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Active Distribution Network Fault Location Based on Petri Nets and Improved Particle Swarm Optimization Algorithm

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ABSTRACT

To address issues such as inadequate fault tolerance, long computation time, and limited universality in fault location for active distribution networks, this paper proposes a fault location method that combines Petri nets with an improved particle swarm optimization (PSO) algorithm. This method enhances the efficiency of fault location in distribution networks with distributed power sources, demonstrating good applicability and convergence, especially in complex network scenarios. The results from two test functions and simulation analyses of two types of node distribution networks show that (1) in the single-point fault simulation, the improved algorithm successfully located the fault in the ninth iteration, outperforming the 14th iteration result of the standard PSO algorithm. (2) In networks with randomly interconnected distributed power sources, the algorithm accurately located both single and multiple faults. (3) Experimental verification further supports the simulation results, proving the effectiveness of this method in practical applications.

***Index Terms*—**Active distribution network, fault location, Petri nets, particle swarm optimization algorithm.

I. INTRODUCTION

As modern power grid technology advances, the distribution network has become increasingly resilient, playing a less burdensome role in the overall power system [1]. This ensures the distribution network's stable operation, allowing swift identification and resolution of faults. Consequently, electricity users can rely on a safe and uninterrupted power supply. The inclusion of distributed energy sources adds complexity to fault detection in the distribution grid, which in turn reduces the reliability and consistency of the power supply for consumers [2]. It is particularly important to ensure the reliability and continuity of user electricity consumption. Therefore, it is very important to quickly detect faults and ensure the speed and reliability of fault location, so as to facilitate rapid maintenance by power grid maintenance personnel [3]. In 2008, the International Large Grid Conference introduced the concept of active distribution networks. This concept aims to effectively manage the diverse distributed generation (DG) sources connected to the network. The goal is to optimize the utilization of existing distribution network infrastructure and resources to address the evolving requirements of the distribution network. Automation in distribution networks relies on data gathered by feeder terminal units (FTUs) to facilitate fault location algorithms. These fault location methods are categorized into direct and indirect approaches [4]. Fossil fuels such as coal, oil, and gas are a finite resource that is being exhausted, while wind, solar, geothermal, and other renewable energy sources are being applied more and more. As distributed power sources continue to integrate into the power grid, they significantly alter its network structure. This complexity in the grid's layout results in shifts in power flow distribution and compromises the reliability of the distribution network system. Consequently, traditional fault localization methods become inadequate, exacerbating the challenges in pinpointing faults [5]. Given that the distribution network serves as the sole conduit for electricity users, it bears immense significance in meeting the rising electricity demands accompanying China's economic growth and improved living standards. Thus, ensuring the safety and reliability of electricity consumption is paramount, alongside safeguarding the integrity of the power grid itself. Therefore, further research on fault location in distribution networks has great theoretical significance [6].

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II. Literature Review

Faced with power grid fault diagnosis with temporal information constraints, improvements have been made in Petri net fault diagnosis both domestically and internationally. As proposed by Xu et al., the time information in alarm information is applied to the Petri net fault diagnosis model, which makes the fault diagnosis results more accurate and also provides a certain degree of fault tolerance for uncertain alarm information [7]. Moreover, this approach enables the prediction of component failure timing by leveraging the outcomes of the fault diagnosis process. It also aids personnel in assessing protection mechanisms and circuit breaker actions indicated in alarm data. Cheng et al. proposed a new approach combining Fuzzy Petri net (FPN) and Comprehensive Learning Particle Swarm Optimization (CLPSO). They employed this approach in diagnosing faults in intricate motor systems. The research results showed that using the established system model for fault diagnosis can accurately and intuitively express the fault propagation process of motors, and it is possible to improve failure treatment and device maintenance of motors [8]. Jiang et al. proposed using Petri nets to formalize and integrate the structures of power transmission systems and their control systems, which can avoid output interruptions during important power source fault diagnosis and fault recovery processes [9]. However, both of these methods require experienced supervisors to choose the appropriate fault recovery method, which still relies to some extent on manual experience. Jiang et al. designed an offline expert system for diagnosing faults in distribution networks, utilizing the operational structure and functions of relays and circuit breakers [10].

