

An Improved Electromagnetic-Structural Coupling Vibration Model of Wound Core Under SPWM Excitation

Beichao Yang , Fei Xiao , Xinsheng Zhang , Ruitian Wang , Xuexin Fan, Guisheng Jie, Haolan Shen, and Luyuan Song

Abstract—The modeling and analysis of transformer core electromagnetic vibration considering hysteresis and magnetostrictive effects are challenging multiphysical problems. For SPWM application scenarios, a new vibration-predicting method of the wound core based on electromagnetic-structural coupling model is presented. First, the magnetostriction neural network model based on time-domain characteristics (MNNM-TD) of core strips is established. Compared with the conventional Jiles–Atherton–Sablik (J-A-S) physical model, MNNM-TD can more accurately describe the features of the magnetostriction under SPWM excitation. Second, a variable-parameter J-A model based on the simplified Newton’s method is presented to obtain the precise flux density distribution. Then, an improved electromagnetic-structural coupling vibration model is built, which is an anisotropic model that simultaneously considers core saturation, hysteresis, and magnetostriction characteristics. Finally, the proposed wound core vibration model is verified by experiments. Under SPWM excitation, the errors of the main components of the acceleration level spectrum are less than 1.65 dB. This article realizes the accurate prediction of the wound core vibration under SPWM excitation, which will contribute to the development of vibration suppression technology for the power electronics system.

Index Terms—Core vibration prediction, coupling modeling, magnetostriction neural network model, SNVP J-A model, SPWM excitation.

I. INTRODUCTION

IN THE change context of transportation electrification, the number of power electronic equipment in the new ship power

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Beichao Yang, Fei Xiao, Xinsheng Zhang, Ruitian Wang, Xuexin Fan, Guisheng Jie, and Haolan Shen are with the National Key Laboratory of Electromagnetic Energy, Naval University of Engineering, Wuhan 430033, China, and also with East Lake Laboratory, Wuhan 430204, China (e-mail: d22180807@nue.edu.cn; zhangxs23@nue.edu.cn; wangrt123@nue.edu.cn; fxxaim0224@nue.edu.cn; zhenyujie@nue.edu.cn; d22180802@nue.edu.cn).

Luyuan Song is with the School of Electrical and Electronic Engineering, Huazhong University of Science and Technology, Wuhan 430070, China (e-mail: m202272009@hust.edu.cn).

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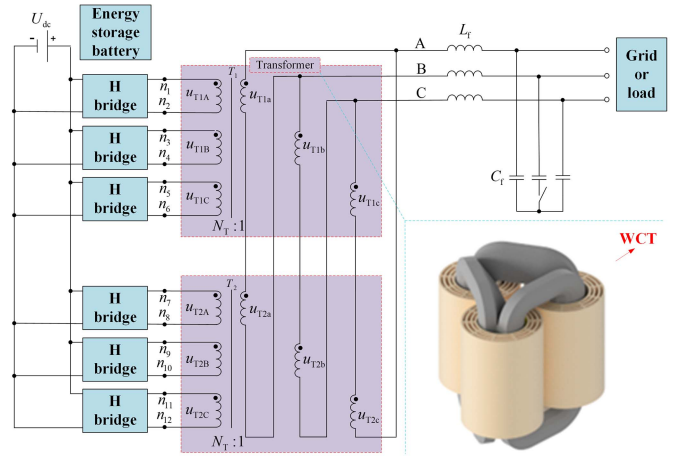


Fig. 1. Topology diagram of the cascaded H-bridge inverter.

system has significantly increased [1]. Especially, in vessel integrated power systems, electrical energy is converted by power electronics to suit different loads, which leads to an increase in the installed capacity of transformers in the power electronics. Fig. 1 shows a topology of a three-phase cascaded H-bridge inverter, which includes the three-dimensional (3-D) wound core transformer (WCT). The wound core flux density contains significant harmonic due to SPWM excitation [2]. The above factors contribute to severe vibration from the WCT.

Many scholars have studied the magnetostrictive modeling of ferromagnetic materials [3] and power transformer vibration modeling [4]. In the field of power electronics, the nonsinusoidal excitation contains abundant harmonics, which intensifies transformer vibration. While the literatures [5] and [6] focus on the vibration modeling of the medium-frequency transformer, this article focuses on transformer vibration under SPWM excitation. The high-frequency components of SPWM can lead to increased transformer vibration, which directly affects the stability and safety of power electronic equipment. Long-term vibration will accumulate mechanical stress in the core and windings, which may trigger structural fatigue and damage to structural components. High-frequency vibration will accelerate the aging of insulating materials, potentially destroying the transformer insulation system and leading to turn-to-turn short circuits. These can reduce the life of the transformer and cause accidents such as

power outages. In addition, severe transformer vibration cannot satisfy the low-noise operation requirements of electrified mobile platforms, such as electric locomotives and luxury cruise ships, which require a quiet and comfortable user experience. Therefore, detailed modeling is essential to accurately predict and suppress transformer vibration characteristics.

From the perspective of the vibration mechanism, the two vibration sources are the core and the winding in the WCT under SPWM excitation. The core is mainly affected by the magnetostrictive effect and Maxwell stress, and the winding is mainly affected by Ampere's force. The wound cores are generally jointless, and the effect of Maxwell stress can be neglected. The core vibration usually contributes more to the transformer foot vibration than windings, which is the focus of transformer vibration and noise reduction [7], so there is an urgent need to accurately predict the vibration characteristics of transformer cores.

In terms of magnetostriction modeling, the following traditional methods have been proposed.

1) *The magnetostriction model based on the J-A hysteresis model and the quadratic domain rotation model*

In [8], the accuracy of the J-A model is improved by introducing a variable pinning parameter. In [9], magnetic field strength is obtained by the indirect coupling method and the J-A model with two variable parameters. However, the problem of anisotropic distribution calculation of transient flux density field have not been solved. Based on the J-A model [10] and combined with the quadratic domain rotation model, a magnetostriction model for the silicon steel sheet is established [11]. The simulation errors of the magnetostrictive response for different working conditions are less than 2%. To include the effects of dynamic magnetization and mechanical stress, Li et al. [12] modified the traditional J-A model and propose a new model combined with the quadratic domain rotation model to estimate the magnetostriction and core losses of amorphous materials. However, none of the above works have carried out experimental validation of the spectral components of the core vibration acceleration to fully verify the accuracy of the model.

