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State Identification of Transformer Under DC Bias Based on Wavelet Singular Entropy

JUN LIU[1,2], (Member, IEEE), HUARONG ZENG[2], WEI NIU[2], PEILONG CHEN[2], KUI XU[2], PENG ZENG[2], LU ZHAO[3], AND SHENG LIN[3], (Senior Member, IEEE)

[1]College of Electrical and Information Engineering, Hunan University, Changsha 410000, China
[2]Electric Power Research Institute, Guizhou Power Grid Company Ltd., Guiyang 550000, China
[3]School of Electrical Engineering, Southwest Jiaotong University, Chengdu 610031, China

Corresponding author: Sheng Lin (slin@swjtu.edu.cn)

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ABSTRACT To identify the DC bias state of transformers, a DC bias state identification method of transformer based on wavelet singular entropy is proposed in this paper. The vibration principle of transformers under DC bias has been analyzed. By combining continuous wavelet transform, singular value decomposition, and information entropy, the analysis method of wavelet singular entropy is proposed. The vibration signal of the transformer before and after DC bias is transformed by continuous wavelet transform, and then the wavelet time-frequency diagram is compared and analyzed. Furthermore, the DC bias state of the transformer is identified by wavelet singular entropy of vibration signal. The wavelet singular entropy under different states is in different numerical ranges, and the wavelet singular entropy of vibration signal under DC bias is significantly greater than that under no DC bias. The wavelet singular entropy effectively reflects the DC bias state of transformers. Then the proposed method is applied to a 500 kV transformer and a 220 kV transformer in the China Southern Power Grid. The results show that the proposed method can accurately and effectively identify the DC bias state of transformers.

INDEX TERMS Transformer, DC bias, vibration signal, wavelet singular entropy, state identification.

I. INTRODUCTION

DC bias is an abnormal working condition that often occurs in the operation of transformers. As the DC current flows into the neutrals of the transformer with the neutral grounded, the DC magnetic flux of the iron core is superimposed on the AC magnetic flux, and the magnetic flux of the transformer is shifted, thus the DC bias occurs. There are three main reasons for DC bias of transformers: geomagnetic storm caused by solar activity, the unipolar operation of the DC transmission system, and stray current of rail transit [1]–[3]. DC bias easily leads to local overheating, the aggravation of noise and vibration of transformers, and mal-operation operation of relay protection. It will seriously threaten the safe operation of power transformers [4]. So, how to identify the DC bias state of transformers is of vital importance.

DC bias identification is also an important foundation to ensure the reliable operation of the urban power grid and to arrange the maintenance strategy reasonably. In the current research on DC bias of transformer, the correlation between the transformer circuit and the magnetic circuit is mainly used to establish a mathematical and simulation model. Then, the excitation current and its distortion rate are calculated to analyze the DC bias of transformers [5], [6]. However, the excitation current is not easy to be measured in the actual running of the transformer. Therefore, it is difficult to meet the requirements of on-line supervision for the operation state of power transformers.

DC bias will intensify the vibration of transformers [7]. The vibration signals are collected through vibration sensors adsorbed on the transformer tank. Then the characteristics of vibration signals are analyzed to identify the state of transformers. Thus, the operation state of transformers can be observed through vibration detection, which can be performed online [8]. Aiming to deal with nonstationary signals like vibration signals, many methods have been proposed, such as, empirical mode decomposition (EMD) and the Hilbert spectrum [9], [10], Fourier decomposition method (FDM) [11], a new formulation of the FDM using the discrete cosine transform [12]. The vibration characteristics before

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and after DC bias are compared and analyzed in [13]–[15], and the characteristic quantities of DC bias are obtained in the time domain, frequency domain, time-frequency domain. However, the obtained characteristic quantities are not further applied to DC bias state identification of transformers.

In terms of DC bias identification, characteristic parameters such as odd to even harmonic ratio, spectrum complexity, and wavelet packet energy are proposed in [16]. And then the principal component analysis (PCA) and support vector machine (SVM) method are used to identify the DC bias of transformers. However, vibration signals of transformers are non-stationary signals. The traditional Fourier transform, which is not suitable for nonstationary signals, will lead to low reliability and accuracy for DC bias identification. Therefore, a large number of scholars have studied wavelet transform for different application, and proposed a series of new wavelet methods, which have great achievement in signal processing [17]–[22]. Wavelet transform has been effectively applied to the characteristic analysis of vibration signals, which is a typical method for non-stationary signal analysis. However, it is not only the computational complexity, but also the energy leakage and aliasing that solely rely on the wavelet decomposition method to extract the transient signal characteristics of the power system, and the signal feature extraction effect will also be affected.

