The Method of BP Algorithm for Genetic Simulated Annealing Algorithm in Fault Line Selection

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Abstract. Aiming at the shortcomings of low accuracy and poor applicability of the traditional ground fault line selection method for small current grounding systems, an BP neural network algorithm based on genetic simulated annealing algorithm (GSAA-BP) is used to select the fault line. This algorithm not only avoids the extortionate proportion of the initial weight and threshold of the traditional BP neural network, but also improves the population diversity by changing the crossover and mutation probability of the genetic algorithm. It avoids the result of the algorithm converge to a local optimum. Comparing with other BP neural network algorithms shows that this method in training has higher convergence speed, better complex adaptability and more accurate judgment accuracy.

1. Introduction
At present, most of the 10kV-35kV distribution networks in China use a low current grounding system. With the gradual expansion of the distribution network, single-phase ground faults have become more common. In particular, the selection of small current single-phase ground faults is always a huge problem, and there is still much room for improvement. Because the short-circuit current cannot form an effective loop in the switching network, the fault current is relatively weak, when a small current ground fault occurs in the system. It leads resulting in the failure to determine the fault phase by direct detection [1]. At present, commonly used fault line selection methods include injection signal method, transient signal method and steady-state signal method [2]. These methods are based on a formula or a combination of multiple criteria of the current line’s single to judge which one is fault [3], so it is often misjudged for complex situations and is not applicable. Therefore, many scholars have begun to use artificial neural networks to judge faults through complex multi-criteria fusion, and research has proved that this is a better method. BP neural network has predictive learning ability, high applicability, generalization and strong reorganization, but there are some problems such as slow convergence speed, insufficient and optimization ability; literature [4] optimize BP neural network (GA-BP) by genetic algorithm to line selection method overcomes the slow speed of convergence, but the genetic algorithm is very weak in local search ability, and cannot jump out of the conflict of local optimal values; The simulated annealing algorithm-optimized BP neural network (SA-BP) has good global search capabilities, but a large number of iterative operations lead to insufficient convergence ability; the literature [5] uses deep convolutional network structure for line selection, which improves the training convergence effect. However, there are many network structures and parameter settings need to be established, and the training process is too complicated.
In order to improve the performance of the BP neural network, this paper uses genetic simulated annealing algorithm to optimize the BP neural network: according to the diversity of the population, cross-change nonlinearity and mutation probability to improve the genetic algorithm. This method can improve the convergence speed and prevent the network from the local optimal value. Through modelling and simulation, the characteristic data of the small current ground fault is obtained, and the selection of the characteristic data is optimized by the GSAA algorithm. And then it is used as the initial parameters of the BP neural network for training. Training speed of complex ground faults and higher line selection accuracy.

2. Principle of GSAA-BP algorithm line selection

2.1. Fault feature extraction

Under ideal conditions, full use of steady-state and transient characteristics can accurately identify which line the ground fault point is on. However, due to the complexity of the distribution network and the large number of disturbances in the environment, it is impossible to accurately judge in different situations based on a single feature. Therefore, the three typical ground fault zero-sequence current characteristics of steady state, 5th harmonic and transient energy. As a criterion for line selection, input the BP neural network to train the line selection model after optimization by GSAA algorithm.

2.1.1. Steady state feature. In the moment of metal grounding in the transmission line of the distribution network, each line will generate zero-sequence current. When the grounding resistance becomes larger, each zero-sequence current decreases rapidly, which makes it impossible to directly identify the faulty line by the fundamental frequency amplitude; meanwhile, in the resonant grounding system, the zero-sequence current amplitude and phase of the faulty line can no longer be distinguished from the normal line. Therefore, the amplitude and phase characteristics of the zero-sequence current cannot be used. However, the active features in the steady-state features are not affected by the above problems. In the grounding system, the arc suppression coil will only overcompensate the grounding capacitor current to eliminate the arcing effect of the grounding point, and will not affect the active current in the system, so the active characteristics are also applicable to the resonant grounding system in. You can use the fast Fourier transform to calculate the active and reactive components in the zero-sequence current signal.

