Mechanical Fault Diagnosis of Circuit Breaker Based on Improved BREMD and ELM

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Abstract. In order to accurately and quickly obtain the fault information from the circuit breaker vibration signal, a novel feature extraction method based on improved bandwidth restricted empirical mode decomposition (IBREMD) is proposed, and then the extreme learning machine (ELM) is employed for fault diagnosis. Since it is difficult to determine the optimal bandwidth frequency in traditional bandwidth restricted empirical mode decomposition, the introduced IBREMD approach adopts an optimization function to select the bandwidth restricted signal frequency, which is used during the process of empirical mode decomposition. In this way, the frequency resolving ability is dramatically improved, resulting in excellent feature extraction performance. The experimental results show that the diagnosis accuracy is 98.3\%, which promise to be effective in terms of fault diagnosis of circuit breaker.

1. Introduction

The circuit breaker is an important part of power grid, which not only protects the power grid but also controls the normal operation of the power system [1]. The mechanical failure plays a vital role in the circuit breaker failure categories, and using effective mechanical vibration monitoring means can accurately find the hidden trouble of the problems and improve the reliability of the circuit breaker. The operation condition of circuit breaker significantly affects the stability and reliability of power grid, therefore, it is necessary to monitor and diagnose circuit breakers [2].

The false closing and incomplete opening are two failures that commonly occurred in the operating process of circuit breaker. The reason for false closing is that the main contacts of the circuit breaker are not in contact with each other. As a result, the resistance at the contacts increases to cause the device to overheat. This process may reduce the remaining useful life of the device or even cause fire and other adverse consequences. Incomplete opening may result from the contact distance or speed is not enough, which would produce sparks between the two contacts, and will cause serious equipment damage or even safety accidents. Therefore, whether the circuit breaker works normally directly affects the reliability of the power system distribution network [3, 4], this paper will mainly study the vibration signals of the two types of circuit breaker failure types.

When the circuit breaker is monitored by a vibration signal, no electrical parameters about the circuit is required. The circuit under test would not be interfered by the detection circuit, and the circuit breaker structure would not be destroyed by using vibrational signal for condition monitoring.
The vibration signal of circuit breaker is non-linear and non-stationary [6], which can be decomposed into multiple instantaneous non-stationary vibration events. In traditional, the signal are processed by the time-frequency joint domain analysis methods such as short time Fourier transform (STFT), wavelet transform (WT), wavelet packet decomposition (WPD) and empirical mode decomposition (EMD) [7-11]. Among the abovementioned approaches, the short time Fourier transform is not suitable for dealing with abrupt signals because its window size cannot be changed with frequency variation. Although the wavelet transform overcomes the disadvantages of the window size, the frequency resolution is not satisfactory at the high frequency, and the time resolution of the low frequency is not reliable. Neither of these two methods is suitable for non-stationary signal processing [5]. Wavelet packet decomposition is an optimized wavelet transform approach, with excellent multi-scale time-frequency resolution. EMD is a time-frequency localization analysis method with self-adaptability, orthogonality and completeness, which can decompose vibration signals into different frequency bands. Therefore, wavelet packet and EMD are more suitable for dealing with non-stationary and non-linear signals [12].

In [7], the wavelet packet decomposition and reconstruction method is used for time-frequency analysis. To make the reconstructed IMF component suitable for the frequency bandwidth of the signal, wavelet packets are required to be decomposed into enough layers, and a large number of simulation analysis are used to determine the appropriate wavelet packet parameters, and the wavelet packet decomposition effect is determined by the decomposition scale and the wavelet basis, and does not have self-adaptability. In [11], EMD method was used to decompose the vibration signal of low-voltage circuit breakers. Although EMD is an adaptive time-frequency localization analysis method, it has mode aliasing phenomenon and signal components interacting, and there are problems such as under envelope, over-envelope and endpoint effect [13]. The Bandwidth Restricted Empirical Mode Decomposition (BREMD) method is introduced in the process of EMD decomposition to obtain appropriate limited-bandwidth signals. This method can suppress mode aliasing and improve the frequency resolving power of EMD [14, 15]. However, the ability of this method to suppress modal aliasing depends on the choice of bandwidth and frequency. For this reason, this paper introduces the evaluation criteria of mode aliasing index based on BREMD, and selects the optimal bandwidth Frequency according to this index, so that the limited bandwidth signal can achieve the best effect of suppressing mode aliasing.

