

# Distribution network reconstruction with DG based on improved sparrow search algorithm

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**Abstract:** *In order to solve the problem that the search efficiency and optimal solution quality of intelligent optimization algorithm cannot be taken into account in distribution network reconfiguration, a distribution network reconfiguration method based on improved sparrow search algorithm is proposed. Firstly, the ordered basic loop matrix is formed according to the distribution network topology and branch information, and the dynamic coordination matrix is generated with the help of the heuristic rules in the optimal flow pattern; secondly, aiming at the sparrows with different division of labor in the sparrow search algorithm, the position update rules of the explorer are improved by using the dynamic coordination matrix to prevent it from falling into local optimization. At the same time, a static coordination matrix is constructed to deeply mine the adjacent schemes of the optimal individual. Finally, the simulation results of the IEEE33 node system show that the improved sparrow search algorithm has higher optimization stability and faster convergence speed, and can meet the requirements of optimal solution quality and search efficiency when solving the distribution network reconfiguration problem.*

**Keywords:** *distribution network reconfiguration; sparrow search algorithm; heuristic rule; coordination optimization matrix*

## 1. Introduction

Distribution network reconfiguration is one of the means of optimal operation of distribution network, which optimizes the network topology by changing the opening and closing state and combination mode of branch switches and contact switches in the network, in order to reduce the network loss and improve the voltage quality<sup>[1]</sup>. In the process of optimizing the topology of distribution network, it is necessary to meet the overall situation of the optimal solution and ensure the speed of the solution, so many scholars have put forward many solutions. There are usually three types of traditional mathematical optimization algorithms, heuristic algorithms and intelligent optimization algorithms.

The advantage of traditional mathematical optimization algorithm<sup>[2-3]</sup> is that it does not depend on the initial structure of distribution system, and has a better optimization effect for simple small-scale distribution system, but the disadvantage is that with the complexity of distribution system and the addition of DG, the calculation time of mathematical optimization algorithm is long, the solution efficiency is low, and the applicability to large-scale system is greatly reduced. Heuristic algorithms are divided into optimal flow pattern method<sup>[4-5]</sup> and branch exchange method<sup>[6]</sup>. Most of these methods rely on heuristic rules, and the number of power flow calculation is less, and the speed of solution is faster, but it is easy to fall into local optimization. The intelligent optimization algorithm<sup>[7-9]</sup> provides a new idea for solving the problem of distribution network reconfiguration. In references [7] and [8], the author utilized Genetic algorithm and Particle Swarm Optimization algorithm to solve the loads' dynamic restoration problem and restored a maximum of loads. In reference [9], Chang and Kuo also applied simulated annealing to the network reconfiguration problem for loss minimization. They presented a set of simplified line flow equations to compute the line loss and developed an efficient perturbation scheme and initialization procedure for dynamically determining a better starting temperature for the simulated annealing so that the entire computation could be sped up.

Based on the above analysis, based on the sparrow search algorithm (SSA), this paper generates a dynamic coordination matrix by referring to the heuristic rules in the optimal flow pattern, and uses the dynamic coordination matrix to improve the local search performance of the explorer. At the same time, the constructed static coordination matrix is used to deeply mine the adjacent schemes of the optimal solution. The improved algorithm meets the requirements of fast convergence and high optimization quality when solving the problem of distribution network reconfiguration.

## 2. Reconfiguration Model

### 2.1. Objective Function

In distribution network reconfiguration, network loss is one of the most important indicators, so the minimum active power loss of distribution network system is taken as the objective function studied in this paper, and its mathematical description is shown in formula (1).

$$\min f = \sum_{k=1}^K n_k r_k \frac{P_k^2 + Q_k^2}{U_k^2} \quad (1)$$

Where  $k$  is the number of the current branch,  $K$  is the total number of branches in the distribution network,  $n_k$  is the breaking state of the  $k$  branch,  $r_k$  is the resistance of the  $k$  branch,  $U_k$  is the effective value of the terminal node voltage of the  $k$  branch,  $P_k$  and  $Q_k$  is the reactive power of the terminal node of the  $k$  branch.