2) *The magnetostriction model based on the Preisach model*

Xin et al. [13] derived a nonlinear Preisach model based on the classical Preisach model and Mayergoyz model from the hysteresis principle of ferromagnetic materials and propose a mathematical model capable of describing the magnetostrictive properties of the silicon steel sheet. However, the mathematical model results are not compared with the measurements of the silicon steel sheet, and we are not able to judge the model's accuracy.

3) *The magnetostriction model based on the Energetic model and the improved Jiles–Atherton–Sablik (J-A-S) model*

The Energetic model is a phenomenology model based on the intrinsic energy conservation and the statistical properties of magnetic domains in ferromagnetic materials. Liu and Li [14] proposed a dynamic Energetic hysteresis model based on the field separation technique and loss statistics theory. In [15], a dynamic magnetostriction inverse model is established combining the dynamic Energetic hysteresis model with the improved J-A-S model, and expected simulation results of hysteresis loops and

magnetostriction butterfly curves are obtained under sinusoidal excitations. As the excitation frequency increases, skin effect appears on the surface of the ferromagnetic material, which increases the error of the classical eddy current magnetic field component, and leads to a decrease in the accuracy of the dynamic J-A-S model [15].

Transformer vibration has prominent spectral characteristics that should be of great concern. The magnetostrictive strain spectrum of core strips contains abundant harmonics, which is the main reason for the rich spectrum of core vibration. Wang et al. [3] established a magnetostriction model based on a simple BP neural network considering the frequency-domain characteristics of the magnetostrictive effect of the silicon steel sheet under the dc bias condition, and verify the accuracy of the magnetostrictive strain prediction. However, the simple structure of BP neural network is unable to deal with complex conditions such as SPWM excitation, and it is regretted that this literature fails to realize the coupled modeling of core vibration.

There are significant electromagnetic and structural parameter differences between insulating varnish and core strips in the wound core laminated structure, which introduces significant errors if the wound core is modeled as a solid continuum. However, layer-by-layer modeling of the wound core introduces an unacceptable amount of computational effort, therefore, equivalent modeling of the core laminated structure needs to be carried out.

In terms of core vibration homogenization modeling, homogenization modeling that simultaneously considers the anisotropy of structural and electromagnetic parameters of the core has rarely been reported in the literature. In terms of structural parameter anisotropy, Lahyaoui et al. [16] calculated the corresponding strain energies through tensile tests in three directions of the coordinate axes and then use the structural parameter anisotropy model to estimate the equivalent Young's modulus with the same strain energies. Lv et al. [17] used the modal test calibration method to obtain the equivalent Young's modulus and Poisson's ratio in different directions of the motor stator by cyclic correction. Compared with the test values of modal frequency, the relative error of the finite element method (FEM) values is 3.2%, and the FEM model can reflect the mode shape of the stator.

Regarding electromagnetic parameter anisotropy, Peng et al. [5] established a homogeneous anisotropic core model using equivalent permeability and compare it with the isotropic model. The comparison shows that the magnetic anisotropy of the core caused by the laminated structure significantly affects the magnetic field distribution in the core.

Compared with previous work related to core vibration, the main contributions of this article include.

- 1) The MNNM-TD is proposed to realize the accurate prediction of magnetostrictive strain of core strips under the complex working conditions of single-frequency in the low and middle frequency ranges, superimposed harmonic, and SPWM excitation.
- 2) Aiming at improving the narrow application scope of the parameters of the traditional J-A hysteresis model, a SNVP J-A model is established is used to realize the convergence

calculation of the model. This model can more accurately describe the hysteresis behavior of the core in different flux density distribution regions.

- 3) Based on the MNNM-TD and the SNVP J-A model, the anisotropic wound core vibration model that simultaneously considers core saturation, hysteresis, and magnetostriction is proposed, and the complete vibration modeling process from electrical steel sheet to core is completed. The modeling, calculation and experimental verification of the wound core vibration under SPWM excitation are realized.

The rest of this article is organized as follows. In Section II, the MNNM-TD is proposed and realizes the accurate portrayal of magnetostrictive effect of core strips under the complex working conditions of single-frequency in the low and middle frequency ranges, superimposed harmonic, and SPWM excitation. In Section III, the SNVP J-A model is established, and the “Magnetic flux density-Strain-Stress” calculation module (MSS-CM) is developed, based on which an anisotropic wound core vibration model that simultaneously considers core saturation, hysteresis, and magnetostriction is proposed. In Section IV, the prototype is developed and test verification is conducted. Finally, Section V concludes this article.

II. MAGNETOSTRICTION MODELING OF THE CORE STRIPS

In this section, first, a magnetostriction model based on the J-A model and the improved J-A-S model is established. Second, the MNNM-TD under the complex working conditions is proposed. Finally, the comparative analysis of the two models is carried out.

A. Traditional Physical Model of Magnetostriction

This article associates the J-A hysteresis model and the J-A-S magnetostriction model. The J-A hysteresis model derives flux density B from the input magnetic field strength H . Then, the J-A-S magnetostriction model is used to derive strain λ from the input B .

The J-A hysteresis model is [10]

$$\frac{dB}{dH} = (1 - c) \frac{\delta_M (M_{an} - M)}{\delta k - \alpha \delta_M (M_{an} - M)} + c \frac{dM_{an}}{dH} \quad (1)$$

where k is the pinning parameter, which determines the amount of energy dissipated, α is the mean-field parameter of the internal coupling of the magnetic domains, a is the shape parameter of the anhysteretic magnetization curve, c is the reversible magnetization coefficient, M_{an} is the anhysteretic magnetization strength, and δ_M is the coefficient for avoiding the appearance of nonphysical solution of (1).

Sablik proposes the improved J-A-S model based on the energy minimization principle. The improved J-A-S model with magnetic induction strength as input when no external stress is applied [15]

$$\lambda = -\frac{4n(1+\delta)}{9E} \left\{ \left[1 + \frac{9E}{2n^2(1+\delta)^2} \rho_{\text{mag}} \left(\frac{B_s}{\mu_0} \right) \right]^{1/2} \right.$$

$$\left. - \left[1 + \frac{9E}{2n^2(1+\delta)^2} \left(\rho_{\text{mag}} \left(\frac{B_s}{\mu_0} \right) - \rho_{\text{mag}} \left(\frac{B_p h}{\mu_0} \right) \right) \right]^{1/2} \right\} \quad (2)$$

where n is the magnetoelastic coupling coefficient, δ is the Poisson's ratio, E is Young's modulus, μ_0 is the permeability in a vacuum, B_s is the saturated magnetic induction, M_s is the saturated magnetization strength, h is the normalized magnetic induction, $h = B/B_p$, and B_p is the peak magnetic induction. $\rho_{\text{mag}}(B_p h/\mu_0)$ is the magnetic energy density of the electrical steel sheet, and $\rho_{\text{mag}}(B_s/\mu_0)$ is the magnetic energy density of the electrical steel sheet at the saturation of magnetization, respectively [15].