2.1.2. 5th harmonic characteristic. In the resonant grounding system, it is affected by the compensation of the arc suppression coil and the nonlinearity of the line. Because it is basically symmetrical, the fundamental wave and odd harmonics are the main components. Because the 3rd harmonic will form a circulating current in the transformer, resulting in a reduction in its content in the zero-sequence current; the 5th harmonic has obvious characteristics and is used as one of the fault selection criteria [6]. The zero-sequence current signal of a power frequency period is collected, and after the fast Fourier transform, the 5th harmonic signal can be extracted.

2.1.3. Transient energy characteristics. At the instant of the fault, the distributed inductance and capacitance in the circuit are charged and discharged a lot, so that the transient value in the zero-sequence current is much larger than the steady state value. Collect the zero-sequence current signal, perform 4-layer decomposition of Db5 wavelet packet, remove the influence of the fundamental frequency signal, and extract the transient feature from the maximum energy band [7]. The calculation formula of the band decomposition energy is:

\[ E = \sum_n (\omega_j)^2. \]  

2.2. Genetic simulated annealing algorithm to optimize BP neural network
2.2.1. **BP neural network.** The general BP neural network structure diagram is shown in Figure 1.

![BP neural network diagram](image)

**Figure 1.** Schematic diagram of BP neural network structure.

The BP neural network forwards the data and generates an error compared with the expected output, and then propagates the error back to each node. The weights and thresholds of each node are continuously revised, and the error is reduced along the gradient, constantly approaching the target output. However, there are many problems in itself: when the error change is small during the training process, the weight threshold correction will be slow; the global search ability will be lost after falling into the local minimum value; when the initial weight threshold setting differs greatly from the ideal, the network iterative convergence efficiency is low, and the training time is very long [8]. To solve the above problems, this paper uses the GSAA algorithm to optimize the initial weight and threshold of the BP neural network, thereby improving the performance of the neural network.

2.2.2. **Genetic simulated annealing algorithm.** Genetic algorithm is a random search optimization algorithm designed with reference to the principle of genetic mutation of biological genes. The algorithm has a faster convergence speed. The disadvantage is that once it falls into the dilemma of local optimization, it is likely to lose the global optimization ability; simulated annealing is a global search algorithm designed with reference to the annealing method of solid matter in molecular thermodynamics. The algorithm has strong global optimization ability, but there are always problems of slow convergence speed and easy oscillation of results.

Genetic Simulated Annealing Algorithm (GSAA) takes genetic algorithm as the basic framework, and introduces simulated annealing algorithm for optimization in the genetic screening stage. The process is as follows:

2.2.3. **Improved crossover and mutation algorithms.** Crossover and mutation are an important part of the genetic algorithm. Crossover is the random exchange of the genetic code of the same location of different individuals to obtain two different new individuals to ensure the population diversity; mutation is to randomly change the genetic code of the individual to ensure the population globality. Therefore, the appropriate cross mutation probability can ensure the efficiency of the genetic algorithm. However, the actual application of cross-mutation probability no longer changes after initialization, making it
unable to adapt to population changes and make appropriate adjustments. In order to solve the above problem, the cross-probability $P_c$ and the mutation probability $P_m$ are adaptively modified in accordance with the concentration and dispersion of population fitness, as follows.

$$P_c = \begin{cases} \frac{\arcsin \frac{f_{\text{avg}}}{f_{\text{max}}}}{\pi/2} & \text{arcsin} \frac{f_{\text{avg}}}{f_{\text{max}}} < \frac{\pi}{6} \\ k_1(1 - \frac{\arcsin \frac{f_{\text{avg}}}{f_{\text{max}}}}{\pi/2}) & \text{arcsin} \frac{f_{\text{avg}}}{f_{\text{max}}} \geq \frac{\pi}{6} \end{cases}$$

