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SENSOR FAULT DIAGNOSIS BASED ON CORRENTROPY FILTER AND PROBABILISTIC NEURAL NETWORK

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Abstract. *This paper mainly proposes a correntropy-based filtering algorithm for non-Gaussian systems that are subject to random interference. When the system is subjected to non-Gaussian interference noise, the filtering algorithm can accurately estimate the state of the system, and then proposes a two-stage sensor fault diagnosis method based on correntropy filters. When the sensor fails, the residual will be generated, different sub-filters are driven by different residual signals, and then input the estimated state obtained by the sub-filter into the Probabilistic Neural Network (PNN), which can effectively determine the sensor failure and achieve fault location. Finally, the two-level fault diagnosis method designed in this paper is applied to the wind energy conversion system with high wind speed and random noise, and the simulation results show that this method can effectively achieve sensor fault diagnosis.*

Keywords: Non-Gaussian system, Correntropy, Probabilistic neural network, Sensor fault diagnosis

1. **Introduction.** With the development of fault-tolerant control and computer technology, the control effect of the system has reached a high level of reliability, and the sensor fault has become one of the major causes of system fault. Therefore, it is necessary to study how to implement sensor fault diagnosis. The state of the system can directly reflect the operating status of the system. Using the state estimation method combined with the appropriate model can achieve sensor fault diagnosis. The Kalman Filter (KF) [1] algorithm is one of the commonly used state estimation algorithms for linear systems, since almost all actual systems contain nonlinearities, the Extended Kalman Filter algorithm (EKF) [2] is often used to implement the state estimation. However, the noise in the actual industrial process may not obey the Gaussian distribution. The traditional state estimation method may not be able to obtain the ideal estimation result. Recently, [3] proves the possibility of correntropy applied to the state estimation. Current sensor fault detection methods mainly include hardware redundancy method, analytical redundancy method, expert system method, and neural network method. [4] studies the method of fault diagnosis of the sensor based on hardware redundancy. Although the result of fault diagnosis is feasible, this method is difficult to implement due to its large number of equipment, large space and high cost. In [5], the analytical redundancy method is applied to the fault detection, separation and identification of sensor faults, which improves the performance of fault diagnosis methods. However, the analytical redundancy method requires an accurate mathematical model, which is difficult to implement for complex systems. [6] applies expert system to fault diagnosis. It can find fault components quickly

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and accurately. However, the expert system method is difficult to acquire knowledge, and it cannot diagnose new difficulties. While neural networks have many advantages because they can effectively solve these problems and can identify the type of fault and the cause of the fault. Therefore, it is one of the effective methods to realize the fault diagnosis.

In this paper, Probabilistic Neural Network (PNN) [7] is chosen to study sensor fault diagnosis. PNN is based on Radical Basis Function (RBF) neural network, which combines the density function estimation of Parzen window and Bayesian decision theory. The structure is simple and the algorithm is easy to design. It is especially suitable for solving classification problems, so sensor fault diagnosis can be realized. Then combine the PNN with the correntropy filter to diagnose the sensor fault.

The rest of this paper is organized as follows. Section 2 designs filter models for non-Gaussian system models. Section 3 proposes the use of correntropy as a performance index to solve the optimal solution of the filter gain matrix. Section 4 designs a two-level fault diagnosis method by using the correntropy filter proposed in the previous section and the PNN network. Section 5 applies the two-level fault diagnosis method proposed in the previous section to a wind energy conversion system and verifies its effectiveness. Finally, some conclusions are drawn in Section 6.

2. **System Model and Filter Design.**

The state space model for a non-Gaussian system is presented as follows:

$$\begin{cases} \dot{x}(t) = A(t)x(t) + B(t)u(t) + W\omega(t) \\ y(t) = C(t)x(t) + \zeta(t) \end{cases} \tag{1}$$

where $x \in R^n$ is system state vector, $u \in R^r$ is system input and $y \in R^m$ is system output. $\omega \in R^n$ and $\zeta \in R^m$ are system noise and measurement noise that do not necessarily satisfy Gaussian assumptions. Assuming that ω and ζ are both bounded and independent. A, B, C, W are the system parameter matrices of the corresponding dimension.

For the system model described in (1), the following filter model can be established:

$$\begin{cases} \dot{\hat{x}}(t) = A(t)\hat{x}(t) + B(t)u(t) + L(y(t) - \hat{y}(t)) \\ \hat{y}(t) = C(t)\hat{x}(t) \end{cases} \tag{2}$$

where $L \in R^{n\times m}$ is the filter gain matrix to be solved.