Entropy is a powerful and effective tool to extract fault characteristics, which has been widely used in the state identification. Entropy can not only represent the complexity of signal, but also measure the uncertainty of system or signal, so it is perfect for dealing with vibration signal of transformers. In the aspect of entropy, many scholars have done a lot of research and made great achievement [23]–[32]. However, the main purpose of this paper is to choose a simple and efficient entropy approach to identify the DC bias of transformer in real time. Most of the entropy approaches mentioned above have problems, such as, low computational efficiency, complicated calculation and low noise immunity. As a result, by combining wavelet transform and information entropy, the wavelet entropy is proposed, which combines the unique advantages of the wavelet transform in the processing of the irregular abnormal signal and statistical properties of the information entropy in the signal complexity.

Singular value decomposition (SVD) is sensitive to the fault features of signals, and has a good effect of noise elimination. Thus, based on the wavelet entropy and singular value decomposition theory, the wavelet singular entropy is proposed. Wavelet singular entropy is used widely for electric power system automatic fault detection [33]–[35], which is highly suitable for measuring the uncertainty and complexity of the analyzed signals and is sensitive to transient signals generated by faults. Thus, based on the continuous wavelet transform, the wavelet singular entropy of vibration signal is obtained as the characteristic quantity to identify the DC bias of transformers in this paper.

To identify the DC bias of transformers, the vibration principle of transformers under DC bias is analyzed. By combining continuous wavelet transform, singular value decomposition, and information entropy, the analysis method of wavelet singular entropy is proposed. The vibration signals of transformers before and after DC bias are transformed by continuous wavelet transform. And then the wavelet time-frequency diagram is compared and analyzed. Based on continuous wavelet transform and singular value decomposition, the wavelet singular entropy of vibration signals is obtained. The result shows that the wavelet singular entropy can effectively reflect the DC bias state of transformers. Thus, a DC bias state identification method based on wavelet singular entropy is proposed. Then the method is applied to a 500 kV transformer and a 220 kV transformer in the China Southern Power Grid, and the results prove the accuracy and effectiveness of this method.

II. ANALYSIS OF VIBRATION PRINCIPLE OF TRANSFORMERS UNDER DC BIAS

The vibration signals of transformers are mainly the winding vibration and the core vibration, which transmit to the wall of transformers through different paths. On the one hand, the core vibration is caused by magnetostriction effects due to magnetization of the core. Within a certain magnetic flux range, the magnetostriction of the iron core is approximately proportional to the square of the magnetic flux. The magnetostriction of the core is:

$$\lambda = \frac{1}{2}\alpha B_a^2 (\cos 2\omega t + 1)\,. \tag{1}$$

where α is a constant related to the core material, B_a is the magnitude of flux density, ω is the frequency of supply voltage.

On the other hand, the winding vibration is caused by the electromagnetic force due to leakage flux associated with the current. The vibration signal of transformer winding is proportional to the square of the load current. Thus, the electrodynamic force acting on the winding coil is:

$$F = \frac{1}{2}pI^2 (\cos 2\omega t + 1)\,. \tag{2}$$

where p is the electrodynamic coefficient, and I is the magnitude of load current. In summary, the fundamental frequency of the core vibration signal is twice that of the power supply voltage, and the fundamental frequency of the winding vibration signal is twice that of the load current [36].

Excessive DC current flowing through the earthed neutral will lead to DC bias of transformers. Under DC bias, the DC flux produced by excessive DC current is superimposed on AC flux, resulting in a significant increase in the flux density in half period. The magnetic flux curve presents the phenomenon that the upper and lower half waves are asymmetric and the saturation occurs once every half period. The operating point of the magnetization curve enters the nonlinear saturation region, resulting in an aggravation of distortion and an increase of the magnitude of excitation current [6]. The distortion of excitation current will lead to higher-order harmonic components in the winding current and the flux

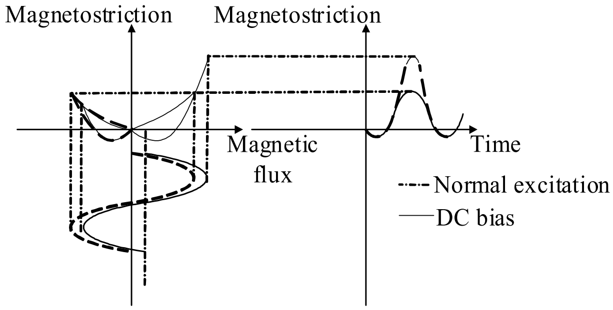


FIGURE 1. The relation between magnetic flux and magnetostriction of the core under DC bias.

of core, and the magnitude of each harmonic component increases. Under DC bias, it can be considered that the DC flux is superimposed on the AC flux of the transformer core. The relationship between magnetic flux and magnetostriction under DC bias is shown in Fig. 1 [37].

Under DC bias, the magnitude of vibration signals increases. Compared with the normal state, due to the distortion of the excitation current, the frequency components of the core and winding vibration signals become complicated, and the odd multiple harmonics and the higher orders harmonics also occur obviously. After the appearance of DC bias, each frequency band of vibration signals changed, and the attenuation or enhancement varied in different frequency bands [37].