In this article, the particle swarm optimization algorithm with linearly decreasing inertia weights (PSO-LDIW) is used to extract the parameters (a , k , c , M_s , and α) of the J-A hysteresis model [12]. The principle of the PSO-LDIW algorithm is simple. It can avoid falling into the local optimum too early and owes the global fast search ability. As the number of iterations increases, the inertia weight decreases linearly to ensure better search ability. The extracted parameters of the J-A hysteresis model are used as the known quantities of the J-A-S magnetostriction model. The PSO-LDIW algorithm is also used to extract the J-A-S magnetostriction model parameters (n , α' , and α'').

B. Magnetostriction Neural Network Model Based on Time-Domain Characteristics

In the power electronics industry, different neural network methods have been applied to model identification, reliability prediction, complex modeling, and optimal design [18], [19], [20], [21], [22], [23].

1) *Convolutional Neural Network (CNN)*: CNN is a feed-forward neural network with a convolutional structure, mainly composed of a convolutional layer, a pooling layer, and a fully connected layer [24]. The convolutional and pooling layers have excellent feature extraction capabilities. The primary role of the convolutional layer is to extract features from the input data by continuously iterating the model parameters and sharing the weights. The pooling layer usually follows after the convolutional layer to extract important features and finally outputs them through the fully connected layer. Transformations (e.g., rotation, scaling, and cropping) are applied to the training data to increase the data's diversity and improve the model's generalization ability. The Dropout function is used to randomly discard some neurons during the training process to reduce the model's dependence on specific training samples.

The convolution formula [25] is as follows:

$$G(i, j) = \sum_m \sum_n K(m, n) \bullet D(i - m, j - n) \quad (3)$$

$$C = f(G) \quad (4)$$

where K is the convolution kernel, f is the nonlinear activation function, G denotes the feature mapping, D is the input vector, and C is the convolution result.

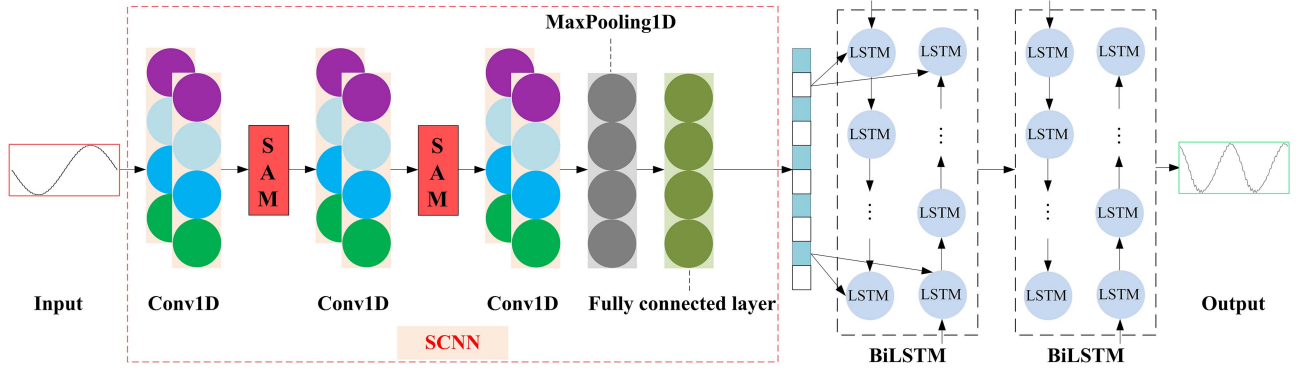


Fig. 2. MNNM-TD.

The formula for the pooling layer is as follows:

$$y = \text{pool}(C, p, s) \quad (5)$$

where p denotes the pool size, and s denotes the step size.

2) *Spatial Attention Mechanism (SAM)*: SAM is an attention mechanism for processing spatial information, which is mainly used to dynamically adjust the importance of different spatial locations of the input data in a neural network model to enhance valid information and suppress invalid information [26]. In fields such as image processing, the SAM can help the model pay better attention to the features of different regions in the image, thus improving the model's representational ability and performance.

Global maximum pooling and global average pooling in the channel dimension are performed on an input feature map of size $J \times W \times C$ to obtain two $J \times W \times 1$ feature maps, and two pooling methods are used in the channel dimension to produce 2-D feature maps

$$\begin{cases} F_{avg}^s \in R^{J \times W \times 1} \\ F_{max}^s \in R^{J \times W \times 1} \end{cases} \quad (6)$$

The results of global maximum pooling and global average pooling are spliced, and a 7×7 convolution operation is performed on the spliced results to obtain the feature dimensions as $J \times W \times 1$. Then, the spatial attention weight matrix W_s is obtained by the Sigmoid activation function S_f

$$\begin{aligned} W_s(F) &= S_f(f^{7 \times 7}([\text{AvgPool}(F); \text{MaxPool}(F)])) \\ &= S_f(f^{7 \times 7}[F_{avg}^s; F_{max}^s]). \end{aligned} \quad (7)$$

3) *Bidirectional Long Short-Term Memory (BiLSTM)*: BiLSTM is a special type of recurrent neural network (RNN) that is able to process sequence data and maintain long-term memory. Unlike traditional RNN models, BiLSTM considers both historical time and future time information, which can allow the model to capture better the contextual relationships in sequence data [27]. Long short-term memory network (LSTM) solves the problem of gradient vanishing or gradient explosion in traditional RNNs by introducing a gating mechanism. BiLSTM is a variant of LSTM, which consists of a combination of forward LSTM and backward LSTM. The hidden state in the BiLSTM

layer is computed as follows [28]:

$$h_{i,t} = f_B(c_{i,t}, \vec{h}_{i,t-1}, \overleftarrow{h}_{i,t+1}) \quad (8)$$

where $h_{i,t}$ is the hidden state of time slice i at time t , f_B denotes the BiLSTM model, $c_{i,t}$ denotes the input features at time t , $\vec{h}$ denotes the forward hidden state, and $\overleftarrow{h}$ denotes the backward hidden state.