Defining the estimation error as $e(t) = x(t) - \hat{x}(t)$, according to (1) and (2) we can obtain:

$$\dot{e}(t) = \dot{x}(t) - \dot{\hat{x}}(t) = A(t)e(t) + L(C(t)e(t) + \zeta(t)) + W\omega(t) \tag{3}$$

Define the output error as:

$$e_y(t) = y(t) - \hat{y}(t) = C(t)e(t) + \zeta(t) \tag{4}$$

The filter is designed to make the system state and estimated state as close as possible, and this requires the solution of the optimal filter gain matrix L^*. The next section will use correntropy as a performance index to solve it.

3. **Correntropy Filter Design.**

3.1. **Performance.**

The filter optimal gain matrix L^* can make the system state and the filter estimation state as close as possible, that is to say the randomness of the system is the smallest at this moment. Recently, in the case of non-Gaussian, the Maximum Correntropy Criterion (MCC) has been successfully applied in the design of the filter.

The correntropy is the generalized similarity measure of two random variables. The greater the correntropy between two sequences is, the more similar the two sequences are.

Given the random variables X and Y, the correntropy is defined as:

$$V(X,Y) = E[\kappa(X,Y)] = \int \kappa(x,y)\mathrm{d}F_{XY}(x,y) \tag{5}$$

where E is the expectation, $F_{XY}(x,y)$ the joint probability distribution function of (X,Y) and $\kappa(x,y)$ a translation-invariant Mercer kernel. In general, Gaussian kernel function is the most commonly used, which is presented as follows:

$$\kappa(x,y) = G_\sigma(e) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{e^2}{2\sigma^2}\right) \tag{6}$$

where $e = x - y$, $\sigma > 0$ is kernel width.

In most cases, only limited data are available and the joint distribution function $F_{XY}(x,y)$ is usually unknown, so the correntropy can be estimated from a finite number of samples, which can be obtained by:

$$\hat{V}(X,Y) = \frac{1}{N}\sum_{i=1}^{N} G(x_i - y_i) = \frac{1}{N}\sum_{i=1}^{N} G(e_i) \tag{7}$$

where N is sample number.

This section selects correntropy as the performance index for filter design, the state error vector dimension is n, so $e_k = [e_k^1 \; e_k^2 \; \cdots \; e_k^n]$, for the j-th estimation error e_k^j ($j = 1, 2, \ldots, n$), sample number is N, the sample of the estimated error is ee_i^j ($i = 1, 2, \ldots, N$), then the correntropy of e_k^j can be expressed as:

$$J_j = \frac{1}{N}\sum_{i=1}^{N} G_\sigma\left(ee_i^j\right) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{\left(ee_i^j\right)^2}{2\sigma^2}\right) \tag{8}$$

To simplify the calculation, this section uses the sum of the correntropy of each estimation error as a performance indicator, which is:

$$\begin{aligned} J &= J_1 + J_2 + \cdots + J_j + \cdots + J_n \\ &= \sum_{j=1}^{n}\left(\frac{1}{N}\sum_{i=1}^{N} G_\sigma\left(ee_i^j\right)\right) = \sum_{j=1}^{n}\left(\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{\left(ee_i^j\right)^2}{2\sigma^2}\right)\right) \end{aligned} \tag{9}$$

3.2. **Optimal filter gain solution.** The greater the correntropy is, the more similar the two sequences are, so the optimal filter gain can be obtained by maximizing the correntropy. There are many methods to solve this problem. The gradient ascending method is simple in form, but the convergence speed is slow. The convergence speed of Newton's method is faster due to its second-order convergence, so this section selects the Newton method, and Theorem 3.1 gives the recursive formula for the optimal filter gain by using the Newton method.

