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Research on islanding detection of solar distributed generation based on best wavelet packet and neural network

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Abstract: The active distribution network (ADN) represents the future development of distribution networks, whether the islanding phenomenon occurs or not determines the control strategy adopted by the ADN. The best wavelet packet has a better time-frequency characteristic than traditional wavelet analysis in the different signal processing, because it can extract better and more information from the signal effectively. Based on wavelet packet energy and the neural network, the islanding phenomenon of the ADN can be detected. Firstly, the wavelet packet is used to decompose current and voltage signals of the public coupling point between the distributed photovoltaic (PV) system and power grid, and calculate the energy value of each decomposed frequency band. Secondly, the network is trained using the constructed energy characteristic matrix as a neural network learning sample. At last, in order to achieve the function of identification for islanding detection, lots of samples are trained in the neural network. Based on the actual circumstance of PV operation in the ADN, the MATLAB/SIMULINK simulation model of the ADN is

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established. After the simulation, there are good output results, which show that the method has the characteristics of high identification accuracy and strong generalization ability.

Key words: active distribution network, islanding detection, neural network, solar distributed generation, wavelet pocket transform

1. Introduction

The type identification of the active distribution network (ADN) various operating states and the timely processing can seriously affect the temporary and steady state stability and the quality of power supply. The ADN focuses on the consumption of intermittent energy [1, 2]. In order to consume PV and wind power to the greatest extent, it is generally not regulated by power, which brings many problems to distributed photovoltaic grid-connected.

For distributed energy resource (DER) systems with significant capacity differences [3], general detection methods cannot meet the needs. The traditional method only provides effective protection for the changes of a fixed network structure system with static parameters. However, for some DERs with large number and large capacity differences, there are many difficulties in the detection methods. For the devices that provide island protection, their power systems are nonlinear systems in which there are a large number of nonlinear primitives and many nonlinear problems. Moreover, the complex network structure brings computer modeling and simulation great difficulties. The distributed generation devices with different access points have different parameters, which cannot be tested by a static threshold value. And the measurement device and network parameters have tolerance, which makes the measured parameters discretized and may cause the protection device misoperation. When the detection is performed, the state information of the monitoring point should be extracted, and the extraction of fault electrical parameters is complex, so it is difficult to carry out simple quantization.

2. ADN island effect detection method

2.1. Necessity of ADN island detection and common detective methods

On the one hand, the distributed photovoltaic islanding operation is limited by the IEC 61727 standard, IEEE 929, and IEEE 1547 standards, the distributed power supply will apply the anti-islanding operation strategy. The distributed power supply generally works in the current control mode, and the voltage is difficult to control after the islanding phenomenon [4]. On the other hand, it is difficult to match the power-load power in isolated islands. Therefore, it is necessary to detect this isolated phenomenon in time to determine the transformation of a distributed generator (DG) from grid connection to an isolated operation mode [5]. Therefore, island detection has important research value.

Island detection methods can be divided into three categories: a passive method, active method and communication method (based on the communication between a grid and PV grid-connected inverter) [6]. Currently, some countries adopt German standards DIN VDE 0126 and 0126-1-1 [7].

A traditional concept holds that all photovoltaic power generation systems must be constructed with protective measures and the distribution network generally does not have continuous island operating conditions [8]. The operation of an isolated island will have an impact on the frequency and voltage of a distribution network, so the distribution network will only adopt the operation mode of the isolated island in a short emergency, and it needs a good control strategy and coordination between a transmission system operator (TSO) and a distribution system operator (DSO) to maintain the operation of the isolated island in a controllable state.

2.2. Problems in ADN island effect detection

The traditional isolated phenomenon recognition elements usually take the power frequency as the basis, and they also carry on the optimization combination to the abrupt quantity and the steady state quantity. Most of the measuring components can passively discriminate the island phenomena correctly, but they are susceptible to system operation, load variation at the distributed power inlet, and harmonics of the power grid, resulting in unsatisfactory results. At the same time, the traditional island detection method cannot meet the sensitivity requirements, and there is a large detection blind zone and longer detection time.

The harmonics injected into the power grid by the active island detection scheme affect the power supply quality of the ADN, while there are a large number of distributed PV power sources in the ADN. The injected harmonics will distort the output current of more grid-connected inverters, resulting in the decline of output power of the PV inverter.

The access of the distributed DG in the ADN not only affects the operation of the grid, but also changes the voltage distribution, transmission power, steady-state current and short-circuit current to a large extent. Considering ADN's large-scale access of renewable DERs in the future, the operating parameters of the grid will change dynamically over a long period of time. The original fixed threshold setting scheme cannot meet the detection requirements. This paper proposes a solution based on wavelet analysis and a neural network to solve the nonlinear problem with parameter variation according to time series. The advantage of neural network re-learning makes the detection device maintain optimal detection characteristic.

