CIT. Journal of Computing and Information Technology, Vol. 32, No. 3, September 2024, 159–176
doi: 10.20532/cit.2024.1005850

PW-FBPNN: A Hybrid Fault Diagnosis Method for Power Circuit Systems Combining Principal Component Analysis, Wavelet Packet Transform, and Fuzzy Neural Networks

Xu Chen, Chao Zhang, Haomiao Zhang, Zhiqiang Cheng and Yu Yan

State Grid Ningxia Marketing Service Center, State Grid Ningxia Metrology Center, Yinchuan, Ningxia, China

Due to the complexity of fault states and the non-linear relationship between input and output responses, fault diagnosis in complex power circuit systems faces significant challenges. This study proposes a novel hybrid method, PW-FBPNN, which integrates principal component analysis (PCA), wavelet packet transform (WPT), and fuzzy back propagation neural network (FBPNN) to enhance fault diagnosis. The effectiveness of this method was demonstrated through experiments on the voltage divider basic operational amplifier and the second-order filter circuit of the four operational amplifiers. PW-FBPNN achieved 100% accuracy in diagnosing most types of faults, with a minimum accuracy of 91.67% for challenging faults. This method was significantly superior to existing methods such as FCM-HMM-SVM and KICA-DNN in terms of accuracy and computational efficiency and could complete the diagnosis in just 0.01 seconds. These results indicate that PW-FBPNN has the potential to improve fault diagnosis in power circuit systems, providing a promising solution for enhancing system reliability and maintenance efficiency.

ACM CCS (2012) Classification: Applied computing → Physical sciences and engineering → Electronics

Keywords: power circuit system, fuzzy neural network, principal component analysis, wavelet packet transform method, fault diagnosis

1. Introduction

The adjustment of China's energy structure has made the construction of a power system an important task in the current power sector [1]. According to the prediction of State Grid Energy Academy, by 2030, China's new energy will become the largest power source in terms of installed capacity, which also marks the development of the power system into a critical stage [2]. The power system mainly based on new energy is a complex giant system with multi-temporal and spatial scales, multi-level and multi-system coupling, which supports the access of a large number of power electronic devices [3–4]. The fast response characteristics of power electronic devices for power circuit system (PCS) bring new stable forms of power electronics related to broadband oscillation [5]. However, when a fault occurs in a PCS system, analog circuits face great challenges in fault diagnosis due to the complexity of fault states, the complexity and variety of fault characteristics, and the existence of various nonlinear relationships between the input and output responses, which cannot be analyzed by constructing the corresponding mathematical models [6]. A fuzzy neural network can handle fuzzy knowledge well with self-learning ability and strong parallel processing capability. It is well suited for the uncertainty and complexity of relationships in power circuit fault diagnosis. The nonlinearity, high difficulty, and multiplicity of influencing factors inherent to fault diagnosis in the extant power system impose severe constraints on its intelligent development. The study combines principal component analysis (PCA) with wavelet packet transform (WPT) for circuit fault characterization. The study then introduces fuzzy theory for optimization on the basis of error back propagation neural network (BPNN), which leads to fuzzy BPNN (FBPNN). Finally, it obtains a complete intelligent fault diagnosis method (PW-FBPNN) based on the PCA method, the WPT method and FBPNN. The objective of this research is to address the limitations of analog circuits, and the challenges associated with identifying and accurately diagnosing faults when the PCS system encounters failure. The research method solves the problem of high dimensionality of raw data in power circuit fault diagnosis through the PCA-WPT method and solves the problem of easily getting stuck in local minima in PCS fault diagnosis through the PW-FBPNN fault diagnosis method. The innovations of the study are mainly the following. First, a PCA method combined with WPT method is proposed to solve the problem of too high dimensionality of the original data and to remove the redundant information. Second, a PW-FBPNN-based fault diagnosis method is designed to solve the problem of easily getting trapped into local minima with slow convergence speed. The structure of the study is divided into four main parts. The first part is a review of the relevant research results. The second part is the design of the PCS system with PE-FBPNN-based circuit fault diagnosis method. The third part is the validation of the effectiveness of the proposed method of the study. The last part summarizes the research. The objective of the research is to address the tolerance issues and inability to locate and accurately analyze faults in simulated circuits during PCS system failures. This is done in order to ensure the safe and stable operation of PCS systems and to promote the development of circuit fault diagnosis technology.

2. Related Work

The electric power system is an important power source for industrial production and an important energy support module for commercial on-line services, which has an important practical value. However, circuit faults can adversely affect the regional power quality of the power system. Moreover, circuit fault diagnosis is difficult and requires long time troubleshooting by relevant personnel. The fuzzy neural network (FNN) is particularly well-suited for representing fuzzy experience and knowledge, and thus is an effective tool for processing fuzzy information in practical applications, whereby valuable insights can be gleaned. Cho et al. proposed a fault diagnosis algorithm based on switch functions to protect power systems from fatal damage caused by circuit faults. The simulation results demonstrated that the system exhibited robust resistance to discontinuous current mode operation, enabling it to make decisions in response to fault occurrence and fault type within a time frame of less than two switching periods [7]. Liu et al. proposed a wireless sensor control strategy for a five-phase permanent magnet synchronous motor based on a medium- and high-speed twisted sliding film observer to improve the reliability of the system position estimation during single-phase open-circuit faults. The results revealed that the method was robust to various external variations in circuit fault diagnosis [8]. Zhang et al. designed a hybrid DC circuit breaker natural commutation current topology with integrated fault current limitation for realizing short circuit fault protection in high voltage DC transmission. The ring experiments verified the correctness and feasibility of the research method [9]. Mahfoudh et al. proposed a mutual correlation based electromagnetic interference analysis to extract open switching fault characteristics in three level circuit inverters. Simulation results verified the effectiveness of the research method for fault diagnosis [10]. Ivanov et al. provided a method for training datasets for FNNs that could be applied to quickly obtain probabilistic estimates of anomalous critical events or causes of accidents in diagnostic systems. It enabled relatively accurate probabilistic estimation of faults at a low cost of computational resources [11]. Liu et al. designed a locally linear FNN based on the realization of developing a generalized method for different time-varying processes. The results demonstrated that the method was able to extract parsimonious model results while identifying time-varying parameters without adding additional computational burden [12]. Shankar et al. introduced an artificial neural network with adaptive neuro-fuzzy inference system as a classifier and proposed a method for breast cancer diagnosis based on whale optimization algorithm and dragonfly algorithm. The results showed that the accuracy of the method was 98% and the AUC value was 0.998 ± 0.001 [13]. Choudhury et al. developed an easily solvable mathematical model for the cathode of phosphate fuel cells in the field of fuel cells for power generation and distributed generation. The maximum phase angle relative to frequency and position were employed as diagnostic markers, and the experimental results validated the efficacy and viability of the method [14].

A comprehensive analysis reveals that FNN currently outperforms other methods in a variety of fields. However, circuit faults are predominantly observed in the field of electric power engineering. Furthermore, the development of fault diagnosis in power systems is constrained by the nonlinearity, high difficulty, and numerous influencing factors inherent to the system. Consequently, the study employs the PCA method in conjunction with the WPT method to meticulously extract the circuit fault characteristics within the PCS system. It then proposes the FBPNN model for network diagnosis, which ultimately culminates in the circuit fault diagnosis method based on PW-FBPNN.

3. Design of PW-FBPNN-based Circuit Fault Diagnosis Method in PCS System

A circuit fault diagnosis method based on PW-FBPNN is studied and designed. It includes three parts: PCS and fault data preprocessing, fault feature extraction of analog circuits, and FBPNN fault diagnosis training. The study first constructs a PCS and introduces fault data acquisition and preprocessing methods. Then, a fault feature extraction method combining the PCA and WPT method is proposed. Finally, FBPPNN is introduced to complete the training.

3.1. Power Circuit System and Fault Data Preprocessing

The power system is a large and complex network that contains four links: power generation, transmission, distribution and consumption, which are interrelated and influenced by each link [15–16]. The advent of high-voltage transmission technology has necessitated the interconnection of power plants that are geographically separated by a certain distance via power lines. This enables the reliable and economic supply of power to isolated power plants, thereby constituting a unified PCS system [17–18]. If a fault occurs in one of the circuits, it may have a great impact on the power supply of the region, so it is extremely important to implement intelligent fault diagnosis methods. The architecture of the PCS system is schematically shown in Figure 1.

