A New Fault Diagnosis Method for High Voltage Circuit Breakers Based on Wavelet Packet and Radical Basis Function Neural Network

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Abstract: A new method that researching fault diagnosis of high-voltage (HV) circuit breaker (CB) is proposed. The method combines Wavelet Packet (WP) with Radical Basis Function (RBF) Neural Network (NN). Firstly, by applying the theory of WP decomposition and reconstruction, the mechanical vibration signal of CB was decomposed into different frequency bands, and the coefficients are reconstructed in the corresponding node. After that, the feature vector was extracted by equal-energy segment entropy from reconstructed signals. Finally, fault diagnosis has been realized through the classification of feature parameters combined with RBF neural network. The experiment outputs show that the method can be applied in diagnosis.

Keywords: Characteristic entropy, equal-energy segment, fault diagnosis, RBF Neural Network, wavelet packet.

1. INTRODUCTION

As a key component of power system, HV CB can protect power equipment and insulate the fault. HV CB status affect the safety operation of the power system, so HV CB fault diagnosis is of great significance. Mechanical fault occupies a large proportion in the high voltage circuit breaker fault. Therefore, mechanical faults were extensively studied at present [1-3].

Mechanical vibration signals generated by circuit breaker operation which contains a lot of important information, the information showed circuit breaker device status. Hence, mechanical vibration signals can be used to detect the circuit breaker status. The past 30 years, with the development of science, the improvement of computer performance, the progress of signal processing technology, fault diagnosis field has obtained many achievements. Related technologies including EMD [4, 5], singularity analysis [6], wavelet [7-9], and wavelet packet [10, 11], etc.

Entropy is a measurement scale of irregularity and information entropy is the description of uncertainty to the system. Information entropy was the content of the information theory originally, but has been widely used in many fields, such as water quality evaluation, hydropower unit operation quality degree evaluation, and science and technology competitiveness evaluation, rotating machinery health evaluation [12, 13], etc.

Through the study of WP and the information entropy, this paper proposes a combination of WP and RBF neural network method for mechanical fault diagnosis. First of all, the breaker mechanical vibration signal were decomposed in three layer with wavelet packet, and then reconstructed the signal in the corresponding node of three layers. After that, we put the standard signal energy time segment and computed the integral energy entropy. At last, fault diagnosis has been implemented on the classification of feature parameters combined with RBF neural network.

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2. WAVELET PACKETS

Wavelet transform is developed by Fourier transform and is a multi-scale signal analysis method. Both in time and scale wavelet transform has an ability of denoting local signal characteristics, so it is suitable for analysis of transient non-stationary signal and time-frequency characteristics.

Compared with wavelet transform, wavelet packet decomposition (WPD) was carried out from low to top of frequency part. WPD improve the time-frequency resolution, which provides more elaborate non-stationary signal analysis methods [14].

Under the condition of meet the uncertainty principle, the signal can be decomposed into different frequency bands according to arbitrary time-frequency resolution through WPD. And composition of time-frequency can be projected corresponding orthogonal wavelet packet space which all represents different frequencies.

Signal *S*, the wavelet packet transform:

$$C_{j,k}^{i}(t)=\left\langle S,\varphi_{j,k}^{i}(t)\right\rangle ;i=1,2\cdots$$

Where, $C_{j,k}^{i}(t)$, wavelet packet coefficients

i, frequency range parameter

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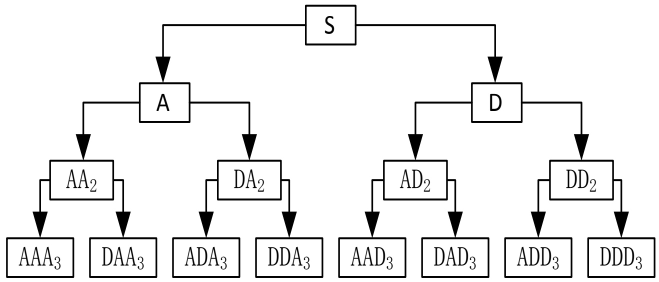

Fig. (1). Wavelet packet decomposition.

