GIS Mechanical Fault Diagnosis Method Based on Middle Time Mel Cepstrum Coefficient

Yi Jiang¹, Mingyue Xu², Rui Lin¹, Lezhou Hong¹, Guosheng Lu¹ and Zhe Li²

¹ China Southern Power Grid Corporation, Guang Zhou, Guang Dong, 510405, China
² Department of Electrical Engineering, Shanghai Jiao Tong University. Shanghai, 200240, China

luna_xu@sjtu.edu.cn

Abstract. Mechanical fault is a common fault of gas insulated switchgear (GIS). If not found in time, it will cause major safety hazards such as opening and closing fault. In this paper, a diagnosis method based on improved Mel cepstrum coefficient for GIS mechanical fault on-line monitoring is proposed. Firstly, the Mel frequency cepstral coefficients (MFCC) are extracted from the preprocessed sound signals; in order to adapt to the characteristics of smooth sound energy change in GIS operation, the MFCC is optimized to obtain improved features; Support Vector Machine (SVM) is introduced to build a GIS mechanical fault diagnosis model based on acoustics and uses bagging algorithm to integrate the SVM model. In this study, mechanical fault is simulated on real GIS to obtain real fault sound signals for training and testing. The experimental results show that compared with the traditional MFCC, the improved MFCC has a higher recognition accuracy in GIS fault sound recognition system. The F1-score is generally over 80%, and the F1-score of specific mechanisms can even reach 99%.

1. Introduction
The common faults of GIS equipment are internal discharge fault and mechanical fault. In recent years, the monitoring methods for the internal discharge fault of GIS equipment have become mature, and the common methods are UHF method, ultrasonic monitoring method, pulse current method, etc. [1]. The internal mechanical fault of GIS equipment is mainly caused by the body of the circuit breaker and disconnector and its operating mechanism. The main diagnosis method is the vibration signal analysis method [2-4]. The vibration signal analysis method usually places sensors on the surface of the equipment shell to receive the vibration signal. Through the qualitative analysis of the obtained vibration signal, it can detect whether there is any abnormality in the equipment interior. However, the general vibration signal can only be obtained separately in the individual position of the equipment shell, which is difficult to reflect the overall operation of the equipment. Compared with the vibration signal, the sound signal is not easy to be affected by the installation mode of the sensor and has the portability of operation, and the sound sensor belongs to the non-contact sensor device, which will not affect the operation of the equipment itself.

In the field of substation inspection, experienced inspectors can judge the operation status of GIS equipment only by sound, and even judge the cause of fault by abnormal sound, which provides a practical basis for fault diagnosis using voice recognition technology. Mel frequency cepstral coefficients (MFCC) are a kind of sound characteristic parameter which accords with the auditory characteristics of human ear. It has the good anti-interference ability [5-6] and is widely used in speech...
recognition. It is feasible to use MFCC as a feature to identify GIS mechanical fault, but the characteristics of GIS equipment voice and human voice are different, the change of GIS equipment voice energy is gentle, MFCC can not adapt to this feature very well.

To solve this problem, this paper proposes a GIS mechanical fault diagnosis method based on improved Mel cepstrum coefficient: through fault simulation experiment, the sound signals of common mechanical faults of circuit breakers and disconnectors of true GIS equipment are collected, the MFCC eigenvectors are extracted and optimized after pre-processing operation, and the improved eigenvectors are introduced into support vector machine (SVM) The mechanical fault diagnosis model of GIS based on acoustics is constructed, and the SVM model is integrated by bagging algorithm, so as to judge the operation state of GIS. This method can not only realize the real-time monitoring and diagnosis of GIS equipment but also effectively improve the reliability and practicability of the diagnosis.

2. GIS fault diagnosis model based on acoustics

2.1 MFCC feature vector extraction and improvement

2.1.1 MFCC feature vector extraction method. The purpose of feature extraction is to extract useful information from the sound signal and form the acoustic feature vector of the signal. Traditional signal analysis methods are mainly focused on time domain and frequency domain, which are easy to be interfered by environmental noise. The human ear can hear the voice signal in the noisy environment noise. This is because the basic membrane of the human ear can regulate the external signal, and the signals of different frequencies can cause vibration at different positions on the basic membrane. Mel frequency cepstral coefficients (MFCC) is to use a series of band-pass filter banks with different weights to imitate the regulation of human ear basic membrane [7], nonlinear the spectrum, reduce the proportion of interference frequency band, and thus reduce the impact of noise [8].

