Circuit Breaker Fault Detection Based on CEEMD-GSA-SVM

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Abstract: To accurately extract the fault characteristics of circuit breakers, a fault detection method based on comprehensive sensitive empirical mode decomposition (CEEMD), gravitational search algorithm (GSA) and support vector machine (SVM) is proposed. Firstly, the CEEMD is used to process the circuit breaker signal, and using Hilbert transform to establish the marginal spectrum of the obtained components. Select energy entropy as the feature vector. Aiming at the problem that the parameter setting in SVM method affects the classification performance, using GSA to determine SVM parameters. Finally, Kernel-based Fuzzy C-Means (KFCM)-SVM is used for fault detection. In the end, the fault detection accuracy of the CEEMD-GSA-SVM method is 97.5%.

Keywords: Complementary Ensemble Empirical Mode Decomposition; Gravitational Search Algorithm; Circuit Breaker; Fault Detection; Support Vector Machine

1. Introduction

As a key circuit breaker component in the power grid, it is a crucial element to ensure the stable operation of the system [1-3]. When it is divided or closed, the movement and impact of the operating mechanism will cause vibration response, and the impact vibration signal. Therefore, the in-depth analysis and feature extraction of the vibration signal can accurately reflect the operating state of the equipment, thus realizing fault diagnosis and eliminating potential hazards [4-6].

In terms of signal analysis and processing, due to the nonlinear characteristics of circuit breaker vibration signal, the common signal processing methods currently include: Continuous wavelet transform, variational mode decomposition (VMD), empirical mode decomposition, etc. [7-12]. Among them, the spectrum obtained by Fourier transform and continuous wavelet transform is discretely distributed in a wide range near the central frequency band, resulting in problems such as energy leakage, information loss, broadband ambiguity and band aliasing in the spectrum, which greatly affects the final outcome [13-15]. Empirical mode decomposition (EMD) method will produce end effect when decomposing signals, while the VMD effectively overcomes the end effect problem of EMD method, but its key parameters need to be set manually, and once set improperly, the signal processing effect will be affected [16-18].

In the aspect of fault classification, the SVM algorithm is simple, has good robustness and excellent generalization ability, which makes up for the shortcomings of less circuit breaker fault data, but it has high requirements for initial parameters, which will affect the effect of fault classification if the initial parameters are not set properly. Therefore, it is necessary to reasonably set the initial parameters of SVM [19-23].

In summary, a CEEMD-GSA-SVM model has been proposed for fault detection. Firstly, CEEMD is used to decompose the vibration signal, and perform Hilbert transform on the obtained components to obtain their marginal spectrum, and the energy entropy is used as the feature vector. Finally, KFCM-SVM model is used for fault detection.

2. Basic Model Algorithm

2.1 CEEMD

CEEMD method introduces a positive and negative paired white noise sequence on the basis of ensemble empirical mode decomposition (EEMD) [24-27]. This white noise sequence is used to improve the stability and accuracy of the signal decomposition results. The applicable white noise sequence should conform to two principles: first, It cannot disrupt the distribution of extreme values in the original signal. The second is to reduce the distance between extreme points to make their distribution uniform. In order to meet principle 1, the amplitude standard deviation of white noise sequence should be as low as possible, but it is difficult to achieve the effect of improving the distribution of extreme points. 2. Therefore, the key of CEEMD method is the selection of appropriate amplitude standard deviation of white noise sequence.

1) The high pass filtering method is used to decompose the initial signal, and calculate the amplitude standard deviation.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x_{mean})^2}{n}} \tag{1}$$

2) Ratio coefficient of amplitude a is:

$$a = \sigma_n / \sigma_0 \tag{2}$$

The relative error e between vibration signal and modal component is:

$$e = a / M = \sigma_n / (\sigma_0 \cdot M) \tag{3}$$

Where, M is the integration times.

In order to ensure that the relative error e between the vibration signal and the modal component is low, σ_n of the white noise sequence should be as low as possible. The upper limit of the standard deviation of σ_n is the upper limit of the white noise sequence that does not change the extreme value distribution of the signal. When $\sigma_n = \sigma_n / 3$ is taken, 99.73% of the white noise discrete points have an absolute amplitude smaller than σ_h, so the added white noise will basically not disrupt the distribution of extreme values. Therefore, the range of standard deviation is determined to be $0 < \sigma_n \le \sigma_h / 3$.