In Figure 1, the PCS system broadens the traditional relatively homogenized electric energy transmission network into a multifaceted intelligent transmission network. Each part of the energy conduction is connected through the circuit to further enhance the optimized allocation of electric energy in a wide range. The traditional circuit fault diagnosis method is mainly through the instrument to carry out point-by-point testing and then through the experience and knowledge of the relevant personnel to identify the faults that occur in the system. However, with the continuous development of industrial and intelligent technologies, analog circuits are developing towards a larger scale and a more complex trend, which makes the traditional human-made circuit fault diagnosis methods face great challenges [19–20]. Troubleshooting is to test the faulty circuit and analyze and judge the category from the result, then it can be convenient for the subsequent repair. However, the following problems exist when performing fault diagnosis. First, since the parameter variations of different components are continuous, it is difficult to realize rapid diagnosis once the components produce faults. Second, the components themselves have a certain tolerance range, and when only one component is in the safe tolerance range, it cannot be regarded as a fault. However, a number of component tolerances can lead to cumulative effects, which can cause the entire circuit to deviate from the normal operating point. Therefore, the circuit fault judgment has a certain degree of ambiguity. Third, there are also nonlinear components in the circuit, which leads to nonlinearities in the circuit, and the difficulty of testing is increased. The data preprocessing process is as follows: Monte Carlo analysis is used to analyze the collected data, and different faults in the circuit are tested separately. The voltage information corresponding to each node is extracted and simulated using the Saber software. Moreover, the voltage value corresponding to the subsequent node during the normal operation of the circuit must be evaluated, with a tolerance value of 5% for the components. A total of 50 tests should be conducted for each fault type, with the voltage information set for 12 nodes in the circuit. This will result in the generation of a 12-dimensional matrix for each fault type.

3.2. Features Extraction of Faults in Analog Circuits in PCS System Faults

After the above data acquisition is complete, the task of fault feature extraction can be carried out. But the difficutly of the current research is how to get the feature parameters that contribute the most to the circuit fault diagnosis from the huge amount of initial feature signals. The PCA method is an effective means of reducing the dimensionality of data, improving computational efficiency and quality, and discovering the main features in the data. This enables the understanding of the essence of the data. The WPT method can provide localized information in both time and frequency domains, effectively analyzing the instantaneous frequency characteristics of signals. It is particularly effective for non-stationary signal processing in circuit fault diagnosis. Consequently, research is being conducted on feature extraction processing, employing PCA and WPT methods to identify

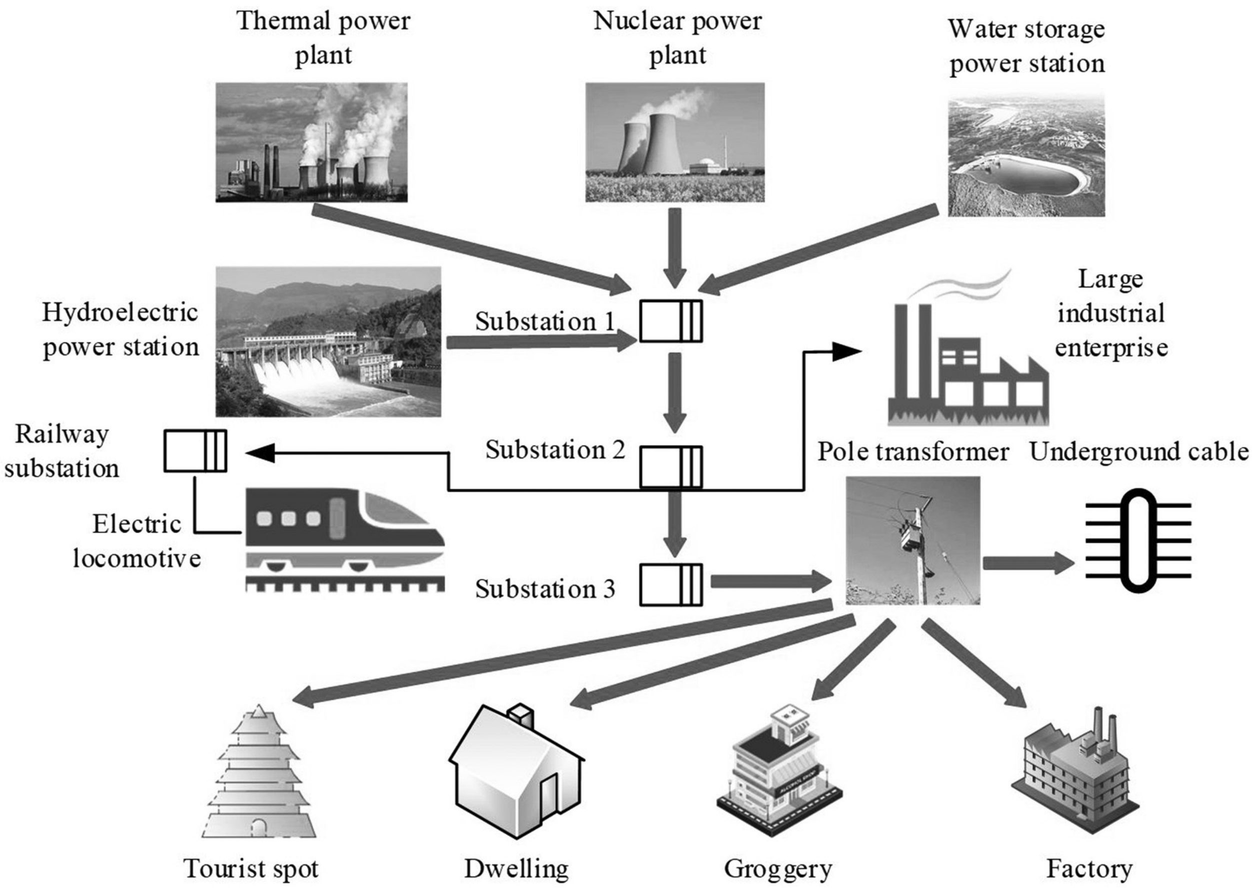


Figure 1. PCS system architecture diagram.

the optimal feature parameters that can effectively reflect circuit faults as sample data for FBPNN. This approach aims to reduce redundant sample data and input dimensionality, ultimately enhancing the execution efficiency of PCS systems. The WPT method builds upon the concept of localization of the short-time Fourier transform, addressing its inherent limitations. One such limitation is the fixed window size, which does not adapt to varying frequencies. The WPT method addresses this by providing a time-frequency window that changes with frequency. This adaptability makes it an ideal tool for time-frequency analysis and processing of signals. The wavelet transform process is described as follows. After shifting the basis function $A(t)$ displacement translation factor b, then the process of inner product with the same waiting analysis information under different scale factor a. For $\forall A \in L^2(R)$, if $A(t)$ is Fourier transformed, the wavelet mother function $\hat{A}(w)$ can be obtained, which satisfies the tolerability condition of Equation (1).

$$C_A = \int_{-\infty}^{+\infty} \frac{\hat{A}|w|^2}{|w|} dw < +\infty \tag{1}$$

$\hat{A}(w)$ produces a continuous wavelet function as in Equation (2).

$$\hat{A}_{a,b}(t) = |a|^{-\frac{1}{2}} A\left(\frac{t-b}{a}\right) \tag{2}$$

If there exists an arbitrary signal $x(t) \in L^2(R)$, $x(t)$ corresponds to the continuous wavelet transform with the corresponding inverse transform givern in Equation (3).

$$\begin{cases} B_x(a,b) = \dfrac{1}{\sqrt{a}} \displaystyle\int_R x(t)\alpha'\left(\frac{t-b}{a}\right) dt \\ x(t) = C_\alpha^{-1} \displaystyle\int_{R^2} B_x(a,b)\alpha_{a,b}(t)\frac{1}{a^2} dadb \end{cases} \tag{3}$$

In Equation (3), α' and α are conjugate functions of each other while satisfying $x_R|\alpha(t)|dt < \infty$. Where $\alpha(t)$ has bandpass, fluctuation and attenuation. Moreover, the discrete wavelet transform is discretized for a and b. Let $a = D^k$, $b = nED^k$, where n and k correspond to the time-step transformation index and frequency range index, respectively. The result of E is related to $\alpha(t)$. The expression of the discrete wavelet basis function A is given in Equation (4).

$$\begin{aligned} \alpha_{k,n}(t) &= \frac{1}{\sqrt{a}} \alpha\left(\frac{t-bED}{D}\right) \\ &= D^{-\frac{k}{2}} \alpha\left(\frac{t}{D^k} - nE\right) \end{aligned} \tag{4}$$

The discrete wavelet variation of $x(t)$ is shown in Equation (5).

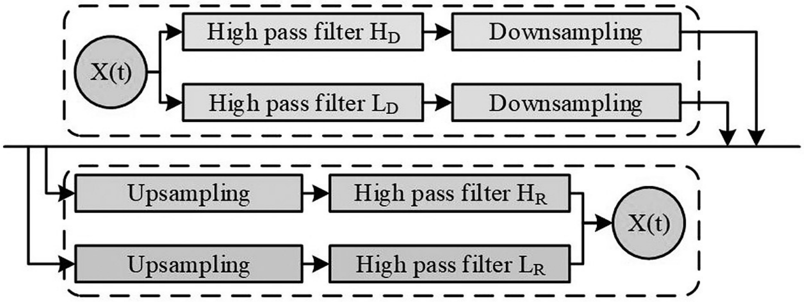
$$(x, \alpha_{k,n}) = D^{-\frac{k}{2}} \int_{-\infty}^{+\infty} x(t)\alpha\left(\frac{t}{D^k} - nE\right) dt \tag{5}$$

Let $D = 2$, $E = 1$, $\alpha_{k,n}(t)$ can then be transformed into a binary wavelet. The corresponding wavelet inverse transform expression is shown in Equation (6).

