Application of Improved BPNN Algorithm in GIS Insulation Defect Type Identification

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Abstract. In this paper, a new BP neural network has been built with GA algorithm, which possesses high effectivity, parallel processing ability and global search feature, in order to overcome the original shortcomings such as the low convergence rate and the confusion of local minimum points. Ten parameters of partial discharge characteristics are obtained as input of BPNN to identify four typical insulation defect physical models designed in this paper for the purpose of measuring the recognition accuracy of the improved BPNN. Experiments show that the improved BPNN has a better performance of convergence speed and recognition accuracy than that of adaptive momentum BP neural network.

1. Introduction

Recently, the partial discharge detections have implemented digital detection, handheld and on-line monitoring technology with the development of computer science and wide application of sensors. For processing the huge quantity of data collected and estimating the insulation status, pattern recognition methods for identifying defects are applied. The artificial neural network used in PD detection of GIS [1-4] is similar to the cerebrum of human beings, which possesses the advantages of self-organizing learning and self-optimization skill as well as understanding and inferring ability. As a result, the neural networks have been widely applied to determine the defects type in GIS. More importantly, BP neural network are the most representative and popular algorithm because it can analyze internal relationships between data faults and acquire consistency through model training, which is the reflection of the complicate non-linear relation between input and output.

Nevertheless, the BP network is sensitive to the initial weight and threshold selection, and the convergence point may easily drop into the local minimum, which leads to the failure of the learning result, low convergence rate and low efficiency. Differently, Genetic Algorithm (GA) is an algorithm with parallel processing ability as well as stochastic and adaptive search performance, so it is less dependent on the initial weight and threshold selection. The genetic algorithm overcomes the shortcomings of the BP algorithm that the convergence speed is slow and the convergence point drops into the local minimum by error. Consequently, GA has an excellent global search ability, which is different from the BP algorithm better applied in local search. Furthermore, GA can be optimized to a
new combined learning algorithm given a name of GA-BP, which overcomes the deficiencies of each algorithm by absorbing the features of the other algorithm. Therefore, this paper studies this improved BPNN algorithm, GA-BP, and uses it in PD defect identification of GIS, which significantly improves the recognition accuracy.

2. Fundamentals of BPNN and GA

2.1. BPNN
BPNN (back propagation neural network) which is firstly researched and conceived by Rumelhart in 1986[5-6], is multiple forward network based on deviation. As shown in Figure 1, the fundamental topology of BPNN model is mainly composed of three neurons layers respectively called input layer [7-9], hidden layer and output layer.

![Figure 1. Typical BPNN structure](image)

2.2. GA-BP optimized algorithm
Compared with most of the search methods that easily converge to local extreme point by error, the GA uses the search method with the multiple-point and multiple-way features [10], thus having the advantage of overall search and high speed of convergence for the reason that its process is parallel and includes more independent methods enabling synchronous evaluations for more elements [11]. Therefore, the essential characteristics of GA is the high parallelism, multi-purpose and global search ability. Besides, its strong practicability also provides the possibility to optimize the BP network [12].

The optimization steps are described in detail as below:

a) Finish the initial weight and threshold selection for BPNN. Select a specific size for the population P (here P = 30) including Pc and Pm.

b) Determine the target function of BPNN; In general, select the accumulation of squares of every error between actual output result and desired output value.

\[ E(i) = \sum_{k} (Y_k - T_k)^2 \]  \hspace{1cm} (1)

Where i refers to the ordinal number of chromosomes; k indicates the ordinal number of the output layer nodes; Yk describes the actual output value after BPNN is trained; Tk describes the expected output result.
According to the value of $E(i)$, calculate the adaptive value for every individual, noted as $f$. Then determine if this value should be evolutionarily computed.

$$P_i = f_i / \sum_{j=1}^{N} f_j, f_i = 1 / E(i)$$  \hspace{1cm} (2)

d) Seek the weights and threshold values of individuals the adaptive value of which are $f$, note them as $A_1$, if $f$ is not satisfied, jump to step c; or else, jump to step h;

e) Transmit $A_1$ obtained by step d back to the input layer. This back propagation path will no doubt pass through the hidden layer. Calculate the deviations of every neuron layer. Adjust $A_1$ according to formula and mark the new weights and thresholds as $A_2$.

f) Copy and cross genetic chromosomes to make them changes, thus creating a different generation of groups.

g) Choose individuals from the new groups generated by step f as the parent of $P$, they and $A_2$ build a new group, then jump to step c;

h) Execute the decoding for those individuals whose adaptive values are $f$, record and preserve weights and thresholds of the current BPNN.

3. PD recognition neural network based on GA-BP

In order to enhance the accuracy of the recognition in this paper, a PD detection system was established based on the 110 kV GIS model, and the experiment was conducted.