III. DEFINITION OF WAVELET SINGULAR ENTROPY

Wavelet analysis reflects the characteristic change of vibration signal in the time-domain and frequency-domain simultaneously. Singular value decomposition can obtain time-frequency characteristics. And information entropy energy can calculate the uncertainty and complexity of signals. Therefore, by combining wavelet analysis, singular decomposition, and information entropy, the characteristics of vibration signals under DC bias are obtained.

A. THE CONTINUOUS WAVELET TRANSFORMER

The continuous wavelet transform uses different nodes to reflect different frequency ranges, and can more intuitively reflect the details of original signals. It has good time-frequency localization ability. The continuous wavelet transform of signal f is defined as:

$$\left(W_{\psi}f\right)(a,b) = \left\langle f, \psi_{a,b}\right\rangle = |a|^{-\frac{1}{2}} \int_{-\infty}^{\infty} f(t)\, \overline{\psi\left(\frac{t-b}{a}\right)} dt. \tag{3}$$

where a and b are scale factor and shift factor respectively; $\langle\,\rangle$ denotes the inner product; $\overline{\psi(t)}$ is the complex conjugate of $\psi(t)$, $\psi(t)$ is the parent wavelet function; $\psi_{a,b}(t)$ is a continuous wavelet function. If the function $\psi \in L^1(R) \cap L^2(R)$ and $\hat{\psi}(0) = 0$, then $\psi_{a,b}(t)$ can be obtained by scaling and shifting from $\psi(t)$:

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}} \psi\left(\frac{t-b}{a}\right). \tag{4}$$

The scale factor a determines the bandwidth and center frequency of the bandpass filter [38]. The wavelet function of each scale a has different frequency band range and different frequency center. Therefore, the wavelet coefficient reflects the content of the frequency component around the frequency center. If the magnitude of the wavelet coefficient is high, there are more frequency components around the frequency center [39]. The corresponding relation between scale and frequency is:

$$F_a = \frac{f_s \cdot F_c}{a}. \tag{5}$$

where a is the scale factor, F_c is the central frequency of the wavelet, and f_s is the sampling frequency.

B. THE WAVELET SINGULAR ENTROPY

Information entropy is an important measure for evaluating the uncertainty of analyzed data. The higher the information entropy is, the higher the disorder degree of information, and the smaller the contribution of information [40]. Supposing that several different states occur in a system X: $\{x_1, x_2, \ldots, x_n\}$, $p(x_i)$ is the probability of each state x_i, $0 \le p_i \le 1$, and $\sum p_i = 1$. Then the information entropy $H(X)$ of the system X is defined as:

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log\left(p(x_i)\right). \tag{6}$$

In scale j ($j = 1, 2, \ldots, m$), the wavelet coefficient $D_j(n)$ can be obtained after wavelet transform. Thus, the decomposition results of m scales will form an $m \times n$ order matrix $D_{m\times n}$ Based on the singular value decomposition theory, there must be an $m \times m$ order matrix U, an $n \times n$ order matrix V, and an $l \times l$ order matrix Λ, makes the $m \times n$ order matrix D be decomposed into:

$$D_{m\times n} = U_{m\times m} \begin{pmatrix} \Lambda_{l\times l} & 0 \\ 0 & 0 \end{pmatrix}_{m\times n} V^T_{n\times n}. \tag{7}$$

where

$$\Lambda_{l\times l} = \begin{bmatrix} \lambda_1 & 0 & \cdot & 0 & 0 \\ 0 & \lambda_2 & \cdot & 0 & 0 \\ \cdot & \cdot & \lambda_i & \cdot & \cdot \\ 0 & 0 & \cdot & \lambda_{l-1} & 0 \\ 0 & 0 & \cdot & 0 & \lambda_l \end{bmatrix}. \tag{8}$$

and its diagonal elements λ_i are the singular value of the matrix obtained by the wavelet transform. The singular values are nonnegative and arranged in nonincreasing order, namely $\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_l > 0$. The singular wavelet entropy is defined as:

$$WSE = \sum_{i=1}^{l} -\left(\lambda_i / \sum_{j=1}^{l} \lambda_j\right) \ln\left(\lambda_i / \sum_{j=1}^{l} \lambda_j\right). \tag{9}$$

Wavelet singular entropy provides briefly numerical representation for the uncertainty of the time-frequency distribution of vibration signals. Wavelet singular entropy maps the correlative wavelet space into independent linearity space, and it is sensitive to the transient signals produced by the faults. The simpler the analyzed signals are, the more concentrated the energy, and the smaller the wavelet singular entropy. On the contrary, the more complex the signals are, the more dispersed the energy, and the higher the wavelet singular entropy. The wavelet singular entropy is suitable for measuring the complexity and uncertainty of the analyzed signals, and provide a quantitative and intuitive outcome for the state identification research [41].