But when diagnosing power grid failure, it is very hard to forecast its topology. When faults occur, the protection of suspicious faulty components and the action of circuit breakers are complex, and the corresponding database applied by the expert system is also changing. Therefore, when conducting fault diagnosis, the knowledge base and rule base often require more time for searching and reasoning, but in practical work, they often cannot meet practical needs. KAluđer et al. proposed applying rough set theory to fault diagnosis of power transformers and transmission lines, which can effectively determine the types of transformer equipment faults and line faults [11]. This paper explored the method of power transformer fault diagnosis using rough set theory, and combines the advantage based rough set technology. advantage-basedThe advantage based rough set method was applied to the research of power transformer orderly maintenance, and the algorithm flow chart of transformer orderly maintenance was established. Furthermore, this paper presents an integrated failure diagnosis system with DS Proof Theory to solve the problem of uncertain information and data loss in the failure of transformer, and has achieved good performance in information fusion. Fault diagnosis of power lines in distribution networks is also an important component, responsible for the transmission of electricity and energy. Liu et al. proposed applying a genetic optimization algorithm to fault location of DC distribution network lines. By adopting the genetic algorithm in the distribution network, not only can a series of interference factors be avoided, such as the interference caused by errors in fault information collection, but this method also has strong resistance to transition resistance [12]. However, for large and complex distribution networks, simple genetic optimization algorithms are prone to premature convergence of optimization results, leading to local optima. Dashtdar and colleagues proposed a novel approach utilizing the impedance matrix and phasor measurement units (PMUs) within the network to enhance fault localization, considering various fault types and resistances during line faults. Their study suggests that increasing the number of PMUs enhances the accuracy of fault localization [13]. This approach identifies fault locations by analyzing impedance transfer between PMUs and faults, using the fault distance as a key parameter. It notably factors in uncertainties in network parameters and applies the least squares method for fault data to achieve the best possible outcome. One key advantage of this method is its resilience to variations in fault types and short-circuit resistances, ensuring robust fault localization regardless of these factors.

The use of Petri nets can indeed quickly and accurately locate faults in small distribution networks with fewer nodes, and Petri nets have many advantages [14]. However, in reality, large-scale distribution networks have a vast number of nodes, leading to complex fault localization, significant computation, and model scalability issues, especially with the integration of distributed power sources. The network structure evolves from a traditional single power source to a complex multi-power source network, making it difficult to predict actual conditions and necessitating multiple assumptions when using Petri nets. Therefore, a single Petri net-based fault localization method is insufficient for fast and accurate fault detection in distribution networks with distributed power sources. It is necessary to use optimization algorithms to enhance Petri nets for fault localization in such networks, ultimately meeting the need for rapid and accurate fault detection in complex distribution networks with distributed power sources. Particle swarm optimization possesses strong global and local search capabilities, and the Petri net model is suitable for analysis within discrete event-related dynamic models. Theoretically, the search operations of PSO correspond to discrete dynamic events, providing a solid rationale for using PSO to optimize Petri net-based fault localization methods [15].

Therefore, this paper adopts an improved PSO algorithm to enhance the Petri net-based fault localization method. The inertia weight of the improved PSO is updated in a nonlinear dynamic adaptive manner, while the learning factor is updated asynchronously. This accelerates the search speed in the initial iterations, prevents the algorithm from converging prematurely to a local optimum, and improves search precision in later iterations, thereby enhancing the accuracy of the PSO. Experimental results and simulations demonstrate that the improved algorithm shows high efficiency and accuracy, particularly in complex network structures, and outperforms other methods in terms of computational load and fault tolerance, ensuring faster convergence and fault detection.

III. RESEARCH METHODS

A. Basic Concepts of Petri nets

Definition 1: Elementary Petri nets, as illustrated in (1):

$$\sum C = \left(S, T; F, M\right) \tag{1}$$

$\sum C$ has the following transition occurrence rules:

1) For any transition $t \in T$, if (2):

$$\forall s \in S : s \in {}^{\cdot}t \rightarrow M_{(s)} \geqslant 1, \tag{2}$$

Then it is said that t has permission to occur at the identifier M, marked as M [t>;

2) If M [t>, then t can satisfy the condition in M, as shown in (3):

$$0 < q_{(M,t)} \leqslant min\left\{M_{(s)} \# s \in \cdot t\right\} \tag{3}$$

3) If $q_{(M,t)}$ occurs and t obtains a new identifier M' (denoted as M [t, q (M, t)>M'), then (4) is used:

$$M'(s) = \begin{cases} M_{(}(s) - q(M,t), \text{if } s \in \cdot t - t' \\ M_{(s)} + q(M,t), \text{if } s \in t^{\cdot} - t^{\cdot} \\ M_{(s)}, \text{other} \end{cases} \tag{4}$$

Definition 2: Let $\sum D = (B, E; F, c_0)$ be one basic network, $e_1, e_2 \in E$, c be one state of $\sum D$, if (5) and (6):

$$c\left[e_1 > \quad c\left[e_2 >;\right.\right. \tag{5}$$

$$c\left[e_1 > c_1 \to c_1\left[e_2 > \quad c\left[e_2 > c_2 \to c_2\left[e_1 > 0\right.\right.\right.\right. \tag{6}$$

Then it is said that e_1 and e_2 are concurrent in state c, denoted as c [{e_1, e_2}>.

Definition 2: The basic network system sublimated from Definition 1 can be used to analyze the occurrence of parallel states [16, 17].

B. Basic Particle Swarm Optimization Algorithm

Particle swarm optimization is a method to solve the problem of finding the best way to solve the problem. In each iteration, the algorithm updates the system's velocity vi and position xi by recalculating their values. The iteration process is governed by (7) and (8):

$$v_{id}^{k+1} = \omega_{id}^{k} + c_1 r_1\left(p_{\text{best},id}^{k} - x_{id}^{k}\right) + c_2 r_2\left(g_{\text{best},id}^{k} - x_{id}^{k}\right); \tag{7}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{8}$$

In the formula, x_{id}^{k+1} and v_{id}^{k+1} represent the position and velocity of particle i in the next iteration, respectively; ω is the inertial weight, $c1$ and $c2$ are the learning factors, and $r1$ and $r2$ are any real numbers produced in the present iteration from [0,1].

