Research on Fault Diagnosis of Low voltage Transformer Based on Sound Feature Analysis

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Abstract: This paper analyzes the frequency spectrum of the sound and vibration signals during the operation of the transformer, extracts various sound characteristics for fault classification, accurately carries out real-time early warning of the operation state of the transformer, reduces the occurrence of various power consumption faults and disasters, and improves the "intelligent" means of transformer management.

1. Introduction

With the increasing scale of the power grid system, as the core component of the power system, the transformer has a great impact on the transmission of electric energy and the normal operation of the substation. After the equipment is put into use, it will fail due to excessive electrical load, material, environment or man-made problems. Therefore, it is extremely urgent to detect the fault of the transformer, that is, by monitoring the operation status of the transformer to detect and give real-time warning, It reduces the occurrence of various power consumption faults and disasters, and also improves the "intelligent" means of transformer management.

At present, the fault diagnosis methods of low-voltage transformer mainly include: First is to analyze the fault through the content of dissolved gas in the transformer, and use gas chromatograph to analyze the content of dissolved gas in the oil to judge whether the transformer has abnormal conditions. However, professional equipment is required and it is difficult to realize [1]. Second, fault analysis is carried out through the vibration signal of the transformer, and the latent fault of the transformer is diagnosed by online monitoring of the vibration signal of the transformer itself. It is necessary to install a vibration acceleration sensor, but the vibration frequency of the transformer varies with the change of the position, and the core vibration of the transformer is very small due to the improvement of the core stacking method [2]. The third is to analyze the fault through the partial discharge signal of the transformer, and detect the insulation state of the transformer by extracting the partial discharge signal. However, the partial discharge signal has high requirements for noise removal, and the noise has a great impact on the research results of the model [3].

2. Contents

2.1. Overall scheme

By collecting the sound and vibration signals of the transformer during operation for spectrum analysis, based on the data of zero crossing rate, spectrum centroid, sound spectrum attenuation, MFCC and other sound characteristics, and combined with machine learning Xgboost algorithm, a transformer fault diagnosis model in the low-voltage substation is built [4]. The specific flow chart is as follows:

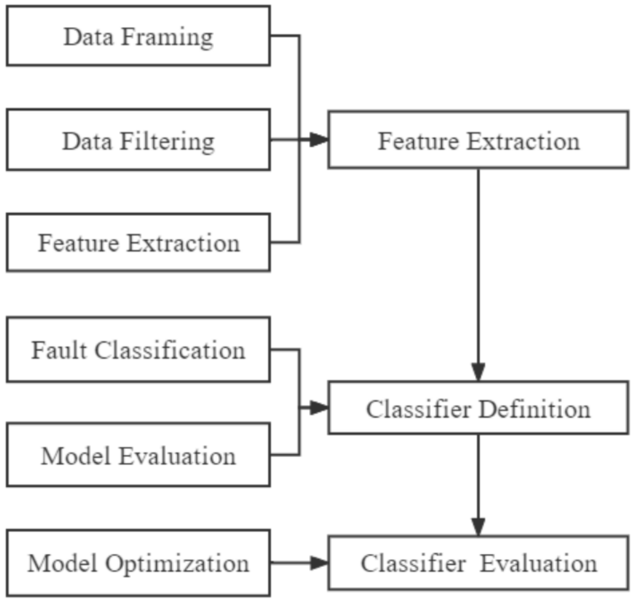

Fig.1 The flow chart

2.2. relevant principles

2.2.1.data quantification. After the sound is sampled, the analog voltage signal needs to be converted into discrete sampling values. This process is sound quantization, which will introduce distortion. Non uniform quantization can be selected. Large quantization interval is used for large input signals and small quantization interval is used for small input signals to ensure that the data accuracy loss is small and the storage space is small as much as possible.

2.2.2. Acoustic feature extraction. Through the data analysis of various characteristics of the sound signal, the frequency spectrum data of the transformer and various indicators reflecting the sound characteristics are calculated, and the low-voltage transformer fault feature model is constructed to prepare for the later low-voltage transformer fault classification model. The extracted sound feature indexes are as follows:

(1) Zero crossing rate

The zero crossing rate is the ratio of signal symbol change, that is, the number of times a speech signal changes from positive to negative or from negative to positive in each frame. The higher the zero crossing rate, the higher the frequency approximation.