The magnetostrictive strain has strong nonlinearity, which is difficult to handle for J-A-S models due to its complex and fixed formula form. In this article, from the time-domain characteristics of the magnetostrictive strain curve, we use the MNNM-TD to portray magnetostrictive strain accurately. As shown in Fig. 2, The main body of the MNNM-TD consists of two parts. First, SAM is utilized to improve the traditional CNN network structure, and SAM is nested into the CNN network to establish the improved network structure SCNN. The time-domain waveform of magnetic flux density is encoded, and spatial characteristics are extracted by CNN. Local features of the waveform are captured using its convolutional layers. Meanwhile, SAM can help the model better focus on the essential features of different regions in the flux density waveform by labeling the weight factors at different regions, such as flux density peaks, changes in the sign of the derivative, and intersection zeros, to pay more attention to the critical identification regions of the time-domain curves of the flux density under single-frequency in the low and middle-frequency ranges, superimposed harmonic, and SPWM excitation, and to further highlight the critical information related to the prediction. Finally, the time-domain sequence of flux density is decoded by BiLSTM to explore further the sequence corresponding features between flux density and magnetostrictive strain, and the feature vectors are extracted by both positive and negative directions to thoroughly analyze the time-domain correspondence between the flux density and the magnetostrictive strain under different complex working conditions.

In this article, the magnetostriction measurement system is used to measure the magnetostrictive strain under the complex working conditions of single-frequency in the low and middle frequency ranges, superimposed harmonic, SPWM excitation, and establish a database [29]. 1) The range of single-frequency

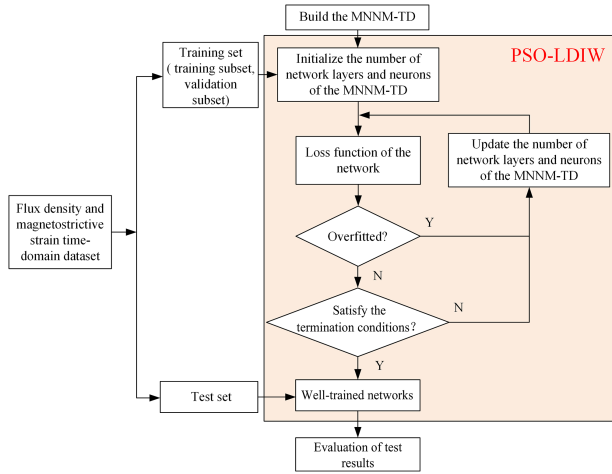
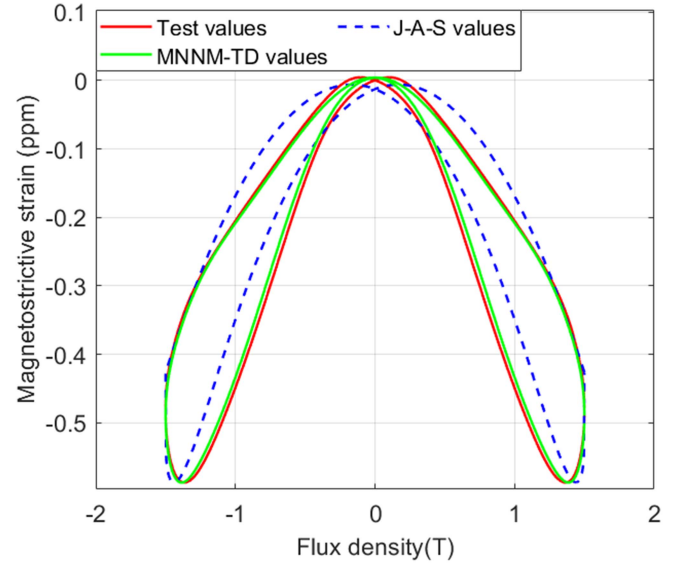


Fig. 3. Workflow for MNNM-TD training.

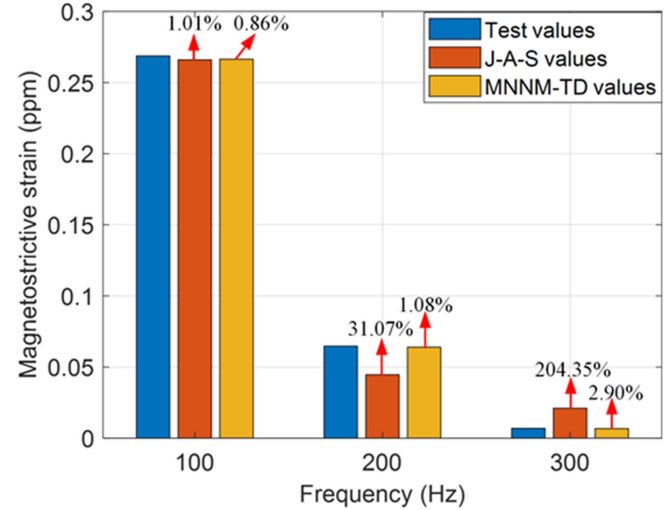
excitation is 50 Hz–400 Hz. 2) The fundamental frequency of superimposed third-harmonic excitation is 50 Hz, the ratio of flux density third-harmonic amplitude to fundamental amplitude varies from 0–0.6, and the phase difference varies from 0° – 180° . 3) The SPWM excitation adopts the unipolar double-frequency modulation, and the modulation ratio varies from 0.5–1, and the carrier frequency varies from 500 Hz–2 kHz. The measured samples of flux density and magnetostrictive strain time-domain characteristics are randomly divided into a test set and a training set, typically 80% of the samples used for training and 20% for testing. The training set is further subdivided into a training subset and a validation subset. Again, the grouping is done randomly, usually 80% of the samples are used for training and 20% for validation.

The PSO-LDIW algorithm is used to optimize the number of network layers and neurons for SCNN and the number of network layers and neurons for BiLSTM in the MNNM-TD. The training process of the MNNM-TD is shown in Fig. 3. When initializing iterations using the PSO-LDIW algorithm, these hyperparameters are usually given in an upper and lower range. For the next iteration, the hyperparameters are selected based on the loss function of the training subset in the previous iteration. A widely used loss function is the mean square error (MSE) [30]. The MSE of the training and validation subsets are compared, and training is stopped if overfitting occurs. If overfitting does not occur and the convergence condition is not satisfied, the number of network layers and neurons for the next iteration is improved based on the MSE.

