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# Bias magnetic characteristic analysis and condition identification of transformers under DC bias magnetism conditions based on electromagnetic vibration and convolutional neural network

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ABSTRACT

Abnormal vibration of transformers under DC bias magnetism may cause permanent damage to its mechanical structure. Considering the magnetostrictive effect of the core is the main source of vibration in transformers, this paper proposes a method called 2DWT-CNN for identifying DC bias magnetism conditions in transformers by studying the magnetostrictive effect of ferromagnetic materials and analyzing the dynamic process of core deformation. Specifically, the electromagnetic vibration signals of the core and the shell of the transformer were acquired separately on the experimental platform. Then, based on the expansion and contraction characteristics of the core under DC bias magnetism conditions, the magnetic vibration features were extracted using the 2D wavelet transform. Finally, a bias magnetism recognition method called two-dimensional wavelet-convolutional neural network (2DWT-CNN) was established by combining convolutional neural networks as the classifier. The experimental results show that the recognition model has a classification accuracy of almost 100% for the core test points and a prediction accuracy of around 97% for the points located in the transformer's shell. Therefore, the 2DWT-CNN, which takes magnetostrictive effects into account, is an effective method for identifying bias magnetic conditions and can successfully apply the microscopic process of magnetostriction to the macroscopic and practical detection of transformer bias magnetic conditions.

## 1. Introduction

As the most critical electrical component of the power system, the transformer requires stable operating conditions with low vibration and low noise levels. The main source of vibration in transformers is the magnetostriction of the internal iron core. Magnetostriction is a special property of magnetic materials, i.e. the deformation of magnetic materials at different strengths of magnetic fields. The core of a transformer under DC bias conditions can suffer severe abnormal vibrations due to the magnetostriction effect, resulting in serious damage to its mechanical structure. However, with the construction of high-voltage DC transmission systems, the DC bias problem of transformers caused by unipolar operation has been unavoidable. When the DC system is in unipolar operation, there is a DC intrusion at the neutral point of the power transformer [1,2], resulting in a DC bias in the transformer. The mixing of DC in the excitation current of the transformer causes a sudden increase and distortion of the excitation current [3], which may make the core enter the magnetic saturation region. This operating condition leads to an increase in transformer losses [4] while causing an increase in transformer vibration and noise [5], which seriously threatens the safe operation of the transformer and the entire power system [6]. Therefore, accurately identifying the DC bias condition of the transformer is an important part of maintaining the safety of the power system.

Several studies have investigated the bias magnetization conditions of transformer DC from a theoretical point of view, [7] analyzed DC bias

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magnetization using circuit and magnetic circuit methods, and [8,9] simulated the core magnetic saturation phenomenon and vibration of transformers. However, all of the above studies are only at the theoretical and simulation stage. In order to identify the working conditions of transformers in practical industrial applications, more and more studies have measured the vibration signals of transformers to judge the working conditions. Considering that magnetostriction of iron core [10–12] is the main source of transformer vibration, in order to reveal the relationship between vibration and DC magnetic bias, the deformation of transformer iron core under magnetic bias conditions was measured in the study [13]. Further, based on the time–frequency characteristics of transformer vibration signals, some studies have extracted characteristic quantities to reflect transformer DC bias working conditions [14–16]. Hilbert-Huang transform(HHT) was used to analyze the proportion of different frequency bands of DC bias vibration signals, and [17] proposed the ground state energy ratio to quantify the intensity of DC bias. In the study [18], based on the deformation characteristics of silicon steel magnetostrictive core, the energy difference between half-cycle vibration signals is analyzed, and the half-wave energy ratio is proposed to quantitatively analyze DC magnetic bias conditions, which has been applied to the actual measurement of transformer stations. Although the above research extracts DC bias characteristic quantities for transformer operation judgment, it is not reliable to judge the operation state of transformers only relying on several indexes due to the complex working environment of transformers and many external interference sources. Meanwhile, the diagnosis of transformer faults and the analysis of transformer operating conditions by vibration analysis is a new field, and the research on the identification of DC bias conditions is in a vacant state.

To study the deformation of transformers cores under DC bias conditions, a transformer vibration experimental platform is built in this paper. Piezoelectric acceleration sensors are arranged at both ends of the top of transformers shell and the top of the iron core to collect the vibration signals of these points when DC invades the neutral point of the transformer. Taking into account the magnetostrictive properties of the core, the one-dimensional signal is converted into a two-dimensional digital matrix containing the spatial information of the vibration signal in order to extract the DC bias characteristic quantities contained in the vibration signal, and then four similar matrix components are obtained by decomposing the numerical matrix by two-dimensional wavelet transform. Finally, a model called two-dimensional wavelet-convolutional neural network (2DWT-CNN) for transformer bias magnetic condition identification is developed by using four similarity matrix components as inputs to the convolutional neural network. The experimental test results show that the classification accuracy of the recognition model reaches over 97% on all vibration test points, and the classification results on the core test points achieve almost zero error. The main contributions of this paper are as follows:

·Based on the magnetostrictive effect of ferromagnetic material, a two-dimensional wavelet convolution neural network model was established by analyzing the deformation process of transformers core, and the recognition of DC bias conditions of transformers was realized for the first time.

·2DWT-CNN can successfully apply the microscopic process of magnetostriction to the macroscopic and practical detection of transformer bias conditions.

·2DWT-CNN can identify the bias condition of the transformer through the vibration signal of the transformer shell, which effectively avoids the engineering and technical problems that it is difficult to measure the neutral point current of the transformer. The convenience and efficiency of this method lay a foundation for industrial practical application.

·Different from the previous research methods of DC bias, the 2DWT-CNN method realizes the clear classification of transformer operating conditions, avoiding the uncertainty of the indicator threshold setting when judging the transformer operating conditions by a single indicator.

## 2. Transformer core magnetostriction measurement experiments

In this section, the transformer DC magnetic bias vibration experimental platform is introduced in detail, the specific location of each vibration test point is explained and the vibration signals of the iron core and the shell are measured respectively. Then, the vibration signals at different points are analyzed in the time domain and frequency domain.

### 2.1. Magnetostrictive vibration signal collection system

In the transformer vibration experiment system, acceleration sensors are used to collect the signal, and a conditioner is selected to amplify and process the signal. Then, the vibration signal is transmitted through a multi-channel data acquisition card to the computer upper computer software for storage. The specific experimental structure of the above process is shown in Fig. 1(a), where g represents the acceleration of gravity. The actual measurement platform is shown in Fig. 1(b), in which the specific parameters of the piezoelectric transducer are shown in the Table1. The transformer under test is a dry three-phase unit (5kVA, 50 Hz) with a YNy0 type vector group, and the specific parameters are shown in Table 2.

### 2.2. Location of vibration measurement points

The core will vibrate due to magnetostrictive effects and the winding will repeatedly contract radially due to electromagnetic forces. Both core and winding vibrations are transmitted to the transformer housing via the transformer's internal support. The whole process of vibration transmission is shown in Fig. 2.