(2)

$$P_m = \begin{cases} \frac{\arcsin \frac{f_{\text{avg}}}{f_{\text{max}}}}{\pi/2} & \text{arcsin} \frac{f_{\text{avg}}}{f_{\text{max}}} < \frac{\pi}{6} \\ k_2(1 - \frac{\arcsin \frac{f_{\text{avg}}}{f_{\text{max}}}}{\pi/2}) & \text{arcsin} \frac{f_{\text{avg}}}{f_{\text{max}}} \geq \frac{\pi}{6} \end{cases}$$

(3)

In the formula, $f_{\text{avg}}$ is the average fitness value; $f_{\text{max}}$ is the maximum fitness value; $k_1$ and $k_2$ are the setting parameters.

In order to be more in line with the characteristics of the genetic algorithm, the non-linear transformation $\arcsin \left( \frac{f_{\text{avg}}}{f_{\text{max}}} \right)$ is adopted. If $\arcsin \left( \frac{f_{\text{avg}}}{f_{\text{max}}} \right) < \pi/6$ is satisfied, the current optimal individual fitness value is far from the average fitness value in this population. The smaller the value, the more dispersed the population characteristics; If $\arcsin \left( \frac{f_{\text{avg}}}{f_{\text{max}}} \right) \geq \pi/6$ is satisfied, the optimal individual fitness value is close to the average fitness value in this population. The larger the value, the more concentrated the population characteristics. It can be seen from formulas (2) and (3) that this method can produce more diverse individuals during the crossover process, enrich the population and enhance the global search capability, and at the same time adaptively reduce the mutation probability, ensure the existence of excellent individuals, and accelerate the algorithm convergence speed.

2.2.4. Process of GSAA-BP algorithm. GSAA-BP algorithm is divided into two parts: the single-pass BP algorithm calculates the fitness value and the genetic simulated annealing algorithm determines the weight threshold.

(1) Initialize various parameters.
(2) Enter characteristic data and initialize the BP neural network to enter the stage of calculating population fitness value.
(3) Data (chromosome) decoding, as the initial weight and threshold of each node of BP neural network.
(4) The reciprocal of mean square error of single operation results and the expected result is taken as the fitness value of individual. The size of the fitness value determines individual's excellence.
(5) Chromosome encoding the weight and threshold data and enter the stage of genetic simulated annealing algorithm.
(6) Perform improved crossover and mutation operations on population chromosomes.
(7) Select and anneal populations.
(8) When the maximum genetic algebra and annealing temperature are reached, the optimal individual is output; otherwise, return to step (2).
(9) Output the optimal solution individual and decode its chromosome code.

Finally, the optimized weights and thresholds are output and set as the initial weights and thresholds of the BP neural network to start the complete training of the neural network.

2.3. Route selection process
The principle structure of ground fault line selection is shown in Figure 2.
First, build a simulation model of the small current ground fault system to obtain the zero-sequence signals of each line within one cycle of the fault start, and use the Fast Fourier Transform (FFT) and Wavelet Packet Transform (WPT) to calculate the fundamental wave characteristics and 5th harmonic Wave characteristics, transient characteristics. Then, the normalized part of the feature data is used as training set and the other as the test set. GSAA algorithm is used to optimize the initial weights and thresholds of the BP neural network, and the data is input into the optimized BP neural network for training. Finally, the trained model is used for fault line selection.

3. Simulation and verification

3.1. Ground fault system simulation model
Using MATLAB/Simulink to build a 35kV distribution network small current grounding fault model, using an arc suppression coil to ground the three-phase power supply, the transmission line is a π-type equivalent circuit, and the system operating frequency is 50Hz. The simulation model is shown in Figure 3.

Figure 3. Simulation Model of Arc Suppression Coil for Neutral Grounding System Fault.