The optimal solution of the MNNM-TD structure parameters is obtained after 200 iterations using the PSO-LDIW algorithm. The convolutional layer has three layers, the number of neurons is 415, 583, and 385, respectively; the BiLSTM has two layers, the number of neurons is 498 and 512. The mean absolute percentage error (MAPE) is 8.24%, the root-mean-square error (RMSE) is 0.0076, and the coefficient of determination (R^2) is 0.9906. The average training time for one iteration of the PSO-LDIW algorithm is 3.62 min. The prediction of the corresponding magnetostrictive strain based on a set of flux density



(a)



(b)

Fig. 4. Comparison of test values with calculation values by J-A-S model and prediction values by MNNM-TD under single-frequency excitation. (a) Magnetostrictive curves. (b) Spectral components of magnetostrictive strain.

data using the trained model took only 426 μ s on average each time.

C. Model Comparison

The above two models are used to calculate the magnetostrictive strain of the silicon steel sample (20SQG080) under different excitation conditions for comparison.

1) *Single-Frequency Excitation*: As shown in Fig. 4(a), under the flux density peak $B_m = 1.5$ T condition, the magnetostrictive curve calculated by the improved J-A-S model basically matches the peak-to-peak values of the test values, but the matching accuracy of butterfly curve contour is not high. The RMSE is 0.0672, and the MAPE is 59.80%. However, the magnetostrictive curve predicted by the MNNM-TD is basically

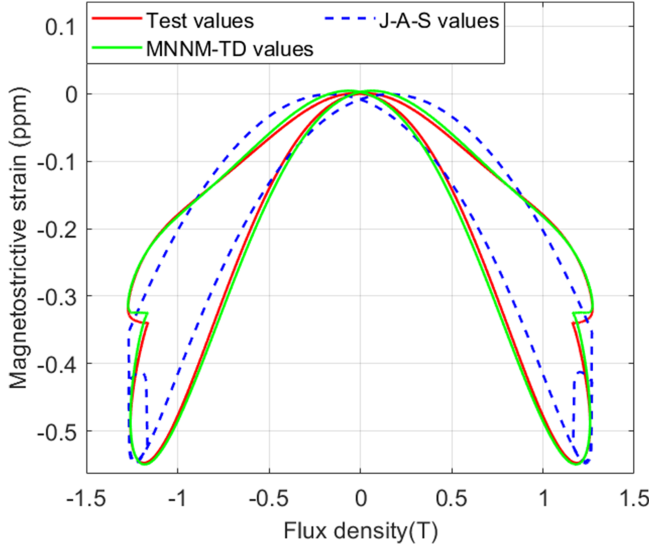


Fig. 5. Comparison of test values with calculation values by J-A-S model and prediction values by MNNM-TD under superimposed harmonic excitation.

consistent with the test values. The RMSE is 0.0065, and the MAPE is 7.23%.

As shown in Fig. 4(b), compared with the test values, the relative error of 100 Hz, 200 Hz, and 300 Hz components of the J-A-S model are 1.01%, 31.07%, and 204.35%, respectively. The main component errors of magnetostrictive strain of the MNNM-TD proposed in this article are lower than 3%, so the accuracy of magnetostrictive strain prediction is higher.

2) *Superimposed Harmonic Excitation*: As shown in Fig. 5, compared with the test values, the J-A-S model is less effective in calculating magnetostrictive curves due to its rigid form under the excitation condition of the fundamental flux density 1.5 T with the third harmonic flux density 0.3 T (phase difference 0°). The RMSE is 0.1288, and the MAPE is 74.94%. However, the magnetostriction curves predicted by the MNNM-TD generally agree with the test values. The RMSE is 0.0095, and the MAPE is 9.12%.

3) *SPWM Excitation*: As shown in Fig. 6, compared with the test values, the J-A-S model is less effective in calculating magnetostrictive curves under the excitation condition of unipolar double-frequency SPWM with carrier frequency 1 kHz, modulation ratio 0.8, and flux density fundamental component 1.5 T at 50 Hz. The RMSE and MAPE are 0.1069 and 138.37%. However, the magnetostriction curves predicted by the MNNM-TD generally agree with the test values. Specifically, the RMSE and MAPE are 0.0087 and 7.94% lower than the J-A-S model.

III. ELECTROMAGNETIC-MECHANICAL COUPLING VIBRATION MODELING METHOD FOR THE WOUND CORE

A. Electromagnetic Field Modeling

1) *Modeling of Electromagnetic Anisotropy*: Due to the fine layering of silicon steel strips, it is considered impractical to model the core layer by layer in FEM simulation. Instead, a

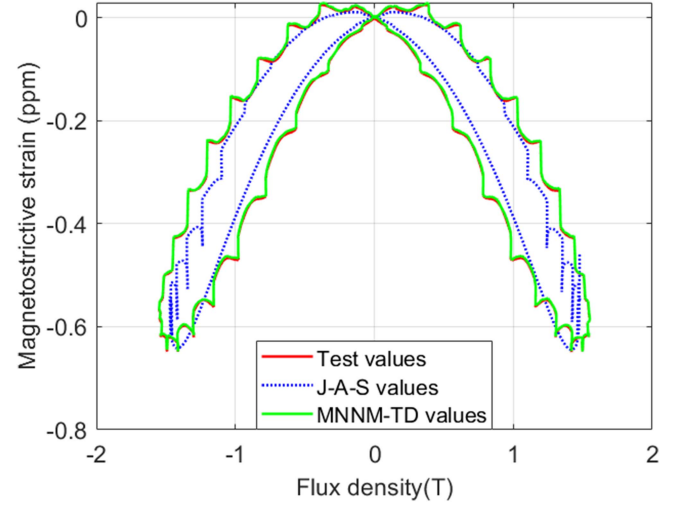


Fig. 6. Comparison of test values with calculation values by J-A-S model and prediction values by MNNM-TD under SPWM excitation.

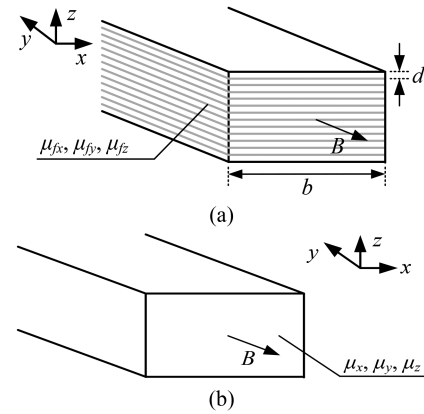


Fig. 7. Schematic diagram of the homogenized anisotropic parameters. (a) Laminated model. (b) Homogenized anisotropy model.

homogenized model with anisotropic permeability has been adopted [31], as shown in Fig. 7.

