Fault Location of Distribution Network Base on Improved Cuckoo Search Algorithm

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This work was supported in part by the ChunHui plan project of Ministry of Education, China, under Grant z2011089, and in part by the Graduate Innovation Fund of Xihua University, China, under Grant ycjj2018083.

ABSTRACT A new method for fault location of a power distribution network based on Improved Cuckoo Search Algorithm is proposed. Cuckoo Search Algorithm uses Lévy flight to simulate the global parasitic propagation mechanism of the cuckoo population. Therefore, the algorithm avoids falling into local optimum easily. According to the requirements of quickness and accuracy for fault location, the algorithm is improved by combining the search step size of the algorithm and the number of iterations. It improves the algorithm’s early iteration speed and subsequent search accuracy. In this paper, the improved Cuckoo Search Algorithm is used to generate random status for all line segments. Then, convert it to the expected status for each switch. And next, update the line segment status by iteration of the algorithm, which makes the expected status of the switches approach to status uploaded by the FTU. Finally, the model outputs the fault location. In this way, a new generic switching function is proposed. It is suitable for single or multiple faults under single and multiple power conditions, which greatly extends the range of applications and versatility. In the evaluation function, the anti-false positive factor and the assumed fault number are introduced. Both of them improve effectiveness and adaptability. And, the validity of these ideas was proved by simulation. Compared with Cuckoo Search Algorithm, Binary Particle Swarm Optimization Algorithm and Genetic Algorithm, Improved Cuckoo Search Algorithm turns out to be good at finding an optimal solution to multiple faults location problems with a faster convergence speed and higher accuracy.

INDEX TERMS Improved Cuckoo search algorithm, distribution network, fault location, switching function, evaluation function.

I. INTRODUCTION
The distribution network plays a very important role in delivering power to users. Due to a huge number of various devices are used, the network architecture tends to be complex. The working environment is harsh, and many lines and equipment cannot be effectively maintained. Therefore, the distribution network is the most prone to failure in the power grid. Accurate and rapid positioning of faults in the distribution network contributes to the improvement of supply reliability in grid power and power quality. Moreover, the safe and effective operation of the power grid is also conducive to the steady and rapid development of the economy.

As more and more feeder terminal equipment (Feeder Terminal Unit, FTU) is used in power distribution networks, how to use FTU to upload fault status signals to achieve fast and accurate fault location and analysis has become an important research topic. So far, scholars from various countries have proposed some fault location methods based on FTU and algorithm. For example, some scholars use Matrix Algorithm (MA) [1]–[3]. This method is simple in principle and quick in the calculation. But, when the FTU is affected by other factors, it is easy to cause inaccurate results. Besides, the Genetic Algorithm (GA) has better fault tolerance [4]–[7]. But GA is easy to fall into a local optimum for the random iteration and lack of guidance. Some researchers also use pattern recognition methods. They use the already-trained artificial neural networks to judge the fault location [8]–[10]. This method has good fault tolerance. But when the power network operation mode has changed, it needs to retrain. For the open-loop operation of the multi-power ring network in power distribution networks, it can be combined with the theory of regional division [11]–[13]. The power distribution network can be divided into many
single-power radiation-type distribution networks. This idea greatly improves the effectiveness of judging the fault location. Also, for the distribution network with Distributed Generation (DG), it is necessary to study the influence of the DG installation position on the direction of the fault current [14]–[17] and build the appropriate switching function. Some researchers can also introduce the concept of “minimum set” while establishing the objective function [18]–[21]. Firstly, expand the single-objective optimization problem into multiple goals. Then convert it to a single-objective optimization in a weighted manner, and use an algorithm to optimize. But the traditional Evolutionary Algorithms are usually less efficient. Moreover, it is sensitive to change in weight.

This paper applies the Cuckoo Search Algorithm (CS) to the fault location in power distribution networks. CS uses Lévy flight to simulate the global parasitic propagation mechanism of the cuckoo population. In this way, the algorithm avoids falling into local optimum easily. According to the requirements of quickness and accuracy for fault location, the algorithm is improved by combining the search step size of the algorithm and the number of iterations. It improves the algorithm’s early iteration speed and subsequent search accuracy. This paper builds a new switching function, which is suitable for single or multiple faults under single and multiple power conditions. It greatly extends its range of applications and versatility. We consider the fault tolerance of fault location, possible signal loss, and distortion of the FTU. In the evaluation function, the anti-false positive factor and the assumed fault number are introduced. Both of them improve their effectiveness and adaptability. Compared with Cuckoo Search Algorithm, Binary Particle Swarm Optimization Algorithm and Genetic Algorithm, the Improved Cuckoo Search Algorithm has the advantages of fast convergence speed and high accuracy, and can well solve the problem of multiple fault location.

II. THE WAY OF CODING

In the fault location of the power distribution network, the switches are used as the nodes, and the power distribution area between adjacent switches is a unit line segment. The unit line has two conditions: normal and fault. “1” indicates that the line segment is faulty. “0” indicates that the line segment is normal. The status of each line segment is recorded in order: \(x_1, x_2, \ldots, x_n\).

\[
x_i = \begin{cases} 
0 & \text{Line segment is normal} \\
1 & \text{Line segment is faulty} 
\end{cases}
\] (1)

In (1): \(x_i\) is the status of the line segment \(i\) in the power distribution network.

Rule 1: When the grid is operating normally, the direction of the current is the positive direction of the network.

