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FAULT DIAGNOSIS OF WAVELET NEURAL NETWORK IN DISTRIBUTION NETWORK BASED ON D-PMU MEASUREMENT INFORMATION

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ABSTRACT

In order to improve the reliability and continuity of smart distribution network, the wavelet neural network (WNN) fault diagnosis method based on distributed phasor measurement units (D-PMU) measurement information has been presented in this paper. Firstly, the D-PMU uploads the collected local data to the main station system, and obtains signals such as voltage and current from the main station, constructed the feature signal after the wavelet packet decomposition and as the input signals of the neural network for algorithm training, and output the training result after satisfying the error requirement, accomplish fault diagnosis. Finally, the effectiveness of the algorithm by simulation analysis using MATLAB software is verified.

Keywords: D-PMU, distribution network, neural network, fault diagnosis

1. INTRODUCTION

With a large number of distributed power sources into the network, the network structure of the distribution network has undergone tremendous changes. While improving the resilience and self-healing capabilities of the distribution network, it will also threaten the normal operation of the distribution network. With the integration of the D-PMU, it has great significance to use the high-precision, high-sampling rate, time-stamped voltage, current and frequency signals provided by the D-PMU for fault diagnosis of the intelligent distribution network.

Based on the existing literature[1-5], this paper proposes a wavelet neural network fault diagnosis method based on D-PMU information. The adaptive learning rate and momentum combined gradient descent backpropagation algorithm is used to accelerate the convergence speed of the algorithm and improve the fault diagnosis algorithm accuracy. Compared with the existing neural network fault diagnosis method, it has the characteristics of fast convergence and high precision.

2. FAULT FEATURE EXTRACTION OF D-PMU MEASUREMENT DATA

2.1 Obtain the D-PMU measurement data

The D-PMUs distributed throughout the grid (distributed power, transformer station, electric power plant, etc.) upload local information to the main station system, then complete the fault diagnosis by the feature vector extracted from main station, which is a computer system installed at the power system dispatch center for receiving, managing, storing, analyzing, alerting, making decisions, and forwarding dynamic data. The D-PMU data communication system is shown in Figure 1.

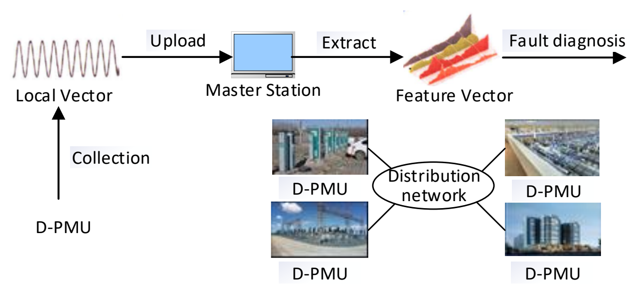

Fig 1 D-PMU data communication system

2.2 Wavelet transform analysis

The wavelet is a wave that has a short duration and must satisfy certain tolerances. Unlike the Fourier analysis, the basis of wavelet analysis is not unique. All functions satisfying the wavelet base condition can be used as wavelet functions. Therefore, the basic wavelet is determined according to the wavelet admissibility condition.

Set $\psi(t) \in L^2(R)$, whose Fourier transform is $\psi(\omega)$. if it is satisfied:

$$\int_{-\infty}^{+\infty} \frac{|\psi(\omega)|}{\omega} \mathrm{d}\omega < +\infty \tag{1}$$

Then $\psi_{a\tau}(t)$ is called the basic wavelet. Stretch and translate $\psi_{a\tau}(t)$ to get:

$$\psi_{a\tau}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-\tau}{a}\right) a>0 \ \tau\in R \tag{2}$$

Where $\psi_{a\tau}(t)$ is the continuous wavelet function; a is the expansion factor, also known as the scale parameter; τ is the displacement factor, also known as the translation parameter.

given the function $f(t)$ wavelet transform :

$$\left\langle f(t),\psi_{a,b}(t)\right\rangle=\frac{1}{\sqrt{a}} f(t)\psi^{*}\left(\frac{t-b}{a}\right)dt \tag{3}$$

2.3 Fault feature extraction of wavelet packet

Wavelet packet analysis can divide the frequency band into multiple layers and adaptively select the corresponding frequency band according to the characteristics of the analyzed signal to match the signal spectrum, thereby improving the time-frequency resolution and making the fault feature extraction more fine in the frequency band. Wavelet packet decomposition algorithm: Let X_{ij} be the decomposition coefficient of the original signal S after wavelet packet decomposition, and then reconstruct a single branch of each wavelet packet decomposition coefficient to extract the signals of each frequency band. The single reconstructed signal X_{ij} is represented by S_{ij}, then the total signal can be expressed as S: $S=\sum_{j=1}^{2^i} S_{ij}$, i is the number of layers wavelet packet decomposition.

