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An application of ensemble empirical mode decomposition and correlation dimension for the HV circuit breaker diagnosis

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ABSTRACT

During the operation process of the high-voltage circuit breaker, the changes of vibration signals reflect the machinery states of the circuit breaker. The extraction of the vibration signal feature will directly influence the accuracy and practicability of fault diagnosis. This paper presents an extraction method based on ensemble empirical mode decomposition) and correlation dimension and a classification method with BP (back propagation) neural network. Firstly, original vibration signals are decomposed into a finite number of stationary intrinsic mode functions (IMFs). Secondly, correlation dimension of the top four IMFs by the G–P algorithm is calculated and the characteristic vector of the vibration signal of the circuit breaker is formed. At last, the classification of characteristic parameter is realized with a simple BP neural network for fault diagnosis. The experimentation without loads indicates that the method can easily and accurately diagnose breaker faults and exploit a new road for diagnosis of high-voltage circuit breakers.

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High-voltage circuit breaker; vibration signal; ensemble empirical mode decomposition; correlation dimension; BP neural network; fault diagnosis

1. Introduction

High-voltage (HV) circuit breaker plays a key role in controlling and protecting the power network. Therefore, the action reliability of the HV circuit breaker is very important in the electric system. In recent years, research studies on the diagnosis of the circuit breaker are increasing. The vibration signals produced by the circuit breaker contain a lot of important information, which can be used to evaluate the mechanical state of circuit breaker, the techniques based on vibration signal analysis have gradually become hot [1–3].

Hung et al [4] used empirical mode decomposition (EMD) to decompose the mechanical vibration signal of high-voltage circuit breaker, but the EMD method has the disadvantage of modal aliasing, and Hu et al. [5] has clearly analysed the cause of modal aliasing in EMD. Huang et al. [6] used one-class support vector machine (SVM) to diagnose the fault of a high-voltage circuit breaker, but the design of the internal parameters of the SVM has large impact on its performance. In consideration of that, the vibration signals of the HV circuit breaker often represent certain chaotic characteristics. We can analyse the vibration signals of HV circuit breaker from the chaotic dynamics [7,8]. Therefore, this paper presents a feature extraction method of vibration signal with the combination of fractal theory and ensemble empirical mode decomposition (EEMD) and a classification method with the

back propagation (BP) neural network. The EEMD method can effectively reduce the modal aliasing problem of the EMD. Furthermore, the internal characteristics of the signal can be well reacted through the fractal theory. By restructuring the phase space and calculating the correlation dimension of the top four intrinsic mode functions (IMFs), we can obtain the characteristic parameter of the signal. BP neural network is a network structure based on gradient descent algorithm, unlike the SVM, it can adjust the weights by error BP. At present, it is widely used in the fault diagnosis field. The experiment indicates that the method can easily and accurately diagnose breaker faults and exploit a new road for diagnosis of HV circuit breakers.

2. EEMD method

EMD is the method suitable to process nonlinear and non-stationary signals [9]. However, the mode mixing problem brought by the EMD greatly restricts its application in practice. EEMD is a modification of the EMD method, which takes advantage of the uniform distribution statistical characteristics of Gauss white noise in the frequency domain and adds the Gauss white noise to original signal [10,11] so that the EEMD could process signal continuously in different scales, the problem of mode mixing will be eliminated effectively.

2.1. Steps of EEMD decomposition

EEMD is a new method of signal process, the specific decomposition steps and principles are as follows [12]:

Step 1: Adding the random Gauss white noise $n_i(t)$ with the mean zero of amplitude and the constant of standard deviation to the original signal $x(t)$ (The standard deviation of white noise is 0.1–0.4 times the size of the original signal.) The function is as follows:

$$x_i(t) = x(t) + n_i(t), \quad (1)$$

where $x_i(t)$ is the signal that is added to the i_{th} Gauss white noise. The addition of Gauss white noise will directly affect the decomposition of signal by the EEMD.

Step 2: Signal $x_i(t)$ is decomposed into several IMFs $c_{ij}(t)$ and the margin $r_i(t)$, in which, $c_{ij}(t)$ is the j_{th} IMF component after the i_{th} Gauss white noise is added to original signals.

