optimal relative error percentage, and average relative error percentage as indicators to analyze the performance of the model. The convergence measurement algorithm measures the speed at which the algorithm reaches the optimal solution during the iteration process, the proximity of the optimal solution measures the distance between the solution found by the algorithm and the known optimal solution, the resource utilization rate represents the efficiency of the scheduling scheme in using resources, the optimal relative error percentage measures the relative error between the optimal solution found by the algorithm and the global optimal solution, and the average relative error percentage measures the average relative error of the algorithm over multiple runs. The intelligent equipment scheduling optimization model for transmission lines on the ground of the improved BFO algorithm has superior global and local search capabilities. It can effectively improve the optimization level of scheduling results while maintaining the diversity of equipment status. The number of iterations and equipment deviation control of the model also demonstrated good performance, proving its effectiveness in practical applications. The detailed evaluation of model parameter settings provides strong theoretical support for the optimization of intelligent equipment scheduling optimization models for transmission lines. The focus of the research is on how to improve the model's search ability and optimize scheduling results while maintaining the diversity of equipment states, providing a theoretical basis for practical applications. The relevant parameter are showcased in Table 1.

Table 1 System parameter

Parameter	Configuration	Parameter	Configuration
Operating System	Windows 10 Pro 64-bit	Processor	Intel Core i9-10900K
RAM	32GB DDR4-3200	Storage	1TB SSD NVMe PCIe M.2
Programming Language	Python 3.8	Optimization Library	Scipy 1.6.2
Number of Transmission Line Intelligent Equipment	200 Units	Max Iterations	5000 Times
Average Deviation Threshold	0.001	Initial Duplication Proportion	0.2
Initial Swinging Proportion	0.1	Experimental Environment Temperature	25℃
Experimental Environment Humidity	50%	Population Size in BFO Algorithm	100
Step Size in Search	0.1	Chemotactic Step Length	20
Swim Length	4	Elimination-dispersal Probability	0.25
Attraction Coefficient in BFO Algorithm	0.2	Repulsion Coefficient in BFO Algorithm	0.1

To verify the availability and progressiveness of the intelligent equipment scheduling optimization model on the ground of improved BFO proposed by the research institute, the algorithm proposed by the research institute is first verified. The study selected the actual data of intelligent equipment scheduling for transmission lines as the dataset. Then it compares two multi-objective (MO) optimization algorithms, Multi-objective Evolutionary Algorithm On the ground of Decomposition (MOEA/D) and Multi-objective Particle Swarm Optimization (MOPSO), on the ground of decomposition [21-22]. In a unified hardware environment, all algorithms were tested using the same intelligent transmission line equipment scheduling optimization problem to minimize the impact of objective conditions on experimental results. In the experimental setup, the population size of each algorithm reaches 100, the maximum of iterations reaches 5000, and the capacity of external documents is set to 200. To further decrease the influence of random factors on the experimental outcomes, each algorithm was independently run 50 times in numerical experiments and the average value was taken. Comparing the convergence of three algorithms, the comparison results are shown in Figure 7.

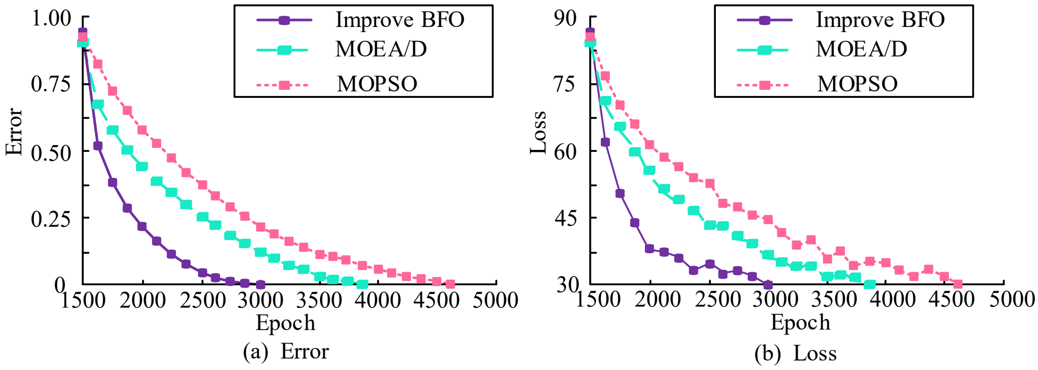

Fig.7 Convergence of three algorithms

In Figure 7, the intelligent equipment scheduling optimization model for transmission lines proposed by the research institute on the ground of improved BFO can reach the optimal situation in 3000 iterations, which is 900 and 1600 fewer than the MOEA/D algorithm and MOPSO algorithm, respectively. It compares the optimization results obtained by three algorithms in dealing with the optimization problem of intelligent equipment scheduling for transmission lines. Firstly, it performs a comparison of 2D optimization problems. The comparison results are shown in Figure 8.