3) When each order of IMF component contains different frequency components and is stable, the applicable standard deviation of amplitude of white noise sequence σ_n is determined. Then according to equation (3), the integration times M is obtained.

$$M = \sigma_n / (\sigma_0 \cdot e) \tag{4}$$

The integration times calculated according to equation (4) can ensure the stability of decomposition results. After determining σ_n and M.

2.2 Hilbert Marginal Spectrum

1) The IMF component obtained by CEEMD decomposition is transformed by Hilbert transform.

$$\hat{u}_k(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{u_k(t)}{t-\pi}d\tau \tag{5}$$

2) Construct the analytic function $z(t)$.

$$z(t) = u_k(t) + ju_k(t) = A_k(t)e^{j\theta_k(t)} \tag{6}$$

The original signal $x(t)$ is:

$$x(t) = \mathrm{Re}\sum_{k=1}^{K} A_k(t)e^{j2\pi\int f_k(t)dt} \tag{7}$$

Where, $f_k(t)$ is the frequency. Then the expressions of $A_k(t)$, $\theta_k(t)$ and $f_k(t)$ are:

$$A_k(t) = \sqrt{u_k^2(t) + \hat{u}_k^2(t)} \tag{8}$$

$$\theta_k(t) = \arctan\frac{\hat{u}_k(t)}{u_k(t)} \tag{9}$$

$$f_k(t) = \frac{1}{2\pi}\frac{d\theta_k(t)}{dt} \tag{10}$$

Hilbert spectrum is defined as:

$$H(f,t) = \mathrm{Re}\sum_{k=1}^{K} A_k(t)e^{j2\pi\int f_i(t)dt} \tag{11}$$

Compared with Fourier spectrum, Hilbert marginal spectrum has higher resolution and accuracy, which is defined as:

$$h(f) = \int_0^T H(f,t)dt \tag{12}$$

2.3 Energy Entropy

The solving steps of energy entropy are [28-30]:

1) Determine the energy E_n of each IMF.

2) Determine the total energy E.

$$E = \sum_{n=1}^{K} E_n \tag{13}$$

3) Determine the energy ratio p_n of each IMF.

$$p_n = \frac{E_n}{E} \tag{14}$$

4) Determine the energy entropy T_n of each IMF.

$$T_n = -\sum_{n=1}^{K} p_n \ln p_n \tag{15}$$

2.4 GSA

GSA has good global search ability. It can find the optimal solution by simulating the gravity and force relationship between celestial bodies. Its core idea is to regard each candidate solution as a celestial body in space, and adjust its position according to the gravity relationship between its mass and position, so that the closer the group is to the real value, the larger the mass of particles will move towards the real value, so as to obtain the solution closest to the real value [31-35].

Let the total number of particles be N , $H_p = \{h_p^1, h_p^2, \cdots, h_p^d\}$ be the position of the p , and $\theta_p = \{\theta_p^1, \theta_p^2, \cdots, \theta_p^d\}$ be the velocity of particle p . $M_p(t)$ is the weight of p at time t .

$$\begin{cases} m_p(t) = \dfrac{Z_{fitness\,p}(t) - U_{worst}(t)}{U_{best}(t) - U_{worst}(t)} \\ M_p(t) = \dfrac{m_p(t)}{\sum_{q=1}^{N} m_q(t)} \end{cases} \tag{16}$$

Where, $m_p(t)$ is the intermediate quantity, which is used to calculate the mass of particles. The force of particle q on particle p at time t is:

$$F_{pq}^d(t) = G(t)\frac{M_q(t) \cdot M_p(t)}{\left\| H_q(t), H_p(t) \right\|_2 + \varphi} \cdot [h_q^d(t) - h_p^d(t)] \tag{17}$$

Where, φ is a minimal constant, which is used to prevent the denominator from being zero. $G(t)$ represents the gravitational constant of the particle.