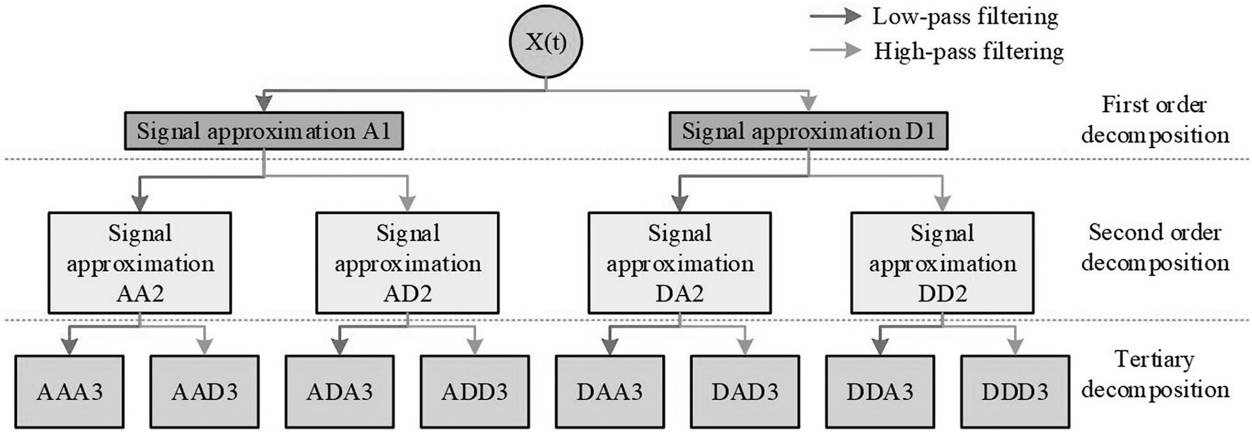
$$x(t) = \sum_k \sum_n d_{k,n}\alpha_{k,n}(t) \tag{6}$$

According to the transformation of k-value, the discrete wavelet transform function corresponding to different scales can be obtained. Wavelet multi-resolution analysis is to observe and analyze the signal from coarse to fine according to the change of k-value from large to small. Wavelet decomposition is first obtained from the original signal $X(t)$ through the low-pass filter to obtain the low-frequency signal A1, and then by the high-pass filter to obtain the high-frequency signal D1, thus realizing the first layer of decomposition. The wavelet decomposition only continuously decomposes the low-frequency components to obtain A2, A3, D2 and D3, and does not decompose the high-frequency components sexually. However, after the signal enters the wavelet decomposition, reconstruction processing is also required to restore the $X(t)$. The wavelet decomposition and reconstruction and the three-level wavelet packet decomposition process, as shown in Figure 2.

In Figure 2, $X(t)$ acquires twice as much data as the original after completing the wavelet decomposition. Through the Nyquist sampling theorem, the study uses one of every 2 samples in each channel and then reconstructs it using the upsampling with filtering process to obtain $X(t)$. In the three-layer wavelet packet decomposition, $X(t)$ is obtained after three wavelet



(a) Wavelet decomposition and reconstruction.



(b) Three-level wavelet packet decom position.

Figure 2. Wavelet decomposition and reconstruction and three-level wavelet packet decomposition process diagram.

decompositions to obtain 8 components, and also reconstructs it using the upsampling with filtering process to obtain $X(t)$. The WPT method decomposes the high-frequency component, which contains various disturbing factors such as noise. This enables insignificant noise signal frequency features to be represented by significant energy changes at various resolutions. Consequently, wavelet packet analysis is more commonly used in the extraction of analog power supply faults than wavelet analysis. The PCA method can then be performed to transform a number of variables that are correlated with each other into a linear combination of several uncorrelated variables through the eigenvalue decomposition of the data covariance matrix and then removing the invalid information. The input raw data feature matrix is $U_{M\times N}$ and the calculation is shown in Equation (7).

$$U_{M\times N} = (U_1, U_2, ..., U_M) \tag{7}$$

In Equation (7), M and N are the corresponding number and sample size in each sample variable, respectively. If M is large, it is necessary to carry out dimensionality reduction to reflect the original information as much as possible through fewer indicators. At the same time different values are independent of each other. The key to solving PCA is to solve the coefficients. At this time the covariance matrix needs to be solved. That is, the matrix diagonalization operation is carried out, thus obtaining a new matrix as an orthogonal matrix. The values on the corresponding diagonal are the eigenvalues of the covariance matrix. The smaller variance is the corresponding noise information or redundancy, and only the larger eigenvalues are taken to achieve the purpose of dimensionality reduction. This leads to the fault feature extraction process of the PCA method combined with the WPT method, as shown in Figure 3.

In Figure 3, it is first necessary to apply the PCA method to downscale the original data, se-

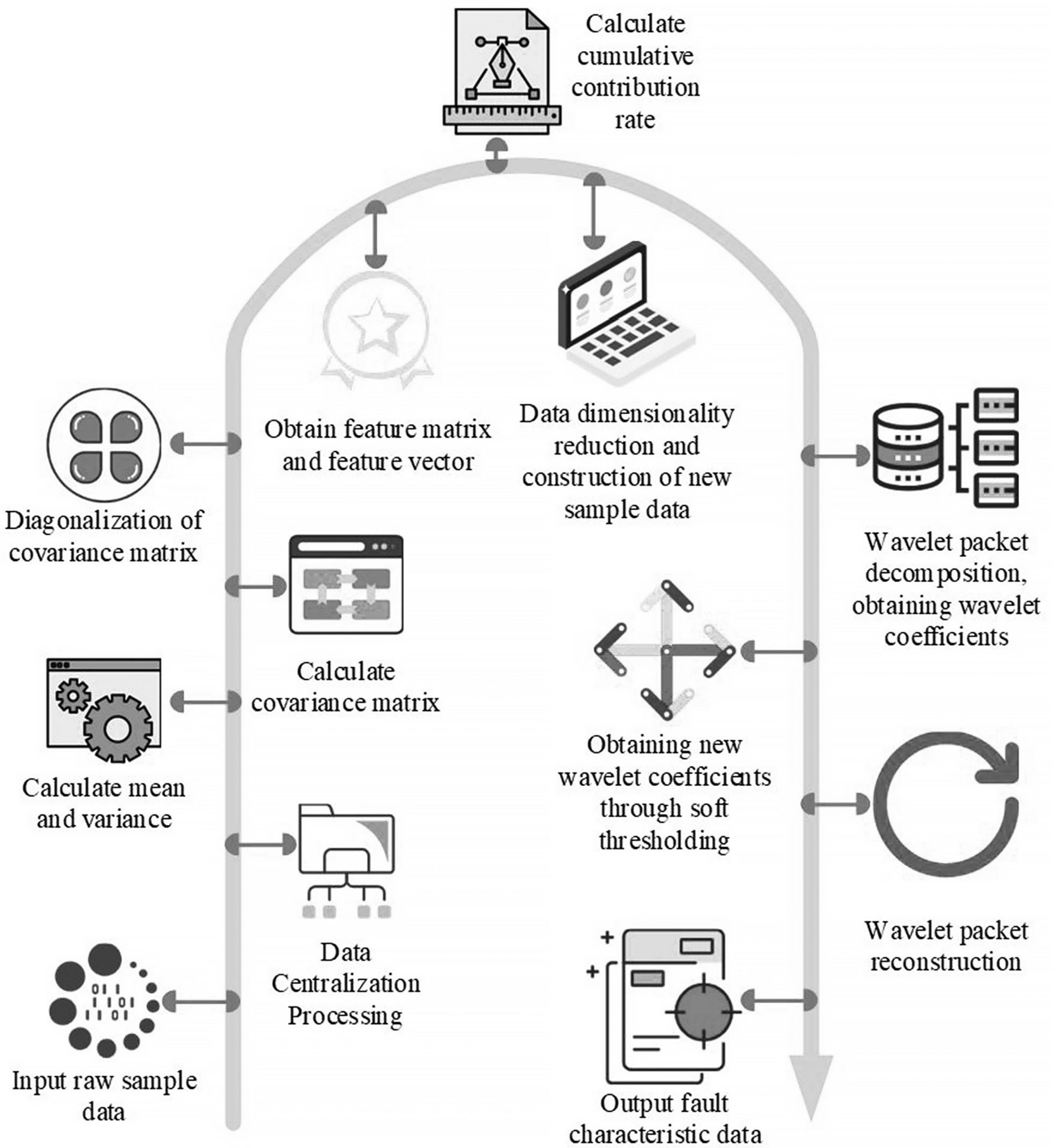


Figure 3. Fault feature extraction flow diagram of PCA method combined with WPT method.

lect the first p principal components to form the new data, and then perform a wavelet packet decomposition task at the k-th layer. This is followed by the reconstruction of the signal after denoising using high-frequency filtering with soft thresholding, which yields new fault information features. This process lays a solid foundation for subsequent network diagnosis.