Theorem 3.1. *For a given accuracy $\varepsilon > 0$, the approximate solution of the optimal gain matrix of the maximum correntropy filter can be expressed as:*

$$l_{k+1} = l_k + \lambda_k P_k \tag{10}$$

where $\lambda_k = \frac{-\nabla J(l_k)^T P_k}{p_k^T H(l_k) P_k}$, $P_k = -H^{-1}(l_k)\nabla \overline{J}(l_k)$, *and the Hessen matrix is:*

$$H(l_k) = \left[\frac{\partial J(l_k)}{\partial l_i \partial l_j}\right]_{mn\times mn} = \begin{bmatrix} \dfrac{\partial^2 J(l_k)}{\partial l_1^2} & \cdots & \dfrac{\partial^2 J(l_k)}{\partial l_1 \partial l_{mn}} \\ \vdots & \ddots & \vdots \\ \dfrac{\partial^2 J(l_k)}{\partial l_{mn}\partial l_1} & \cdots & \dfrac{\partial^2 J(l_k)}{\partial l_{mn}^2} \end{bmatrix}$$

The steps for solving L^* using Newton's method can be expressed as:

1) Step 1: Initialize l_0, let $k = 0$, accuracy $\varepsilon > 0$;
2) Step 2: Calculate the gradient $\nabla J(l_k) = \left[\frac{\partial J(l_k)}{\partial l_1} \frac{\partial J(l_k)}{\partial l_2} \cdots \frac{\partial J(l_k)}{\partial l_{mn}}\right]^T$, if the accuracy requirement meets $\nabla J(l_k) < \varepsilon$, then stop the calculation and the approximate optimal solution is l_k, otherwise go to Step 3;
3) Step 3: Let $P_k = -H^{-1}(l_k)\nabla \overline{J}(l_k)$, $\lambda_k = \frac{-\nabla J(l_k)^T P_k}{p_k^T H(l_k) P_k}$ is approximate optimal step size, $H(l_k)$ is the Hessen matrix, and $l_{k+1} = l_k + \lambda_k P_k$;
4) Step 4: Proceed to the next step, $k = k+1$, calculate the gradient $\nabla J(l_{k+1})$, and then go to Step 2.

4. **Sensor Fault Detection and Diagnosis.** The common sensor faults in the control system are mainly divided into three categories: constant deviation faults, constant gain faults, and stuck faults. Assuming that only one sensor fails in the system, the system model with sensor fault (1) can be obtained as follows:

$$\begin{cases} \dot{x}(t) = A(t)x(t) + B(t)u(t) + W(h)\omega(t) \\ y_{ideal}(t) = C(t)x(t) \\ y_{real}(t) = y_{ideal}(t) + f_s y_F(t) + \zeta(t) \end{cases} \tag{11}$$

where $y_{ideal}(t)$ is ideal output when the sensor is trouble-free and has no measurement noise, $y_{real}(t)$ actual output, $f_s = E_i = [0 \ldots 1 \ldots 0]^T$ sensor fault vector, which indicates that the i-th sensor has failed and $y_F(t)$ fault signal.

Assume that the i-th sensor in the system has gone wrong, $y_{iideal}(t)$ indicates the ideal output of the i-th sensor, $y_{ireal}(t)$ indicates the real output of the i-th sensor, and then the three faults of the sensor can be expressed as:

1) Constant deviation fault

$$y_{ireal}(t) = y_{iideal}(t) + \Delta_i + \zeta(t) \tag{12}$$

where Δ_i is a constant.

2) Constant gain fault

$$y_{ireal}(t) = \beta_i y_{iideal}(t) + \zeta(t) \tag{13}$$

where β_i is scale factor.

3) Stuck fault

$$y_{ireal}(t) = \alpha_i + \zeta(t) \tag{14}$$

where α_i is a constant.

In this section, the main work is adopting the correntropy filter designed in the previous section to implement the sensor fault diagnosis. Figure 1 shows the two-level fault diagnosis method designed in this paper.

The red dotted box in the upper part of Figure 1 shows the first level of fault detection, where the correntropy filter is used to estimate the state variables of the system. When one of the sensors in the system fails, the residual will be generated, which can be expressed as follows:

$$E\left[e_y(t)\right] \neq 0 \tag{15}$$

where $e_y(t)$ is residual error when the sensor goes wrong. In other words, when a sensor goes wrong, the mean value of the system residuals is no longer zero. Therefore, the following detection rules can be obtained:

$$\begin{cases} E\left[e_y(t)\right] \neq 0, & \text{When a fault occurs} \\ E\left[e_y(t)\right] = 0, & \text{When no fault occurs} \end{cases} \tag{16}$$

The green dotted box at the bottom of Figure 1 shows the second-level fault location. Different signals are used to drive each correntropy filter. Each filter can get n estimated