### 2.2. Constraint Conditions

1) Power flow constraint

$$\begin{cases} P_i - P_{il} = U_i \sum_{j=1}^H U_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \\ Q_i - Q_{il} = U_i \sum_{j=1}^H U_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \end{cases} \quad (2)$$

Where  $P_i$  and  $Q_i$  represent the active and reactive power flowing into node  $i$ ;  $P_{Li}$  and  $Q_{Li}$  represent the active and reactive load at node  $i$ ;  $U_i$  and  $U_j$  represent the voltage amplitude at node  $i$  and  $j$ ;  $G_{ij}$  and  $B_{ij}$  represent the conductance and admittance of the lines connecting node  $i$  and  $j$ ;  $\theta_{ij}$  represents the voltage phase difference between node  $i$  and  $j$ .

2) Node voltage amplitude constraint

In order to ensure the voltage stability of the system, the upper and lower limits of the node voltage amplitude of the distribution system are specified, as shown in formula (3).

$$U_{i \min} \leq U_i \leq U_{i \max} \quad (3)$$

Where  $U_{i \min}$  and  $U_{i \max}$  represent the minimum and maximum values of node  $i$  voltage amplitude respectively.

3) DG output power constraint

$$P_{DG \min}^i \leq P_{DG}^i \leq P_{DG \max}^i \quad (4)$$

Where  $P_{DG \min}^i$  and  $P_{DG \max}^i$  represent the lower limit and upper limit of the DG output active power connected to node  $i$ , respectively.

4) Topological structure constraint

In distribution network reconfiguration, the network topology should be kept as a radial network and should not contain any loops or isolated nodes, as shown in formula (5).

$$g \in G \quad (5)$$

Where  $g$  represents the reconstructed network topology and  $G$  represents the set of radial network structures.

## 3. Improved Sparrow Search Algorithm

### 3.1. Sparrow Search Algorithm

Xue modeled the behavior of sparrows in reference [10]. The matrix representation of the position

available formula (6) of the sparrow population in the algorithm,

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,m} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n,1} & x_{n,2} & \cdots & x_{n,m} \end{bmatrix} \quad (6)$$

where  $n$  is the number of sparrows and  $m$  shows the dimension of the variables to be optimized.

Then, the fitness value of all sparrows can be expressed by the following vector(7):

$$F(X) = \begin{bmatrix} f(x_{1,1} \ x_{1,2} \ \cdots \ x_{1,m}) \\ f(x_{2,1} \ x_{2,2} \ \cdots \ x_{2,m}) \\ \vdots \ \vdots \ \vdots \ \vdots \\ f(x_{n,1} \ x_{n,2} \ \cdots \ x_{n,m}) \end{bmatrix} \quad (7)$$

Where the value of each row in  $F(X)$  represents the fitness value of the individual.

In each iteration, according to the fitness value of sparrows, the population can be divided into explorers and followers, those with better fitness values are regarded as explorers, and those with poor fitness values are regarded as followers. The position of the seeker is updated as shown in formula (8).

$$x_{n,m}^{t+1} = \begin{cases} x_{n,m}^t \cdot \exp\left(-\frac{n}{\alpha \cdot iter_{max}}\right) & , R_2 < ST \\ x_{n,m}^t + Q \cdot L & , R_2 \geq ST \end{cases} \quad (8)$$

where  $t$  indicates the current iteration,  $x_{n,m}^t$  represents the value of the  $m$ th dimension of the  $n$ th sparrow at iteration  $t$ .  $iter_{max}$  is the set maximum number of iterations,  $\alpha \in (0, 1]$  is a random number.  $R_2$  ( $R_2 \in [0, 1]$ ) and  $ST$  ( $ST \in [0.5, 1.0]$ ) represent the alarm value and the safety threshold respectively.  $Q$  is a random number which obeys normal distribution.  $L$  shows a matrix of  $1 \times d$  for which each element inside is 1.

When  $R_2 < ST$ , which means that the sparrow is in a safe position and can continue to search extensively; when  $R_2 \geq ST$ , which means that the sparrow is in a dangerous position, the individual needs to be transferred to other safe areas.