IV. IDENTIFICATION METHOD OF DC BIAS BASED ON WAVELET SINGULAR ENTROPY

From section I, it can be known that the vibration signal changes both in time and frequency domain. Continuous wavelet transform characterizes the DC bias of vibration signals in the time domain and frequency domain. However, the intuitive distribution of the time-frequency domain is not sufficient to identify the DC bias state of transformers. Considering that singular value decomposition obtains the fault features of signals, and information entropy reflects the uncertainty and complexity of signals, the wavelet singular entropy is used to quantify the time-frequency characteristics of DC bias. Based on that, the DC bias of transformers can be more simply and quickly reflected. Based on characteristics of DC bias obtained by wavelet singular entropy, a DC bias identification method based on wavelet singular entropy is proposed.

A. CHARACTERISTIC ANALYSIS OF VIBRATION SIGNAL UNDER DC BIAS

To obtain characteristics of DC bias, the continuous wavelet transform is performed on the collected vibration signals, and the wavelet time-frequency diagrams with and without DC bias are compared and analyzed. The singular value decomposition of the wavelet coefficient matrix obtained by continuous wavelet transform is carried out, and then the wavelet singular entropy of the transformer is obtained.

The vibration detection of a 500 kV main transformer in the China Southern Power Grid was carried out. The CJBPZ-1 velocity vibration sensor is used to collect vibration signals at the lower-middle position of the side of the transformer tanks, and the sampling frequency is 2000 Hz. Then, continuous wavelet transform function (CWT) in MATLAB is used for the wavelet analysis of vibration signals. Daubechies series wavelets are orthogonal and compact supported, and are sensitive to irregular signals. Therefore, the db4 wavelet is selected as the mother wavelet function of the wavelet transform in this paper.

By combining the above principle analysis of vibration signals and the existing research on vibration signals of transformers, it is found that the magnitude of 50 Hz frequency multiplier components of vibration signals is significantly greater than that of other frequency components. Therefore, the center of frequency window of each scale y_1, y_2, …, y_{20} is set as the frequency multiplier of 50 Hz, namely 50, 100, …and 1000 Hz. According to the sampling theorem,

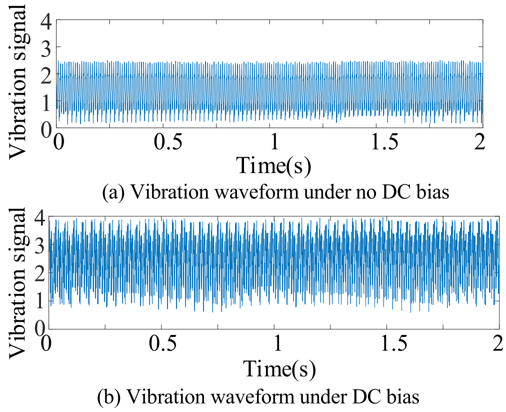


FIGURE 2. Monitored vibration waveform under DC bias and no DC bias.

the sampling frequency is f_s, so the actual frequency range of the signal is $f_s/2$. To make the frequency range of the wavelet transform to be $f_s/2$, according to (5), the wavelet transform scale y_n is selected as:

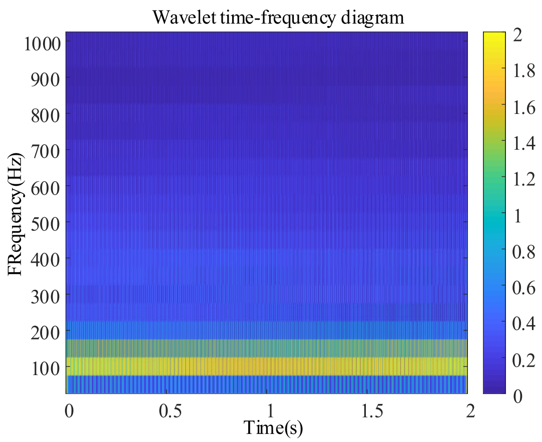
$$y_n = \frac{2F_c f_s}{F_a} = \frac{2F_c N}{n}. \tag{10}$$

where F_c is the center frequency of the mother wavelet, and F_a is the frequency center of the frequency window in y_n scale. Choose $N = 20, n = 1, 2, 3, \ldots,$ and 20. And the center frequency of db4 mother wavelet function is 0.714 Hz.

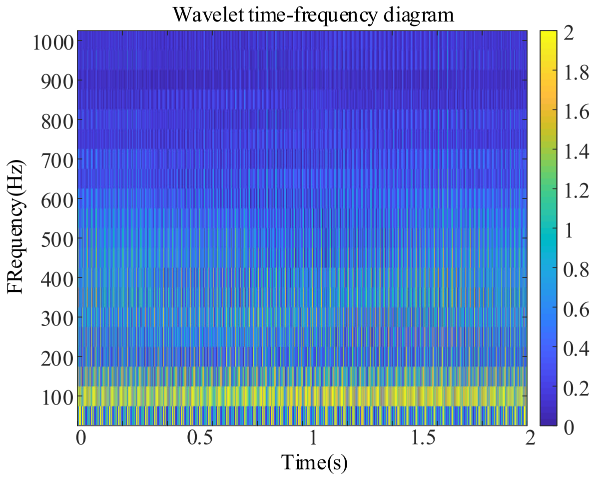
The continuous wavelet transform is applied to the vibration signals of the transformer under DC bias and no DC bias. The waveforms of vibration signals are shown in Fig. 2, and the time-frequency diagram after continuous wavelet transform is shown in Fig. 3.