In the equations, x_{id}^{k+1} and v_{id}^{k+1} denote the position and velocity of particle i in the upcoming iteration, respectively. The parameterol represents the inertia weight, while c1 and c2 are the cognitive and social learning factors. $r1$ and $r2$ are random real numbers from 0 to 1 produced during the current iteration; $p_{\text{best},id}^{k}$ is the historical best position of the iteration cutoff point i; $g_{\text{best},id}^{k}$ is the overall optimal position for the time cutoff point subgroup iteration [18].

Calculated to the k+1st order, the update site of the ith particle can be obtained from (9) [19].

$$\begin{cases} x_{id}^{k+1} = 1 & rand(\cdot) < Sigmoid\left(v_{id}^{k+1}\right) \\ x_{id}^{k+1} = 0 & rand(\cdot) \geqslant Sigmoid\left(v_{id}^{k+1}\right)^{\circ} \end{cases} \tag{9}$$

In (9), *rand* (ned from (9) is the i-th subgroup iteration earning factors, $r1$, [0, 1]. The *sigmoid* function is defined in (10):

$$\text{Sigmoid}\left(v_{id}^{k+1}\right) = \frac{1}{1 + e^{\left(-v_{id}^{k+1}\right)}} \tag{10}$$

From (10), it can be seen that the higher the velocity, the closer the value of the sigmoid function is to 1, and when the velocity is very small, the value of the sigmoid function also tends to 0 [20]. In order to prevent overflow of the sigmoid function due to excessive particle velocity, the particle velocity is set within the range of [−4, 4], and the corresponding sigmoid function is adjusted within the range of [−0.98, 0.98], as shown in (11):

$$\text{Sigmoid}\left(v_{id}^{k+1}\right) = \begin{cases} 0.98 v_{id}^{k+1} > 4 \\ \dfrac{1}{1 + e^{\left(-v_{id}^{k+1}\right)}} - 4 \leqslant v_{id}^{k+1} \leqslant 4 \\ -0.98 v_{id}^{k+1} < -4 \end{cases} \tag{11}$$

C. Improving Particle Swarm Optimization Algorithm

In order to address the common phenomenon of premature convergence in standard PSO algorithms, improvements are usually made to the algorithm in terms of its own parameters and integration with other optimization algorithms [21]. In this paper, the basic parameters of PSO, the inertial mass, and the learning factors c_1 and c_2 have been specified. The effect of these two factors on PSO optimization is seen as follows: increasing the number increases the overall search power of the algorithm, but reducing it increases the local search power. Specifically, c_1 and c_2 represent the significance of individual and collective experience in the population's search process. To strengthen the global search performance, increasing c_2 and decreasing $c1$ is required. Conversely, to enhance local search capability, c_1 should be raised, and c_2 should be reduced.

The author's discussion on inertia weight ω using the nonlinear dynamic adaptive update method shown in (12) explains that the learning factors c_1 and c_2 are updated according to asynchronous linear laws, as shown in (13) and (14). Inertia weight in the initial stage of optimization iteration ω learning factor c_1 has a larger value and c_2 has a smaller value, which is opposite in the later stages of iteration. This approach is advantageous as it speeds up the search at the beginning of the iteration, avoids the convergence of the PSO method to the local optimum, and increases the precision of the final iteration, thereby enhancing the accuracy of the PSO algorithm [22].

$$\omega = \begin{cases} \omega_{min} + \left(\omega_{max} - \omega_{min}\right) \cdot sin\left(\dfrac{\pi \cdot f}{f_{\text{avg}}}\right), f \le f_{avg} \\ \left(\omega_{max} - \omega_{min}\right) \cdot sin\left(\dfrac{\pi \cdot f}{f_{max}}\right), f > f_{\text{avg}} \end{cases} \tag{12}$$

$$c_1 = c_{1s} + \frac{t_{\text{iter}}}{t_{\text{iter},max}} \times \left(c_{1e} - c_{1s}\right) \tag{13}$$

$$c_2 = c_{2s} + \frac{t_{\text{iter}}}{t_{\text{iter},max}} \times \left(c_{2e} - c_{2s}\right) \tag{14}$$

In the formula ω_{max}, ω_{min}——inertial weight ω upper and lower limits; f—the fitness function value of a certain particle; f_{avg}—the average fitness function of the current population; f_{max}—maximal number of Fit Function for Current Population; C_{15}, C_{1e}—the initial and final values of the learning factor c_1; C_{2s}, C_{2e}—initial and terminal values of the learning factor c_2; t_{iter}— current iteration count; and $t_{\text{iter},max}$—Maximal Iterative Count of Algorithm.