The transformation equations of homogenized anisotropic parameter for magnetic permeability are as follows:

$$\begin{cases} \mu_x = F\mu_{fx} + (1 - F)\mu_0 \\ \mu_y = F\mu_{fy} + (1 - F)\mu_0 \\ \mu_z = \frac{\mu_{fz}\mu_0}{F\mu_0 + (1-F)\mu_{fz}} \end{cases} \quad (9)$$

where F is the stacking coefficient, d is the thickness of the core strip, and b is the width of the core strip; μ_{fx} , μ_{fy} , and μ_{fz} are the absolute magnetic permeability in the x -, y -, and z -directions of the core strip, μ_x , μ_y , and μ_z are the equivalent absolute magnetic permeability in the x -, y -, and z -directions, and μ_0 is the vacuum magnetic permeability.

The method shown in Fig. 7 and (9) is applicable when the permeability of the core material is linear. To characterize the hysteresis effect of the transformer core, the J-A hysteresis model will be applied and the above method cannot be used.

The schematic diagram of the electromagnetic anisotropic model established in this article is shown in Fig. 8. The core is divided into column, yoke, and chamfer and the column and yoke

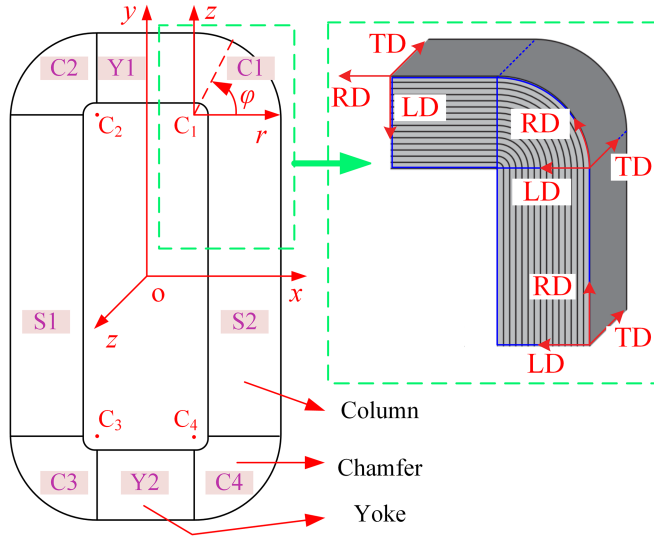


Fig. 8. Schematic diagram of the electromagnetic anisotropic model.

TABLE I
COMPARISON OF J-A MODEL PARAMETERS UNDER DIFFERENT FLUX DENSITY
CONDITIONS (20SQG080 SILICON STEEL SAMPLE)

$B_m(T)$	J-A model parameters				
	$a(A/m)$	$k(A/m)$	c	$M_s(A/m)$	α
1.0	10.18	11.91	0.02263	2.000e+06	5.426e-06
1.1	10.44	13.17	0.02268	2.100e+06	5.749e-06
1.2	10.80	13.54	0.02274	2.050e+06	6.125e-06
1.3	10.80	13.54	0.02274	1.950e+06	6.125e-06
1.4	10.10	14.86	0.02193	1.810e+06	6.080e-06
1.5	7.67	16.01	0.01819	1.514e+06	6.070e-06
1.6	5.66	16.28	0.02269	1.364e+06	7.874e-06
1.7	3.92	21.62	0.02270	1.360e+06	1.060e-05
1.8	2.32	22.84	0.02274	1.432e+06	1.306e-05

use the global rectangular coordinate system, corresponding to the S1, S2, Y1, and Y2 partitions, respectively. The four chamfer partitions use independent local cylindrical coordinate system C_1 – C_4 , corresponding to C1, C2, C3, and C4 partitions, respectively. Then, the anisotropic magnetization model is set up according to the corresponding coordinate system of each partition. The J-A hysteresis model is used for rolling direction (RD) and transverse direction (TD). Considering the effect of the stacking gap of the wound core, the flux component in the laminated direction (LD) is tiny, and equivalent permeability is also significantly lower than that in the RD and TD. Therefore, the linear permeability is used in LD, which is calculated by the initial permeability of the silicon steel sheet according to (9).

2) *Limitations of the J-A Model and the SNVP J-A Model:* The nine sets of detailed J-A model parameters extracted from the measured hysteresis loop under the flux density peak of 1.0 T–1.8 T condition are shown in Table I.

To analyze the effect of the J-A model parameters in different working conditions, the hysteresis loop for the 1.5 T working condition is calculated using the Group a J-A parameters

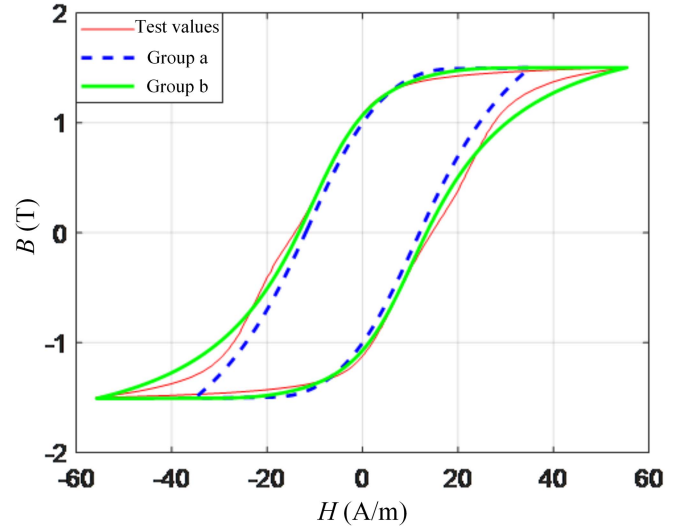


Fig. 9. Comparison of hysteresis loops using different J-A model parameters.

($B_m = 1.2$ T) and the Group b J-A parameters ($B_m = 1.5$ T), respectively. As shown in Fig. 9, The maximum error of H is 19.32 A/m for Group a and 3.25 A/m for Group b. The reason is that the five parameters of the J-A model determine the model's behavior in each condition, and the model parameters extracted by the optimization algorithm perform best only in the condition of the same flux density peak. At a specific excitation voltage, the magnetic flux density has a distributed characteristic within the core cross section, though the magnetic flux within the core is deterministic. Therefore, the hysteresis characteristics over a wide range of flux density cannot be accurately described using the fixed-parameter J-A model in field analysis.

