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Analysis and Optimization Direction of Fault Self-Healing Performance of New Energy Distribution Grid Based on Improved Algorithm

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Abstract Power systems have various structures, and the occurrence of faults is inevitable. In this project, the recovery and reconstruction problem of new energy distribution network faults is studied, the mathematical model of distribution network reconstruction is constructed, the particle swarm algorithm is chosen as the intelligent optimization algorithm for solving the recovery and reconstruction problem of distribution network, and it is optimized by combining the parameter improvement and the genetic algorithm. The improved hybrid particle swarm algorithm in this paper has better optimization searching effect, and the number of evolutionary generations to reach the best fitness value is much smaller than that of the traditional particle swarm algorithm. Taking the IEEE33 node system as an example for case analysis, it is found that this paper's method has good universality, and when accessing the DG and reconfiguring, the node voltages of the whole system are significantly improved (6.09% and 4.37%) to ensure that all node voltage distributions satisfy the confidence constraints, and at the same time the system's active network losses are also significantly reduced (57.35% and 40.59%), which reflects the superior fault self-healing performance, and has a very good performance. The performance of fault self-healing has good practical value.

Index Terms particle swarm algorithm, genetic algorithm, optimization reconstruction model, new energy distribution network, fault self-healing

I. Introduction

Distribution network is an important part of the power system, which is used to connect the high-voltage transmission network and low-voltage users, and shoulders the important task of energy distribution [1]. With the social and economic development, the degree of user dependence on power supply is increasing, and the economic losses and adverse effects caused by the interruption of power supply in distribution networks are also increasing [2], [3]. At present, the self-healing reconfiguration capability of distribution network has become one of the important indicators to measure the automation level of distribution system, which is gradually emphasized by electric power enterprises [4], [5]. Considering that there are more new energy generation units in the active distribution network, how to optimize the topology of grid operation, reduce power supply loss, and improve the carrying capacity of new energy access also puts forward higher requirements for distribution network reconfiguration [6]-[8].

Fault self-healing technology can maximize the recovery of outage loads, minimize network losses, and minimize the number of switching operations by designing effective power supply restoration schemes after a fault occurs [9], [10]. The traditional distribution network self-healing usually adopts the relay protection system to realize the automatic isolation of distribution network faults, but this method can only realize the basic isolation function, and cannot further realize the optimal operation of the distribution network [11]-[13]. In contrast, there are usually multiple optimization schemes to choose from during the self-healing reconfiguration of distribution networks [14]. Since the distribution network usually consists of many interconnected distribution feeders, interconnecting switches and disconnecting switches, after a fault occurs, the faulty lines can be removed by a combination of different switches, and the radial topology can be reorganized to realize the self-healing reconfiguration of the distribution network [15]-[17].

For the automated self-healing reconfiguration control of new energy distribution networks, literature [18] proposes a real-time reconfiguration method for new energy distribution networks based on heuristic algorithms, which effectively improves the operational performance of distributed distribution networks by real-time measuring and analyzing the state of the remote-controlled switches and giving commands according to the actual situation. Literature [19] combines dynamic topology analysis and network reconfiguration to form a dynamic reconfiguration method, which is applied to the real-time distribution network optimization task, and can be used to identify faulty areas by detecting the initial topology change of the distribution network, and at the same time, carry out the real-time network reconfiguration in order to improve the voltage distribution of the distribution network. Literature [20] shows that network reconfiguration of new energy distribution networks can minimize the power loss of the system in distributed voltage, for this reason, a variety of objective functions that can enhance the performance of the distribution system are investigated to construct network reconfiguration methods and algorithms to guarantee the stability and operational benefits of the distribution system.

Literature [21] investigated an adaptive reconfiguration method for electrical topology in active distribution networks, which significantly improves the efficiency of signal exchange between various power entities by designing distribution network optimization algorithms with strong convergence as well as high performance. Literature [22] proposes a network reconfiguration method for distribution systems under unbalanced AC conditions, which analyzes the operating characteristics of unbalanced networks, distributed energy sources and voltage regulators by constructing an optimal current framework, and further combines intelligent algorithms to achieve the control and optimization of new energy distribution networks. Literature [23] uses the proposed three-stage self-healing algorithm to optimally reconfigure the faulty distribution network under the consideration of load and generation uncertainty environment, which effectively improves the system efficiency and node voltage distribution, and then improves the resilience of the distributed power system. In summary, although scholars at home and abroad have carried out a large number of related studies, the synergistic optimization of new energy access carrying capacity and line loss in the active distribution network is still one of the problems facing the active distribution network in the future, and the research on its performance analysis and optimization methodology is still in the ascendant.

The study designs a mathematical model for the optimal reconfiguration of new energy distribution networks, analyzes the topology of the distribution network with the knowledge of graph theory, selects the depth-first search algorithm to detect the radiality of the distribution network, and proposes the “minimum broken circle method” to modify the topology for the case of the existence of the ring network. Subsequently, the objective function and constraints of the model are constructed, and the forward and backward generation method is selected as the current calculation method. On this basis, the particle swarm algorithm is adopted as the solution method of the model, and its parameters are improved by changing the inertia weights in the parameters from the traditional linear decreasing to the evolutionary ratio squared decay, which is capable of retaining the global search ability for a longer time, and it is verified that this strategy is effective in avoiding falling into the sub-optimal solution in the repetition of the optimization case of an extremum search. The parameter-improved particle swarm algorithm is then combined with the genetic algorithm to obtain an improved particle swarm algorithm with which the model is solved. Finally, simulation experiments are carried out in the IEEE33 node system to analyze the active network loss and node voltage changes of the system after reconfiguration of the method in this paper, and to explore the effect of the proposed method on the fault self-healing of new energy distribution networks.