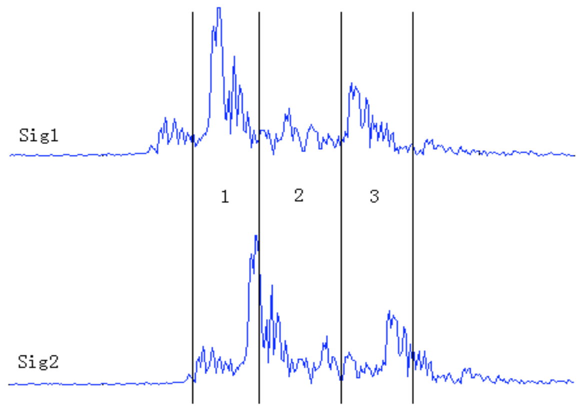

Fig. (2). Segments with equal energy.

j, scale parameters

k, translation parameters

$\varphi^i_{j,k}(t)$ wavelet packet function

$$\varphi^i_{j,k}(t) = 2^{\frac{j}{2}}\varphi^i(2^j t - k); i = 1,2\cdots$$

$\varphi^i_{j,k}(t)$, Calculated by wavelet function through h_k filter and g_k filter.

$$\begin{cases}\varphi^{2i}(t) = \sqrt{2}\sum h(k)\varphi^i(2t-k) \\ \varphi^{2i+1}(t) = \sqrt{2}\sum g(k)\varphi^i(2t-k)\end{cases} \quad (1)$$

WP is the combination of a series of wavelet basis function, it still has the orthogonality and the time-frequency features of wavelet basis functions [15]. Wavelet packet is superior to wavelet in high frequency resolution. WP can get different frequency resolution though choosing different basis functions. Wavelet packet decomposition tree of the signal in different scales is shown in Fig. (**1**).

3. ENTROPY

Entropy is measure of microstate diversity or homogeneity in thermodynamics and which can reflect thedisorder of the system. In information theory, the random interference is inevitable in the communication, the communication system has the characteristics of statistics, and information sources can be considered as a set of random events, the set of randomness and uncertainty is similar to chaos of microscopic in thermodynamic. So the concept of information entropy is proposed by Shannon in 1948 [16], derived from the concept of thermodynamics, expanded to a variety of source signal [17-19].

Define，a system X has several different state x_1, x_2,…, x_N, $x_i(i = 1,2,\cdots n)$ probability is $p(x_i)$

Its information entropy $H(x)$ is:

$$H(x) = -\sum_{i=1}^{N} p(x_i)\log(p(x_i)) \quad (2)$$

$0 \le p(x_i) \le 1$, $\sum_{i=1}^{n} p(x_i) = 1$

Define: $p(x_i) = 0$, $0\log 0 = 0$

Fault diagnosis of CB is essential for distinguishing normal state from fault state. Fault statuses have different mutations in relative to the normal state. Base on this principle, we can use segmentation method to extract the entropy.

This paper proposes a scheme for CB mechanical fault diagnosis with equal-energy segment entropy. In the diagnosis method, according to the integral energy equivalent principle, the standard envelope signal time axis is segmented and the testing signal is segmented in the same way.

In Fig. (**2**), Sig1 is normal envelope signal and Sig2 is the fault envelope signal. Mutation events are delayed, Sig2 was

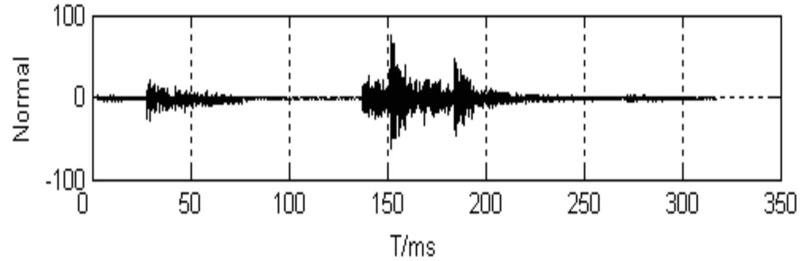

Fig. (3). Standard signal of normal state.

compared with Sig1. Sig1 was segmented according to the energy equivalent principle. Each of them has three segments: Seg1, Seg2, and Seg3. Because the Sig 2 is changed compared with the Sig1, Seg1, Seg2, and Seg3 energies of the Sig2 compared with the Seg1, Seg2, Seg3 energy of Sig1 are also changed, indicating that energy distribution is changed. Therefore, we can transform the changes of Sig1 and Sig2 into the change of energy distribute on uniformity of each segment.

4. METHODOLOGY

The steps of WP- feature entropy are [20, 21]:

Step 1: Getting rid of the vibration signals noise using soft threshold. Vibration signals were decomposed at nth layer, radix wavelet selected db10, and signals in 2^n nodes at the nth layer were reconstructed;

Step 2: Extract envelope energy of the reconstituted signals obtained in Step 1 respectively with Hilbert transform.