3.3. FNN-based Circuit Fault Diagnosis Method

BPNN has the advantages of a simple operation and stable operation, which is very suitable for fault diagnosis in analog circuits. However, there are limitations such as that the connection of each layer cannot be expressed in language and the meaning of different nodes is not clear. Therefore, the study proposes a fuzzy BPNN method for circuit fault diagnosis. The use of fuzzy theory for linguistic interpretation of the meaning of each node and connection relationship can make the network structure clearer. In biological neural networks, dendrites receive electrical signals from a neuron. The signals are processed in the nucleus and then the processed signals are transmitted to the next neuron through the axon. The operation of computerized neurons in BPNNs, on the other hand, mimics biological neurons. The biological neurons as well as the structure of the BPNN are shown in Figure 4.

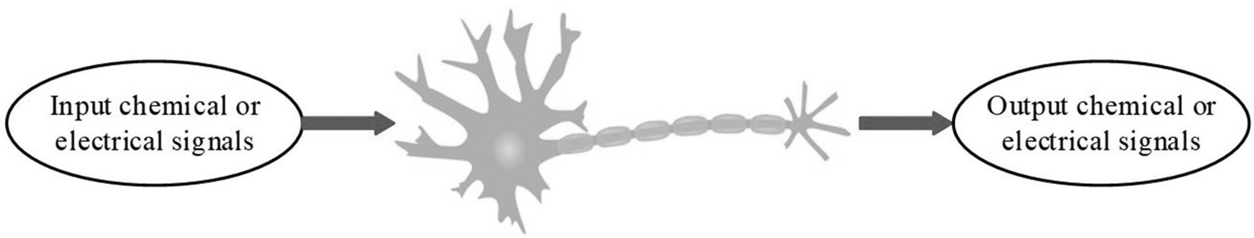
In Figure 4, BPNN is the most widely used neural network, whose signals are propagated through the connecting lines, while the signals and weights need to be multiplied, where i, o and y correspond to the neurons in the input, output and hidden layers, respectively. Assume that the training sample in the sample data is $F = (u_1, v_1), (u_2, v_2), ..., (u_m, v_m)$, while the output result is given in Equation (8).

$$\hat{y}_j^k = g\left(\beta_j - \chi_j\right) \tag{8}$$

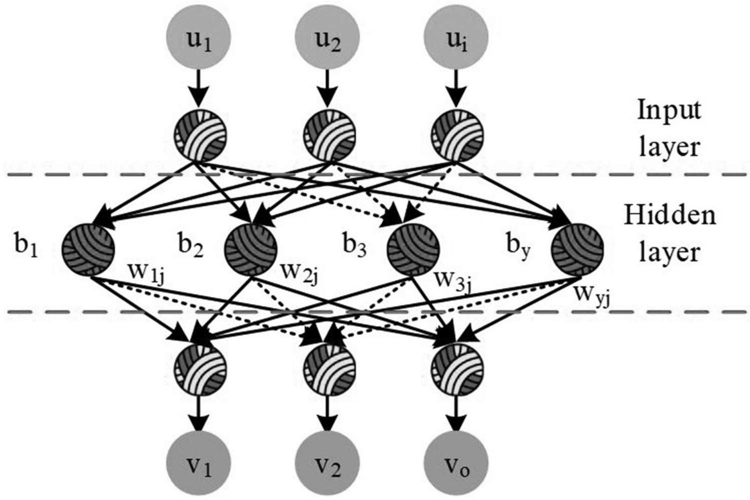
In Equation (8), g denotes the sigmoid function. β_j and χ_j are the input and output layers corresponding to the j-th (u_k, v_k) is calculated in Equation (9).

$$J_k = \frac{1}{2}\sum_{j=1}^{l}\left(\hat{v}_j^k - v_j^k\right)^2 \tag{9}$$

The BPNN provides a systematic method for determining the error of the implicit layer. Once the error of the implicit layer has been determined, the estimation parameters can be updated by the perceptual learning rule to obtain the final solution. Furthermore, fuzzy theory is concerned with the fuzzy characteristics



(a) Biological neurons.



(b) BP neural network structure.

Figure 4. Structure diagram of biological neuron and BPNN.

of things by simulating the fuzzy logic way of thinking of the human brain and constructing the mapping relationship on [0, 1], as shown in Equation (10).

$$L: S \rightarrow [0, 1], s \rightarrow L(a) \in [0, 1] \tag{10}$$

In Equation (10), L represents the fuzzy set on the argument domain S. $L(a)$ represents the affiliation function. This study adds a fuzzification layer after the input layer on the basis of BPNN and introduces fuzzy values to fuzzify the parameters. Assume there exist q kinds of circuit faults and the fault space is $U = (u_1, u_2, ..., u_M)$. There are K kinds of fault causes. The elements of both U and V spaces are fuzzy variables. The fuzzy relationship that the two have is expressed in Equation (11).

$$V = X \circ \left(r_{ij}\right)_{K\times q} \tag{11}$$

In Equation (11), $\circ$ and $(r_{ij})_{K\times q}$ are the generalized fuzzy operator and fuzzy relationship matrix, respectively. Through Equation (11) and combined with the diagnostic criteria we can determine whether the circuit is faulty or not. To solve the problem of traditional BPNN weight adjustment, the study introduces a momentum term. The calculation is shown in Equation (12).

$$\begin{cases} \omega_{ij}\left(h+1\right) = \omega_{ij}\left(h\right) + \delta\left[1-\varepsilon\right]\varphi_{ij}\left(h\right) + \varepsilon\Delta\omega_{ij}\left(h\right) \\ \Delta\omega_{ij}\left(h\right) = \omega_{ij}\left(h\right) - \omega_{ij}\left(h-1\right) \end{cases} \tag{12}$$

In Equation (12), ε and δ are the additional momentum factor and learning rate, respectively. $\omega_{ij}(h)$ is the connection weight matrix from layer i to layer j for the h-th $\varphi_{ij}(h)$ $\Delta\omega_{ij}(h)$ h-th training, respectively. The flow of the circuit fault diagnosis method based on PW-FBPNN is shown in Figure 5.

In Figure 5, it is necessary to apply the corresponding excitation signal of the circuit to obtain the raw data through simulation experiments. This is followed by the extraction of features using the PCA and WPT methods, the division of the data into training and test samples, and the input of the features into the FBPNN model for learning. Finally, the final fault information can be obtained. The training flow of FBPNN-based circuit fault diagnosis method is shown in Figure 6.

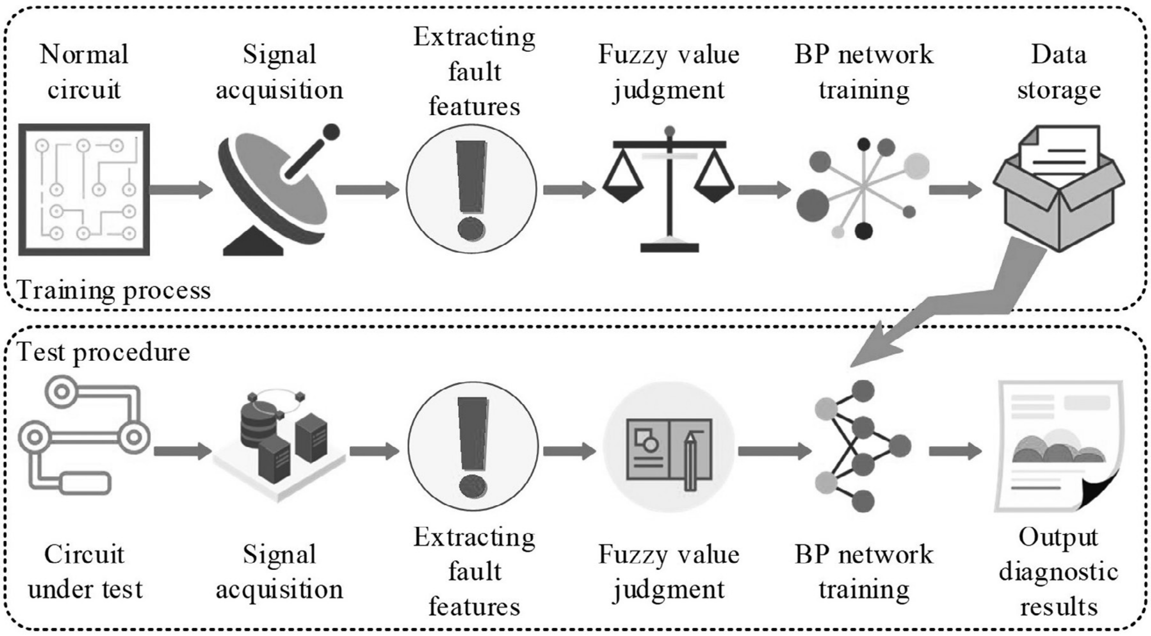


Figure 5. Process flow of circuit fault diagnosis method based on PW-FBPNN.