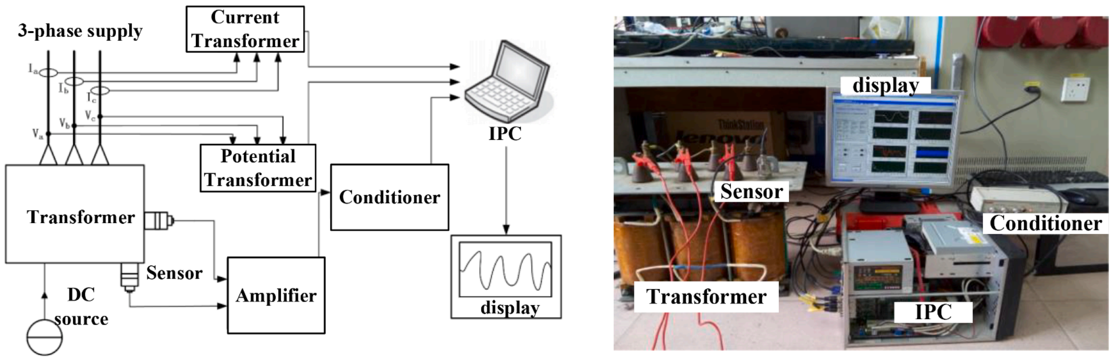
Various parts of the transformer would vibrate as the core and winding are vibrating. Experimental results differ when collecting signals of different parts. To better study the vibration characteristics of the transformer core under DC bias and to avoid a large number of irregular and non-selected signals being measured, sensors are placed in the transformer shell and the top of the core in this experiment. The specific measuring points are shown in Fig. 3.

To compare the effects of signals gained from different measuring points on the classified performance of the recognition model, five different test points were set up on the shell and core. In the actual industrial measurement, only the vibration signal of the transformer shell can be obtained to judge the working condition of the transformer. Therefore, the vibration measuring point of the transformer shell should reflect the real vibration of the transformer core as much as possible. Considering that the transformer core has both longitudinal vibration and transverse contraction, three sensors are respectively placed on the top of the shell just above the three core columns (E, F, L)to collect the longitudinal vibration signals of the core, and two sensors are placed on the left and right sides of the top of the core (A, B) to collect the transverse vibration signals of the core.

### 2.3. Measurement results in the experiment

In actual industrial operation, the DC current intruding into the neutral of the transformer is unstable. The expansion and contraction of the core change in response to the intrusion current, and so does the vibration of the transformer, which makes identification of the transformer's operating conditions very difficult. To simulate this situation, different vibration signals of the transformer with DC intrusion in the neutral points were tested in the experiment, and the signals were divided into two categories: magnetic bias and normal. The measurement results of individual points are shown in Table 3.

In order to observe the variation of transformer vibration signal with the injection of DC more intuitively, the time domain waveform and frequency domain waveform of transformer in normal operation and transformer with its neutral point injected with 2A DC are given in




(a) Experimental system block diagram (b) Vibration experiment platform

**Fig. 1.** Transformer vibration experiment platform. (a) Experimental system block diagram (b) Vibration experiment platform.

**Table 1**
IC piezoelectric acceleration sensor.

| Sensitivity | Range | Frequency | Resonant | Resolution |
|---|---|---|---|---|
| mV/g<br>1000 | g<br>5 | Hz(±10%)<br>0.1–2000 | kHz<br>7.5 | g<br>0.00002 |

**Table 2**
SG-5 Transformer parameters.

| Normal voltage | No-load current | Short-circuit loss | Rated capacity | No-load loss | Impedance voltage |
|---|---|---|---|---|---|
| 400 V | 1.2% | 160 W | 5 kVA | 75 W | 3.50% |

Fig. 4.

The vibration signal at point A, located at the left end of the core, mainly becomes a 50 Hz component and a 200 Hz component. When DC bias occurs the 50 Hz component at point A increases and the 200 Hz component decreases, while the signal amplitude in the time domain increases obviously. The main vibration component of point B located at the right end of the core is 50 Hz component, and the amplitude of the high frequency signal increases significantly with the increase of the intrusion current.

Compared to the core vibration condition, the measurement signals of E, F, L located in the transformer shell are smoother and contain less high frequency noise, and the vibration components of these three points are mainly composed of 100 Hz-350 Hz components. The vibration signal generated by the magnetostriction of the core is lost in the high-frequency vibration portion during transmission through the transformer's internal support, so that the invading DC causes a significant increase in the amplitude of the low-frequency component of the shell while the high-frequency component barely changes.

In the measurement results of the transformer case, the complexity of time and frequency domain signals of point L, located in the middle of the case, is higher than that of test points E, F at both ends. This is because the transformer shell is a rigid body and the three measurement points are close, thus the measured signals of L contain the interference transmitted from points E, F.

According to the above analysis, DC intrusion causes a reduction in the low frequency component and an increase in the amplitude of the high frequency component of the vibration signal located at three points (E, F, L) of the transformer shell. The time and frequency domain complexity and amplitude of the signals located at two points (A,B) of the transformer core increase significantly under the influence of the DC intrusion, but there are no obvious features that can be used to identify DC-biased magnetic conditions.