II. Mathematical modeling of distribution network reconfiguration

In order to cope with large power outages caused by extreme events such as natural disasters, chain failures, and cyber attacks, this paper designs the mathematical model and solution algorithm of distribution network optimization and reconfiguration for new energy distribution networks containing distributed power sources (DG). This chapter focuses on the analysis of the mathematical model for the restoration and reconfiguration of the new energy distribution network.

II. A. Topology of the network

New energy distribution network reconfiguration is to find the power supply network represented by the optimal target grid of the distribution network, i.e., a multi-objective optimization problem, for which the structural problem of distribution network reconfiguration is firstly described by the knowledge of graph theory in mathematics.

II. A. 1) Foundations of graph theory

In a topological graph, if there exists at least one path consisting of branches between any two nodes, the graph is said to be connected. Removing some branches, or both some branches and nodes from a given graph gives its subgraph. A tree is a subgraph of a connected graph which contains all the nodes of the original graph but does not contain any loops, in distribution network topology a subgraph tree which does not contain any loops is called a radial network. If all the branches in the graph are directional, then it is a directed graph and vice versa it is an undirected graph, in the topology graph of distribution network the direction in the directed graph can be used to indicate the direction of power transmission, the transmission of power is described by defining the parent node and child node, the power flowing out of the parent node flows to the child node.

II. A. 2) Detection of topology radiosity

In order to ensure the normal operation of the power system, it is necessary to ensure that the topology of the network is a radial network, so it is necessary to detect whether the topology of the operational target grid of the distribution network is a radial network or not, and the detection methods are depth-first search algorithm (DFS) and breadth-first search algorithm (BFS). In the search process of depth-first search method, it can not only determine whether the topology of distribution network is a radial network, but also get the inheritance relationship between the nodes, which can be combined with the trend calculation, so in this paper, depth-first search algorithm is chosen for the detection of radiality of the topology of distribution network.

II. A. 3) Network topology modification

After detecting the radiality of the topology of the distribution network through the depth-first search algorithm, it can be concluded that there are loops or islands in the non-compliant topology. In order to correct and transform the topology non-compliant solutions, the broken circle method is introduced in this paper to deal with the topology with the presence of ring network. That is, if a loop is detected in the diagram, one of the sides of the loop will be removed until there is no more loop in the diagram, the definition of "loop" is introduced into the distribution network topology refers to loops, if there are n loops in the original topology, then remove the n branch can ensure that the modified topology is radial shape.

II. B. Objective function and constraints

(1) Line active loss minimization

This type of objective function is more common in distribution network reconfiguration problems, optimization reconfiguration problems are mostly based on network loss minimization as the objective function, in the restoration reconfiguration problem, reducing the active loss of the system can make the active power issued by the generator be utilized to a greater extent, so that each load node restores a greater degree of active power, and its mathematical expression:

$$\min Fitness(x) = \sum_{i=1}^{n} k_i \times \left(\frac{P_i^2 + Q_i^2}{V_i^2} \right) \times R_i \tag{1}$$

where n is the number of switches in the solved distribution network, k_i is the casting state of the i th branch, which is 1 when connected to the distribution network and 0 when disconnected, P_i and Q_i are the active and reactive power consumed on the i th branch, respectively, V_i is the voltage at the i th end node of the branch and R_i is the branch resistance.

(2) Maximize the degree of load restoration

The purpose of distribution network restoration and reconfiguration is to restore as much load in the system as possible, such objective function directly reflects the purpose of restoration and reconfiguration, and its mathematical expression:

$$\max Fitness(x) = \sum_{i=1}^{m} a x_i L_{1i} + \sum_{j=1}^{n} b x_j L_{2j} + \sum_{k=1}^{l} c x_k L_{3k} \tag{2}$$

where m,n,l are the number of primary, secondary and tertiary loads in the system, x_i is the power supply state of the i th load, which is 1 when it is supplied, and 0 when it is not supplied, and L_1, L_2, L_3 are the magnitude of power restored to primary, secondary and tertiary loads, respectively, a,b,c are their weighting factors, respectively.

(3) Minimization of the number of switching operations

This type of objective function is related to the economy of the actual operation of the distribution network, and its mathematical expression:

$$\min Fitness(x) = \sum_{i=1}^{Ns} | S_i - S_{0i} | \tag{3}$$

where Ns is the number of switches in the system, S_i is the state of the switch after reconfiguration of the distribution network, S_{0i} is the state of the switch before reconfiguration, and S_{0i} of each switch in the restoration and reconfiguration of the distribution network problem is zero.