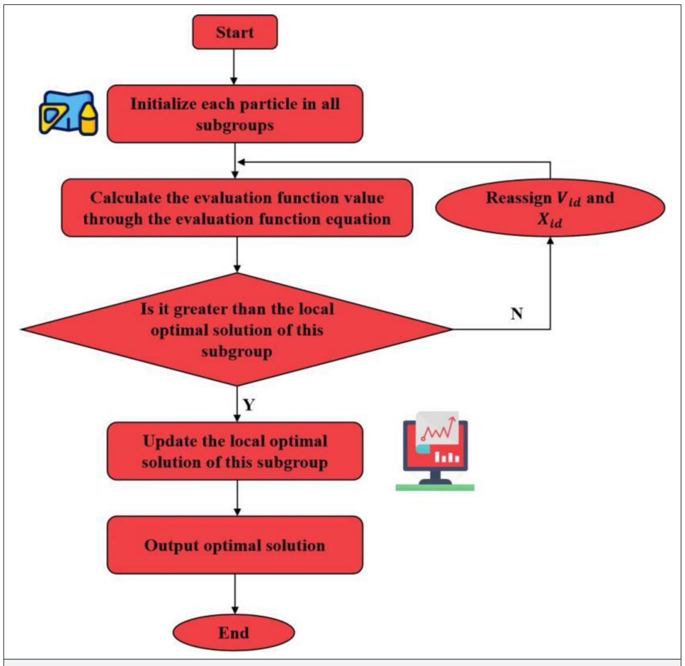

Fig. 1. Subgroup grouping flowchart based on the optimization algorithm.

D. Research on Fault Location Method for Distribution Network Based on Particle Swarm Optimization Petri Net

Exploring fault localization methods in distribution networks with distributed energy sources presents significant potential for reducing the impact of these sources on overall network performance. The Petri net fault location method discussed earlier has drawbacks such as a complex process, large computational load, and easy model enlargement. The utilization of the Petri net approach for fault localization in distribution networks with distributed power sources is constrained by significant limitations. Thus, in the next chapter, PSO is introduced as a way to enhance Petri Nets governance. This improved methodology can then be effectively employed for real-world analysis of fault sections within distributed power distribution networks. The conclusion that the optimization algorithm can accurately locate fault sections is drawn, proving the feasibility of the optimization algorithm.

1) Petri Net Optimization Based on Particle Swarm Optimization

The Petri network, which is improved by PSO, makes use of the advantages of PSO. This synergy ensures optimal control of the Petri net, enhancing its effectiveness in fault localization within distribution networks. That is, the problems to be processed by the Petri net are first divided into blocks and then processed by the Petri net. This greatly improves the computational speed and saves a lot of time by reducing the size of the problem. There are generally two methods for block processing. The first is domain decomposition, which decomposes a large problem area into multiple small problem areas and then processes them one by one. The second method is functional decomposition, which decomposes a large problem into multiple small problems and then processes them one by one [23]. The Petri net optimized by the PSO Algorithm adopts the first method mentioned above, which is the domain decomposition method. The subgroup grouping process and population grouping process of the Petri net algorithm based on PSO are shown in Figs. 1 and 2, respectively. Before using optimization algorithms for fault location, the first step is to set the encoding method in the form of 1, 0, −1, and construct switch functions and evaluation functions. Then, combined with the structure of the distribution network, label the switch nodes and sort the corresponding lines of each node. The fault status information is provided by the feeder terminal device and processed before the 1 or −1 element appears, the circuit corresponding to element 0 must have no faults. The more elements there are, the faster the operation speed. Moreover, there are continuous and