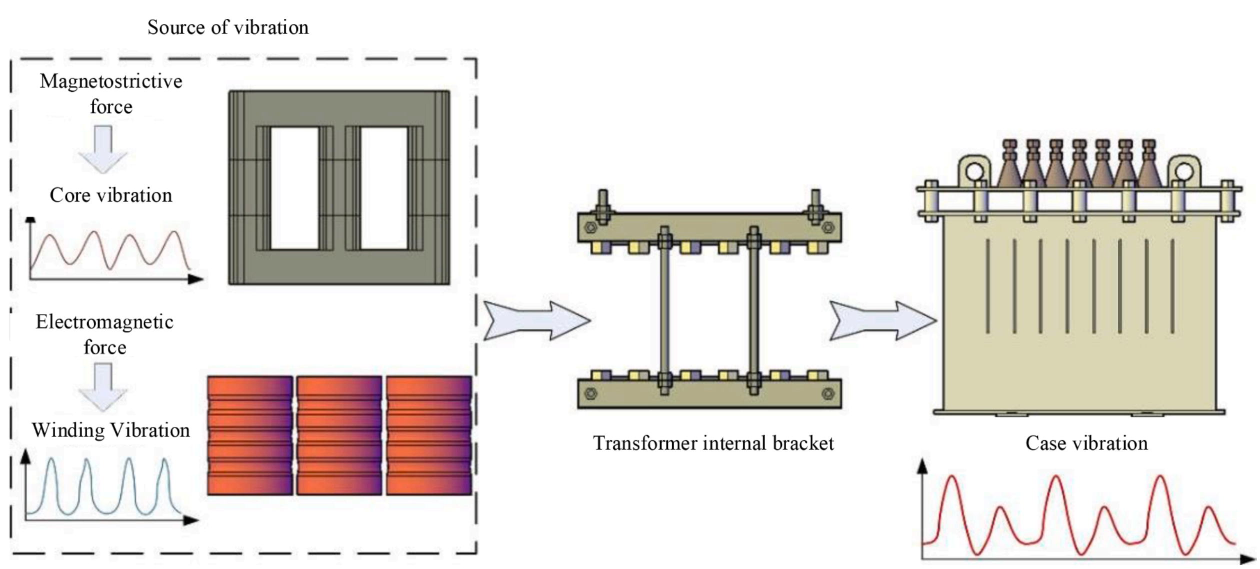



**Fig. 2.** Vibration propagation process.

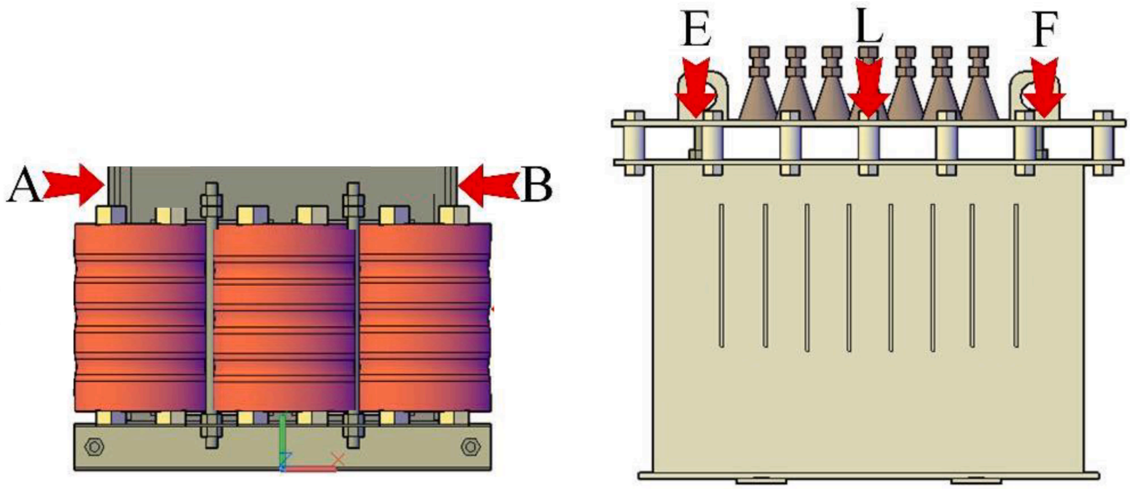



**Fig. 3.** Transformer vibration measurement point.

**Table 3**
Measurement results for each test point.

| Working condition | Injected DC (A) | Number of data sets | Total number of data | Single data length |
|---|---|---|---|---|
| Normal operation | 0 | 3375 | 3375 | 600 |
| DC bias | 0.4 | 675 | 3375 | |
| | 0.8 | 675 | | |
| | 1.2 | 675 | | |
| | 1.6 | 675 | | |
| | 2.0 | 675 | | |

## 3. Vibration signal processing and establishment of recognition model

In this section, the vibration mechanism of a transformer is analyzed from a magnetostrictive point of view and the conversion of a one-dimensional vibration signal into a two-dimensional numerical matrix is described. Then, the matrix is decomposed by the two-dimensional wavelet transform, and the similarity matrix obtained from the decomposition is used to train a convolutional neural network to build a two-dimensional wavelet-convolutional neural network recognition model. Finally, four indicators for evaluating the performance of the classification model are introduced.

### *3.1. Vibration mechanisms analysis and signal processing*

#### *3.1.1. Analysis of vibration mechanism based on magnetostrictive effect*

The magnetostrictive effect of the core is the main source of vibration in transformers and it is essential to understand the vibration characteristics of the core in order to analyze the vibration characteristics of transformers. The core expands and contracts regularly under changing magnetic fields along a magnetostrictive curve as shown in Fig. 5: During the process of changing the magnetic field strength from 0 to the maximum and decreasing from the maximum to 0, there are hysteresis effects, i.e. different amounts of expansion and contraction for the same magnetic field strength.

When DC bias occurs, there is DC intrusion at the neutral point of the transformer, so the excitation current consists of a superposition of sinusoidal and direct currents. The flux is lifted by the mixed excitation current, further causing the core to stretch in the negative half-cycle asymmetrically to the contraction in the positive half-cycle, the whole process described above is shown in Fig. 6. When the DC current is higher, the negative half-wave of the mixed current is smaller and the positive half-wave is larger, which leads to a smaller contraction of the negative half-wave of the core and a larger contraction of the positive half-wave. Therefore, the vibration of the positive and negative half-waves of the transformer can effectively reflect the DC bias working condition.

#### *3.1.2. Two-dimensionalisation of vibration signals considering magnetostrictive characteristics*

The measured vibration signal is one-dimensional with time sequence and with no information on the space sequence. However, according to the magnetostrictive vibration characteristics of the core, important DC bias features are hided between half-periodic waves [14]. Fig. 7 gives the approximate measured signal at point A of the transformer under DC bias conditions and normal conditions respectively. When DC injects 2A, the magnitude of the positive half-cycle signal variation increases and the difference between the positive and negative half-cycle periods increases. To extract the embedded spatial information of the DC bias features, in this paper, the one-dimensional vibration signals are transformed into a two-dimensional numerical matrix, which can be represented by the following equation(1):

$$p(j,k) = \frac{L(jK+k) - MinL}{MaxL - MinL} \tag{1}$$

where L is the length of the 600 vibration signal and P is the numerical matrix obtained through transformation, $k \in (1,30)$ $K \in (0,29)$, $j \in (1,20)$. With the above equation, the $1 \times 600$ serial signal can be transformed into a $20 \times 30$ two-dimensional signal. The specific transformation process is depicted in Fig. 6.

#### *3.1.3. Two-dimensional wavelet decomposition*

The numerical matrix is directly transformed from the one-dimensional vibration signal, which contains the same interference such as noise. In order to reduce the interference and obtain more effective DC bias features, in this paper, two-dimensional wavelets are used to decompose the numerical matrix. The wavelet transform uses a series of wavelets of different scales to decompose the original function, and what obtained is the coefficient [19] of the original function at different scales of wavelets. The wavelet transform has four main steps as follows.

·Step1: Compare the wavelet w(t) with the beginning part of the original function f(t) and calculate the similarity factors between f(t) and the wavelet.

·Step2: Shift the wavelet to the right by k units to get the wavelet w(t-k), and repeat Step 1. Repeat the step until the end of the function f(t).

·Step3: Expand wavelet w(t) to get wavelet w(t/2), repeat Step 1,2.

