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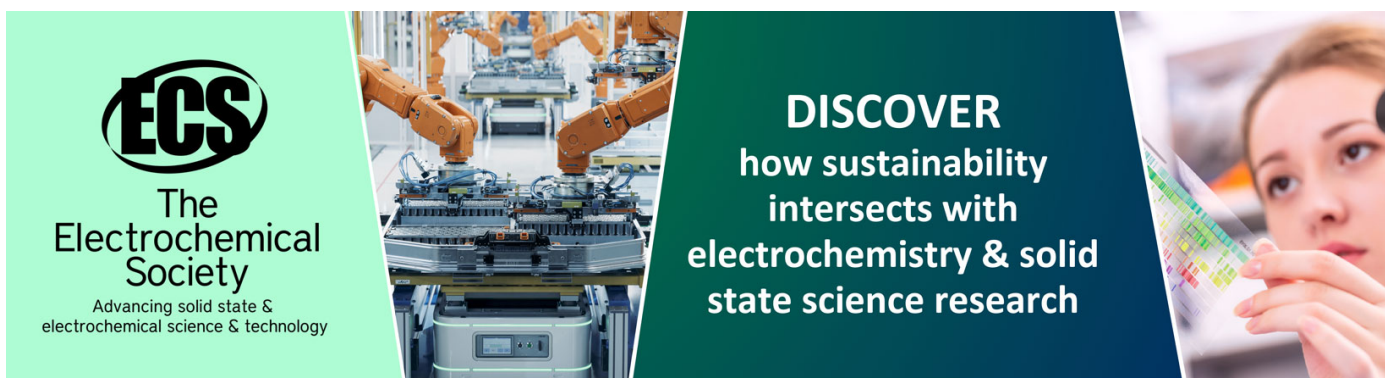
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Fault identification based on BP neural network and wavelet packet in power systems

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Abstract: This paper proposes a fault identification method based on BP neural network and wavelet packet, which extracts the fault transient eigenvalues of the three-phase current and zero-sequence current from measurement data under the fault conditions. Firstly, the eigenvalues of three-phasors are sampled under the typical faults, such as single-phase ground fault, two-phase short-circuit fault, two-phase ground short-circuits fault, and three-phase short-circuit fault. Secondly, the three-phase current and the zero-sequence current are subjected to wavelet packet transform to extract the eigenvalues, which are viewed as the input of the neural network to determine the fault type. Finally, simulation results show that the proposed method can give reliable identification results under different fault conditions.

1. Introduction

Fault identification is a vital function of the advanced applications in distribution networks. At present, a large number of works have begun to focus on the phasor measurement unit (PMU) in fault identification. Reference [1-5] proposed many fault diagnosis methods using synchronous measurement data. Reference [6] established a reference failure mode containing timing stamps based on the typical failure types. When a fault occurs, the phasors under a fault condition is different from that under normal operation condition. Reference [7] proposed an online fault identification method based on PMU measurement data. Firstly, the grid was divided into multiple monitoring areas. Then, the abrupt characteristic of the positive sequence, negative sequence, and zero sequence current at boundary nodes are used to identify the fault types. Reference [8] proposed a method of fault identification and location for a smart grid based on the Petri net (PN). Reference [9-11] uses the PMU measurement data and the bus node impedance matrix to determine the fault section, diagnose the specific fault line, and identify the fault types. In [12], a fault identification method based on positive, negative, and zero sequence components and probabilistic neural network (PNN) is proposed. Reference [13-15] uses voltage phasor and switching information post-failure to identify faulty type through the PMU and the direction relay status. In [16-20], the fault diagnosis methods of active distribution networks based on D-PMU information and Petri net are proposed, where fault diagnosis is carried out by using Petri net technology through fault element library and fault diagnosis model.

In this paper, the three-phase current and the zero-sequence current are subjected to wavelet packet transform to extract the eigenvalues viewed as the input of the neural network. Firstly, this paper



analyzes the transient fault characteristics of various faults in Section 2. Then, the fault feature values extracted by the wavelet packet transform for measurement data are viewed as the input of the BP neural network in Section 3. Finally, the proposed method can be verified by using PSCAD under various faults types in Section 4. Conclusions are drawn in Section 5.

2. Wavelet packet transform

The overall framework of the proposed identification algorithm is shown in Figure 1. According to the three-phase current and zero-sequence current, the eigenvalues demonstrate the difference under different conditions. The extracted eigenvalues are normalized to get e_A , e_B , e_C and e_0 . Then the processed data are input into the trained BP neural network to identify the fault type, which has been classified into two steps: fault feature extraction and data training^[21-24].