2.3. ADN passive detection technology based on wavelet and neural network

In view of the above problems, island detection needs to collect real-time parameters of the monitoring points and separate the data effectively and improve the generalization ability of the simulation system to cope with the tolerance effect of the collected signals.

The study based on the wavelet transform and artificial neural network has a very important theoretical and applied value for solving practical problems of nonlinear complex systems. Since there is a large amount of state information when the islanding phenomenon occurs, the harmonic signals of different frequencies and amplitudes carrying the information are superimposed on the fundamental frequency signal. The combination of fault signal processing based on wavelet decomposition and artificial intelligence recognition technology can achieve accurate detection. The research on the detection method of the islanding effect of the distributed solar power generation device in the ADN, provides a feasible program guidance for the timely discovery and protection of the islanding phenomenon during DG grid connection.

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3. Application of wavelet theory in feature signal extraction analysis

3.1. ADN island detection signal selection

By comparing the signals of the distributed power supply and the common coupling point (PCC) of the public coupling point of the power system during the occurrence of isolated islanding phenomenon, it is found that the voltage and current at the common coupling point contain state information of the system operation. The detection method proposed in this paper is based on the voltage and current information at the common coupling point (PCC) that is easy to be collected. It can be reliably detected by analyzing the sample information of the voltage transformer (PT) and current transformer (CT) at the PCC node. It avoids a more complicated power conversion rate, harmonic distortion rate, frequency change rate, frequency versus power, and unbalanced sampling and analysis [10], so it is economical and reliable for on-site measurement.

3.2. Selection of wavelet basis functions

At present, there is no theoretical standard for selecting the optimal wavelet base. The general method is based on the nature of the wavelet basis function, depending on the specific requirements of the analysis and the characteristics of the signal being tested. If the waveform contained in the signal is similar in shape to the selected wavelet basis function, then the characteristics of the signal that are similar to the wavelet basis function waveform will be amplified [11, 12]. According to the above principle, a suitable wavelet can be selected by shape matching the signal to be analyzed with the wavelet basis function.

The energy value of a signal has a specific relationship with the signal itself, so it is generally used to express the characteristics of a signal. The energy value by a sampled value signal can be expressed as [13]:

$$E_s(W) = \sum_{i=1}^{N} |W(s,i)|^2 , \tag{1}$$

where N is the number of wavelet coefficients, $W(s,i)$ is the wavelet coefficient.

When the wavelet transform is applied, if there is a main frequency component corresponding to a certain scale in the signal, the signal of the specific frequency component is analyzed, and the corresponding wavelet coefficient of the scale has a higher amplitude. The energy associated with this frequency can be separated from the signal. The more energy is extracted from the signal, the more efficient is the signal processing. Therefore, the energy value can also be designed as a criterion for selecting a wavelet basis function.

A variety of wavelet basis functions including a dbN wavelet are selected for signal processing in this paper, and the results shows that the difference in the signal energy value was the most obvious after using db1 wavelet processing, and its islanding detection effect was the best. Therefore, the db1 wavelet was selected as the generating function of the wavelet used for islanding detection.

3.3. Signal energy feature extraction and reorganization based on wavelet packet

The frequency band range of each decomposition node can be obtained according to the sampling frequency of the signal. According to the requirements of classification accuracy, detection speed and real-time performance of hardware, the sampling frequency of a test signal is set at

10 kHz in this paper. According to Shannon's theorem, a maximum of 7 layers of decomposition can be carried out above the fundamental frequency, and each layer of high-frequency components (detail component) frequency band range of D1–D7 is as follows: Layer 1 (D1):2500 ~ 5000 Hz; Level 2 (D2):1250 ~ 2500 Hz; Layer 3 (D3):625 ~ 1250 Hz; Layer 4 (D4):312.5 ~ 625 Hz; Layer 5 (D5):156.25–312.5 Hz; Layer 6 (D6):78.125 ~ 156.25 Hz; Layer 7 (D7):39.0625 ~ 78.125 Hz. Considering the validity of the data, 6 layers of the decomposition is enough to obtain the signal characteristics (above the fundamental frequency).