The FTU is installed at every switch. A current threshold is set on the FTU. It records as \(I_d\). When a short-circuit fault occurs in the distribution network, the short-circuit current flows from the power supply to the fault location. The short circuit current is much larger than the normal operating current. It is also much larger than the current threshold of the FTU. At this point, the FTU will upload the status of each switch. The status of the switch is indicated by “1”, “−1”, and “0”. “1” means that a fault current larger than \(I_d\) flows through the switch, and its direction is the same as the positive direction of the network; “−1” indicates that a fault current larger than \(I_d\) flows through the switch, and its direction is opposite to the positive direction of the network; “0” indicates that no current greater than \(I_d\) flows through the switch.

Therefore, when the distribution network fails, the FTU uploads the status of the switches according to the above requirements. This paper refers to that status as the actual status of the switches, which recorded as \(I_k\). So, \(I_k\) is used to store the status of the switches when the fault occurs. Moreover, before the next fault occurs, the status of the switches stored by \(I_k\) do not change.

\[
I_k = \begin{cases} 
0 & \text{Fault free current} \\
1 & \text{Same as the positive direction} \\
-1 & \text{Contrary to the positive direction} 
\end{cases}
\] (2)

In (2): \(I_k\) is the fault status of the switch \(k\) in a power distribution network.

III. FUNCTION CONSTRUCTION

A. SWITCHING FUNCTION

In the fault location study based on FTU and an intelligent algorithm, the switching function reflects the conversion relationship between the line segment status and the switch status. The status of the line segment is generated by an intelligent algorithm. It is converted to the expected status of the switch by a switching function. This algorithm updates the expected status of the switch through continuous iteration. It keeps going to approach the status of switches (\(I_k\)) uploaded by FTU. This is the process of fault location.

To facilitate the establishment of the switching function, make the following rules:

Rule 2: Starting from the switch \(K\), traverses along the positive direction of the network, and the passing segment is the downstream segment of the switch \(K\).

Rule 3: In the entire network, excepting the downstream segments, other line segments are the upstream segment of switch \(K\).

I) TRADITIONAL SINGLE POWER SWITCHING FUNCTION

After the FTU uploading the actual status of the switch, the algorithm begins to randomly generate and update the status of the line segment \((x_i)\). The status of the line segment is converted to the expected status of the switch by the switching function. The expected status of the switch is recorded as \(I_k^e\).

As shown in Fig. 1 above, it is a Single power distribution network. \(k_1\) is the circuit breaker. \(k_2\) to \(k_6\) are section switches. \(x_1\) to \(x_6\) represents the line sections. The switching function can convert the status of the line segment to the expected status of the switch. Therefore, under the conditions
of rules 1, 2, 3, the fault location switching function of a typical single-supply condition is as follows.

\[ I^*_k = \bigvee_m x_m \]  

(3)

In (3): \( I^*_k \) represents the expected fault status of the switch \( k \); \( x_i \) represents the fault status of the downstream segment of the switch \( k \); \( \bigvee \) represents logical OR operation.

Taking Figure 1 as an example, the switching function expressions of switches k1~k6 are as follows.

\[
\begin{align*}
I^*_{k1} &= x_1 \lor x_2 \lor x_3 \lor x_4 \lor x_5 \lor x_6 \\
I^*_{k2} &= x_2 \lor x_3 \lor x_4 \lor x_5 \lor x_6 \\
I^*_{k3} &= x_3 \lor x_4 \lor x_6 \\
I^*_{k4} &= x_4 \\
I^*_{k5} &= x_5 \\
I^*_{k6} &= x_6 
\end{align*}
\]

2) New generic switching function

When the distribution network is a multi-supply structure, the traditional switching function is no longer applicable. Therefore, according to the structure characteristics and fault logic of multi-power distribution network, a new switch function is proposed in this paper. It is also suitable for distribution networks with single and multiple power conditions.

Rule 4: Use the interconnection switch as a boundary. Divide a multi-supply distribution network into several single-supply networks. The current direction of each single power network when it is operating normally is its positive direction.

Under the conditions of rules 1, 2, 3, 4, the new switching function constructed in this paper is as follows.

\[
\begin{align*}
I^*_{k} &= \left( \bigvee_m x_m \right) \cdot \left( \bigvee_{p=1}^{N} \left( \left( \bigvee_{q=1}^{M} \left( \left( \bigvee_{n=1}^{9} \left( x_{ksp} \right) \right) \cdot K_{spk} \right) \right) \cdot K_{Lp} \right) \right) \\
&- \left( \bigvee_n x_n \right) \cdot \left( \bigvee_{q=1}^{M} \left( \left( \bigvee_{m=1}^{9} \left( x_{ksq} \right) \right) \cdot K_{Lq} \right) \right) \\
\end{align*}
\]  

(4)

In (4): \( I^*_k \): the expected status of the switch \( k \); \( \bigvee \) represents logical OR operation. \( x_m \): the status of the mth downstream segment of the switch \( k \); \( N \): total number of upstream power supplies of the switch \( k \); “−” : logical non-operation; \( x_{ksp} \).

Starting from switch \( k \) to its pth upstream power source. The status of the passing line segment; \( K_{spk} \): Starting from switch \( k \) to its pth upstream power source. The status of the passed interconnection switch. “0” means the interconnection switch is open, and “1” means it is closed. If the switch \( k \) to its pth upstream power source does not pass the interconnection switch. At this time, \( K_{Lp} = 1; x_9 \): the status of the nth upstream segment of the switch \( k \); \( M \): total number of downstream power supplies of the switch \( k \); \( x_{ksq} \): Starting from switch \( k \) to its qth downstream power supply. The status of the passing line segment; \( K_{Lq} \): Starting from switch \( k \) to its qth downstream power supply. The status of the passed interconnection switch. “0” means the interconnection switch is open, “1” means it is closed.

FIGURE 1. The single power distribution network.

