Mechanical Fault Diagnosis of Circuit Breakers Based on XGBoost and Time-domain Features

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Abstract: In order to improve the efficiency of feature extraction of mechanical vibration signal of circuit breaker and the reliability of state recognition of circuit breakers, a mechanical fault diagnosis method of high voltage circuit breaker based on XGBoost is adopted. Firstly, 17 time-domain features are extracted from the measured vibration signals of circuit breakers, constructing feature vector and the separability of eigenvectors is analyzed. Then the feature vector is input into XGBoost, the depth and size of the tree are optimized to realize the high reliability discriminant analysis of the mechanical state of circuit breaker. Experiments on vibration data of circuit breakers prove that, this method has high efficiency in feature extraction and the overall recognition accuracy is high.

1. Introduction
With the development of ubiquitous power Internet of things, the importance of condition monitoring and fault diagnosis of power equipment is increasing. Among them, the high-voltage circuit breakers (HVCBs) are widely used in power system and the internal structure is complex. The fault signal acquisition is easy to be affected by the external conditions, and the fault diagnosis is difficult[1]. By analyzing the vibration signals generated by actions, we can diagnose a variety of HVCBs mechanical faults[2]. Therefore, HVCBs fault diagnosis based on vibration signal is of great significance.

HVCBs vibration signal processing mostly uses time-frequency analysis method. In common time-frequency analysis methods, when empirical mode decomposition (EMD)[3] and local mean decomposition (LMD)[4] are used to deal with vibration signals, it is difficult to separate the close frequency components with modal aliasing problem; aggregate empirical mode decomposition (EEMD)[5] improves modal aliasing, but increases the amount of computation, and decomposes multiple components beyond the true composition of the signal. The above methods are complex in processing and time complexity, which improves the application cost and industrialization difficulty of related technologies.

Traditional vibration signal features include time-domain features, frequency-domain features and time-frequency-domain features. Although the existing features can accurately describe the different
state signals, the frequency-domain distribution of HVCB vibration signals' fault features is wide, and the actual work is affected by the specific installation environment, it is difficult to extract the relevant effective features from the specific frequency domain. Due to the difference in amplitude, attenuation degree and vibration starting time of different fault state signals in the vibration signal of the circuit breaker, the time-domain features such as mean value, variance and standard deviation can be directly extracted from the original vibration signal to analyze the HVCB fault state[6].

Common HVCBs fault diagnosis methods include support vector machine (SVM)[7], convolution neural networks (CNNs), etc. Because HVCB has few types and degrees of mechanical faults, it is difficult to get training samples covering the overall fault degree. Therefore, higher requirements are put forward for the classification effect of the classifier.

In order to improve the efficiency of feature extraction of vibration signal and the accuracy of fault diagnosis, a new method of mechanical fault diagnosis of circuit breaker based on feature extraction without signal processing is proposed. Firstly, the time-domain features of the mechanical vibration signals of high-voltage circuit breakers are extracted directly to form the feature vector; then the separability of the extracted time-domain features is verified; finally, the extracted features are input into XGBoost to identify the mechanical state and fault type of the equipment. The effectiveness of the new method is verified by the experimental results.

2. XGBoost principle
XGBoost algorithm has high precision, parallelization, portability and can effectively prevent over fitting. XGBoost is optimized based on the second-order Taylor expansion of loss function, which improves the separability. In order to avoid over fitting and reduce the complexity of XGBoost model, in addition to the loss function, regular term is introduced to find the optimal solution as a whole.