When the islanding phenomenon occurs in an ADN, the amplitude-frequency characteristics and phase-frequency characteristics of the common coupling point will change. The orthogonal wavelet decomposition filters the signal to be decomposed by a high-pass filter and a low-pass filter to obtain a set of low-frequency signal A and a set of high-frequency signal D, and decomposes the low-frequency signal A and the high-frequency signal D until the number of layers meet the requirements. After each decomposition, the length of the low frequency and high frequency signals is half of the original signal length, the sum of them is equal to the original signal length. In other words, the interval sampling is carried out after orthogonal wavelet decomposition, so that the information does not suffer any loss.

4. Construction and training of back propagation (BP) neural network

A neural network has many excellent characteristics [14, 15]: (1) The artificial neural network can analyze the data of the learning input to improve its ability to solve similar problems. (2) The artificial neural network has the ability to be generalized, and the network can process any data that is appropriate for the problem to obtain an optimal solution, although the programmer did not specify the processing mode of specific data and the neural network did not analyze and calculate the sample data before. (3) The artificial neural network can be used to approximate arbitrary nonlinear systems. Compared with other linear algorithms, neural network algorithms have obvious advantages in solving complex systems. (4) The artificial neural networks can be easily applied to complex systems with multiple variables. (5) The artificial neural network has large-scale parallel processing capability and good fault tolerance. This is similar to the function of the human brain.

The system fault detection neural network usually adopts a three-layer BP neural network structure model, and the algorithm is as follows:

1) The input layer node i ($i = 1, 2, 3, \ldots, n$), the output O_i is equal to the input x_i, and the control variable value is passed to the second layer.

2) The hidden layer node i ($i = 1, 2, 3, \ldots, n$), which input and output are [16]:

$$I_j = \sum_{i=1}^{n} w_{ji} o_i + \theta_j\,, \tag{2}$$

$$o_j = f(I_j), \tag{3}$$

where: w_{ji} indicates the connection weight from cell j to cell i (for the excited state, take a positive value, for the suppression state, take a negative value), θ_j denotes the threshold of the hidden layer node, f is called the transfer function, also called the excitation function, and is generally represented by a 0, 1 binary function or an sigmoid function.

3) Output node k ($j = 1, 2, 3, \ldots, K$), input i_k and output y_k are [16]:

$$i_k = \sum_{j=1}^{n} w_{kj} o_j + \theta_k , \tag{4}$$

$$y_k = f(i_k). \tag{5}$$

w_{kj} represents the connection weight from cell k to cell j, and θ_k represents the bias of the output layer node k.

For a given set of experimental training samples, P is the number of experimental samples ($p = 1, 2, 3, \ldots, p$), and the mean square error between the neural network operation results and the target output of the experimental training samples can be expressed as [16]:

$$E = \frac{1}{P} \sum_{P=1}^{P} E_P , \tag{6}$$

$$E_P = \frac{1}{2} \sum_{1}^{L} \left(T_{pl} - o_{pl}\right)^2 . \tag{7}$$

p is the number of experimental samples; T_{pl} is the result of the target output of the l-th output node unit of the p-th experimental sample; o_{pl} is the result of the l-th output unit operation of the p-th experimental sample.

If there is a difference between the data output value and the expected value, then the error of the output signal will be transmitted back along the previous connected path to the input layer unit. By modifying the connection weight between interconnected neurons of each layer; and then the error between expected output and actual value gradually reaches the allowable error range [18, 19]; the calculation formula can be derived by the gradient descent method, where the correction can be expressed by the following formula [16]:

$$\Delta W_{ji}^{k}(m+1) = -\eta \partial E / \partial W_{ij} . \tag{8}$$

The error is reduced by adjusting the initial weight, and the network training is completed when the number of iterations reaches a preset value or the error is reduced to a specified range.

5. Example verification

5.1. Construction of active distribution network photovoltaic power generation model

The active distribution network model is built by Matlab8.3.0.532 (R2014a), which mainly simulates many situations that the system should face by setting up short circuit fault, load change at the access point, the action of the network side circuit breaker and so on. Its structure is mainly composed of three parts: distributed photovoltaic power generation side model, common coupling side control measurement model and power system side model.

The distributed photovoltaic power generation device is connected to the power system model through the inverter as shown in Fig. 1, and the solar cell module is introduced in Fig. 2. In Fig. 3