Step 3: Repeat step 1 and step 2 N times. Next, the overall average operation for the corresponding IMF by applying the principle that the statistical mean of random and independent sequence is zero could eliminate the effects of multiple Gauss white noise on the real IMF. The final IMF by the EEMD is written as

$$c_j(t) = \frac{1}{N} \sum_{i=1}^N c_{ij}, \quad (2)$$

where the c_j is the j_{th} IMF component of the original signal by the EEMD. When the N is larger, the sum of the white noise of IMFs will tend to zero. At this time the results for the EEMD are written as

$$x(t) = \sum_j c_j(t) + r(t), \quad (3)$$

where $r(t)$ is the final residual component, representing the average trend of signal. The EEMD method can put any signal $x(t)$ into several of the IMFs and a residual component. The intrinsic mode components $c_j(t)$ ($j = 1, 2, \dots$) represent the elements of signal from high- to low-frequency band, each frequency band is different from others, and will change with the vibration signal $x(t)$.

According to the decomposition steps of the EEMD, we take the normal signal as an example for the

EEMD decomposition now. The time domain waveform shown in Figure 1 is a normal state vibration signal which has denoised. We can see from Figure 1, this vibration signal exhibits short-time non-stationary and nonlinear characteristics, it can be thought of as a chaotic vibration.

The signal can get eight major components and a residual component by the EEMD, as shown in Figure 2. From the diagram, we can see the normal state of non-stationary vibration signal is decomposed into a number of stationary IMF components by the EEMD, and different IMF components contain different time scales.

2.2. Selection of principal IMF components

EEMD decomposes the signal into several IMF components from high frequency to low frequency, the IMF components fully embody the details of the original signal. However, we have to filter the principal IMF components for two reasons:

- (1): For different signals, the number of IMF components obtained by the EEMD decomposition is different.
- (2): The most effective information of the original signal is often concentrated in some certain IMF components, and the other components are spurious components.

In view of these reasons, cross-correlation function is introduced in our research, cross-correlation function is an index to judge whether the two signals are related in frequency domain [13]. It is defined as follows:

$$R(f, g) = \frac{\text{cov}(f, g)}{\sqrt{\text{cov}(f, f)} \sqrt{\text{cov}(g, g)}}, \quad (4)$$

where $R(f, g)$ is the correlation coefficient of function $f(t)$ and $g(t)$, $\text{cov}(f, g)$ is the covariance of $f(t)$ and $g(t)$.

On the above theoretical basis, firstly calculate the cross-correlation coefficients between each IMF component and the original signal, then select the IMF components which are more relevant to the original signal.

The signals of the normal state (normal), the lack of lubrication state (fault I), the foundation bolt looseness state (fault II) and the energy storage spring

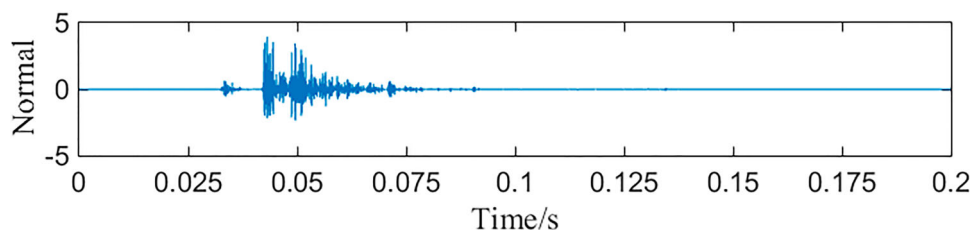


Figure 1. Standard signal of the normal state.