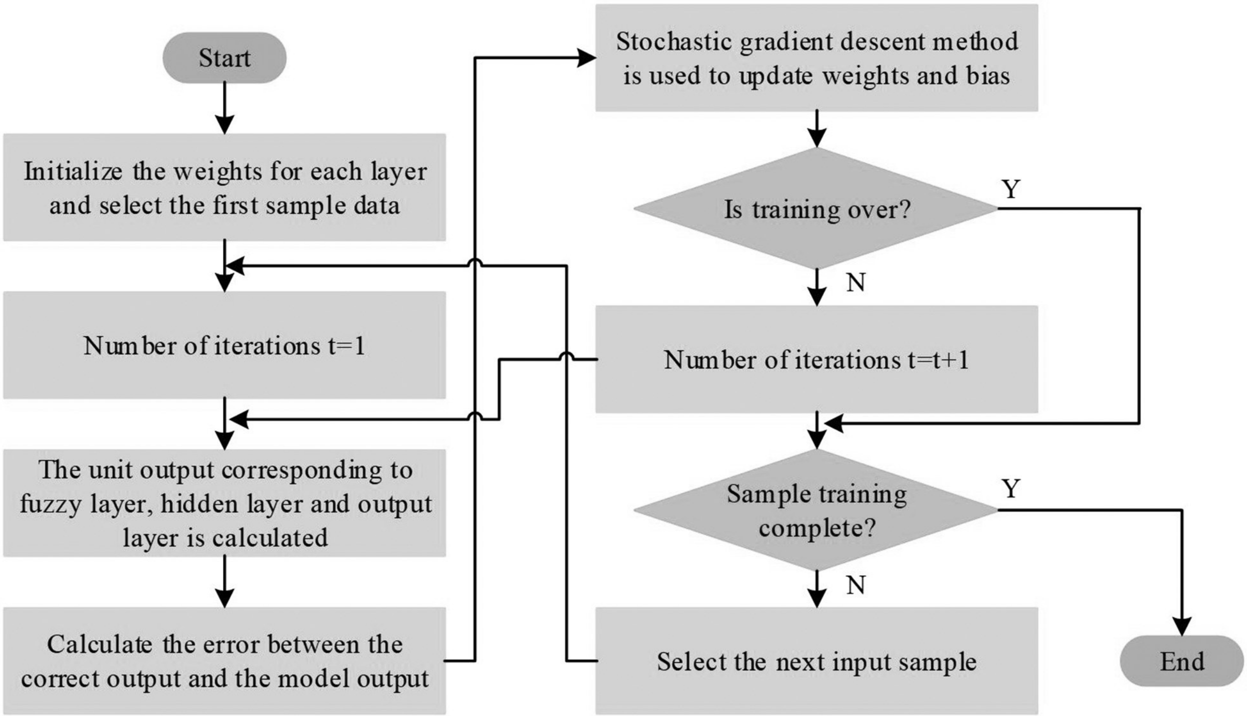


Figure 6. Training process of circuit fault diagnosis method based on FBPNN.

In Figure 6, it is necessary to initialize the weights of each layer, calculate the outputs of different layers, determine the error between the correct output and the model output, and then update the bias and weights until the samples are trained. Once this process is complete, the training can be terminated.

4. Result Analysis of PW-FBPNN-based Diagnostic Method in PCS System Faults

To investigate the validity and feasibility of the research method, two circuits are designed for performance evaluation and comparative experiments are conducted using mainstream fault diagnosis methods.

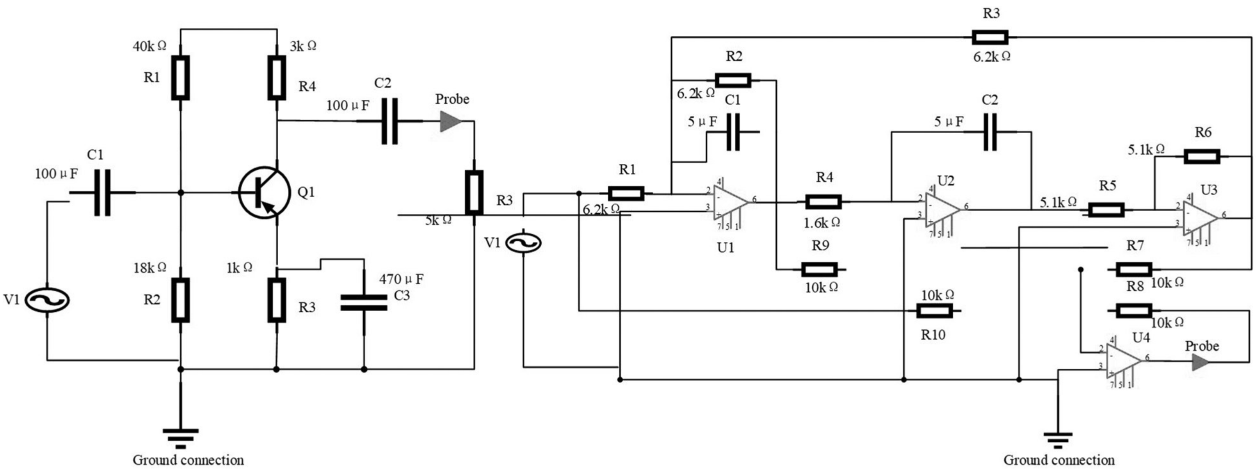
4.1. Experimental Preparation of a Diagnostic Method Based on PW-FBPNN

The study sets two circuits to analyze and evaluate different circuit troubleshooting methods, namely, a voltage-divided basic operational amplifier circuit (Circuit 1) and a four-op-amp second-order filter circuit (Circuit 2). The corresponding schematic diagrams are shown in Figure 7.

In Figure 7, the normal values of different components have been given. By analyzing the UI circuit, it is possible to search for the components that are most likely to affect the functioning of the circuit and thus get the corresponding type of fault. The fault markings for different circuits are shown in Table 1.

Note: "+" and "−" indicate the increase and decrease of the corresponding components, respectively.

The specific experimental parameters are set as follows. The number of input and output neurons is 360 and 16, respectively, and the number of fuzzy and hidden layers is 30. ε and δ is 0.75 and 0.03, respectively. The error is taken to be 0.05, and the data dimensions are set to be 5. In addition, the study is evaluated using diagnostic effectiveness, correctness, and time. In order to more scientifically validate the effectiveness of the research method in the application of PCS system faults, the study conducts comparative experiments using the current mainstream methods, i.e., the method based on fuzzy c-means clustering, hidden Markov model and support vector machine (FCM-HMM-SVM) and the method based on kernel independent component analysis and deep neural network (KICA-DNN).



(a) Circuit 1. *(b)* Circuit 2.

Figure 7. Schematic diagram of two circuits.

Table 1. Fault marking of different circuits.

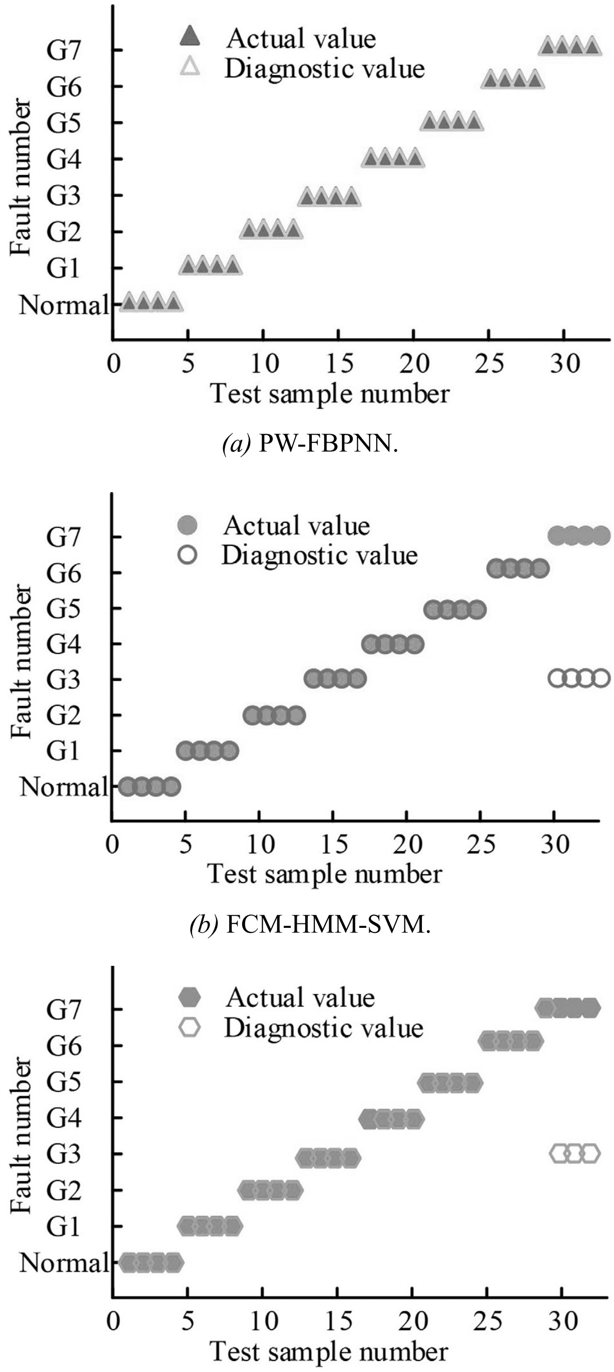
Circuit type	Fault number	Fault type	Nominal value	Fault value
Circuit 1	G0	Normal	/	/
	G1	R1+	40 K	45–90 K
	G2	R1−	40 K	10–35 K
	G3	R2+	19 K	20–40 K
	G4	R3+	1 K	1.3–3 k
	G5	R3−	1 K	0.1 k–0.9 k
	G6	R4+	2 K	3.6 k–6.6 k
	G7	C3+	480 μF	500–750 μF
Circuit 2	G0	Normal	/	/
	G1	R1+	6.3 K	9–12 K
	G2	R1−	6.3 K	1–3 K
	G3	R3+	6.3 K	9–12 K
	G4	C1−	5 μF	0.5–2 μF
	G5	R4+	1.5 K	2.5–4 K
	G6	C2+	5 μF	10–15 μF
	G7	R7+	10 K	15–20 K
	G8	R7−	10 K	1–5 K

4.2. Diagnostic Results of Voltage-divided Basic Operational Amplifier Circuits in PCS System Faults

The study begins with the validation of the efficacy of disparate diagnostic methods through the utilization of Circuit 1 and experiments employing identical fault feature vectors, fault markers, training sets and test sets. The results are presented in Figure 8.

