ANALYSIS OF WAVELET NEURAL NETWORK ALGORITHM IN INVERTER FAULT DIAGNOSIS

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Abstract - The frequency conversion speed regulation system powered by inverter is widely used in various fields. It is particularly important that the inverter that is most prone to failure can quickly and accurately locate the fault location and analyze the cause of the fault. The Wavelet Neural Network (WNN) is used as the entry point, and the fault diagnosis of the inverter is studied. Firstly, the Back Propagation (BP) algorithm commonly used in WNN is analyzed. A variable learning rate factor is introduced, and a variable learning rate variable weighted recursive least squares algorithm is proposed. Then, the relevant parameters are set. The inverter fault diagnosis simulation experiment is designed. Experiments show that the improved Learning Rate and Variable Weight Recursive Least Squares (LWRLS) algorithm completes fitting 1200-1300 steps faster than the BP algorithm in terms of operation speed. In terms of network error, the error value of the WNN of the BP algorithm can only reach 104. The error of the WNN of the LWRLS algorithm reaches 106. Therefore, when the algorithm is improved, the network error of WNN is reduced a lot. In the fault diagnosis accuracy, the average accuracy of the BP algorithm is 98.37%, and the standard deviation is 1.2571. The average accuracy of the LWRLS algorithm is 99.56% with a standard deviation of 0.3920. The fault recognition rate after the improved algorithm is significantly better, and the stability is better. Theoretical analysis and simulation results show that the improved LWRLS algorithm in WNN has the advantages of fast operation speed, small network error and high diagnostic accuracy in the inverter fault diagnosis method. The proposed improved WNN algorithm provides a reference for the application of inverter fault diagnosis.

Keywords: Inverter fault; Wavelet Neural Network; Simulation experiment; Back Propagation algorithm; LWRLS algorithm.

1. Introduction

With the high-speed update of semiconductor technology and the update and iteration of power devices, inverter-powered variable frequency speed control systems are widely used in various fields of the national economy due to their excellent speed control performance [1]. A large number of data show that the link with the highest failure rate in the inverter circuit is the power switching device, because the power electronic device is relatively fragile. Failure of the switching device can increase the voltage and current stress on other power devices. If this fault is not diagnosed and isolated in time, it will cause secondary faults and eventually lead to system downtime. This will not only damage the power device itself, but also affect the reliability and safety of the entire system, resulting in economic losses and even casualties [2]. Therefore, the research of inverter fault diagnosis method is of great significance in reducing losses and maintaining stable operation of equipment. With the increasing safety and reliability requirements, timely diagnosis and location of inverter faults is an urgent problem that needs to be solved at present. It has also attracted more and more researchers' attention.

So far, scholars have put forward many fault diagnosis methods through continuous research. The first is the fault diagnosis method based on the model, the model includes quantitative model and qualitative model. Quantitative models are mainly used in fault diagnosis [3]. At present, model-based inverter fault diagnosis methods can be divided into model-based inverter fault simulation, fault diagnosis based on state estimation and parameter estimation, etc. [4]. The second is knowledge-based fault diagnosis methods. The method utilizes the mastery of the object model and the memory of daily summarized experience, and relies on certain discriminative inference to establish the mapping relationship related to the failure mode, and then realize the fault diagnosis of the research object model. Knowledge-based fault diagnosis methods mainly include neural network method, support vector machine method, expert system method and so on. In addition, there are state estimation method, bond graph theory, etc. [5]. Although these methods are simple and easy to use, each model in the first type of model-building diagnostic methods can only correspond to a specific fault, and may not respond or be insensitive to other faults, resulting in inaccurate fault interpretation and failure to meet actual production requirements. needs. In addition, the disadvantage of knowledge-based diagnosis method is that it has great limitations to identify by empirical data, such as slow derivation, difficulty in establishing knowledge base, and poor real-time performance.

