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Inrush current method of transformer based on wavelet packet and neural network

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Abstract: The transformer is an important equipment of power system; its operation state is directly related to the security and stability of the power system. Aiming at the problem that the differential protection of power transformer has been plagued by inrush current, a recognition method based on wavelet packet and the neural network is proposed. The inrush current and fault current signal are decomposed and reconstructed by using wavelet packet to extract wavelet packet reconstruction coefficients and calculate the energy of each band. These feature vectors are chosen as input values for the neural network. It has been shown by experiments that the inrush current and internal fault current can be accurately identified and the identification method can meet the requirement of the transformer inrush current real-time identification system.

1 Introduction

The power transformer is one of the most important electrical equipment in the power system. Its safe operation is related to the continuous and stable work of the whole power system. Differential protection is widely used in transformer protection because of its simple principle, good selectivity and high reliability [1, 2]. However, the problem is how to distinguish the inrush current of the transformer from the internal fault current, so as to avoid the maloperation of the protection [3].

The traditional method of distinguishing inrush current of the transformer is usually based on some waveform characteristics of inrush current such as the DC component, discontinuous angle, second harmonic etc. Among them, the second harmonic braking principle is the most widely used [4–6]. However, in the actual power system, the inrush current and internal fault current waveform of the transformer are affected by many factors such as system parameters, operation mode and so on. The traditional discriminant principle has some limitations in practical application. With the rapid development of economic construction and electric power industry in China, the electric force system becomes more and more large and complex and develops toward the large-scale AC/DC hybrid interconnected large power grid, which makes the factors affecting transformer protection become more and more complex. This will also greatly increase the difficulty of inrush identification. Therefore, it is urgent to use the new principle and method to distinguish the inrush current of the transformer [7, 8]. In this paper, an inrush current recognition algorithm based on wavelet packet and radial basis function (RBF) neural network is proposed. Wavelet packet algorithm is used to analyse the inrush current and internal fault current and extract the energy feature, which can be used as the sample input of the RBF network. The results confirm the feasibility of the transformer inrush current recognising method based on wavelet packet and neural network.

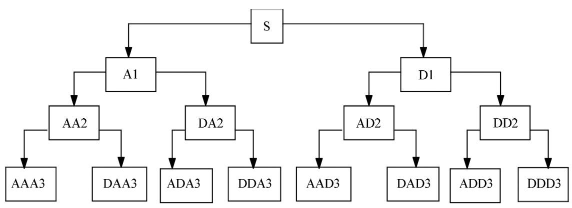

Fig. 1 *Wavelet packet decomposition structure*

2 Wavelet packet energy feature extraction

2.1 Introduction of wavelet packet analysis

The Mallat fast algorithm is the theoretical method commonly used in wavelet transform. However, when Mallat fast algorithm is decomposed into time and frequency, it has the disadvantages of poor frequency resolution in the high-frequency band and poor time resolution in the low-frequency band. Wavelet packet decomposition is an improvement on wavelet analysis [9]. It overcomes the shortcoming of wavelet analysis that the high-frequency signal is discarded and only the low-frequency information is analysed [10]. The high-frequency information is also analysed, and the signal is decomposed into any frequency band.

Three-layer decomposition is made for the measured signal based on wavelet packet algorithm. Wavelet packet three-layer decomposition tree structure graphics is shown in Fig. 1, where A represents the low-frequency band and B represents the high-frequency band.

2.2 Feature energy extraction

After wavelet packet decomposition, the detailed calculation process of the required band energy is as follows.

If the energy corresponding to each frequency band S_j is E_j, there are

$$E_j = \int \left|S_j(t)\right|^2 \mathrm{d}t = \sum_{k=1}^{n} \left|d_k^j\right|^2 \tag{1}$$

d_k^j is the amplitude of the reconstructed signal and S_j is the corresponding discrete signal point.

Reconstruction node energy makes up feature vector $\boldsymbol{T}$

$$\boldsymbol{T} = [E_1, \quad E_2 \ldots E_j]$$

To avoid large energy differences in the characteristic vector, characteristic vectors are normalised. The total energy of the reconstructed signal is $E = \left(\sum_{j=1}^{n} |E_j|^2\right)^{(1/2)}$, then the normalised vector can be expressed as

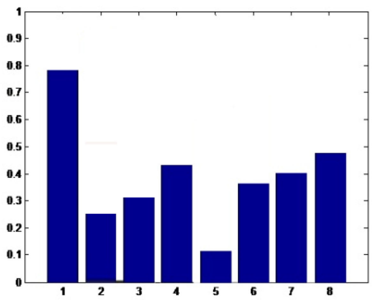

Fig. 2 *Energy spectrum of the inrush current signal by wavelet packet decomposition*