In the study of distribution network restoration and reconstruction, a multi-objective optimization method can be chosen, i.e., multiple objective functions are selected and given certain weight coefficients to be added to obtain a total objective function value. In the solution process of this paper, according to the load level problem that needs to be considered in the process of restoration and reconfiguration of the distribution network, combined with the overall objective of restoration and reconfiguration, i.e., restoring as much as possible the lost loads in the distribution network, the objective function is selected as Eq:

$$\max Fitmess = a\sum_{i=1}^{m} x_i L_{1i} + b\sum_{j=1}^{n} x_j L_{2j} + c\sum_{k=1}^{l} x_k L_{3k} + d\sum_{t=1}^{m+n+l} x_t \tag{4}$$

In addition to the objective function of maximizing the degree of load restoration as part of the formula introduced earlier, the total number of restored loads is also introduced, and d is assigned as its weight coefficient, and x_t is the restored state of the load t, which is 1 when the power is normally supplied, and 0 when it is in the disconnected state.In this way, not only the power magnitude of the restored loads is taken into account, but also the restored loads. This not only takes into account the power size of the restored loads, but also the total number of restored loads, which is more in line with the total objective of restoring as many loads as possible in the system as required by the recovery reconfiguration. The inequality constraints in the recovery target grid are as follows:

$$\begin{aligned} &P_1 \le P_{\max} \\ &V_{\min} \le V_i \le V_{\max}, i \in N \\ &S_{\min} \le S_j \le S_{\max}, j \in M \end{aligned} \tag{5}$$

where P_1 is the active power of the generator node obtained from the current calculation, $P_{\max}$ is the maximum output of the generator node, V_i is the voltage of the node i, $V_{\min}, V_{\max}$ are the node-qualified minimum and maximum voltages, respectively, and N is the distribution network in the set of nodes, S_j is the power flowing through line j, $S_{\min}, S_{\max}$ are the line-qualified minimum and maximum power capacities, respectively, and M is the set of branches in the distribution network.

II. C.Trend calculation

The value of the objective function of distribution network restoration and reconstruction needs to be obtained through the trend calculation of the distribution network in the case of the topology that meets the requirements of the radial network, and the radial structure of the distribution network determines the uniqueness of the trend solution of the distribution network, and there are three main types of methods for the distribution network trend calculation: Newton-based methods, busbar-based methods, and branch-circuit-based methods.

The most typical branch method is the forward back generation algorithm, which is widely used in the distribution network trend calculation, and its basic idea is: set the whole network voltage as the rated voltage, according to the load power from the end of the end of the segment by segment forward to calculate the power loss in the branches, so as to obtain the first end power. Then according to the given voltage and the first end of the power from the first end to the end of the segment-by-segment calculation of the voltage drop in each segment, so as to obtain the voltage at each node. This is repeated until the voltage deviation at each node is within tolerance. This algorithm does not have to solve the higher-order equations, is simple to compute, converges quickly, and is very practical, so this paper chooses the forward back generation method as the current calculation method.

III. Solution methods for distribution network reconfiguration

In this chapter, the solution method of new energy distribution network fault self-healing is analyzed, based on particle swarm algorithm, its parameters are improved and optimized by combining with genetic algorithm, and the improved hybrid particle swarm algorithm is used to solve the mathematical model of new energy distribution network reconstruction.

III. A. Improved hybrid particle swarm algorithm

III. A. 1) Particle Swarm Algorithm

The standard particle swarm algorithm (PSO) is a heuristic, parallel intelligent optimization algorithm. Each particle represents a solution in the search space and searches for the global optimal solution by constantly updating the positions and velocities of the population particles. In each iteration, the particles update the velocity and position of the particles based on the optimal position of the individual extremes with respect to the population extremes.

Suppose there are many populations in an n-dimensional search space, each including M particles, and denote the velocity of the current particle i by $v_i = (v_{i1}, v_{i2}, v_{i3}, \cdots, v_{ij})$ and denote the velocity of the current particle i by $x_i = (x_{i1}, v_{i2}, v_{i3}, \cdots, v_{ij})$ to denote the current position of particle i, $P_i = (P_{i1}, P_{i2}, P_{i3}, \cdots, P_{ij})$ to denote the particle i passes through the best position of an individual, and $P_g = (P_{i1}, P_{i2}, P_{i3}, \cdots, P_{ij})$ denotes the optimal position of the whole particle to reach the global search of the population, $i = 1,2,3,\cdots,M$, $j = 1,2,3,\cdots,n$ Then the optimal position experienced by particle i can be expressed as $Pbest_i = Pbest_{i1}, Pbest_{i2}, Pbest_{i3}, \cdots, Pbest_{in}$. Let $l(x)$ be the objective function to be optimized, then the current optimal position of particle i can be expressed as:

$$Pbest_i^{(k+1)} = \begin{cases} Pbest_i^k, \text{if } l(x_i^{(k+1)}) \geq l(Pbest_i^k) \\ x_i^{(k+1)}, \text{if } l(x_i^{(k+1)}) < l(Pbest_i^k) \end{cases} \tag{6}$$

When there are M particles in the population, then the global best position experienced by these M particles can be expressed as $gbest^k, gbest^k$ then:

$$gbest^k = min\{l(Pbest_1^k), l(Pbest_2^k), l(Pbest_3^k), \cdots, l(Pbest_M^k)\} \tag{7}$$