With the development of artificial intelligence, machine learning algorithms have been widely used in the field of fault diagnosis, the traditional methods include error Back Propagation (BP) neural network, Support Vector Machine (SVM), etc. The BP neural network can easily fall into the local optimal solution, and the learning speed is slow. For linear inseparable data, SVM transforms low-dimensional nonlinear samples into high-dimensional space by using nonlinear mapping algorithm to make them linearly separable. However, if the number of training samples is too large, the SVM training speed will be too low, and the SVM method requires parameter optimization, which is relatively complex [16]. Huang et al. proposed Extreme Learning Machine (ELM). The algorithm does not need to adjust the input weight of the network and the bias of the hidden element in the execution process. There will only be one optimal solution, and the training speed is fast, which is more conducive to the use in reality [17].

In conclusion, this paper firstly proposes an improved BREMD algorithm to solve the mode aliasing phenomenon, and applies this algorithm to fault signal feature extraction of circuit breakers. Secondly, this article focuses on the switch-off failures in the course of contact actions. The energy of the intrinsic modal components of the vibration signal under fault conditions is used as a characteristic sample to establish a knowledge base for fault diagnosis and to train the ELM diagnostic model. The vibration fault of circuit breaker is diagnosed and good results are obtained.
2. The basis of theory

2.1. Traditional EMD algorithm
A complex multi-component signal can be decomposed by empirical mode decomposition to obtain a set of intrinsic modal functions and remainders. EMD is more suitable for processing non-linear and non-stationary signals than steady-state analysis methods such as FFT. The calculation steps of EMD are as follows:

A. Determine all local extreme points of the signal $x(t)$ and perform spline interpolation on the maximum and minimum points, respectively, to determine the upper envelope $u(t)$ and the lower envelope $l(t)$. Then, the average value $m_1(t)$ of the two envelope lines is obtained, and this average value is removed from the signal as the initial value $h_1(t)$ of IMF.

\[ h_1(t) = x(t) - m_1(t) \]  

B. If $h_1(t)$ meets IMF conditions, it is the first IMF component of $x(t)$. If not, $h_1(t)$ is used as an input signal to repeat the above operation steps for $k$ times. If $h_{1k}(t)$ satisfies the IMF condition, the first IMF component $c(t)$ can be obtained, and $c(t)$ can be separated from $x(t)$:

\[ r_k(t) = x(t) - c_k(t) \]  

C. Repeat the first two steps with $r(t)$ as raw data until the components of the IMF have been decomposed or there is only a residue term $r(t)$ for the extreme point, the loop terminates and the final $x(t)$ is decomposed into:

\[ x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \]  

2.2. Improved EMD algorithm
The traditional empirical mode decomposition will have the phenomenon of mode mixing and signal components influencing each other. Usually, the empirical mode decomposition will first separate the high-frequency IMF components, and by using this property to add to the limited bandwidth in the process of the EMD, the method can limit the magnitude of the modal function, and to some extent suppress the low-frequency portion of the modality. This algorithm is called BREMD algorithm, and the general steps are as follows [15]:

A. The input signal $x(t)$ was decomposed by EMD, and the signal was decomposed into the sum of an intrinsic modal function $IMF_{1i}$ and a residual term $x_i(t)$:

\[ x(t) = IMF_{1i} + x_i(t) \]  

B. Hilbert transform was performed on IMF and its average frequency was calculated:

\[ f = M \frac{\sum A_i(t) f_i^2(t)}{\sum A_i(t) f_i(t)} \]  

Where $M$ is the limiting bandwidth factor, $A_i(t)$ is the instantaneous amplitude of the IMF, and $f(t)$ is the instantaneous frequency.

