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Prediction of Pollution Flashover Voltage of Insulators Based on Genetic Algorithm

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Abstract: In order to explore the prediction method of insulator flashover voltage, this paper uses genetic algorithm and BP neural network to optimize the initial weight and threshold of BP neural network by using the global search ability of genetic algorithm, and established a prediction model for salt density, gray density and pollution flash voltage. In this paper, the flashover voltage of FXBW-10/70 composite insulator under different salt density and gray density is obtained by artificial contamination test. Combine with the simulation results show that compared with the traditional BP neural network prediction model, the BP neural network optimized by genetic algorithm can speed up the convergence speed of the network and improve the prediction accuracy of the insulator flashover voltage. According to the prediction method, the external insulation state of the insulator can be evaluated by monitoring the contamination state of the insulator, which has certain guiding significance for maintaining the safe and stable operation of the power system.

1. Introduction

With the rapid development of my country's economy, industrial pollution and air pollution have become more and more serious, which has led to an increase in the degree of pollution on the surface of insulators [1]. Salt density and gray density are characteristic parameters that represent the degree of pollution on the surface of insulators, the study of the influence of salt density and gray density changes on the flashover characteristics of insulators has certain guiding significance for the safe and stable operation of the power grid and the development of anti-pollution work [2].

The BP neural network can basically approximate all nonlinear functions. Because of its strong learning ability, it has a very wide range of applications in prediction, however, because the BP neural network randomly selects the initial weight and threshold, its training speed is slow and it is easy to fall into local extremum and other problems. Kontargyri [3] applied the BP neural network model to the prediction of insulator pollution flashover voltage. Zhang Youpeng estimated the leakage current of insulators through genetic algorithm [4]. Ding Long used SVM to predict the flashover voltage of insulators under contaminated conditions, but this method has disadvantages such as a large amount of calculation and slow operation speed [5]. Cheng Jiatang used a combination of BP neural network and ant colony algorithm to predict the pollution flashover voltage in ice-coated insulation, but the ant colony algorithm has problems such as long search time and easy stagnation [6]. Wang Zili and others proposed to train the weights and thresholds of BP neural network through genetic algorithm to predict the pollution degree of insulators [7]. Based on this, this paper combines genetic algorithm and BP neural network, with the help of genetic algorithm's global optimization ability, establishes a prediction model of polluted insulator flashover voltage, which improves the prediction accuracy and training speed of BP neural network.

2. BP neural network model optimized by genetic algorithm

2.1 BP neural network

BP neural network is a type of multi-layer feedforward neural network that learns and trains based on error back propagation, according to the "negative gradient descent" theory, the error adjustment direction of the network is always along the direction of the fastest error. By constantly adjusting the

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weight and threshold of the network, the ideal result is input. The three-layer neural network topology with multiple inputs and single outputs is shown in Figure 1. The BP neural network includes an input layer, a hidden layer, and an output layer. The upper and lower layers of the network are fully connected, but the neurons in the same layer are not connected.