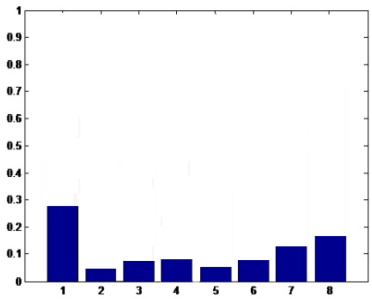

Fig. 3 *Energy spectrum of the inter-turn fault signal by wavelet packet decomposition*

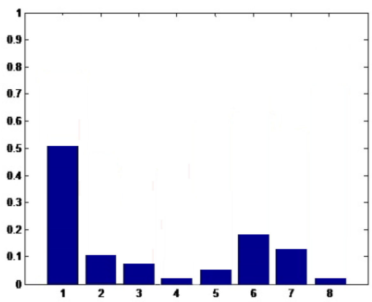

Fig. 4 *Energy spectrum of the phase fault signal by wavelet packet decomposition*

$$\boldsymbol{T} = \left[\frac{E_1}{E}, \frac{E_2}{E} \cdots \frac{E_j}{E}\right] \tag{2}$$

After data normalisation, the vector can be trained and applied as the input of subsequent neural network.

In view of the interference (such as harmonic interference) in the field application, it is necessary to improve the frequency response of the filter in the transition zone and the requirements of frequency band segmentation. Through the analysis and comparison of many kinds of wavelets, the three-layer decomposition of the db3 wavelet is selected, because of its good frequency band segmentation, the signal distortion of decomposition and reconstruction is small. The nodes in the third layer of the decomposition tree fully highlight the characteristics of the signal. Therefore, in this paper, the energy value of the third layer reconstruction coefficient is selected.

In this paper, samples are selected to include two types of inrush current and internal fault current. Internal fault current includes interphase fault and inter-turn short circuit. According to the characteristics of the signal, the Daubechies wavelet function is selected to decompose the signal into three layers of wavelet packets, and the energy values of eight frequency bands are obtained by calculation. The energy of the signal (excitation inrush, interphase fault, and inter-turn short circuit) is shown in Figs. 2–4.

In Table 1, E_{30}–E_{37} represent the energy value of the third layer node for the wavelet packet three-layer decomposition tree structure. That is the normalised energy value of eight frequency bands from low frequency to high frequency.

On the basis of the results in Table 1, it can be seen that the energy eigenvalues of the eight frequency bands corresponding to the inrush current are much larger than the energy eigenvalues of the current in the case of internal faults.

3 Neural network model based on RBF

Artificial neural network is an adaptive non-linear dynamic system composed of a large number of simple basic components connected to each other [11]. A simple neurone processor can handle very simple pattern recognition problems, but the complex situation requires a multi-layer forward neural network to handle the problem [12, 13]. There is no theory to calculate the number of neurones needed to solve a specific problem and the number of layers of neural networks. The number of neurones in the input and output layers of the neural network can only be determined by their own experience. The number of nodes in the input and output layers is determined by the nature of the problem and the thinking of the research. The number of layers of hidden layers and the number of neurones in them are determined by the complexity of the training data. Generally speaking, as long as a three-layer neural network is used, there is no limit on the number of neurones in each layer. A geometric figure of any degree of complexity can be constructed in the pattern space, so as to classify any complex objects. For the inrush current of the transformer, the speed and precision of identification depend on the complexity of the neural network [14]. While determining the number of layers of the neural network, the requirements of these two aspects should be taken into account.

RBF neural network in Fig. 5 is a three-layer forward network with a single hidden layer, which is composed of an input layer, hidden layer and output layer. The input layer is composed of the signal source node, namely the input signal. Hidden layers make the zero-memory non-linear transform for input signals and the transformation functions are non-linear and non-negative, which are axial symmetries about the radial centre, generally Gaussian function is used. The output layer weight parameter is linear. The output layer is the linearly weighted sum of the hidden layer output to realise the mapping of the input to the output and to achieve the purpose of recognition.

P represents the input sample vector of the network and T represents the target vector of the network. The creation code for the RBF network is as follows:

$$\text{net} = \text{newrb}(\text{P, T, GOAL, SPREAD}) \tag{3}$$

The SPREAD is the propagation rate of the radial basis function. According to the experimental data, this paper is selected as 0.1 after repeated debugging. The goal is the target error and the target error of setting the network is 0.00001.

About 100 sets of inrush current samples and internal fault current samples are as input samples for training RBF. Another 160 sets of inrush current samples and internal fault current samples are used as samples for testing the network. The error curve of 100 sets of data training networks is shown in Fig. 6.

It can be seen from Fig. 6 that the target error of RBF identification network is achieved when the iteration number is about 120, and the error is almost zero, which shows that the neural network converges well and does not fall into local minima.

The trained RBF network is tested with a random set of 160 samples (including 80 sets of inrush current samples and 80 sets of internal fault current samples). The absolute values of the deviation between the actual network output and expectations are shown in Fig. 7.