FIGURE 2. The dual power distribution network.
The same: $I_k^1 = 1; I_k^a = -1; I_k^s = -1; I_k^* = 0; I_k^o = 0$; $I_k^{10} = 1; I_k^o = 1; I_k^s = 0$.

Therefore, $I_k^* = [1 1 -1 0 0 1 1 1 0 ]$. $I_k$ is consistent with $I_k^*$. This shows the correctness of the new switching function.

When the algorithm generates and converts the expected status of the switch $(I_k^e)$, it coincides with the actual status $(I_k)$ of the switch uploaded by the FTU. At this time, the status of the line segment generated by the algorithm is the status at the time of the failure. Therefore, the fault location is obtained.

### B. Evaluation Function

The evaluation function indicates the degree of closeness of expected and true status of switches. It should be emphasized that while applying the search algorithm, the evaluation function is the objective function of the algorithm. The process of realizing fault location in CS is equivalent to the optimization process, which evaluates the minimum of the function. When the evaluation function is the smallest, $I_k$ is closest to $I_k^e$. In other words, the status of the line segments corresponding to $I_k^e$ at this time is the status we want.

The most traditional evaluation function is as follows:

$$E = \sum_{k=1}^{n} |I_k - I_k^*|$$

In (6): $I_k$: the actual status of switch $k$; $I_k^*$: the expected status of switch $k$; $n$: Number of switches in the network; $m$: Number of line segments in the network.

Due to various factors, the information uploaded by a few FTUs may be lost or distorted. This paper improves the traditional evaluation function. The improved function is shown below:

$$E = \sum_{k=1}^{n} |I_k - I_k^*| + \omega \left| \sum_{j=1}^{m} x_j - \alpha \right|$$

In (7): $I_k$: the actual status of switch $k$; $I_k^*$: the expected status of switch $k$; $n$: Number of switches in the network; $m$: Number of line segments in the network; $\omega$: the factor for preventing misjudgment; $\sum_{j=1}^{n} s_j$: the total number of faults in all line segments in the network; $\alpha$: the number of assumed faults, This paper takes $1$. If a large number of FTUs have signal loss or distortion, this formula does not verify applicability. However, a few FTUs have these conditions. Equation (7) is correct and has been verified in subsequent simulation experiments.

### IV. Algorithm and Improvement

The algorithm plays two roles in the fault location. First, the status of the line segment is randomly generated or updated. Second, the evaluation function is optimized.

#### A. Introduction to Cuckoo Search Algorithm

The cuckoo search algorithm is a new intelligent optimization algorithm. It is also a new meta-heuristic search algorithm [22]. The idea is mainly to solve the optimization problem based on the characteristics of the parasitic reproduction and the overall optimization ability of Lévy Flight. Parasitic reproduction mainly refers to the fact that cuckoos do not nest during breeding. The main thing to birds is to put the eggs in nests, and then breed and feed offspring. Cuckoos look for birds that are similar in hatching and reproduction. And they quickly send eggs when the birds come out to replace the birds. Lévy Flight is a model for random walks. This mode balances local and global optimization by generating specific long steps and shorter steps.

One advantage of CS is the use of Lévy Flight throughout the space. Because Lévy Flight has unlimited mean and variance. So in addition to being able to explore locally, CS can search the search space more accurately than algorithms that use standard Gaussian processes. Enable CS for efficient optimization.

The difference between cuckoos and other birds is that the cuckoos themselves do not nest and do not hatch the next generation. Instead, they look for nests of other birds. And rely on other birds to hatch and train the next generation. The goal of the cuckoo is similar to that of it. The shape and color of their eggs are similar to those produced by cuckoos.

When parasitic birds are discovered, the cuckoo will wait for the parasitic birds to leave for food and quickly lay eggs in the nest. The cuckoo will take the same number of eggs without being noticed. Make sure the number of eggs does not increase. Nestlings hatched by parasitic birds have their instincts to drive other chicks out of the nest. This ensures that the owner of the nest will only self-improve and increase the likelihood of survival.

To simplify the parasitic process of the cuckoo, CS has somehow changed the process of the following three rules:

1. Each cuckoo only lays one egg at a time and selects a parasitic nest for hatching by random walk;
2. Among the selected parasitic nests, only the best nests can be retained to the next generation;
3. The number of parasitic nests is constant. The probability that the owner of the nest perceives that it is not its egg is $P_a$. If found, either choose to abandon or re-build the nest.

According to these three rules, the path to update the nest is as follows.

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \odot \text{Levy}(\lambda); \quad i = 1, 2, \ldots, n \quad (8)$$

In (8): $x_i^{(t)}$ is the position of the $i$th bird nest in the $t$th generation; $\alpha$ is the step factor, $\alpha > 0$, generally $\alpha = 1$; $\odot$ represents the point multiplication; $\text{Levy}(\lambda)$ represents the search path of Lévy Flight, as shown in (8).

$$L(s, \lambda) \sim s^{-\lambda}, \quad (1 < \lambda \leq 3) \quad (9)$$

In (9): $s$ represents the random step size obtained by Lévy flight.

After each new solution is obtained, some solutions will be thrown away according to the corresponding probability $P_a$. Then according to the method of preference random walking, the corresponding new solution is obtained. And complete
an iteration.

\[ x_{i}^{t+1} = x_{i}^{t} + \alpha \cdot s \otimes H (P_{a} - \varepsilon) \otimes (x_{i}^{t} - x_{i}^{t}) \] (10)

In (10): \( x_{i}^{t} \) and \( x_{i}^{t} \) are two different solutions chosen by random permutation; \( H(u) \) is a Heaviside function; \( \varepsilon \) is a random number extracted from a uniform distribution; \( \otimes \) represents the entry-wise product of two vectors.