C. Set a limited bandwidth signal:

\[ s(t) = A_{hi} \cos(2\pi ft) \]
D. The EMD decomposition of the signal $y(t) = x(t) + s(t)$ yields the intrinsic modal function $IMF_{in}(t)$ and a residual term, and the improved $i$-th component $IMF_i$ of the original signal is:

$$IMF_i(t) = IMF_{in}(t) - s(t)$$ (7)

E. Take $i=i+1$ and use the residual term as the original signal. Then repeat the above steps until all IMF is decomposed.

It is determined that in the BREMD method, it is critical to construct a limited bandwidth signal, and to distinguish the similar frequency components, the bandwidth of each order intrinsic modal function component can be adjusted by adding a limited bandwidth signal. The ability to suppress mode aliasing in this algorithm largely depends on whether the selection of the limited bandwidth frequency is appropriate, and the M value of the limited bandwidth coefficient is the key to determining the frequency f. Most of the M values given by experience today do not apply to all signals, and the unsuitable M signal will reduce the ability to suppress mode aliasing. In order to ensure that the bandwidth restricted signal can best inhibit the mode aliasing, the IMF needs to have good single frequency. And this paper defines a mode aliasing index K evaluation standard, which is:

$$K = 1 - \frac{A_1}{\sqrt[2]{\sum_{i=1}^{N} A_i^2}}$$ (8)

A1 is the amplitude of the main frequency component in the intrinsic mode function component, mainly the component of high frequency and large energy. A2 to AN are other component amplitudes of the intrinsic mode function component. If the algorithm can suppress mode aliasing better, the better the single frequency property of the intrinsic mode function component is, the closer the value of k is to zero. This method of using the mode aliasing index k to obtain a suitable bandwidth limited coefficient m is called IBREMD.

2.3. Extreme learning machine
In the traditional machine learning algorithms, in order to make the algorithm gets satisfactory learning ability, it needs learning for many times, and will be not only the non-unique optimal solution, the parameters of network training also need to set up in advance. ELM is a new kind of learning method, compared with the traditional machine learning algorithms, ELM is a single hidden layer feed forward neural network, do not need to set many intermediate parameters like SVM, and also don't need a lot of training data. Only need to set a good number of neurons in hidden layer, and it can determine the optimal solution.

ELM is a typical single hidden layer feed forward neural network, which is mainly composed of the input layer of n neurons, the hidden layer of l neurons and the output layer of l neurons, all of which are fully connected. As shown in figure 1, the network structure has n input variables corresponding to m output variables. Where, $\omega$ represents the connection weight between the J-th neuron of the hidden layer and the i-th neuron of the input layer, and represents the connection weight between the J-th neuron of the hidden layer and the K-th neuron of the output layer.
3. Feature extraction and fault diagnosis

In this paper, signal feature extraction and fault diagnosis based on IBREMD and ELM are shown in the figure.

![Figure 1. Single-hidden-layer feed-forward neural network](image)

Figure 1. Single-hidden-layer feed-forward neural network

3.1. Simulated vibration signal

In a circuit breaker, if the signal is generated by impact, and the vibration during the operation of the storage mechanism motor is excluded, the effective signal is usually maintained between tens to hundreds of milliseconds, in which there will be damping, which can be described by a set of attenuated simple harmonic vibration signals.

\[
x(t) = \sum_{i=1}^{n} A_i e^{-\alpha_i(t-t_i)} \sin[2\pi f_i(t-t_i)] u(t-t_i)
\]  

(9)

Where, \( u(t) \) is the unit step signal, and \( A_i, \alpha_i, f_i, t_i \) are respectively the maximum amplitude, attenuation coefficient, oscillation frequency and starting time of the \( i \)-th vibration wave.