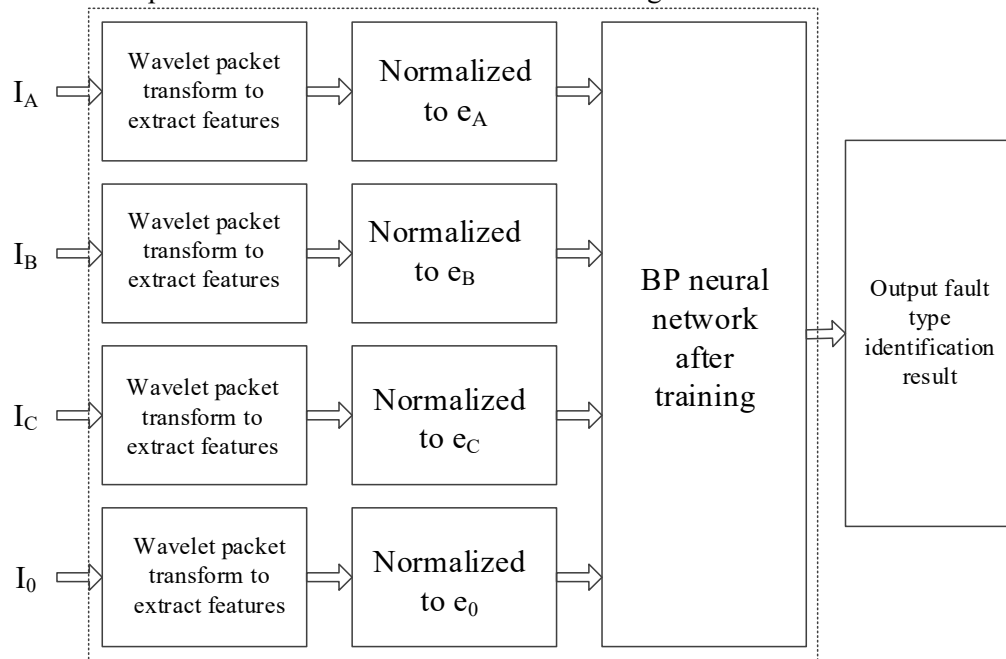


Fig1. Block diagram for fault type identification algorithm

In this paper, the proposed identification method can identify 10 different fault types, such as single-phase grounding fault (AG, BG, CG), two-phase phase short-circuits fault (AB, BC, CA), two-phase grounding short-circuits fault (ABG, BCG, CAG), three-phase short-circuit fault (ABC)[25,26].

The traditional identification method is based on Fourier transform (FT) or the corresponding improved methods [27,28]. In non-stationary cases, FT displays special frequencies due to some power quality indices errors [29,30]. Different from FT, wavelet analysis can represent signals in any frequency domain by using Wavelet Packet Transform (WPT), which provides more accurate results than FT especially for non-stationary voltage or current waveform under the sinusoidal or non-sinusoidal situations[31,32]. To obtain the high-frequency detail signal coefficient $d1(k) \sim d8(k)$ and low-frequency signal coefficient $a8(k) \sim d\delta j(k)$ are used to represent the wavelet packet coefficients of the k th node in the j th layer. The energy values of three-phase current and zero sequence current calculated by wavelet packet are used as fault features to identify fault types. From formula (1), the high-frequency energy values E_A , E_B , E_C , and E_0 of the I_A , I_B , I_C , I_0 wavelet packet can be obtained.

$$E_{\delta} = \sum_{k=1}^{100} \left| d_{\delta j}(k) \right|^2 \quad (1)$$

$$j = \delta$$

Where δ represents A, B, C, and zero sequence components.

If the calculated value E_{δ} is too large, it will make it difficult for researchers to understand the effective information. Thus, it is necessary to normalize energy eigenvector. The normalized value of e_A 、 e_B 、 e_C 、 e_D can be obtained simply by equation (2).

$$e_{\delta} = E_{\delta} / \max(E_A, E_B, E_C, E_0) \quad (2)$$

When a fault occurs, the energy e_{δ} will increase rapidly, which is significantly greater than that under normal operating conditions [33]. For the grounding faults, the zero-sequence current eigenvalue under a ground fault will be significantly greater than that under the non-ground-fault conditions [34]. According to the above analysis, whether the fault occurs or not can be completed by the energy normalizing processes, which are shown in Figure 2 under 10 different fault types.

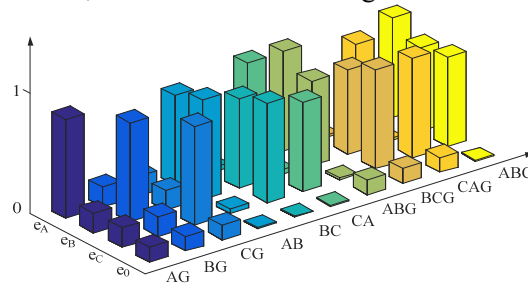


Fig.2 Energies under 10 different fault types

It can be obtained from Fig. 2 that the eigenvalues of three phases are also significantly larger than that of the zero-sequence current under the non-ground fault. Similarly, when other types of faults occur, these eigenvalues will also show different characteristics.

3. Back propagation neural network

3.1 Model

Compared with traditional methods, Back Propagation (BP) neural network has excellent advantages in adaptability, calculation efficiency, learning ability, and prediction accuracy, which can effectively solve the non-linearity problems with arbitrary variables. In the proposed BP neural network, the calculation direction is unidirectional, and the neurons have no correlation process [35]. Figure 3 shows the basic structure of the BP neural network, where both the connection weight between the two layers of the network and the calculation threshold of each neuron can make the output of the BP neural network tend to reach the forecasting value y_n .

In Figure 3, $x_1, x_2, \dots, x_n$ are the input values of the neural network, $y_1, y_2, \dots, y_n$ are the forecasting values of the neural network, ω_{ij} and ω_{jk} are the connection weights between the different layers.