In this article, the SNVP J-A model is adopted. During the field analysis, the J-A model parameters are selected according to the flux density peak at different positions of the core so that the J-A model can accurately characterize the hysteresis effect in the entire core region. According to the multiple sets of J-A parameters in Table I, the functional relationship between the parameters and the flux density peak B_m is established. The regression curves of the parameters a and M_s are shown in Fig. 10.

Fig. 10(a) shows the relationship of a with B_m . The regression expression is

$$a = 110.402B_m^4 - 584.927B_m^3 + 1119.95B_m^2 - 923.099B_m + 287.763. \quad (10)$$

Fig. 10(b) shows the relationship of M_s with B_m . The regression expression is

$$M_s = 4.7902e6B_m^4 - 1.8121e7B_m^3 + 1.8781e7B_m^2 - 6.9204e5B_m - 2.7602e6. \quad (11)$$

3) *Anisotropic Electromagnetic Field Model Validation:* When using the SNVP J-A model to carry out electromagnetic field simulation, since the flux density peak at each position cannot be known in advance, it is necessary to make the SNVP J-A model converge step by step through the iterative method

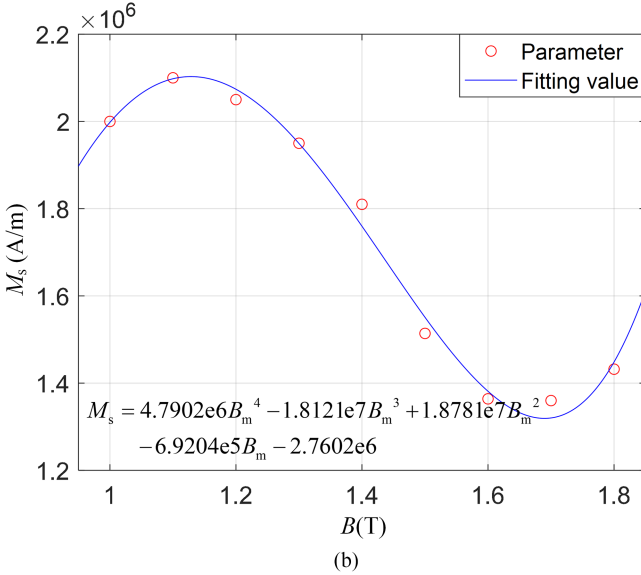
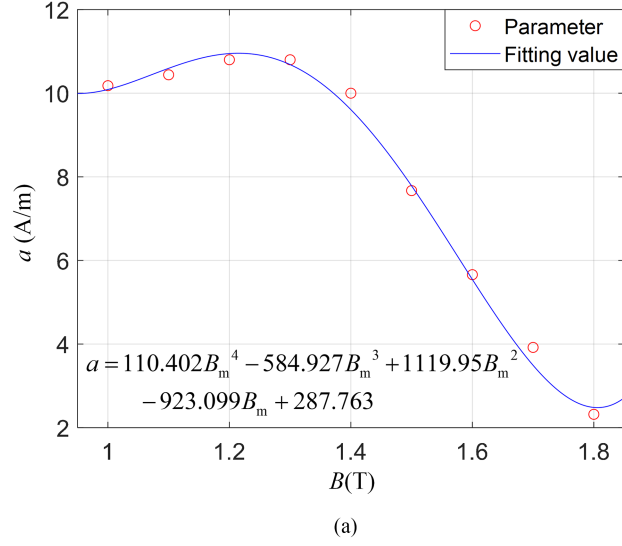


Fig. 10. Extracted J-A model parameters versus B_m . (a) Parameter a . (b) Parameter M_s .

during the calculation process. The function to be solved is as follows:

$$\varphi_{\text{FEM}}(B_{\text{ref}}) = B_{\text{ref}} \quad (12)$$

where $\varphi_{\text{FEM}}(B_{\text{ref}})$ denotes the process of solving the magnetic field in the FEM electromagnetic field model, B_{ref} denotes reference flux density.

In this article, a simplified Newton's method is used

$$f(B_{\text{ref}}) = \varphi_{\text{FEM}}(B_{\text{ref}}) - B_{\text{ref}}. \quad (13)$$

Since, it is not convenient to find the derivative in the FEM simulation, the constant D_c is used instead of the derivative, and the iterative formula is

$$B_{\text{ref}(i+1)} = B_{\text{ref}(i)} - D_c [\varphi_{\text{FEM}}(B_{\text{ref}(i)}) - B_{\text{ref}(i)}] \quad (14)$$

The 2-D FEM electromagnetic anisotropic model of a rectangular cross-section wound core is established by COMSOL.

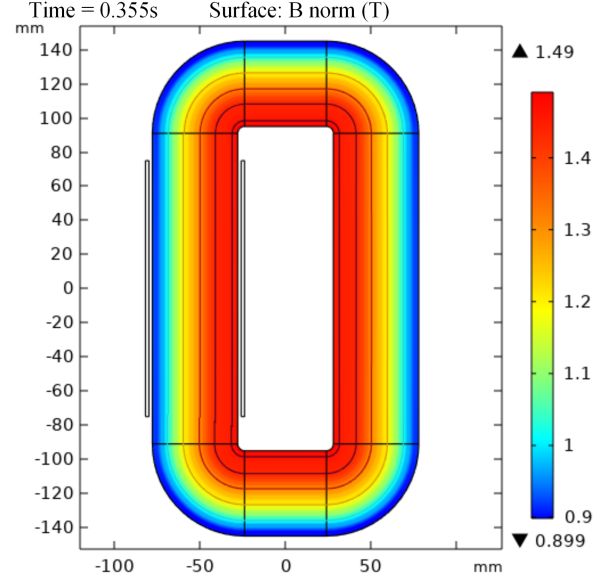


Fig. 11. Magnetic flux density distribution of the FEM model.