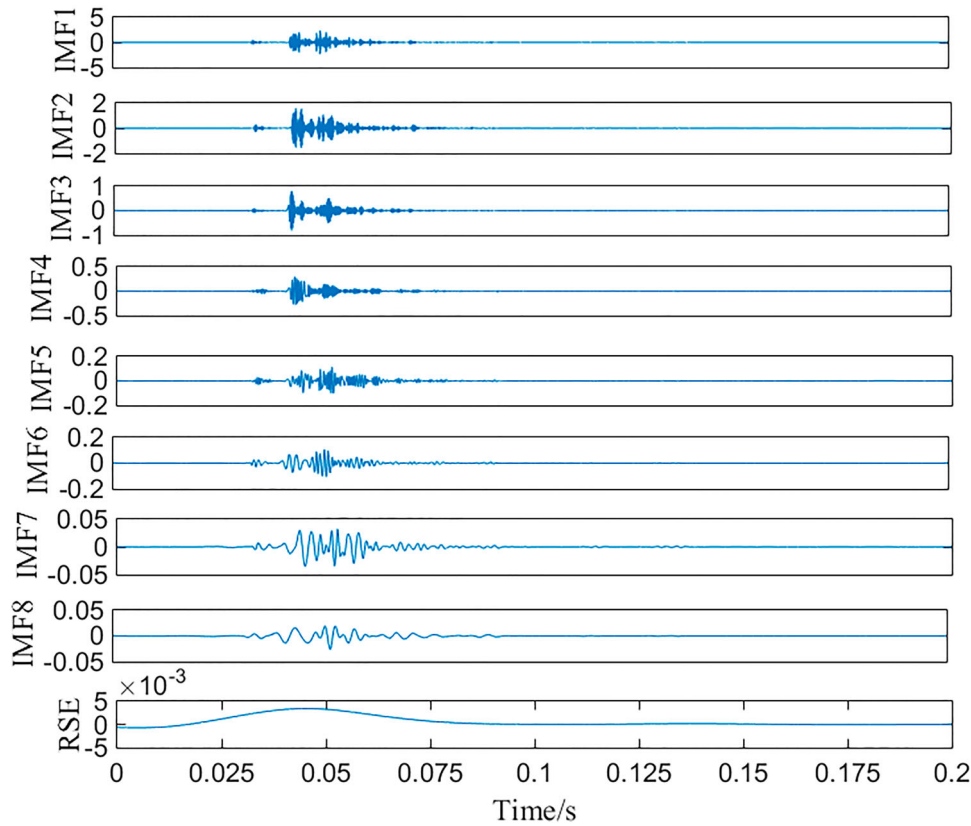


Figure 2. Results of EEMD decomposition.

Table 1. Cross-correlation coefficient between each IMF components and each state of original signals.

State	Cross-correlation coefficient					
	IMF1	IMF2	IMF3	IMF4	IMF5	\geq IMF6
Normal	0.7148	0.5738	0.4415	0.3084	0.0295	≤ 0.01
Fault I	0.6635	0.5617	0.5234	0.2543	0.0245	≤ 0.01
Fault II	0.7223	0.5002	0.5453	0.2453	0.0179	≤ 0.01
Fault III	0.6978	0.6324	0.6451	0.3986	0.0374	≤ 0.01

shed state (fault III) are decomposed by the EEMD algorithm. Screening the principal IMF components is done by using the cross-correlation coefficient criterion i.e. the average number of cross-correlation coefficient between each IMF components.

We can see, from Table 1, the value of the cross-correlation coefficients between the first four-order IMF components and the original signal is much larger than other higher order IMF components (more than 10 times), that's to say the first four-order IMFs are more associated with the original signal. Therefore, analysis of the top four IMF components can satisfy the requirement of vibration signal feature extraction.

3. Correlation dimension

Correlation dimension is one of the fractal dimensions. It is sensitive to the time course of system, reflecting the dynamics of the system well. The G-P algorithm put forward by Grassberger and Procaccia in 1983 is a classic method to define and calculate the correlation dimension [14].

According to the G-P algorithm [15], calculating the correlation dimension mainly has two aspects: (1) Reconstructing the phase space. $\{x_1, x_2, x_3, \dots, x_N\}$ is the time series that its time interval is Δt and reconstructing the phase space by Shi Yanfa. Constructing a series of vectors $X_i = [x_i, x_{i+\tau}, x_{i+2\tau}, \dots, x_{i+(m-1)\tau}]$ adopting the delay time τ , in which, m is the embedding dimension; $i = 1, 2, \dots, L$; $L = N - (m-1)\tau$ is the number of vector after the phase space reconstruction.

(2) Define the correlation dimension. Correlation function $C(r)$ can be obtained by calculating the mutual distance of each vector in the phase space.

$$C(r) = \frac{1}{L(L-1)} \sum_{i \neq j} [H(r - |X_i - X_j|)]. \quad (5)$$

In (5) $H(s)$ is the Heaviside function:

$$H(s) = \begin{cases} 0 & s < 0 \\ \frac{1}{2} & s = 0 \\ 1 & s > 0 \end{cases}, \quad (6)$$

where r is the sphere radius of phase space. Then the definition of correlation dimension is as follows:

$$D(r) = \frac{d \ln C(r)}{d \ln r}. \quad (7)$$

In the process of actual calculation, fitting the linearity better part from the double logarithm curve $\ln C(r) - \ln r$ on the least squares, the slope is the correlation dimension for the corresponding time sequence.