When different types of faults occur in the distribution network, there is a big difference in the energy of the same frequency band on the output signal, and the energy of each frequency output signal can be used as the fault feature vector. This feature vector can be used as a fault feature of the distribution network.

Since the original signal and the constructed signal are random signals, there are:

$$E_{ij}=\int\left|S_{ij}(t)\right|^{2} \mathrm{d}t=\sum_{k=1}^{n}\left|x_{jk}\right|^{2} \tag{4}$$

Where A is the amplitude of the discrete point of the reconstructed signal B. Construct the feature vector as:

$$T=\left[E_{i1},E_{i2},E_{i3},\cdots,E_{i2^{i}}\right] \tag{5}$$

When the energy is huge, it brings inconvenience to the analysis, and the T can be normalized:

$$T'=\left[\frac{E_{i1}}{E},\frac{E_{i2}}{E},\frac{E_{i3}}{E},\cdots,\frac{E_{i2^{i}}}{E}\right] \tag{6}$$

Using the feature vector or the normalized feature vector as the input signal of the WNN.

3. WAVELET NEURAL NETWORK

3.1 Compact WNN structure

The compact WNN directly fuses the wavelet decomposition with the feedforward neural network. Using the wavelet function to replace the hidden node function of the neural network, and the weight of the corresponding input layer to the hidden layer is replaced by the scale factor of the wavelet function, and the threshold of the output layer to the hidden layer is replaced by the translation factor of the wavelet function. The compact WNN structure is shown in Figure 2.

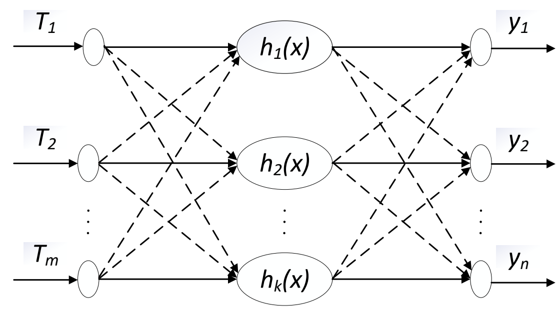

Fig 2 Compact WNN structure

In Figure 2, there are *M* nodes at the input end, T_m is the input sample, the hidden layer has *K* nodes, and $h_j(j=1,2,\cdots,K)$ is the wavelet function. Using the Morlet wavelet in this paper, which is a cosine-modulated Gaussian wave, and the resolution in the time-frequency domain is better High, and meet compatibility conditions. The wavelet function of the j-th neuron in the hidden layer is $h\left(T-\tau_j/a_j\right)$, and the output layer has *N* nodes, $y_k(k=1,2,\cdots,\mathrm{N})$. ω_{ij} denotes the connection weight of the i-th neuron in the input layer with the j-th neuron in the hidden layer, ω_{jk} denotes the connection weight of the j-th neuron in the hidden layer with the k-th neuron in the output layer, a_j and τ_j are the scale factor and translation coefficient of each neuron of the wavelet function. The output of the WNN can be expressed as:

$$y_n=\sum_{j=1}^{K}\omega_{jk}h_j(T)=\sum_{j=1}^{K}\omega_{jk}h_j\left(\frac{\sum_{i=1}^{N}T_i-\tau_j}{a_j}\right)h_1(T) \tag{7}$$

3.2 *The compact WNN training algorithm*

The adjustment of the weight of WNN is the gradient descent method. Due to the inherent characteristics of the gradient descent method, the training process of WNN has several shortcomings such as slow convergence rate, easy to fall into local minimum value, and easy to cause an oscillating effect. In view of the above shortcomings, two improvements have been made in this paper: one is to introduce the momentum term; the other is to use the variable learning rate method. The gradient descent backpropagation algorithm combined with an adaptive learning rate and momentum used in this paper is as follows:

(1) If the k-th training error exceeds the last learning error, the learning is canceled. At this time, the learning rate is multiplied by a decreasing scale factor L(0<L<1); the momentum coefficient is zero.