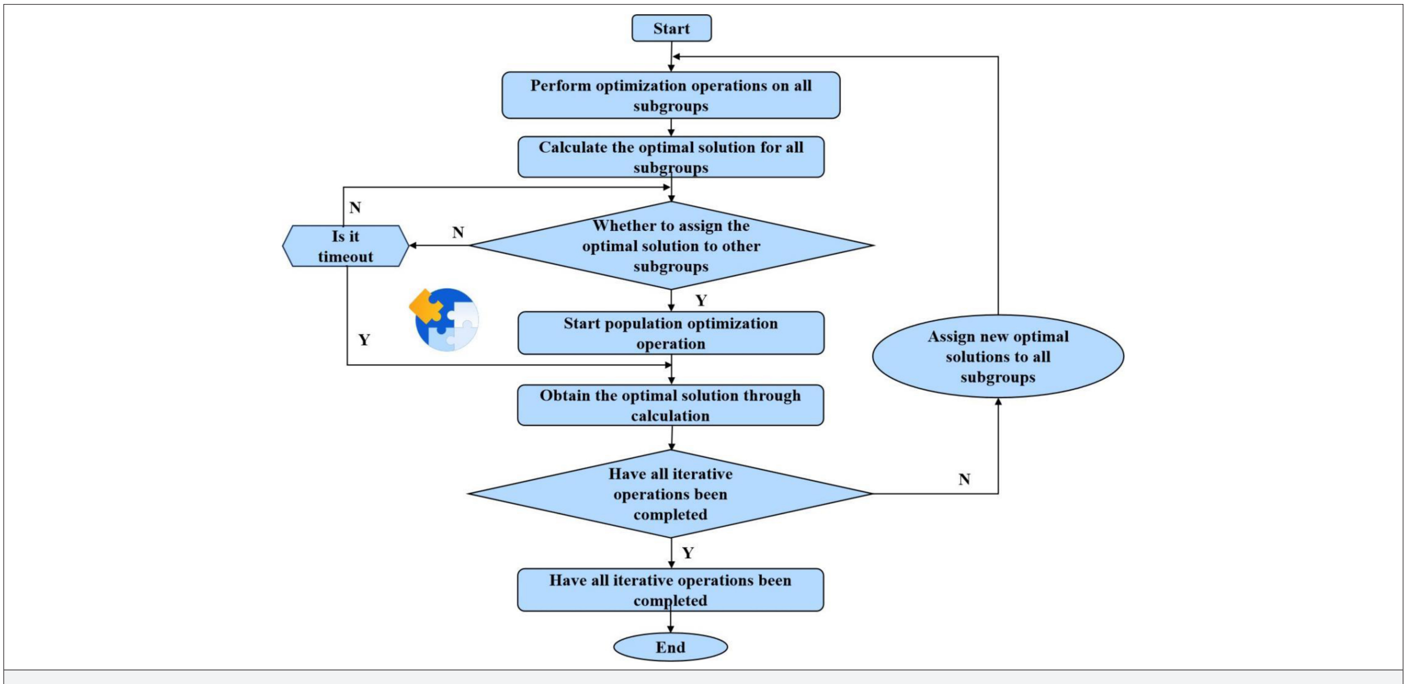

Fig. 2. Flow chart of population grouping based on optimization algorithm.

TABLE I. TEST RESULTS

Tested Functions	Number of Tests	Test Cycle	Test Type	Petri Net	Optimization Algorithm
$f(a)$	50	500	Average value	$6.0502 \times 10^{0\text{-}1\text{-}2\text{-}3\text{-}4\text{-}5\text{-}6\text{-}7\text{-}8}$	$2.1861 \times 10^{0\text{-}1\text{-}2\text{-}3\text{-}4\text{-}5\text{-}6\text{-}7\text{-}8\text{-}9}$
$f(b)$	50	500	Average value	10.5363	1.4704

concentrated areas corresponding to element 0 that can be directly processed by optimization algorithms through block operations.

To validate the optimization algorithm's feasibility, its performance was assessed using two test functions: the Sphere function and the Rosenbrock function. Testing parameters and cycles were uniformly set, with values of 50 and 500, respectively. The test type focused on evaluating the average values. Table I presents the test results, accompanied by (15) and (16) below:

$$\text{Sphere function: } f(a) = \sum_{i=1}^{k} a_i^2 \tag{15}$$

$$\text{Rosenbrock function: } f(b) = \sum_{i=1}^{k-1} 100\left(b_{i+1} - b_i\right)^2 + \left(b_i - 1\right)^2 \tag{16}$$

From Table I, it is evident that Petri nets optimized based on PSO have superior performance compared to ordinary Petri nets and can significantly save computational time.

2) Petri Net Fault Location Process Based on Particle Swarm Optimization

Employing Petri nets, which are improved by PSO, is used to locate the fault in the grid. These steps outline the optimization algorithm's implementation process effectively [24]:

1. Begin by initializing all parameters associated with the optimization algorithm. The population size is set to N, the space is defined as d, and the largest iteration count is set as K. Finally, set two acceleration factors to C_1 and C_2, with $C_1 = C_2$.
2. Initialize the positions and velocities of all particles in the optimization algorithm as v_{id} and X_{id}, respectively.
3. According to the established maximum number of K steady operations, calculate the evaluation function values of each particle through the fitness function.
4. Compare the calculated evaluation function value with the pbest value.
5. Compare and select the optimal evaluation function value with GBest through comparison and contrast.
6. By comparing the information sequence with the feeder terminal device, check if they match. If they match, end the operation and directly output the result. If they do not match, continue the operation according to the established maximum of K times until they match or the number of iterations is exhausted [25].

3) Fault Localization in Distribution Networks with Distributed Power Sources Based on Optimization Algorithms

Considering the IEEE standard node distribution network interconnected with distributed power sources as a case study, the inclusion of distributed power sources necessitates a modification in line coding. Specifically, a "−1" notation needs to be introduced alongside the traditional "0-1" form to accommodate these connections. This means that the feeder terminal device measures the current information state opposite to the specified positive direction, monitors the line status through the feeder terminal device in the distribution network, and outputs a sequence of fault status information based on the alarm information. According to the pre-set function expression, the fault state information sequence is operated on, and the Petri net is enhanced and managed through grouping with the PSO algorithm. Then, by using the optimized algorithm, a failure can be recognized in a power grid, which can accurately determine the position of a failure by means of a comprehensive comparison.

The flowchart of Petri net fault localization based on PSO is shown in Fig. 3.

For Petri nets optimized based on PSO, in what aspects are they superior to the original Petri net algorithm?