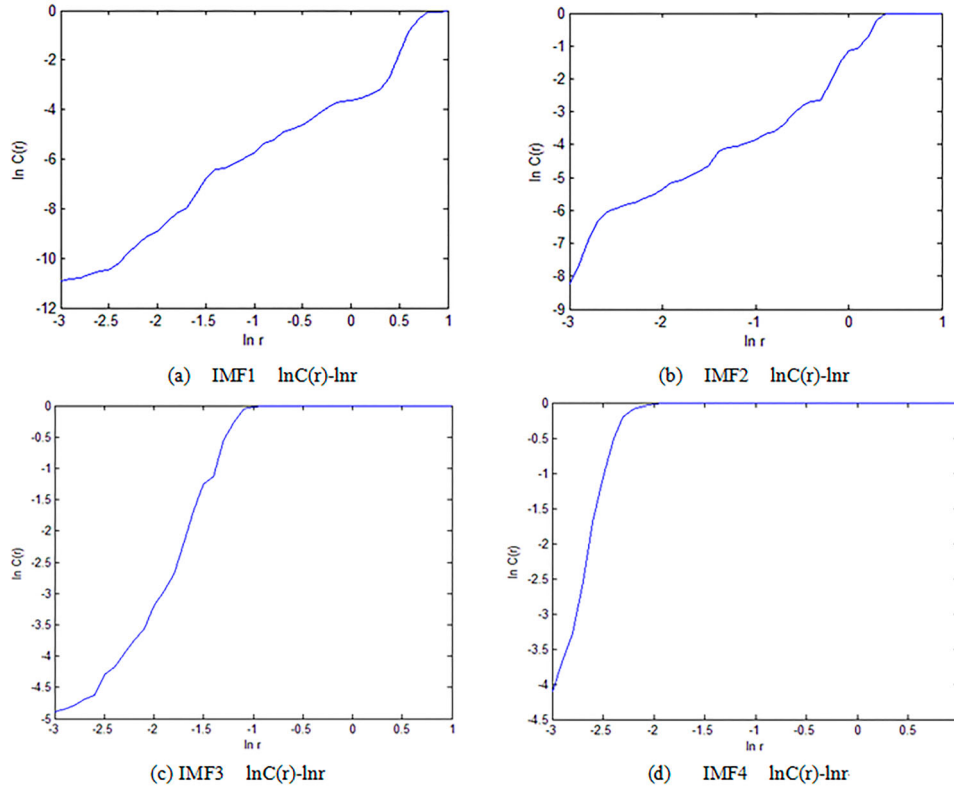


Figure 3. The double logarithm curve of top IMF of the normal vibration signal.

Fractal dimension was applied to fault diagnosis of the high-voltage circuit breaker, using correlation dimension depict fault feature of vibration signal. The non-integer fractal dimension can be used to describe the complexity and nonlinear characteristics of the mechanical system to some extent.

Calculate the correlation dimension of the normal closing vibration signal by the G–P algorithm. Delay time τ and embedding dimension m are two important parameters of phase space reconstruction. The delay time τ is commonly determined by using the C–C algorithm [16]. The embedding dimension m is calculated by a method from the geometric point of view which is called the false neighbouring point method [17].

Using the Matlab to realize the G–P algorithm, the main process is as follows:

Firstly, reconstructing the time series data with the function $Y(i, j) = \text{data}((i - 1)\tau + j)$ and storing the phase space vectors in the matrix $Y(i, j)$.

Secondly, calculating distance between every two points in the phase space with $d(i, j) = \text{abs}(Y(:, i) - Y(:, j))$. The distances are stored in the $d(i, j)$. Counting up the number of less than r from the $d(i, j)$, then getting $C(r)$.

At last, according to formula (7), the double logarithm curve is done by processing logarithmic for $C(r)$ and r . As shown in Figure 3, in which the slopes of the curve $\ln C(r) - \ln r$ of the linear part are different from different IMF components. Then, obtaining the slope of linear part of the double logarithm

curve with linear fitting of the least squares, the slopes also are the correlation dimensions. The correlation dimensions of IMF1 ~ IMF4 represent the feature vector $H = [3.7090, 7.4334, 5.0600, 2.9481]$.

