Fault diagnosis for high voltage circuit breaker based on timing parameters and FCM

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Abstract: The high voltage circuit breaker (CB) play an important role in the power systems, so fault diagnosis of CB has great significance. A new fault diagnosis method based on timing parameters and Fuzzy C-means clustering (FCM) is proposed in this paper. First, the cause of CB vibration signal is analyzed theoretically, it is found that the vibration events will be change in different states. Then the short time energy entropy ratio of vibration signal is calculated, which can enhance the impact feature of vibration event. The occurrence time and the end time of vibration events are extracted as feature vector by the double threshold method. Finally, FCM is used to calculate the cluster center of feature vector, depending on the approach degree, fault diagnosis of CB is completed. The experimental test shows that the proposed method can extract feature vector effectively and diagnose the fault type of CB accurately.

Keywords: circuit breaker, fault diagnosis, timing parameters, short time energy entropy ratio, FCM

Classification: Power devices and circuits

References


1 Introduction

High voltage circuit breakers are important equipment in the power systems. They have the function of protect and control. The reliability of them related to the security and stability of the power system, so check and maintenance is one of the important contents of daily work of electric power department. In order to get the CB operating characteristics, preventive test is adopted in the preventive maintenance. This kind of method has a series of disadvantages, including time-consuming, frequent operation and excessive maintenance; all of this will reduce the reliability of the CB and bring negative influence [1, 2]. So vibration diagnostic techniques of CB have gradually become a research hotspot in recent years [3]. It has great significance.

Vibration diagnosis is a non-intrusive diagnostic method for monitoring CB condition, and it can solve the problem of high voltage isolation. Therefore, vibration diagnosis is suitable for the mechanical condition monitoring of high voltage CB [4, 5]. In some recent years, researchers have done a lot of work in these fields. To extract fault feature from vibration signal, scholars adopt different methods to achieve the goal. Some scholars converts the vibration signal from the time domain to the frequency domain [6, 7], and the fault type and wear degree of the CB can be identified by using a frequency analysis, such as zoom spectrum analysis and modal analysis. On the other side, many scholars analyze the vibration signals of CBs by using data sequence method, the vibration data are used to establish a mathematical model, the essential characteristics of the signal is extracted from the mathematical model, such as integral parameter method [8],

fractal method [9], information entropy [10] and phase-space reconstruction [11]. Although the fault features extraction has achieved certain effect, the physical meaning of the extracted fault feature is ambiguity, these methods pay attention to find statistical regularities in the data, also the recognition results depend on the experimental data, it is results of statistical classification.

The CB vibration is caused by a series of impacts, an impact is corresponds to a vibration event [12], so the acquired vibration signal contains valuable information. It is helpful for fault diagnosis of CB. Most scholars did not pay enough attention to the essential characteristics of vibration signal.

To solve the above problem, this paper attempts to explore the cause of the failure and the vibration change in high voltage CB, vibration event timing parameters is extracted as fault feature, so the fault identification depends on the characteristics change of the CB. The experimental analysis shows that vibration event timing parameters can effectively express the fault characteristics of the CB.

The rest of the paper is organized as follows. Section 2 devotes to investigation of correlation between timing parameters and vibration signal. The vibration of the CB is analyzed in section 2. Feature extraction and classification algorithm is presented in section 3. Application of short time energy entropy ratio and FCM is discussed in section 4. Some conclusions are given in section 5.

2 Analysis of circuit breaker vibration

2.1 Source of vibration signal

The closing and opening process of the high voltage CB is instantaneous action, so the energy stored in the operating mechanism will release in a very short time, and the energy is transmitted to the moving contact through the mechanical components finally. Due to extrusion, friction and impact of mechanical components, a series of percussion waves are generated in the energy transfer process, which will cause vibration in high voltage CB, also the vibration signal is instantaneous and non-stationary. In the process of closing and opening, the mechanical components of CB are in high-speed movement and high-intensity impact, vibration acceleration can even reach 500 gf, moving contact accelerates from zero to several meters per second in tens of milliseconds. Furthermore, the impact is more intense in the braking and cushioning process. Vibration response caused by high-intensity shock is easy to monitor.