A method is proposed to complete the discrimination of the fault mode through Wavelet Neural Network (WNN), and use the wavelet theory operation to obtain the eigenvalues of the collected fault information. Finally, this method is successfully applied to the diagnosis of inverter faults. Wavelet transform has excellent ability of multi-resolution analysis. In the time-frequency domain, the size and area of the wavelet window is fixed but its shape can be changed. That is, the product of the time resolution and the frequency resolution is constant, and it is also used in various fault detection. Its advantages are also obvious, it does not need a mathematical model of the research object. It is easy to use, and the diagnosis efficiency is high.

2. WNN Algorithm and Design of Inverter Fault Simulation Experiment

2.1 Analysis of Inverter Failure Modes

As the output part of the variable frequency speed regulation system, the inverter is directly connected to the load. If there is a failure, it will have a serious impact on the system.

The failure of the inverter mainly refers to the failure of the power switching device. Among them, the open circuit and short circuit of power switching devices are the most common, which can also be called hard faults. Because the power switching device has to withstand high voltage and large current when it is working, its overload capacity is limited, which leads to a high probability of damage to the switching device. Once the switching device fails, it will not only damage the power switching device itself, causing the system to fail to operate normally, but also affect the reliability and safety of the entire power system, resulting in huge economic losses and even casualties. When a fault is detected in the system, the conventional protection system of the inverter will trip and alarm, but the location and severity of the fault cannot be determined. The power switching device in the inverter is driven by the driving circuit, and the failure of the driving circuit will lead to the failure of the power switching device. Assuming that the fault in the system is a single fault, and the faults are independent of each other and will not propagate each other. The open-circuit fault and short-circuit fault of the power switch tube are deeply studied [6].

(1) Analysis of inverter open circuit fault

The open-circuit faults of the inverter switch tube include Insulated Gate Bipolar Transistor (IGBT) open-circuit faults and anti-parallel diode open-circuit faults. Typically, diodes have good characteristics, long service life, and are less prone to failure. IGBT switches are controlled by a separate drive circuit, and drive failures often cause IGBT switch failures. When the drive circuit of the power switch tube fails, the power switch tube does not work. The U-phase current of the inverter is connected to the positive pole of the DC bus through the freewheeling diode. The polarity of the U-phase of the inverter will be determined by the direction of the current and the switching state of the power switch tube of the lower arm [7].

(2) Fault analysis of inverter short circuit

There are many reasons for the short circuit of the power switch tube IGBT, such as high operating temperature, low voltage withstands performance of the device, and reverse breakdown of itself. When a short-circuit fault occurs in the IGBT, the current increases rapidly. If the corresponding measures are not taken to protect the circuit, the IGBT will burn out quickly. When the power switch tube of the upper bridge arm is short-circuited, the power switch tube of the lower bridge arm is also forcibly turned off. This is to protect the inverter and prevent the bridge arm from passing through, causing a larger fault [8].

2.2 WNN

Wavelet analysis is a new analysis theory and method in mathematical theory, and it is also a major innovation in tools and technologies. The unique local optimization performance of wavelet analysis enables it to perform well in both time and frequency domains. The reason why wavelet analysis has this characteristic is that it relies on the flexible and variable time-frequency window. The time-frequency window can expand the research scope in the time domain and frequency domain at the same time, which is convenient for better problem discovery. This property makes it applicable to nonlinear sciences such as differential equations, pattern recognition, and computer vision [9-11].

(1) Construction of WNN

The input and output equations of WNN are shown in equation (1):

$$Y_k = \sum_{j=1}^{H} C_{jk} g\left(\frac{\sum_{i=1}^{I} x_i \omega_{ij} - b_j}{a_j}\right) \tag{1}$$

Y_k refers to the output value of the *k-th* output node; C_{jk} refers to the connection weight between the j-th hidden layer node and the *k-th* output node; x_i refers to the input value of the *i-th* input node; ω_{ij} refers to the connection weight between the *i-th* input node and the *j-th* hidden layer node; a_j refers to the scaling factor of the *j-th* hidden layer node; b_j refers to the translation factor of the *j-th* hidden layer node; g(x) refers to the wavelet basis function.