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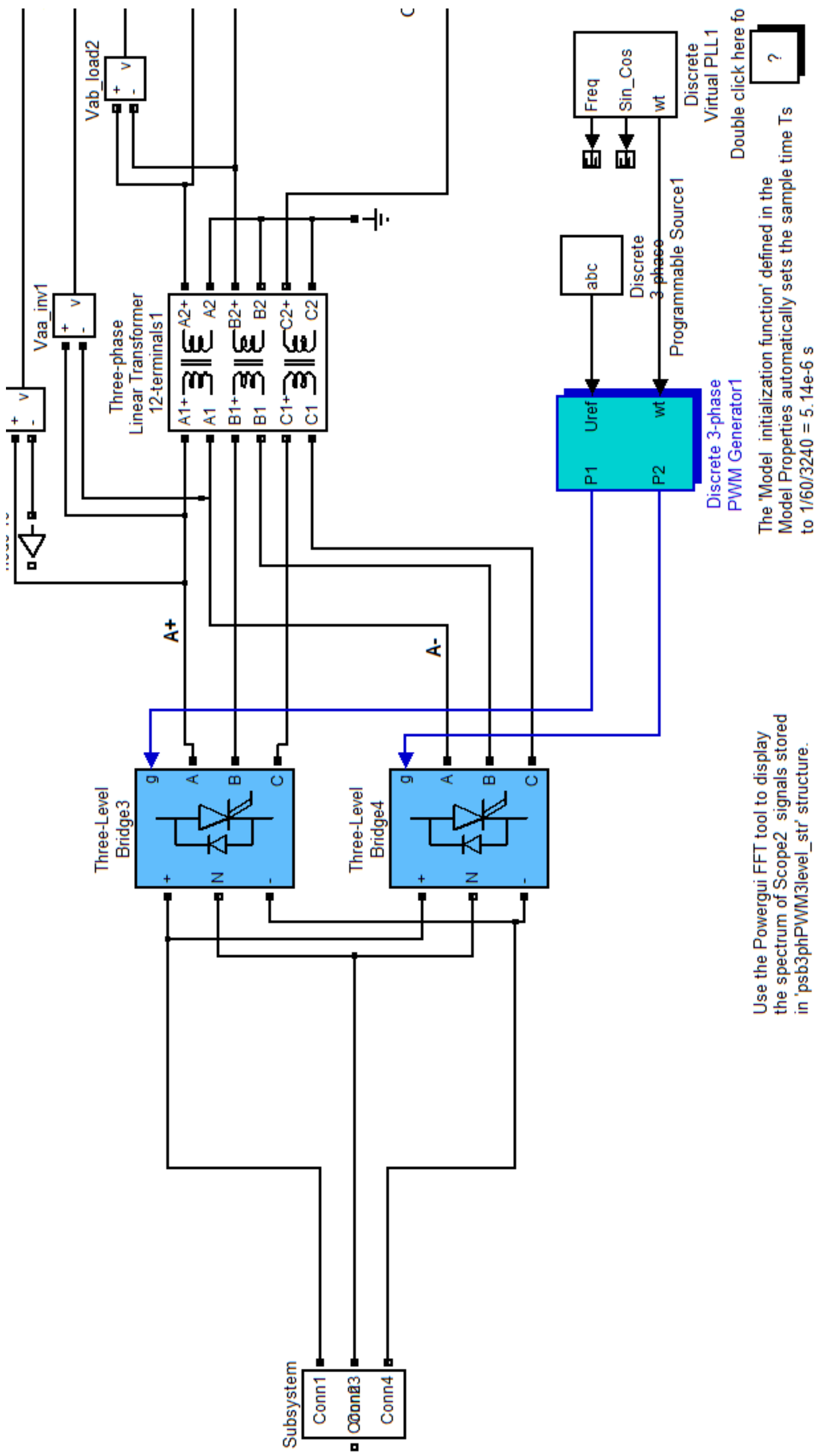

Fig. 1. Matlab model of islanding effect detection photovoltaic power generation unit