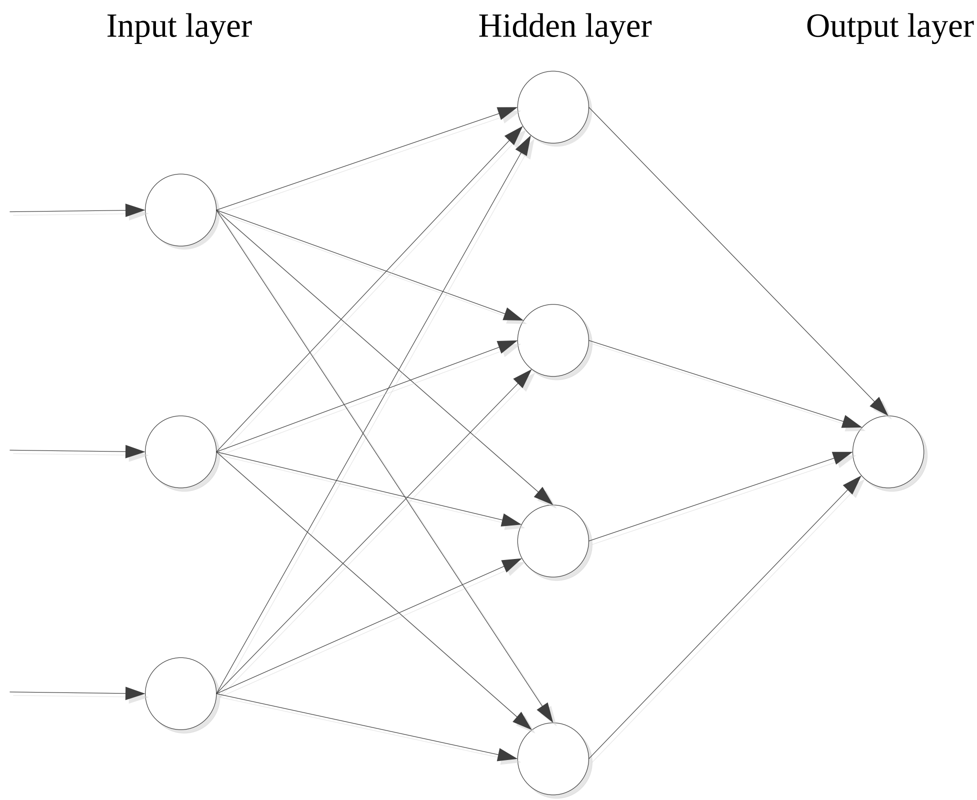

Fig 1. BP neural network structure

2.2 Genetic algorithm optimizes BP neural network

2.2.1 Basic ideas

When BP neural network assigns the weights and thresholds of the network, it is generally a random number initialized to the interval [-0.5, 0.5] by random initialization. This assignment method has a great impact on the training of the network, which will reduce the convergence speed of the network and the accuracy of the prediction results. Genetic algorithm has strong global search ability, while BP neural network is more effective only when performing local search. Therefore, combining genetic algorithm with BP neural network can improve the prediction accuracy and the convergence speed of the network.

Based on this, this paper uses genetic algorithm to optimize the weights and thresholds of BP neural network, through genetic operator selection, crossover and mutation operations of genetic algorithm, the population individuals are selected from generation to generation, find the optimal initial weight and threshold of the network and assign the value,and then learn and train the BP neural network model to obtain the optimal prediction value. The specific process of genetic algorithm optimizing BP neural network is shown in Figure 2.

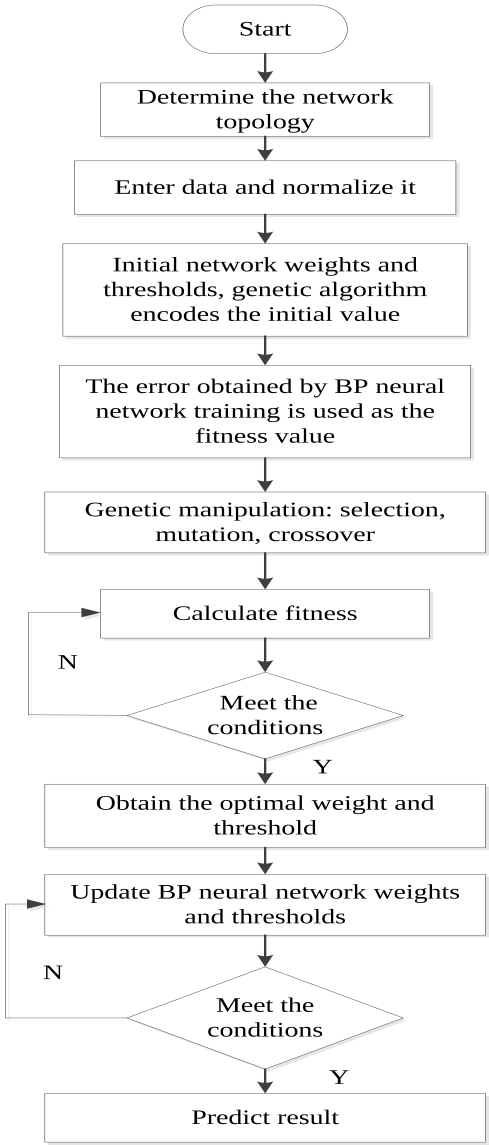

Fig 2. Genetic algorithm optimization BP neural network flow chart

2.2.2 Optimization steps

1) Topological structure of BP neural network. In this paper, the input is salt density and gray density, and the output is pollution flashover voltage, the hidden node of the network is set to 1, and the number of hidden nodes can be determined by the following empirical formula:

$$l = \sqrt{m+n} + a \tag{1}$$

Where: m and n are the number of input nodes and output nodes respectively; a is a constant between 1 and 10.

2) Preprocessing of sample data. The size of data input and output will affect the convergence of the network, so it is necessary to normalize the parameters. Perform normalization processing according to formula (2) to make the change interval in [-1, 1]:

$$x_k = \frac{x_k - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

3) Determine the weights and thresholds of the network and perform population initialization coding.

4) Select operation. This article uses the roulette method to operate, the probability of a single individual i being selected is

$$p_i = \frac{f_i}{\sum_{i=1}^{p} f_i} \tag{3}$$

Where: f_i is the reciprocal of individual fitness, and p is the population size.

5) Cross operation. This paper adopts the real number crossover method, the cross operation method of k chromosome a_k and l chromosome a_l at j position is as follows

$$\begin{cases} a_{kj} = a_{ij}(1-b) + a_{lj} \\ a_{lj} = a_{lj}(1-b) + a_{kj} b \end{cases} \tag{4}$$

Where: b is a random number in the interval [0,1].

6) Mutation operation. Select the j-th gene a_{ij} of the i-th individual for mutation, and the mutation operation method is

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) \times f(g) & r > 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) \times f(g) & r \le 0.5 \end{cases} \tag{5}$$

Where: amax is the upper bound of gene aij; amin is the lower bound of gene amax; $f(g) = r_2(1 - g / G_{\max})^2$, r2 is a random number, g is the current iteration number, Gmax is the maximum number of evolution; r is a random number in the interval [0,1].

7) By solving the optimal chromosome of the genetic algorithm, the optimal weight and threshold of the BP network are obtained, and the optimal value is assigned to the prediction model for training to obtain the optimal prediction value.

3. Test plan

3.1 samples

This article selects FXBW-10/70 composite insulator for artificial pollution test, and its basic technical parameters are shown in Table 1.

Tab 1. Parameters of samples

model	Height /mm	Crawl distance /mm	Disk diameter /mm	Surface area /mm
FXBW-10/70	400	525	118/95	844

3.2 Test device

This article uses artificial pollution test, The test was carried out in an artificial fog chamber, the smearing of the test sample refers to the quantitative smearing method in the solid coating method recommended by GB/T 4585, the pressure increase method uses the uniform pressure increase method. the test voltage is provided by a 150kV/900kVA test transformer, the maximum short-circuit current is 30A, which meets the requirements of IEC 61245 [8] for the pollution test power supply. The test circuit is shown in Figure 3.