As individuals monitoring the explorer, when the follower senses that the explorer is searching for a better food location, the follower will give up the current position and move to the explorer's position to compete for food resources. The position of followers is updated as shown in formula (9).

$$x_{n,m}^{t+1} = \begin{cases} Q \cdot \exp\left(\frac{x_{worst}^t - x_{n,m}^t}{n^2}\right) & , n > \frac{N}{2} \\ x_{best}^{t+1} + |x_{n,m}^t - x_{best}^{t+1}| \cdot A^+ \cdot L & , n \leq \frac{N}{2} \end{cases} \quad (9)$$

Where  $N$  represents the total number of sparrows, the best position currently occupied by the explorer, and the global worst position.  $A$  represents a matrix of  $1 \times d$  for which each element inside is randomly assigned 1 or -1,  $A^+ = A^T (AA^T)^{-1}$ . When  $n > N/2$ , the position of the  $n$ th sparrow is poor and needs to move to other locations to find food to obtain a better fitness value; when  $n \leq N/2$ , the position of the  $n$ th sparrow is better at this time, and it can be searched randomly near the current optimal position to get better food.

In addition, in order to measure the safety of the sparrow population, some sparrows in the population are randomly selected as vigilants before each iteration, and when the vigilant is aware of the danger, they will adjust their position to move to the center of the population. The position of the vigilante is updated as shown in formula (10).

$$x_{n,m}^{t+1} = \begin{cases} x_{best}^t + \beta \cdot |x_{n,m}^t - x_{best}^t| & , f_n > f_g \\ x_{n,m}^t + H \left( \frac{x_{n,m}^t - x_{worst}^t}{|f_i - f_w| + \varepsilon} \right) & , f_n = f_g \end{cases} \quad (10)$$

Where  $\beta$  is the control step size, obeys the normal distribution with mean value 0 and variance 1,  $H$  is a random number between -1 and 1,  $\varepsilon$  is a non-zero minimum constant,  $f_n$  is the fitness value of the  $n$  th sparrow,  $f_w$  and  $f_g$  are the worst individual and the best individual, respectively. When  $f_n > f_g$ , it means that the position of the  $n$ th sparrow is not optimal at this time, and it needs to constantly change its position to approach the optimal individual; when  $f_n = f_g$ , it means that the  $n$ th sparrow is in the optimal position at this time, and it will continue to approach its nearby companions so as to stay away from the dangerous area.

### 3.2. Analysis on the Deficiency of Sparrow Search Algorithm

1) The algorithm is more inclined to search the area near the origin. In the sparrow search algorithm, the formula in the form of formula (11) is used for iterative update.

$$x(t+1) = \delta h(x(t)) + \sigma \quad (11)$$

Where  $h$  is a function of  $x(t)$ , and  $\delta$  and  $\sigma$  are random numbers that satisfy a specific distribution.

In formula (11),  $\delta$ ,  $\sigma$ ,  $h(x(t))$  and  $x(t+1)$  are replaced by  $\exp(-n/(\alpha \cdot \text{itermax}))$ , 0,  $x_{n,m}^t$  and  $x_{n,m}^{t+1}$  then the iterative formula of the explorer in formula (8) is obtained. In formula (11),  $\delta$ ,  $\sigma$ ,  $h(x(t))$  and  $x(t)$  are replaced by  $Q$ , 0,  $\exp((x_{worst}^t - x_{n,m}^t)/n^2)$ ,  $x_{n,m}^{t+1}$  respectively, and then the iterative formula of the follower in formula (9) is obtained when  $n > N/2$ . The formula in the form of satisfaction 11 usually makes  $x$  search the area near the origin with great probability, so that the algorithm can easily jump out of the effective solution region in some cases. It will also make the optimization performance of the algorithm worse when solving some optimization problems where the optimal value is not near the origin. Considering the application scenario of this paper, that is, for a specific distribution network structure, a set of optimal combination of connection switches is found to minimize the active power loss of the distribution network. Therefore, the sparrow search algorithm is obviously insufficient to solve the problem that the optimal value is not near the origin.

2) The randomness of  $R_2$  in the explorer update formula is not suitable for solving the problem of distribution network reconfiguration.

For the application scenarios to solve the problem of distribution network reconfiguration, the reconfiguration schemes represented by some sparrows have certain similarities. If the reconstruction scheme represented by the individual sparrow is the same as that of more sparrows in some dimensions, which weakens the diversity of the population to a certain extent, so the value of the early warning value  $R_2$  should be improved to make it applicable to the application scenario of this paper.

3) The follower update formula will aggravate the algorithm to fall into local optimization when  $n \leq N/2$ .

