

# Diagnosis of DC Bias in Power Transformers with Vibration test Method

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**Keywords:** Power transformer; DC bias; feature extraction; pattern recognition

**Abstract:** This paper deals with a vibration test method to diagnose DC bias in power transformers. Vibration variation process of a 500kV autotransformer is tested under the influence of DC bias. Transformer vibrations in normal and DC-biased conditions are compared. Three features are proposed and is validated by sensitivity analysis. The Principal Component Analysis method is employed for feature de-correlation and dimensionality reduction. The least square support vector machine algorithm is used and verified successful in DC bias recognition. The suggested diagnostic method could be useful in targeted DC bias control and improving the safe operation level of power transformers

## 1. Introduction

Substantial efforts have been devoted to diagnosis anomalous operation state in power transformers [1]. When the HVDC transmission system operates in monopole earth return mode, direct current will flow through the AC power transformer with grounded neutral, which causes DC bias problem [2]. DC bias will induce high-order harmonics in the magnetization current. Consequently, local overheating, anomalous noise and vibration are generated in the power transformers [3-4].

The vibration of transformer oil tank is caused by that of core and windings after a complex transmission process. Thus, the operation condition of transformer core and windings can be observed through vibration detection on the oil tank surface [5]-[8]. According to field test results, vibration of transformer oil tank increases simultaneously with increasing direct current flowing into the neutral. Compared with the electric method, vibration test method is much more efficient and has not electrical connection with power transformer. Therefore, it can be employed as an alternative method to detect DC bias in power transformer.

In this paper, a vibration feature extraction and pattern recognition method is proposed for assessing the DC bias condition of power transformers. Field vibration test of a 500kV autotransformer is carried out. A few vibration features are defined and the extraction and recognition method are introduced. The proposed method is verified by field test data.

## 2. Field Vibration Tests

The frequency band of transformer vibration is commonly in the 50Hz-2 kHz range. To detect the vibration in this range, the accelerometer B&K 4534 is used, which is a sensor with the frequency response range of 0.2Hz-12.8 kHz. Its sensitivity and scope are 100mV/g and  $\pm 70g$ , respectively. The signals from the sensors are input to B&K 3053 data acquisition module for multi-channel synchronous sampling. The sampling frequency is 32768 Hz. Location determination of the measurement point is always a practical issue encountered in the vibration test of power transformers. As the vibration on the oil tank surface is the composite result of the core and winding vibrations, picking up more information of both the core and winding is essential for effective vibration measurement. In addition, stiffeners on the outer surface increase the structure nonlinearity of the tank, leading to spectral and amplitude variation of the vibration signal. Thus, choosing the measurement positions is influential to the vibration test result. These positions should be sensitive to the vibrations

of the core and windings. At these positions, the vibration signals have little attenuation and the spectra are not obviously influenced by the structure of the oil tank. According to the previous research achievement, three accelerometers are installed on the plane area roughly one-fourth of the transformer oil tank with magnetic seats [5]. Locations of the vibration measurement points on a 500kV autotransformer are shown in Fig. 1. These measurement points are uniformly distributed on the oil tank.



Fig 1. Locations of the vibration measurement points.

The transformer vibration in normal operation condition without DC bias is measured. As transformer vibration is in stable state approximately, the vibration could be viewed as periodic signal in seconds. Fast Fourier transform is conducted to obtain the frequency spectrum. The vibration waveform and spectrum distribution of the measurement point 2 on the oil tank of the transformer without DC bias are given Fig. 2. In normal condition, the vibration acceleration amplitude of the measurement point 2 is about  $2.2 \text{ m/s}^2$ . The majority of the frequency components are in the range of 1 kHz. The dominant frequency of the transformer vibration is 200 Hz with the amplitude about  $0.6 \text{ m/s}^2$ . The main frequency components are 100 Hz, 200 Hz, 400 Hz, and 700 Hz.