Step 3: The envelope signal of each node was divided into M parts in accordance with the principle of equal energy along the time axis and the piecewise point in time was extracted.

Step 4: A testing signal was processed according to Step 1 and Step 2. Then the extracted envelope signal was divided into L parts according to the obtained piecewise points of normal signal, and the energy of each segment was calculated according to Eq. (3).

$$Q_k(i) = \int_{t_a}^{t_b} \left| f(x) \right|^2 dx \tag{3}$$

$i = 1,2,\cdots,l$, $k = 1,2,\cdots,n$. t_a and t_b are start point and end point of Segment *I*.

Step 5: Corresponding piecewise energy is normalized as Eq. (4):

$$\phi_k(i) = \frac{Q_k(i)}{\sum_{i=1}^{l} Q_k(i)} \tag{4}$$

The characteristics entropy of the signal $x(t)$ is [20, 22]:

$$H_k = -\sum_{i=1}^{l} \phi_k(i) \lg \phi_k(i) \tag{5}$$

Step 6: Wavelet Packet - characteristic entropy vector were defined as:

$$T = [H_0, H_1, H_2......H_{2^n-1}] \tag{6}$$

Partition number "*l*" is related to complexity of signal, if more vibration events occur in the vibration signal extraction, the value of *l* is large, otherwise the value of *l* is small. The n value distribution range size reflects the characteristic frequency, which is the size of the signal frequency resolution.When the method of Wavelet Packet-entropy is used in fault detection, it is assumed that the normal state signal is uniformly distributed and that the testing signal distribution under fault condition is not uniform. The entropy is a measure of signal heterogeneity degree. Therefore, we can use WP-entropy to detect the deviation degree of the fault state [23, 24].

5. RESEARCH DESIGN

5.1. Normal Signal Processing

Fig. (**3**) shows the normal standard signal of a vacuum circuit breaker. The signal was processed according to the Wavelet Packet - entropy. According to previous circuit breaker vibration signal processing method [22], we selected the following parameters: n=3; m=15; 8 node reconstruction signals. The energy fragments of 15 equal time scales were shown in Table **1**. The method is analyzed by simulating the frequency-variation signal Fig. (**3**).

5.2. Frequency Variations

The normal signal shown in Fig. (**3**), and was added with random noise to obtain 5 analog signals. As shown in Fig. (**4**), noise attenuation starts from 0.8mv and the highest frequency is attenuated from 4 kHz amplitude within 40 ms. Et1 is the original vibration signal. Ef1 signal was the interfered at 50 ms to form Ef2 signal; Ef2 signal was the interfered at 100 ms to form Ef3 signal; Ef4, Ef5, Ef6, and so forth. The series of signal frequency was changed gradually and the vibration impact time of each event was not changed. According to the feature entropy extraction Steps 4 to 6, we respectively processed each signal in Fig. (**4**). Wavelet packet feature entropy vector In Table **2**. We can see that the entropy of low frequency segment increases slightly and that the entropy of the high frequency segment is less changed.

Table 1. Time points of each equal-energy segment (Unit: ms).

	[3,0]	[3,1]	[3,2]	[3,3]	[3,4]	[3,5]	[3,6]	[3,7]
1	29.20	31.94	40.15	36.95	33.76	31.94	41.06	31.48
2	42.43	46.99	95.35	89.88	46.99	47.90	98.09	45.17
3	57.48	62.65	112.76	115.46	67.07	70.26	129.57	81.66
4	73.45	85.95	132.45	131.89	120.90	127.74	142.80	129.57
5	93.98	108.73	144.66	143.47	148.73	146.90	148.73	143.25
6	126.83	127.40	153.59	152.40	161.50	160.13	155.03	151.92
7	152.38	145.13	161.70	160.59	169.26	173.82	162.59	159.22
8	163.33	165.15	169.72	166.52	188.88	188.42	168.15	165.15
9	176.10	177.93	180.66	177.02	193.26	192.53	173.37	177.93
10	196.18	192.53	191.61	191.16	199.83	197.55	182.97	190.70
11	209.41	197.55	199.37	198.00	206.67	204.39	192.98	198.91
12	231.31	210.32	209.41	210.78	218.53	218.08	204.39	212.14
13	264.15	229.02	229.02	229.94	238.15	240.89	223.55	232.22
14	301.56	268.26	260.50	269.17	281.03	283.32	257.31	275.56
15	333.50	333.50	333.50	333.50	333.50	333.50	333.50	333.50