The simulation signals \( m_1 \sim m_4 \) composed of attenuated sinusoids are generated by Matlab, and the attenuation sinusoidal parameters are shown in Table 1.

| \( m_i \) (t) | \( t_i \)/ms | \( f_i \)/Hz | \( A_i \) | \( \alpha_i \) |
|--------------|-------------|-------------|----------|----------|
| \( m_1 \)    | 16          | 1300        | 0.1      | 84       |
| \( m_2 \)    | 20          | 4100        | 0.3      | 96       |
| \( m_3 \)    | 26          | 5600        | 1        | 77       |
| \( m_4 \)    | 35          | 7000        | 0.5      | 61       |

Table 1. Simulation of vibration signal parameters
The generated signal is shown in Figure 3.

![Simulated vibration signal of circuit breaker](image)

**Figure 3.** Simulated vibration signal of circuit breaker

### 3.2. Determination of mode aliasing index in IBREMD

It can be seen from Section 2.3 of this paper that the determination of the mode aliasing index $K$ is the key to the IBREMD decomposition. The $K$ can be used to obtain the appropriate bandwidth limited coefficient $M$, which makes the IBREMD suppression mode aliasing ability optimal. In this paper, the $M$ value between 1.2 and 1.7 was tested, and the $K$ value result was shown in figure 4.

![Bandwidth restrict coefficient and mode aliasing index](image)

**Figure 4.** Bandwidth restrict coefficient and mode aliasing index

If the algorithm defined for $K$ can suppress the mode aliasing well, the better the single-frequency of the intrinsic mode function, the closer $K$ is to 0. It can be seen from the results that when $K$ value is closest to 0, the value of $M$ value is around 1.6, so the appropriate value of $M$ in this paper is 1.6.

### 3.3. The EMD and IBREMD decomposition of signals

In section 3.1, the vibration signal of the circuit breaker is decomposed by EMD, and the component of the intrinsic mode function is obtained. According to the simulation results, when the component of the intrinsic mode function is decomposed to the sixth order, its energy is very small and negligible. Most of the vibration signal energy is concentrated in the first five steps. Therefore, to understand the vibration signal and the main mechanical state information in the circuit breaker, only the first five-order modal function components need to be selected. The first five intrinsic mode function components of EMD are listed in Fig. 5(a). It can be seen from the figure that the intrinsic mode function component is not a single frequency component, and the frequency band aliasing...
phenomenon is serious. And because the frequencies of the vibration signals are somewhat similar, it is impossible to distinguish the vibration signals of the respective frequencies. Then the IBREMD decomposition of the signal is performed, and the first five intrinsic modal function components are also obtained as shown in Fig. 5(b). It can be seen that, compared with the EMD, in the IBREMD method, the frequency components of the respective modal function components are single. And in the time dimension can be divided, so the decomposition effect of IBREMD is even better.

Further observation of the marginal spectrum of time-frequency distribution shows that the marginal spectrum of EMD is not clearly distinguished at low frequencies and deviates at high frequencies. The IBREMD method can clearly distinguish the frequency of each band without any aliasing.

4. Case analysis of diagnosis

4.1. Acquisition of vibration signals and establishment of sample library

The faults that are easy to occur in the working process of the circuit breaker are mostly mechanical faults, and are often caused by the contact action, including false closing and incomplete opening. In this paper, the state of these two faults is selected as the experimental research object. The vibration signals of circuit breakers are different in normal state, in the state of false closing and incomplete switching. The fault diagnosis of circuit breakers can be made by analyzing the vibration signals of different states. Figure 7 is the vibration signal diagram of the circuit breaker in different states.
The vibration signal of the circuit breaker under different conditions is decomposed by IBREMD. It can be seen from Section 3.3 of this paper that in the normal, false closing and incomplete opening, the vibration signal energy and effective to distinguish the frequency domain signal components are mainly distributed in the first four order on the intrinsic mode function components, so the selection of IMF1, IMF2, IMF3, IMF4 for feature extraction. The ratio of the energy of each of the four sets of intrinsic modal components to the sum of the four energy is used as a method to measure the difference of frequency distribution.

Table 2 shows the ratio of the energy value of the first four order natural modal function components obtained by the circuit breaker after multiple tests and IBREMD decomposition in the normal state, false closing state and incomplete opening of sluice separation. The last column is the total energy of the vibration signal.