According to the follower's formula (9), when  $n > N/2$ , the sparrow will converge with a negative exponential trend until it converges to zero; when  $n \leq N/2$ , the current sparrow will jump directly to the optimal position instead of moving to the optimal position, which will make the algorithm easier to fall into the local optimal solution. For example, when the current discoverer finds the local optimal value, the follower will jump around the discoverer, thus increasing the number of sparrows near the current local optimal value and reducing the population diversity in the later stage of iteration. It is difficult for the sparrow to transfer from the local optimal value to the global optimal value, which makes this phenomenon more serious.

### 3.3. Improved Sparrow Search Algorithm

On the basis of the basic ring matrix, the ordered basic ring matrix can be generated by sorting according to the connection order of its branches. The specific generation method is as follows: first, the near power end node in each loop is selected as the first node of the loop. The branches on both sides of the first node are taken as the first and end branches of the loop, respectively, and then the switch numbers



value with the similarity among the sparrows. Therefore, the improved explorer update formula is shown in formula (15).

$$x_{n,m}^{t+1} = \begin{cases} x_{n,m}^t \cdot \exp\left(-\frac{n}{\alpha \cdot iter_{max}}\right) + rand \cdot D(m, x_{n,m}^t), & R_n < ST \\ x_{n,m}^t + Q \cdot L & , R_n \geq ST \end{cases} \quad (15)$$

Where  $D$  represents the dynamic coordination matrix, and the random term indicates that the dynamic coordination matrix produces an additional displacement during iteration, so that the  $m$ -dimensional variable of the  $n$  th sparrow moves to the current optimal solution, and  $R_n$  is the early warning value of the  $n$  th sparrow. The random early warning value  $R_2$  in the original algorithm is changed to the early warning value determined by the current scheme represented by the sparrow, which highlights the individual difference. The improved early warning value  $R_n$  is shown in formula (16) and (17).

$$R_n = \frac{1}{N} \sum_{g=1}^N S_{n,g} \quad (16)$$

$$S_{n,g} = \begin{cases} 1, & s_{n,g}^t > T \\ 0, & \text{else} \end{cases} \quad (17)$$

Where  $s_{n,g}^t$  represents the same number of digits in the reconstruction scheme represented by the  $n$ th sparrow and the  $g$  sparrow in the  $t$  iteration, and  $T$  is the sparrow similarity threshold. Formula (17) means that when the same number of bits in the reconstruction scheme represented by the  $n$ -th sparrow and the  $g$ -th sparrow exceeds the threshold  $T$ , the  $n$ -th sparrow is considered to be similar to the  $g$ -th sparrow, and  $S_{n,g}$  is assigned to 1.

It can be seen from equations (15-17) that when  $R_n$  is greater than  $ST$ , that is, when the  $n$ th sparrow is similar to other sparrows in the population, the sparrow will move to other safe areas to continue foraging, which is helpful to prevent the sparrow population from falling into local optimization. When  $R_n$  is less than  $ST$ , it indicates that the similarity between the  $n$ th sparrow and other sparrows in the population is not high. On this basis, the dynamic coordination matrix  $D$  will guide the  $n$ th sparrow to update its position, and the heuristic rules will be used to guide the disconnect switch represented by the sparrow to move to the minimum branch current in the loop network, so as to avoid falling into local optimization in each iteration.

In the basic sparrow search algorithm, the followers will change with a negative exponential trend until it converges to zero when  $n > N/2$  or when  $n \leq N/2$ , the followers will jump directly to the current optimal value, which is not conducive to solve the problem of optimization of distribution network reconfiguration in this paper. Therefore, in order to ensure the diversity of the population, this paper uses roulette strategy to improve it. At the same time, in order to make each follower approach the selected explorer during position update, the follower position update formula in the original algorithm is modified to a formula, and a better one is randomly selected from the explorer as a benchmark, and an adaptive mediation strategy is added to automatically adjust the amplitude of position transformation according to the advantages and disadvantages of individual sparrows. The updated formula of the improved follower is shown in formula (18).

$$x_n^{t+1} = x_{p,rand}^{t+1} + |x_n^t - x_{p,rand}^{t+1}| \cdot rand(1,m) \cdot \left(1 + \frac{n}{N}\right) \quad (18)$$

Where  $x_n^t$  and  $x_n^{t+1}$  represents the reconstruction scheme represented by the  $n$ th sparrow in the  $t$  and  $t+1$  iterations, and  $x_{p,rand}^{t+1}$  represent the explorer randomly selected by the roulette strategy, and  $rand(1,m)$  represent the randomly generates a 1-row  $m$ -column random number matrix.