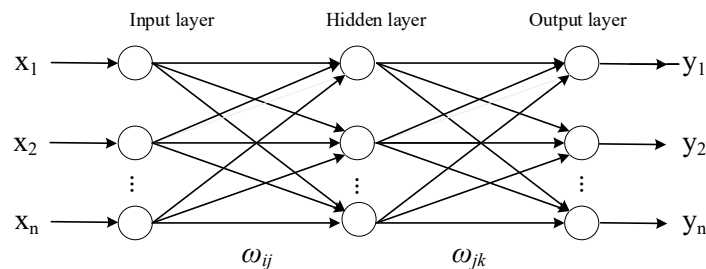


Fig.3 BP neural network

Before training based on BP neural network, it is necessary to input a certain number of fault samples in advance. The training steps are shown in Figure 4.

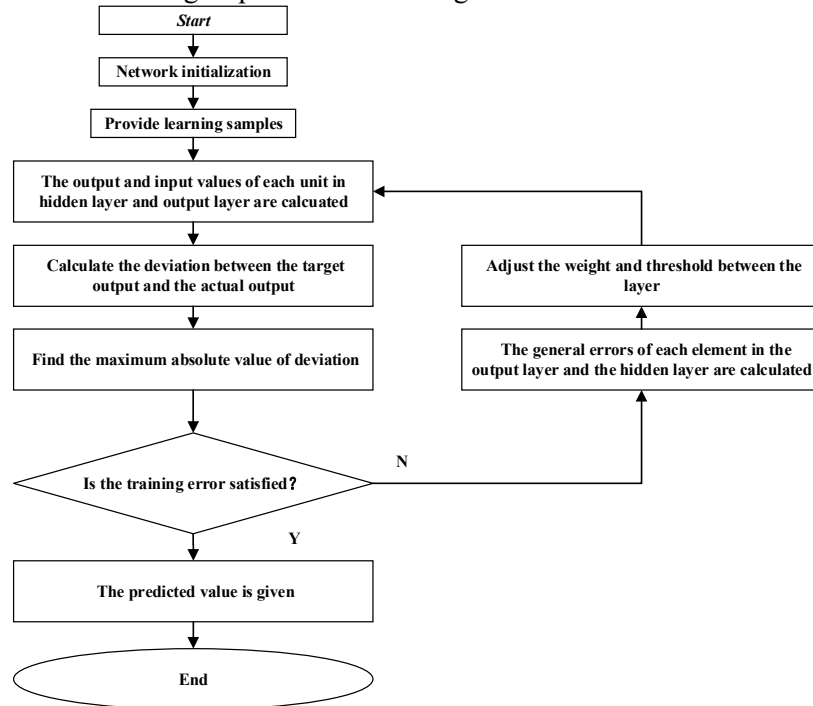


Fig.4 training steps in BP neural network

3.2 Algorithm

The BP neural network is mainly composed of forwarding propagation and back-propagation. In the first stage, the algorithm transmits the input data to the input layer, and then to obtain the output layer after calculating the hidden layer [36]. The state of the next layer is only affected by the state of the upper layer. If the output value in the first stage does not reach the expected value, the back-propagation will be transferred to the second stage, where the weight of each layer will be adjusted in real-time according to the difference of each layer. After adjusting the weights of each layer in propagation, the proposed algorithm is terminated until the output layer meets the expected value [37].

- (1) Using forward propagation to calculate the output value of each layer

The output y^l of l -th layer can be expressed as:

$$u^l = w^l \cdot x^{l-1} + b^l \quad (3)$$

$$y^l = f(u^l) \quad (4)$$

Where w^l is the weight, x^{l-1} is the input of layer $l-1$, y^l is the output of layer l , and b^l is the offset. $f(\bullet)$ is the activation function.

- (2) Calculate cost function

In the learning phase, the given data consists of N training samples. The square error function is described as

$$E^N = \frac{1}{2} \sum_{k=1}^c (t_k^n - y_k^n)^2 = \frac{1}{2} \|t^n - y^n\|_2^2 \quad (5)$$

Where y_k^n and t_k^n are the k -th output and input respectively in the training sample, c is the number of fault types. Equation (5) represents the sum of the errors for the training samples, where the error of the n -th sample can be expressed by equation (6).

$$E^N = \frac{1}{2} \sum_{k=1}^c (t_k^n - y_k^n)^2 = \frac{1}{2} \|t^n - y^n\|_2^2 \quad (6)$$

(3) Calculate the error of output layer

The sensitivity of output layer neurons can be expressed as follows

$$\delta^L = f'(u^L) \circ (y^n - t^n) \quad (7)$$

Where y^n and t^n represent the real output value and label value of the n -th sample respectively, and l is the l -th output layer.

(4) Calculate the error of the layers

The sensitivity of the neuron can be expressed by the derivative of the backpropagation error, its definition is as follows:

$$\frac{\partial E}{\partial b} = \frac{\partial E}{\partial u} \frac{\partial u}{\partial b} = \delta \quad (8)$$

Where δ is the sensitivity of each neuron and $\partial u / \partial b = 1$ can be obtained from formula (8), so $\partial E / \partial b = \partial E / \partial u = \delta$.