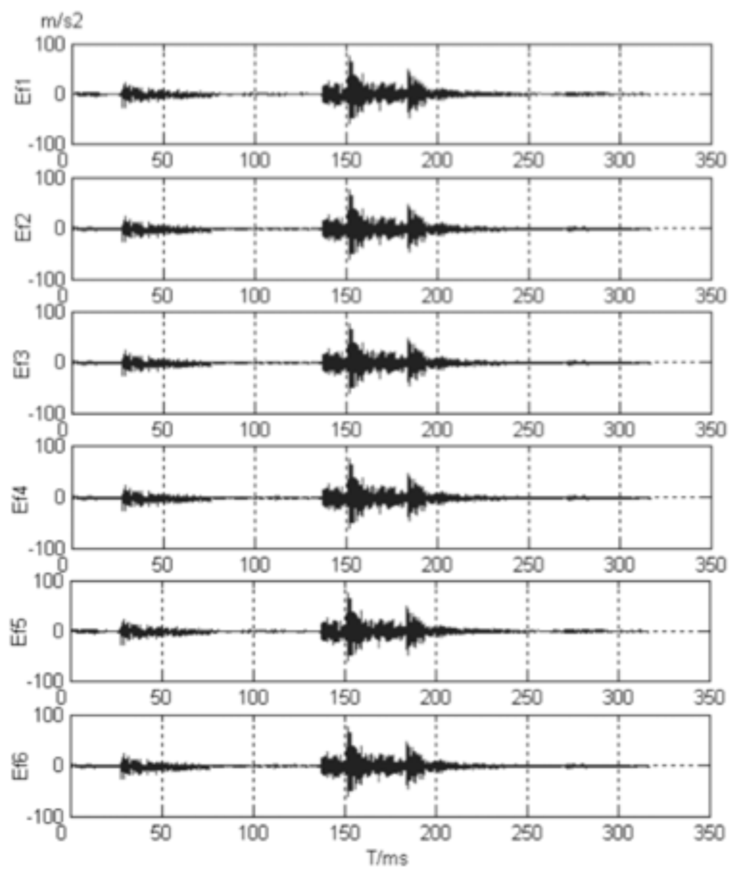

Fig. (4). Simulated signals of frequency-variation.

Table 2. Testing entropy vectors of frequency-variation.

	H_0	H_1	H_2	H_3	H_4	H_5	H_6	H_7
*Ef*1	1.2499	1.1801	1.0906	1.2250	1.2533	1.2829	1.0699	1.1721
*Ef*2	1.2639	1.1939	1.0915	1.2262	1.2545	1.2835	1.0704	1.1721
*Ef*3	1.2630	1.1971	1.0914	1.2262	1.2551	1.2828	1.0709	1.1715
*Ef*4	1.2645	1.2017	1.0924	1.2269	1.2549	1.2829	1.0706	1.1722
*Ef*5	1.2656	1.2054	1.0930	1.2271	1.2550	1.2828	1.0705	1.1713
*Ef*6	1.2662	1.2081	1.0956	1.2271	1.2549	1.2826	1.0733	1.1713

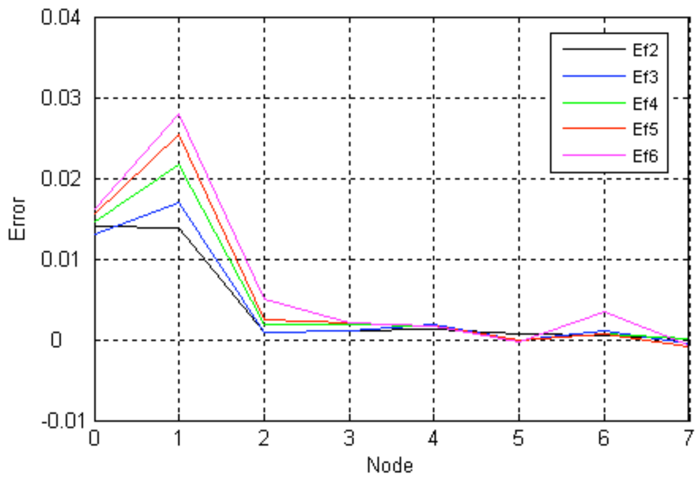

Fig. (5). Variation curves of entropy-variation.