4. The working process of BP neural network

The BP neural network was developed by Rumelhart and McClelland, which is a multilayer feed-forward network. The characteristic of this network is the signal-forward transmission and error-BP. When signals are transmitted forward, they will pass through the input layer, hidden layer and output layer in sequence. If the output layer fails to achieve the desired output, then BP is performed, and the network weights and thresholds are adjusted according to the prediction error. In this way, the predicted output of the neural network approaches the desired output continuously. The topological structure of BP neural network includes input layer, hidden layer and output layer, as shown in Figure 4: where X_0, X_1, \dots, X_n are the input values of the BP network, Y_1, Y_2, \dots, Y_m are the output values of the BP network. Here w_{ij} and w_{jk} are weights of the BP network.

The working process of the BP neural network consists of the following steps [18]:

- (1): Initialize network parameters; determine the number of the nodes in the input layer (marked n) and the number of the nodes in the hidden layer (marked l) and the number of the nodes in the

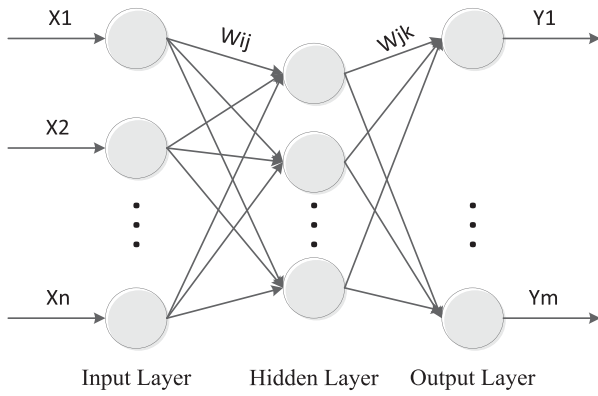


Figure 4. The structure of the three-layer BP neural network.

output layer (marked m) based on the input and output sequence (X, Y). Initialize the connection weight w_{ij} between the input layer and the hidden layer and the connection weight w_{jk} between the hidden layer and the output layer. Initialize the hidden layer threshold (also called bias) a_j and the output layer threshold b_k given learning efficiency η and neuron excitation function $f(x)$.

- (2): Calculate outputs of the hidden layer by the following formula:

$$H_j = f\left(\sum_{i=1}^n w_{ij}x_i - a_j\right) \quad j = 1, 2, \dots, l \quad (8)$$

where l is the number of the nodes in the hidden layer, f is the excitation function of the hidden layer, usually in the following form:

$$f(x) = \frac{1}{1 + e^{-x}}. \quad (9)$$

- (3): Calculate outputs O_k of the output layer by the following formula:

$$O_k = \sum_{j=1}^l H_j w_{jk} - b_k \quad k = 1, 2, \dots, m. \quad (10)$$

- (4): Calculate prediction error e_k as follows:

$$e_k = Y_k - O_k \quad k = 1, 2, \dots, m, \quad (11)$$

where Y_k is the desired output and O_k is the predictive output.

- (5): Update weights; update connection weight w_{ij} and w_{jk} based on the value of e_k . The update formula is as follows:

$$w_{ij} = w_{ij} + \eta H_j (1 - H_j) x(i) \sum_{k=1}^m w_{jk} e_k$$

$$i = 1, 2, \dots, n; j = 1, 2, \dots, l \quad (12)$$

$$w_{jk} = w_{jk} + \eta H_j e_k \quad j = 1, 2, \dots, l; \\ k = 1, 2, \dots, m. \quad (13)$$

We always want the error function e_k to be as small as possible [19,20]. The partial derivative of error functions e_k can be calculated by the following formula:

$$\frac{\partial e_k}{\partial w_{jk}} = \sum_{k=1}^m (Y_k - O_k) \left(-\frac{\partial O_k}{\partial w_{jk}}\right) \\ = (Y_k - O_k)(-H_j) = -H_j e_k. \quad (14)$$

So we can obtain formula 13, similarly we can obtain formula 12 by formula 15 as follows:

$$\frac{\partial e_k}{\partial w_{ij}} = \frac{\partial e_k}{\partial H_j} \frac{\partial H_j}{\partial w_{ij}} = H_j (1 - H_j) x(i) \sum_{k=1}^m w_{jk} e_k. \quad (15)$$

- (6): Update threshold; update threshold a_j and b_k based on the value of e_k .