There are N groups of observation data input in the structure of WNN. For the convenience of explanation, only the case of single output is considered. The network structure is shown in Figure 1:

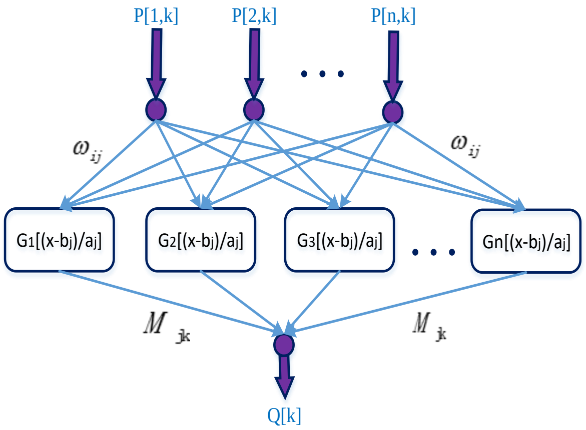

Figure 1: Model structure of WNN

In Figure 1, the first layer of the network is the input node layer. The wavelet basis function is used as the hidden layer node in the neural network, that is, the node of the second layer. The third layer is the output layer. After the input sample is operated by the wavelet function, the obtained output value is multiplied by the corresponding weight, and the calculated estimate will be output here [12].

(2) Determination of the number of nodes in each layer of WNN

A neural network consists of an input layer, a hidden layer and an output layer. The number of neurons in the input layer is related to the number of signal features. The number of neurons in the output layer is determined according to the method of nonlinear function approximation. In the inverter fault diagnosis of the variable frequency speed regulation system, the number of neurons in the input layer is 3, and the number of neurons in the output layer is 1. The determination of the number of hidden layer nodes is the most critical. At present, the existing theoretical basis cannot be well supported. The usual practice in practice is to repeatedly compare or calculate based on empirical equations. A reasonable number of neurons in the hidden layer can make the whole network work normally and effectively. If the number of hidden layer nodes is small, the training cannot start. If the number of hidden layer nodes is too large, it will consume a lot of additional computing resources, which will ultimately affect the training speed and greatly prolong the training time. The principle to follow to determine the number of hidden layer nodes is to balance the network convergence speed and prediction accuracy in a test-by-test method from small to large [13]. The experience of determining the number of hidden layer nodes is shown in equation (2):

$$h \geq \sqrt{n+m} + a \tag{2}$$

n is the number of input neurons; *m* is the number of output neurons; *a* is a constant between 1 and 10.

(3) Initialization of WNN parameters

The initial value of WNN has a lot to do with whether the learning reaches a local minimum and whether it can converge, and the length of training time. If the initial value deviates greatly and the weighted input falls in the saturation region of the activation function, the conditioning process will almost stop. Therefore, it is generally required that the output value of each neuron after initial weighting is close to zero. This ensures that the weights of each neuron are adjusted at the maximum change in their activation function.

(4) Learning algorithm of wavelet network

The wavelet network is very similar to the three-layer Back Propagation (BP) network. Therefore, the adjustment rules of the weights of the wavelet network can be borrowed from the BP algorithm [14]. The essence of the BP algorithm is the gradient descent method. The gradient descent method is derived from the optimization calculation method. It is the most basic of all kinds of learning algorithms. The basic idea is to use the sum of squares of errors between the expected output of the neural network and the actual output of the network as the learning objective function, and to adjust the network weights according to the principle of its minimization. The error function is defined as equation (3):

$$E(W) = \frac{1}{2}\left\|Y(k) - \hat{Y}(W,k)\right\|^2 \tag{3}$$

k is a discrete time variable. W is a vector composed of the weights of the network. $\hat{Y}(W,k)$ is the actual output of the network. $Y(k)$ is the desired output of the network. $\|\cdot\|$ represents the Euclidean norm of the vector. The gradient descent method is to continuously correct the value of W along the negative gradient direction of E until $E(W)$ reaches the minimum value, as shown in equation (4):

$$W(k+1) = W(k) + \eta(k)\frac{\partial E(W)}{\partial W}/W = W(k) \tag{4}$$

$\eta(k)$ is a variable that controls the speed of weight adjustment, usually related to the step size of the calculation.