The standard particle swarm algorithm for updating speed and position can then be expressed as:

$$v_{ij}^{(k+1)} = \omega v_{ij}^k + c_1 r_1^k (P_{ij}^k - x_{ij}^k) + c_2 r_2^k (P_{gj}^k - x_{gj}^k) \tag{8}$$

$$x_{ij}^{(k+1)} = x_{ij}^k + v_{ij}^{(k+1)} \tag{9}$$

In Eq. (6): i denotes the ith particle, k denotes the current number of iterations, and $Pbest_i^k$ denotes the component of $Pbest_i$ that is the best position of the individual of particle i in the jth dimension at the kth iteration: $gbest^k$ denotes the j-dimensional global best position $gbest$ component of the particle i in the kth iteration, v_{ij}^k denotes the velocity of the j-dimensional component of the i-particle at the kth iteration, x_{ij}^k denotes the k-dimensional velocity vector of the i-particle at the position of the j-dimensional component of the velocity vector in the kth iteration, ω denotes the inertia weights of the particle swarm algorithm, c_1, c_2 are the learning factors of the standard particle swarm algorithm, and r_1, r_2 are the random numbers randomly and uniformly distributed between [0, 1], which are designed to conserve the diversity of the population.

The specific flow of the standard PSO algorithm:

(1) First randomly initialize the velocity and position of each particle, and set the learning factor c_1, c_2, inertia weights ω, velocity v_i, x_i, number of iterations, and population size and other related parameters of the particle swarm algorithm.

(2) Calculate the fitness value of each particle.

(3) Judge the best position of the previous particle i and the individual best position of the current particle i.

(4) Judge whether the particle reaches the set maximum number of iterations or the set error. If the set conditions are met, the algorithm ends the run, if the conditions are not met, update the velocity and position of the population particles according to Eq. (8) and Eq. (9), recalculate the fitness value and execute the algorithm.

III. A. 2) Genetic algorithms

Genetic algorithm as a kind of intelligent algorithm of global search and optimization based on the mechanism of biological genetic evolution, in using genetic operators to imitate the genetic characteristics of organisms is to use the mechanism of selection, crossover, and mutation in biological heredity and evolution to complete the search for the optimal solution. The genetic algorithm consists of the following four main points:

(1) Determining the representation of variables

Encoding is the process of representing each possible point in the search space of the problem as a feature string of definite length. The feature string is the individual or chromosome, and the individual is represented by a string, in the multivariate problem coding, a variable corresponds to a component in the whole string, this component is also known as the gene or genetic factor, and all the individuals form a population. Combining the characteristics of each coding method, this paper adopts the binary coding method.

(2) Determine the fitness function

Adaptation is a measure used to distinguish the degree of survival of the population advantage of good or bad, the degree of adaptation is calculated by the fitness function, the algorithm in the search for evolution is only based on the fitness function and the adaptive value of each individual to carry out the search. Therefore, the fitness function is related to whether the algorithm can quickly and accurately complete the search for the optimal solution.

The fitness function generally has the following two ways:

a) If the objective function is a maximum solution problem, there are:

$$F(x)=\begin{cases}C_{\max}+f(x), f(x)<C_{\max}\\ 0, \text{other}\end{cases} \tag{10}$$

where $C_{\max}$ is the maximum estimate of the objective function $f(x)$, $f(x)$ is the objective function, and $F(x)$ is the fitness function.

b) If the objective function is a minimax solution problem, we have:

$$F(x)=\begin{cases}f(x)-C_{\min}, \text{when } f(x)>C_{\min}\\ 0, \text{other}\end{cases} \tag{11}$$

where $C_{\min}$ is the maximum estimate of the objective function $f(x)$, $f(x)$ is the objective function, and $F(x)$ is the fitness function.

(3) Determine the genetic operator of the algorithm

The simulation of the superiority and heredity process of biological evolution in the genetic algorithm is accomplished by three basic operation operators: selection, crossover, and mutation.

a) Selection

Before performing the selection operation, the fitness is first calculated. The fitness of the individuals in the population and its distribution determine the probability of selection for each individual in the alternative set. The operator chosen in this paper is the proportional fitness distribution, also known as roulette selection method.

The size of the probability of offspring retention is determined by calculating the probability of fitness of each individual. If an individual i, whose fitness is f_i, its probability of being selected is denoted as:

$$p_i=\frac{f_i}{\sum_{i=1}^{u} f_i}(i=1,2,\ldots\ldots,u) \tag{12}$$

where p_i is the probability of an individual being selected, u is the size of the population, and f is the fitness of the individual.

b) Crossover

Crossover operation is the process by which two new individuals are created by partial gene crossing over of two parent paired chromosomes according to certain principles.

c) Mutation

After the crossover operation, the mutation operator is to change some genes of the individual string in the population with a small probability, which plays a limiting role on the premature convergence of the algorithm while expanding the diversity of the population. In this paper, binary mutation is used.

(4) Determine the guidelines for stopping the run

The convergence of the genetic algorithm is heuristic, there is no strict convergence criterion, the basis for determining convergence is to determine whether the algorithm has reached convergence by whether the number of calculations reaches the maximum number of iterations, and whether the optimal solution has no change within a certain time number of conditions.