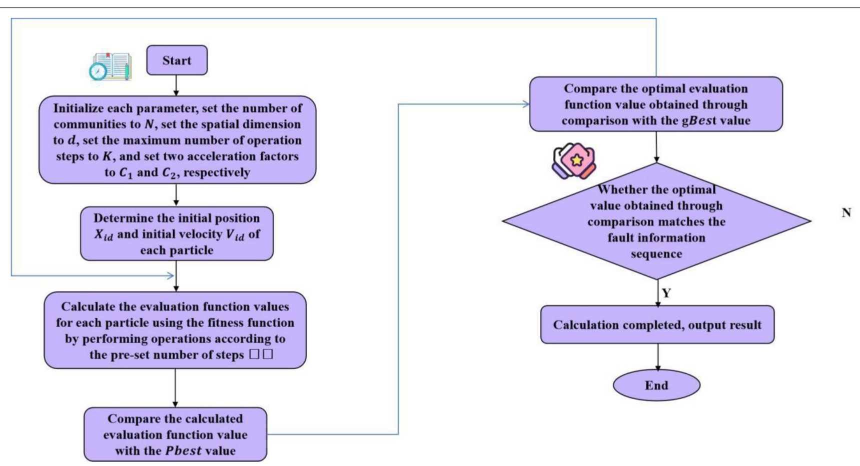

Fig. 3. Flow chart of Petri net fault localization optimization based on particle swarm optimization.

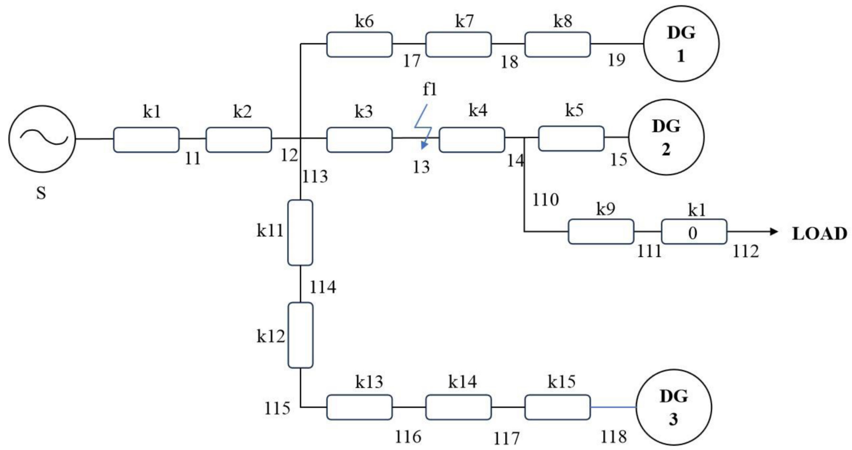

Fig. 4. Simulation example.

1. Through testing with the Sphere function and Rosenbrock function, it was found that the optimized algorithm significantly improved computational speed and saved computational time.
2. In distribution networks featuring extensive distributed power sources, the optimization control facilitated by the PSO Algorithm streamlines the process by requiring only a single assumption of the positive direction. In contrast, conventional Petri nets necessitate multiple assumptions of the positive direction when applied to fault localization in such networks.
3. Optimization algorithms can achieve immediate priority processing of faulty sections, greatly improving the accuracy of the algorithms.
4. The Petri net optimized based on PSO is not affected by the increase of lines and the connection of distributed power sources, while the ordinary Petri net is greatly affected by the above two reasons and has limitations [26, 27].

IV. RESULT ANALYSIS

A. Example 1

Assuming the active distribution network example shown in Fig. 4 contains three DGs, k_1–k_{15} are switch nodes with FTUs, l_1–l_{18} are the feeder sections corresponding to each switch node, and Figure 4 is a single point fault schematic diagram of l_3 fault [28].

When iterating the improved particle swarm, the particle swarm has a dimension of 20 and iterates 25 times. The learning factor $c_1 = c_2 = 2.1$ is used, and the weights are assigned between 0.2 and 0.9 for debugging. According to flowchart 3, write a program for single-point fault simulation. When all three DGs are connected to the distribution network and the iterative calculations yield consistent results with the overcurrent information uploaded by the FTU—denoted as [111-1-1-100-1-1-1]—it indicates that DG l_3 has encountered a failure. This is illustrated by the convergent profile of the single-spot failure, as shown in Fig. 5. Remarkably, PSO reaches the optimum solution in the ninth iteration and is able to quickly detect the failure. On the other hand, the PSO can only get the best result at the 14th iteration, which is not as effective as the modified one. These differences show that the PSO is more effective in optimizing the location of the fault in the grid [29].

In comparison with PSO, this approach makes use of the Petri net's concurrent operational properties, significantly curtailing the time needed for fault localization. Comparison of operations between the two methods. As shown in Table II.

B. Example 2

To further validate the accuracy of the optimization algorithm, this section chooses a more representative structure of the IEEE standard 33-node distribution network, illustrated in Fig. 6.

Fig. 6 illustrates the configuration of the distribution network, where G serves as the primary power source, and DG1, DG2, and DG3 are distributed power sources connected to the end of each branch. RL represents the connected load [30]. Simulation results are summarized in Table III.