Compared with the waveform and spectrum distribution without DC bias, great changes have been observed to that of transformer vibration with DC bias, as shown in Fig. 3. The direct current flowing into the transformer is 10.6A. The amplitude of vibration acceleration rises up to  $37.2 \text{ m/s}^2$ , which is approximately 17 times the value in normal condition. On the other hand, much more high-order harmonics of 50 Hz present in the frequency spectrum. The range of frequency components increased from 1 kHz to 2 kHz. Many frequency components at odd times of 50 Hz are generated, such as 250 Hz, 350 Hz, 450 Hz, and 650 Hz. Moreover, the dominant frequency component becomes 700 Hz and the amplitudes of the frequency components over 1 kHz increase in a large degree. At some components like 100 Hz, 200 Hz, and 400 Hz, the vibration energy proportion decreases dramatically. It is found that DC bias has great impact on transformer vibration characteristics.

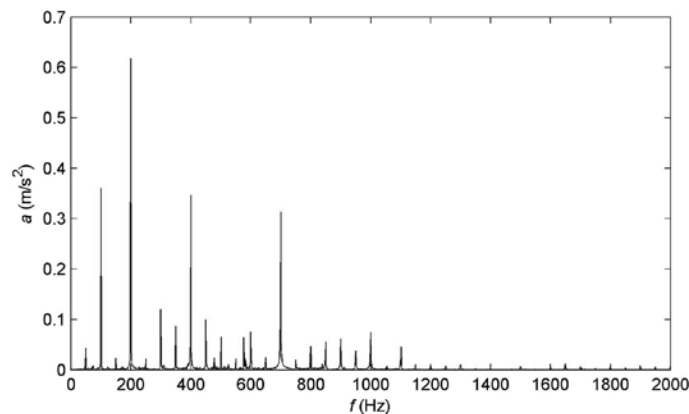


Fig 2. Transformer vibration spectrum without DC bias.

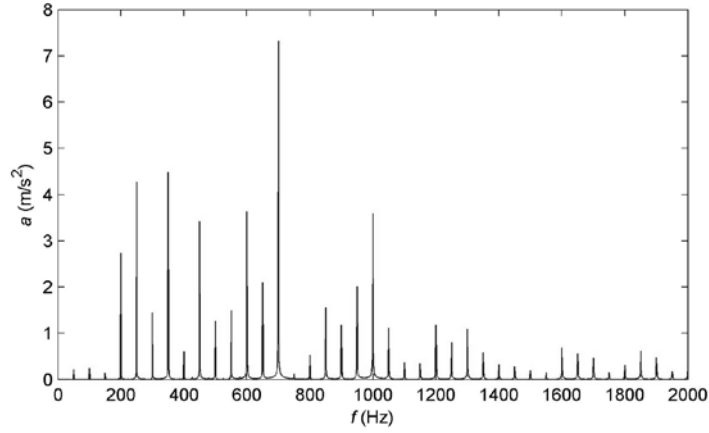


Fig 3. Transformer vibration spectrum with DC bias.

### 3. Feature Extraction

Vibration features should be sensitive to the DC bias status of power transformers. As sudden variation commonly does not occurs to transformer vibration, the time-domain features such as vibration amplitude or its envelope are not considered in this paper. The frequency-domain features based on FFT analysis and wavelet packet decomposition are proposed to detect DC bias. In order to make the measured results representative, frequency spectra of the three vibration measurement points are averaged.

#### 3.1 Feature Definitions

##### 3.1.1. Odd-to-Even Harmonic Ratio

The feature odd-to-even harmonic ratio is defined by

$$R_{oe} = \sqrt{\sum_{i=1}^{N/2} A_{2i-1}^2} / \sqrt{\sum_{i=1}^{N/2} A_{2i}^2} \quad (1)$$

where  $N=40$  is the vibration harmonic number of 50 Hz in the frequency range of 2 kHz,  $A_{2i}$  and  $A_{2i-1}$  are the vibration amplitudes of the even and odd harmonics of 50Hz, respectively.