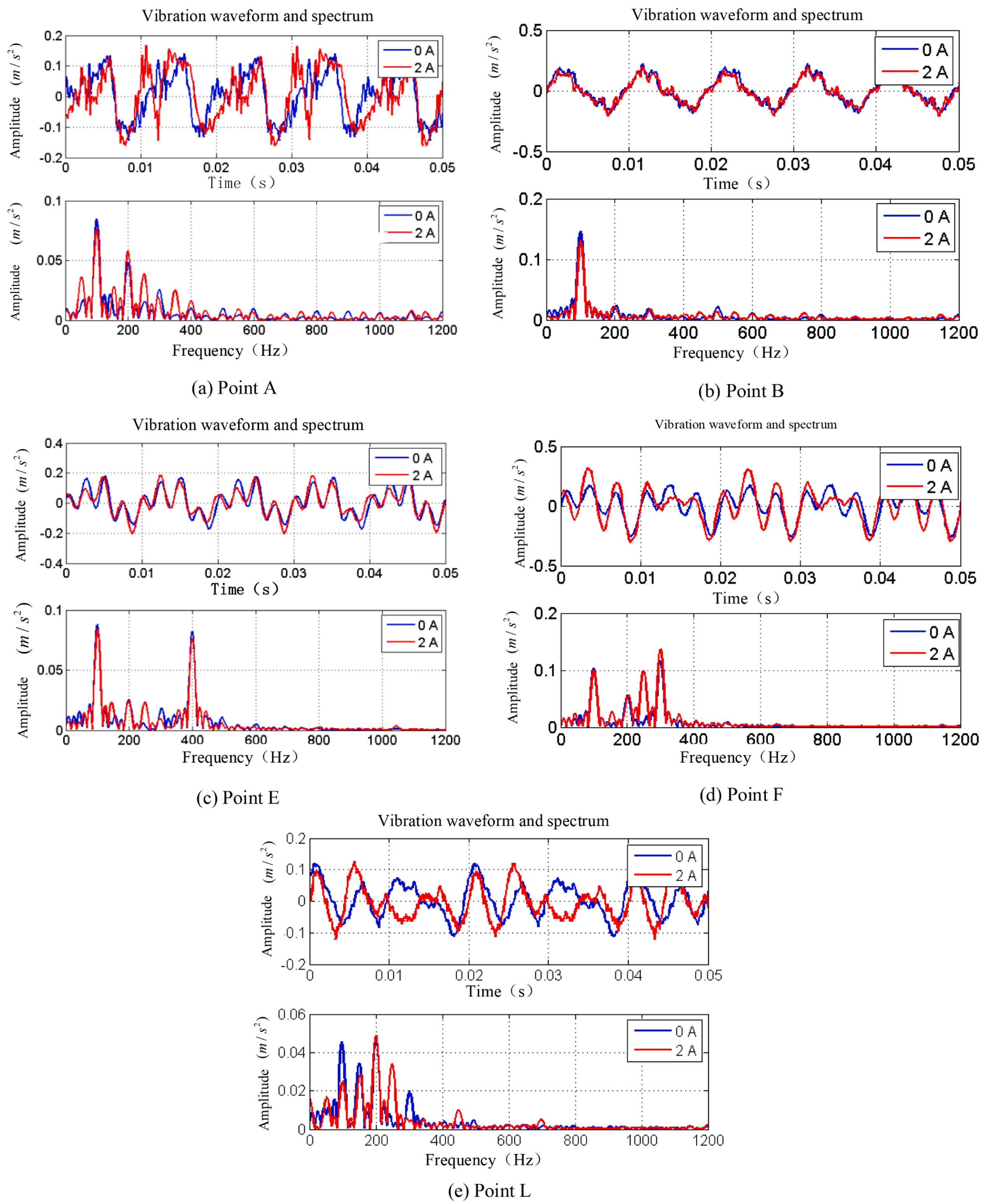



**Fig. 4.** Measurement results at various points.

·Step4: Keep expanding the wavelet and repeat Step 1,2,3.

The decomposition of two-dimensional wavelet is the high-pass and low-pass filtering of the numerical matrix based on the one-dimensional wavelet. The decomposition process of two-dimensional discrete wavelet is shown in Fig. 8.

The process can be described as follows: first, a one-dimensional wavelet transform (1D-DWT) is performed on each row of the image to obtain the low-frequency component L and the high-frequency component H in the horizontal direction of the original image, and then a 1D-DWT is performed on each column of the transformed data to obtain the low-frequency component LL (approximate matrix), the low-frequency in the horizontal direction and the high-frequency in the vertical direction LH (horizontal approximate matrix), the high-frequency in the horizontal direction and the high-frequency in the vertical direction of the numerical matrix in the horizontal and vertical directions (horizontal approximate matrix), high frequency in the

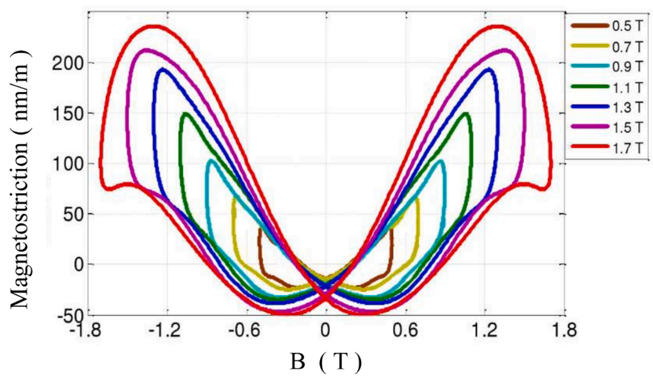



**Fig. 5.** Magnetostrictive Curve.

horizontal direction and low frequency in the vertical direction HL (vertical similarity matrix), and high frequency components in the horizontal and vertical directions HH (diagonal similarity matrix). Taking the vibration signal of point A as an example, the gray-scale image of the vibration numerical matrix of this point after two-dimensional wavelet transform is shown in Fig. 9.

### 3.2. Recognition model based on convolutional neural network

Convolutional neural network (CNN) is a classical deep neural network structure, which has the advantages of weight sharing and automatic feature extraction on training data compared with traditional methods [20]. Therefore, it is a desirable and effective method to use the automatic feature extraction of CNN on the four similarity matrices obtained from the two-dimensional wavelet transform to further extract the DC bias feature information. In this paper, a 7-layer convolutional neural network structure is proposed for the identification of transformer condition under DC bias, which is shown in Fig. 10.