$$G(t) = G_0 \cdot e^{-a_0 \frac{t}{K_{\max}}} \tag{18}$$

After each iteration, the particles update their position and velocity.

$$\begin{cases} h_p^d(t+1) = h_p^d(t) + \theta_p^d(t+1) \\ \theta_p^d(t+1) = rand * \theta_p^d(t) + c_p^d(t) \end{cases} \tag{19}$$

2.5 SVM

SVM is a nonlinear classifier for small sample data proposed by Cortes et al. [36-38]. In the classification problem, given the sample data $\{x_{i_2}, y_{i_2}\}$, x_{i_2} as the input and y_{i_2} as the output, the optimal classification function $f(x)$ constructed is:

$$f(x) = w^T x_{i_2} + b \tag{20}$$

At this time, the optimal classification function becomes:

$$f(x) = w^T K_r(x_{i_2}, x_{j_2}) + b \tag{21}$$

To determine the values of w and b , the classification problem can be expressed as the following constrained optimization problem. Let $\varphi(w, \xi_{i2})$ be the constraint function, then:

$$\begin{cases} \min \varphi(w, \xi_{i_2}) = \dfrac{1}{2}\|w\|^2 + c\sum_{i_2=1}^{M} \xi_{i_2} \\ s.t.\ y_{i_2}[(w^T x_{i_2}) + b] - 1 + \xi_{i_2} \ge 0 \end{cases} \tag{22}$$

Where, c is the penalty coefficient and ξ_{i_2} is the relaxation variable. It is a convex quadratic programming problem, and its dual problem can be obtained by Lagrange multiplier method.

$$L(w, b, a_{i_2}) = \frac{1}{2}\|w\|^2 - \sum_{i_2=1}^{M} a_{i_2}[y_{i_2}(w^T x_{i_2} + b) - 1] \tag{23}$$

Using the duality principle, the optimal classification function can be changed into:

$$f(x) = \mathrm{sgn}\left\{ \sum_{i_2=1}^{M} a_{i_2}^* y_{i_2} Kr(x_{i2} \cdot x_{j2}) + b^* \right\} \tag{24}$$

Where, sgn is a symbolic function. Kernel function is very important for the construction of support vector machine. When dealing with linear inseparable problems, the classification performance of radial basis kernel function is the best, so this paper uses this kernel function, whose expression is:

$$K_r(x_{i_2} \cdot x_{j_2}) = \exp[-\left\| x_{i_2} - x_{j_2} \right\| / (2g^2) \tag{25}$$

Where g is a super parameter in the Gaussian kernel function that needs to be set manually. The setting of SVM parameters c, g determines its performance. Gravity search algorithm is used to optimize its parameters.

2.6 Fault State Identification based on KFCM-SVM

The kernel function based fuzzy c-means clustering algorithm (KFCM) introduces the concept of kernel function on the basis of FCM, and enlarges the difference between samples. Compared with FCM, KFCM classification is more accurate [39]. The objective function of KFCM is defined as follows:

$$J_m(U, V) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m \left\| \phi(x_k) - \phi(v_i) \right\|^2 \tag{26}$$

The Gaussian radial basis function is:

$$K(v_i, x_k) = \exp(-\|X - Y\|^2 / \sigma^2) \quad (27)$$

Using optimization strategy, u_{ik} and v_i are obtained as:

$$u_{ik} = \frac{\{1/[K(x_k, x_k) + K(v_i, v_i) - 2K(x_k, v_i)]\}^{1/(m-1)}}{\sum_{j=1}^{c} \{1/[K(x_k, x_k) + K(v_i, v_j) - 2K(x_k, v_j)]\}^{1/(m-1)}} \quad (28)$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^m K(x_k, v_i) x_k}{\sum_{k=1}^{n} u_{ik}^m K(x_k, v_i)} \quad (29)$$

When $i(1 \le i \le c)$, make $\sum_{j=1}^{n} u_{ij} = 0$, and the algorithm stops iteration.

3. Experimental Analysis

3.1 Experimental Process

The process of circuit breaker fault detection based on CEEMD-GSA-SVM proposed in this paper is as follows:

1) Firstly, CEEMD method is used to process the vibration signal, which is decomposed into a series of IMF components under different operating conditions.
2) Calculate the Hilbert marginal energy spectrum of each component.
3) KFCM method was used for pre classification.
4) The SVM method optimized by GSA is used for fault classification.
5) The classification results are analyzed and the fault detection results are obtained.