The wavelet time-frequency diagrams of vibration signal under DC bias and no DC bias are significantly different. From Fig. 3 (a), the vibration signal is mainly distributed in the low-frequency band (0 Hz to 0.4 kHz). Whereas the distribution of the high-frequency band (0.4 kHz to 1 kHz) is very small. The frequency distribution is relatively concentrated, and the wavelet coefficients in the high-frequency band are significantly smaller than those in the low-frequency band. From Fig. 3 (b), the wavelet coefficients in the low-frequency band and the high-frequency band increase. The frequency distribution is relatively divergent. The wavelet coefficients of the low-frequency band are still larger than those of the high-frequency band. The wavelet coefficients of transformers in the same state but at different scales have different magnitudes and different distribution rules. Therefore, the wavelet transform can be used to obtain characteristics of the DC bias state of transformers.

The singular value decomposition of the wavelet coefficient matrix obtained after the above continuous wavelet transform is carried out. And the singular value matrix under DC bias and no DC bias is obtained. According to the definition of wavelet singular entropy, the wavelet singular entropy WSE_1 under no DC bias is 1.67, and the wavelet singular entropy WSE_2 under DC bias is 2.11. Setting the time window as 2 s and the step length as 1/20 s, the curves of the wavelet



(a) Wavelet time-frequency diagram under no DC bias



(b) Wavelet time-frequency diagram under DC bias

FIGURE 3. Wavelet time-frequency diagram under DC bias and no DC bias.

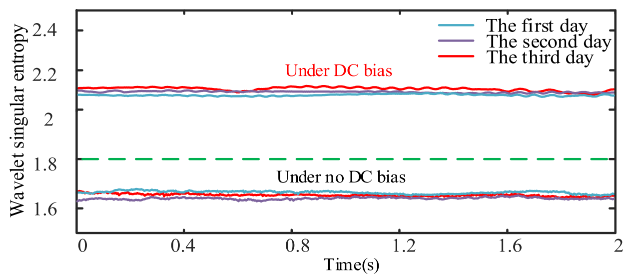


FIGURE 4. Wavelet singular entropy under DC bias and no DC bias.

singular entropy are obtained with the sliding of the time window. The changing trends of wavelet singular entropy of a 500 kV transformer under DC bias and no DC bias in three consecutive days are selected, as shown in Fig. 4.

As can be seen from Fig. 4, the difference of wavelet singular entropy between DC bias and no DC bias is obvious. Under no DC bias, the wavelet singular entropy fluctuates mainly in the range from 1.6 to 1.7. Whereas under DC bias, the wavelet singular entropy increases significantly and mainly fluctuates in the range from 2 to 2.2. Thus, the wavelet singular entropy value is used as the characteristic quantity

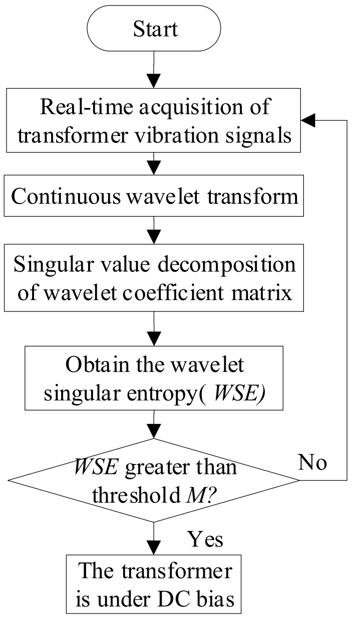


FIGURE 5. Identification flow chart of DC bias.

to identify the DC bias state of transformers. Moreover, the threshold M is set as 1.8 to judge whether the transformer is under DC bias. If so, the transformer is judged to be under DC bias.

B. IDENTIFICATION METHOD OF DC BIAS

Based on the above analysis, a DC bias state identification method based on wavelet singular entropy is proposed in this work. The flow chart is shown in Fig. 5.

Specific steps are as follows:

1) Continuous wavelet transform is carried out for the collected transformer vibration signals to obtain the wavelet coefficients at various scales.

2) The singular value decomposition of the wavelet coefficient matrix is carried out to obtain the singular value of the wavelet coefficient matrix.

3) According to (9), the wavelet singular entropy WSE is calculated.

4) The wavelet singular entropy in different states of transformer is different, so the DC bias of transformers can be identified by the wavelet singular entropy.

5) The wavelet singular entropy is compared with the threshold M. If $WSE > M$, it can be judged that the transformer appears DC bias phenomenon. If $WSE < M$, repeat steps from 1 to 5 with a step length of 1/20 s. The transformer with different structures and parameters will have different thresholds. Thus, in the actual application, the threshold M is determined based on the analysis of a large number of measured data and expert experience.