Figure 8(a)–Figure 8(c) correspond to the fault diagnosis results of the PW-FBPNN diagnostic method, the FCM-HMM-SVM diagnostic method, and the KICA-DNN diagnostic method, respectively. In Figure 8, the PW-FBPNN diagnostic method correctly diagnoses all fault types present in Circuit 1, while the FCM-HMM-SVM diagnostic method is very ineffective in diagnosing the G7 fault types, and the KICA-DNN diagnostic method is ineffective in diagnosing most of the G7 fault types. The above results may be attributed to the difficulty in troubleshooting the G1, G7, and G8 fault types due to the minimal difference in output voltage changes. Additionally, the failure of components in the aforementioned fault types has a relatively minor impact on the overall circuit performance. The performance results of different fault diagnosis methods in the training and test samples are compared in Table 2.

In Table 2, the PW-FBPNN diagnostic method achieves high accuracy in fault identification in a short period of time. It takes 22.43s in the training sample and only 0.01s in the test sample to achieve 100% correctness in the G0-G6 fault types, with only a slightly lower correctness of 93.33% in the G7 type. Whereas FCM-HMM-SVM is more than 90% correct in most fault categories, the diagnostic correctness is only 53.33% in the G7 fault category. The KICA-DNN diagnostic method has a more general correct rate of recognizing various circuit fault categories, which are all greater than 80%. This is due to the fact that the research method makes the network structure clearer, which can effectively determine the best structure through the actual needs of various circuit fault diagnosis and then improve the correct rate of the fault diagnosis method.



(a) PW-FBPNN.

(b) FCM-HMM-SVM.

(c) KICA-DNN.

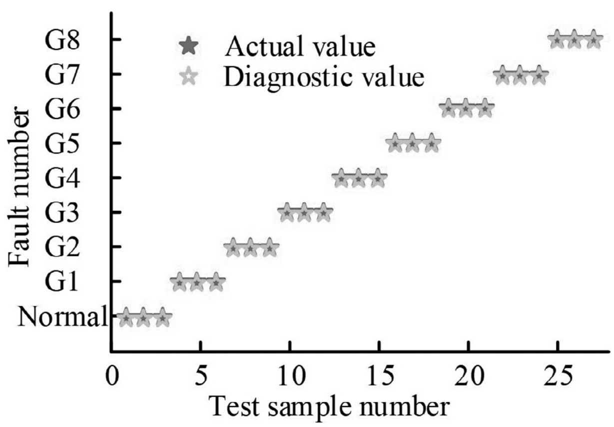
Figure 8. Diagnosis results of different fault diagnosis methods in Circuit 1.

4.3. Diagnostic Results of a Four-op-amp Second-order Filter Circuit in PCS System Faults

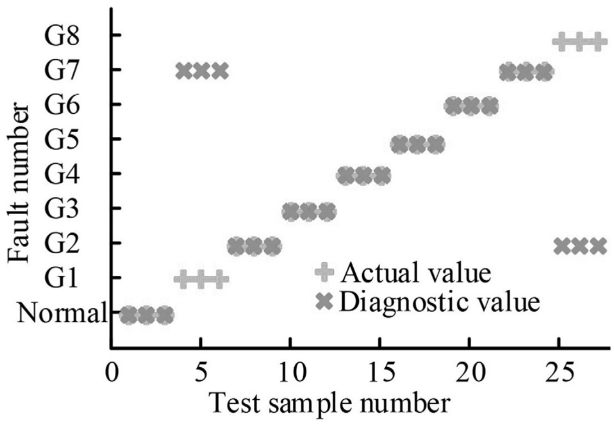
The study conducts experiments using the same setup as Circuit 1 and obtains the diagnostic results of different circuit troubleshooting methods under Circuit 2, as shown in Figure 9.

Table 2. Comparison of performance results of different fault diagnosis methods in training samples and test samples.

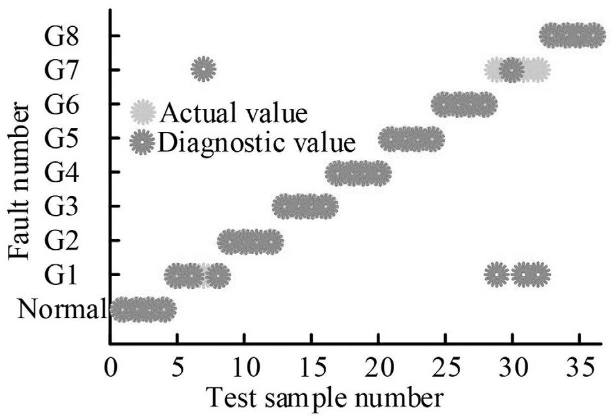
Diagnostic method	Fault number	Training sample		Test sample			
		Sample size	Time/s	Sample size	Correct quantity	Correct rate/ %	Time/s
PW-FBPNN	G0	72	22.43	30	30	100	0.01
	G1	72		30	30	100	
	G2	72		30	30	100	
	G3	72		30	30	100	
	G4	72		30	30	100	
	G5	72		30	30	100	
	G6	72		30	30	100	
	G7	72		30	28	93.33	
FCM-HMM-SVM	G0	72	30.66	30	30	100	0.11
	G1	72		30	28	93.33	
	G2	72		30	29	96.67	
	G3	72		30	28	93.33	
	G4	72		30	25	83.33	
	G5	72		30	27	90	
	G6	72		30	29	96.67	
	G7	72		30	16	53.33	
KICA-DNN	G0	72	27.68	30	30	100	0.15
	G1	72		30	26	86.67	
	G2	72		30	29	96.67	
	G3	72		30	27	90	
	G4	72		30	28	93.33	
	G5	72		30	30	100	
	G6	72		30	28	93.33	
	G7	72		30	24	80	



(a) PW-FBPNN.



(b) FCM-HMM-SVM.

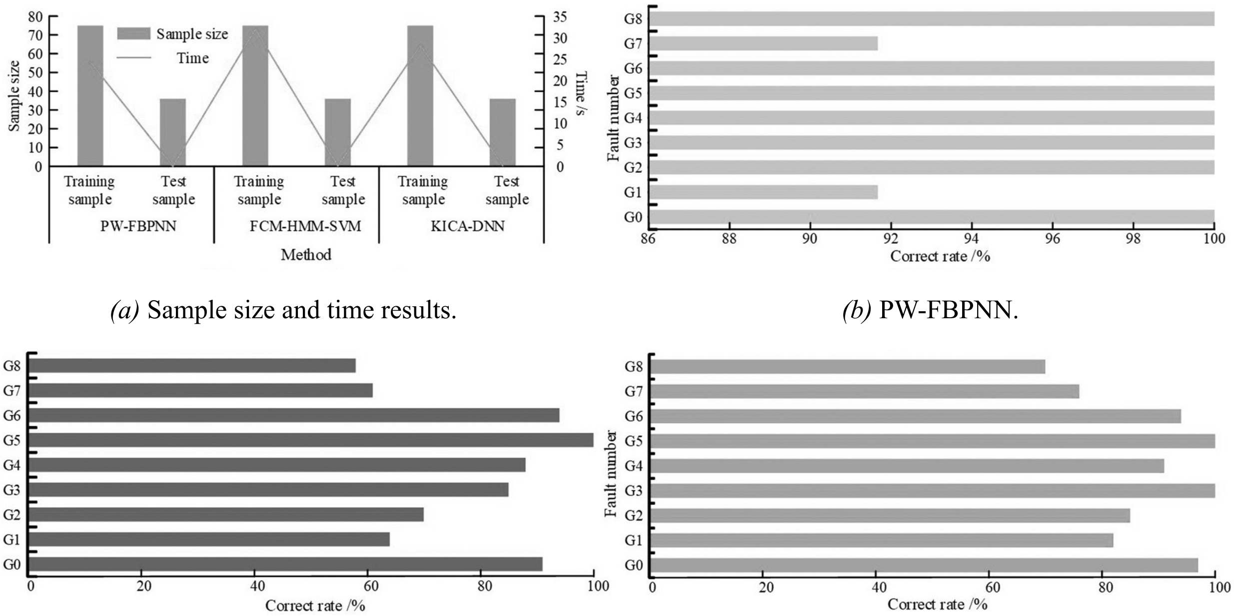


(c) KICA-DNN.