##### 3.1.2. Spectral Complexity

The feature spectral complexity is defined by the following formula:

$$H = \left| \sum_{i=2}^N R_i \log_2 R_i \right| \quad (2)$$

$$R_i = A_i^2 / \sum_{j=1}^N A_j^2 \quad (3)$$

Where  $A_i$  is the  $i$ th harmonic amplitude,  $R_i$  is the energy ratio of the  $i$ th harmonic.

##### 3.1.3. Wavelet Packet Energy Distribution

A wavelet packet function can be defined as

$$W_{l,k}^n(x) = 2^{l/2} W^n(2^{-l}x - k) \quad (4)$$

Where  $n$  is the modulation parameter,  $l$  is the scale level,  $k$  is the localization parameter.

The wavelet packet functions can be defined with the following sequence of recursive functions.

$$W^{2n}(x) = \sqrt{2} \sum_k h(k) W^n(2x - k) \quad (5)$$

$$W^{2n+1}(x) = \sqrt{2} \sum_k g(k) W^n(2x - k) \quad (6)$$

Where  $h(k)$  and  $g(k)$  are respectively the low-pass and high-pass finite impulse filters.

The first two wavelet packet functions can be defined by a scale function and a mother wavelet function, i.e.

$$W^0(x) = \varphi(x), \quad W^1(x) = \psi(x). \quad (7)$$

For  $l$  levels of decomposition, WPD of vibration signal  $f(x)$  produces  $2^l$  different sets of coefficients.

$$C_{l,k}^n(x) = \int f(x) W_{l,k}^n(x) dt \quad (8)$$

Each WPD sub-band signal corresponding to  $C_{l,k}^n(x)$  can be reconstructed with

$$f_l^n(x) = \sum_k C_{l,k}^n W_{l,k}^n(x) \quad (9)$$

The vibration signal of power transformer can be expressed as

$$f(x) = \sum_{n=0}^{2^l-1} f_l^n(x) \quad (10)$$

WPD sub-band energy is calculated by

$$E_l^n = \int |f_l^n(x)|^2 dx = \sum_k |C_{l,k}^n|^2 \quad (11)$$

Hence, the total energy of vibration signal  $f(x)$  is

$$E_l = \sum_{n=0}^{2^l-1} E_l^n \quad (12)$$

Finally, the feature of wavelet packet energy distribution can be written as the vector

$$\mathbf{T} = [E_l^0, E_l^1, \dots, E_l^{2^l-1}] / E_l \quad (13)$$

### 3.2 Principal Component Analysis

The parameters  $R_{oe}$ ,  $H$ , and  $\mathbf{T}$  comprise the vibration features of power transformers in DC bias condition. In order to reduce the dimensionality of vibration features, the principal component analysis (PCA) method is employed. Assuming  $\xi_i$  ( $i=1,2,\dots,c$ ) are the new chosen vibration features of DC bias obtained by linear combination of the original features  $x_i$  ( $i=1,2,\dots,p$ ), the relation between original and new features can be expressed as

$$\begin{bmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_c \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1p} \\ a_{21} & a_{22} & \cdots & a_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ a_{c1} & a_{c2} & \cdots & a_{cp} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix} = \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \\ \vdots \\ \mathbf{a}_c \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix} = \mathbf{A} \mathbf{x} \quad (14)$$

$$\sum_{n=1}^p a_{mn}^2 = 1 \quad (15)$$

Where  $a_{mn}$  is coefficient of  $n$ th original feature constitutes the  $m$ th Principal component,  $\mathbf{a}_m$  is the normalized coefficient matrix of the  $m$ th Principal component,  $\mathbf{A}$  is the feature transformation matrix,  $\mathbf{x}$  is the original feature matrix.