In general, mechanical vibration is a kind of movement under force. For the CB vibration, connecting rod drives the contact movement after the energy is released. In the process of the entire movement, the mechanical components are stared, moved, cushioned and impacted in logical order, and this series of impacts produce shock waves in the support and spring operating mechanism of CB. Since the energy is gradually decayed in the transmission, the detected vibration is a series of superimposed attenuation waves, with strong time sequence. Therefore, the impact of the mechanical parts corresponds to the wave crest in the time domain, also corresponds to the change of travel curve. So there is a one-to-one correspondence between travel curve and vibration signal. This is the theoretical basis for feature extraction from vibration signals.
2.2 Analysis of vibration signal in different conditions

Vibration is the response of a variety of impacts. For the CB vibration, the impact is caused by the movement of cam mechanism, four-bar linkage, spring mechanism, and so on. When the CB is running at the electric substation, it will open and close according to the instructions, the wear becomes serious with the increase of the operations, and then the movement of the spring operating mechanism will change, including the occurrence time of the vibration events and its time interval. So the collected vibration signals will change in time domain, it is different from the normal condition. Based on the analysis, vibration event timing parameters is extracted as fault feature.

This section is the comparison of the CB vibration in different conditions. The vibration signal in different operating conditions is shown in Fig. 1. Fig. 1.(a) is the vibration signal of the CB under the normal condition, Fig. 1(b) is the vibration signal of the CB under the opening spring force decrease, Fig. 1(c) is the vibration signal of the CB under the closing spring force decrease, Fig. 1(d) is the vibration signal of the CB under the base screw loosed.

![Vibration signal comparison](image)

For the vibration signal in closing process of the CB, the largest two impacts are the vibration caused by the cam extrusion and the contact impact. By comparing the vibration signals of the different states, it can be found that the occurrence time and the time interval of the vibration events are different. In the theoretical analysis, the damping and stiffness of the system will change when the CB occur fault, which lead to a change in the system response, that is the vibration change of the CB. So the timing parameters can be effectively used as the fault feature of the CB, they can represent the operating states of the CB.

3 Feature extraction and classification algorithm

3.1 Endpoint detection based on short time energy entropy ratio

Learn from the voice signal processing technology, the double threshold method is used for endpoint detection usually. The principle of double threshold is introduced
as follow. First set up two threshold \( Y_1 \) and \( Y_2 \) (\( Y_1 < Y_2 \)), then compare \( Y_2 \) with the short time energy entropy ratio, the short time energy entropy ratio above \( Y_2 \) is considered to be voice signal, the starting point and the ending point should be nearby. Last, looking from voice segments to both sides, the starting point and the ending point are found when the short time energy entropy ratio is equal to \( Y_1 \). The double threshold method is described detailedly in reference [13].

This section provides the calculation step of short time energy entropy ratio. In short-term analysis, the vibration signal is multiplied by a finite length window function, then it is divided into a series of sections, each section is called a “frame”, frame length generally take 10~30 ms. The feature parameter of the whole vibration signal is composed of each frame feature parameter.

1) Assume data \( x(i) \), \( i = 0, 1, 2 \ldots N - 1 \), after multiplying the window function, we can get the \( i \)-th frame vibration signal is \( x_i(m) \). Fast Fourier transform is performed on \( x_i(m) \), the \( k \)-th line corresponds to the frequency component \( f_k \), the energy spectrum of the frequency component \( f_k \) is \( Y_i(k) \), the normalized spectral probability density function for each frequency component is defined as follows:

\[
p_i(k) = \frac{Y_i(k)}{\sum_{l=0}^{N/2} Y_i(l)}
\]

Where \( p_i(k) \) is the probability density corresponding to the \( K \)-th frequency components \( f_k \) of the \( i \)-th frame. \( N \) represents the length of FFT.

2) Short spectral entropy is

\[
H_i = -\sum_{k=0}^{N/2} p_i(k) \log p_i(k)
\]

3) Defined energy is \( EL_i = \log_{10}(1 + EN_i/a) \), where represent \( EL_i = \sum_{m=1}^{N} x_i^2(m) \) the energy of the \( i \)-th frame, \( a \) is a constant, the dramatic changes in \( EN_i \) can be mitigated in \( EL_i \).

4) Short time energy entropy ratio is defined as follows:

\[
EEF_i = \sqrt{1 + |EL_i/H_i|}
\]

### 3.2 Fuzzy c-means clustering algorithm

FCM has a series of advantages, such as simple principle, easy to realize and high calculation speed. The sample data \( x = \{x_1, x_2, \cdots, x_n\} \) is divided into \( c \) kinds of state (\( 2 \leq c \leq n \)), but any sample \( x_i \) is ambiguous, they can’t be divided into a certain kind state precisely. So \( \mu_{ij} \) (\( 0 \leq \mu_{ij} \leq 1 \)) is the possibility that sample data \( x_i \) belonging to the \( j \)-th fault type, the membership matrix corresponding to the sample set can be denoted as \( U = \{\mu_{ij}\} \).