Table 3. Frequency-variation euclidean distance.

	$\|T_1 - T_2\|$	$\|T_1 - T_3\|$	$\|T_1 - T_4\|$	$\|T_1 - T_5\|$	$\|T_1 - T_6\|$
σ	0.0322	0.0355	0.0424	0.0487	0.0574

The curve of the entropy difference between analog signal and the normal signal of each node are shown in Fig. (**5**). In the curve, Node 0 and Node 1 showed significant difference and other nodes showed no significant difference. The difference among difference nodes can be interpreted as follows. Node 0 indicate the entropy of the frequency components within the frequency ranges of [0~3kHz], and Node1 corresponds [3~6 kHz], frequency components of that attenuated 4 kHz interference are also distributed in the same two frequency ranges. The simulation results are fully consistent with the expected results. Euclidean distance also reflected effects on frequency change of characteristics of entropy in Table **3**.

5.3. Applications

A vacuum circuit breaker working without load was used for test. Firstly, we selected the insufficient lubrication circuit breaker to test time-delay fault. Then, A phase base screw was loosed to test incorrect fault under the condition of loose screw. Under each condition, circuit breaker was continuously operated for 3 times to obtain 6 groups of vibration signal of Phase A. Then, plus the normal working state of circuit breaker, we obtained 7 groups of vibration signals. According to previous vibration signal acquisition method and environment [21-24], as shown in Fig. (**6**), the recorded signals from top to bottom are respectively standard signal, signals under the condition of loose screw (3 signals for Fault I,), and signals under the condition of time-delay fault (3 signals for Fault II).

We processed signals shown in Fig. (**6**) according to above six steps in Section 4 and time scale is shown in Table **1**. The characteristic entropy vector of each signal is shown in Table **4**. Through the analysis of the vectors, it is found that after the segmentation with equal-energy distribution

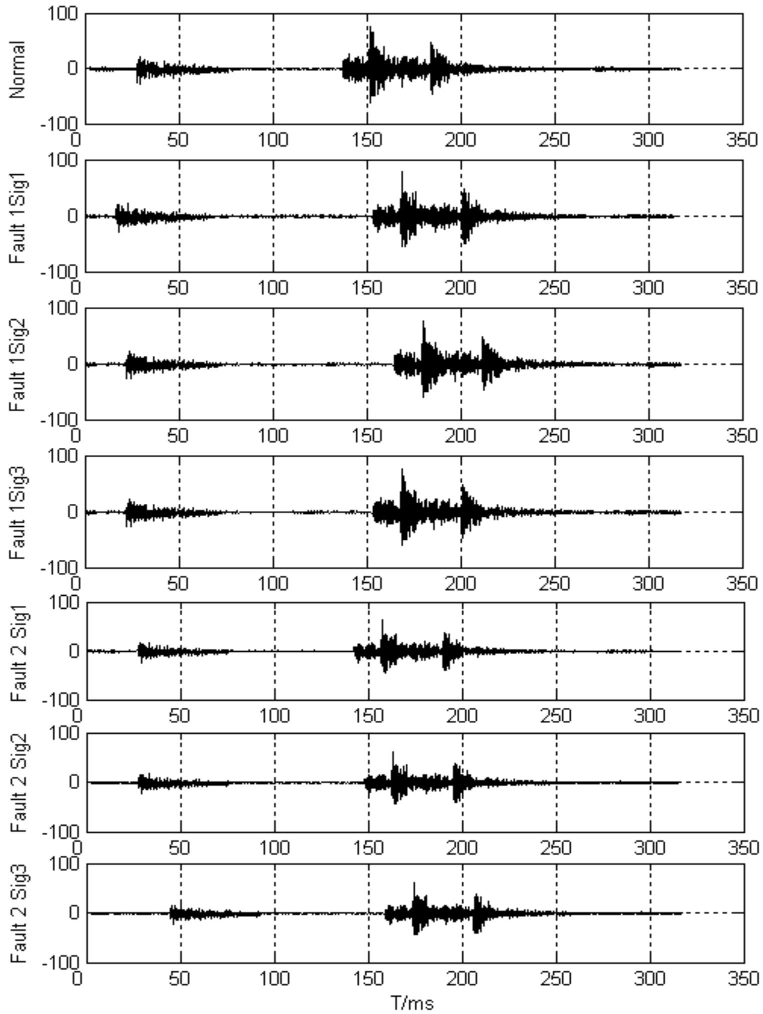

Fig. (6). Original signal of A.