V. APPLICATION AND VERIFICATION OF IDENTIFICATION METHOD

To verify the feasibility and accuracy of the method while identifying the state of transformers in operation, based on

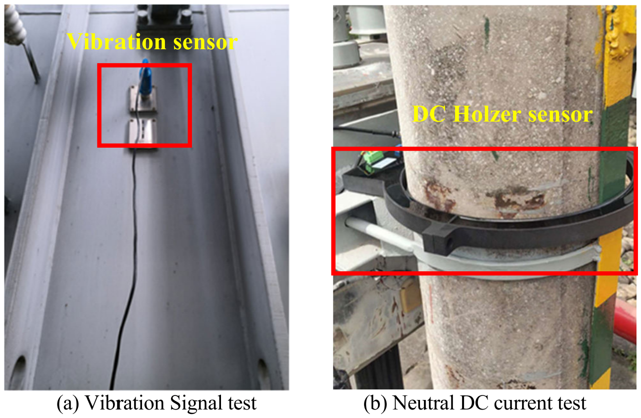


FIGURE 6. Scene diagrams while testing.

the method proposed above, the following works are carried out: Initially, vibration signals of a 500 kV transformer in the China Southern Power Grid are monitored in real-time, and the wavelet singular entropy of vibration signals is obtained to identify the DC bias of the transformer. Then, the neutral DC monitored at the same time is used to verify whether the conclusion obtained by wavelet singular entropy is correct. Finally, to verify the applicability of this method for transformers with multiple voltage levels, this identification method is applied to a 220 kV transformer in the China Southern Power Grid.

A. CASE ANALYSIS 1

The 500 kV transformer in the China Southern Power Grid is selected as the monitoring object. The type of the transformer is ODFPSZ9-250000/525/$\sqrt{3}$. Its rated current is 824.8 A and it is a single-phase three-coil transformer with on-load tap changer. A large number of historical measured vibration signals are analyzed and processed, and according to the expert experience and knowledge, the threshold M of the transformer is set as 1.8. The vibration signal and the neutral DC current within an hour from 5:22 to 6:22 am on May 11, 2019, are monitored in real-time with a sampling frequency of 2000 Hz. The CJBPZ-1 velocity vibration sensor is used to collect vibration signals at the lower-middle position of the side of the transformer tanks. And the HDIE-C41-100P1O23 DC Holzer sensor is used to collect the neutral DC of the transformer, as shown in Fig. 6. And the waveforms of vibration signal and neutral DC monitored from 5:22 to 6:22 am on May 11, 2019, are shown in Fig. 7.

According to Fig. 7, the magnitude of vibration signals fluctuates between 0-2.5 m/s during the period from 5:22 to 5:52, it began to rise during the period from 5:52 to 6:02, and it fluctuates between 0.5-4 m/s during the period from 6:02 to 6:22. Compared with the time before 5:52, the magnitude and fluctuation range of the vibration signal presents an upward trend in the period from 5:52 to 6:02, whereas they are larger in the period from 6:02 to 6:22. According to Fig. 5, the time window is selected as 2 s and the step length is 1/20 s. With the sliding of the time window, the curves of wavelet

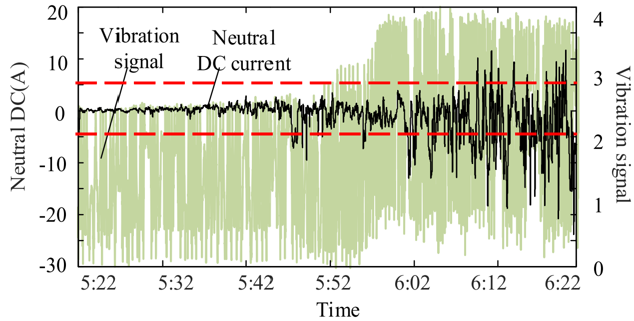


FIGURE 7. The waveform of vibration signal and neutral DC current.

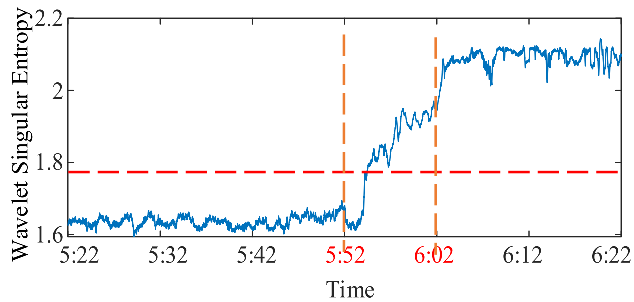


FIGURE 8. The curves of wavelet singular entropy.

singular entropy of vibration signal changing with time can be obtained, as shown in Fig. 8.