It can be seen from formula (18) that with the increase of  $n$  value, the amplitude of position transformation is greater, and the individual randomness of sparrows is stronger, so the improvement can adaptively adjust the individual transformation amplitude of sparrows and further ensure the diversity of the population.

#### 4. Distribution Network Reconfiguration Process Based on Improved Sparrow Search Algorithm

Step 1: The parameters of distribution network and DG are determined, based on which the ordered basic loop matrix and dynamic coordination matrix are formed.

Step 2: Enter the basic parameters of the improved sparrow search algorithm, including the ratio of explorers to followers, the proportion of vigilante, the alert threshold  $ST$ , etc.

Step 3: Update the position of the explorer, follower and vigilant in turn and calculate the fitness of all sparrows.

Step 4: According to the ranking of the fitness values of all sparrows, the reconstruction scheme represented by the sparrow with the smallest fitness value is taken as the current optimal scheme, and the dynamic coordination matrix is updated by the distribution network structure under the current optimal reconfiguration scheme.

Step 5: Determine whether the current number of iterations reaches the maximum, if not, jump to the third step. If the maximum number of iterations is reached, the final reconstruction scheme and fitness value are output.

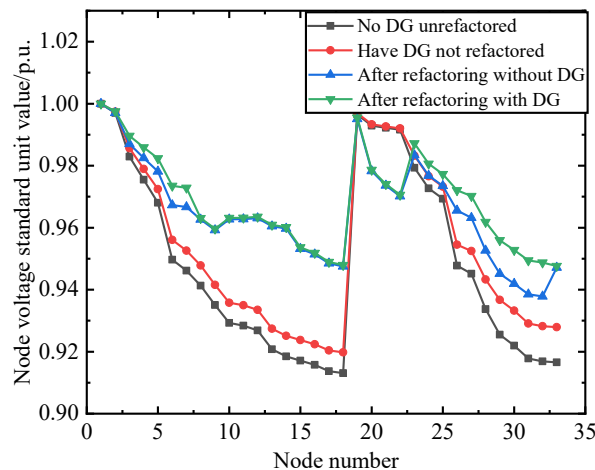
#### 5. Verification and Analysis of Numerical Example

The IEEE33 node system model is shown in figure 1. There are 37 branches in the system, including 5 contact branches. The system reference value, node load and branch parameters can be found in reference [11]. The DG connected to the system is equivalent to the PQ model, and the specific parameters are shown in Table 1.

*Table 1: DG parameters in IEEE33-bus system*

DG number	Access node	Active power/kW	Power factor
1	6	50	1
2	23	200	0.8
3	29	100	0.9

After testing, the safety value  $ST$  of the explorer of the improved sparrow search algorithm is 0.8, the threshold  $T$  is 4, and the maximum number of iterations is 20. Before reconfiguration, the connection switch scheme for disconnection of distribution network is {B33, B34, B35, B36, B37}. When not connected to DG, the lowest voltage unit value of node is 0.9131p.u., the network loss is 202.7kW. After DG access, the node lowest voltage unit value is 0.9198p.u. And the network loss is 157.6kW. ISSA is used to reconfigure the distribution network, and the connection switch scheme for disconnecting the reconfigured distribution network is {B7 B14 B9 B37 B32}. At this time, the standard value of the lowest node voltage of the network is 0.9378p.u. And the network loss is 139.55kW, compared with the loss reduction rate of 31.15% when the DG is not connected and reconfigured. The voltage standard values of each node of the network before and after joining DG and before and after reconfiguration are shown in figure 2. It can be seen from the figure that the connection of DG can raise the node voltage without reconfiguration, and the reconstructed node voltage will be further significantly increased.