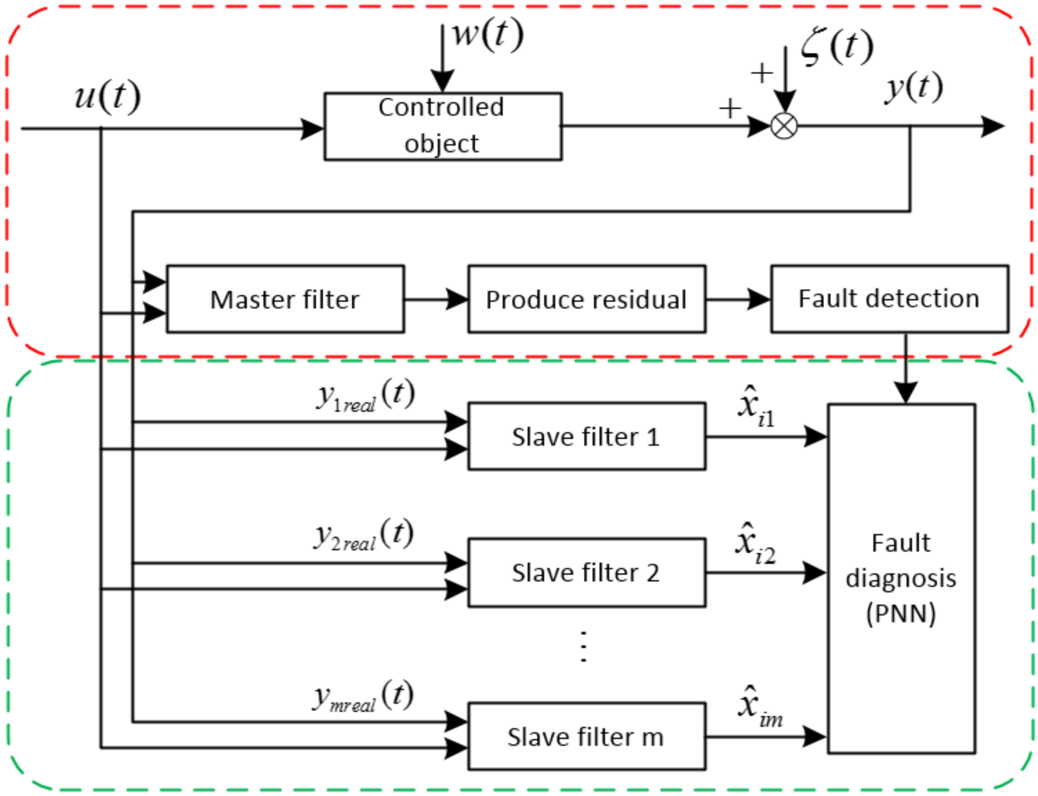

FIGURE 1. Sensor fault diagnosis block diagram

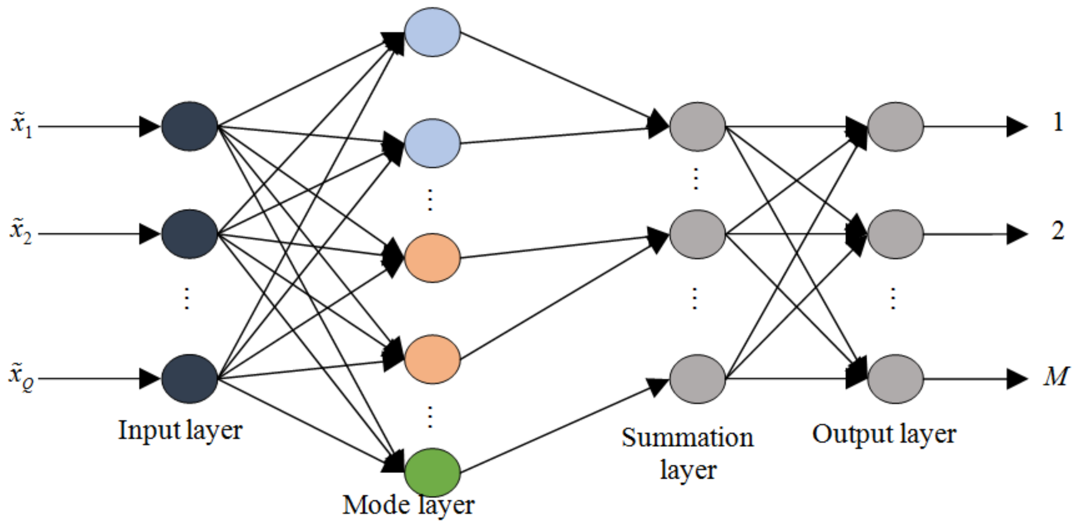

FIGURE 2. Probabilistic neural network structure diagram

states. Using any state to construct the input vector and input it to the PNN can achieve fault location.