In the algorithm, since the value of the learning rate is the same, the step size in the learning process is also the same, and the learning rate cannot be maximized and stable at the same time. When the learning rate is too large, the algorithm may be extremely unstable. If the learning rate is too small, the convergence speed will be slow, resulting in prolonged training time. The choice of learning rate has a great impact on the performance of the algorithm. Therefore, a variable learning rate factor is introduced based on the improved algorithm, which is called Learning Rate and Variable Weight Recursive Least Squares (LWRLS).

The algorithm can adjust the learning rate according to the current state of the wavelet neural network, thereby further improving the convergence speed of parameter learning, as shown in equation (5):

$$mc(k) = \begin{Bmatrix} (1+\alpha)mc(k-1), E(k) < E(k-1) \\ (1-\alpha)mc(k-1), E(k) > E(k-1) \end{Bmatrix} \quad (5)$$

mc(k) is the variable learning rate, and *E(k)* is the error value.

2.3 Simulation Experiment Design of Inverter Fault Diagnosis

The inverter fault diagnosis scheme consists of three stages: rotor three-phase current acquisition when the inverter fails, WNN training and fault discrimination [15]. The fault flow chart is shown in Figure 2:

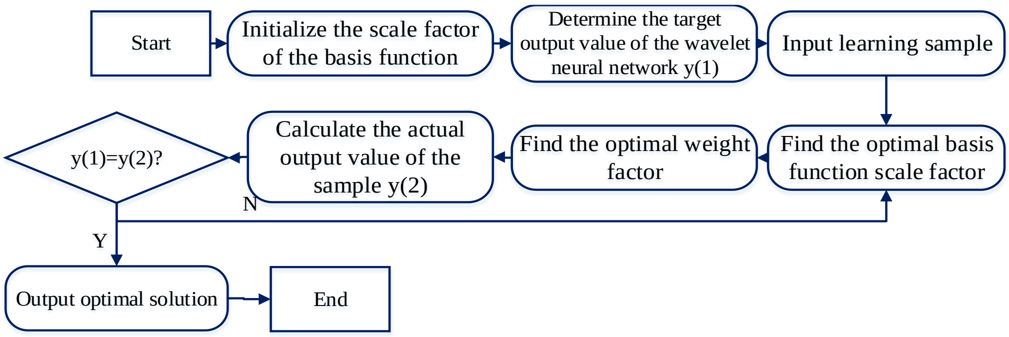

Figure 2: Flowchart of fault diagnosis

In Figure 2, appropriate variables are selected for reasonable data sampling. These collected data are used as learning samples and detection samples of WNN. In order to provide the network with an input-output pattern that can accurately reflect the characteristics of the system, the learning samples should have three characteristics: compactness, ergodicity and compatibility [16]. In general, the selection of samples should follow these principles:

(1) The sample reflects the working range and parameter characteristics of the research object as comprehensively as possible.

(2) The sample-trained network should have good interpolation and extrapolation performance.

(3) The number of samples is as small as possible to reduce the number of trials and the resources occupied by the training network.

The simulation experiment platform is used to simulate the operation state of a single power switch when open-circuit and short-circuit faults occur, and the relevant graphs are drawn. Thereafter, variable graphs are analyzed and compared. Variables such as rotor phase current, electromagnetic torque, active power, reactive power, and rotor voltage all show certain changes when a fault occurs. Variables or data with large amplitude changes and certain regularity are selected as input samples of WNN. This facilitates the fitting of WNN to the data [17, 18].

The target error value is set. Three algorithms are used to train the WNN. Because the collected samples are the three-phase currents of the rotor, the number of nodes in the input layer of the WNN is 3. The number of nodes in the hidden layer is calculated according to the empirical equation, and the result is 8. The number of nodes in the output layer is 1. The wavelet function selects the Mexican Hat wavelet basis function. Because the Mexican Hat wavelet basis function is more suitable for parameter identification.