III. A. 3) Algorithm Parameter Improvement

In the particle swarm algorithm, w is the inertia weight, the physical meaning of which is the strength of a particle to continue a previous particle state. When the inertia weight is large the global search ability is sufficient, while this parameter is small is more helpful for local search. In general, the algorithm is more realistic when the initial value of inertia weight $\omega_{start} = 0.9$ and the final value $\omega_{end} = 0.4$. And different inertia weight decreasing strategies are suitable for different optimization seeking process, this paper proposes to construct three ways for inertia weight ω decreasing strategies.

Strategy one:

$$w(i) = ws - (ws - we) * (i / \max gen) \tag{13}$$

Strategy two:

$$w(i) = ws - (ws - we) * (i / \max gen)^2 \tag{14}$$

Strategy Three:

$$w(i) = we * (\frac{ws}{we})^{1/(1+10i/\max gen)} \tag{15}$$

where: ws is the initial inertia weight, generally taken as 0.9. we is the inertia weight at the end, generally taken as 0.4. i is the current number of evolutions, and $\max gen$ is the maximum number of evolutions.

The comparison of the three decay strategies is shown in Fig. 1. Strategy I is in between the other two methods, while the decreasing approach of Strategy II maintains a large inertia weight by decreasing slower in the early stages of evolution. Although strategy three can ensure better local search ability in the late evolution, the early decreasing is too fast, and the degree of decay is already more than half before approaching the 5th evolution, and this method can only approximate the final inertia weight, and the final value is slightly larger than we, and the inertia weight is even higher than that of the other two methods in approaching the last iteration, and the local search ability is insufficient.

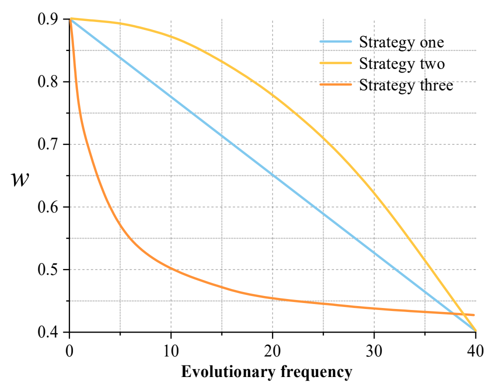

Figure 1: Comparison of three attenuation strategies

Through the analysis should be the decay strategy two optimal, this paper proposes to three strategies to a nonlinear function of algorithmic optimization to find out the point of great value to verify whether the conjecture is correct or not. The nonlinear function is shown below:

$$f(x) = \frac{\sin\sqrt{x^2 + y^2}}{\sqrt{x^2 + y^2}} + e^{\frac{\cos 2\pi x + \cos 2\pi y}{2}} - 2.71289 \tag{16}$$

Both X and Y take values ranging from -2 to 2.

Each method performs 100 maximum value optimization of the function and records the average value and the number of times it falls into a suboptimal solution, and the results of the three strategies are recorded into Table 1. The inertia weight decreasing strategy of strategy 2 does not fall into suboptimal solution once, and approaches the optimal solution most frequently, 100 times, and the average value is closer to the optimal solution of 1.0045 than the other two methods.This strategy retains the global search ability for a longer period of time in the first and middle phases, and can avoid falling into the suboptimal solution effectively.

Table 1: Results of the three policies

Strategy	Optimal value	Mean value	The number of suboptimal solution	The number that close to optimal solution
Strategy one	1.0089	0.9719	15	83
Strategy two	1.0089	1.0045	0	100
Strategy three	1.0089	1.9824	11	88

III. A. 4) Algorithm Combination Implementation

The particle swarm algorithm converges faster, but in the middle and late process of evolution, even if the parameters are improved, the problem of insufficient global search ability in the late evolution cannot be solved completely. Therefore, on the basis of improving the particle swarm algorithm, we add the crossover and mutation process in the genetic algorithm, and use the crossover of individual and group information as well as the way of generating its own mutation to increase the randomness.

When applying the improved hybrid particle swarm algorithm for fault recovery, assuming that the number of operable switches is k , the dimension of the particle swarm algorithm and the chromosome coding length of the genetic algorithm are both k . Meanwhile, the crossover probability, mutation probability, self-learning factor, social learning factor, maximum number of evolution, population size, upper and lower bounds of particle update rate, upper and lower bounds of particle position, and the range of variable values are set.

Using the $rands$ function to generate the initial population matrix and the initial speed matrix, the number of columns of the matrix is the number of dimensions of the particle swarm, analyze the topology of the current distribution network restoration model, and derive the expression of the evaluation function for completing the assignment of the weighted values in the form of the fun function as a fitness function in the algorithm's evolutionary process.

After the successful input of each parameter and the initial state of the distribution network reconstruction, the loop body is set up so that between the first evolution and the maximum number of evolution times, each loop goes through the particle velocity update, the particle position update, the crossover operation, and the mutation operation, and the $f\min con$ function is introduced every 10 generations of evolution times outside of this loop.

Every iteration is completed, if the evaluation value of the actual solution corresponding to the current evolved particle is less than the evaluation value of the current optimal solution, the current particle becomes the new optimal solution set, otherwise the original solution is kept unchanged, and enters the next generation of evolutionary comparison.