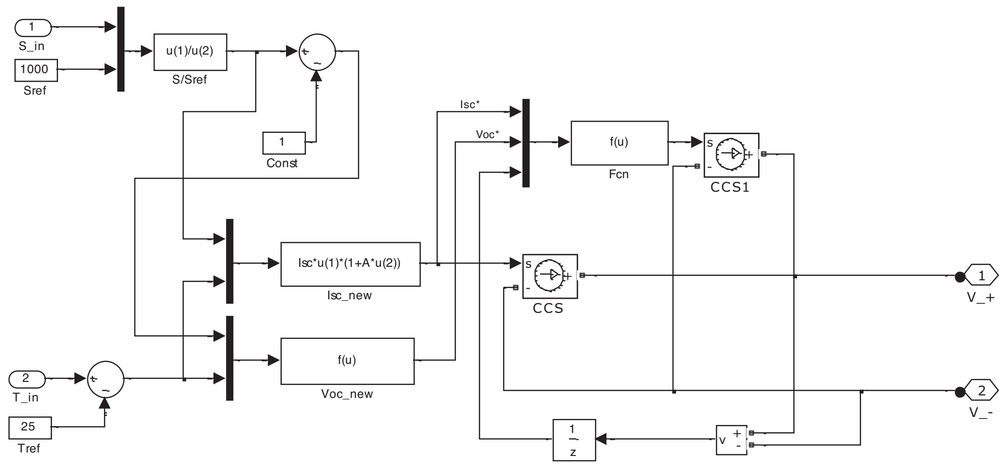

Fig. 2. Simulation model of Matlab solar cell module

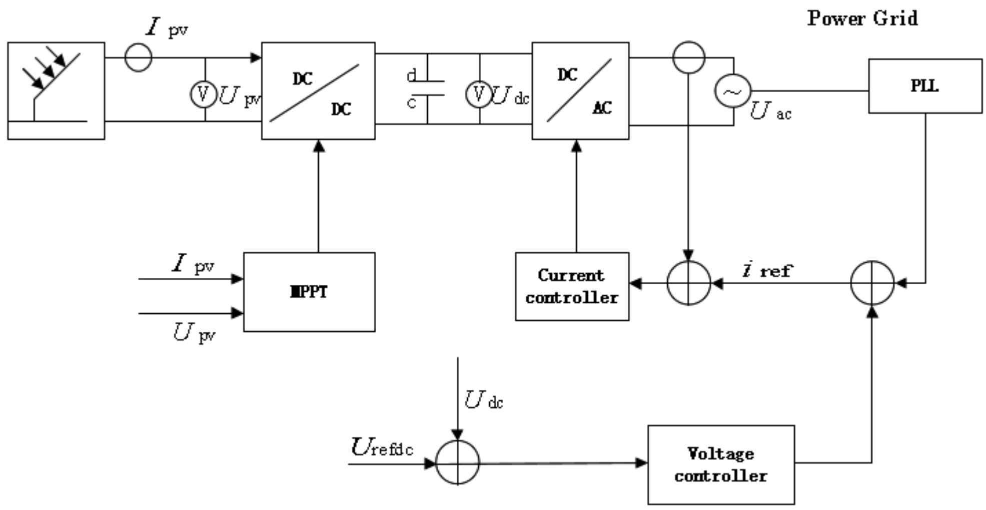

Fig. 3. Networking principle and control model of solar power generation

the energy from the distributed power source is delivered to the power system via a PWM controlled inverter.

The power part of the system is a three-phase programmable voltage source, through its programming function; we can test the reliability of the protection device by injecting different harmonic functions into the grid. In Fig. 4, the collection of signals such as voltage and current at the common coupling point of distributed power supply and power system provides original data for later signal analysis and type discrimination. The circuit breaker set in the model can simulate the normal state of the system, the short-circuit fault state, the load change at the access point, and the grid-side circuit breaker-action state.