$$a_j = a_j + \eta H_j (1 - H_j) \sum_{k=1}^m w_{jk} e_k \quad j = 1, 2, \dots, l \quad (16)$$

$$b_k = b_k + \eta e_k \quad k = 1, 2, \dots, m. \quad (17)$$

Imitate formula 14 and 15, we can obtain formula 16 and 17 by formula 19 and 18, respectively:

$$\frac{\partial e_k}{\partial b_k} = (Y_k - O_k) \left(-\frac{\partial O_k}{\partial b_k}\right) = -e_k \quad (18)$$

$$\frac{\partial e_k}{\partial a_j} = \frac{\partial e_k}{\partial H_j} \frac{\partial H_j}{\partial a_j} = H_j (1 - H_j) \sum_{k=1}^m w_{jk} e_k. \quad (19)$$

- (7): Determine whether the iteration is over and if not, repeat step two.

5. Analysis of practical application

5.1. Extraction and analysis of feature parameters

Collecting the vibration signals of the normal state (normal), the lack of lubrication state (fault I), the foundation bolt looseness state (fault II) and the energy storage spring shed state (fault III) from the type ZW32-12 of vacuum circuit breaker in the laboratory, as shown in Figure 5. Each state collected 25 groups of close-brake vibration signal and totally 100 groups of data are gained.

After obtaining the test signals in each group, data are, respectively, processed by wavelet soft-threshold de-noising firstly. Data in each group after de-noising are decomposed by the EEMD, and the correlation dimension of the top four IMF components of data in each group is calculated. In this way, we can obtain 100 feature vectors of the four states, and some results are shown in Table 2. As we can see from the table, the vibration signals with the same condition have the similar correlation dimensions; however, the correlation

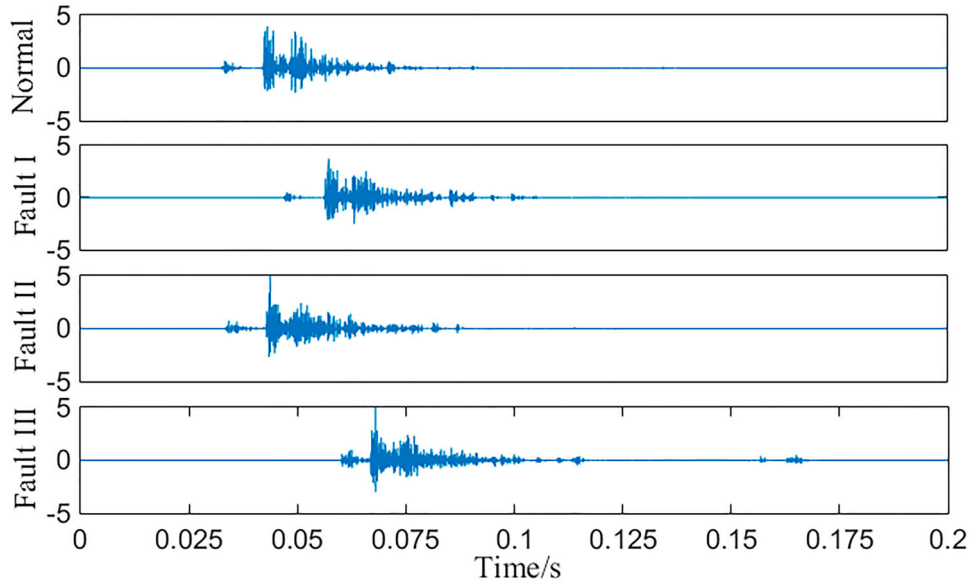


Figure 5. Four types of vibration signals.

Table 2. The correlation dimensions of IMF1-IMF4.

	IMF1 (H1)	IMF2 (H2)	IMF3 (H3)	IMF4 (H4)
Normal	3.7090	7.4334	5.0600	2.9481
	3.8419	7.8574	4.9044	3.2259
	3.2142	6.6805	5.2809	3.2477
	3.3265	7.3719	5.9668	4.2950
Fault I	3.2904	3.5946	1.2125	0.9350
	3.5609	2.6978	0.9408	0.9630
	4.2526	2.9600	1.0028	0.6697
	4.5570	3.4017	1.3729	1.2963
Fault II	4.6105	8.7775	5.0410	3.3082
	4.8515	8.1683	5.1993	3.9393
	5.7225	8.2179	5.3124	4.1334
	5.0115	8.0247	5.2189	3.9701
Fault III	4.2666	4.2799	2.5500	1.2443
	5.4193	3.7254	2.2891	1.2421
	5.9329	3.3691	2.5340	1.1931
	5.3453	4.0003	2.3620	1.5314

dimension of vibration signals varies greatly in different states.