Before 5:52, the wavelet singular entropy fluctuates in a small range around 1.65, with the minimum value of 1.61 and the maximum value of 1.69. Within about ten minutes after 5:52, the wavelet singular entropy presents a trend of continuous increase, and its value continuously increasing to 2.1. After 6:02, the wavelet singular entropy fluctuates in a small range around 2.1, with a minimum value of 2.02 and a maximum value of 2.15. Therefore, it is judged that the transformer is under DC bias during the period from 5:32 to 5:52. In the period from 5:52 to 6:02, the transformer gradually begins to appear DC bias. The transformer is under DC bias during the period from 6:02 to 6:22.

According to technical specification for HVDC Transmission Land Return Operation System Design (DL/T 5224-2014), the permissible neutral DC of all kinds of transformers can be as follows: 0.3% of rated current for a single-phase transformer, 0.5% of rated current for a three-phase three-pole transformer, and 0.7% of rated current for a three-phase five-pole transformer. The degree of DC bias is closely related to the DC current flowing in the winding of the transformer. Therefore, 0.3% of the rated current is taken as the neutral DC allowed for the transformer. In other words, whether the neutral DC is greater than 5 A is used to judge whether the transformer is under DC bias.

And it can be known from Fig. 7 that, within the period from 5:22 to 5:52, the maximum and minimum values of the magnitude of neutral DC are 1.441 A and −0.913 A, and the fluctuation range is 2.354 A. The magnitude of the neutral DC of the transformer and its magnitude variation

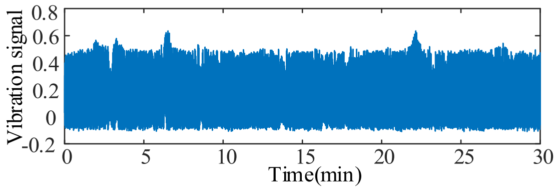


FIGURE 9. The waveform of the vibration signal.

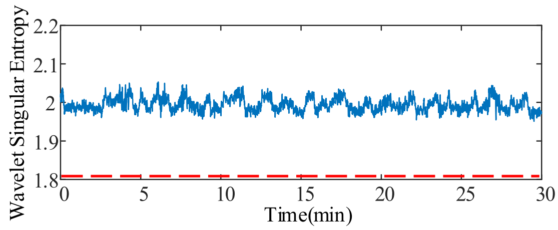


FIGURE 10. The curves of wavelet singular entropy.

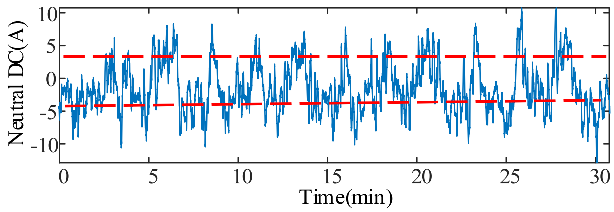


FIGURE 11. The waveform of neutral DC current.

range is relatively small. Within the period from 5:52 to 6:02, the magnitude of the neutral DC increases gradually. Within the period from 6:02 to 6:22, the maximum and minimum values of the magnitude of the neutral DC are 11.59 A and −18.76 A, and the fluctuation range reaches 30 A. The magnitude of the neutral DC increases significantly, and its magnitude changes in a wide range. Thus, the transformer is under no DC bias from 5:22 to 5:52, it begins to appear DC bias from 5:52 to 6:02, and it is under DC bias from 6:02 to 6:22. The above conclusions are consistent with the results based on wavelet singular entropy, showing the feasibility of the method proposed in this paper.

During the operation of the urban rail transit system, the stray current is easily generated. Part of the stray current may flow into the neutrals of the transformer with the neutral grounded, which makes the working point of the magnetization curve deviate and causes DC bias. The shortest distance of the transformer from the train line is 600 m. The transformer is greatly affected by the stray current caused by urban rail transit. The first train departed at 5:52 am, coinciding with the start time of abnormal vibration of the transformer. There is no DC grounding pole near the area where the test transformer is located. Therefore, it is concluded that DC bias is caused by stray current rather than HVDC transmission. Part of the stray current generated by running trains flows into the neutral grounded transformer, then result in DC bias. The train starts to leave after 5:52, the continuous operation of trains will generate stray current, which makes the transformer under DC bias constantly. Therefore, the train starts at 5:52 and the transformer will continue to be affected by DC bias. The above conclusions are consistent with the results based on wavelet singular entropy, which proves the accuracy and effectiveness of the method proposed in this paper again.

B. CASE ANALYSIS 2

The 220 kV main transformer in the China Southern Power Grid is selected as the monitoring object. The type of the transformer is SFSZ11-K-240000/220. Its rated current is 699.8 A and it is a three-phase three-coil transformer with on-load tap changer. A large number of historical measured vibration signals are analyzed and processed, and according to the expert experience and knowledge, the threshold M of the transformer is set as 1.8. The same data acquisition method as in case 1 is selected to monitor vibration signals of transformers. The vibration signal is shown in Fig. 9.

The vibration signal of the transformer is analyzed and processed by the DC bias identification method proposed in this paper. And the curve of wavelet singular entropy changing with time is shown in Fig. 10.