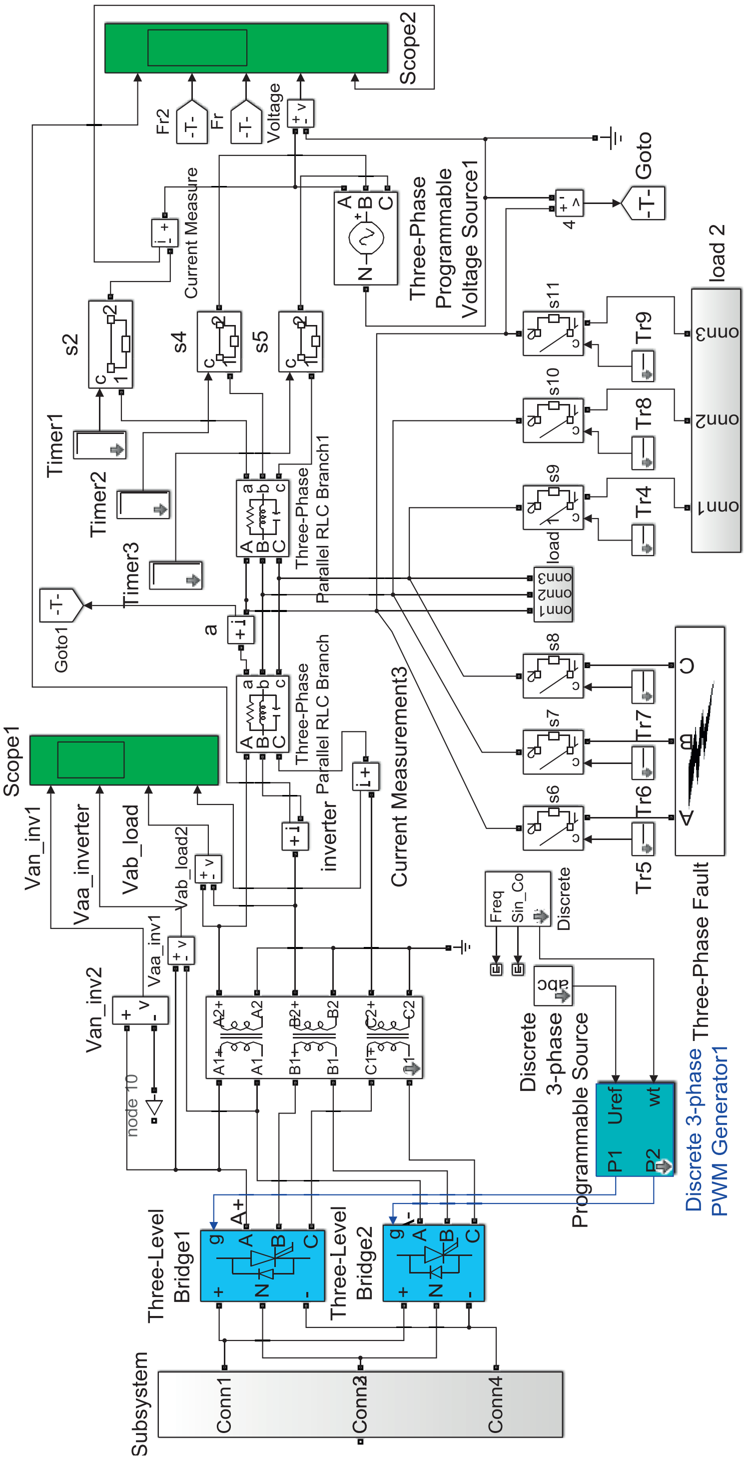

Fig. 4. Matlab model of islanding detection system

5.2. Extraction of islanding recognition signal

It can be seen in Fig. 5 that the grid voltage and current at the common coupling after the islanding phenomenon will fluctuate due to changes in system parameters.

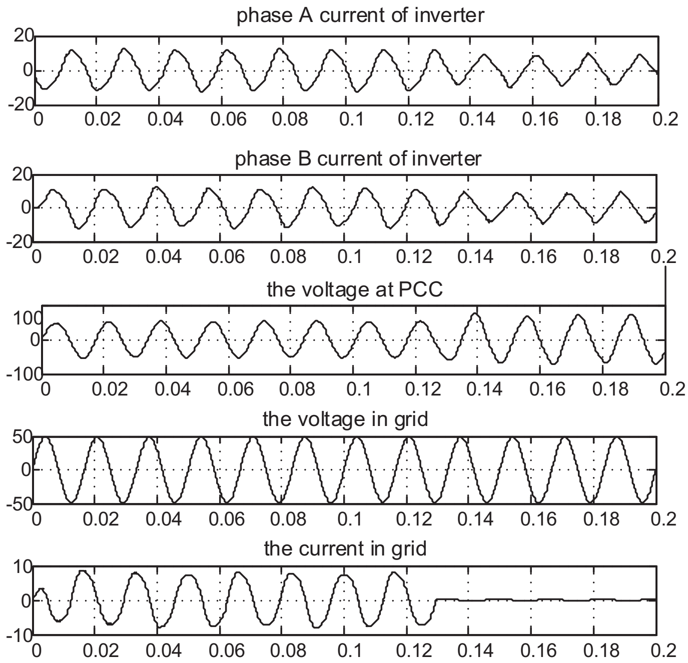

Fig. 5. System waveform of islanding effect after sampling 0.133 s

Since the occurrence time of the islanding phenomenon is unknown in the actual situation, how to reliably extract the signal of the common coupling point plays an important role in the correct identification of the island effect. The device should be able to detect the islanding phenomenon in a short time to prevent the asynchronous reclosing of the distributed power generation device. The automatic reclosing device usually re-closes after a delay of 0.5 s to 1 s, and the anti-islanding scheme should stop the DG before the reclosing occurs. IEEE Std.929-2000 stipulates that the island detection time should be within 2 s [20], Literature [21] points out that islanding operation is a temporary abnormal operation mode. That is to say, the fault should be connected to the grid as soon as possible after the fault is removed. Therefore, this paper chooses to use 0.2 s as an extraction cycle for signal acquisition, which fully meets the technical requirements and relevant regulations.