The information content of each Principal component can be represented by its variance. Generally, minor features are chosen to characterize DC bias in the vibration feature extraction process for dimension reduction. The cumulative variance proportion  $r$  can be calculated by

$$r = \sum_{m=1}^c \lambda_m / \sum_{m=1}^p \lambda_m \quad (16)$$

$$\lambda_m = \text{var}(\xi_m) = \mathbf{a}_m^T \boldsymbol{\Sigma} \mathbf{a}_m \quad (17)$$

Where  $\lambda_m$  the variance of is  $\xi_m$ ,  $\boldsymbol{\Sigma}$  is the covariance matrix.

#### 4. Pattern Recognition

Recently, support vector machine (SVM) based algorithms have been used as a powerful tool to solve the classification problems. The SVM is a machine learning algorithm. It tries to find out a hyper-plane to separate the data points according to their classes with the maximum distance. In that case, the hyper-plane is called the optimal hyper-plane. The least square SVM (LS-SVM) algorithm is a simplified version of SVM, which maintains the advantages and the attributes of the original SVM theory. It possesses excellent generalization performance and is associated with low computational costs. Compared with SVM, it requires less effort in model training. Attribute to these advantages, the LS-SVM algorithm is chosen to recognize the vibration features of DC-biased power transformers. The following is a brief account on the theory of LS-SVM.

Given the training data set  $\{\mathbf{x}_k, y_k\}$  ( $k=1, 2, \dots, M$ ) With input samples  $\mathbf{x}_k$ , binary class labels  $y_k \in \{-1, 1\}$  and sample number  $M$ , the SVM formulations starts from the assumption that

$$y_k [\boldsymbol{\omega}^T \phi(\mathbf{x}_k) + b] \geq 1 \quad (18)$$

The classification hyper-plane is

$$f(\mathbf{x}) = \boldsymbol{\omega}^T \phi(\mathbf{x}) + b \quad (19)$$

Where  $\boldsymbol{\omega}$  is the normal vector of the hyper-plane,  $b$  is the bias term,  $\phi(\mathbf{x})$  is the nonlinear function mapping input data into a higher dimensional feature space.

According to structural risk minimization, the solution of  $\boldsymbol{\omega}$  and  $b$  can be equivalent to the following minimization problem

$$\min J(\boldsymbol{\omega}, \boldsymbol{\varepsilon}) = \frac{1}{2} \|\boldsymbol{\omega}\|^2 + \frac{1}{2} \gamma \sum_{k=1}^M \varepsilon_k \quad (20)$$

$$y_k [\boldsymbol{\omega}^T \phi(\mathbf{x}_k) + b] = 1 - \varepsilon_k \quad (21)$$

$$L = J(\boldsymbol{\omega}, \boldsymbol{\varepsilon}) - \sum_{k=1}^M \alpha_k \{y_k [\boldsymbol{\omega}^T \phi(\mathbf{x}_k) + b] - 1 + \varepsilon_k\} \quad (22)$$

Where  $\varepsilon_k$  the error is variable,  $\alpha_k$  is the Lagrange multiplier,  $\gamma$  is the regularization parameter.

According to Karush-Kuhn-Tucker condition, the solution of above problem concludes in a constrained optimization with the conditions:

$$\begin{cases} \boldsymbol{\omega} = \sum_{k=1}^M \alpha_k y_k \phi(\mathbf{x}_k) \\ \sum_{k=1}^M \alpha_k y_k = 0 \\ \alpha_k = \gamma \varepsilon_k \\ y_k [\boldsymbol{\omega}^T \phi(\mathbf{x}_k) + b] - 1 + \varepsilon_k = 0 \end{cases} \quad (23)$$

After application of the Mercer condition, the LS-SVM classifier results into the following equation:

$$f(\mathbf{x}) = \sum_{k=1}^M \alpha_k \Psi(\mathbf{x}, \mathbf{x}_k) + b \quad (24)$$

$$\Psi(\mathbf{x}, \mathbf{x}_k) = \exp\{-\|\mathbf{x} - \mathbf{x}_k\|^2 / (2\sigma^2)\} \quad (25)$$

Where  $\Psi(\cdot, \cdot)$  the radial basis is function kernel,  $\sigma^2$  is the kernel parameter.