The PNN is based on the RBF neural network, the Bayesian decision theory and the density function estimation of the Parzen window. The PNN structure is simple, consisting of the input layer, the mode layer, the summation layer, and the output layer. The structure is shown in Figure 2.

The input layer passes the feature vector $X = [\widetilde{x}_1, \widetilde{x}_2, \ldots, \widetilde{x}_Q]$ to the PNN network, and the number of neurons is equal to the dimension of X expressed by Q. The mode layer can calculate the relationship between X and the fault mode categories in the training sample. The number of neurons is equal to the sum of the number of training samples. The output of each model neuron can be obtained by:

$$f\left(X, W_i\right) = \exp\left(-\frac{\left(X - W_i\right)^T\left(X - W_i\right)}{2\delta^2}\right) \tag{17}$$

where W_i is weight, connecting the input layer to the pattern layer; δ smoothing factor, is an important parameter used to adjust the PNN.

The summation layer accumulates the probabilities belonging to a certain pattern category according to (17), the number of neurons is equal to the number of fault modes, and the summation neurons are only connected with the pattern layer neurons belonging to their own category. Each neuron in the output layer corresponds to a fault mode, so the number of neurons is equal to the number of fault modes, and it accepts the output of the summation layer and performs a simple discrimination. So the neuron with the largest PDF value is output as 1, and other neurons are 0, so as to achieve fault location.

In summary, the two-level fault diagnosis method designed in this paper is summarized as follows. First, collect the state estimation value of each correntropy filter, select the feature vector and training sample as the input vector of the PNN. Second, initialize the PNN, determine the relevant parameters of the PNN, and train the PNN with the given training data. Third, input the test data into the trained PNN to test the validity of the network.

5. **Verification with Simulation.** To illustrate the effectiveness of the two-stage fault diagnosis method based on correntropy filters proposed in this paper, this section applies the above method to the wind energy conversion system under high wind speed established in [8] to implement sensor fault location. Assume that only one sensor goes wrong at a time in the system, and all other sensors work normally. Model of wind energy conversion system at high wind speed is shown in (11).

In this simulation, the sampling time is 1 second. The parameters of the wind energy conversion system at high wind speeds can be obtained from [8].

5.1. **Health system simulation.** When the sensor works normally, the simulation results of the wind energy conversion system are shown in Figure 3 and Figure 4.