The scale factor, the learning rate change factor, and the initial value of the learning rate are obtained through many experiments and through the experimental results. The parameter settings of each layer of the constructed WNN are shown in Table 1:

Table 1: Parameter settings

Parameter setting	Input layer node	Hidden layer nod	Output layer node	Basis function selection	Scale Factor	Initial learning rate (mc)	Learning rate change factor
	3	8	1	Mexican Hat	2	1.5	0.08

3. Simulation Results and Analysis

3.1 Comparison Before and After Algorithm Improvement

In order to verify the effect of the improved algorithm, the WNNs of the two algorithms before and after the improvement are trained separately. Meanwhile, the least squares recursion algorithm is added to the training, and the effect is compared. The target error value is set until the output value error of the wavelet network reaches the predetermined accuracy requirement. The training speed is shown in Figure 3:

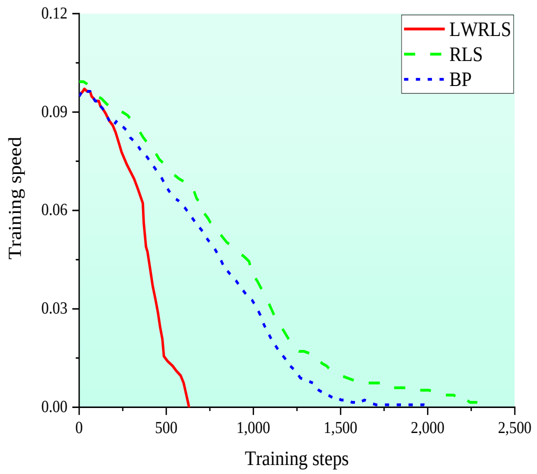

Figure 3: Training speed of different algorithms

In Figure 3, the initial fitting speed of the three algorithms is fast. At about 150~200 steps, the downward trend of the training fit of the first two algorithms becomes very slow. The fitting speed of the improved LWRLS algorithm has been fast. Meanwhile, the introduction of the momentum term effectively avoids the occurrence of shocks, and the smoothing effect is obvious.

The error curves of the WNN for three different algorithms are shown in Figure 4:

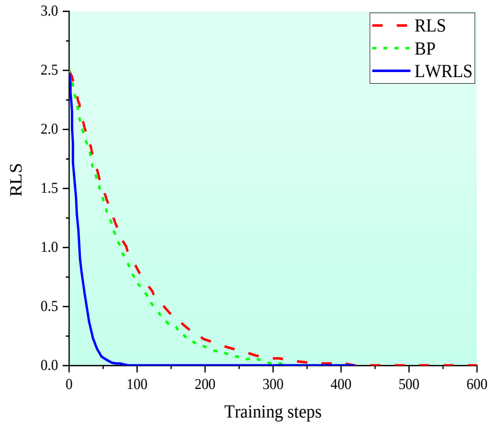

Figure 4: Error curves of three different algorithms

In Figure 4, the identification errors of the WNN of the three different algorithms gradually decrease, and all have good dynamic followability and accuracy. However, the error reduction speed of the improved LWRLS algorithm is faster. The error value is close to the accuracy requirement when it is close to 100 steps. The algorithm before the improvement only meets the accuracy requirements when it is close to 400 steps. In general, the effect of the improvement of the algorithm is obvious, which shows that the improved algorithm is more effective.

3.2 Comparison of Simulation Results of Different Algorithms

The fault condition of the inverter in the variable frequency speed control system is simulated by Matlab/Simulink, because the measured voltage and current change with time. A regulation module is added to the simulation module to eliminate the interference of noise in the detection stage. The conditioning block consists of a low-pass filter and an averaging block. The output simulation waveforms of the alternating current (AC) phase current and AC phase voltage after filtering are shown in Figure 5:

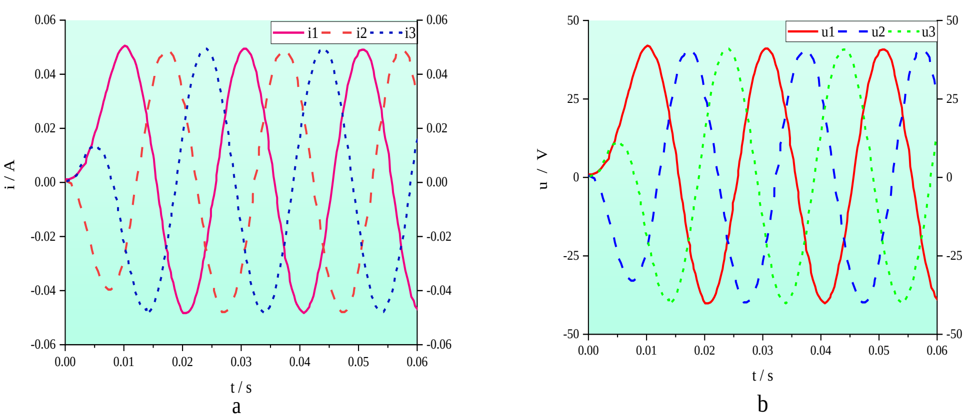

Figure 5: Simulation waveforms of current and voltage (a: AC phase current waveform; b: AC phase voltage waveform)

In Figure 5, in the case of no fault, the three-phase current and three-phase voltage output by the inverter change in a sinusoidal form.

When the switch has an open-circuit fault, the simulation waveforms of the output load current i1, i2, and i3 are shown in Figure 6.

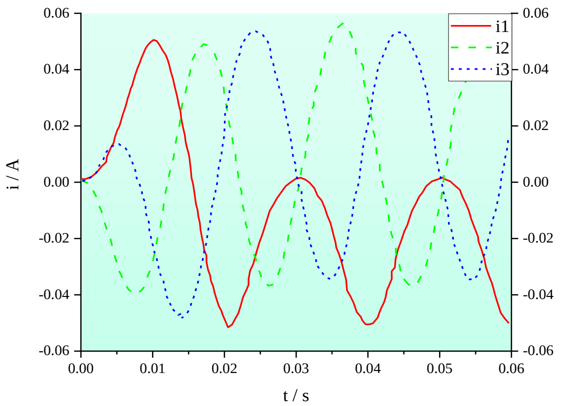

Figure 6: Waveform of inverter's three-phase current output during open circuit fault

In Figure 6, at 0.03s, the power switch has an open-circuit fault, and the positive half-wave of the load current i1 at the output end is missing.

When the power switch tube has a short-circuit fault, the output load current of the inverter is shown in Figure 7:

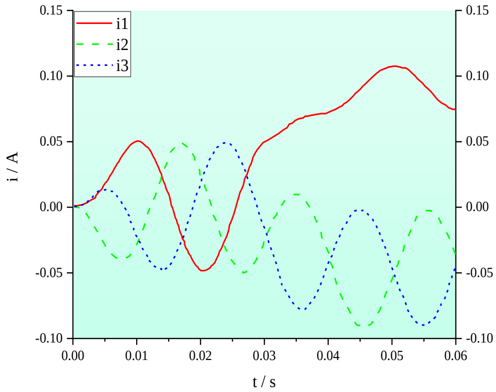

Figure 7: The three-phase current output waveform of the inverter during short-circuit fault

In Figure 7, the load current i1 at the output end oscillates violently. This kind of fault is more serious, and the motor may stop or burn out.

When the switch has a short-circuit fault, the residual waveforms before and after improvement are shown in Figure 8:

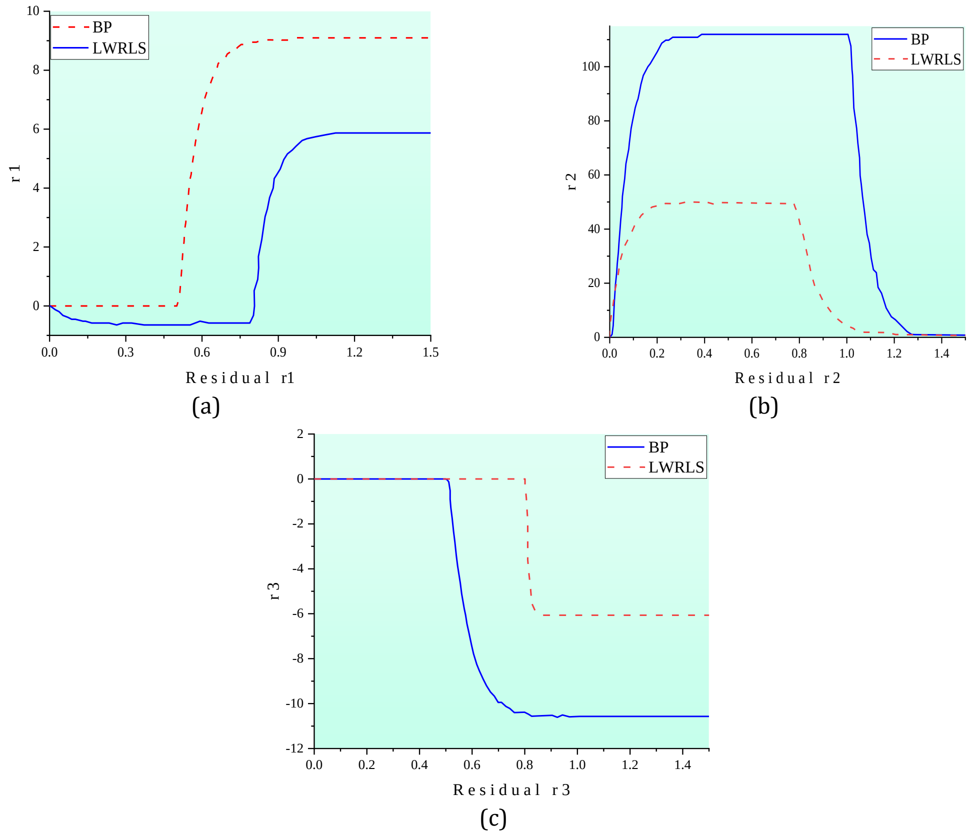

Figure 8: Residual waveforms of short-circuit faults under the two algorithms (a: waveform of residual r1; b: waveform of residual r2; c: waveform of residual r3)

In Figure 8, the initial non-zero residual r2 is due to the uncertain causality in the algorithm. According to the residual waveform obtained by the simulation, although there is a residual change when a short-circuit fault occurs. But the residual magnitude of the LWRLS algorithm is smaller.

When the switch has an open-circuit fault, the residual waveforms before and after improvement are shown in Figure 9:

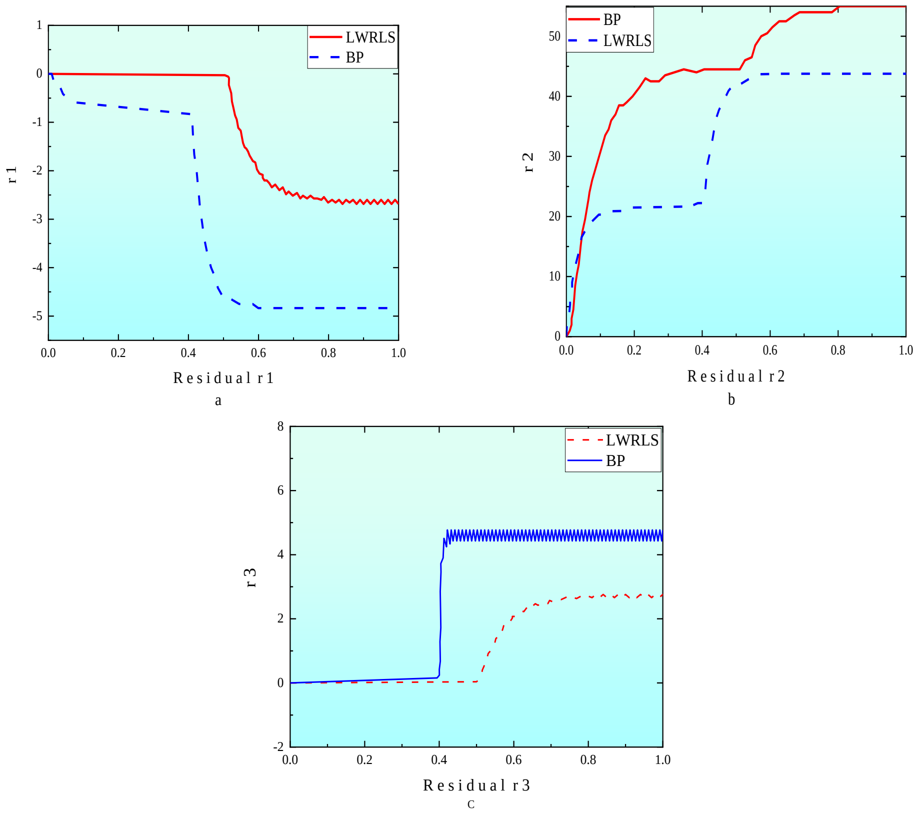

Figure 9: Residual waveforms of open-circuit faults under the two algorithms (a: waveform of residual r1; b: waveform of residual r2; c: waveform of residual r3)

In Figure 9, when the inverter power switch has an open-circuit fault, the waveforms of the residuals r1, r2, and r3 all change to varying degrees. However, the residual error of the improved LWRLS algorithm is smaller compared with the traditional BP algorithm.

In order to further analyze the BP algorithm and LWRLS algorithm for the diagnosis of inverter faults, Tensflow is used to draw the accuracy and loss curve of the network on the training set and validation set, as shown in Figure 10:

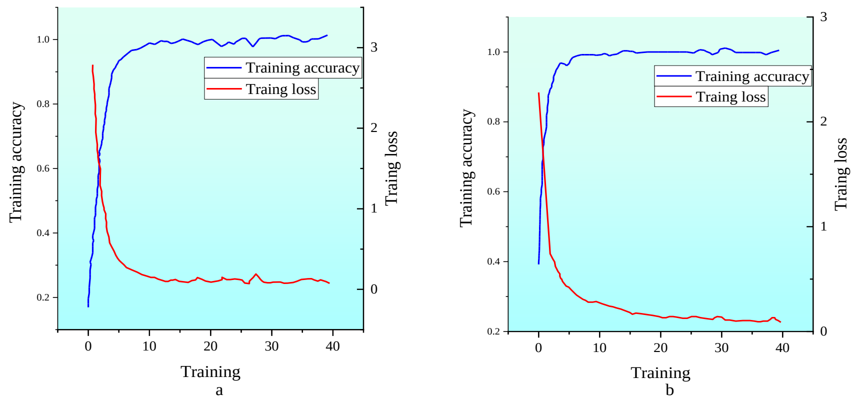

Figure 10: The curves of the accuracy and loss size of the two WNN algorithms in the training set (a: BP algorithm; b: LWRLS algorithm)

In Figure 10, the WNN diagnostic method has better diagnostic performance for inverter faults under disturbance. Among them, the average accuracy of the BP algorithm is 98.37%, and the standard deviation is 1.2571. The accuracy on the validation set fluctuates within 3%.

The average accuracy of the LWRLS algorithm is 99.56% with a standard deviation of 0.3920. The accuracy on the validation set fluctuates within 3%. The LWRLS algorithm has higher average accuracy and more stable diagnostic performance under perturbation.

4. Conclusions

The application of WNN algorithm in inverter fault diagnosis is analyzed. The commonly used BP algorithm and the improved LWRLS algorithm are compared and studied. Simulation experiments are designed separately through Matlab/Simulink.

The results show that the improved LWRLS algorithm is faster in terms of operation speed. Around 600-700 steps, it completes the fitting to the accuracy required for the experiment. The traditional BP algorithm needs more than 2000 steps to complete the fitting. In terms of network error, the error value of the WNN of the BP algorithm can only reach 104, while the error of the WNN of the LWRLS algorithm has reached the order of magnitude of 106. Therefore, when the algorithm is improved, the network error of WNN is reduced a lot. In fault diagnosis, the average accuracy of BP algorithm is 98.37%, and the average accuracy of LWRLS algorithm is 99.56%.

The fault recognition rate after the improved algorithm is obviously better. The proposed method can be further improved and developed in theory and practice, and can really play a role in practical application. Of course, there are still some problems to be solved in the experimental process. For example, the noise and interference in the actual circuit, the asymmetry of the power supply voltage, etc. are ignored in the simulation.

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