For the training problem of LS-SVM, performance of the LS-SVM algorithm is influenced by the regularization parameter and the kernel parameter. The grid search and cross validation approaches could be used to get the optimal parameters.

## 5. Feature Sensitivity Analysis

In order to verify the effectiveness of the vibration features to the change of DC bias condition, the time variation process of odd-to-even harmonic ratio and spectral complexity and the discrepancy of wavelet packet energy distribution have been analyzed.

Figure 4 gives the time variation process of the feature  $R_{oe}$  and the vibration acceleration. In the first 30 min, DC bias is nearly absent. The transformer vibration amplitude  $a$  stays in a low level and increases gradually from 1.5 m/s<sup>2</sup> to 1.6 m/s<sup>2</sup>, which variation is not obvious. However, an apparent increase can be observed in the curve of the feature  $R_{oe}$  from 0.16 to 0.30. In the next 10 min, sharp increase of both the feature  $R_{oe}$  and the vibration acceleration present. The feature  $R_{oe}$  and the vibration amplitude rise up to 0.77 and 11.56 m/s<sup>2</sup>, respectively. After 40 min, both the feature  $R_{oe}$  and the vibration amplitude fluctuate in a high level. During the whole process, the variation of the feature  $R_{oe}$  can always keep in accordance with that of the vibration amplitude. It seems more sensitive than the vibration acceleration even when the direct current flowing in the neutral of power transformer is in small amplitude.

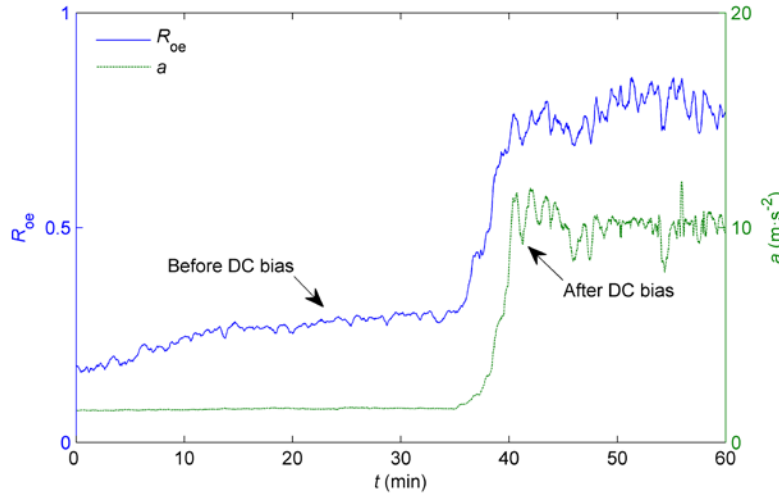


Fig 4. Feature  $R_{oe}$  variation process with time.

Figure 5 shows the time variation process of the feature  $H$  and the vibration acceleration. Like the feature  $R_{oe}$ , the feature  $H$  has similar variation curve with the amplitude of vibration acceleration. Obvious increase is also found in the first 30 min from 2.25 to 2.44. When DC bias occurs, the feature  $H$  rises up to 2.94. Compared with vibration acceleration, higher degree of fluctuation can be observed from the curve of the feature  $H$ , which means that the proposed feature is more sensitive to the DC bias status of power transformers.

The wavelet packet energy distribution before and after DC bias is shown in Fig. 6. The db4 wavelet and Shannon entropy are used in the 4-level wavelet packet decomposition. In order to scatter the wavelet packet energy distribution and make it more uniformly distributed in the whole frequency band, the vibration signal is re-sampled from the frequency of 32768 Hz to 4096 Hz. Based on the theory of wavelet packet (WP), the upper limit of the vibration frequency band is 2048 Hz after resample. The vibration energy is mainly distributed in the sub-bands of 1 to 8 after WPD, which is in the frequency range of 1024 Hz. Before DC bias occurs, the dominant vibration energy is in the frequency range of 0~128 Hz and 256~384 Hz. When DC bias occurs, the dominant vibration energy

presents in the frequency range of 256~384 Hz. The vibration energies in the sub-bands of 3 to 8 increase greatly compared with that of power transformers in normal operation condition. Therefore, the wavelet packet energy distribution can be used as the vibration feature to detect DC bias.