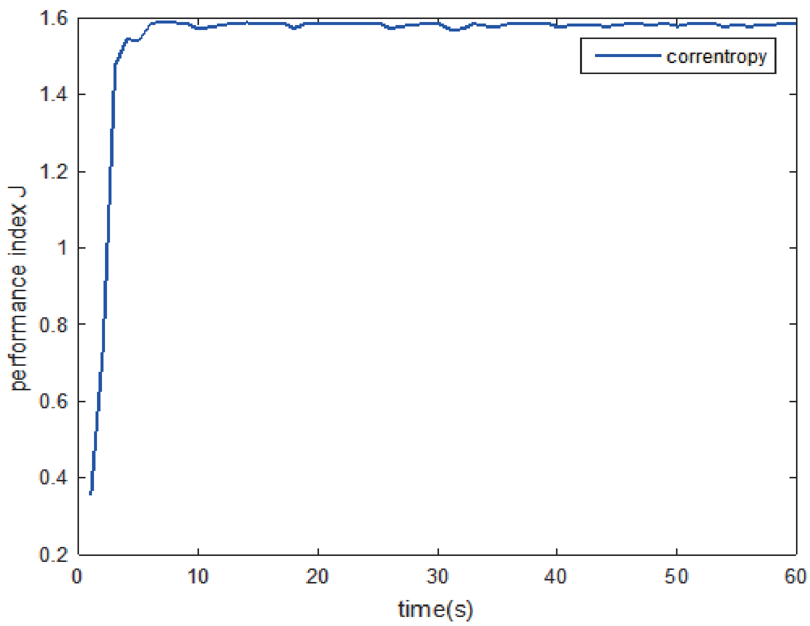

Figure 3. The change curve of performance index

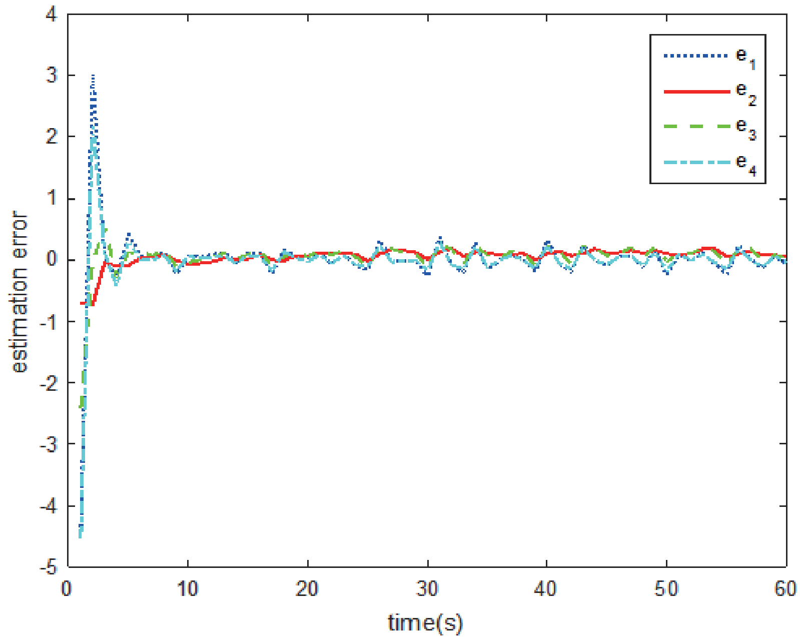

FIGURE 4. The change curve of state estimation error

It can be seen from Figure 3 that the filter based on correntropy can reach the optimal performance index, the value of correntropy increases with time, and finally reaches a maximum value, indicating that the randomness of the dynamic error of the filter can be effectively minimized change. It can be seen from Figure 4 that when the wind energy conversion system is operating in a normal state, the state estimation error by using the correntropy filter is near zero. The fluctuation indicates that when the system is disturbed by random wind speed and non-Gaussian measurement noise, a more satisfactory state estimation result can be obtained by using a correntropy filter.

5.2. **Fault system simulation.** Next, we consider the fault of a sensor in wind energy conversion system under high wind speed and use the two-level fault diagnosis method designed in this paper to achieve fault diagnosis, taking account of the nine common types of sensor faults, as shown in Table 1.

TABLE 1. The types of sensor faults

Fault name	Fault description	Fault number
F_1	Wind wheel speed sensor constant deviation fault	1
F_2	Wind wheel speed sensor constant gain fault	2
F_3	Wind wheel speed sensor stuck fault	3
F_4	Generator speed sensor constant deviation fault	4
F_5	Generator speed sensor constant gain fault	5
F_6	Generator speed sensor stuck fault	6
F_7	Torsional angle sensor constant deviation fault	7
F_8	Torsional angle sensor constant gain fault	8
F_9	Torsional angle sensor stuck fault	9

Due to taking account of 9 types of faults, in order to fully reflect the operating conditions of the system, we choose 9 eigenvalues as the input of the PNN, that is $Q = 9$.

In order to train the PNN, consider selecting 20 training samples for each fault, and a total of 180 training samples. Normalize these training samples and input them into the PNN to train the PNN.