The factors affecting CS are population size \( N \), step factor \( \alpha \), and probability of discovery \( P_{a} \). The size of the cuckoo population will affect the running time of the algorithm. If the \( N \) is too small, the precision will be small. If the \( N \) is too large, the algorithm will take too long. The \( \alpha \) and \( P_{a} \) jointly determines the relationship between CS in local exploration and global exploration.

**B. IMPROVEMENT OF CUCKOO SEARCH ALGORITHM**

In the fault location of the distribution network, quickness and accuracy are the top priority of fault location. For the above two points, an Improved Cuckoo Search (ICS) algorithm is obtained.

CS has the advantages of simple structure, few input parameters, easy implementation, random search path and strong optimization ability [20]. However, the search result of the CS is largely affected by the step factor. When the step size is getting too large, the search precision is low. And too small step size causes the convergence speed to be slow. CS is affected by the step factor and the probability of discovery of \( P_{a} \). They together determine the global and local search accuracy of CS, which has a great impact on the optimization effect. The step size and \( P_{a} \) are set to a fixed value at initialization time. They will not change during subsequent operations. When the step size is getting too large, the search accuracy is lowered. And it is not easy to converge. When the step size is set too small, the search speed is slowed down. And it is easy to fall into a local optimum.

In this paper, by combining the step size and the number of iterations, the longer initial step size is set. As the number of iterations increases, the step size decreases. So the step size is large in the initial stage of the algorithm. It speeds up the iteration of global optimization. Search through small step size in the later stages. This increases the accuracy of the search. Moreover, in the process of iteration, when the current optimal solution does not change during continuous iterations. It shows that the target solution has been obtained or is close to the target solution. At this time, reduce the search step size, and continue to improve the accuracy of the global search. The improved formula is as follows.

\[ r = 0.5 \cdot \frac{1}{\log_{10}(N_{G})} \cdot (U_{b} - L_{b}) \cdot (1 / (t + 1)) \] (11)

In (11): \( r \) is the search step size; \( iter \) is the current number of iterations; \( NG \) is the maximum number of iterations; \( U_{b} \) is the upper bound of the variable; \( L_{b} \) is the lower bound of the variable; \( t \) indicates that the optimal solution has not changed for continuous \( t \) iterations.

**C. THE SPECIFIC ROLE OF ICS IN THE LOCATION PROCESS**

It is known from the previous description when the fault occurs, the FTU uploads \( I_{k} \). At this time, the algorithm needs to generate the status \( (x_{i}) \) of line segments randomly. We assume that there are \( i \) line segments in the current distribution network. Therefore, the number of cuckoos in a population within the cuckoo algorithm is set to \( i (nd = i) \). The cuckoo population is \( N \). It is assumed that the initial value of the line segment status generated by the algorithm is \( z_{i} \). Therefore, CS randomly generates a matrix of \( N \times i \). In the behavioral bounds, the \( n \)th row of the matrix is the initial value of the line segment status generated by the \( n \)th population.

The number generated by the cuckoo algorithm is decimal. Therefore, before the line segment status is converted to the switch expected status, different values of \( z_{i} \) indicate different statuses. As shown in the following equation.

\[ x_{i} = \begin{cases} 0 & \text{round}\left(z_{i}\right)/2 = 0 \\ 1 & \text{round}\left(z_{i}\right)/2 \neq 0 \end{cases} \] (12)

In (12): \( x_{i} \): status of line segment \( i \); \( \text{round}(z_{i}) \): rounding \( z_{i} \). From (10), we can get the status \( (x_{i}) \) of the line segment. After that, we can bring \( x_{i} \) into the switching function. The expected status \( (f_{k}^{i}) \) of the switch is obtained by the switching function.

**D. ADAPTIVE GENETIC ALGORITHM**

Among the parameters of genetic algorithms, the choice of crossover probability \( (P_{c}) \) and mutation probability \( (P_{m}) \) is the key to affecting their behavior and performance.

Srinivas proposed Adaptive Genetic Algorithm (AGA). \( P_{c} \) and \( P_{m} \) automatically change with fitness. When the individual fitness of the population tends to be consistent or locally optimal, \( P_{c} \) and \( P_{m} \) of mutation are increase. When the group fitness value is relatively scattered, the \( P_{c} \) and the \( P_{m} \) are reduced.

Therefore, AGA can provide the best crossover probability and mutation probability relative to a solution. The improved equation is as follows:

\[ P_{c} = \begin{cases} \frac{k_{1} (f_{\text{max}} - f)}{f_{\text{max}} - f_{\text{avg}}} & f \geq f_{\text{avg}} \\ k_{2} & f < f_{\text{avg}} \end{cases} \] (13)

\[ P_{m} = \begin{cases} \frac{k_{3} (f_{\text{max}} - f')}{f_{\text{max}} - f_{\text{avg}}} & f' \geq f_{\text{avg}} \\ k_{4} & f' < f_{\text{avg}} \end{cases} \] (14)

In (13) and (14): \( f_{\text{max}} \): the maximum fitness value in the population; \( f_{\text{avg}} \): the average fitness value of the population; \( f' \): the larger fitness value of the two individuals to be crossed; \( f'' \): the fitness value of the individual to be mutated; \( k_{1}, k_{2}, k_{3}, k_{4} \) are constants.
Since the AGA algorithm is optimized for the maximum value, in this paper, its evaluation function is:

$$E = 10 - \left( \sum_{k=1}^{n} |I_k - I_k^*| + \omega \sum_{j=1}^{m} |x_j - \alpha| \right) \quad (15)$$

**E. IMPROVED BINARY PARTICLE SWARM OPTIMIZATION**

Although the binary particle swarm optimization algorithm has the advantages of good convergence and high stability. However, the algorithm is easy to fall into local optimum. Cheng Pu improved it to get an Improved Binary Particle Swarm Optimization (IBPSO)[23].