\[
0 \leq \mu_{ij} \leq 1; \quad \sum_{j=1}^{c} \mu_{ij} = 1; \quad 0 < \sum_{j=1}^{n} \mu_{ij} < n
\]

The minimum of the objective function \( J_{fcm} \) is defined as:

\[
J_{fcm}(U, C) = \sum_{i=1}^{n} \sum_{j=1}^{c} \mu_{ij}^m d_{ij}(x_i, c_j)
\]
Where \( m \) is the fuzzy weighting exponent and \( m > 1 \). \( c_j \) is the cluster center of the \( j \)-th fault. And \( d^2_{ij}(x_i, c_j) = \|x_i - c_j\| \) is the Euclidean distance from testing sample \( x_i \) to the cluster center \( c_j \). Through iteration calculation of FCM, the minimum of the objective function is obtained, and the calculation process is introduced in the follow.

Step 1. Assuming \( c \) is the number of fault type, \( m \) is the fuzzy weighting exponent, and \( \varepsilon \) is the convergence threshold. \( k \) is the Initial iteration number, \( k = 0 \). \( k_{\text{max}} \) is the maximum iteration number. Initialize membership matrix \( U^{(k)} \) by the constraints.

Step 2. Compute the cluster centers by initialized membership matrix.

\[
c_j = \frac{\sum_{i=1}^{n} \mu_{ij}^m x_i}{\sum_{i=1}^{n} \mu_{ij}}
\]

Step 3. Update membership matrix \( U^{(k+1)} \) by the cluster centers \( c_j \).

\[
\mu_{ij}^{(k+1)} = \left[ \sum_{l=1}^{c} \left( \frac{d_{ij}^{(k+1)}}{d_{lj}^{(k+1)}} \right)^{2(m-1)} \right]^{-1} \quad (l = 1, 2, \ldots, c)
\]

Step 4. The convergence threshold \( \varepsilon > 0 \), if \( \| U^{(k+1)} - U^{(k)} \| \leq \varepsilon \), stop iteration calculation. Else \( k = k + 1 \) and return to Step 2.

After iteration calculation, the cluster center \( C = \{ c_j \} \) is obtained by FCM, and then, calculate the approach degree between the test data and the cluster centers, finally fault type of the CB can be identified by the approach degree. That is the process of using FCM to identify faults.

For the approach degree, there are three main commonly used methods, including maximum membership principle, minimal distance principle and proximity principle. In this paper, the proximity principle is selected to calculate the approach degree, and it is introduced in the follow.

Assuming \( A_j \) represents the cluster centers, \( j = 1, 2, \ldots, c \). B represents the test sample data. If there is \( i_0 \), which can satisfy the following formula:

\[
N(A_{i_0}, B) = \max \{ N(A_1, B), N(A_2, B), \ldots, N(A_c, B) \}
\]

Fault type of B is most similar to \( A_{i_0} \), so B and \( A_{i_0} \) is the same fault type. That is the proximity principle.

Where \( N(A, B) \) is computed by Hamming approach degree, the formula can be denoted as:

\[
N(A, B) = 1 - \frac{1}{n} \sum_{i=1}^{n} |A(x_i) - B(x_i)|
\]

It can be seen from Eq. 9, the more similar the test data \( B(x_i) \) to the cluster centers \( A(x_i) \), the higher approach degree \( N(A, B) \).

The classification coefficient \( F \) and the average fuzzy entropy \( H \) are indicators for evaluating the clustering effect. The closer to 1 the classification coefficient \( F \), the better the clustering effect. Similarly, the closer to 0 the average fuzzy entropy \( H \), the better the clustering effect. They are defined as follows:

Classification coefficient \( F \) is defined as:
The average fuzzy entropy $H$ is defined as:

$$H = -\frac{1}{n} \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij} \ln u_{ij}$$

3.3 Fault diagnosis steps

The characteristic parameters extraction steps are described as follows:

1) Collect the vibration signal of the CB in different fault states by acceleration sensor.

2) To enhance the impact characteristics of vibration events, the short time energy entropy ratio of vibration signal is calculated.

3) The double-threshold method is used to extract the occurrence time and the end time of the vibration event, then the extracted timing parameters is serve as feature vector, the construction of the feature vectors of different fault states is completed finally.

4) FCM is applied to process the feature vectors, which is constructed by the timing parameters, and then according to the cluster centers, the fault type of the CB is identified.