2.1.2 Medium time MFCC eigenvector. Generally speaking, the characteristics of sound signals can be divided into three categories: short-term, medium-term, and long-term. The short-term characteristics are more sensitive to the micro change of sound. Generally, the unit time is 10ms-100ms, and the long-term characteristics can better reflect the macro characteristics of sound. Generally, the unit time is 1s-10s, and the medium-term characteristics are between them. The MFCC described above belongs to the short-term characteristics of sound. Generally, it takes a frame signal of 20-25ms as a sample, which is more consistent with the characteristics of human voice. In this paper, based on the difference between GIS voice and human voice, the mid term has proposed The concept of MFCC) takes the middle time interval as a single sample, and takes the mean value of the MFCC eigenvectors of several adjacent frames in the sample as the middle time MFCC eigenvectors of the sample. The improved features are more consistent with the features of stable sound energy change of GIS operation, with more stable and stronger robustness. At the same time, it can reduce the impact of individual abnormal frames on the overall recognition, so as to obtain better performance.

2.2 Bagging-SVM Model

Support vector machine (SVM) [9] is an algorithm to complete multi-classification tasks by finding the optimal classification hyperplane, which can better adapt to the small sample, non-linear multi-classification problem [10], and is suitable for GIS mechanical fault type judgment. As a single SVM model can not solve the overfitting phenomenon caused by the problem of small sample classification, the bagging algorithm can be used to optimize the SVM model. The bagging algorithm obtains multiple SVM based classifiers by extracting different training sets and produces the final classification results by majority voting on the classification results of the base classifiers [11]. Bagging algorithm can effectively reduce the variance of the model, improve the accuracy and generalization ability of the model, so as to avoid over fitting phenomenon.
3. Simulation and collection of mechanical fault sound signal in GIS

As the main module of GIS equipment, circuit breaker and disconnector operate most frequently. Their operating mechanism and transmission link are the main parts of mechanical failure in GIS. Taking the zf23-126 GIS produced by a GIS manufacturer as the research object, the common mechanical faults of the circuit breaker module and the disconnector module are simulated respectively, and the repeated operation under various fault conditions is conducted three times, and the sound signals under normal working conditions are collected as reference.

4. Results and analysis

4.1 Feature extraction of mechanical fault sound signal in GIS

Firstly, preprocess the collected GIS sound signal: set the frame length as 25ms, frame displacement as 10ms, and the threshold value of mute detection as 0.6 times of the average short-time energy of sound signal. The MFCC eigenvector of each frame of sound signal is calculated, and then the corresponding medium time MFCC eigenvector is calculated. In this paper, taking the sound signal with a low voltage of the energy storage motor of the spring mechanism of the circuit breaker as an example, a sample of 2.5s long is randomly selected to show the MFCC vector and the medium time MFCC vector of the sample in the form of colour gamut diagram, as shown in Figure 1.

![Figure 1. Colour gamut of features.](image)

Comparing the two images, we can see that there is similar sample distribution between MFCC and MFCC, which not only retains the characteristic information of MFCC but also eliminates the influence of individual abnormal frames on the whole. The recognition effect of medium time MFCC at different time intervals is not the same.

4.2 The selection of middle time interval

In the experiment, the training samples of MFCC and medium time MFCC were input into the bagging SVM model for training, and two diagnostic models based on different characteristics were obtained. The median time interval length of the median time MFCC is taken every 50ms starting from 50ms. Table 1 shows the comparative experimental results of MFCC and MFCC in medium time.

| features    | F1-score% | circuit breaker module | disconnector module |
|-------------|-----------|------------------------|---------------------|
| MFCCs       | 97.13     | 97.93                  |
| 100ms-MFCCs | 98.28     | 97.86                  |
| 150ms-MFCCs | 96.68     | 96.99                  |
| 200ms-MFCCs | 97.45     | 97.28                  |
| 250ms-MFCCs | 99.21     | 98.35                  |
From the experimental results, it can be seen that the medium time MFCC has higher recognition accuracy than the traditional MFCC, and the F1-scores of each mechanism are improved to varying degrees. In order to show the changing trend of F1-score more intuitively, this paper takes the circuit breaker spring mechanism and disconnector motor mechanism as examples, continues to increase the medium time length, records the F1-score corresponding to different time length, and obtains the change curve of F1-score with the medium time interval length, as shown in figure 2.