Fig. 7 shows that the network test deviations of the 160 test samples are basically <0.5, and a few test samples have errors >1, but all of them are within 2. After a large number of samples are trained and tested on the network, the deviation between the actual output and the expectation of the samples conforms to this rule.

Although the convergence of RBF network is good, the recognition rate of the network is not high when it is used to identify the network. The reason is that there is more information. If all the omen information is input into the same network at the

Table 1 Energy values of three kinds of normalised signal

	Inrush current	Inter-turn fault	Phase fault
E_{30}	0.7937	0.2987	0.5011
E_{31}	0.2289	0.0275	0.1101
E_{32}	0. 3097	0.0673	0.0865
E_{33}	0.4211	0.0701	0.0043
E_{34}	0.1179	0.0234	0.0571
E_{35}	0.3789	0.0675	0.2004
E_{36}	0.3982	0.1534	0.1801
E_{37}	0.4323	0.1922	0.0011

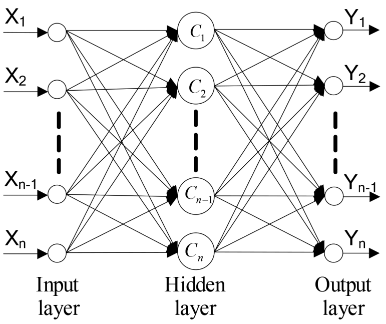

Fig. 5 *Structure of RBF neural network*

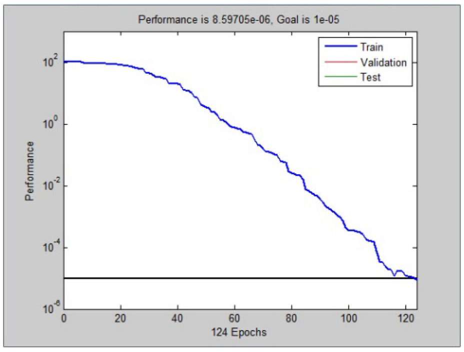

Fig. 6 *Training curve of RBF neural network*

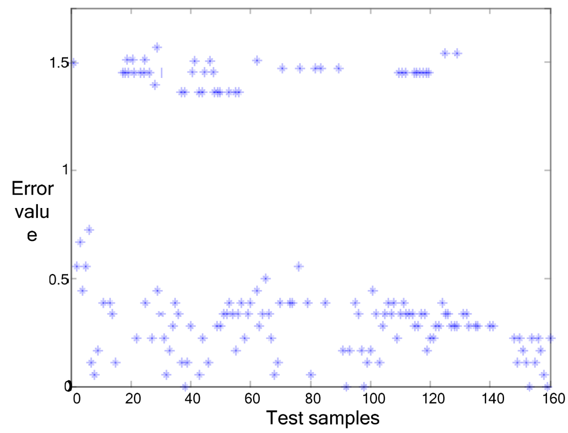

Fig. 7 *Value of the deviation between network actual output and the expected*

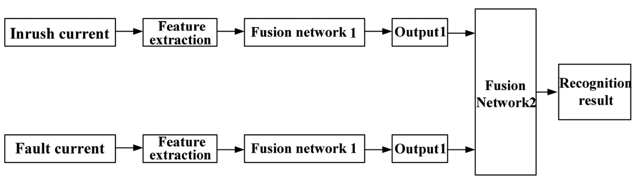

Fig. 8 *Model diagram of two-level RBF neural network fusion recognition*

Table 2 Comparison between one-level RBF and two-level RBF on identification number and training times

Network model	First-level RBF network	Two-level RBF network
right amount	24	28
training number	120	90

same time, the recognition effect of the neural network will be greatly affected. To overcome the above problems, we can use multiple neural networks to classify different low-dimensional symptom spaces and obtain the recognition results. In this way, the complex structure of single recognition neural network and the bad effect of a data source error on the whole recognition system are avoided. It also improves the speed and efficiency of network training. The model diagram of two-level RBF neural network fusion recognition is shown in Fig. 8.

The inrush current and the fault signal are formed into a primary neural network for feature level fusion. The decision data they output are then fused as the input of the two-level neural network. The networks of the first-level RBF and two-level RBF are trained and simulated with 30 groups of data. The results of identification and training times are compared as shown in Table 2.

It can be seen from the above table that the two-level RBF neural network model has enhanced the reliability and robustness of the recognition system by processing redundancy and complementary information. The recognition rate has been improved and the number of training has been reduced.

4 Conclusion

Aiming at the problem of how to distinguish inrush current from internal fault current, the recognition scheme of wavelet packet energy neural network is expounded. First of all, the implementation steps of wavelet packet algorithm to extract the energy feature of the tested signal are given. Then, the classification of the recognition model of the RBF network is introduced, and a new protection criterion is put forward. A lot of simulation results show that this scheme has certain theoretical and practical values.

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