3.1. Experimental defect

There are various GIS insulation defects leading to the partial discharge, and the PD has different features with the diverse defects types. In this paper, four insulation defects usually occurring in GIS are designed, including conductor metal bump at high voltage, suspended electrode, internal insulated gap and free metal particulate at the bottom of the casing. These four defects are respectively the factors of causing corona discharge, suspended electrode discharge, air discharge and particle discharge.

3.2. Experimental analysis

This experiment firstly obtained 222 groups of GIS PD data, then for every group of data, extracted the 10 features in total containing four dimensions parameters (peak–peak $X_{pk}$, rectified average $X_{av}$, standard deviation $X_{sd}$ and RMS $X_{rm}$) as well as six dimensionless parameters (kurtosis $X_{ku}$, skewness $X_{sk}$, peak factor $X_{c}$, pulse factor $X_{i}$, form factor $X_{s}$ and margin factor $X_{l}$). After that, the analysis data of these features formed a vector waiting for being input into the GA-BP to train the network. The vectors at output represent the diverse defect conditions. Afterwards, choose 120 groups of data in the random manner as the test data to verify the accuracy of recognition by GA-BP network. The result is shown in table 1.

| $X_{im}$ | $X_{av}$ | $X_{sd}$ | $X_{ku}$ | $X_{av}$ | $X_{sk}$ | ... | $X_{l}$ | Output | reality |
|---------|---------|---------|---------|---------|---------|-----|--------|--------|---------|
| 0.252   | 12.826  | 10.106  | 1.182   | 0.252   | 0.0116  | ... | 5.727  | 1       | 1       |
| 0.208   | 14.042  | 22.001  | 3.808   | 0.208   | 0.013   | ... | 9.273  | 3       | 3       |
| 0.208   | 16.480  | 9.727   | 2.657   | 0.208   | 0.017   | ... | 11.456 | 4       | 4       |
| 0.261   | 13.308  | 9.972   | 1.164   | 0.261   | 0.0115  | ... | 5.712  | 1       | 1       |
| ...     | ...     | ...     | ...     | ...     | ...     | ... | ...    | ...    | ...     |
| 0.214   | 9.379   | 9.598   | 0.496   | 0.214   | 0.011   | ... | 6.836  | 2       | 2       |

Table 1. GIS PD feature parameters and defects recognition
By analyzing the feature parameters acquired, it is possible to predict the output and error of Adaptive Momentum BPNN, as shown in figure 2.

**Figure 2.** Adaptive Momentum BPNN output and error

The red blocks refer to the expected results at out port while the blue points are the forecasted output. The results indicate a dispersive distribution of predicted output and a relatively great error the sum of which value 44.4137.

Figure 3 illustrates the prediction of the output and error in GA-BPNN. Compared to figure 2, it is obvious that the prediction of accuracy has been improved significantly. What’s more, the error has been reduced a lot. The sum of error prediction is 16.2632, only one-third of the sum of error prediction in figure 2. And diagnostic accuracy rate is improved to 93.3%. 

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[Graphs showing adaptive momentum BP neural network output and error]
Figure 3. Predicted output and error in GA-BPNN

The experiments were executed under different conditions; the results of the accuracy rate, the average absolute of errors, the variance of each measurement are listed in Table 2.

Table 2. Improved BPNN results table

| Graph recognition model       | Accuracy rate | Average absolute of errors | Variance  |
|-------------------------------|---------------|-----------------------------|-----------|
| Adaptive momentum BPNN        | 77.5%         | 0.14949                     | 0.3533    |
| GA-BPNN                       | 93.3%         | 0.08989                     | 0.2134    |

As Table 2 shows, the improved BPNN with the GA-BP algorithm obtained the recognition results which nearly consist with the real situation. The accuracy rate of recognition can reach 93.3%. The algorithm enables GIS PD type recognition systems to obtain a higher convergence speed and accuracy of type identification.
4. Conclusion
The achievement in the paper can be concluded as follows.

(1) In this paper, there are in total 10 characteristic parameters including signal peaks, kurtosis, etc. These extracted parameters form a vector as the input of BPNN.

(2) Genetic Algorithm optimized weights and thresholds of BPNN thanks to its parallel processing and global search ability, thus enhancing recognition accuracy and simultaneously raising convergence speed.

(3) The improved BPNN with new GA-BP algorithm has a much higher identification accuracy rate, a smaller average absolute error and a lower variance than the adaptive momentum BP neural network, thus provides a better reliability.

(4) Despite the advantages of GA-BP neural network, some large individual data identification errors may still occur. Therefore, there is the necessity to optimize the input vector.

Both the theoretical study and experiment results indicate that GA-BP neural network algorithm has great application value in recognizing the diverse types of GIS PD defects.

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