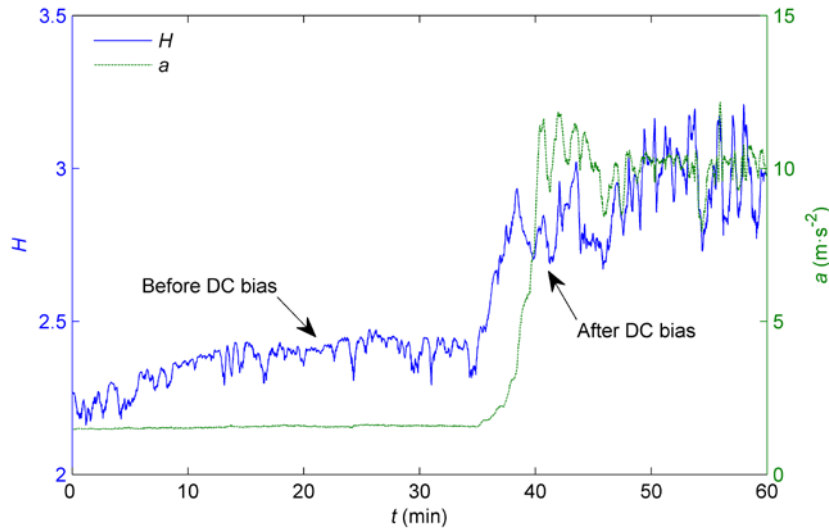


Fig 5. Feature H variation process with time.

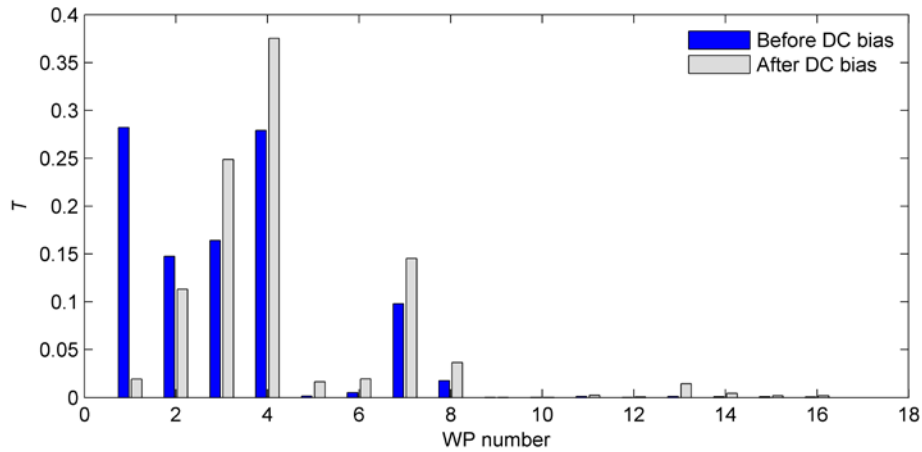


Fig 6. Feature  $T$  variation before and after DC bias.

## 6. Application and Analysis

### 6.1 Principal Features Calculation

In the trial operation process of the  $\pm 800\text{kV}$  Jiuquan-Hunan HVDC power transmission system with monopole earth return mode, vibration of the 500kV autotransformer is tested. The vibration signal in each 10 s is treated as a sample. Rough vibration features of each sample are calculated. The PCA method is used to extract the Principal features of DC bias.

There are totally 126 vibration samples used to train the classifier of LS-SVM, including 108 sets of DC bias samples classified with label “1” and 18 sets of normal samples classified with label “-1”. These DC bias samples are obtained when the HVDC system is operated in the transmitting power of 600, 2000, and 2100 MW, respectively. In each operation condition, 36 sets of vibration data are selected.