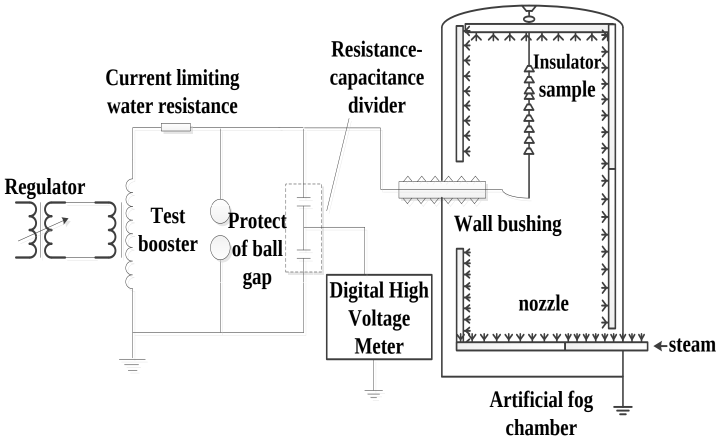

Fig 3. Test circuit diagram

3.3 Test plan

This test refers to GB/T 4585 recommended quantitative brushing method for staining, using NaCl to simulate conductive substances, and diatomite to simulate insoluble substances. The pollution salt density selected in this paper is 0.03, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35 mg/cm^2, and the gray density is 0.5, 1.0, 1.5, 2.0, 2.5, 3.0 mg/cm^2, respectively. According to the surface area of the sample and the tested salt density and ash density, calculate and weigh out the required amount of NaCl and diatomaceous earth, and apply the configured dirt evenly on the insulating surface of the sample insulator.

The test uses the uniform boost method. Perform 4~5 flashover tests on each string of insulators; perform pollution 3 times under the same pollution degree, and take the average value of all points with an error of no more than 10% from the average value as the flashover voltage Uf under the pollution degree, which is

$$U_f = \frac{\sum_{i=1}^{N} U_i}{N} \tag{6}$$

$$\sigma = \sqrt{\left(\sum_{i=1}^{N}\left(U_i - U_f\right)\right) / \left(N-1\right)} / U_f \times 100\% \tag{7}$$

In the formula: U_f is the average pollution flashover voltage of the insulator, kV; U_i is the i-th pollution flashover voltage, kV; N is the number of tests; σ is the relative standard deviation.

4. Prediction of insulator pollution flashover voltage

4.1 Establishment of the prediction model of pollution flashover voltage

The pollution degree of the surface of the insulator is an important factor affecting the pollution flashover of the insulator, the salt density and gray density are the parameters that reflect the pollution degree, which can effectively reflect the influence of the pollution degree on the external insulation capacity of the insulator. Therefore, this paper establishes a prediction model of pollution flashover voltage through salt density and gray density, which can monitor the operating status of insulators and avoid pollution flashover accidents.

The number of BP neural network training is 1000, the learning rate is 0.1, the target error is 0.001, the number of hidden nodes selected is 4~10, and the test one by one shows that when the hidden node is 7, the error is the smallest, so the implicit node is taken as 7. In order to obtain better prediction results, by adjusting the simulation parameters of the genetic network: population number, crossover and mutation probability, it can be concluded that when the population number is 50, the crossover probability is 0.8, and the mutation probability is 0.2, a better prediction result is obtained.

4.2 Simulation results

In this paper, 48 sets of data are obtained through artificial pollution tests, 40 sets of data are randomly selected as training samples, and 8 sets of data are used as prediction samples. The error training result of BP neural network is shown in Figure 4, and the error training result of BP neural network optimized by genetic algorithm is shown in Figure 5.