The sensitivity δ^L of the first layer can be expressed as:

$$\delta^L = (w^{L+1})^T \delta^{L+1} \circ f'(u^L) \quad (9)$$

Where: " $\circ$ " is the multiplication of all elements in the above formula, δ^{L+1} is the sensitivity of neurons in the $L+1$ layer.

(5) Update the weight

The weight of each neuron is updated by using the following equations.

$$\frac{\partial E}{\partial w^L} = x^{L-1} (\delta^L)^T \quad (10)$$

$$\Delta w^L = -\alpha \frac{\partial E}{\partial w^L} \quad (11)$$

Where α is the learning rate. The number of neurons in the input layer is the same as that of three-phase current and zero sequence current extracted by the wavelet packet transform. The number of hidden layers can be obtained by the following formula:

$$k = (m+n)^{1/2} + a \quad (12)$$

Where m is the number of output layers, k is the number of hidden layers, n is the number of input layers, a is the given constant, and the output layer is [A B C G]. When a fault occurs, the energy in the fault phase is 1 and that in the non-fault phase is 0[38].

(6) Algorithm

The BP neural network[39] based *Algorithm* is proposed as follows:

Algorithm 1

- Set the small initial value;
- Train the continuous input samples $X_0, X_1, \dots, X_{N-1}$ and output samples $d_0, d_1, \dots, d_{M-1}$;
- Calculate the actual output value $Y_0, Y_1 \sim Y_{M-1}$;
- Adjust the weights according to the following formula, and do the next step:

$$W_{ij}(t+1) = W_{ij}(T) + \eta \delta_j x'_j \quad (13)$$

Where W_{ij} is the weight from the hidden layer node i to the next layer node j , x'_j is the output of node j .

- If the output does not meet the threshold, return to the second step and update it as follows:

$$\Delta W_{ij} = \eta \delta_j x'_j + \beta \Delta W_{ij}(t-1) \quad (14)$$

In Algorithm 1, the result is usually not equal to the ideal value $\{0, 1\}$. To identify the fault types, the line can be regarded as the fault flag when the output is greater than 0.8 [40].

4. Case study

The simulation model of 500kV transmission network in Fig. 5 is constructed by PSCAD, which is used to simulate various short-circuit faults of transmission lines. In Fig. 5, the length of the transmission line is $L = 300\text{km}$, and the main parameters include the frequency 50 Hz, the positive sequence impedance. $Z_{G1} = 9.19 + j52.10\Omega$, $Z_{H1} = 8.19 + j42.11\Omega$, the zero-sequence impedance $Z_{G0} = 6.69 + j37.92\Omega$, $Z_{H0} = 6.52 + j34.16\Omega$ at terminal G and H respectively, the line positive-component impedance per unit $Z_l = 0.035 + j0.43\Omega/\text{km}$, the line zero-component impedance per unit $Z_0 = 0.30 + j1.15\Omega/\text{km}$, the line positive-component admittance $Y_l = (0.1 + j2.73) \times 10^{-6}\text{S}/\text{km}$, the line zero-component admittance $Y_0 = (0.1 + j1.95) \times 10^{-6}\text{S}/\text{km}$.

In this section, A-phase grounding fault (AG), AB two-phase grounding short-circuit (ABG), AB phase to phase short-circuit (AB) and ABC three-phase short-circuit (ABC) are simulated in PSCAD, and the transient waveform is recorded by PMU. The fault distance is 60km, and the transition resistance is set to 50Ω .