Eigenvalue of the covariance matrix of the original rough features are calculated and sorted. Then, the cumulative variance proportion of each Principal feature is obtained.

$$r = [0.6961 \quad 0.9790 \quad \dots \quad 1.0000] \quad (26)$$

It is observed that the cumulative variance proportion of the first two Principal components reaches 97.9%. Thus, the information contained in the first two Principal components is deemed enough to represent that of all the rough features. These two Principal features are extracted as the vibration features of DC-biased power transformers. After PCA, the consequent Principal features are plotted in Fig. 7.

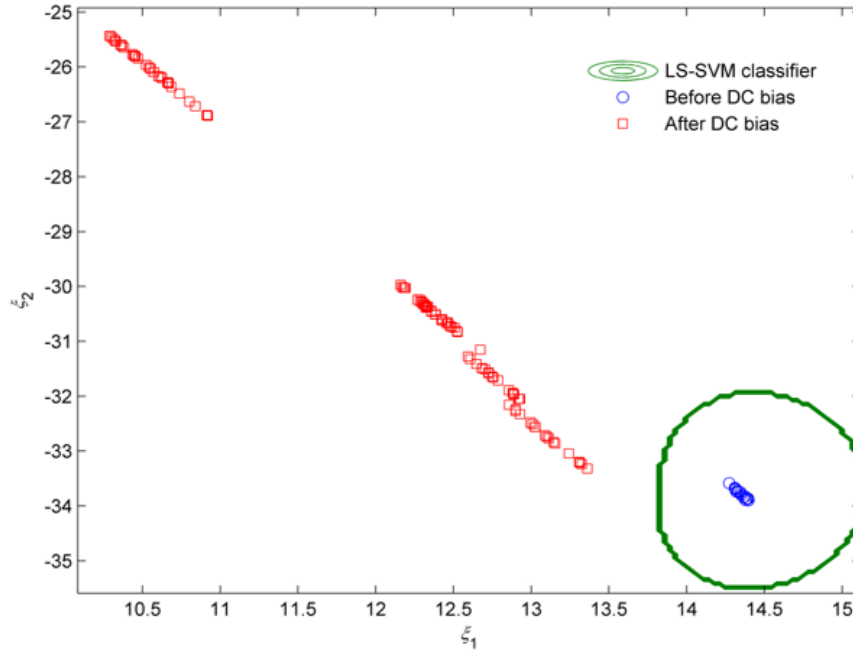


Fig 7. Principal vibration features of DC-biased power transformers.

## 6.2 Recognition results

Another 36 sets of samples are used to test the effectiveness of the LS-SVM classifier in which 18 normal vibration samples and 18 DC-biased vibration samples are included. The rough features are calculated and transformed to the two-dimensional Principal features with the matrix  $A$ . As shown in Fig. 8, all the samples are correctly predicted, which verifies the proposed LS-SVM method in pattern recognition of DC bias.