By applying optimization algorithms to perform various experiments on IEEE standard 33-node distribution networks with integrated distributed power sources, the experimental results in the table above show that in various situations of distributed power source access, that is, by randomly integrating distributed power sources into the distribution network, the optimization algorithm can effectively identify faults within networks that include distributed power

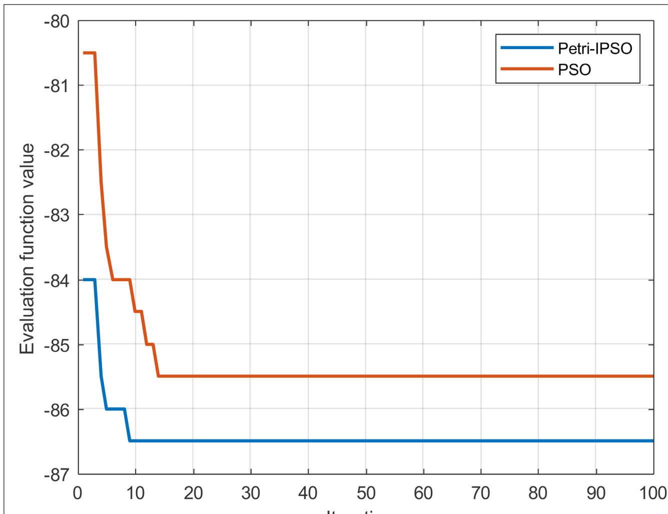

Fig. 5. Single point fault convergence curves of two algorithms.

TABLE II. COMPARISON OF OPERATIONS BETWEEN TWO ALGORITHMS

Algorithm	Convergence Times	Simulation Time/ms
Basic particle swarm optimization	14	20.72
Particle swarm otimization algorithm based on Petri nets	9	14.65

sources, addressing both single and multiple point faults [31]. This proves that the optimization algorithm has high accuracy. When ordinary Petri nets are applied to fault location in distribution networks with distributed power sources, the exponential increase in the amount of state information often occurs due to the addition of equipment and the expansion of the network, resulting in a decrease in the fault tolerance ability of Petri net methods. It is difficult to detect erroneous alarm information and cannot meet the basic requirements of accurate and fast fault location in distribution networks with distributed power sources.

C. Experimental Verification

The test is conducted on a 30-node grid with a nominal voltage of 12.45 KV, which is composed of 28 branches, 10 connecting switches, 10 condenser sets, and 2 distributed power supplies. The distributed supply has a reactive power range of 0–750 KW, 3 MW of active power, and a nominal capacity of 3715 KW. The three phase power foundation is 10 MVA, and the baseline is 12.45 KV. Each two nodes are grouped into one section, dividing the network into 15 sections. Fifteen wireless sensors are installed, collecting 1.26 GB of state data, and MATLAB is used to simulate and supplement the historical fault data. According to the design approach, the error location is automatic, and 8 randomly chosen results are selected (as illustrated in Table IV). The results indicate that the detected fracture segments are consistent with the real fault segments. The detailed performance of the location approach is assessed.

Based on the above experiments, multiple test results of automatic fault location in distribution networks can be obtained. To achieve quantitative testing of fault location performance, the experiment

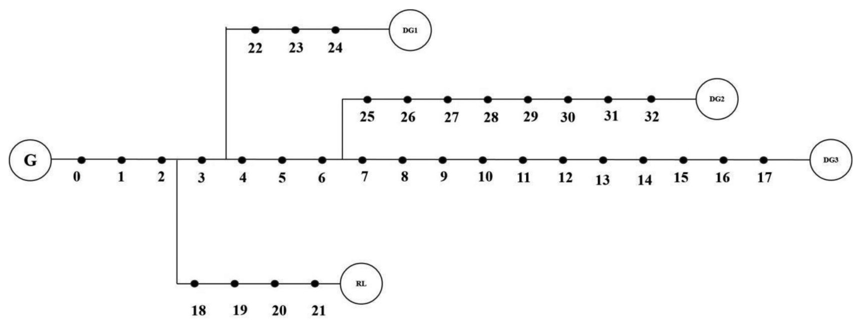

Fig. 6. Schematic diagram of a 33-node distribution network with multiple distributed power sources.

TABLE III. LIST OF SIMULATION RESULTS FOR 33 NODE DISTRIBUTION NETWORK

Fault Information	Fault Type	Number of DG Connections	Final Solution	Anchor Point
[111000000000000000000011-100000000]	Single-point	DG1	[00000000000000000000001000000000]	23
[11-1-1-1-100000000 0000000-1-1-1-1-1-1-1-1-1-1]	Single-point	DG1,G2	[01000000000000000000000000000000]	2
[1111111111-1-1-1-1-1-1-1000000000000000]	Single-point	DG1, DG3	[00000000010000000000000000000000]	10
[11111100000000000000000111111-1-1]	Single-point	DG2	[00000000000000000000000000000100]	30
[11111111111111110000001-1-100000000]	Multipoint	DG1	[00000000000000100000010000000000]	15, 22
[111111000000000001100000111111-1]	Multipoint	DG1, DG2	[00000000000000000010000000000010]	19, 31
[1110000000000000000010-100000000]	Multipoint	DG1, DG2, DG3	[00000000000000000000010100000000]	22, 24
[111111111111111-1-100000001111-1-1-1-1]	Multipoint	DG2, DG3	[00000000000000100000000000010000]	15, 28
[1111111-1-1-1-1-1-1-1-1-1-1000000011100000]	Multipoint	DG1, DG3	[00000010000000000 000000000100000]	7, 27
[1111111111111111-100001-1-11111111-1]	Multipoint	DG1, DG2, DG3	[00000000000000010 000010000000010]	16, 22, 31
[11111111111-1-1-1-1-1-1111011000000000]	Multipoint	DG2, DG3	[00000000001000000 001001000000000]	11, 20, 23