Improvement strategy 1: Because the learning factor $c_1$ indicates its own learning ability, $c_1$ can accelerate the particle to the individual optimal particle, and the particle optimization ability becomes weaker when $c_1$ is larger. The learning factor $c_2$ represents the ability of social learning, which is the ability to learn all particles. $c_2$ can accelerate the particles to approach the globally optimal particle. When $c_2$ is larger, the particle swarm tends to be locally optimal. Therefore, an equation is set for the two acceleration factors to establish the compression factor.

$$\phi = \frac{2}{\sqrt{\left(c_1 + c_2\right)^2 - 4(c_1 + c_2)}} \quad (16)$$

Improved strategy 2: $\omega$ is called inertia weight, and its value directly affects the search ability of the function. When $\omega$ is large, the particles can avoid reaching local optimum values. When $\omega$ is small, the function can reach convergence as quickly as possible. In view of this, combined with the actual situation of the algorithm, the initial iteration of the function tends to global search, and the end of the iteration requires the function to converge as quickly as possible. Propose a linear adjustment of $\omega$ from large to small, the formula is as follows:

$$\omega = \omega_{\text{max}} - \frac{T (\omega_{\text{max}} - \omega_{\text{min}})}{T_{\text{max}}} \quad (17)$$

In (17): $\omega_{\text{max}}$ and $\omega_{\text{min}}$ are the maximum and minimum values of $\omega$, respectively, and generally take $[0.4, 1]$; $T$ is the number of iterations currently in progress; $T_{\text{max}}$ is the maximum number of iterations.

**V. FAULT LOCATION PROCESS BY ICS**

The main processes of the ICS-based distribution network fault location are shown in Fig. 3.

The detailed processes of the entire fault location are explained as follows:

1) According to the structure type of the distribution network, we construct a suitable switching function and evaluation function.

2) Set the parameters of functions and algorithms according to the corresponding structure of the target network. Set $F_{\text{min}}$ as the storage parameter of the minimum value of the evaluation function.

3) The distribution network has failed.

4) FTU uploads the actual status of switches ($I_k$).

5) CS randomly generates or updates the status of all line segments ($z_i$).

6) Set $F_{\text{min}}$ as the storage parameter of the minimum value of the evaluation function.

7) $I_k$ and $I_k^*$ are brought into the evaluation function to obtain $E$.

8) In the evaluation function value ($E$), the minimum value $E_{\text{min}}$ is taken.

9) Compare $F_{\text{min}}$ and $E_{\text{min}}$, and take the smaller of them as the new $F_{\text{min}}$.

10) If the condition is met, the fault segment is output. Otherwise, return to the fifth step to continue until the condition is met.

**VI. CASE ANALYSIS**

This section mainly analyzes the comparison between the improvement of the switching function and the evaluation function before and after the improvement, the influence of...
algorithm parameters on the location, and the effects of the four algorithms on various fault locations. All the following simulations were performed in MATLAB2015b. The computer configuration is as follows: System: Windows 10 64-bit; CPU: Core i7-7700HQ @ 2.80GHz; GPU: Nvidia GeForce GTX 1050 (2 GB); Memory: 8GB.

A. SINGLE POWER DISTRIBUTION NETWORK
Take the single power distribution network of Fig. 1 as an example. Table 1 shows the simulation results based on ICS. In ICS, \( N = 50, Pa=0.2, nd=10, Lb=0, Ub=100, NG=10, T = 3. \)

The end conditions of the iteration are:
1. The evaluation function \( = 0 \); 2. The optimal solution is unchanged for 3 consecutive iterations; 3. The maximum number of iterations (10 iterations) is reached.

It only needs to satisfy one condition.

As shown in Table 1, when the line segments x3 and x6 respectively fail, all the actual statuses of the switches \( (I_k) \) uploaded by the FTU are [111000] and [111001]. The location model is positioned according to the input \( I_k \). The output fault location information is [001000] and [000001]. Among them, “1” indicates fault. Therefore, the output fault locations are x3 and x6, corresponding to the actual fault location. Therefore, the ICS-based fault location model performs well in fault location for a single power network.

| Fault segment | \( I_k \) uploaded by FTU | Signal distortion | Output segment |
|---------------|---------------------------|------------------|---------------|
| x3            | 111000                    | none             | x3            |
| x6            | 111001                    | none             | x6            |

B. COMPARISON OF SWITCHING FUNCTIONS
Take the dual power distribution network shown in Fig. 2 as an example to analysis, and assume KL is closed. Simulate (3) and (4) for 50 times separately, and compare the simulating results. The evaluation function uses (7). The following table shows the simulation results based on ICS. In ICS, \( N = 100, Pa=0.2, nd=10, Lb=0, Ub=100, NG = 15, T = 3. \)

The end conditions of the iteration are:
1. The evaluation function \( = 0 \); 2. The optimal solution is unchanged for 3 consecutive iterations; 3. The maximum number of iterations (15 iterations) is reached.

It only needs to satisfy one condition.

As shown in Table 2, when the line segment x3 fails, all the actual statuses of the switches \( (I_k) \) uploaded by the FTU is [111-1001110]. The accuracy of location using (3) and (4) is 2% and 98%. At the same time, for (3), there are multiple faults that match \( I_k \).

For (3), take \( x3 = 1 \) and get:

\[
I_{k4}^x = (x4 \lor x7 \lor x8 \lor x9 \lor x10) \cdot (\neg (x1 \lor x2 \lor x3))
\]

From the derivation of \( I_{k4} \) by (3) and (4), the result of (3) is different from the \( I_k \) uploaded by FTU, and the result of (4) is the same as the \( I_k \) uploaded by FTU.