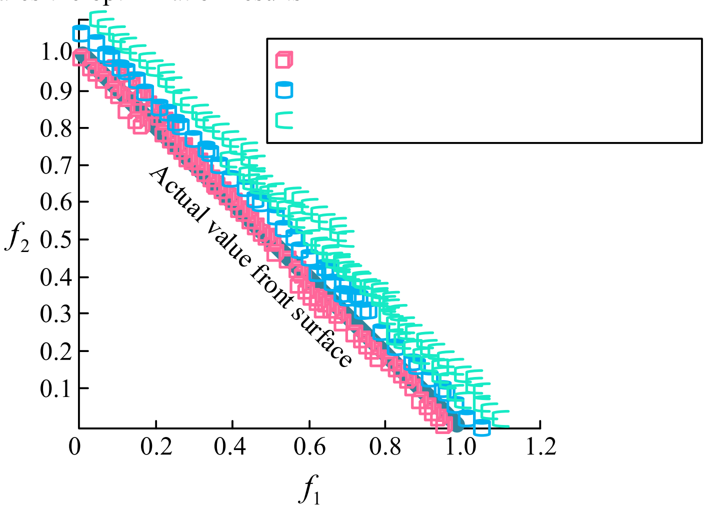

Fig. 8 Optimal solutions obtained by the three algorithms on the biobjective test set

In Figure 8, among the three algorithms, the optimization results of the transmission line intelligent equipment scheduling optimization model on the ground of improved BFO proposed by the research institute show excellent convergence and uniformity, and are closest to the optimal solution. It compares the optimization results from the three algorithms in dealing with 3D optimization problems, and the comparing outcomes are showcased in Figure 9.

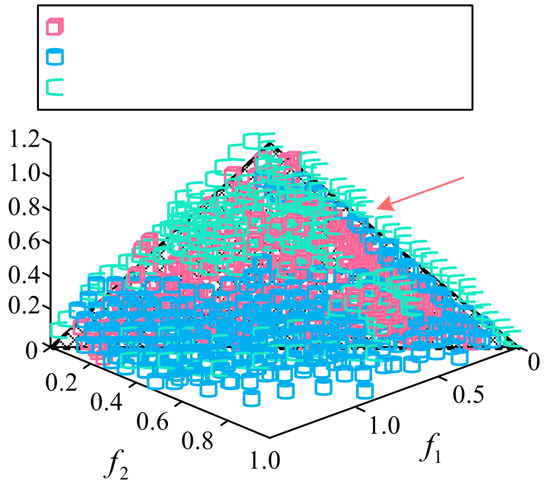

Fig. 9 Optimal solutions obtained by the three algorithms on the three-objective test set

In Figure 9, the intelligent equipment scheduling optimization model for transmission lines on the ground of improved BFO proposed by the research institute exhibits excellent performance in terms of convergence and diversity. Compared to MOEA/D algorithm and MOPSO algorithm, it has more excellent performance in addressing MO optimization problems. The study randomly selected several transmission lines and conducted statistical analysis and comparison of the line utilization efficiency of two scheduling schemes. It is shown in Figure 10.

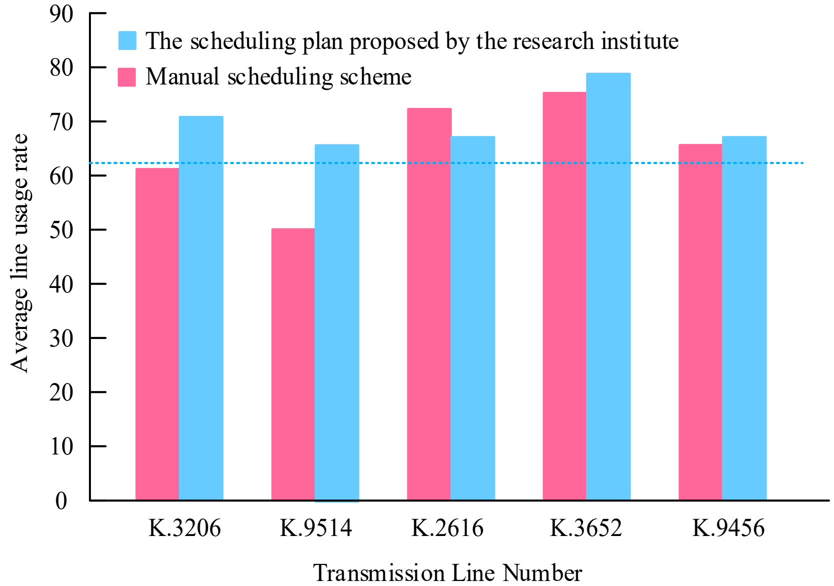

Fig. 10 Statistical Analysis and Comparison of Line Usage Efficiency between Two Schemes

In Figure 10, the average line usage rate of the scheduling scheme proposed by the research institute is 70.69%, while the average line usage rate of the manual scheduling scheme is 64.63%. This proves that the intelligent equipment scheduling optimization model for transmission lines on the ground of improved BFO proposed by the research institute can more fully utilize resources. The comparison chart of the optimal relative error percentage (BRE) and average relative error percentage (ARE) of the improved BFO algorithm proposed by the research institute with the Binary Bacterial Foraging Optimization (BBFO) algorithm and Differential Bacterial Foraging Optimization (DBFO) algorithm is showcased in Figure 11.