III. B. Algorithm superiority analysis

After obtaining the improved hybrid particle swarm algorithm, an optimization iteration is performed using the same simple function to compare it with the traditional particle swarm algorithm. The function selected is shown below:

$$y = x(1)^2 + x(2)^2 - 10 * \cos(2 * pi * x(1)) - 10 * \cos(2 * pi * x(2)) + 22 \tag{17}$$

Both algorithms set slower particle speed and, after the same maximum number of evolutions, the optimization curves obtained are shown in Fig. 2. The traditional particle swarm algorithm has a smooth and slow evolutionary process, and the optimal fitness value of the function is still not found until the maximum number of evolution times of 50 generations. 2 Its fitness at 50 generations is about 2.5. On the other hand, the improved hybrid particle swarm algorithm increases the optimization speed dramatically and there are sudden changes in the evolution process, especially after the introduction of the fmincon function in the 15th generation, the best fitness value is found at the evolution number of 17. Although the initial populations of both algorithms are randomly generated, the initial value of the improved algorithm is closer to the global optimal solution, which still shows that the improved algorithm has a great advantage.

IV. Analysis of examples

In order to verify that the method proposed in this paper can effectively optimize and reconfigure the new energy distribution network, the algorithm is applied to analyze the fault self-healing performance of the improved IEEE33 node system. The model IEEE33 node distribution system is used in this section. According to GB/T 12325-2008, the three-phase supply voltage deviation limit below 20kV is ±7% of the nominal voltage, so the normal range of the system node voltage magnitude is 0.93p.u. to 1.07p.u.. In addition, the chance constraint parameter is set to 0.9.

IV. A. Fault self-healing without DGs

The improved hybrid particle swarm algorithm and genetic algorithm (GA) in this paper are applied to the reconfiguration of the IEEE33-node distribution network, respectively, where the GA algorithm uses an integer-type ring coding method. The population size of both algorithms is set to 25, and the number of iterations is 50. Fig. 3 shows the iteration process of the two algorithms, and Fig. 4 shows the node voltage distribution of the system under the reconfiguration scheme. The GA algorithm has a slower convergence speed, and the convergence is completed only in 40 generations. The improved hybrid particle swarm algorithm can converge within 20 generations. The overall node voltage level of the system is significantly improved after the optimization and reconstruction. The reconfiguration schemes of the two algorithms are shown in Table 2. The reconfiguration scheme of the two algorithms is the same, and the active network loss is reduced from 202.1935kW to 138.2241kW, which indicates that the improved hybrid particle swarm algorithm in this paper can effectively realize the optimal reconfiguration of the distribution network, and promote the self-healing of new energy distribution network faults.

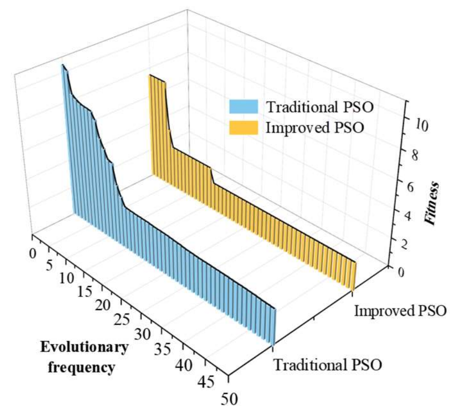

Figure 2: Optimization curve of two algorithms of the function

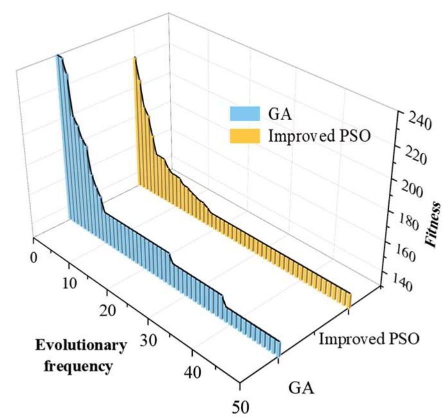

Figure 3: The iterative process of two algorithms

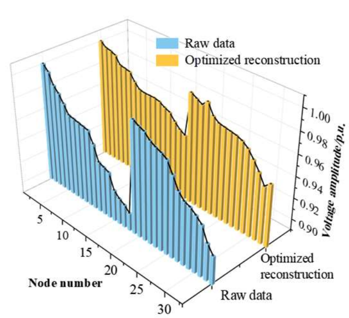

Figure 4: The node voltage distribution of the system under the reconstruction scheme

Table 2: Two algorithm reconstruction schemes

Methods	Broken branch	Active loss/kW	Minimum node voltage/p.u.
Initial network	[32, 33, 34, 35, 36]	202.1935	0.9161
GA	[8, 10, 13, 32, 36]	138.2241	0.9383
Improved PSO	[8, 10, 13, 32, 36]	138.2241	0.9383

IV. B. Fault self-healing with DGs

Distributed strip power (DG) is added to the model in the previous section, with photovoltaic power, wind power, and micro gas turbine at positions 10, 20, and 30. The shape parameter of the wind speed model is 12.08, the scale parameter is 12.55, and the two distribution parameters of light intensity are 4 and 2.

The reconfiguration schemes are set up as follows:

Scenario I: IEEE33 node system (considering load uncertainty, hereinafter) without adding DG and without reconfiguration.

Scenario II: IEEE33 node system with DG added but no reconfiguration.

Scheme III: IEEE33 node system, joining DG and with reconfiguration.

