Research on the Mechanical Fault Diagnosis Method for Circuit Breakers Based on KFCM

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Abstract. According to the characteristics of non-stationary vibration signals of circuit breakers, a new fault diagnosis method for circuit breakers is proposed in this paper. In this method, the time domain waveform of the collected vibration signal is decomposed by CEEMDAN, and its high-frequency component is reconstructed according to the entropy weight method to obtain the denoised signal. The denoised signal is decomposed by LMD, and the multi-scale permutation entropy is calculated for the decomposed PF component as the input characteristic component of KFCM recognition algorithm. The results of KFCM identification show that this method has a high recognition rate for typical faults such as circuit breaker shaft jam, loose base and refusing action.

1. Introduction

As a key control and protection device in modern smart grids, the circuit breaker’s operational reliability directly affects the safety and stable operation of the entire power system[1,2]. According to the reliability investigation of circuit breakers put into operation at home and abroad, it is found that malignant accidents caused by mechanical faults account for more than 80% of the total accidents [3,4]. Therefore, it is crucial to monitor the mechanical operation status of circuit breakers and find faults in a timely manner.

Different types of mechanical faults will trigger the corresponding natural frequency on the circuit breaker. The signal energy caused by the same fault is generally distributed on one or several frequency components, and the fault signal energy in different frequency bands is also different [5-7]. Therefore, how to effectively extract and analyze the rich information contained in the vibration signal becomes the key to diagnose the mechanical fault of the circuit breaker.

Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is an improved method based on EEMD. The CEEMDAN method can effectively decompose vibration signals into a series of accurate high and low frequency IMF components, which improves the accuracy of traditional wavelet denoising and lays a foundation for the extraction and reconstruction of high-frequency signals.

Compared with EMD and EEMD, Local Mean Decomposition (LMD) has the advantages of small reconstruction error, high completeness and strong adaptability. It overcomes the problems of low EEMD Decomposition efficiency and mode aliasing, and improves the endpoint effect [4]. Therefore, it is more suitable for the extraction of feature components of vibration signals. Compared with the traditional fuzzy c-means (FCM) algorithm, the kernelized fuzzy c-means (KFCM) introduces the kernel learning process. Through the nonlinear mapping of kernel space, the data samples...
to be classified are mapped to the high-dimensional space, highlighting the feature differences of the samples [8-10] and making the classification results more accurate.

Based on the advantages of the three methods and the shortcomings of preprocessing, feature extraction and fault identification of circuit breaker vibration signals, the authors propose a mechanical fault diagnosis method for circuit breakers, which is based on the CEEMDAN algorithm to denoise, is combined with LMD algorithm to obtain multi-scale permutation entropy extraction features, and uses KFCM algorithm for fault diagnosis.

2. Mechanical Fault Diagnosis Process of Circuit Breaker Operating Mechanism

In view of the non-stationary and non-linear characteristics of the vibration signal, the following diagnostic process is adopted in this paper, as shown in Figure 1.

![Mechanical fault diagnosis process of circuit breaker operating mechanism](image)

Figure 1. Mechanical fault diagnosis process of circuit breaker operating mechanism

When the CEEMDAN entropy weight method is used as signal preprocessing method, the vibration signal is decomposed by CEEMDAN, each component is weighed by the entropy weight method, and the high frequency component is selected for reconstruction as denoising signal. When the LMD-KFCM method is used as the feature extraction and diagnosis method, the PF components of each order are obtained by LMD decomposition of the denoised signal, and the multi-scale permutation entropy of each order of the PF components is obtained as the fault index for the KFCM classifier.

3. Preprocessing, feature extraction and fault identification of circuit breaker vibration signals

3.1. Preprocessing of circuit breaker vibration signals: CEEMDAN decomposition-Reconstruction by Entropy Weight method

Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is an improved algorithm proposed by M.A Colominas [11] based on the research results of Huang et al. The CEEMDAN method adds self-adaptive white noise to smooth the pulse interference in each decomposition, which can effectively solve the modal aliasing phenomenon [12] and realize the stabilization of vibration signal time series. The CEEMDAN algorithm flow is as follows.

Information entropy weight method (EWM) is an objective weighting method to determine the weight of each index according to the amount of information provided by the original data of each index. This indicator indicates the degree of difference in the comprehensive evaluation of the data. The entropy value decreases with the increase of information, that is, the importance degree of data increases.