As shown in Fig. 9 above: the network contains two convolutional layers, two pooling layers, two fully connected layers and one deactivation layer. The 15 × 20 numerical matrix, which is a stitching of the approximation matrix and the diagonal similarity matrix, is input. The first convolutional layer is set with 16 convolutional kernel of size 5 × 5, and the second convolution layer set 16 convolution kernels with a size of 2 × 2. Different convolution kernels can extract different features, and convolution kernels are the most important part of feature extraction. The input numerical matrix is convolved with each kernel, and after adding the bias, a convolution layer is gained through the activation function, with 16 feature maps. The equations for the convolution are shown in (2) and (3) below.

$$x_j^{(l)} = \sum_{i \in N_j} a_j^{(l-1)} k_{ij}^l + bc^l \tag{2}$$

$$a_i^{(l)} = f\left(x_j^{(l)}\right) \tag{3}$$

where:$l$ is the number of layers of the neural network,$j$ is the feature

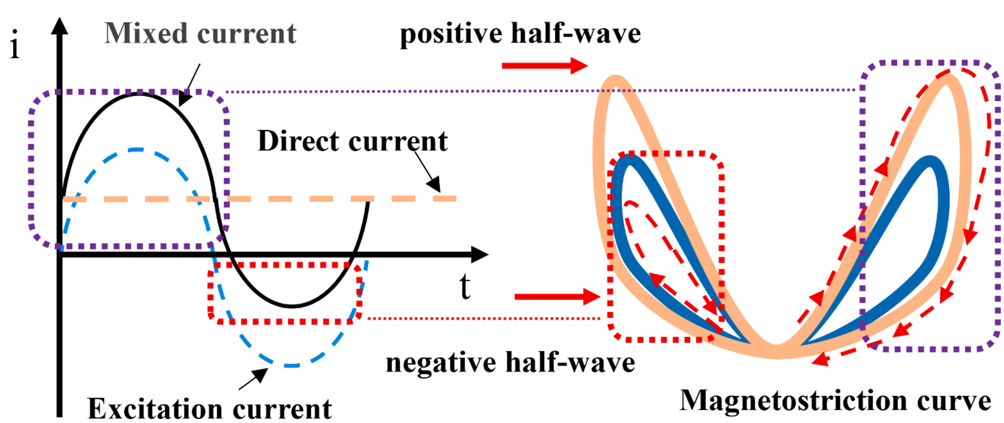



**Fig. 6.** Effect of DC on Magnetostriction.

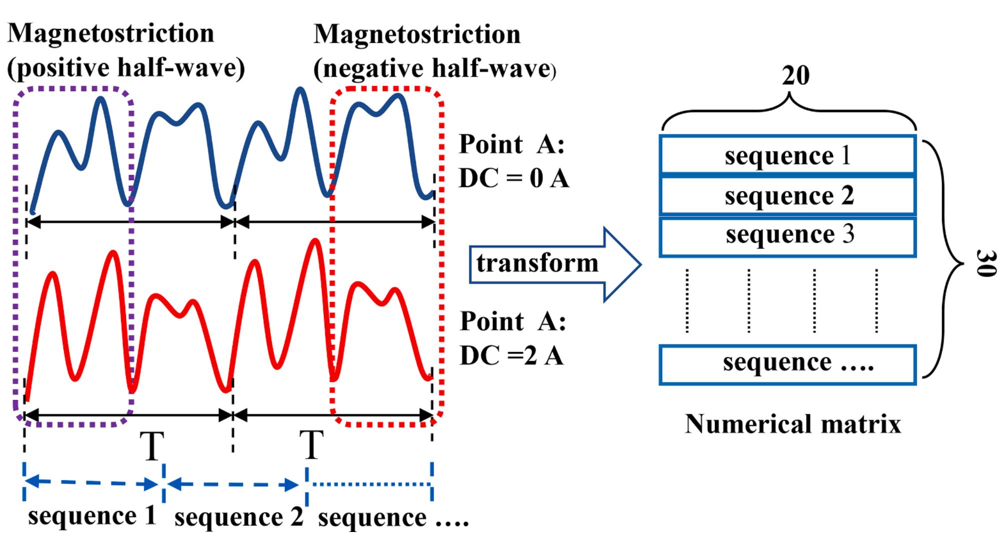



**Fig. 7.** 2D Numerical Matrix Transformation Process.

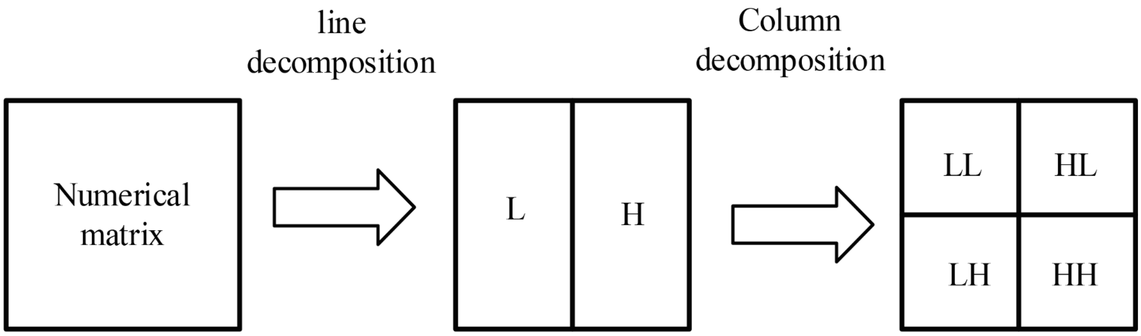



**Fig. 8.** Two-dimensional wavelet decomposition process.

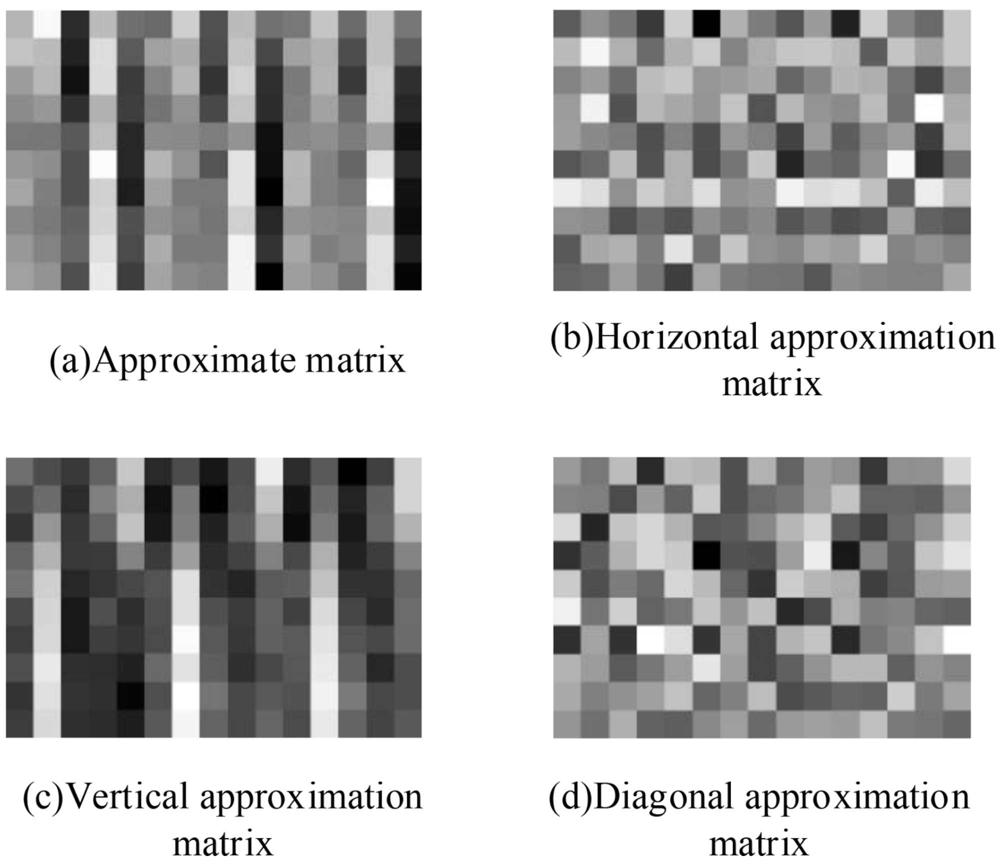



**Fig. 9.** Two-dimensional wavelet transform results.

map,k is the convolution kernel, *bc* is the bias value,$N_j$ is the set of input feature maps, $f$ is the activation function, this paper uses the *ReLU* activation function, the expression is (4).

$$f\left(x_j^{(l)}\right) = \max\left(0, x_j^{(l)}\right) \tag{4}$$

Both pooling layers were pooled using average pooling, the former with a pooling size of 2 × 2 and the latter with 1 × 2. The first fully connected layer with 48 neurons is followed by a deactivation layer with deactivation rate of 0.2, and the last fully connected layer has 2 neurons, with softmax activation function used for classification.

### 3.3. Performance evaluation of classification model

In terms of statistical prediction, it is important to evaluate the performance and correctness of predictors. To examine the effectiveness of classifiers in applications, four metrics, Sensitivity (Sn), Specificity (Sp), Accuracy (Acc), and Mathew's correlation coefficient (MCC) are used to evaluate the classification performance, and they can be expressed by equation (5).