TABLE IV. AUTOMATIC POSITIONING RESULTS OF POWER DISTRIBUTION NETWORK SFAULT

Fault Section	Suspected Section	Located Fault Section
10-11	9-10, 10-11	10-11
13-14	10-11, 13-14	13-14
2-3	1-2, 3-4	2-3
5-6	4-5, 5-6	5-6
7-8	7-8, 8-9	7-8
3-4	2-3, 3-4	3-4
14-15	8-9, 14-15	14-15

uses the zone selection error rate and Root Mean Square Error (RMSE) as accuracy evaluation metrics for the automatic fault location method. The region choice error ratio is defined as the ratio of misrecognized samples to the sum of failure samples, which can be used as a measure of the precision of failure location. A formula is given in (17).

$$\eta_{\text{Line}} = 1 - \frac{N_{\text{cor}}}{N} \times 100\% \tag{17}$$

In the equation, η_{Line} represents the zone selection error rate for fault location in the distribution network. N_{cor} denotes the number of accurately identified fault zones, while N refers to the total number of fault samples. A lower zone selection error rate indicates higher accuracy in fault location. Root Mean Square Error, which measures the precision of fault location, is calculated using (18).

$$RMSE = \sqrt{\frac{1}{m}\sum_{m=1}\left(r - r'\right)^2} \tag{18}$$

In the formula, *RMSE* represents the Root Mean Square Error of fault location in the distribution network; m is the number of fault samples; r is the located value; and a r' is the actual value. A higher *RMSE* indicates lower accuracy in fault location.

Based on these two metrics, a comparison is made between the proposed method, the quantum annealing algorithm-based method, and the basic PSO-based method. Experimental data are substituted into (17) and (18), resulting in the distribution network fault zone selection error rate (Table IV) and RMSE for automatic fault location (as shown in Fig. 7).

By analyzing the information presented in Table IV and Fig. 7, the following conclusions can be drawn regarding the zone selection error rate. The proposed method performs best, with a maximum rate of only 1.54%, nearly 11% lower than the quantum annealing algorithm and 15% lower than the Hilbert-Huang transform algorithm. This indicates almost no mislocation, enabling accurate fault localization. Regarding RMSE, the basic PSO algorithm shows the highest error, followed by the quantum annealing algorithm. The proposed method achieves a maximum RMSE of 0.17, far lower than the other two methods, demonstrating excellent automatic fault location performance with high accuracy.

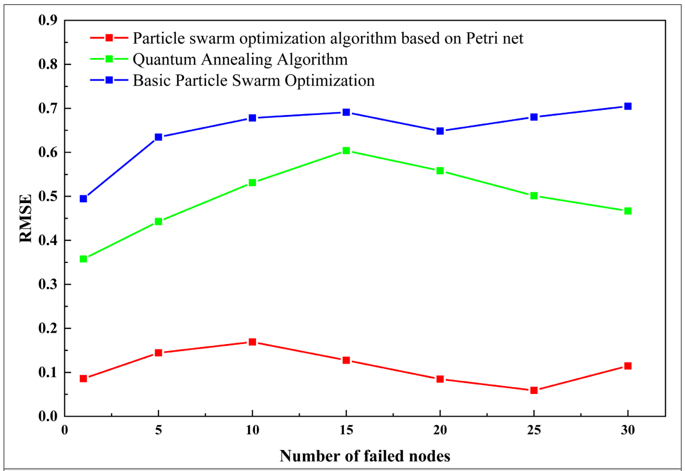

Fig. 7. Root mean square error of automatic fault location in distribution network.

V. CONCLUSION

Given the rapid advancement of distributed power generation, there is a pressing need to efficiently address faults that arise within the distribution network. To overcome the limitations of the conventional particle swarm algorithm, the author suggests enhancing it by incorporating the parallel reasoning attributes of Petri nets. This approach aims to mitigate the risk of encountering local extremum points during the particle swarm algorithm's computation process, ensuring more accurate fault localization and expedited fault resolution. Applying this method to abnormal state search in active distribution network operation, constructing a switch function, and conducting experiments using MATLAB software, the feasibility and good convergence of this method for fault location in some areas of active distribution networks are obtained, which improves the fault tolerance of active distribution system fault searches, shortens computation time, and achieves its universality requirements. Moreover, it provides a theoretical basis for the in-depth study of multipoint fault localization in the next active distribution network.

Availability of Data and Materials: The data that support the findings of this study are available on request from the corresponding author.

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