In Fig. 6 by analyzing the energy characteristic quantity of the wavelet packet fault signal expressed by energy, it is found that the energy of the lower layer signal obtained by filtering the signal to be decomposed by the orthogonal wavelet decomposition through the band pass filter is extremely low and almost zero, indicating that the amount of information in this band is very small. In the latter process, the redundant frequency bands with zero energy are removed. We extract the low-frequency signal energy of the sixth layer after wavelet decomposition and the

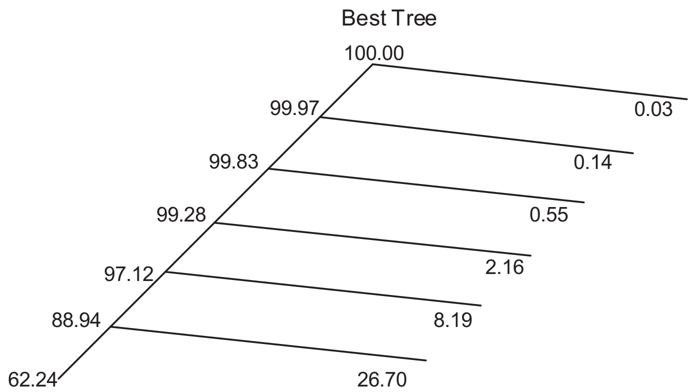

Fig. 6. Energy tree based on optimal wavelet packet algorithm

energy of the high frequency signals of other layers to obtain a set of system state information within 0.2 s.

The DG in the Matlab program for optimal orthogonal wavelet decomposition of the sample signal and system common coupling point voltage is defined as a PCC, an inverter input into the grid current is defined as T. And six layers of db1 wavelet decomposition are performed on this set of two sampled signals. After performing the orthogonal wavelet transform, the voltages and currents are extracted from the energy of seven frequency bands. After decomposing, it is found that these energy differences are large. Therefore, the signal energy of each group is normalized by Formula (9) [16].

$$E = \sqrt{\sum_{j=0}^{2^n-1} |E_{NJ}|^2}. \tag{9}$$

After orthogonal wavelet extraction, it is found that the high-frequency components of the third layer, the second layer and the first layer of the inverter current and the common coupling point voltage have little relationship with the extracted sample types. Eliminating these redundant quantities also solves the problem of excessive input dimension based on neural network pattern recognition, so that the feature vector of the common coupling side voltage and the characteristic quantity of the inverter current are recombined into the artificial vector state analysis [22].

5.3. The composition of the neural network pattern recognition structure

Fig. 7 is the structure of the established neural network. The principle of back propagation of error divides learning into two processes: signal forward propagation and error back propagation. The input samples are processed from the input layer neurons and then sent to the output layer via the hidden layer. The state of each layer of node units only acts on the output of the next level of node units. If the desired output value is not obtained at the output layer, the error value is sent back along the previous node unit connection path by back-propagation, and the connection weight is modified one by one during the return process.

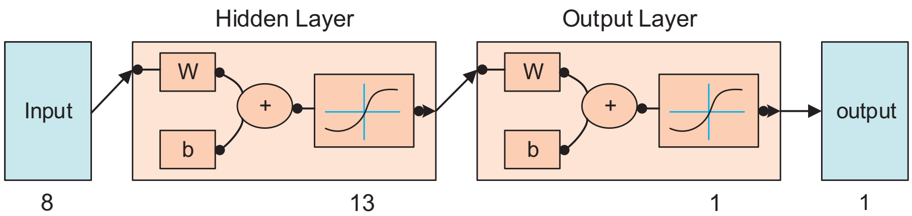

Fig. 7. Neural network structure for pattern recognition

The 8 input signals are the eigenvectors of the neural network which are constituted of the wavelet coefficient absolute average values of the selected voltage and current of D1 and D2, which are obtained after the wavelet transform, and the difference between them. And the input sample feature matrix is preprocessed by the process input and then is sent to the neural network layer. After pattern recognition, the output can use the number 0, 1 to indicate whether an island effect occurs, so the output node unit is set to one. The number of the hidden layer neurons is 13 which is derived from empirical Formula (10) [16] of the number of the hidden layer node units.

$$N = \sqrt{i + o} + k, \tag{10}$$

where i and o are the number of the input and output neurons, respectively, k takes the empirical value, and the range is generally (1, 10).

The relative error between the neural network output expectation and the actual output value is shown in Fig. 8. As shown in Fig. 8, when the number of learning samples is more than 200, the relative errors are always around –5e–5. So the pattern recognition neural network can have a good pattern recognition capability with enough learning samples.