(2) If the Kth learning error is less than the last learning error, the learning is retained, at which time the learning rate is multiplied by a growth ratio factor g(g> 1), and if the momentum coefficient is set to zero, the initial value is restored. In this paper, the initial value α is set to 0.85.

The threshold of WNN and the scaling factor and translation factor of wavelet can be adjusted by the following formula:

$$\omega_{jk}(k+1)=\omega_{jk}(k)-\eta_{\omega}\frac{\partial C}{\partial \omega_{jk}}+\alpha_{\omega}\Delta\omega_{jk}(k) \tag{8}$$

$$a_j(k+1)=a_j(k)-\eta_a\frac{\partial C}{\partial a_j}+\alpha_a\Delta a_j(k) \tag{9}$$

$$\tau_j(k+1)=\tau_j(k)-\eta_\tau\frac{\partial C}{\partial \tau_j}+\alpha_\tau\Delta\tau_j(k) \tag{10}$$

Where η_ω , η_α and η_τ are the learning rates of ω_{jk} , ω_{jk} and τ_j , respectively, and α_ω , α_a , and α_τ are the momentum factors of ω_{jk} , ω_{jk} and τ_j , respectively.

The training steps are as follows:

(1) Initialization of network parameters: Set the number of nodes of the input layer, hidden layer and output layer of the WNN to *m*, *k*, *n* respectively, the expansion coefficient a of the initialization network, the translation coefficient α ; the network weight coefficients ω_{ij} and ω_{jk} ; the learning rate η ; the momentum factor α ;

(2) Select samples: Select n input learning samples X_n to calculate the actual output value and learning error;

(3) Correct the parameters: Error back propagation, correcting each parameter;

(4) Updating the learning rate and the momentum factor: judging the error magnitude, and updating the learning rate and the momentum factor according to the gradient descent backpropagation algorithm;

(5) Error calculation: Calculate the error value after training to meet the requirements. If it is meet, the training ends; if not, return to step (2) until the error meets the requirements.

3.3 *Smart distribution network fault diagnosis method*

When the distribution network fails, the local D-PMU uploads the time-stamped data to the main station through the communication device, and can determine whether the distribution network has failed according to the information of the D-PMU. The fault diagnosis steps are shown in Figure 3.