Suppose the model has $k$ decision trees, i.e

$$\hat{y}_i = \sum_{i=1}^{k} f_i(x_i), f_i \in \mathcal{F}$$

(1)

Its loss function is

$$L = \sum_i L(\hat{y}_i, y_i) + \sum_k \Omega(f_k)$$

(2)

Where $\Omega(f) = \gamma T + \frac{1}{2} \lambda \| \theta \|^2$, $T$ is the number of leaves and $\theta$ is the weight of leaves.

$$\hat{y}_j^{(i)} = \hat{y}_j^{(i-1)} + f_i(x_j)$$

(3)

Then the loss function can be expressed as

$$L'^{(i)} = \sum_{i=1}^{n} L(\hat{y}_j^{(i-1)}, y_i + f_i(x_j)) + \Omega(f_i)$$

(4)

The Taylor expansion of loss function has

$$L'^{(i)} = \sum_{i=1}^{n} [L(\hat{y}_j^{(i-1)}, y_i) + g_i f_i(x_j) + \frac{1}{2} h_i f_i^2(x_j)] + \Omega(f_i)$$

(5)

The removed constant has
\[
L^{(i)} = \sum_{j=1}^{N} [g_i f_j(x) + \frac{1}{2} \sum_{i=1}^{N} h_i f_j^2(x)] + \Omega(f_i) \quad (6)
\]

\[
I_j = \{ |q(x_j) = j} \] is defined as the jth leaf point, i.e.

\[
L^{(ii)} = \sum_{j=1}^{N} [g_i f_j(x) + \frac{1}{2} \sum_{i=1}^{N} h_i f_j^2(x)] + \gamma T + \frac{1}{2} \sum_{j=1}^{N} \sum_{i=1}^{N} w_{ij}^2 = \sum_{j=1}^{N} \left[(\sum_{i \in J_j} g_i) w_j + \frac{1}{2} \sum_{i \in J_j} h_i + \lambda w_j^2 \right] + \lambda T \quad (7)
\]

Then, if we make the derivation of the above formula and make the result equal to 0, we can get

\[
\omega_j^* = \frac{\sum_{i \in J_j} g_i}{\sum_{i \in J_j} h_i + \lambda} \quad (8)
\]

Taking the \(\omega_j^*\) optimal solution \(\omega_j^*\) into the objective function, we get

\[
L'(q) = -\frac{1}{2} \sum_{j=1}^{N} \left[ \sum_{i \in J_j} g_i \right]^2 - \gamma T \quad (9)
\]

The segmentation steps of XGBoost take place in every existing leaf node. Instead of the traditional method of minimizing the mean square deviation of GBDT segmentation standard, XGBoost can enumerate the tree structure more effectively. Suppose IL and IR are a set of left and right nodes after segmentation. The information gain is as follows

\[
Gain = \frac{1}{2} \left[ \left( \sum_{i \in IL} g_i \right)^2 \left( \sum_{i \in IR} g_i \right)^2 \right] + \left( \sum_{i \in IL} h_i + \lambda \right) + \left( \sum_{i \in IR} h_i + \lambda \right) - \lambda \quad (10)
\]

It can be seen from the above formula that this information gain is a value after splitting minus a value before splitting. The scale of control tree with threshold \(\gamma\) is introduced. \(\gamma\) is the coefficient of leaf node. The goal function of node segmentation is optimized on the premise that the gain value is greater than \(\gamma\).

3. Time domain feature extraction

3.1. Vibration signal analysis of high voltage circuit breaker

The measured vibration signal is shown in Figure (Fig. 1). Compared with the normal signal, the maximum amplitude of iron core jamming waveform appears later; Screw loosening not only has small wave amplitude and long vibration maintenance time, but also has slow attenuation process; the amplitude of crank arm insufficient lubrication waveform is relatively small. Therefore, the time-domain features can be extracted directly to identify the mechanical state of HVCB.
3.2. Feature extraction in time domain
Considering that the development of edge computing and cloud computing technology can be applied to the field of condition monitoring of power equipment, in order to relieve the pressure of data transmission in practical engineering, the feature extraction link directly extracts the time-domain features of 17 vibration signals for the mechanical condition analysis of circuit breakers. Since the acceleration value of vibration signal only reflects the vibration amplitude, its positive and negative does not affect the analysis of signal characteristics, so the absolute value of signal data is taken for entropy calculation. The specific calculation formulas for the features in 17 fault diagnosis fields are shown in Tables (Table 1).