The parameters of the algorithm in this paper are set as follows: the population size is set to 25, and the number of iterations is 50. The optimized reconfiguration scheme for the IEEE33 node system is shown in Table 3. Fig. 5 shows the voltage expectation of all nodes after the reconfiguration, and Fig. 6 shows the voltage cumulative distribution curve of the end node 18, where the boundaries of the voltage crossing zone and the voltage safety zone are 0.93 p.u. After the reconfiguration of the distribution network containing DG, the amount of active loss of the whole system decreases by 57.35% and 40.59% compared to the two scenarios before reconfiguration (with and without DG) in that order, and the minimum voltage of the whole system improves by 6.09% and 4.37% compared to the two scenarios before reconfiguration (with and without DG) in that order, respectively. When the system is not connected to the DG, the voltage drop at the end of the system is relatively large, and there is a high risk of overrun at nodes 10 to 18 and nodes 30 to 33. When the system accesses DG but does not perform reconfiguration, although the overrun risk of some nodes can be reduced to some extent, the effect is not obvious, and the node voltage at the end of the feeder still has a high overrun risk, such as the overrun probability of node 18 in Fig. 6 is 69.87%. When the system is connected to the DG and reconfigured, the node voltage of the whole system is significantly improved, the voltage drop at the end of the system is reduced, and the voltage distribution at all nodes satisfies the confidence conditions. The above analysis shows that the new energy distribution network reconfiguration model has good fault self-healing performance.

Table 3: Optimization reconstruction scheme of the IEEE33 node system

Methods	Broken branch	Active loss/kW	Minimum node voltage/p.u.
Initial network	[32, 33, 34, 35, 36]	202.1935	0.9161
GA	[32, 33, 34, 35, 36]	145.1416	0.9312
Improved PSO	[8, 12, 20, 31, 36]	86.2276	0.9719

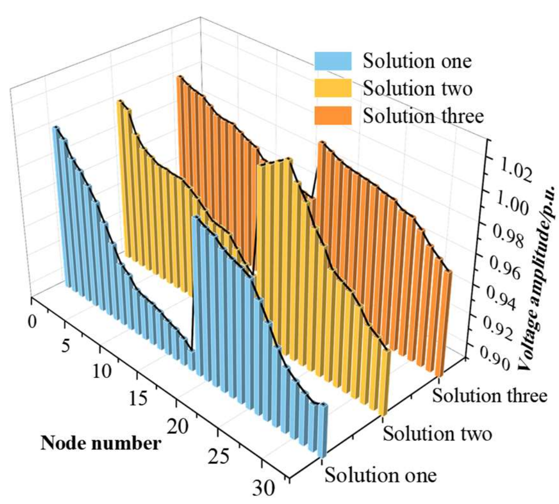

Figure 5: The expected value of all node voltage after refactoring

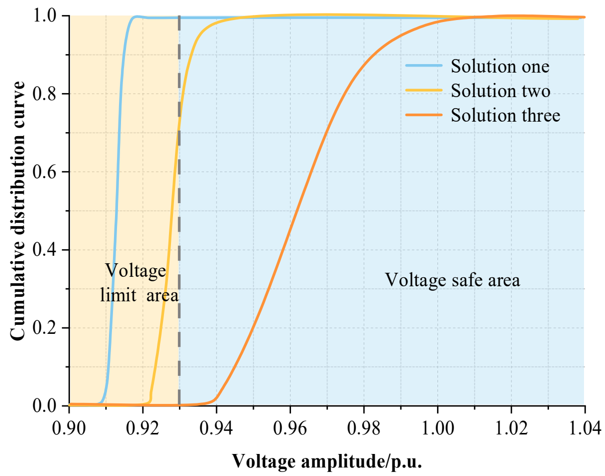

Figure 6: The voltage cumulative distribution curve of node 18

V. Conclusion

In this study, we construct an optimal reconfiguration model of distribution network for the fault recovery of new energy power grid, solve it with the improved hybrid particle swarm algorithm, and investigate the fault self-healing performance of new energy distribution network of the model through the analysis of examples. The improved particle swarm algorithm in this paper reaches the optimal fitness value of 2 when it evolves to 17 generations, while the fitness of the traditional particle swarm algorithm is still 2.5 when it evolves to 50 generations, which verifies the effectiveness of the optimization of the particle swarm algorithm in this paper. In the experiments of the IEEE33 node system, both in the reconfiguration of the distribution network without distributed power supply and in the reconfiguration scenario of the distribution network with distributed power supply, the node voltages of the system after the optimization and reconfiguration of this paper's method are greatly improved. In the case containing distributed power sources, the active losses of the system are reduced by 57.35% and 40.59%, the minimum voltage is improved by 6.09% and 4.37%, and the nodal voltages of the system are within the safety zone when the system is connected to the DG and undergoes reconfiguration. It is verified that the optimal reconfiguration method of new energy distribution network in this paper can effectively search for the optimal reconfiguration scheme to meet the requirements of safe operation of the distribution network, reduce the potential risk of system operation, and have better fault self-healing function.

The paper has made some research on the fault recovery problem of new energy distribution network containing distributed power sources, but the paper still has many shortcomings, which should be improved in the future research. For example, the modeling of distribution network uncertainty factors is relatively simple, which may have an impact on the results of trend calculation and needs to be further optimized.