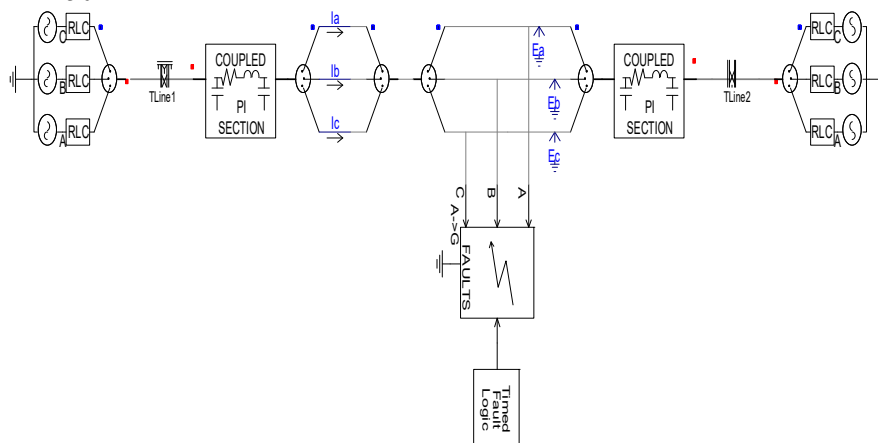


Fig.5 Simulation Diagram of 500kV Transmission Network

4.1 Single-phase grounding fault

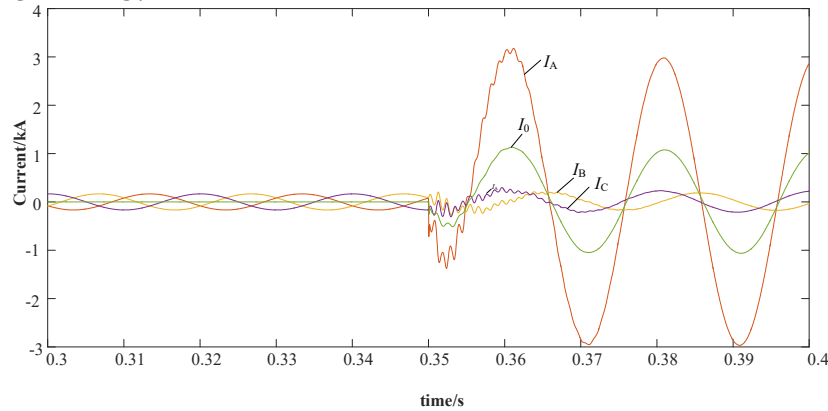


Fig.6 Current waveforms under a single-phase grounding fault

Taking single-phase grounding fault as an example, the waveforms of three-phase fault current and zero sequence currents are shown in Figure 6. It can be seen from Figure 6 that the A-phase current has an obvious distortion during the fault, and the zero-sequence current also increases suddenly. Due to the existence of the zero-sequence current path, a large zero-sequence current will also be generated, and its decomposition is shown in Figure 7.

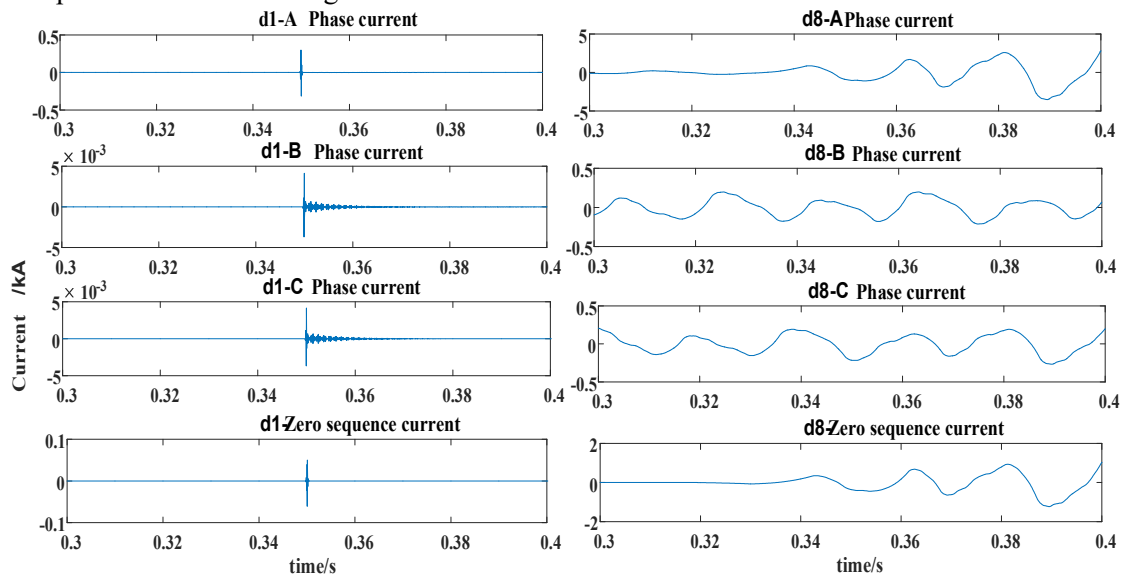


Fig.7 8-layer wavelet packet decomposition for a single-phase grounding fault signals

4.2 Two-phase fault

The current waveforms under two-phase fault are shown in Figure 8. It can be seen that only the AB phase produces abrupt short-circuit current, while there is no significant change for C-phase current. There is no grounding point to form a path for the zero-sequence current, so the zero-sequence current under a two-phase short circuit will not change obviously.

The current waveforms are shown in Figure 9. It is known that the two-phase grounding fault (ABG) gives the path for the flow of zero sequence current, which is different from the two-phase fault (AB). Therefore, it can be seen from Fig 8 and 9 that the zero-sequence current has also changed significantly under two-phase grounding fault.

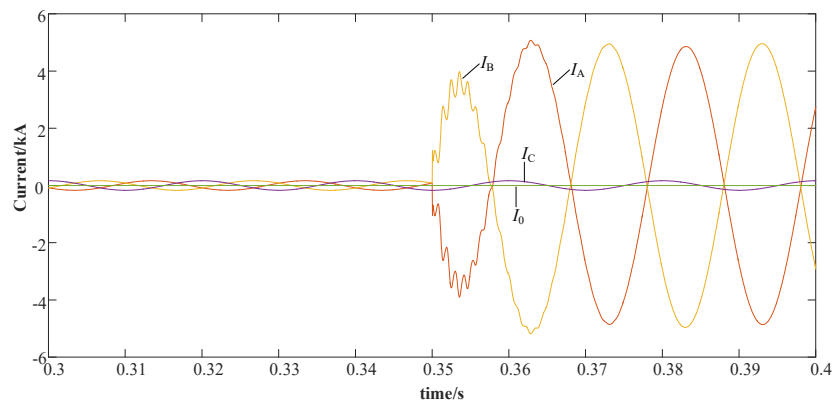


Fig.8 Current waveforms under two-phase fault (AB)