The algorithm steps of CEEMDAN-EWM are as follows.

1. Add the standard normal distributed white noise \( \alpha'(n) \) to the signal \( x(n) \) to be decomposed:

\[
x'(n) = x(n) + \gamma \alpha'(n) \quad (i = 1 \ldots I)
\]

2. Use the EMD method to obtain the modal component mean \( IMF_i(n) \) and the residual signal \( r_i(n) \).

\[
IMF_i(n) = \frac{1}{I} \sum_{i=1}^{I} IMF_i'(n)
\]

3. Define \( E_i \) as the k-th IMF component of the EMD decomposition of the signal, and decompose the sequence \( r_i(n) + \gamma E_i(\alpha'(n)) \). Then the second IMF component and the residual component can be obtained.
3) Repeat 2) until the iteration condition does not satisfy the constraint. The objective function can be expressed by the sum of IMF components and the residual component.

\[ x(n) = \sum_{k=1}^{K} IMF_k (n) + R(n) \]  

4) Calculate the entropy value of the j-th index in each normalization index.

\[ \phi_j = \frac{1}{\ln Y} \sum_{j=1}^{Y} (\lambda_{yj} \ln \lambda_{yj}) \]  

Where \( Y \) is the total number of samples, and \( \lambda_{yj} \) is the proportion of the y-th sample to the j-th term.

5) Calculate the entropy value of the j-th index in each normalization index.

\[ \beta_j = \frac{1 - \phi_j}{\sum_{j=1}^{n} (1 - \phi_j)} \]  

3.2. Feature extraction and fault identification

3.2.1. LMD decomposition. Local mean decomposition (LMD) uses smoothing to form a local mean function and a local envelope function and separates pure frequency modulated signals and envelope signals from complex multi-component signals. The decomposition steps are as follows.

1) Calculate all local extreme points \( n_i \) of signal \( x(t) \) and express their average value and envelope estimated value.

\[ m_i = 0.5(n_i + n_{i+1}) \]  
\[ a_i = 0.5|n_i - n_{i+1}| \]

2) The local mean function \( m_{11}(t) \) and envelope estimation function \( a_{11}(t) \) are obtained from the adjacent mean value and envelope estimation value by sliding smoothing.

3) The product of the envelope estimation function in each iteration is the envelope signal \( a_{1}(t) \), and the product of \( a_{1}(t) \) and the pure frequency modulated function \( s_{in}(t) \) is the product function \( PF_{1}(t) \).

\[ a_1(t) = a_{11}(t)a_{12}(t)\cdots a_{1n}(t) = \prod_{j=1}^{n} a_{1j}(t) \]

\[ PF_{1}(t) = a_{1}(t)s_{in}(t) \]

4) Separate \( PF_{1}(t) \) from the original signal to obtain signal \( y_{1}(t) \), repeat this method k times until \( y_{k}(t) \) is a monotonic function.

5) The original signal \( x(t) \) is equivalent to the sum of all PF components and \( y_{k}(t) \).
\[ x(t) = \sum_{i} \text{PF}_i(t) + y_k(t) \]  

The denoised vibration signal is decomposed by LMD to obtain a series of PF components \( \text{PF}_i \).

### 3.2.2. Multi-scale permutation entropy

Multi-scale permutation entropy is an improvement based on permutation entropy. The basic idea is to take a multi-scale coarse graining processing for the time series and then calculate its permutation entropy [13]. The calculation steps are as follows.

1) Perform a coarse graining processing on a time series with a sequence length of \( N \) to obtain a coarse-grained sequence \( y_j(s) \).

2) Reconstruct \( y_j(s) \) and then we can get:

\[ Y_i(s) = \{ y_i(s), y_{i+\tau}(s), \ldots, y_{i+(m-1)\tau}(s) \} \]  

Where \( m \) is the embedding dimension, \( \tau \) is the delay time, and \( l \) is the \( l \)-th reconstruction component.

3) Sort the time series in ascending order to obtain the symbolic sequence \( S(r) = (l_1, l_2, \ldots, l_m) \).

4) Calculate the permutation entropy of time series when it is multi-scale. \( P_r \) is the probability of the occurrence of symbolic sequence.