Table 1. Characteristic formula.

| Features          | Formula                                      | Characteristics of the serial number |
|-------------------|----------------------------------------------|-------------------------------------|
| Mean              | $F_{mv} = \frac{1}{N} \sum_{n=1}^{N} x(n)$   | F1                                  |
| Standard deviation| $F_{sd} = \frac{1}{\sqrt{N}} \sum_{n=1}^{N} (x(n) - F_{mv})^2$ | F2                                  |
| Variance          | $F_{sv} = \frac{1}{N} \sum_{n=1}^{N} (x(n) - F_{mv})^2$ | F3                                  |
| Skewness          | $F_{sv} = \frac{1}{N} \sum_{n=1}^{N} \left(\frac{x(n) - F_{mv}}{F_{sd}}\right)^3$ | F4                                  |
| Kurtosis          | $F_{kv} = \frac{1}{N} \sum_{n=1}^{N} \left(\frac{x(n) - F_{mv}}{F_{sd}}\right)^4$ | F5                                  |
| Peak value        | $F_{ppv} = \max\{x(n)\} - \min\{x(n)\}$    | F6                                  |
| Root amplitude    | $F_{sta} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} [x(n)]^2}$ | F7                                  |
| Average amplitude | $F_{av} = \frac{1}{N} \sum_{n=1}^{N} |x(n)|$ | F8                                  |
| Root mean square value | $F_{rms} = \left(\frac{1}{N} \sum_{n=1}^{N} x(n)^2\right)^{1/2}$ | F9                                  |
| Peak              | $F_{p} = \max\{|x(n)|\}$                   | F10                                 |
Waveform indicators  
\[ F_{\text{rms}} = \frac{F_{\text{rms}}}{F_{\text{av}}} \]  
Peak metric  
\[ F_{\text{rms}} = \frac{F_{\text{rms}}}{F_{\text{av}}} \]  
Pulse index  
\[ F_{\text{rms}} = \frac{F_{\text{rms}}}{F_{\text{av}}} \]  
Margin index  
\[ F_{\text{rms}} = \frac{F_{\text{rms}}}{F_{\text{av}}} \]  
Shannon entropy  
\[ F_{\text{sh}} = -K \sum_{n=1}^{N} p_n \log p_n \]  
Renyi entropy  
\[ F_{\text{ren}} = \frac{1}{1-\alpha} \log \sum_{n=1}^{N} p_n^\alpha \]  
Tsallis entropy  
\[ F_{\text{tsall}} = -\frac{1}{\alpha-1} \log \left( \sum_{n=1}^{N} p_n^\alpha \right) \]  

3.3. Characteristic analysis of vibration signal of high voltage circuit breaker

After the direct feature extraction of the original vibration signal of the circuit breaker, three groups of four states are selected to display the feature distribution, as shown in Figures (Fig. 2). It can be seen from the figure that there are certain differences between the features of different states, and the input to the classifier has certain class separability.

XGBoost classifiers use gradient lifting algorithm. The more an attribute is used to build a decision tree in the model, the more important it is. Therefore, after the promotion tree is created, the importance value of each attribute can be obtained directly, which measures the value of features in the construction of the promotion decision tree. The higher the importance of features, the better the ability of feature classification. Therefore, after inputting the training set of 17 kinds of time-domain features into XGBoost, we can get the importance value of each feature, and rank the ten features with larger value according to the importance value, as shown in Figures (Fig. 3). It can be seen from the figure that the importance values of features F7,F3,F1,F6,F12,F8 and F13 are greater than other features, and they make greater contributions to state recognition. It can also be seen from the figure (Fig. 3) feature distribution that these seven features have a high degree of separability, and the feature vector as a whole has a better degree of separability.
4. Diagnosis case analysis

4.1. XGBoost parameter optimization
When XGBoost creates or adds decision trees in sequence, each decision tree attempts to correct the mistakes in previous learning. And when the size of the tree reaches a certain degree, the classification effect has reached the best. Even if the tree and the depth of the tree are increased, the better effect will not be achieved. Therefore, the grid search method is used to optimize the size of XGBoost decision tree and the depth of the decision tree, and the optimal parameters are determined with the minimum logarithm loss in the classification process as the goal. During training, set tree threshold value as [1, 5], tree depth threshold value as [0, 250], and the optimization result is shown in Figures (Fig. 4). When the number of trees is 4 and the depth of trees is 144, the XGBoost classification effect is the best.