$$\left\{\begin{array}{l} Sn = 1 - \dfrac{N_-^+}{N^+} \\ Sp = 1 - \dfrac{N_+^-}{N^-} \\ Acc = 1 - \dfrac{N_-^+ + N_+^-}{N^+ + N^-} \\ MCC = \dfrac{1 - \left(\dfrac{N_-^+}{N^+} + \dfrac{N_+^-}{N^-}\right)}{\sqrt{\left(1 + \dfrac{N^+}{N_-^+ - N_+^-}\right)\left(1 + \dfrac{N^-}{N_+^- - N_-^+}\right)}} \end{array}\right. \tag{5}$$

The vibration signals collected under normal conditions are considered as positive samples, and the total number of samples is$N^+$.While the

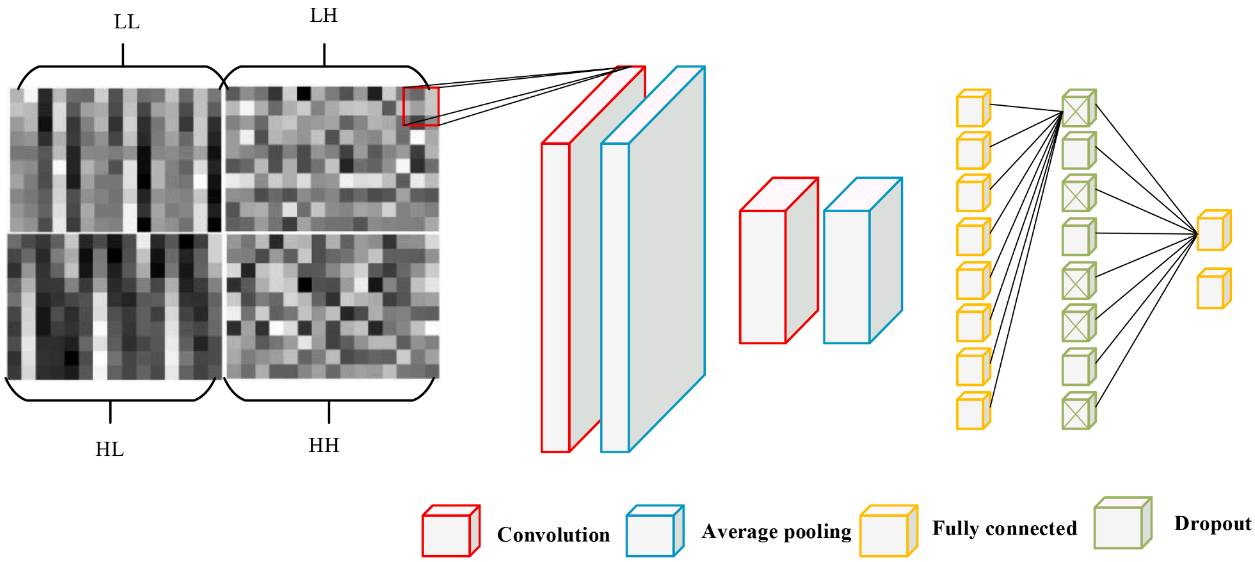



**Fig. 10.** Two-dimensional wavelet convolutional neural network structure.

vibration signals collected under DC bias are considered as negative samples, and the total number is$N^-$. $N_-^+$ is the number of positive samples that are incorrectly predicted as negative samples, and is the number of negative samples that are incorrectly predicted as positive samples. Apparently, Sn is the prediction precision of positive samples, Sp is the prediction precision of negative samples, and MCC is usually used to measure the overall quality of binary classification. When $N_-^+ = N_+^- = 0$, i.e., no positive or negative sample is incorrectly predicted in the baseline dataset, and MCC = 1. When $N_-^+ = N^+/2$ and $N_+^- = N^-/2$, MCC = 0, which means that the prediction result at this point is about the same as random prediction and half of the samples are mispredicted. When$N_-^+ = N^+$and $N_+^- = N^-$, MCC = -1, which means that all samples are predicted incorrectly. Compared with ACC, MCC ranges between −1 and 1, with a higher sensitivity to classification quality. The discussion above shows that the meanings of sensitivity, specificity, overall accuracy, and MCC become more intuitive and easy to understand.

## 4. Results and discussion

In this section, the predicted performance of 2DWT-CNN in the five points on transformer case and core is compared. Besides, the effectiveness of 2D wavelet decomposition on the classification performance improvement is verified, and finally the prediction results of different algorithms as classifiers are compared.

### 4.1. 2DWT-CNN classification results

Eighty percent of the data were used in training the model, and 20% of the data were used to verify the accuracy of the identification model. The predictive performance of the model was verified using a 5-fold cross-check of and the prediction accuracy of each point is shown in Table 4.