Figure 9. Diagnosis results of different fault diagnosis methods in Circuit 2.

Figure 9(a)–Figure 9(c) show the fault diagnosis results of the PW-FBPNN diagnostic method, the FCM-HMM-SVM diagnostic method, and the KICA-DNN diagnostic method in Circuit 2, respectively. In Figure 9, the PW-FBPNN diagnostic method proposed in the study can accurately identify various types of faults occurring in Circuit 2. Meanwhile, the research method can still show better fault diagnosis results when facing larger-scale analog circuits. The FCM-HMM-SVM diagnostic method is not able to diagnose the corresponding fault category in the G1 and G8 fault type diagnosis. The KICA-DNN diagnostic method, on the other hand, is less effective in the diagnosis of a small number of G1 fault categories with most G7 fault categories. This indicates that the research method can effectively and accurately extract the feature vectors in the original fault data, reduce the interference of noise and redundant information, and lay a solid foundation for the subsequent fault diagnosis methods to improve the execution efficiency. In order to further determine the performance of different diagnostic methods, the study uses training samples and test samples to conduct experiments. The number of samples is 75 and 36, respectively. The results are shown in Figure 10.

Figure 10(a) shows the sample size and time results of each diagnostic method under different samples. Figure 10(b)–Figure 10(c) shows the results of the correct rate of PW-FBPNN, FCM-HMM-SVM and KICA-DNN under different fault types in the test samples. The PW-FBPNN method proposed in the study has a lower correct rate only under G1 and G7 fault types, both of which are 91.67%. The rest of the fault types are judged with 100% accuracy, when the time required is 0.01s. The FCM-HMM-SVM diagnostic method has poor recognition correctness in four fault types, G1, G2, G7 and G8, which are lower than 70%, corresponding to a time of 0.12s. The KICA-DNN diagnostic method has low correctness only in two fault types, G7 and G8, which are 70% and 75%, respectively. The correct rate for the rest of the fault types is over 80%, and the corresponding time is 0.13s. The above results may be attributed to the fact that the PCA method combined with the WPT method can effectively reduce the noise and redundant samples and reduce the number of input dimensions. To scientifically evaluate the superiority of research methods, statistical tests are conducted to evaluate whether there are significant differences between different fault diagnosis methods. The Nemenyi test is used to determine whether the research method is significantly superior to other comparative algorithms. It is essential to calculate the critical range (CR) of the average order value difference



(a) Sample size and time results.

(b) PW-FBPNN.

(c) FCM-HMM-SVM.

(d) KICA-DNN.

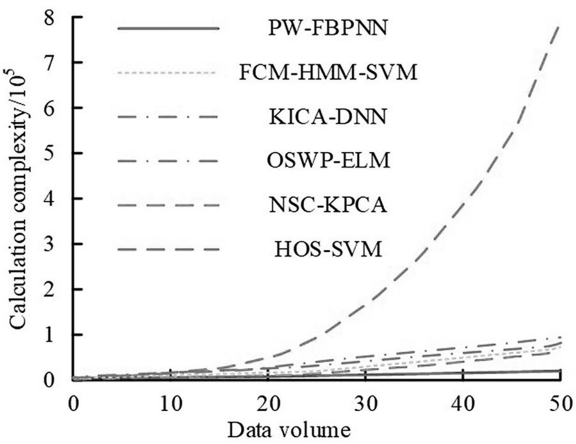
Figure 10. Comparison of the performance of different fault diagnosis methods under different fault types in training samples and test samples.

and the difference in average sorting (DAS) between the two algorithms. The study introduces other advanced methods for comparative experiments. Namely, the optimal selection of wavelet packet and extreme learning machine (OSWP-ELM), fault diagnosis method based on nonlinear spectral characteristic and kernel principal component analysis (NSC-KPCA) and high order spectrum and support vector machine (HOS-SVM) based fault diagnosis methods are used to obtain the average ranking difference results between the research method and other fault diagnosis methods, as shown in Table 3.

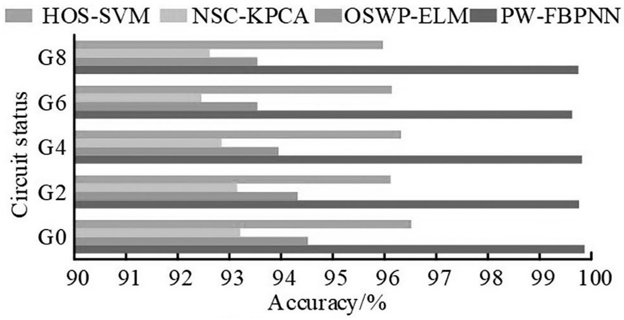
In Table 3, the DAS values of PW-FBPNN, FCM-HMM-SVM method, KICA-DNN method, OSWP-ELM method, NSC-KPCA method, and HOS-SVM method are 3.885, 2.617, 5.103, 2.197, and 3.752, respectively, all exceeding the CR value. It demonstrates that the research method exhibits superior diagnostic performance in identifying PCS faults compared to other mainstream algorithms. The aforementioned outcomes may be attributed to the fact that the PCA method proposed in the study, when combined with the WPT algorithm, is capable of accurately and effectively extracting the diagnostic features of system faults. To further validate the performance of the research method, a comparison is made between the computational complexity, diagnostic accuracy, and diagnostic speed using Circuit 2. The results are shown in Figure 11.

Table 3. The average ranking difference result between the research method and other fault diagnosis methods.

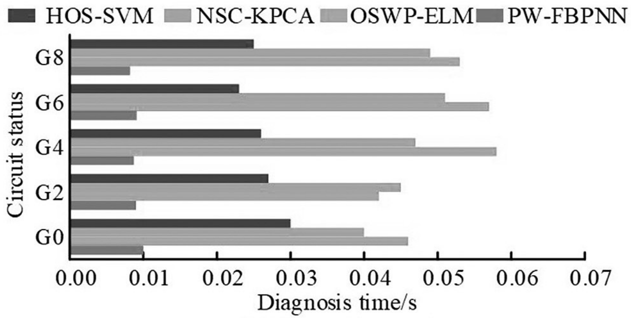
Method	**DAS**	**> CR(1.952)**
FCM-HMM-SVM	3.885	Exceed
KICA-DNN	2.617	Exceed
OSWP-ELM	5.103	Exceed
NSC-KPCA	2.197	Exceed
HOS-SVM	3.752	Exceed



(a) Computational complexity.



(b) Diagnostic accuracy.



(c) Diagnostic speed.

Figure 11. Comparison of performance results of different fault diagnosis methods.

Figures 11(a)–11(c) correspond to computational complexity, diagnostic accuracy, and diagnostic speed results of different fault diagnosis methods, respectively. In Figure 11, with the continuous increase of data volume, only the HOS-SVM method has the fastest growth rate and the largest fluctuation in computational complexity. Whereas the PW-FBPNN method has the slowest growth rate, and the variation amplitude of other mainstream algorithms is also relatively small. In the results of fault diagnosis accuracy, the PW-FBPNN method and OSWP-ELM method utilize wavelet transform and wavelet analysis to denoise the circuit signals. This leads to a significant improvement in their fault diagnosis accuracy. This indicates that the data processed by wavelet transform and wavelet analysis can better reflect the characteristics of simulated state changes. The PW-FBPNN method has the highest diagnostic accuracy due to its optimization of the FBPNN training method, identification of the most suitable parameters, and design of a superior circuit fault diagnosis method. In terms of diagnostic speed results, the diagnostic time of the research method is much shorter than that of other methods, which may be because the PCA method in the research method reduces redundant sample data and lowers input dimensionality. The aforementioned results demonstrate that research methods can facilitate relatively low computational complexity and scalability in power systems of varying scales. Furthermore, the introduction of the fuzzy theory provides a more concise way to determine the optimal structure, which, when combined with the aforementioned reasons, can provide strong support for the improvement of the fault identification rate and the reduction of the computation time. However, there are still certain limitations to the research methods. Due to the inherent shortcomings of neural networks, it is of great importance to explore how to exploit the advantages of algorithms, integrate different algorithms, and fully exploit their strengths in future research.

5. Conclusion

This study proposes PW-FBPNN, a novel fault diagnosis method for PCSs that synergistically combines PCA, WPT, and fuzzy neural networks. Compared with existing methods, this method performed well in terms of accuracy (up to 100% for most fault types) and efficiency (diagnosis time as low as 0.01 seconds). These advances were important to power system operators as they could improve system reliability, reduce downtime, and increase maintenance efficiency. The integration of fuzzy logic and neural networks facilitated the exploration of novel approaches to address uncertainty in fault diagnosis. Future research should focus on extending this method to larger and more complex power systems and exploring its applicability in real-time monitoring scenarios. While PW-FBPNN displays considerable promise, further investigation is required to ascertain its long-term reliability and adaptability to diverse forms of faults, to fully realize its potential in industrial applications.