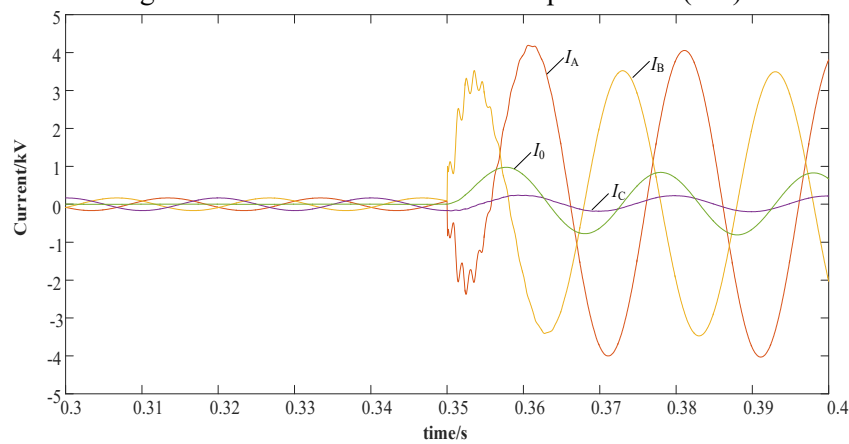


Fig.9 Current waveforms under two-phase grounding fault (ABG)

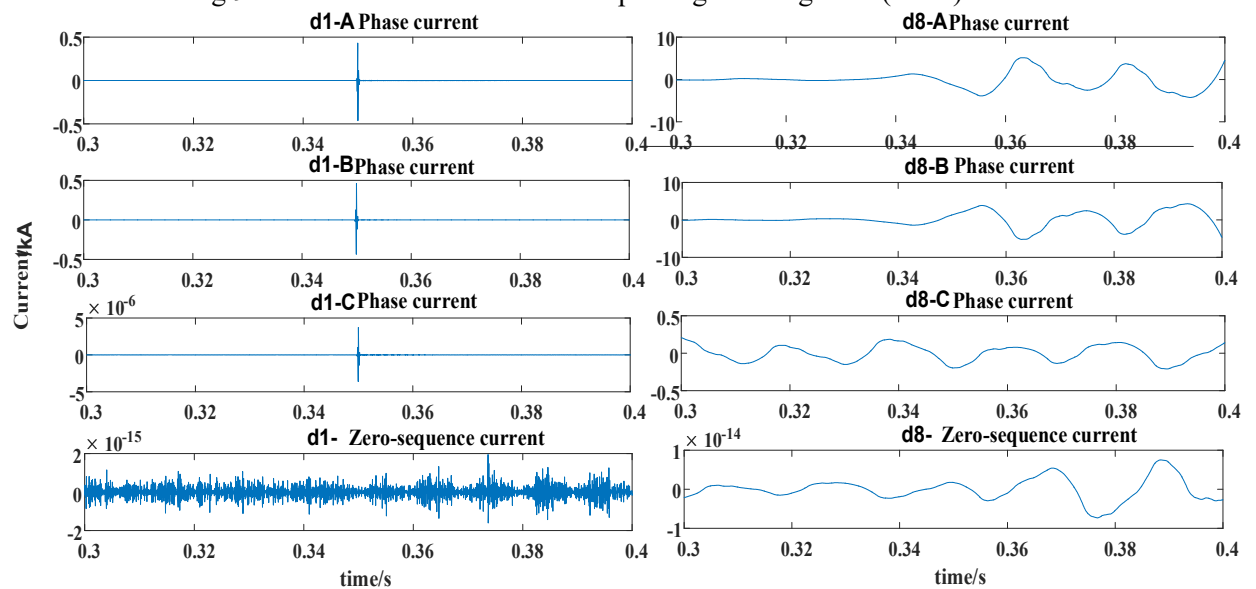


Fig.10 8-layer wavelet packet decomposition for two-phase fault

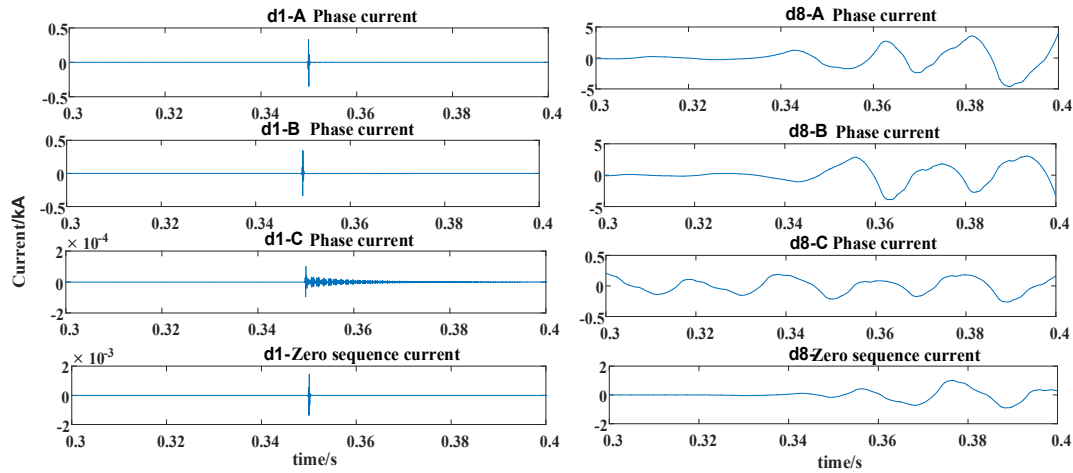


Fig.11 8-layer wavelet packet decomposition for two-phase grounding fault

4.3 Three-phase fault

The waveform of three-phase fault current and zero sequence current of three-phase short-circuit fault is shown in Figure 12 below:

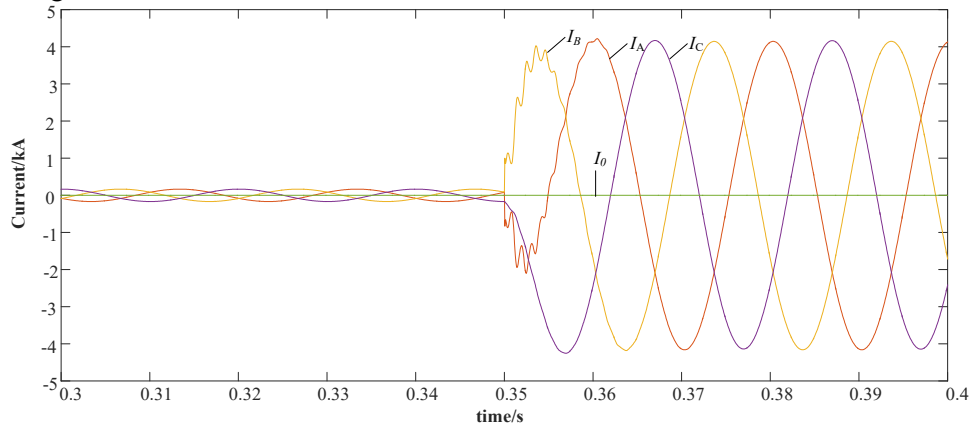


Fig.12 Three-phase current and zero-sequence current waveform during ABC fault

Compared with the short-circuit current generated by any other fault, the value of three-phase short-circuit fault current is the largest, so it is also obvious to the power grid impact. It can be seen from the above figure that the ABC three-phase fault current has changed significantly. At the same time, because there is no channel to make the zero-sequence current flow, the ABC three-phase fault will not produce the phenomenon of zero sequence current mutation.

The transient data of three-phase short-circuit fault current and zero-sequence current waveform obtained from the above four kinds of the simulation are imported into Matlab for 8-level wavelet packet decomposition, and the fault eigenvalues are calculated. The waveforms of various transient signal data decomposed by an 8-layer wavelet packet transform can be obtained, as shown in Fig. 10-13. Only d1 and d8 of the above four fault types are shown here.

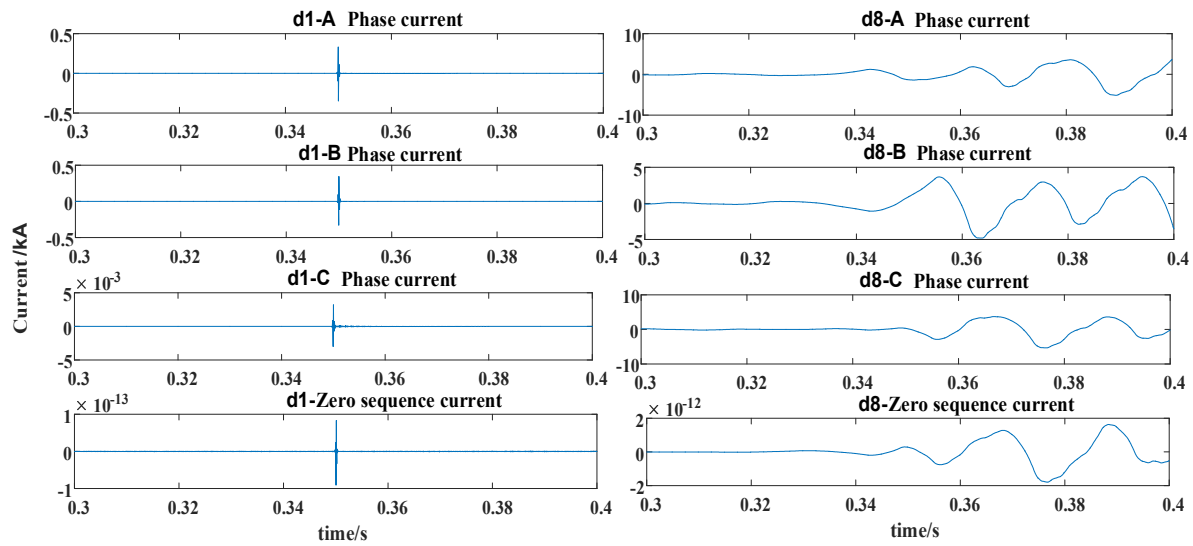


Fig.13 ABC 8-layer wavelet packet decomposition

4.4 Fault identification results

The energy eigenvalues E_A , E_B , E_C , and E_0 of current I_A , I_B , I_C , and I_0 are respectively calculated according to *Algorithm 1*. The corresponding fault characteristic values e_A , e_B , e_C , and e_0 are calculated according to formula (2), which are shown in Table 1.