As shown in Table 4, the prediction accuracy of both points A, B located at the top left and right ends of the core are around 100%. The Acc of both points E, F located in the housing are around 98.7%, and both Sn and Sp are also around 98.8%. It can be easily found from Fig. 11 that the predicted results of four performance indicators at E and F are similar, and the same situation also occurs at point A and point B. This is because E and F have symmetry in transformer structure, which makes the prediction results similar.

The core is the main source of vibration of the transformer, so the vibration signals collected at points A and B are loss-free. The signal acquired in the shell has some components lost in the internal to external transmission is not a true reflection of the vibration of the core, therefore, the predictive performance of the internal core test points A, B of the transformer is higher than the three test points of the shell (E, F, L).

The prediction performance of the E, F points at the outer ends of the transformer shell is better than that of the L points in the shell. According to the results of the bias vibration measurements, this is because the signal complexity in the middle of the transformer shell is much higher than that of E, F. The information of the bias characteristics is disturbed, resulting in the accuracy of the L points being less than that of the E, F points.

Overall, the two-dimensional wavelet convolutional neural network recognition model has excellent classification performance for both points A, B at the top ends of the transformer core and points E, F, L at the top of the case, and can meet the requirements of industrial-grade applications.

### 4.2. Influence of two-dimensional wavelet transform on classification performance

In order to show that 2-D wavelet decomposition can effectively improve the performance of the recognition model, the prediction accuracy when the original matrix is used as input and the prediction accuracy when four similarity matrices are used as input are compared. Again, taking point B as an example, each performance index is shown in the Fig. 12.

The results show that when the numerical matrix is used directly as the input to the convolutional neural network, a prediction accuracy of about 96% is achieved, which is 3% lower than the overall accuracy when the similarity matrix is used as the input, and the MMC value is even lower by 7%. Meanwhile, Fig. 13 shows that when using the similarity matrix to train the CNN, the accuracy has reached 100% by about 100 iterations, and the loss value drops to zero. In contrast, when training the CNN with the numerical matrix, it takes 180 iterations to

**Table 4**
Classification prediction results.

| Test Points | Sn(%) | Sp(%) | MCC(%) | Acc(%) |
|---|---|---|---|---|
| A | 100 | 100 | 100 | 100 |
| B | 99.85 | 100 | 99.85 | 99.93 |
| E | 98.70 | 98.85 | 98.56 | 98.78 |
| F | 98.60 | 98.82 | 98.51 | 98.71 |
| L | 97.35 | 98.07 | 95.41 | 97.70 |

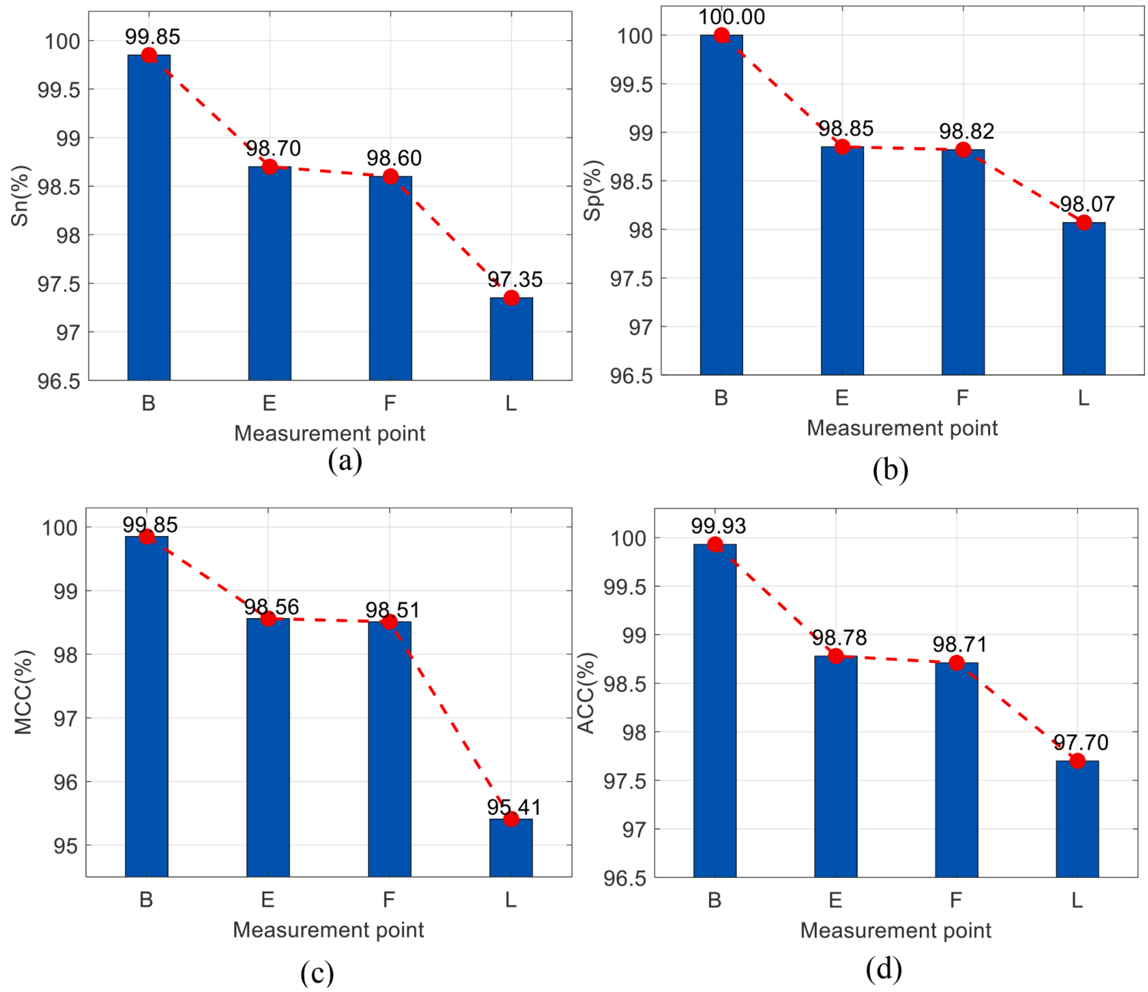



**Fig. 11.** prediction results of different points.

reach 100%, and the convergence speed of the former is substantially higher than that of the latter. This further indicates that the four similarity matrices obtained by the 2D wavelet transform contain richer and more distinct biased magnetic eigenvalues. Therefore, the 2D wavelet transform is an effective method for extracting DC bias features.

### *4.3. Comparison of prediction performance of different classifiers*

The classification accuracy of different predictors are shown in Table 5 and Fig. 14. the prediction accuracy of DT and KNN are both around 80%, while the prediction accuracy of SVM and CNN are over 90%. the CNN method reaches 99%, which is much higher than the MCC of the other four prediction methods. This is due to the convolution operation in CNN, through the weight calculation of the convolution kernel, the nonlinear relationship between adjacent values in the numerical matrix is established, that is, the spatial DC bias magnetic information distributed in the vibration sequence is extracted through the convolution operation, which is not available to other predictors.