References

[1] X. Guan et al., "The Control Strategy of the Electric Power Steering System for Steering Feel Control", *Proceedings of the Institution of Mechanical Engineers, Part D. Journal of Automobile Engineering*, vol. 238, no. (2/3), pp. 347–357, 2024. http://dx.doi.org/10.1177/09544070221132131

[2] Y. Zoka, "Toward a 'Shinayaka (Flexible and Resilient)' Electric Power and Energy System", *The Journal of The Institute of Electrical Engineers of Japan*, vol. 142, no. 1, pp. 4–5, 2022. http://dx.doi.org/10.1541/ieejjournal.142.4

[3] M. Cheng et al., "Power System Abnormal Pattern Detection for New Energy Big Data", *International Journal of Emerging Electric Power Systems*, vol. 24, no. 1, pp. 91–102, 2022. http://dx.doi.org/10.1515/ijeeps-2022-0209

[4] M. I. Danilov and I. G. Romanenko, "Identification of Unauthorized Electric-Power Consumption in the Phases of Distribution Networks with Automated Metering Systems", *Power Technology and Engineering*, vol. 56, no. 3, pp. 414–422, 2023. http://dx.doi.org/10.1007/s10749-023-01530-y

[5] Y. Song et al., "Measurement-Based Wideband Model and Electric Parameter Extraction of Railway Traction Power System", *IEEE Transactions on Transportation Electrification*, vol. 9, no. 1, pp. 1483–1497, 2023. http://dx.doi.org/10.1109/TTE.2022.3170045

[6] F. G. Merconchini et al., "Study of Electric Power Quality Indicators by Simulating a Hybrid Generation System", *International Journal of Power Electronics and Drive Systems*, vol. 14, no. 2, pp. 1044–1054, 2023. http://dx.doi.org/10.11591/ijpeds.v14.i2.pp1044-1054

[7] H. K. Cho et al., "Fault Diagnosis Algorithm Based on Switching Function for Boost Converters", *International Journal of Electronics*, vol. 102, no. 7, pp. 1229–1243, 2014. http://dx.doi.org/10.1080/00207217.2014.966780

[8] G. Liu et al., "Sensorless Control for Five-phase PMSMs Under Normal and Open-circuit Fault Conditions Using Super-twisting Sliding Mode Observers", *Journal of Power Electronics*, vol. 23, no. 7, pp. 1098–1110, 2023. http://dx.doi.org/10.1007/s43236-023-00614-2

[9] X. Zhang et al., "A Natural Commutation Current Topology of Hybrid HVDC Circuit Breaker Integrated with Limiting Fault Current", *IET Generation, Transmission & Distribution*, vol. 17, no. 7, pp. 1509–1524, 2023. http://dx.doi.org/10.1049/gtd2.12760

[10] A. T. C. Mahfoudh et al., "Cross-correlation Based Fault Electromagnetic Signature Extraction for Open-circuit Fault Diagnosis in NPC Inverters", *Electrical Engineering*, vol. 105, no. 3, pp. 1911–1921, 2023. http://dx.doi.org/10.1007/s00202-023-01754-1

[11] V. K. Ivanov and B. V. Palyukh, "Application of Evidence Theory for Training Fuzzy Neural Networks in Diagnostic Systems", *Pattern recognition and image analysis: advances in mathematical theory and applications in the USSR*, vol. 33, no. 3, pp. 354–359, 2023. http://dx.doi.org/10.1134/S1054661823030197

[12] Z. Liu et al., "Extracting Inherent Model Structures and Identifying Parameters of Time-Varying Systems Using Local Linear Neuro-Fuzzy Networks", *IEEE Transactions on Fuzzy Systems: A Publication of the IEEE Neural Networks Council*, vol. 30, no. 1, pp. 233–247, 2022. http://dx.doi.org/10.1109/TFUZZ.2020.3034972

[13] T. Shankar et al., "Breast Cancer: A Hybrid Method for Feature Selection and Classification in Digital Mammography", *International Journal of Imaging Systems and Technology*, vol. 33, no. 5, pp. 1696–1712, 2023. http://dx.doi.org/10.1002/ima.22889

[14] S. R. Choudhury and R. Rengaswamy, "Characterization and Fault Diagnosis of PAFC Cathode by EIS Technique and a Novel Mathematical Model Approach", *Journal of Power Sources*, vol. 161, no. 2, pp. 971–986, 2006. http://dx.doi.org/10.1016/j.jpowsour.2006.05.005

[15] G. Yu et al., "Defect Detection of Small Cotter Pins in Electric Power Transmission System from UAV Images Using Deep Learning Techniques", *Electrical Engineering*, 2023, vol. 105, no. 2, pp. 1251–1266.
http://dx.doi.org/10.1007/s00202-022-01729-8

[16] H. Bai and B. Yu, "Position Estimation of Fault-Tolerant Permanent Magnet Motor in Electric Power Propulsion Ship System", *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 17, no. 6, pp. 890–898, 2022.
http://dx.doi.org/10.1002/tee.23579

[17] J. Yi et al., "Water Consumption of Electric Power System in China: from Electricity Generation to Consumption", *Environmental Science and Pollution Research*, vol. 30, no. 45, pp. 101903–101910, 2023.
http://dx.doi.org/10.1007/s11356-023-29525-2

[18] Z. Xu et al., "Inter-turn Short-circuit Fault Detection with High-frequency Signal Injection for Inverter-fed PMSM Systems", *Journal of Power Electronics*, vol. 23, no. 6, pp. 892–903, 2023.
http://dx.doi.org/10.1007/s43236-022-00585-w

[19] A. Rubaai and P. Young, "EKF-Based PI-/PD-Like Fuzzy-Neural-Network Controller for Brushless Drives", *IEEE Transactions on Industry Applications*, vol. 47, no. 6, pp. 2391–2401, 2012.
http://dx.doi.org/10.1109/TIA.2011.2168799

[20] R. Sivanandan and J. Jayakumari, "Development of a Novel CNN Architecture for Improved Diagnosis from Liver Ultrasound Tumor Images", *International Journal of Uncertainty, Fuzziness and Knowledge-based Systems: IJUFKS*, vol. 30, no. 2, pp. 189–210, 2022.
http://dx.doi.org/10.1142/S0218488522500088

[21] D. P. Manoj Kumar and J. Ananda Babu, "Neural Network-based Game Theory Approach for Personalized Privacy Preservation in Data Publishing", *Journal of System and Management Sciences*, vol. 12, no. 1, pp. 498–520.
https://doi.org/10.33168/JSMS.2022.0132

[22] S. Madhavi and S. P. Hong, "Anomaly Detection Using Deep Neural Network Quantum Encoder", *Journal of Logistics, Informatics and Service Science*, vol. 9, no. 2, pp. 118–130, 2022.
https://doi.org/10.33168/LISS.2022.0207

[23] J. W. Choi and E. R. Jeong, "A Multi-output Convolutional Neural Network-based Distance and Velocity Estimation Technique", *Journal of Logistics, Informatics and Service Science*, vol. 9, no. 1, pp. 11–25, 2022.
https://doi.org/10.33168/LISS.2022.0202

Received: July 2024
Revised: August 2024
Accepted: August 2024

Contact addresses:
Xu Chen*
State Grid Ningxia Marketing Service Center
State Grid Ningxia Metrology Center
Yinchuan
Ningxia
China
e-mail: chenxu3809@126.com
*Corresponding author

Chao Zhang
State Grid Ningxia Marketing Service Center
State Grid Ningxia Metrology Center
Yinchuan
Ningxia
China
e-mail: caozhang_1988@163.com

Haomiao Zhang
State Grid Ningxia Marketing Service Center
State Grid Ningxia Metrology Center
Yinchuan
Ningxia
China
e-mail: hmiaozhang@163.com

Zhiqiang Cheng
State Grid Ningxia Marketing Service Center
State Grid Ningxia Metrology Center
Yinchuan
Ningxia
China
e-mail: zhiqiangchen0318@163.com

Yu Yan
State Grid Ningxia Marketing Service Center
State Grid Ningxia Metrology Center
Yinchuan
Ningxia
China
e-mail: yureng_2000@163.com

XU CHEN received the MSc degree from North China Electric PowerUniversity, China, in April 2016. He is currently engaged in research anddevelopment in the power sector.

CHAO ZHANG received the B.Eng. degree from Ningxia University, China, in June 2009. His expertise lies in electrical engineering, with a focus on power systems.

HAOMIAO ZHANG received the B.Eng. degree from Ningxia University, China, in June 1999. He has a strong background in engineering and has contributed to various projects in the energy field.

ZHIQIANG CHENG received the B.Eng. degree from Ningxia Open University, China, in July 1995. His primary focus is in power measurement fault handling and power system stability analysis.

YU YAN received the B.Eng. degree from Shanghai University of Electric Power, China, in June 2022. He is committed to advancing energy technologies and improving power system reliability.