(2) Spectral centroid

Spectral centroid is one of the important physical parameters describing the timbre attribute, the center of gravity of the frequency component, and the frequency weighted by energy within a certain frequency range. Its unit is Hz. It is important information of frequency distribution and energy distribution of sound signal. The spectral centroid describes the brightness of the sound. The sound with dark and low quality tends to have more low-frequency content, and the spectral centroid is relatively low. Most of the sound with bright and cheerful quality are concentrated in high frequency, and the spectral centroid is relatively high.

(3) Spectral attenuation

Sound spectrum attenuation is a measure of the shape (waveform) of a sound signal, representing frequencies below a specified percentage of the total spectral energy.

(4) MFCC

MFCC is a cepstrum parameter extracted in the frequency domain of mel scale, which describes the nonlinear characteristics of human ear frequency. The calculation process includes preprocessing, fast Fourier transform, Mel filter bank, logarithmic operation, discrete cosine transform, dynamic feature extraction and other steps.

2.2.3. Fault classification. There are differences in frequency spectrum characteristics between the sound signal of fault operation and the signal of normal operation of low-voltage transformer. According to the operating characteristics of the transformer, faults are divided into three categories: transformer overload, internal fault of the transformer and external fault. Among them, the sound characteristics are the input data and the fault type is the output data. Due to the partial digitization of the spectrum data, an Xgboost classifier is defined to classify the transformer fault in the low-voltage station area, and to study and judge whether the transformer in the low-voltage station area is faulty and the fault type.

2.2.4. Model evaluation and optimization. Xgboost's model evaluation and optimization is to calculate the importance of each sound feature of the low-voltage transformer in the station area through the information gain value and rank it, and select the feature that has a deep impact on the model result as the final feature, so as to realize the fault diagnosis of the low-voltage transformer.
Information gain calculation:

$$\mathrm{Gain} = \frac{G_L^2}{H_L+\lambda} + \frac{G_R^2}{H_R+\lambda} - \frac{(G_L+G_R)^2}{H_L+H_R+\lambda} - \gamma \quad (1)$$

G is the first derivative of leaf nodes, H is the second derivative of leaf nodes, L represents the left subtree, R represents the right subtree,γrepresents the difficulty of node segmentation, λrepresents the L2 regularization coefficient.

3. Examples

3.1. data selection

The sound signal monitoring data of the transformer in the low-voltage substation area in a certain area for half a year is selected. The frequency of the audio acquisition device is 44100 per second, and the signal can be intercepted by frame. In combination with the periodicity of power consumption, the sound signal in the peak period of power consumption is collected. The sampling time is 10 minutes. In order to ensure the smoothness of the sound characteristic parameters, the method of overlapping frames is generally adopted. There is overlap between adjacent frames, The overlap time is 1 minute.

3.2. data processing and feature extraction

3.2.1. Data preprocessing. The data preprocessing of the sound signal is mainly smoothing filtering. The savitzky Golay filter is a weighted average algorithm of moving window, which improves the smoothness of the sound and reduces the interference of noise by performing least square fitting on a given high-order polynomial in the sliding window.

3.2.2. Feature extraction. After smooth filtering, part of the noise is eliminated and the sound signal feature is extracted. The main calculation indicators include zero crossing rate, spectrum centroid, sound attenuation and MFCC. The specific characteristics are as follows:

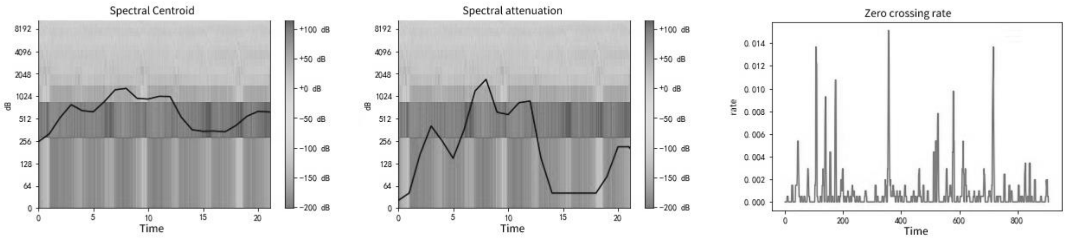

Fig.2 The Figure of the specific characteristics

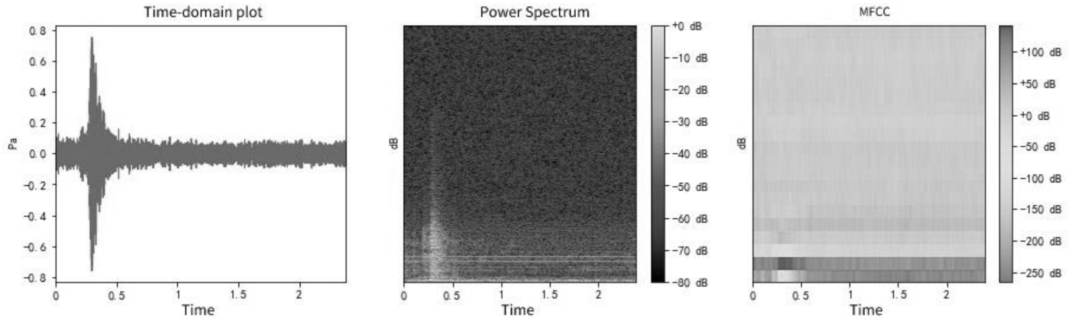

Fig.3 The Figure of the spectral analysis

3.3. Fault classification

3.3.1. Model training. After data filtering and feature extraction of the original data, an Xgboost classifier is defined for low-voltage transformer fault classification model with sound features as input data and fault types as output data to study and judge whether the low-voltage transformer is faulty and the fault types.

Set the parameters of Xgboost algorithm according to the comprehensive effect, specifically:

'booster': 'gbtree', the classifier is a model based on binary classification tree.

'objective': 'binary: Logistic', this parameter defines the loss function that needs to be minimized. In this paper, the logistic regression of two categories is selected to return the predicted probability, that is, the probability of electromagnetic interference is 0-1.

'eval_ Metric ':'auc', this parameter uses the area under the ROC curve to evaluate the model.

'lambda': 50, this parameter refers to the L2 regularization term of the weight to avoid model overfitting.

'eta': 0.3, refers to the learning efficiency. By reducing the weight of each step, the robustness of the model can be improved.

'fit_ Intercept ': 1. This parameter refers to the intercept of the linear model. This parameter is of boolean type. If it is 1, an initial intercept is added to the calculation.

'normalize': 1, refers to the normalization option. By reducing the weight of each step, the robustness of the model can be improved.

3.3.2. Model evaluation. The binary decision tree is created by taking the points with large gain value as the node splitting condition, and the importance of each feature is obtained and sorted. Specific characteristic values and scores are as follows:

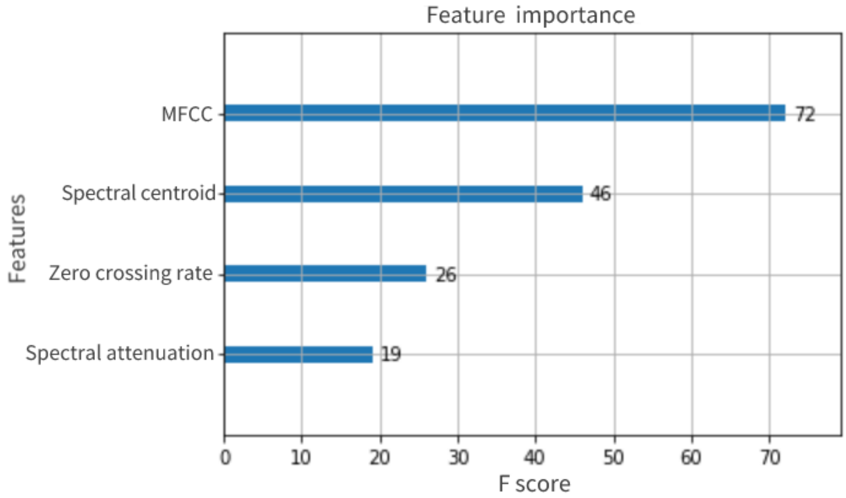

Fig.4 the diagram of Feature importance

Retain the features with high correlation with the model, and conduct comprehensive evaluation through P-R curve, R-P curve and ROC curve to find the best threshold to improve the accuracy of the model.

4. Conclusion

By collecting the sound and vibration signals of the transformer during operation, data preprocessing and feature extraction are carried out, noise data interference is filtered, and various sound features are extracted. Then Xgboost decision tree algorithm is applied to conduct fault diagnosis modeling of the low-voltage transformer, so as to conduct real-time monitoring of the low-voltage transformer [5][6]. The specific advantages are as follows:

(1) Through the mining and analysis of the sound signal of the transformer, the characteristic model of the sound signal of the transformer is established, and the fault diagnosis of the transformer is carried out in combination with the machine learning classification model such as Xgboost;

(2) It has better transformer fault diagnosis performance, good scalability and can meet the actual needs;

(3) Help the station management personnel to monitor the operation of the transformer in real time and give early warning in time.

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