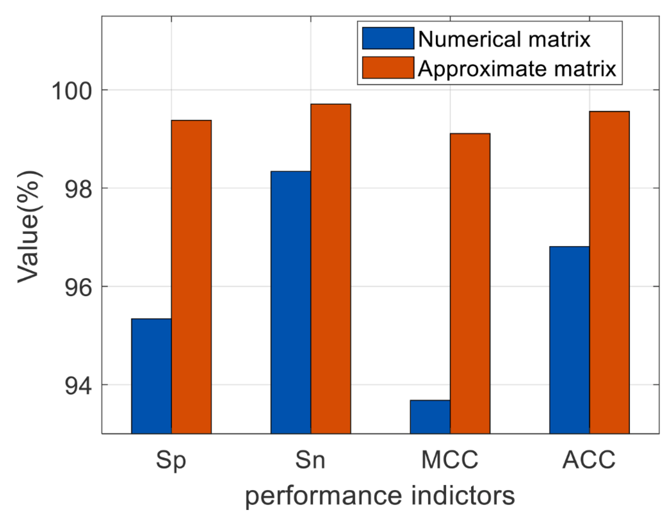



**Fig. 12.** Comparison of classification performance for different input cases.

## 5. Conclusion

Based on the magnetostrictive effect of the iron core, a method called 2DWT-CNN is proposed in this paper to efficiently identify the dc magnetic bias condition of the transformer. According to the magnetostrictive characteristics of the core, the one-dimensional vibration signal is transformed into a two-dimensional numerical matrix, and the DC magnetic bias characteristic in the transformer vibration sequence space is fully considered. Then, the two-dimensional wavelet transform is used to decompose the numerical matrix to further extract the DC bias features, and CNN is selected as the classifier to establish the DC bias condition recognition model. The experimental results show that the classification accuracy of 2DWT-CNN at the core test points is almost 100%, which indicates that the magnetostrictive condition of the core is

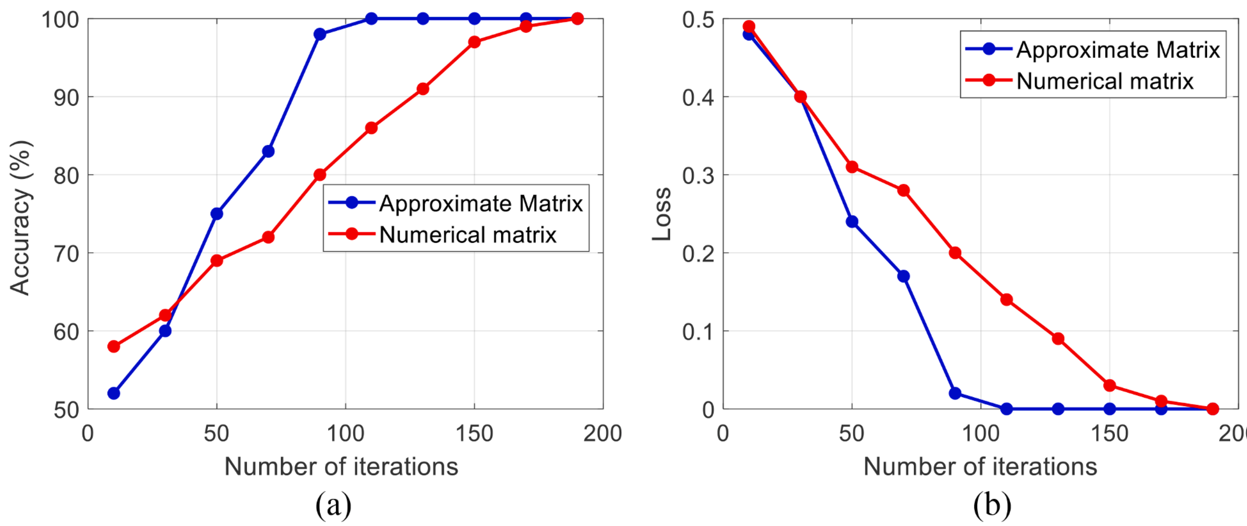



**Fig. 13.** Parameter changes during iteration.

**Table 5**
Classification results of different predictors.

| Predictor | Sn(%) | Sp(%) | MCC(%) | Acc(%) |
|---|---|---|---|---|
| DT | 76.71 | 83.07 | 59.11 | 79.46 |
| RF | 83.33 | 90.61 | 73.69 | 86.67 |
| KNN | 81.37 | 80.24 | 61.62 | 80.75 |
| SVM | 92.29 | 93.85 | 86.08 | 93.04 |
| CNN | 99.85 | 100 | 99.85 | 99.93 |

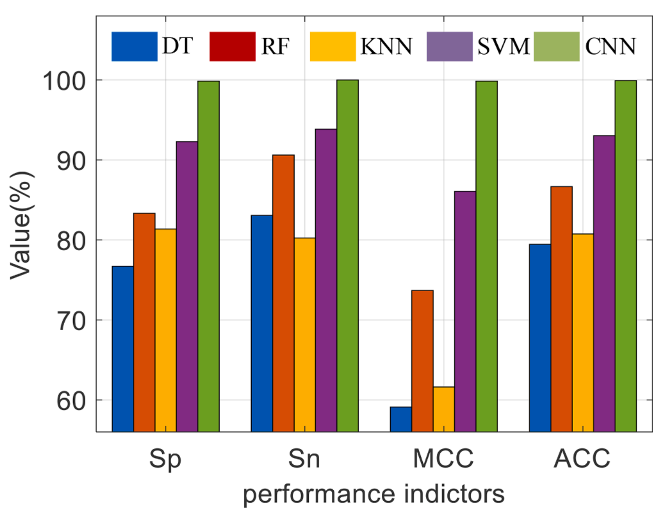



**Fig. 14.** prediction performance of different algorithms.

a direct factor affecting the transformer condition recognition. At the same time, the proposed method achieves more than 97% prediction accuracy at the measuring points of the transformer shell, which can fully meet the needs of industrial practical applications. Therefore, 2DWT-CNN is an efficient and valuable method for transformer condition identification and has successfully applied microscopic magnetostriction to the actual industry.

2DWT-CNN achieves high-precision classification performance on the measuring points of transformers shell, which means that the feasibility of practical operation and the accuracy of prediction classification can meet the requirements of industrial application. Therefore, improving the vibration measurement system and putting it into the application of the power transmission system is the main direction of our future work.

## CRediT authorship contribution statement

**Wang Guo:** Conceptualization, Data curation. **Xingmou Liu:** Investigation. **You Ma:** Resources. **Yongming Yang:** Project administration. **ammad jadoo:** Validation, Visualization.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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