When the line segments x2 and x9 fail at the same time, all the actual status of the switches \( (I_k) \) uploaded by the FTU is [11-1-1001110]. The accuracy of location using (3) and (4) is 2% and 98%. At the same time, for (3), there are multiple faults that match \( I_k \).

For (3), take \( x2 = x9 = 1 \) and get:

\[
I_{k3}^x = x3 \lor x4 \lor x6 \lor x7 \lor x8 \lor x9 \lor x10 = 1
\]

From the derivation of \( I_{k4} \) by (3) and (4), the result of (3) is different from the \( I_k \) uploaded by FTU, the result of (4) is the same as the \( I_k \) uploaded by FTU.

Therefore, (3) does not apply to the positioning of multiple power networks. Equation (4) can accurately locate multiple power networks.

C. COMPARISON OF EVALUATION FUNCTIONS
Take the Dual power distribution network shown in Fig. 2 as an example to analysis, and assume KL is closed. Compare simulations were performed 50 times using (6) and (7). The switching function uses (4). The following table shows the simulation results based on ICS. ICS parameters: \( n = 100, Pa=0.2, nd=10. \)

The end conditions of the iteration are:
1. The evaluation function \( = 0 \); 2. The optimal solution is unchanged for 3 consecutive iterations; 3. The maximum number of iterations (15 iterations) is reached.

It only needs to satisfy one condition.

As shown in Table 2. When the line segments x3 fails and k10 distortion, all the actual statuses of the switches \( (I_k) \) uploaded by the FTU is [111-1001110]. The accuracy of location using (6) and (7) is 62% and 100%.
TABLE 3. Simulation results of the dual power distribution network.

| Fault segment | Signal distortion | I₀ uploaded by FTU | Accuracy of equation (6)(%) | Accuracy of equation (7)(%) |
|---------------|-------------------|-------------------|----------------------------|----------------------------|
| x3            | k10               | 11-1-11 0110    | 62%                        | 100%                       |
| x2,x9         | k4                | 11-1-70 01110   | 4%                         | 100%                       |

Known by x3=1:
\[ I_{k10}^* = x_{10} = 0 \]

If the correct fault x3 is output, the result of (6) is:
\[ E = \sum_{k=1}^{10} |I_k - I_k^*| = 1 \]

However, when x3 and x6 fail simultaneously, the value of (6) is also 1. Therefore, the location may be inaccurate.

For (7), when x3 fails, the above problem does not exist. The value of (7) is only 1.
\[ E = \sum_{k=1}^{10} |I_k - I_k^*| + 0.6 \cdot \sum_{j=1}^{10} x_j - 1 = 1 \]

When the line segment x3 fails and k10 distortion, the actual status of the switches (\(I_k\)) uploaded by the FTU is [11-1001110]. The accuracy of location using (6) and (7) is 4% and 100%. And its accuracy by (6) is lower than the single fault.

Known by x2 = x9 = 1:
\[ I_{k4}^* = \left( x_4 \lor x_7 \lor x_8 \lor x_9 \lor x_{10} \right) \cdot \left( \neg \left( x_1 \lor x_2 \lor x_3 \right) \right) \]
\[ - \left( x_1 \lor x_2 \lor x_3 \lor x_5 \lor x_6 \right) \cdot \left( \neg \left( x_4 \lor x_7 \lor x_8 \right) \right) = -1 \]

If the correct fault x2 and x9 are output, the result of (6) is:
\[ E = \sum_{k=1}^{10} |I_k - I_k^*| = 1 \]

However, when (x2, x5, x9) or (x3, x4, x9) or (x2, x9, x10) or other faults occur, the value of (6) is still 1. Therefore, the location may be inaccurate.

For (7), when x3 fails, the above problem does not exist. The value of (7) is only 1.6.
\[ E = \sum_{k=1}^{10} |I_k - I_k^*| + 0.6 \cdot \sum_{j=1}^{10} x_j - 1 = 1.6 \]

Therefore, for the case of FTU signal distortion, (7) is more accurate than (6).

**D. EFFECT OF COMMON PARAMETERS OF THE ALGORITHMS**

Take the three power structure distribution network in Fig. 4 as an example for analysis. k1, k9, and k15 are circuit breakers. x2~x8, x10~x14, and x16~x18 are segment switches. KL1 and KL2 are interconnection switches. A, B, and C are power supplies.

According to the network structure, we construct the corresponding switch function. At the same time, using four algorithms of ICS, CS, AGA, IBPSO are compared.

1) **THE EFFECT OF POPULATION N ON LOCATION**

In order to test the effect of the population N on the positioning in the algorithm, other parameters are set in advance. In ICS and CS, \(P_a = 0.2, nd = 18, Lb = 0, Ub = 200, NG = 50, T = 10\). In AGA, \(NG = 50, Pc1 = 0.9, Pc2 = 0.6, Pm1 = 0.2, Pm2 = 0.15, L = 18, T = 10\). In IBPSO, \(T = 10, D = 18, c1 = 2, c2 = 1.7, w1 = 1, w2 = 0.9, NG = 50\).

The end conditions of the iteration are:
1. The evaluation function = 0; 2. The optimal solution is unchanged for \(T\) consecutive iterations \((T = 10)\); 3. The maximum number of iterations (50 iterations) is reached.

It only needs to satisfy one condition to end.

When x3 and x11 fail at the same time, k7 and k17 are distorted, and KL1 = KL2 = 1. Fig. 5 and Fig. 6 show the positioning accuracy and average iterations when the algorithm parameter N takes values \([50, 100, 150, 200, 250, 300, 350, 400, 450, 500]\) respectively.