Tab.1 Normalized energy value

fault type	energy value				normalized value			
	E_A	E_B	E_C	E_0	e_A	e_B	e_C	e_0
AG	164.8263	1.6048	3.8984	25.2213	1.0000	0.0097	0.0237	0.1530
AB	745.0309	804.7186	2.2204	0.0000	0.9258	1.0000	0.0028	0.0000
ABG	376.3266	474.7951	2.5684	2.7712	0.7926	1.0000	0.0054	0.0058
ABC	297.2286	615.9241	150.7408	0.0000	0.4826	1.0000	0.2447	0.0000

For the three-phase fault current, the fault characteristic value of the fault phase is larger than that of the non-fault phase. For the zero-sequence current, the extracted fault eigenvalue is very small when the fault is ungrounded. When the fault is grounded, the zero-sequence eigenvalue will increase due to the existence of the zero-sequence current path. The fault eigenvalues extracted by the wavelet packet can be used as the input of the BP neural network.

A, B, C, and zero-sequence current are selected as the index of the output, and a matrix is formed by a BP neural network to represent the fault situation of transmission lines. If the binary variable is 1, it means that a fault occurs at a certain phase in Table 2.

Tab.2 Binary outputs of the current

fault type	A	B	C	G
AG	1	0	0	1
BG	0	1	0	1
CG	0	0	1	1
AB	1	1	0	0
AC	1	0	1	0
BC	0	1	1	0
ABG	1	1	0	1
ACG	1	0	1	1
BCG	0	1	1	1

ABC	1	1	1	0
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The fault eigenvalue calculated by the wavelet packet and BP neural networks is listed in Table 3 by using the training sample set. Table 4 gives the output of test samples based on training samples. If the data in Table 4 is greater than 0.8, it is regarded as 1; otherwise, it is regarded as 0. After testing, it is proved that Algorithm 1 can be used to identify the fault types.

Tab.3 Training sample set

fault type	Fault characteristic				Neural network actual value			
	E_A	E_B	E_C	E_0	e_A	e_B	e_C	e_0
AG	1	0.0340	0.0181	0.0963	1	0	0	1
AB	1	0.9761	0.0173	0	1	1	0	0
ABG	1	0.5374	0.006	0.0881	1	1	0	1
ABC	1	0.9282	0.9025	0	1	1	1	0

Tab.4 test samples by using BP neural network

fault type		Actual output			Target output	R/E
AG	0.9747	0.0613	-0.0422	1.0432	[1001]	Right
	0.9139	0.0625	-0.0124	0.9736		Right
	0.9731	-0.0156	0.0274	0.9524		Right
AB	0.9311	0.9887	-0.0041	0.0298	[1100]	Right
	1.0031	1.0122	0.0207	0.0093		Right
	0.9944	1.0165	0.0326	0.0218		Right
ABG	0.9824	1.0100	0.0206	0.9764	[1101]	Right
	0.8794	0.9403	-0.0724	0.9654		Right
	0.9204	0.9813	-0.0142	0.8765		Right
ABC	0.9986	1.0011	0.9671	0.0078	[1110]	Right
	1.0227	0.9798	1.0213	0.0153		Right
	1.0155	0.9376	1.0746	0.0145		Right

Furthermore, the different transition resistance and fault location are proposed to verify the effectiveness of the proposed fault identification method. Firstly, the two-phase fault occurs at the distance 60km from the left bus. The fault identification results with 0Ω and 50Ω are shown in Table 5 and Table 6 respectively.

In Table 5 and Table 6, the energy eigenvalues of phase A and B are significantly greater than that of phase C. When two-phase grounding fault occurs at different positions with the same transition resistance, the energy eigenvalues of phases A and B are significantly greater than those of phase C, and the zero sequence energy eigenvalues are higher. To sum up, the proposed Algorithm 1 can accurately identify the fault type under different conditions [42].

Tab.5 Fault identification results with different transition resistances

Transitional Resistance	e_A	e_B	e_C	e_0	result
R=0 Ω	0.9415	1.0000	0.0021	0.0000	AB
R=50 Ω	0.9258	1.0000	0.0028	0.0000	AB
R=100 Ω	0.8994	1.0000	0.0050	0.0000	AB
R=150 Ω	0.8715	1.0000	0.0085	0.0000	AB
R=200 Ω	0.8440	1.0000	0.0130	0.0000	AB

Tab.6 Fault identification results at different fault locations

Fault location	e_A	e_B	e_C	e_0	result
L=0km	0.7252	1.0000	0.0089	0.0081	ABG

L=60km	0.7926	1.0000	0.0054	0.0058	ABG
L=120km	0.8527	1.0000	0.0009	0.0046	ABG
L=180km	0.9152	1.0000	0.0013	0.0040	ABG
L=240km	0.9899	1.0000	0.0171	0.0040	ABG
L=300km	1.0000	0.9374	0.0526	0.0043	ABG

5. CONCLUSION

This paper proposes a fault identification method based on BP neural and wavelet packet in power systems. The BP neural network is proposed to compare the characteristic under different fault types by using a sample set from synchronous measurement data. The wavelet packet is used to extract the fault characteristic. Simulation results show the effectiveness of the proposed method. This method can be applied to the fault identification of complex power grid and improves the accuracy.

Acknowledgments

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