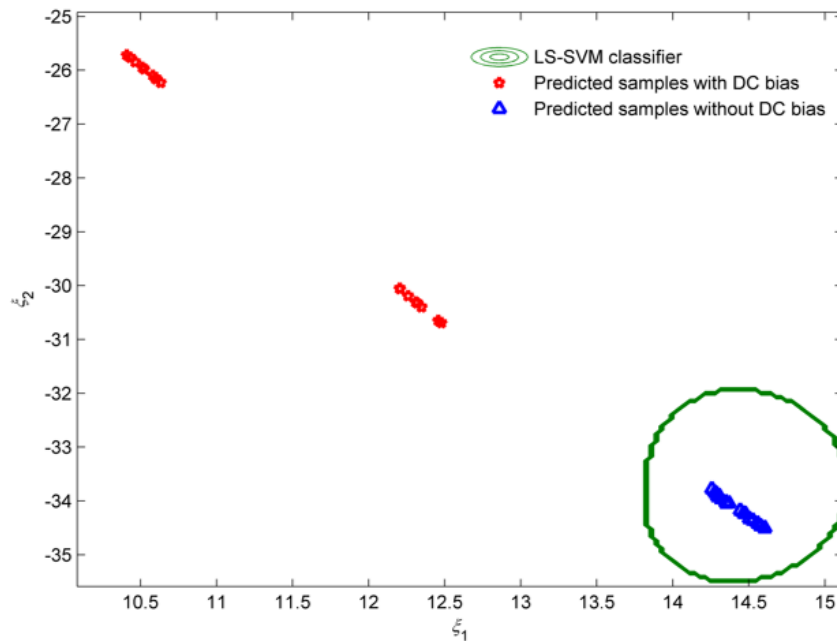


Fig 8. Recognition result of the LS-SVM classifier.



## 7. Conclusion

In this paper, the field vibration test of a 500 kV autotransformer is conducted under the influence of DC bias in the monopole trial operation stage of the  $\pm 800$  kV Jiuquan-Hunan HVDC power transmission project. From the test result, it is proved that the vibration test method is effective to detect DC bias in power transformers. The time-domain waveform and frequency-domain spectrum comparisons between normal and DC-biased vibrations of a power transformer are performed. In addition to vibration amplitude, it is revealed that DC bias changes the frequency spectrum distribution in frequency component and its energy proportion. Three features including odd-to-even harmonic ratio, spectral complexity, and wavelet packet energy distribution are proposed. By the sensitive analysis, these features are proved effective to diagnose DC bias. The PCA method is employed to decorrelate these features. The LS-SVM algorithm is proposed to classify and recognize the extracted features. The proposed algorithm is verified effective in DC bias diagnosis of power transformers. It could be used to diagnose DC bias in power transformers.

## Acknowledgment

This work was financially supported by Science and Technology Project of SGCC (5216A5200002).

## References

- [1] A. Abu-Elanien and M. M. A. Salama, "Asset management techniques for transformers," *Electric Power Systems Research*, vol. 80, no. 1, pp. 456-464, 2010.
- [2] R. Zeng, Z. Yu, J. He, B. Zhang, and B. Niu, "Study on restraining DC neutral current of transformer during HVDC monopolar operation," *IEEE Trans. Power Del.*, vol. 26, no. 4, pp. 2785-2791, Oct. 2011.
- [3] J. He, Z. Yu, R. Zeng, and B. Zhang, "Vibration and audible noise characteristics of AC transformer caused by HVDC system under monopole operation," *IEEE Trans. Power Del.*, vol. 27, no. 4, pp. 1835-1842, Oct. 2012.
- [4] C. Bartoletti, M. Desiderio, D. D. Carlo, G. Fazio, F. Muzi, G. Sacerdoti, and F. Salvatori, "Vibro-acoustic techniques to diagnose power transformers," *IEEE Trans. Power Del.*, vol. 19, no. 1, pp. 221-229, Jan. 2004.
- [5] S. Ji, Y. Luo, and Y. Li, "Research on extraction technique of transformer core fundamental frequency vibration based on OLCM," *IEEE Trans. Power Del.*, vol. 21, no. 4, pp. 1981-1988, Oct. 2006.
- [6] B. García, J. C. Burgos, and Á. M. Alonso, "Transformer tank vibration modeling as a method of detecting winding deformations—Part I: Theoretical foundation," *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 157-163, Jan. 2006.
- [7] B. García, J. C. Burgos, and Á. M. Alonso, "Transformer tank vibration modeling as a method of detecting winding deformations—Part II: Experimental verification," *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 164-169, Jan. 2006.
- [8] B. García, J. C. Burgos, and Á. Alonso, "Winding deformation detection in power transformers by tank vibrations monitoring," *Electric Power Systems Research*, vol. 74, no. 1, pp. 129-138, 2005.