5.2. Design and application of the BP network

The BP neural network with a single hidden layer is constructed with MATLAB neural network tool. The parameters of the BP neural network are designed as follows:

- (1): Taking into account each signal has four characteristics, there are four neurons in the input layer and four neurons in the output layer.
- (2): All transfer function is 'tan-sigmoid' and the training function is 'trainlm'. The maximum iteration number is 200 [21].
- (3): The value of learning efficiency is 0.1.
- (4): The connection weight w_{ij} and w_{jk} are random numbers generated by 'Rand' functions. The values of w_{ij} and w_{jk} are more than 0, less than 1.

- (5): In the design of the BP network, the number of hidden neurons is most difficult to determine, if the number of neurons in the hidden layer is too small, the network will not be able to study well, and the accuracy of the recognition will be affected, if the number of nodes is too large, then the training time increases and the network tends to over-fitting. In this research, we determine the number of hidden nodes by the method of 'trial and error'. When the number of neurons is 16, the average prediction error of the test sample reaches the minimum, since then, as the number of neurons increases, the number of iterations increases, BP networks are easy to fall into local minima. Taking into account these factors, 16 neurons were chosen.

The 60 four-dimension characteristic vectors are randomly selected as training sets and input them to the input layer of BP neural network, correspondingly, the number of neuron in input layer is 4, while, the four nodes at output layer relate to four kinds of state. When a test sample inputs to BP neural network, the corresponding node of output layer will output '1', expresses the 'true', otherwise output '0', and expresses 'false' [22].

The remaining feature vectors are used as test sample inputs to the BP neural network after training, the expected outputs and practical outputs related to each characteristic are partly shown in Table 3. It can be shown from these data that the outputs of designed neural network related to characteristic vector 'true' all above 0.963, and the outputs related to characteristic vector 'false' all below 0.0653, the classification accuracy is much high. In the 40 set of test data of this research, only three sets of data were identified by mistake, and the error data appear at Normal state and fault II. It can also reflect the

Table 3. Testing results of the neural network.

State	Outputs							
	y1		y2		y3		y4	
	practical	expected	practical	expected	practical	expected	practical	expected
Normal	0.9980	1	0.0008	0	0.0006	0	0.0502	0
	0.9798	1	0.0004	0	0.0359	0	0.0095	0
	0.9898	1	0.0013	0	0.0011	0	0.0595	0
	0.9898	1	0.0006	0	0.0073	0	0.0161	0
Fault I	0.0281	0	0.9903	1	0.0000	0	0.0236	0
	0.0161	0	0.9876	1	0.0000	0	0.0267	0
	0.0100	0	0.9907	1	0.0000	0	0.0320	0
	0.0653	0	0.9913	1	0.0000	0	0.0259	0
Fault II	0.0072	0	0.0000	0	0.9871	1	0.0113	0
	0.0235	0	0.0000	0	0.9799	1	0.0249	0
	0.0007	0	0.0000	0	0.9993	1	0.0651	0
	0.0023	0	0.0000	0	0.9981	1	0.0081	0
Fault III	0.0033	0	0.0054	0	0.0016	0	0.9668	1
	0.0059	0	0.0079	0	0.0006	0	0.9742	1
	0.0001	0	0.0043	0	0.0225	0	0.9895	1
	0.0002	0	0.0094	0	0.0162	0	0.9630	1

characteristic extracted with the method proposed in this paper is sensitive to the state change of the high-voltage circuit breaker, so this method is effective for the fault diagnosis of the high-voltage circuit breaker.

6. Conclusion

This paper firstly proposes a method combining the EEMD and correlation dimension to extract the characteristics of vibration signals of the high-voltage circuit breaker. The correlation dimension of the original signal data is difficult to extract the fault information. So, it cannot reflect the complexity and non-linear smooth characteristics of signal in detail. The IMF components of the signal at different frequencies can be obtained by EEMD decomposition. It can separate the mechanical characteristic of the high-voltage circuit breaker. Then, the top four IMF components which contain the most significant information of the original signal are chosen to calculate the correlation dimension. These correlation dimensions form the characteristic vector of the vibration signal of circuit breaker. At last, the classification of characteristic parameter is realized by the simple BP neural network. Practical examples show that this method can effectively diagnose the fault state of the high-voltage circuit breaker. The test results of 40 groups of data show that the recognition rates of four states were 90%, 100%, 80%, 100%. But these data were obtained under ideal laboratory conditions, more data are needed to verify and improve this method in practical engineering applications.