4.2. Comparison of recognition results of different classifiers
In order to compare the classification effect of different classifiers, XGBoost, SVM and elm are used to diagnose four fault states. 30 groups of vibration signals were measured by HVCBs in four states: normal state (C0), iron core jamming state (C1), insufficient lubrication state (C2), screw loosening state (C3). 20 groups were used as training samples, and the other 10 groups were used to test multi-classification effect. The classification results of three multi classifiers are shown in Tables (Table 2).

It can be seen from tables (Table 2) that XGBoost achieves 100% when recognizing four states, while SVM has false recognition when recognizing C1, and elm has false recognition when recognizing C1 and C3 states. Therefore, XGBoost has a higher reliability in identifying the mechanical state of the circuit breaker.

4.3. Comparison of different feature extraction methods
In order to verify the advantages of the feature extraction method compared with the traditional signal processing method, EMD, EEMD and LMD3 signal processing methods are used to process the vibration signal and extract the features, and a comparative test is carried out with the new method.

As shown in Tables (Table 3) (where emd-c0 is the normal state sample of EMD feature extraction method, which has the same meaning), the direct feature extraction method, EMD and LMD can effectively identify four states, and the EEMD processing method has the situation of false identification when identifying three states. In this paper, the feature extraction method is only 17 dimensions, which is lower than the traditional signal method. Therefore, the feature extraction method in this paper can effectively reduce the complexity of the original feature set and the feature extraction efficiency is high.
Table 2. State recognition results of different classifiers.

| Classifier | The test sample | The test results | Accuracy /% |
|------------|----------------|-----------------|-------------|
| XGBoost   | C0 10 0 0 0 100 | C1 0 10 0 0 100 | C2 0 0 10 0 100 |
|           | C3 0 0 0 10 100 | C0 10 0 0 0 90  |
| SVM       | C1 1 9 0 0 100  | C2 0 0 10 0 100 | C3 0 0 0 10 100 |
|           | C0 10 0 0 0 100 | C1 3 7 0 0 70  |
| ELM       | C2 0 0 10 0 100 | C3 1 0 0 9 90  |

Table 3. Comparative analysis of different feature extraction methods.

| The test sample | The test results | Accuracy /% | Feature dimension | Time /s |
|-----------------|------------------|-------------|-------------------|--------|
| C0 10 0 0 0 100 | C1 0 10 0 0 100 | 100         |                   | 17     |
| C2 0 0 10 0 100 | C3 0 0 10 0 100 |             |                   |        |
| EMD-C0 10 0 0 0 100 | EMD-C1 0 10 0 0 100 | EMD-C2 0 0 10 0 100 | EMD-C3 0 0 10 0 100 | 153 12.86385 |
| EEMD-C0 9 0 0 1 90 | EEMD-C1 10 0 0 0 0 | 153 13.76319 |                    |        |
| LMD-C0 10 0 0 0 100 | LMD-C1 0 10 0 0 100 | LMD-C2 0 0 10 0 100 | LMD-C3 0 0 10 0 100 | 119 3.66778 |

5. Conclusion
The new method in this paper can effectively and accurately identify the mechanical faults of high-voltage circuit breakers:

(1) The time-domain feature is extracted directly from the original signal to represent the mechanical state features of different circuit breakers. Compared with EMD, LMD and EEMD, the time-consuming feature extraction method is shorter and the efficiency of fault diagnosis is improved effectively;
(2) The XGBoost method is introduced into the circuit breaker fault diagnosis, and the relevant parameters are optimized. The experimental results show that XGBoost has higher reliability in fault diagnosis than traditional SVM and ELM multi classifiers.

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