3.2 Experimental Analysis

In this paper, the vacuum circuit breaker is used to simulate the four operation states of the circuit breaker, which are: the shaft is jammed, the base is loose and the failure of refusing to move. The piezoelectric acceleration sensor is used to collect the vibration signal of the circuit breaker, which is installed on the circuit breaker bracket, and the sampling frequency is 52kHz. The four kinds of operation state signals are extracted and processed by CEEMD method. The Hilbert marginal spectrum is calculated, and the marginal spectral energy entropy of IMF is further calculated as the eigenvector and input into KFCM-SVM for fault identification. Calculate the IMF-Hilbert marginal spectral energy value according to equation (15), and calculate the energy entropy of each working condition after normalization. The characteristics are shown in Table 1. Set the normal state label as 1, jamming as 2, base looseness as 3, and refusal as 4. A total of 80 sample data were selected randomly, including 10 samples in each state of the training set, a total of 40 samples, and 10 samples in each state of the test set, a total of 40 samples. From table 1, the IMF marginal spectral energy entropy of vibration signals in different states has obvious differences, and the IMF energy entropy of the same signal in different States increases according to refusal, looseness, jamming and normal. Hilbert marginal spectral energy entropy can reflect the transient changes of the waveform in each frequency band of the signal, and it can be used as the eigenvalue to accurately characterize the mechanical state changes of the circuit breaker from different scales.

Table 1. IMF Hilbert Marginal Spectral Energy Values for Four Operating States

Type	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6
1	0.179	0.286	0.305	0.325	0.268	0.137
2	0.158	0.253	0.271	0.281	0.205	0.951
3	0.124	0.215	0.256	0.236	0.183	0.083
4	0.103	0.193	0.201	0.213	0.153	0.071

10 groups of acoustic and vibration signals in each state are randomly selected as training samples, and KFCM is used to cluster the training samples. The number of clusters is 4. The SVM classifier is obtained from the support vector machine with the optimized training parameters of the clustering results, and the test sample set is input. Figure 1 shows the fault detection results.

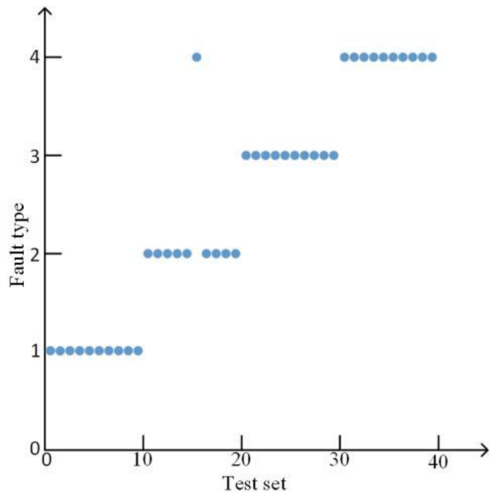

Figure 1. Fault Detection Results

As shown in Figure 1, the fault detection accuracy of the circuit breaker in the normal state is 100%, and only one sample in the jammed state is misclassified as failure, the fault detection accuracy is 90%, the fault detection accuracy of the base loose state is 100%, the fault detection accuracy of the failure state is 100%, and the comprehensive fault detection accuracy is 97.5%, which proves the progressiveness of the CEEMD-GSA-SVM method for circuit breaker fault detection.

4. Conclusion

In this paper, a circuit breaker fault detection method based on CEEMD-GSA-SVM is proposed. Firstly, CEEMD method is used to decompose the circuit breaker vibration signal, and a series of IMF components are obtained. The Hilbert marginal spectral energy entropy of the components is calculated as the fault feature vector. GSA is used to optimize the parameters of SVM model, and the fault feature vector is input into KFCM-SVM model for fault classification. Through the analysis of the four operating states of the circuit breaker, the final comprehensive fault detection rate is 97.5%, which shows the effectiveness of the proposed method for circuit breaker fault detection.

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