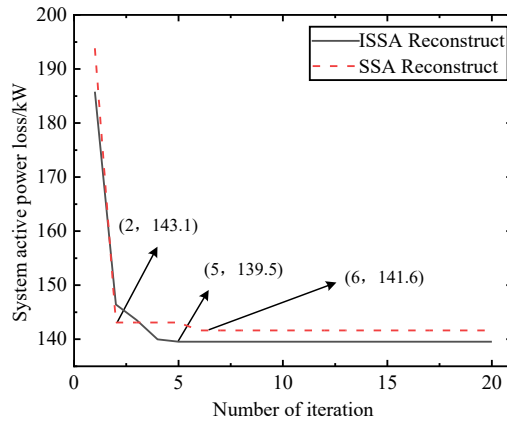


*Figure 2: Comparison diagram of node voltage curve in four cases*

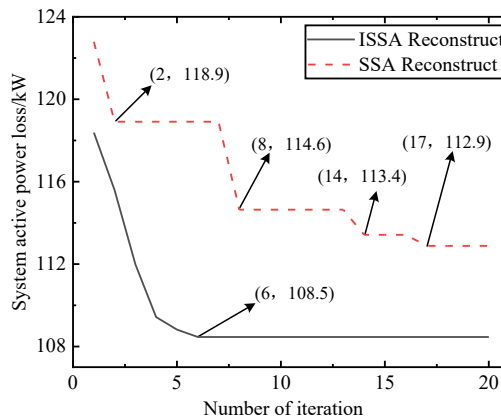
In order to verify the effectiveness of the improved sparrow search algorithm in this paper, four cases in Table 2 are simulated and verified, and the iterative curves can be compared according to whether DG is connected or not, as shown in figure 3 and figure 4.

*Table 2: Case comparison*

	DG	SSA/ISSA	Optimal reconstruction scheme
Case 1	No	SSA	B7,B14,B11,B32,B27
Case 2	Have	SSA	B7,B14,B10,B17,B37
Case 3	No	ISSA	B7,B14,B9,B32,B37
Case 4	Have	ISSA	B7,B14,B9,B32,B37



*Figure 3: Improved pre-and post-iteration curve of the algorithm without DG access*



*Figure 4: Improved pre-and post-iteration curve of the algorithm with DG access*

As can be seen from figures 3 and 4, using the original SSA algorithm for reconstruction can reduce the active power loss of the system, but fall into the local optimization many times in the search for optimization (for example, in figure 4, it is difficult to find the optimal solution under a certain number of iterations). Under the guidance of heuristic rules, the improved ISSA algorithm makes each loop network in the distribution network move to the minimum branch current when selecting the connection switch, avoids falling into the local optimization, and makes the algorithm gradually approach the global optimal solution, which greatly improves the global optimization performance of the algorithm, and the improved ISSA algorithm has faster convergence speed.

In order to further verify that the improved ISSA algorithm has fast convergence speed and global optimization stability, the reconstruction experiment is repeated 50 times, and the number of iterations to obtain the global optimal solution in each experiment is recorded, as shown in figure 5. As can be seen from the graph, the ISSA algorithm can converge to the global optimal solution in 50 reconstruction experiments, and the average number of iterations is only 5.84. It is proved that the ISSA algorithm has the advantages of fast convergence speed and high global optimization stability.



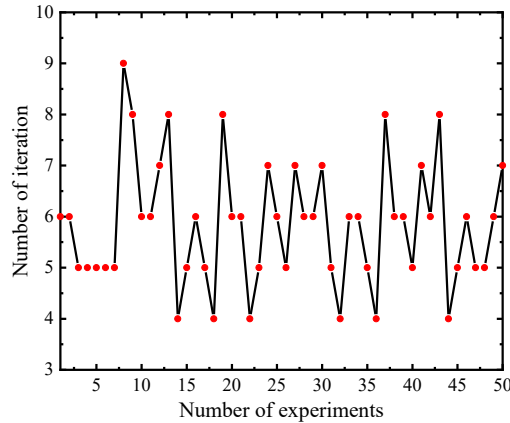


Figure 5: Experimental results of optimization performance of ISSA algorithm

In order to verify the superiority of the coordination optimization matrix constructed in this paper, the coordination optimization matrix is added to particle swarm optimization algorithm (Particle Swarm Optimization, PSO) and grey wolf algorithm (Grey Wolf Optimization, GWO) respectively, and compared with the improved sparrow search algorithm. For PSO and GWO with coordination optimization matrix, the displacement caused by a dynamic coordination matrix is added to all particle displacements or gray wolf position transformations. Each algorithm repeats the experiment 200 times, and the experimental results are shown in Table 3. In Table 3, the average number of iterations and the average convergence time represent the average number of iterations required to converge to the optimal value and the mean time required to converge to the optimal value in 200 repeated experiments. The optimization rate represents the proportion of finding the global optimal solution in 200 repeated experiments.