Disclosure statement

No potential conflict of interest was reported by the authors.

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References

- [1] Lin X, Li YX, Ma YQ, et al. Dynamic characteristics analysis on novel motor actuator of high voltage circuit breaker. *Electr Mach Control*. 2009;13(2):216–221.
- [2] Polycarpou AA, Soom A, Peter JW, et al. Event timing and shape analysis of vibration bursts from power circuit breakers. *IEEE Trans Power Delivery*. 1996;11(2):848–857.
- [3] Huang J, Hu XG, Gong YA, et al. Machinery fault diagnosis expert system for high voltage circuit breaker. *Electr Mach Control*. 2011;15(10):43–49.
- [4] Huang J, Hu X, Geng X. An intelligent fault diagnosis method of high voltage circuit breaker based on improved EMD energy entropy and multi-class support vector machine. *Electr Power Syst Res*. 2011;81(2):400–407.
- [5] Hu A, Sun J, xiang L. Mode mixing in empirical mode decomposition. *J Vibr, Meas Diagn*. 2011;31(4): 429–434.
- [6] Huang N, Chen H, Zhang S, et al. Mechanical fault diagnosis of high voltage circuit breakers based on wavelet time-frequency entropy and one-class support vector machine. *Entropy*. 2016;18(1):7.
- [7] Runde M, Ottesen GE. Vibration analysis for diagnostic testing of circuit breakers. *IEEE Trans Power Deliver*. 1992;11:1816–1832.
- [8] Zhensheng W, Wei W, Xuechang Y, et al. Processing of mechanical vibration signals of high-voltage circuit breakers based on fractal theory. *High Volt Eng*. 2005;31(6):19–21.
- [9] Huang NE, Shen Z, Long S, et al. The empirical mode decomposition and the Hilbert Spectrum for nonlinear and non-stationary time series analysis. *Proc R Soc London Ser A*. 1998;454(1971):903–995.
- [10] Wu ZH, Huang NE. Ensemble empirical mode decomposition: a noise assisted data analysis method. *Adv Adapt Data Anal*. 2009;1(1):1–14.

- [11] Tong W, Mingcai Z, Qihao Y, et al. Comparing the applications of EMD and EEMD on time-frequency analysis of seismic signal. *J Appl Geophys*. 2012;83:29–34.
- [12] Chen L, Zi YY, He Z, et al. Research and application of ensemble empirical mode decomposition on principle and 1.5 dimension spectrum method. *J Xi'an Jiao Tong Univ*. 2009;43(5):94–98.
- [13] Guo X, Zhang W, Yuan Z, et al. Heart sound recognition based on EMD correlation dimension and multifractal spectrum. *Chin J Sci Instrum*. 2014;35(4):827–833.
- [14] Grassberger P, Procaccia I. Characterization of strange attractors. *Phys Rev Lett*. 1983;(50):346–349.
- [15] Zhu H, Ji CC. *Fractal theory and its applications*. Beijing: Science Press; 2011.
- [16] Kim HS, Eykholt R, Salas JD. Nonlinear dynamics, delay times, and embedding windows. *Physica D*. 1999;127:48–60.
- [17] Cao L Y. Practical method for determining the minimum embedding dimension of a scalar time series. *Physica D*. 1997;110(5):43–50.
- [18] Zhenyu F. BP neural network model and learning algorithm. *Softw Guide*. 2011;10(7):66–68.
- [19] Ping W, Lei Z, Qiuju Z, et al. An application of back propagation neural network for the steel stress detection based on Barkhausen noise theory. *NDT&E Int*. 2013;55:9–14.
- [20] Li HF, Li GY. An adaptive BP-network approach to short term load forecasting. *IEEE. DRPT*. 2004;2:505–508.
- [21] Peidong Z, Laijun S, Mingliang L, et al. A new method of fault diagnosis for HV circuit breakers based on wavelet packet. *IEEE. ICIEA*. 2011: 509–513.
- [22] Laijun S, Mingliang L, Jianju Z, et al. A new fault diagnosis method for HV circuit breakers based on wavelet packet-neural network. *IEEE, ICIEA*. 2011: 844–849.