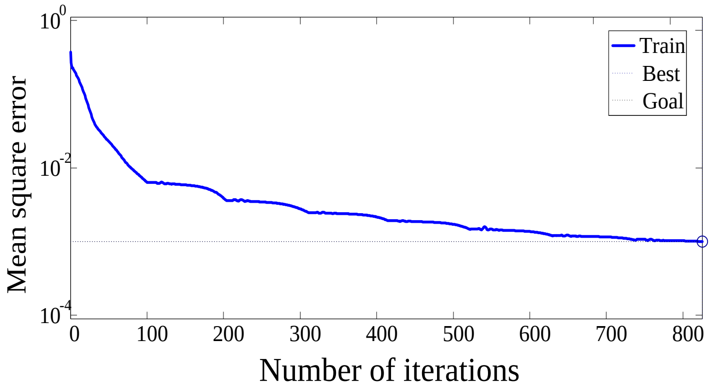

Fig 4. BP neural network training results

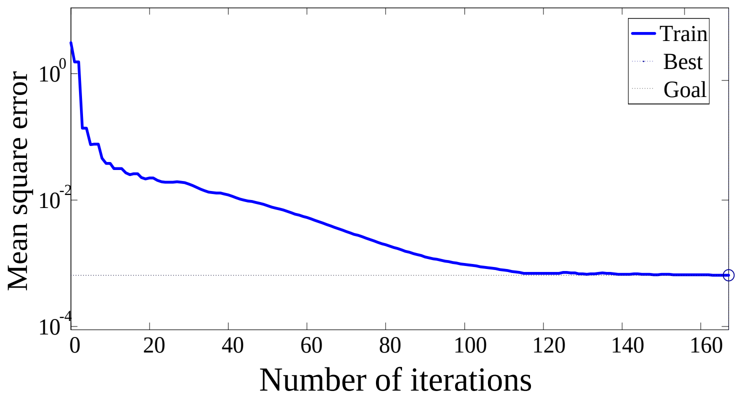

Fig 5. Genetic algorithm optimization of BP neural network training results

It can be seen from Figures 4 and 5 that the number of iterations of the BP neural network is 825, and the number of iterations of the genetic algorithm to optimize the BP neural network is 167. The BP neural network optimized by the genetic algorithm significantly accelerates the convergence speed of the network.

BP neural network and genetic algorithm optimize the prediction value of BP neural network for pollution flashover voltage as shown in Table 2, and the network training results are shown in Figure 6.

Tab 2. Comparison of prediction results with test

Serial number	Salt density mg/cm^2	Gray dense mg/cm^2	Measured value /kV	GA-BP internet	error / %	BP internet	error / %
1	0.03	0.5	34.9	35.9	2.8	36.9	5.7
2	0.1	1.5	24.2	24.1	0.4	26.5	9.5
3	0.2	2.5	21.8	22.9	5.0	22.6	4.6
4	0.15	1.5	24.2	23.1	4.5	22.8	5.8
5	0.1	0.5	29.4	28.6	2.7	27.9	5.1
6	0.15	2.0	23.2	23.9	3.0	24.2	4.3
7	0.25	2.5	21.3	21.6	1.4	21.9	2.8
8	0.35	3.0	20.8	19.8	4.8	19.1	8.2

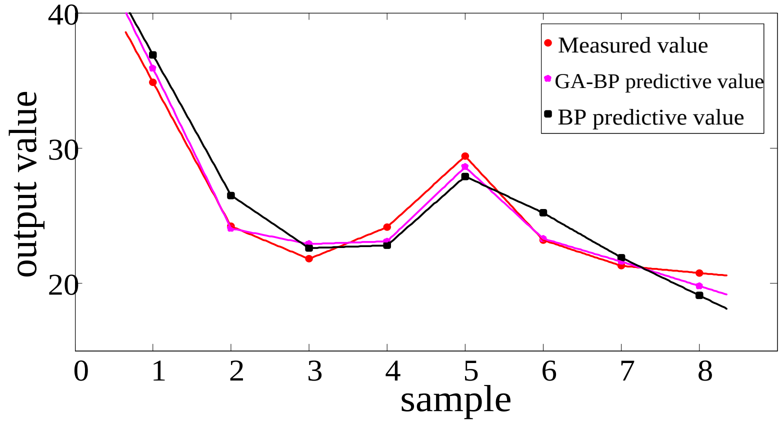

Fig 6. Comparison of training results

It can be clearly seen from Table 2 and Figure 6 that the highest error of genetic algorithm optimization of BP neural network is 5.0%, the lowest is 0.4%, and the average error is 3.1%, while the highest error of ordinary BP neural network is 9.5% and the lowest is 2.8 %. The genetic algorithm is used to find better weights and thresholds, so that the optimized BP neural network has higher prediction accuracy than the ordinary BP neural network.

5. Conclusion

This paper discusses the method for predicting the pollution flashover voltage of insulators, and the following conclusions are obtained:

1) Through the experimental data of the artificial pollution test, this paper verifies that it is feasible to use the genetic algorithm to optimize the BP neural network to predict the pollution flashover voltage. According to the prediction model, the insulation status of the insulator can be evaluated with reference to the real-time contamination status of the insulator surface to prevent the occurrence of pollution flashover accidents.

2) The BP neural network is optimized by genetic algorithm to obtain a prediction model of pollution flashover voltage based on salt density and gray density. Compared with the traditional BP neural network predicting pollution flashover voltage, its convergence speed and prediction accuracy have been greatly improved.

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