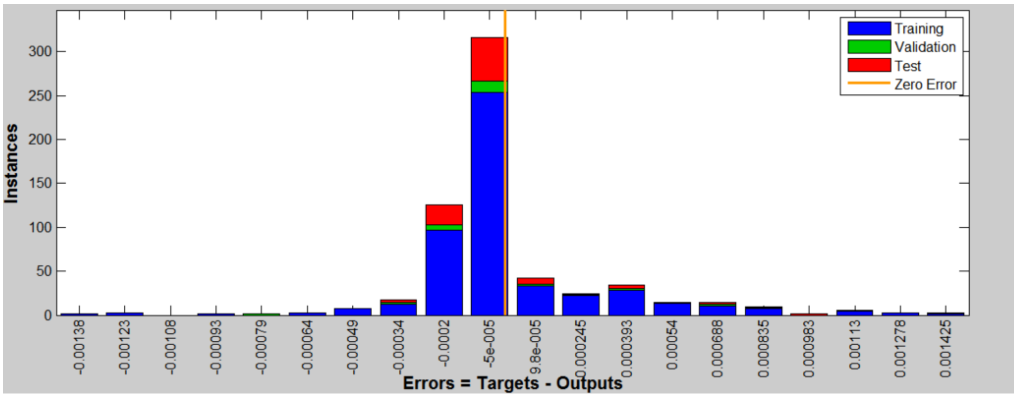

Fig. 8. Output error histogram of pattern recognition neural network after training

Fig. 9 is the variation curve of pattern recognition neural network output error with learning iterations. From Fig. 9, we can see that the pattern recognition neural network output error is decreasing with the learning iterations increasing, and the learning effect reaches the best with

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25 learning iterations. Therefore, the pattern recognition neural network can have a good pattern recognition capability with enough learning iterations.

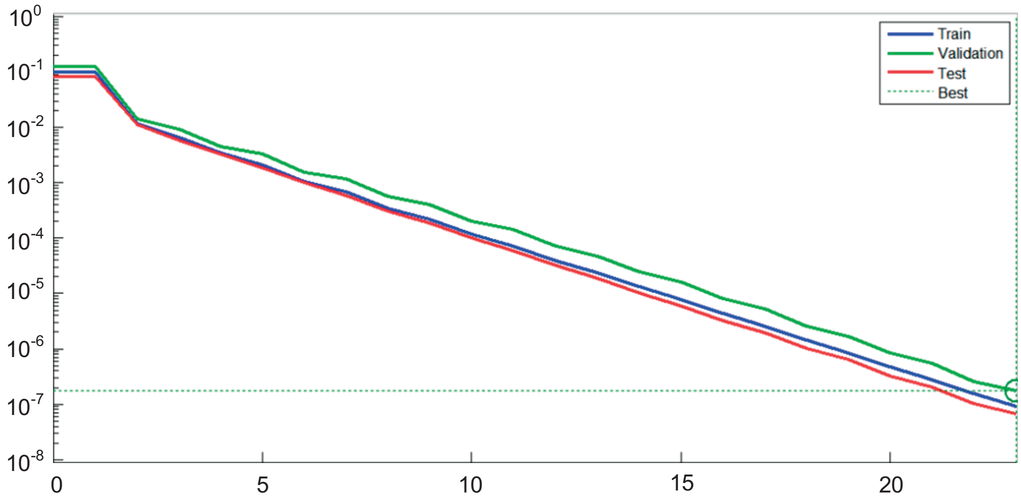

Fig. 9. Output mean squared error decreases with learning iterations

In the simulation, we constructed a single hidden layer back propagation network model with 13 node elements, and the network models have a good pattern recognition capability.

At last, we use 527 learning samples and 93 test samples to do the simulation with the network model. After learning training of the samples processed by the optimal wavelet packet (including normal state, short circuit fault, load change at the access point, and network side circuit breaker action), then use the test samples (including normal state, short circuit fault, load change at the access point, grid side circuit breaker action) to test, the method proposed in this paper can quickly and accurately detect the occurrence of isolated islands, and there will be no false action under the disturbance signal condition such as load mutation, power network voltage mutation and so on. In addition, this method has overcome the disadvantage that the traditional passive island detection method has a blind zone in the load mismatching. Moreover, since the island detection method provided in this paper does not add disturbance to the control signal, it will not have an adverse effect on the power quality compared with the traditional active island detection method.

6. Conclusion

Under the premise of fully considering the actual operation of distributed photovoltaic power generation equipment in an ADN, we constructed a MATLAB/SIMULINK simulation model of the ADN and generated various signals under different operating conditions by the controlling load, circuit breaker and programmable three-phase voltage source, we also performed optimal wavelet packet decomposition on the voltage and current signals at the common coupling point of the acquisition. Then we extracted the energy values of the current and voltage in each frequency band. The reassembly matrix contains most of the network state information by eliminating the redundant band energy and recombining the signal energy in other frequency bands.

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