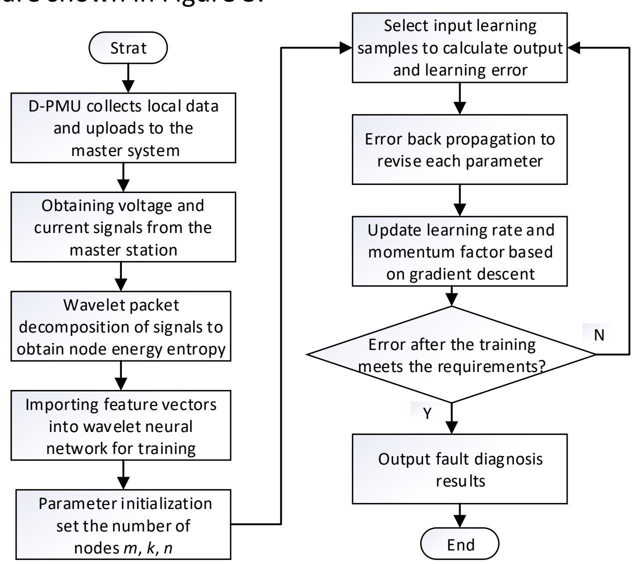

Fig. 3 Fault diagnosis algorithm flow chart

4. SIMULATION EXAMPLE

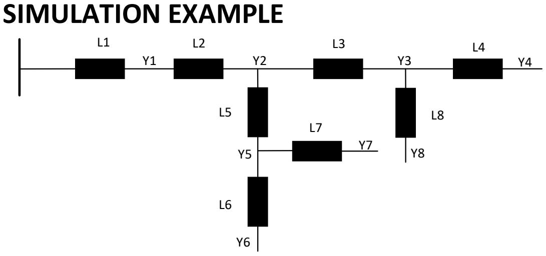

Fig 4 Distribution network simplified topology chart

Figure 4 shows a simplified topology of a distribution network subsystem in a region. In the Figure, L1 represents the circuit breaker of the line, L2 to L18 represent the section switches of the line, and Y1 to Y8 represent the areas of the distribution network. A three-layer network structure is set for the practical application problem of fault diagnosis and positioning studied in this paper. The specific value *k* of the hidden layer will be determined by the formula (11).

$$k = \sqrt{m+n} + a \quad (11)$$

Where k is the number of nodes in the hidden layer, m is the number of input layer nodes, n is the number of output layer nodes, $a \in [1, 10]$ and is an integer. It can be seen from the Figure that the input layer m and the output layer n are both 8. According to the empirical formula, determines a=3, the total number of neurons k=7 as the hidden layer.

According to the working principle of the distribution network, 10 sets of fault data samples are extracted, 4 sets of data are randomly selected as the test data of the neural network, the fault characteristics of the test data are trained by the algorithm, and use the Matlab software to simulation. The results are shown in Table 1.

Tab 1 Fault diagnosis result table

Sample	1	2	3	4
Y1	0.9894	0.0013	0.0019	0.0036
Y2	0.0016	0.0026	0.0033	0.9638
Y3	0.0013	0.0017	0.9558	0.0018
Y4	0.0092	0.0019	0.0028	0.0023
Y5	0.0025	0.9971	0.0085	0.0038
Y6	0.0019	0.0022	0.0014	0.0043
Y7	0.0030	0.0011	0.0019	0.0061
Y8	0.0021	0.0042	0.0027	0.0012
Fault Point	Y1	Y5	Y3	Y2

According to the table, the fault diagnosis accuracy of the WNN is 100%. The fault diagnosis data output of the WNN is selected closest to the area corresponding to the value of 1 is the fault area.

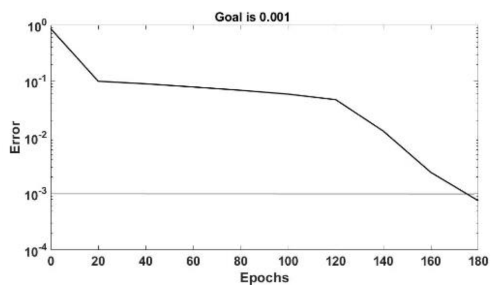

Fig 5 Traditional neural network algorithm

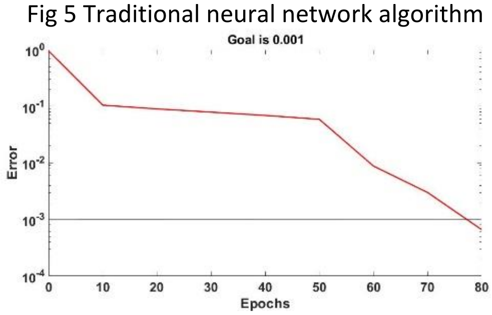

Fig 6 WNN algorithm

According to the selected test samples, the WNN algorithm and the traditional neural network algorithm are used to train the samples. The network error curves of the two algorithms are shown in Figure 5 and Figure 6, respectively. Comparing Figure 5 and Figure 6, it can be seen that the traditional neural network algorithm achieves the training target 0.001 when iterating to 175 steps, and the WNN algorithm only needs to iterate to 77 steps to reach the training target. The improved neural network can effectively improve the training and learning speed of the neural network when performing fault diagnosis of the intelligent distribution network, shorten the training time.

5. CONCLUSION

This paper proposes a fault diagnosis method based on D-PMU for WNN. Combining wavelet analysis and neural network, the main station obtains voltage and current information and wavelet packet decomposition to obtain feature vectors. The adaptive learning rate and momentum combined with gradient descent backpropagation algorithm are trained to output fault diagnosis results. By using Matlab simulation software to compare the traditional neural network algorithm with the wavelet neural network algorithm simulation, both the number of simulation steps and the accuracy of fault diagnosis have great advantages in all aspects.

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