### 3.2.3. KFCM algorithm

Input space \( \chi \) is transformed to high-dimensional space \( F \) by nonlinear mapping \( \phi: \chi \rightarrow F \) based on kernelized fuzzy c-means (KFCM). That is, sample \( x_k \) is mapped to \( \phi(x_k) \) for clustering[15]. The clustering objective function is:

\[ J_m(U, v) = \sum_{i=1}^{c} \sum_{k=1}^{m-1} \| \phi(x_k) - \phi(v_i) \|^2 \]  

Where \( v_j \) is the clustering center, \( c \) is the number of categories, \( u_{ji} \) is the membership degree of the \( k \)-th sample to the \( i \)-th category, and \( m \) is the weight coefficient.

The kernel space euclidean distance of the kernel function \( K(x, y) = \phi(x)\phi(y) \) is:

\[ \| \phi(x_k) - \phi(v_j) \|^2 = K(x_k, x_k) + K(v_j, v_j) - 2K(x_k, v_j) \]  

Membership matrix and objective function are obtained by Lagrange multiplier method.

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

### 4. Test experiment and result analysis

#### 4.1. Experiment and signal processing

Three kinds of mechanical faults are simulated in ZN-65 vacuum circuit breaker: adding shaft damping to simulate the jam fault, placing cushion blocks on the base to simulate the instability of the base, and
adjusting the travel of the iron core so that the pawl cannot be started to simulate the rejection fault. The sensor is fixed on the circuit breaker bracket by bolt, and the current signal of opening coil is used as the trigger for 20 opening experiments.

The four types of original vibration signal waveforms collected are shown in Figure 2, where the ordinate is acceleration, and the unit is m·s\(^{-2}\).

Figure 2. Time domain waveform of vibration signal

After the vibration signal is decomposed by CEEMDAN, 13 IMF components are obtained, and the first 12 orders are selected. The normal signal is taken as an example, as shown in Figure 3.

It was pointed out in literature \[14\] that the high-frequency signal contains a lot of information about the mechanical vibration of the circuit breaker, so how to extract the high-frequency signal becomes the key to denoising.

Figure 3. IMF components obtained by CEEMDAN decomposition of the normal opening signal

The entropy weight method is used to weigh the IMF components of each order decomposed by CEEMDAN, and the weights of the IMF components of each order to the original signal are calculated. The high-frequency signals with the largest proportion of the first 5 orders are reconstructed to obtain the denoised vibration signal. Taking the normal closing signal as an example, five experiments were selected to calculate the entropy weight respectively. The weight percentage of each IMF component is shown in Table 1.

| Each IMF Component | Number of Experiments |
|--------------------|-----------------------|
|                    | 1   | 2   | 3   | 4   | 5   |
| IMF1               | 8.276% | 8.310% | 8.394% | 8.190% | 8.200% |
| IMF2               | 8.223% | 8.335% | 8.509% | 8.234% | 8.248% |
| IMF3               | 8.112% | 8.340% | 8.345% | 8.181% | 8.188% |
| IMF4               | 8.113% | 8.344% | 8.345% | 8.193% | 8.195% |
| IMF5               | 8.123% | 8.345% | 8.350% | 8.192% | 8.198% |
The reconstruction signal waveform obtained is shown in Figure 4. It can be seen from Figure 4 that there are certain differences. However, it is difficult to systematically extract the characteristic parameters of various signals based on the time-domain waveform diagrams alone. Further feature extraction is needed for algorithm fault recognition.

4.2. Feature extraction and result analysis

After LMD decomposition of denoised vibration signal, 5 PF components are obtained. Taking the vibration signal under normal opening as an example, the PF components after LMD decomposition are shown in Figure 5.

Set the parameters of permutation entropy according to the empirical value, with dimension \( m=6 \) and scale factor \( s=11 \). The multi-scale permutation entropy of various signals is shown in Figure 6.

When the scale factor \( s = 7 \), the difference of multi-scale permutation entropy of various types of signals is obvious, and the classification effect is good. Therefore, the multi-scale permutation entropy value at this time is selected as the characteristic component for judgment.
The multi-scale permutation entropy values MPE1, MPE2 and MPE3 generated by the first three PF components of each fault were selected as the three characteristic quantities for KFCM diagnosis. The diagnosis results are shown in Figure 7. The normal state and fault state of the circuit breaker can be identified 100%.