In Fig. 5, the higher the N, the higher the accuracy. When N is the same, it can be known that the accuracy of ICS and CS is much higher than that of AGA and IBPSO. Among them, ICS>CS>IBPSO>AGA. Both ICS and CS are able
to achieve 100% accuracy. As N increases, the accuracy of AGA and IBPSO increases by 36% and 44%, respectively.

Meanwhile, in Fig. 6, for ICS, CS, and IBPSO, as N is larger, the average iterations is smaller. For AGA, when N is less than or equal to 250, the larger the N, the larger the average iterations. When N is greater than 100, the average iterations is IBPSO < ICS < CS < AGA.

Therefore, in combination with Fig. 5 and Fig. 6, within a certain range, the larger the N, the better the algorithm’s location effect on the fault.

2) THE EFFECT OF T ON LOCATION

In order to test the effect of the T on the positioning in the algorithm, other parameters are set in advance. In ICS and CS, N = 500, Pa = 0.2, nd = 18, Lb = 0, Ub = 200, NG = 50. In AGA, N = 500, NG = 50, Pc1 = 0.9, Pc2 = 0.6, Pm1 = 0.2, Pm2 = 0.15, L = 18. In IBPSO, N = 500, D = 18, c1 = 2, c2 = 1.7, w1 = 1, w2 = 0.9, NG = 50.

The end conditions of the iteration are:
1. The evaluation function = 0; 2. The optimal solution is unchanged for T consecutive iterations (T = 3 ~ 20); 3. The maximum number of iterations (50 iterations) is reached.

It only needs to satisfy one condition to end.

When x3 and x11 fail at the same time, k7 and k17 are distorted, and KL1 = KL2 = 1. Fig. 7 and Fig. 8 show the positioning accuracy and average iterations when the algorithm parameter T takes values [3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20] respectively.

In Fig. 7, the higher the T, the higher the accuracy. At the same time, it can be known that the accuracy of ICS and CS is much higher than that of AGA and IBPSO. Both ICS and CS are able to achieve 100% accuracy. However, ICS achieves 100% accuracy earlier than CS. As N increases, the accuracy of AGA and IBPSO increases by 88% and 68%, respectively.

In Fig. 8, when the evaluation function is optimal, it needs to continue T iterations to satisfy the end condition. As T is larger, the average number of iterations is higher. Also, AGA is most affected by T.

As the value of T is larger, the accuracy and the average number of iterations of the algorithm are higher. And, we need both high accuracy of algorithm positioning and fewer iterations. Therefore, T must not be too large or too small, it must be appropriate.

E. SIMULATION OF A THREE-POWER NETWORK

According to the network structure, we construct the corresponding switch function. Adjust the parameters of ICS and CS. N: 500, NG: 50, Pa: 0.2, Lb: 0, Ub: 200. At the same time, the AGA and IBPSO were added for comparison. In AGA, N = 500, NG = 50, Pc1 = 0.9, Pc2 = 0.6, Pm1 = 0.2, Pm2 = 0.15, L = 18. In IBPSO, N = 500, D = 18, c1 = 2, c2 = 1.7, w1 = 1, w2 = 0.9, NG = 50.

Mainly analyzes single-point and multi-point faults and possible FTU signal distortion and loss, under multi-power conditions. The simulation results of the four algorithms are shown in Table 4.

The end conditions of the iteration are:
1. The evaluation function = 0; 2. The optimal solution is unchanged for T consecutive iterations (T = 10); 3. The maximum number of iterations (50 iterations) is reached.

It only needs to satisfy one condition to end. Table 4 shows the results of 100 simulations for various fault conditions of the three-power distribution network.

In Table 4, the first column indicates the serial number and segments of the fault. For example, T1 indicates the serial number of the fault, and x4 indicates the faulty segment. The second column indicates the status of the interconnection switches KL1 and KL2 in the event of a fault. “1” means
TABLE 4. Simulation results of the three power distribution network.

| Fault segment | Status of KL | I_k uploaded by FTU | Signal distortion | AGA | IBPSO | CS | ICS |
|---------------|--------------|---------------------|-------------------|-----|-------|----|-----|
|               |              |                     |                   | Average iterations | Accuracy (%) | Average iterations | Accuracy (%) | Average iterations | Accuracy (%) | Average iterations | Accuracy (%) |
| T1: x4        | [0,0]        | 1111000000 000000000 | none              | 19.03 | 37    | 2.61 | 100 | 8.44 | 99 | 4.52 | 100 |
| T2: x4        | [1,0]        | 1111100001 111000000 | none              | 18.18 | 43    | 2.59 | 99  | 7.78 | 99 | 3.86 | 100 |
| T3:x4         | [1,1]        | 1111100111 111101111 | none              | 19   | 59    | 2.53 | 100 | 7.16 | 100 | 4.41 | 100 |
| T4: x3,x11    | [0,0]        | 111000001 110000000 | none              | 20.95 | 25    | 17.09 | 87  | 18.11 | 97 | 14.97 | 99 |
| T5:x3,x11     | [0,1]        | 111-1000-1 110001111 | none              | 21.29 | 34    | 17.27 | 81  | 17.83 | 100 | 14.83 | 100 |
| T6:x3,x11     | [1,1]        | 111-1000-11 11-1-1011-11 | none | 25.6 | 48    | 16.54 | 75  | 18.23 | 98 | 15.02 | 100 |
| T7: x3,x11    | [1,1]        | 111-107-11 11-1-1017-1 | k7,k17   | 24.41 | 56    | 14.81 | 69  | 18.47 | 96 | 15.35 | 99 |
| T8: x6, x12,x16 | [0,0] | 1100011001 110001100 | none | 20.09 | 22    | 18.91 | 52  | 19.12 | 98 | 16.29 | 98 |
| T9: x6, x12,x16 | [1,0] | 1111100111 11-101100 | k3 | 24.92 | 42    | 18.52 | 33  | 18.21 | 96 | 15.88 | 99 |
| T10: x6, x12,x16 | [1,1] | 1101101111 11-1011-1 | none | 24.55 | 40    | 17.07 | 34  | 18.68 | 95 | 16.51 | 100 |
| T11: x6, x12,x16 | [1,1] | 1111107111 110111-1 | k3,k8 | 25.12 | 44    | 17.09 | 31  | 18.42 | 93 | 16.31 | 98 |