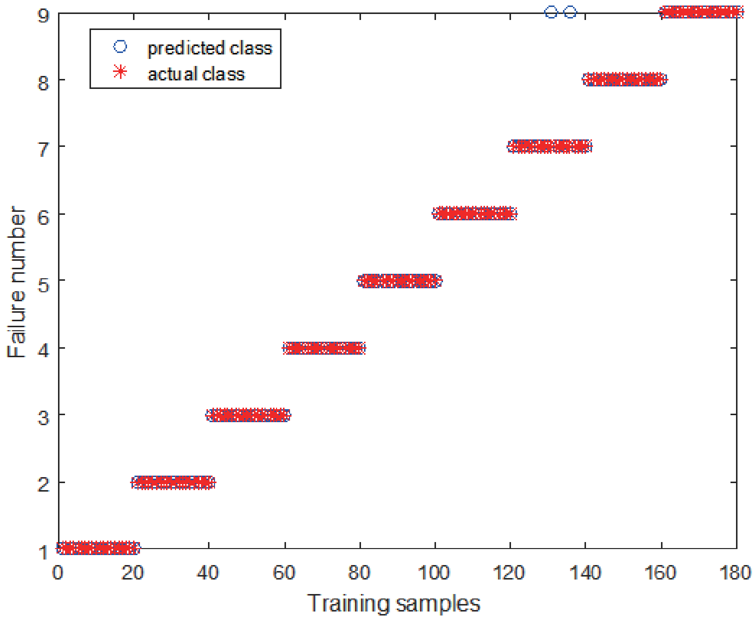

FIGURE 5. PNN network training results

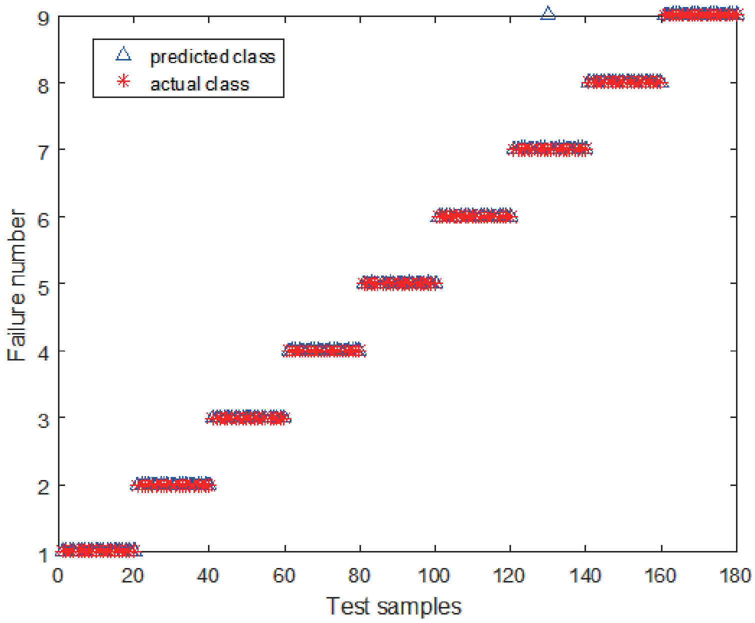

FIGURE 6. PNN network test results

The training results are shown in Figure 5. It can be seen that the training accuracy is 98.8889% (178/180). According to the figure, we can conclude that there is a certain error between the actual fault type of the training sample and the PNN diagnosis fault type, among which the diagnostic types of the faults F_1, F_2, F_3, F_4, F_5, F_6, F_8 and F_9 are the same as the actual fault types, and two sets of training samples in F_7 are diagnosed as F_9. The phenomena result from random interference or errors in data processing. In general, the two-level fault diagnosis method designed in this paper can effectively achieve sensor fault diagnosis.

Next, we should make concentration on verifying the effectiveness of the two-level fault diagnosis method designed in this paper. We select 180 groups of test samples for testing. There are 20 groups of test samples for each fault. The test results are shown in Figure

6. It can be seen that the test accuracy is 99.4444% (179/180). With the exception of a set of test samples in F_7 being incorrectly diagnosed as F_9, the remaining faults can be accurately diagnosed. There are two reasons for this situation: first, since the accuracy of training F_7 is not high enough, it can also be diagnosed as F_9; the other one is that, it may be due to random noise or errors in data processing. In view of this situation, consider using more groups of such fault type samples or changing the feature vector dimension of the PNN and related parameters to comprehensively judge, so that it is possible to further improve the diagnostic accuracy of this fault type.

6. **Conclusions.** This paper mainly focuses on the fault diagnosis of non-Gaussian systems subjected to random interference. First, a filter using correntropy as performance index is designed to estimate the states of the system. Then a two-level fault diagnosis method is proposed adopting a correntropy filter and a PNN network, and it is applied in wind energy conversion system under high wind speed. The simulation results verify that this method can perform well.

The insufficiency in this paper and the direction of further research are as follows. First, the sensor fault diagnosis method based on correntropy filter proposed in this paper is only applicable to the diagnosis of only one type of fault at the same time, and there has been no expansion of research on the number of faults at the same time, or the situation that the previous fault has not yet been resolved and new fault has occurred. Second, the faults in this paper only consider sensor fault. Later studies may consider more types of faults, such as actuator fault.

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