Figure 6. Multi-scale permutation entropy of various signals

Figure 7. KFCM fault classification results

5. Conclusion
In this paper, a fault diagnosis method for vibration signal is proposed, which is based on CEEMDAN to decompose the signal, uses entropy weight method to reconstruct the signal for signal preprocessing, uses multi-scale permutation entropy as the characteristic component through LMD decomposition and uses KFCM algorithm to identify the fault. The following conclusions are drawn.

1) Using CEEMDAN algorithm and entropy weight method to extract the effective high-frequency components of the signal for signal preprocessing can improve the defects of the traditional denoising method, such as low reconstruction accuracy and inconspicuous noise reduction of fuzzy signals.

2) In view of the non-stationary and unsteady characteristics of the vibration signal, LMD is used to decompose the vibration signal, which solves the problems of mode aliasing and endpoint effect of the traditional empirical mode decomposition method. As a result, a high sensitivity to the amplitude change of vibration signal is obtained, and therefore the signal characteristics can be extracted accurately.

3) Using multi-scale permutation entropy as the feature component is more anti-interference and adaptive than the traditional methods of obtaining permutation entropy, information entropy and energy entropy, so it is more suitable to be used as the characteristic index of non-stationary signals. Using
KFCM algorithm can recognize and diagnose all kinds of states of the circuit breaker on the premise of ensuring the accuracy of classification.

References
[1] Laijun Sun, Xiaoguang Hu, Yanrui Ji. Mechanical state classification of high voltage circuit breaker based on support vector machine[J]. Journal of Electrical Technology, 2006(08):53-58.
[2] Xiaojun Yang. Design of testing device for mechanical characteristics of circuit breakers[D]. Tianjin University, 2006.
[3] Zhang Z, Zhang J, Gockenbach E, et al. Life management of SF6 circuit breakers based on monitoring and diagnosis [J]. IEEE Electrical Insulation Magazine, 2009,25(3): 21-29.
[4] POLYCARPOU A A, SWARMAKAR A S V. Event timing and shape analysis of vibration bursts from power circuit breakers[J]. IEEE Trans. on Power Delivery,1996,11(2): 848-852.
[5] RUNDE M, SKYBERG B, OHLEN M. Vibration analysis for periodic diagnostic testing of circuit breakers[J]. IEEE Power Engineering Review,1996,17(13): 53.
[6] Liang Luo, Jiacheng Hu, Jianlong Yin, et al. Application of wavelet denoising and EMD algorithm in gear fault detection[J]. Hubei Agricultural Sciences, 2017, Missing Volume (Missing Period):2339-2343.
[7] Huixuan Wang, Dongmei Sun, Xiangdong Li. Research on simulation algorithm for vibration fault detection of rotating machinery[J]. Computer Simulation, 2014, Missing Volume (Missing Period): 374-377.
[8] Qingyu Zhang, Yugang Fan. Fault diagnosis of check valve based on EEMD and ELM[J]. Journal of Shangxi University of Technology (Natural Science Edition), 2019, Missing Volume (Missing Period) 42-46, 53.
[9] Xiaoyu Zhao, Yan He, Lijin Cai, Tingyi Shang. Wavelet denoising method of Raman spectrum based on EMD decomposition [J]. Journal of Heilongjiang Bayi Agricultural Reclamation University, 2019,31 (03): 81-86+114.
[10] Shutao Zhao, Pei Zhang, Lu Shen, et al. Diagnosis method of vibration sound joint fault of high voltage circuit breaker [J]. Journal of Electrical Engineering and Technology, 2014, Missing Volume (Missing Period): 216-221.
[11] Yuxi Gu. Gearbox fault diagnosis and identification based on EEMD and SVM [D]. [Unknown place of publication]: North China University of Water Resources and Hydropower, 2016.
[12] Renxiong Zhuo. Fault diagnosis of motor rolling bearing based on CEEMDAN and GWO-SVM [D]. [Unknown place of publication]: Nanhua University, 2018.
[13] Yanjie Wang, Lin Yang, Hua Jin. Research on data classification based on Improved SVM and auxiliary information [J]. Television technology, 2019, missing volume (missing period): 66-68, 115.
[14] Shuguang Sun, Qiang Zhang, Taihang Du, et al. Study on evaluation method of opening and closing fault degree of low-voltage universal circuit breaker based on vibration signal [J]. Chinese Journal of Electrical Engineering, 2017, missing volume (missing period): 5473-5482, 5547.