4 Application of short time energy entropy ratio and FCM

4.1 Introduction of experiment

The experimental test is conducted on a 35 kV outdoor high voltage SF6 circuit breaker, as shown in Fig. 2(a). Acceleration sensor was adopted to collect vibration signal in the experiments, its performance parameters as follows, manufacturer: Donghua Testing Technology Company, model number: 1A102E, measuring range: 500 gf, frequency response: 0.5~10000 Hz. Closing time of circuit breaker is $80 \pm 15$ ms, so set acquisition time 200 ms, which can fully acquire the vibration response. Sampling frequency is 10K. The vibration of the CB is mainly coming from the impact of spring operating mechanism, so the acceleration sensor is installed at the spring operating mechanism, as shown in Fig. 2(b).

When the CB carries no load, some faults are simulated on the CB, which are the common faults in the CB, including closing spring force decrease, opening spring force decrease and base screw loosed. In the experiment, the closing spring force decrease and the opening spring force decrease are simulated by adjusting the tightening screw, and the value of opening spring and closing spring are calculated by its length and stiffness coefficient. Also the base screw loosed is simulated, torque of base screw is measured by torque wrench. Fault simulation is shown in Fig. 3. The value of closing spring force (CSF), opening spring force (OSF) and torque of base screw (TBS) is shown in Table I.

According to the design drawings, the values of OSF, CSF and TBS is shown in Table I. Compared with normal condition, the values of OSF, CSF and TBS are changed in different states. OSF decrease and CSF decrease will cause energy
change in the system, and TBS loosed will affect the natural characteristics of the system. This can lead to changes in the vibration response.

4.2 Fault feature extraction
The vibration signal of CB is a high frequency impact signal, it is consist of a series of vibration events. Through time domain analysis, the occurrence time of vibration events can be obtained. In the research of signal processing, the time domain analysis is most simple and intuitionistic. The short time energy, the short time energy entropy ratio, the short time energy zero ratio and the short time self-correlation are main analysis method in time domain.

Take vibration signal of normal state for example. First divide the reconstructed signal into some equal frames, applying Hamming window to the sample signal, window length is chosen as 90 points. Then all the above methods are used to process the closing vibration signal, the result is shown in Fig. 4.

Compared with the vibration signal waveform, the short time energy entropy ratio is match well with the vibration signal, also each vibration event can be found

<table>
<thead>
<tr>
<th>Number</th>
<th>State</th>
<th>OSF</th>
<th>CSF</th>
<th>TBS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Normal condition</td>
<td>5440 N</td>
<td>11310 N</td>
<td>190 N.m</td>
</tr>
<tr>
<td>2</td>
<td>OSF decrease</td>
<td>4980 N</td>
<td>11310 N</td>
<td>190 N.m</td>
</tr>
<tr>
<td>3</td>
<td>CSF decrease</td>
<td>5440 N</td>
<td>10830 N</td>
<td>190 N.m</td>
</tr>
<tr>
<td>4</td>
<td>TBS loosed</td>
<td>5440 N</td>
<td>11310 N</td>
<td>30 N.m</td>
</tr>
</tbody>
</table>
in the short time energy entropy ratio. On the contrary, the rest methods are only sensitive to large impact, and fail to express characteristic of small impact. The short time energy entropy ratio compare with the others method, its value in sudden change time is much larger than the rest. Therefore, the short time energy entropy ratio is more suitable for vibration signal than the others, and it can reflect the characteristic of each vibration event.

The short time energy entropy ratio of the reconstructed signal is calculated and processed by double threshold method. Compare the threshold with the short time energy entropy ratio of vibration signal, when the short time energy entropy of the signal exceeds the threshold, the moment is considered as the sudden change time. After selecting the appropriate threshold, the moment of each event in the closing process can be identified accurately. The results of timing parameters extraction from the vibration signal is shown in Fig. 5.

![Fig. 4. Application of different methods](image)

![Fig. 5. Timing parameters extraction from the vibration signal](image)
By the basic theory of the double threshold method, in Fig. 5, the red solid line in the time domain stands for the occurrence time of each vibration event, also the red dotted line in the time domain stands for the end time of each vibration event. After the analysis of the typical vibration signal, it is found that the occurrence time and the end time of vibration events is different in different fault, so the occurrence time and the end time of the largest two vibration events is extracted, that is 4 timing parameters in total, which is used to construct the feature vector. Test 20 times for each fault, and collect 80 groups of vibration signal for 4 kinds of state. The constructed feature vector is contains 80 groups of timing parameters, part of the extracted timing parameters is shown in Table II.