3.2. Sample collection and pre-treatment
Aiming at different lines, grounding resistance of the fault point, location of the fault point from the busbar and initial phase angle of the fault, the ground fault model is simulated, a total of 675 sets of zero-sequence current data are collected and preprocessed, and the collection parameter settings in different situations are shown in Table 2. Because the collected data are different physical quantities,
the characteristics are quite different, so it needs to be normalized before training as a neural network algorithm:

\[
x'_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}
\]  

(4)

In the formula, \(x\) is the value before normalization, \(x'_i\) is the value after normalization, \(x_{\max}\) and \(x_{\min}\) are the maximum and minimum values of the physical quantity.

After the original data is normalized, it is shown in Table 3, where "1" in the "Whether Failure" list means failure and "0" means non-fault.

3.3. Training test results and analysis

This paper compares the training results of GSAA-BP neural network with BP and GA-BP neural network, divides 675 groups of data into 600 groups as training samples, and 75 groups as test samples, and inputs three algorithm neural networks for training. The relevant parameters of genetic algorithm and simulated annealing algorithm are set as follows: population size 600, maximum iteration number 200, initial crossover probability 0.6, initial mutation probability 0.001, initial temperature 90, termination temperature 70, annealing coefficient 0.99. The BP neural network has a 4-layer structure: 2 hidden layers, 60 and 30 hidden layer nodes; 45 input nodes and 15 output nodes; Sigmoid function is selected as the excitation function of the hidden layer, and Logsig function is selected as the excitation function of the output layer. The output result close to 1 is judged to be a fault, and close to 0 is judged to be normal; the learning rate is 0.01, the expected error of the termination condition is 0.002, and the maximum number of trainings is 1000.

In the evaluation of the test results, the closeness of the output with 1 and 0 is specified to determine whether the output result is correct. The error formula is defined as:

\[
\delta = \begin{cases} 
\frac{|output - 1| \times 100}{output > 0.500} \\
\frac{|output| \times 100}{output \leq 0.500} 
\end{cases}
\]

(5)

Comprehensive error curve of the three network training processes is shown as Fig 4. It can be seen that GA-BP and GSAA-BP neural networks have a greater improvement in the learning and convergence efficiency of the BP neural network; GSAA-BP and GA-BP are in the early stages. The learning speed is similar, but after a period of iterative training, the convergence speed of GA-BP neural network is significantly reduced.

![Figure 4. Comprehensive error curve of network training](image_url)
Analyze the result data, compare the error between the output and expected result according to equation (5), and stipulate that the error δ is greater than 1% as a misjudgment. According to statistics, the traditional BP neural network made errors in the judgment of the data in groups 6, 9, 12, 25, 31, 35, 41, 55, 56, 60, 69, 75, and the accuracy rate was 0.840; GA-BP neural network made errors in the judgment of the data in groups 9, 17, 34, 45, 67, and 72, with an accuracy rate of 0.920; GSAA-BP neural network made errors in the 22nd, 39, 55, and 63 groups of data, with an accuracy rate of 0.947. In addition, the GSAA-BP algorithm achieves the required error accuracy at the 187th iteration, which is superior to the traditional BP algorithm's 416th generation and GA-BP algorithm's 236th generation. It can be sure that the GSAA-BP algorithm has better accuracy and speed for ground fault line selection.

4. Conclusion
This paper aims at the problems of complex method and low accuracy in the method of single-criteria fault current fault line selection, and the low efficiency of training in the BP neural network for multi-criteria fusion, easy to fall into local optimal problems, adopting GSAA-BP algorithm for multi-criteria fusion line selection for small current grounding fault system, giving full play to the advantages of genetic algorithm, simulated annealing algorithm and BP neural network, improving network training speed and line selection accuracy. The simulation results show that GSAA-BP neural network has good adaptability and accuracy to the fault problems in many different situations in the ground fault line selection, and has obvious advantages over the traditional BP and GA-BP algorithms.

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