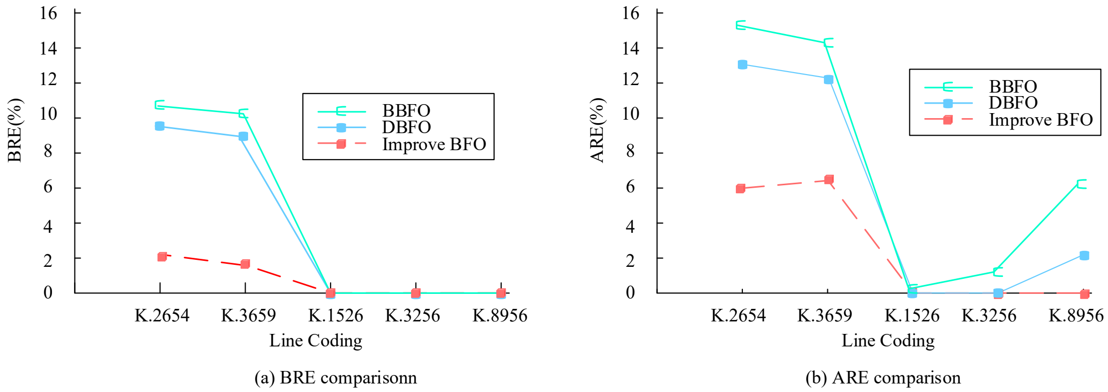

Fig. 11 BRE and Comparison Graph of Algorithms

In Figure 11, the BRE of the improved BFO is less than 2.1%, while the BRE of other algorithms reaches about 10%, and the fluctuation of ARE is smaller compared to other algorithms. This indicates that the global search capability and stability proposed by the research institute are superior to other algorithms.

5. Discussion

The innovation of the research lies in the construction of an intelligent equipment scheduling optimization model for transmission lines by improving the bacterial foraging optimization algorithm, and verifying its application effect in scheduling optimization. From the research results, the improved BFO algorithm performs well in both search accuracy and convergence speed, demonstrating its potential in complex optimization problems. The dynamic adaptive search step size strategy has played an important role in improving the local search capability and global search efficiency of the algorithm. This strategy avoids the problem of the algorithm getting stuck in local optima by using large step sizes for coarse search in the early stages and small step sizes for precise search in the later stages. However, despite the improved BFO algorithm showing good performance in this study, there are still some areas that need further discussion and improvement. Firstly, the adaptability and stability of the proposed model in practical applications still need further verification. Different transmission line environments and conditions may affect the performance of the algorithm, so it is necessary to adaptively adjust and optimize the model in practical applications. Secondly, although the improved BFO algorithm has improved in search accuracy and convergence speed, its computational complexity has also increased accordingly. When dealing with large-scale transmission line scheduling problems, the computational efficiency of algorithms may become a bottleneck that requires further optimization and improvement. In summary, the improved BFO algorithm has great potential and prospects for application in intelligent equipment scheduling optimization of transmission lines. This study provides new theoretical basis and technical support for intelligent dispatching of power systems, but further exploration and verification are still needed in practical applications. Future research should continue to optimize and improve algorithms based on this foundation, enhance their adaptability and stability in different environments and conditions, and provide more comprehensive and efficient solutions for intelligent dispatching of power systems.

6. Conclusion

The intelligent equipment scheduling optimization of transmission lines is an extremely important link in the power system, and its optimization effect directly affects the stable operation and economic benefits of the power system. In order to more effectively solve this problem, design an intelligent equipment scheduling optimization model for transmission lines based on an improved BFO algorithm. This model achieves global and local search capabilities, as well as diversity in equipment status, through an improved BFO algorithm, which significantly improves the optimization level of scheduling results. The results showed that compared to MOEA/D algorithm and MOPSO algorithm, the proposed model reduced the number of iterations by 900 and 1600 respectively, indicating that the model has better performance in solving multi-objective optimization problems. The ARE fluctuation of the model is relatively small, which proves that its global search ability and stability exceed other algorithms. This model provides important reference for the operation and management of power systems, effectively improving operational efficiency and reducing operating costs. However, the model has limitations when dealing with complex multi-objective problems. In the future, research will optimize the model algorithm to improve global search capability and stability, and attempt to apply the model to more intelligent equipment scheduling optimization problems in power system transmission lines to verify its applicability and practicality.

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