As shown in Table II, T1–T4 change obviously in different state. For the same state, there is little difference in the timing parameters, this difference has to do with structural principles of spring operating mechanism. Due to the gaps between the parts, vibration events at different operations are not all coincide, so small differences in timing parameters are inevitable.

### 4.3 Fault diagnosis of circuit breaker

80 groups of timing parameters is calculated by the above method, which is corresponding to the normal condition, OSF decrease, CSF decrease and TBS loosed. 80 groups of timing parameters is divided into two groups, the first 40 groups of data is serve as training samples, and its cluster center is calculated by FCM, the clustering effect is shown in Fig. 6. The rest 40 groups of data is to serve as test samples, the types of test samples is identified by proximity.

![Fig. 6. Clustering results of three-dimensional spatial](image-url)
It can be seen from Fig. 6, the clustering of the CB state has achieved good result. Each cluster stands for one state, four cluster centers are corresponding to four states, including the normal condition, OSF decrease, CSF decrease and TBS loosed. The training samples are distributed around their respective cluster centers, and they are clearly separated in space.

In order to compare different methods, the vibration signal is processed by the mentioned methods in section 3.2, and the timing parameter is extracted by double threshold method. The fault recognition rate of different methods is shown in Table III. No matter which method is used to extract the feature vector, both the fault recognition rate and the FCM clustering effect is 100%, this indicate the proposed feature vector has obvious differences, and is helpful for classification. Furthermore, the classification coefficient of the short time energy entropy ratio is closer to 1 than the others, also the average fuzzy entropy is the smallest of all. So the classification result of the short time energy entropy ratio is the best of all, the feature vector extracted by the short time energy entropy ratio is superior to the others.

To verify effectiveness of the proposed method, the average approach degree for different methods is compared with each other. Since the more similar the test data to the cluster centers, the higher approach degree. The closer to 1 the average approach degree, the better the classification result. The average approach degree for different methods is shown in Fig. 7, blue stands for the average approach degree between the test samples and the normal condition cluster center, green stands for the average approach degree between the test samples and the OSF decrease cluster center, red stands for the average approach degree between the test samples and the CSF decrease cluster center, yellow stands for the average approach degree between the test samples and the TBS loosed cluster center.

It can be seen from Fig. 7, for the feature vector extracted from the short time energy entropy ratio, the average approach degree is more closer to 1 than the rest; on the contrary, for the feature vector extracted from the other methods, the average approach degree is not close to 1, and the average approach degree of different fault types is small.

Theoretically speaking, the short time energy entropy ratio can reflect the vibration events change more effectively than the other methods, the feature vector extracted from the short time energy entropy ratio has obvious differences, and it can stand for the change of vibration events in different states. So the double threshold method based on the short time energy entropy ratio can extract the CB feature vector effectively, fault classification of the CB is easy to realized by FCM.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Fault recognition rate</th>
<th>FCM clustering effect</th>
<th>Classification coefficient</th>
<th>Average fuzzy entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short time energy entropy ratio</td>
<td>100%</td>
<td>100%</td>
<td>0.9898</td>
<td>0.0256</td>
</tr>
<tr>
<td>Short time energy</td>
<td>100%</td>
<td>100%</td>
<td>0.9787</td>
<td>0.0521</td>
</tr>
<tr>
<td>Short time energy zero ratio</td>
<td>100%</td>
<td>100%</td>
<td>0.9697</td>
<td>0.0707</td>
</tr>
</tbody>
</table>
5 Conclusion

In this paper, vibration signal of the CB is taken as research object, a new method based on the short time energy entropy ratio and FCM for the CB fault diagnose is proposed. This research is different from the past research, diagnosis of the CB is realized by the timing parameters of the vibration events. The experimental results show that the extracted fault features have obvious differences and the classification result is good. Through the research, some conclusions can be drawn in the follows:

1) The occurrence time and the end time of the vibration events is studied and extracted by double threshold method based on the short time energy entropy ratio. Feature vector constructed by the timing parameters can reflect the vibration event change effectively.

2) The cluster center of the feature vector is calculated by FCM, and then according to the cluster center, classification of the CB fault type is completed and achieved good result.

3) The experimental results show that the proposed method can extract feature vector quickly and classify state of CB correctly. A new method based on the timing parameters change is provided for the fault diagnosis of CB.

Fig. 7. Average approach degree distribution

(a) The short time energy entropy ratio
(b) The short time energy
(c) The short time energy zero ratio

Fault state 1- normal condition; Fault state 2- OSF decrease; Fault state 3-CSF decrease; Fault state 4- TBS loosed.