Table 4. Vectors of characteristic entropy.

The Type of Fault	H_0	H_1	H_2	H_3	H_4	H_5	H_6	H_7
Normal Signal	1.2499	1.1801	1.0906	1.2250	1.2533	1.2829	1.0699	1.1721
Fault I	1.1320	0.8010	0.6139	0.6341	0.8988	1.0187	0.5067	0.7057
Fault I	1.1890	0.7447	0.6049	0.5399	0.8382	0.9012	0.5209	0.6334
Fault I	1.1889	0.7864	0.7173	0.5685	0.9045	1.0152	0.5420	0.6697
Fault II	1.1640	0.8963	0.8925	0.8353	1.0798	1.2816	0.7964	0.8892
Fault II	1.1276	0.8089	0.7304	0.7653	0.9802	1.1781	0.6418	0.8820
Fault II	1.0883	0.6340	0.4677	0.5491	0.7663	0.8360	0.4072	0.6585

model of normal condition signals, the energy distribution uniformity of the fault signal is destroyed. Therefore, the entropy is changed. The change is related to the fault severity. The each element of entropy vector obtained with fault signals is generally smaller than that obtained with normal signals and the element distribution is scattered. It is indicated that each frequency band energy distribution is obviously disturbed under the fault state and can be used as the judgment criterion of circuit breaker fault. Moreover, the entropy of signals obtained under screw loosening fault is generally less than that obtained under the time delay fault.

As shown in Fig. (**7**), in the RBF neural network structure. Since each wavelet packet characteristic entropy is

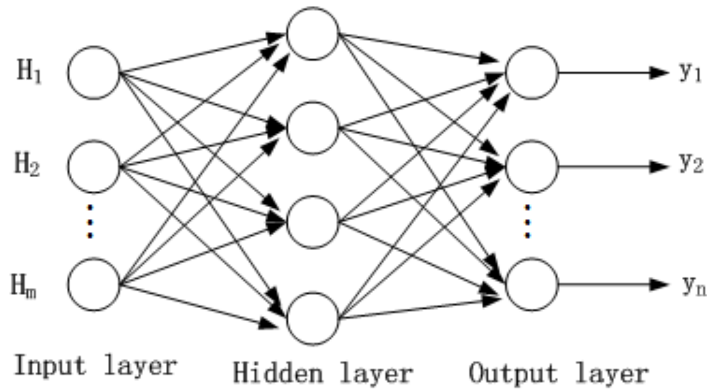

Fig. (7). Structure of REF neural network.

Table 5. Testing results of REF neural network.

Out-puts	Normal Signal	*ex-pected*	Fault I sig 1	*ex-pected*	Fault I sig 2	*ex-pected*	Fault I sig 3	*ex-pected*	Fault II sig 1	*ex-pected*	Fault II sig 2	*ex-pected*	Fault II sig 3	*ex-pected*
y_1	0.9521	1	-0.0241	0	-0.0324	0	-0.1022	0	-0.0742	0	-0.0224	0	-0.0421	0
y_2	-0.1007	0	0.9438	1	0.9180	1	0.9071	1	-0.0295	0	-0.0666	0	-0.0936	0
y_3	0.0251	0	0.2211	0	0.0192	0	0.0437	0	0.9811	1	0.9281	1	0.9750	1

an 8 dimensional vector, so RBF neural network input layer has 8 nodes. There were three kinds' states corresponding to output, two faults, and a normal signal, hence, output layer has 3 neurons. The hidden layer is created by the Newbie function in Matlab [25]. Hidden layer nodes, through trial and error method, repeated comparison diagnostic output as a result, the final number of hidden layer nodes is 15. The network trained with vectors shown in Table **4** gives the output results shown in Table **5**. The experimental data shows that the RBF network design achieved better classification results. This kind of method to extract the characteristic parameters can be used to accurately distinguish between the all kinds of common faults.

CONCLUSION

Instances of this paper results show that the characteristics entropy and RBF neural network can better accomplish fault diagnosis. Moreover, we analyzed two fault conditions of the circuit breaker itself (loose screw and time delay) with the method. At the same time, the simulation results also indicated that the method could be used for soft fault diagnosis of other equipment based on signal processing. However, neural network training requires a lot of samples and the circuit breaker action very little, so we need to continue to improve the accuracy of neural network in few samples.

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CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

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