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References

[1] Zhao, R., Tan, Y., Lu, J., Guo, W., & Du, H. (2024). A resilient self-healing approach for active distribution networks considering dynamic microgrid formation. Energy Science & Engineering, 12(1), 230-248.
[2] Sampaio, F. C., Leao, R. P., Sampaio, R. F., Melo, L. S., & Barroso, G. C. (2020). A multi-agent-based integrated self-healing and adaptive protection system for power distribution systems with distributed generation. Electric Power Systems Research, 188, 106525.
[3] Huang, F., Liu, Z., Wang, T., Zhang, H., & Yip, T. (2020). The Optimization Study about Fault Self-Healing Restoration of Power Distribution Network Based on Multi-Agent Technology. Computers, Materials & Continua, 65(1).
[4] Liu, X., Liu, M., & Yin, H. (2024). Application of QPSO-BPSO in fault self-healing of distributed power distribution networks. Energy Informatics, 7(1), 53.
[5] Arif, A., Ma, S., & Wang, Z. (2018, April). Dynamic reconfiguration and fault isolation for a self-healing distribution system. In 2018 IEEE/PES Transmission and Distribution Conference and Exposition (T&D) (pp. 1-5). IEEE.
[6] Reiz, C., Pereira, C. E., & Leite, J. B. (2023). A Self-Healing Strategy for Modern Distribution Networks. Energies, 16(16), 5890.
[7] Shen, Y., Chen, Y., Zhang, J., Sang, Z., & Zhou, Q. (2019). Self-healing evaluation of smart distribution network based on uncertainty theory. IEEE Access, 7, 140022-140029.

[8] Monadi, M., Farzin, H., & Rodriguez, P. (2019, November). A distributed self-healing method for active distribution systems. In 2019 8th International Conference on Renewable Energy Research and Applications (ICRERA) (pp. 483-488). IEEE.

[9] Shirazi, E., & Jadid, S. (2018). Autonomous self-healing in smart distribution grids using agent systems. IEEE Transactions on Industrial Informatics, 15(12), 6291-6301.

[10] El-Tawab, S., Mohamed, H. S., Refky, A., & Abdel-Aziz, A. M. (2022). Self-Healing of Active Distribution Networks by Accurate Fault Detection, Classification, and Location. Journal of Electrical and Computer Engineering, 2022(1), 4593108.

[11] Campos, R. M., Figueroa, C. C., Oyarzún, H. V., & Baeza, J. M. (2018, May). Self-healing of electric distribution networks: A review. In 2018 7th International Conference on Computers Communications and Control (ICCCC) (pp. 63-70). IEEE.

[12] Arefifar, S. A., Alam, M. S., & Hamadi, A. (2023). A review on self-healing in modern power distribution systems. Journal of Modern Power Systems and Clean Energy, 11(6), 1719-1733.

[13] Nejad, R. R., & Sun, W. (2021). Enhancing active distribution systems resilience by fully distributed self-healing strategy. IEEE Transactions on Smart Grid, 13(2), 1023-1034.

[14] Guan, L., Chen, H., & Lin, L. (2021). A multi-agent-based self-healing framework considering fault tolerance and automatic restoration for distribution networks. IEEE Access, 9, 21522-21531.

[15] Behbahani, M. R., Jalilian, A., Bahmanyar, A., & Ernst, D. (2024). Comprehensive review on static and dynamic distribution network reconfiguration methodologies. Ieee Access, 12, 9510-9525.

[16] Qiao, X., Luo, Y., Xiao, J., Li, Y., Jiang, L., Shao, X., ... & Cao, Y. (2020). Optimal scheduling of distribution network incorporating topology reconfiguration, battery energy system and load response. CSEE Journal of Power and Energy Systems, 8(3), 743-756.

[17] Shi, Q., Li, F., Olama, M., Dong, J., Xue, Y., Starke, M., ... & Kuruganti, T. (2021). Network reconfiguration and distributed energy resource scheduling for improved distribution system resilience. International Journal of Electrical Power & Energy Systems, 124, 106355.

[18] Bernardon, D. P., Mello, A. P. C., Pfitscher, L. L., Canha, L. N., Abaide, A. R., & Ferreira, A. A. B. (2014). Real-time reconfiguration of distribution network with distributed generation. Electric Power Systems Research, 107, 59-67.

[19] Wen, J., Tan, Y., Jiang, L., & Lei, K. (2018). Dynamic reconfiguration of distribution networks considering the real-time topology variation. IET Generation, Transmission & Distribution, 12(7), 1509-1517.

[20] Mishra, A., Tripathy, M., & Ray, P. (2024). A survey on different techniques for distribution network reconfiguration. Journal of Engineering Research, 12(1), 173-181.

[21] Liu, J., & Srikantha, P. (2021). Adaptive topology reconfiguration in smart distribution networks. IEEE Transactions on Signal and Information Processing over Networks, 7, 716-729.

[22] Liu, Y., Li, J., & Wu, L. (2018). Coordinated optimal network reconfiguration and voltage regulator/DER control for unbalanced distribution systems. IEEE Transactions on Smart Grid, 10(3), 2912-2922.

[23] Agrawal, P., Kanwar, N., Gupta, N., Niazi, K. R., & Swarnkar, A. (2021). Resiliency in active distribution systems via network reconfiguration. Sustainable Energy, Grids and Networks, 26, 100434.