It can be seen from Figure 2 that with the further increase of the length of the middle time interval, the F1-score shows a downward trend. This is because the increase in the length of the medium time interval means that the number of frames contained in each sample increases and the number of samples decreases. When a sample contains too many frames, the feature information becomes single after taking the mean value, resulting in the decrease of feature variance and the loss of short-term change information of sound, so the F1-score decreases rapidly. At the same time, the decrease in the number of samples leads to the inadequate training of the classifier and the increase of the contingency of the test, resulting in the fluctuation of F1-score. In this paper, the medium time MFCC with the length of 100-300ms is selected as the feature vector of GIS equipment voice recognition.

5. Conclusion
In this paper, a GIS mechanical fault diagnosis method based on improved Mel cepstrum coefficient is proposed, which is verified by simulating mechanical fault on real GIS equipment, and the following conclusions are drawn:

- It is feasible to use MFCC and bagging SVM to diagnose GIS fault based on sound signal. The F1-score is generally more than 80%, which can effectively judge the operation status of GIS equipment.
- The improved features are more in line with the characteristics of smooth change of sound energy in GIS operation and have more stable advantages on the basis of retaining MFCC feature information. MFCC feature vector can effectively improve the accuracy of model recognition.
- The medium time interval length and the vector dimension of the medium time MFCC have a great influence on the recognition results. By selecting the appropriate medium time interval and the vector dimension, the recognition effect of the model can be further improved.

References
[1] Song Hui, Dai Jiejie, Li Zhe, et al. An assessment method of partial discharge severity for GIS in service 2019 J. Proceedings of the CSEE 39(04) 1231-1241
[2] Huang Nantian, Wang Bin, Cai Guowei, et al. Mechanical fault diagnosis of high voltage circuit breakers utilizing zero-phase filter time-frequency entropy of vibration signal 2019 *J. High Voltage Engineering* 45(05) 1518-1525

[3] Liu Yuan, Yang Jinggang, Jia Yongyong, et al. Connection state diagnosis method of GIS disconnector based on mechanical vibration 2019 *High Voltage Engineering* 45(05) 1591-1599.

[4] Zheng Hao, Zhu Shenglong, Ouyang Yu, et al. Time-frequency analysis of GIS mechanical vibration signals based on improved HHT algorithm 2018 *Electrical Automation* 40(01) 15-18

[5] Sambur M R Selection of acoustic features for speaker identification 1975 *IEEE Transactions on Acoustics Speech and Signal Processing* 23(2) 176-182

[6] Chen Di, Gong Weiguo and Li Bo High frequency weighted MFCC extraction for noise robust speaker verification 2008 *Chinese Journal of Scientific Instrument* 03 668-672

[7] Chen Di, Gong Weiguo and Li Bo. High frequency weighted MFCC extraction for noise robust speaker verification 2008 *Chinese Journal of Scientific Instrument* 03 668-672

[8] Zhang zhongyuan, Luo Shihao, Yue Haptian, et al. Pattern Recognition of Acoustic Signals of Transformer Core Based on Mel-spectrum and CNN 2020 *High Voltage Engineering* 46(02) 413-423

[9] Hsu C W and Lin C J.A Comparison of Methods for Multiclass Support Vector Machines 2002 *IEEE Transactions on Neural Networks* 13(2) 415-425

[10] Zhang Xuegong. Introduction to statistical learning theory and support vector machines 2000 *Acta Automatica Sinica* 01 36-46

[11] Breiman, Leo. Bagging predictors 1996 *Machine Learning* 24(2) 123-140