During this period, the wavelet singular entropy is always greater than the threshold value of 1.8, which indicates that the transformer is under DC bias. According to technical specifications for HVDC Transmission Land Return Operation System Design (DL/T 5224-2014), the neutral DC allowed to pass through the three-phase three-column transformer is 0.5% of rated current. Therefore, the value of neutral DC is compared with 3.5 A. If it is larger than 3.5, the transformer is under DC bias. The same data acquisition method as in case analysis 1 is selected to monitor the neutral DC of the transformer. The waveform of neutral DC is shown in Fig. 11.

During this period, the amplitude of the neutral DC is always greater than 3.5 A, so the transformer is under DC bias. It is consistent with the conclusions obtained by the DC bias identification method proposed in this paper. The accuracy and effectiveness of the proposed method for transformers with multiple voltage levels are further verified.

VI. CONCLUSION

Based on wavelet singular entropy, the vibration signal characteristics of transformers under DC bias are obtained, and a state identification method of transformers under DC bias is proposed. The main conclusions are as follows:

1) The difference of the wavelet coefficients between DC bias and no DC bias is obvious. Under no DC bias, the vibration signal is mainly distributed in the low-frequency band (0 Hz to 0.4 kHz), whereas the distribution of the high-frequency band (0.4 kHz to 1 kHz) is very small. The frequency distribution is relatively concentrated, and the wavelet coefficient in the high-frequency band is significantly lower than those in the low-frequency band. However, under DC bias, the wavelet coefficients in the low-frequency band and the high-frequency band increase, and the frequency distribution is relatively divergent.

2) The wavelet singular entropy of transformer under DC bias state is significantly greater than that under no DC bias. Wavelet singular entropy is sensitive to DC bias of transformer, and can effectively detect and identify the DC bias state.

3) Based on the wavelet singular entropy of vibration signal, a DC bias state identification method is proposed. This method is applied to a 500 kV transformer and a 220 kV transformer in the China Southern Power Grid. The results prove the feasibility and accuracy of this method.

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JUN LIU (Member, IEEE) was born in Hunan, China, in 1982. He is currently pursuing the D.Eng. degree with the College of Electrical and Information Engineering, Hunan University, Changsha, China.

Since 2013, he has been with the Electrical Power Research Institute, Guizhou Power Grid Company Ltd., as a Senior Engineer. His research interests include intelligent transmission and transformation equipment, and power transformer fault diagnosis.

HUARONG ZENG was born in Guizhou, China, in 1969. He received the B.Sc. degree from Shanghai Jiao Tong University, Shanghai, China, in 1992.

Since 1992, he has been with the Electrical Power Research Institute, Guizhou Power Grid Company Ltd., as a Professor-Level Senior Engineer. His research interest includes high voltage technology.

WEI NIU was born in Guizhou, China, in 1988. She received the B.Sc. degree in power system and automation from Guizhou University, Guiyang, China, in 2013.

She is currently working with the Electrical Power Research Institute, Guizhou Power Grid Company Ltd. Her research interest includes high voltage technology.

PEILONG CHEN was born in Guizhou, China, in 1985. He received the B.Sc. degree in technology of electromagnetic field and microwaves from North China Electrical Power University, Baoding, China, in 2012.

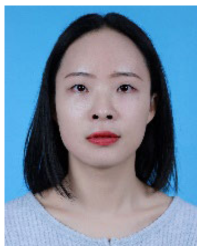
He is currently working with the Electrical Power Research Institute, Guizhou Power Grid Company Ltd., Guizhou, China. His research interest includes high voltage technology.

KUI XU was born in Hubei, China, in 1984. He received the B.Sc. degree in power system and automation from Guizhou University, Guiyang, China, in 2010.

He is currently working with the Electrical Power Research Institute, Guizhou Power Grid Company Ltd. His research interest includes power equipment monitoring technology.

PENG ZENG was born in Hubei, China, in 1988. He received the B.Sc. degree in power system and automation from Guizhou University, Guiyang, China, in 2013.

He is currently working with the Electrical Power Research Institute, Guizhou Power Grid Company Ltd. His research interest includes high voltage technology.



LU ZHAO received the B.Sc. degree in electrical engineering and its automation from Southwest University, Chongqing, China, in 2019. She is currently pursuing the M.S. degree with Southwest Jiaotong University, Chengdu, China.

Her research interest includes evaluation of DC bias.

SHENG LIN (Senior Member, IEEE) received the B.Sc. and Ph.D. degrees from Southwest Jiaotong University, Chengdu, China, in 2006 and 2011, respectively.

From 2009 to 2010, he was a Visiting Scholar with North Carolina State University, Raleigh, NC, USA. He is currently a Professor with the School of Electrical Engineering, Southwest Jiaotong University. His research interests include analysis and mitigation of metro stray current, prediction, and health management of traction power supply systems, protection, and control of AC/DC hybrid systems.