closed and “0” means disconnected. The third column indicates the actual status (I_k) of the switches uploaded by the FTU in the event of a fault. The fourth column indicates the signal distortion that occurs in the I_k uploaded by the FTU in the event of a fault. “?” indicates a signal of distortion. The remaining columns represent the simulation results of the four algorithms for various faults. They include the average number of iterations per simulation of the algorithm and the accuracy of fault location in 100 simulations.

From the results shown in Table 4, we analyze the effects of the four algorithms separately:

1) The AGA algorithm has the lowest accuracy for T8 failures, which is 22%. It has the highest accuracy for T3 failures, at 59%. It can be seen from T1∼T3 and T4∼T6 that as the power supply increases, the accuracy increases. It can be seen from T3, T6, T10 that as the number of faults increases, the accuracy of AGA decreases. But, it can be seen from T6∼T7 and T10∼T11 that the accuracy of AGA increases with the distortion of the signal.

2) The IBPSO algorithm has the lowest accuracy for T11 failures, at 31%. It has the highest accuracy for T1 and T3 failures, at 100%. It can be seen from T1∼T3 and T4∼T6 that as the power supply increases, the accuracy decreases. It can be seen from T3, T6, T10 that as the number of faults increases, the accuracy of IBPSO decreases. It can be seen from T6∼T7 and T10∼T11 that the accuracy of IBPSO is reduced as the signal is distorted. The IBPSO algorithm is more suitable for a single fault with an accuracy rate of over 99%.

3) The CS algorithm has the lowest accuracy for T11 failures, which is 93%. It has the highest accuracy for T3 and T5 failures, at 100%. It can be seen from T1∼T3 and T4∼T6 that as the power supply increases, the accuracy of the change does not change much. It can be seen from T3, T6, T10 that as the number of faults increases, the accuracy of CS decreases. It can be seen from T6∼T7 and T10∼T11 that with the distortion of the signal, the accuracy of CS is decreased. But the extent of the change is small. The CS algorithm is suitable for every fault condition. In each case, the CS algorithm’s fault location accuracy is over 93%.

4) The ICS algorithm has the lowest accuracy for T11 failures, which is 98%. It has an accuracy rate of 100% for multiple faults. It can be seen from T1∼T3 and T4∼T6 that as the power supply increases, the accuracy of the change does not change much. It can be seen from T3, T6, T10 that as the number of faults increases, the accuracy of ICS remains basically unchanged. It can be seen from T6∼T7 and T10∼T11 that as the signal is distorted, the accuracy of ICS is decreased. But the extent of the change is small. The ICS algorithm is suitable for each fault condition. In each case, the fault location accuracy of the ICS algorithm is over 98%.
The convergence curves of the four algorithms are shown below:

![Convergence Curves](image)

**FIGURE 9.** Iterative convergence of four algorithms for T11 failure.

Fig. 9 is the iterative convergence diagram of the four algorithms for the T11 fault. Among them, because the AGA algorithm is the maximum optimization, its evaluation function value increases with iteration. We can see that ICS, CS, IBPSO, and AGA obtained the optimal value of the evaluation function at the 6th iteration, the 9th iteration, the 8th iteration, and the 14th iteration, respectively. According to the end condition, it needs to get the optimal value and continue for 10 times iterations to end. At the same time, it can be seen that their evaluation function values are 3.2, 3.2, 3.6, 6.8, so ICS, CS, and AGA both get the correct fault location. IBPSO gets the wrong fault location.

From Table 4 and Fig.9, we can see that the average number of iterations of the four algorithms: ICS < IBPSO < CS < AGA. Since the parameter $\alpha = 1$ in equation (7), the algorithm is more efficient in locating a single fault. ICS is superior to CS on average iterations and accuracy, which explains the effectiveness of the improvement. At the same time, from the above analysis, the positioning effect of the four algorithms is ICS > CS > IBPSO > CS. And the location effect of ICS is much better than the rest of the algorithm.

**VII. CONCLUSION**

This paper builds a new switching function. It is suitable for single or multiple faults under conditions of single and multiple power. Therefore, it greatly improves versatility and the range of applications. Considering the fault tolerance of fault location and possible signal loss, distortion and so on of the FTU. In the evaluation function, the anti-false positive factor and the assumed fault number are introduced. This improves its effectiveness and adaptability.

In this paper, the Improved Cuckoo Search Algorithm is successfully applied to the fault location problem of the power distribution network. The improved algorithm combines the search step and the number of iterations, which improves the early iteration speed of the algorithm and subsequent search accuracy.

This paper uses four algorithms to simulate. The results of the examples show the location of single or multiple faults and FTU signal distortion or loss, under the conditions of single power supply and multiple power supply. Compared with Cuckoo Search Algorithm, Binary Particle Swarm Optimization Algorithm and Genetic Algorithm, Improved Cuckoo Search Algorithm turns out to be good at finding an optimal solution to multiple faults location problems with a faster convergence speed and higher accuracy. Therefore, the fault location model of the power distribution network based on ICS can achieve a fast and accurate fault location.

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