The respective examples of the four intrinsic modal component energies of IMF1–IMF4 in Table 2 are arranged into a ring diagram as shown in figure 8.
4.2. Fault identification and diagnosis based on ELM

Firstly, the number of input layer nodes and output vector in this ELM experiment were determined. The extracted characteristic data in this paper were five: IMF1, IMF2, IMF3, IMF4 and total energy. And there are three types of states to be classified: normal state, false closing state, and incomplete opening state, therefore, the number of input nodes of the extreme learning machine neural network is \( I = 5 \times 3 = 15 \), and the output state is three. Using the established knowledge base of circuit breaker fault diagnosis, 40 sets of data were collected from three states. A total of 120 sets of data were selected, and 20 sets of data of each state were selected as training samples of ELM, the training steps refer to section 1.4 of this article. After the training is completed, the rest of the 60 sets of data, 1~20 are numbered as normal, 21~40 are false closing state, and 41~60 are incomplete opening state, then forecast the data as a data comparing with the result and training in the ELM. The 0, 1, and 2 in the result category represent the normal state, the false closing state, and the incomplete opening state.

In this experiment, the signal-to-noise ratios of 0db, 10db, and 20db were set as comparisons to test the stability of the method. If the experimental results can achieve better values under different SNR conditions, this method is suitable for fault diagnosis of circuit breakers, and the results are shown in (a), (b), and (c) of Figure 9, respectively.

**Table 2.** Fault diagnosis knowledge base

| No.                | IMF1         | IMF2           | IMF3          | IMF4         | Total energy |
|--------------------|--------------|----------------|---------------|--------------|--------------|
| Normal             | 0.225±0.016  | 0.284±0.05     | 0.233±0.03     | 0.268±0.04   | 12.193±1.58  |
| False closing      | 0.061±0.07   | 0.139±0.02     | 0.239±0.02     | 0.53±0.09    | 22.32±1.3    |
| Incomplete opening | 0.539±0.02   | 0.145±0.04     | 0.136±0.05     | 0.181±0.03   | 13.261±1     |
Figure 9. Comparison of EMD-ELM and IBREMD-ELM test samples under different SNR

Table 3. Comparison result of EMD-ELM and IBREMD-ELM test samples under different SNR

| Classification   | 0db   | 10db  | 20db  |
|------------------|-------|-------|-------|
| EMD-ELM          | 90%   | 91.7% | 93.3% |
| IBREMD-ELM       | 98.3% | 98.3% | 98.3% |

As can be seen from the results of IBREMD and ELM combination in the figure, the method in this paper has a high accuracy rate when diagnosing normal state and incomplete opening, reaching 100%, and there will be some deviation when diagnosing false closing state, but the overall diagnostic accuracy is still high, reaching 98.3%. And the accuracy is stable and robust when SNR changes.
The method of EMD combined with ELM in the figure is to use EMD to decompose the vibration signal in the normal state and the fault state of the circuit breaker. The method is the same as the IBREMD method in Section 4.1 of this paper to establish the fault diagnosis knowledge base of EMD, and then use ELM make a diagnosis. It can be seen that the accuracy of the diagnosis increases with the increase of the SNR, but the maximum is only 93.3%, and the accuracy is also changing with the change of SNR. Compared with IBREMD, it is less robust and less accurate. Therefore, IBREMD method is more suitable for fault diagnosis of circuit breakers.

5. Conclusion
This paper proposes a novel approach for circuit breaker fault diagnosis based on IBREMD and ELM. The IBREMD is proposed to determine the optimum bandwidth frequency, which could decrease the modal aliasing phenomenon. A modal aliasing index K is proposed to realize the selection of optimal bandwidth frequency, which is simple yet effective. In this paper, ELM which requires no training process is adopted to realize fault diagnosis for circuit breaker. In this way, the diagnosis time can be dramatically decreased and local optimum is avoided. The proposed approach realize fault diagnosis for circuit breaker with high speed and accuracy. Experimental results show that the diagnostic accuracy is 98.3%, which meets our expectation well.

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