Table 3: Performance Test of Coordination Optimization Matrix

Method	Optimal reconstruction scheme	Network loss/kW			Lowest voltage/p.u.	Average convergence times	Average convergence time /s	Optimization rate
		Highest	Lowest	Average				
PSO	B7,B14,B9,B37,B32	127.50	108.45	116.94	0.9378	135.5	121.4s	22.5%
GWO	B7,B14,B9,B37,B32	121.77	108.45	117.38	0.9413	146.2	132.2s	18.5%
SSA	B7,B14,B9,B37,B32	123.89	108.45	113.89	0.9413	113.4	104.4s	20.5%
IPSO	B7,B14,B9,B37,B32	109.04	108.45	108.84	0.9378	14.8	15.6s	92.5%
IGWO	B7,B14,B9,B37,B32	109.13	108.45	108.76	0.9378	16.2	17.2s	94.5%
ISSA	B7,B14,B9,B37,B32	108.45	108.45	108.45	0.9378	5.8	4.2s	100%

The following analysis results can be obtained from Table 3:

1) In terms of optimization stability, comparing the three basic algorithms and the three improved algorithms adding the coordination optimization matrix, it is found that the optimization rate of the improved algorithm is significantly improved after adding the coordination optimization matrix, and the optimization rate of the original algorithm is increased to more than 90%, and the optimization rate of the ISSA algorithm in this paper can reach 100%, that is, in 200 repeated experiments. In this paper, the algorithm converges to the global optimal solution, which fully shows that the ISSA algorithm has high optimization stability.

2) In terms of the average number of iterations and the average convergence time, the three improved algorithms are significantly reduced, indicating that the use of coordination optimization matrix can not only improve the accuracy of the algorithm, but also improve the convergence speed, greatly reduce the solution time, and can quickly find the global optimal solution.

## 6. Conclusion

This paper proposes a distribution network reconfiguration method based on the improved sparrow search algorithm. The improved sparrow search algorithm has higher optimization stability and faster convergence speed, and can meet the requirements of distribution network reconfiguration.

## References

- [1] D. Haughton and G. T. Heydt, "Smart distribution system design: Automatic reconfiguration for improved reliability," in *IEEE PES General Meeting*, 2010, pp. 1–8.
- [2] Sarma N, Rao K. A new 0-1 integer programming method of feeder reconfiguration for loss minimization in distribution systems[J]. *Electric Power Systems Research*, 1995, 33(2):125-131.
- [3] Fan J Y, Zhang L, MCDONALD J D. Distribution network reconfiguration: Single loop optimization [J]. *IEEE Transactions on Power Systems*, 2002, 11(3):1643-1647.
- [4] Shirmohammadi D, Hong H W. Reconfiguration of electric distribution networks for resistive line losses reduction [J]. *IEEE Transactions on Power Delivery*, 1989, 4(2):1492-1498.
- [5] S. Goswami and S. Basu, "A new algorithm for the reconfiguration of distribution feeders for loss minimization," *IEEE Trans. Power Del.*, vol. 7, no. 3, pp. 1484–1491, 1999.
- [6] A. Merlin and H. Back, "Search for a minimal-loss operating spanning tree configuration in an urban power distribution system," in *In Proc. 5th Power System Computation Conference (PSCC)*, 1975.
- [7] Juang Chiafeng. "A hybrid of genetic algorithm and particle swarm optimization for recurrent network design." *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 34.2 (2004): 997-1006.
- [8] Shi Yuhui. "Particle swarm optimization: developments, applications and resources." *evolutionary computation*, 2001. *Proceedings of the 2001 Congress on. Vol. 1. IEEE*, 2001.
- [9] R. H. Staunton and B. Ozpineci, "Microturbine power conversion technology review," Oak Ridge National Laboratory, 2003.
- [10] Xue J, Shen B. A novel swarm intelligence optimization approach: Sparrow Search Algorithm[J]. *Systems Science & Control Engineering*, 2020, 8(1):22-34.
- [11] Su C T, Chang C F, Chiou J P. Distribution network reconfiguration for loss reduction by ant colony search algorithm [J]. *Electric Power Systems Research*, 2005, 75(2): 190-199.