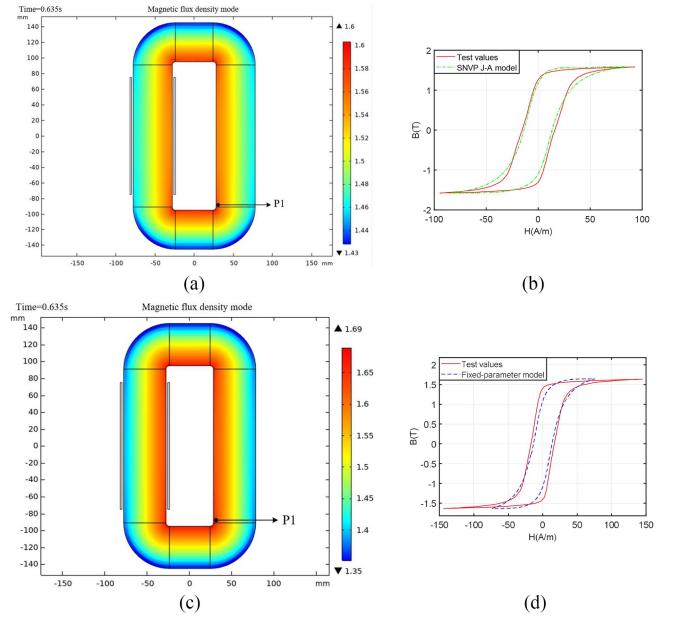


Fig. 12. Comparison of SNVP J-A and fixed-parameter models. (a) Flux density distribution (SNVP J-A). (b) hysteresis loops (SNVP J-A). (c) Flux density distribution (fixed-parameter J-A). (d) Hysteresis loops (fixed-parameter J-A).

Under the power-frequency voltage excitation, the average peak flux density is 1.25 T, and the simulated flux density distribution is shown in Fig. 11. The results show that the flux density of the core is mainly manifested as a gradual decrease from the inner surface to the outer surface.

Under the condition of average peak flux density 1.5 T, the fixed-parameter and the SNVP J-A models are used to carry out the simulation. The hysteresis loops at node P1 are extracted for comparison, as shown in Fig. 12. Compared with the test values, the magnetic field strength peak H_{max} error of the SNVP J-A model is 9.50% at node P1, where the local flux density peak

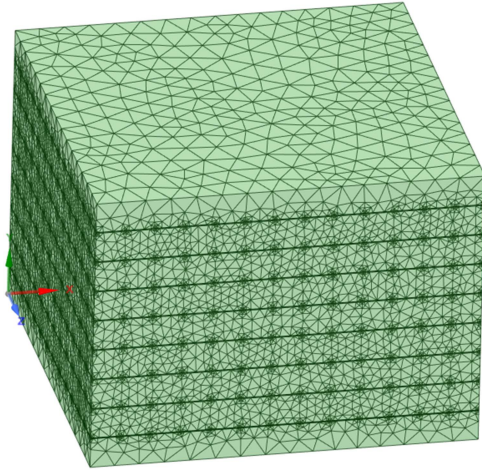


Fig. 13. RVE of the core laminated structure.

is 1.60 T. The magnetic field strength peak $H_{\max}$ error of the fixed-parameter model is 47.64% at node P1, where the local flux density peak is 1.64 T. The accuracy of the SNVP J-A model is significantly higher than the fixed-parameter model. However, the SNVP J-A model has the disadvantage of slower convergence.

B. Structural Field Modeling

1) *Modeling of Structural Anisotropy*: A numerical homogenization method is used to establish the representative volume element (RVE) of the core laminated structure, as shown in Fig. 13. The silicon steel sheet is 0.2 mm thick and alternately laminated with the insulating varnish layer. The silicon steel sheet's volume fraction in the core laminated structure is 0.97.

First, the structural parameters of monolithic silicon steel sheet and epoxy resin varnish are defined. Then, the geometric model is meshed and analyzed by the finite element method to calculate its responses. Finally, the homogenized structural parameters of the core laminated structure are calculated based on the results of these responses. The complex microstructure is simplified into a macro-scale model, thus reducing the computational cost.

The monolithic silicon steel sheet is regarded as a transversely isotropic material. As shown in Fig. 14, the Young's modulus and Poisson's ratio of monolithic silicon steel sheet are measured by a universal tensile testing machine. Young's modulus $E_1 = 118.20\text{GPa}$, $E_2 = 196.12\text{GPa}$, Poisson's ratio $\nu_{12} = 0.40$, and shear modulus $G_{12} = 96.15\text{GPa}$. The epoxy resin varnish is considered as the isotropic material with Young's modulus $E_q = 1.18\text{GPa}$ and Poisson's ratio $\nu_q = 0.38$. The nine homogenized equivalent structural parameters of the laminated structure are shown in Table II. Although the stacking coefficient of the wound core is as high as 97%, the insulating varnish with a volume fraction of 3% causes a significant impact on the mechanical performance of the core.

2) *Anisotropic Structural Field Model Validation*: Consistent with the electromagnetic field modeling, the structural anisotropic parameters also need to be defined separately by

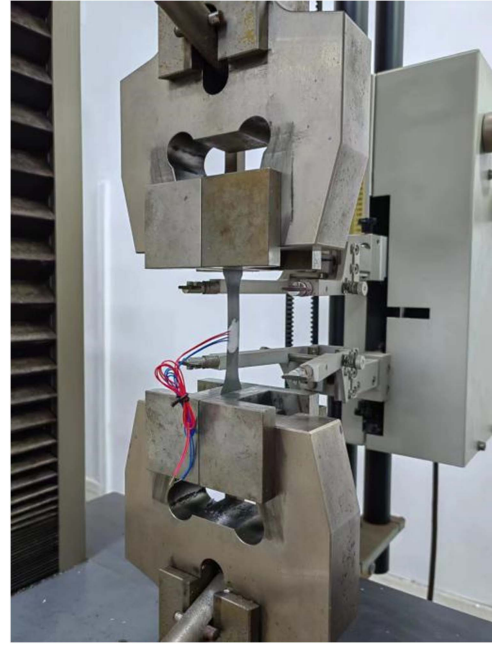


Fig. 14. Test of structural parameters of the monolithic silicon steel sheet.

TABLE II
HOMOGENIZED EQUIVALENT PARAMETERS OF THE LAMINATED STRUCTURE

Homogenized equivalent parameters	Calculated value
E_{RD} (GPa)	114.86
E_{TD} (GPa)	190.37
E_{LD} (GPa)	78.94
ν_{RL}	0.36
ν_{LT}	0.15
ν_{RT}	0.36
G_{RL} (GPa)	10.36
G_{LT} (GPa)	10.16
G_{RT} (GPa)	93.58

region and local coordinate system. The 3-D FEM model of the wound core with the structural parameter anisotropy is established for comparing the modal frequency and mode shape of the wound core with the modal test.

To validate the structural model of the wound core, the single-input multiple-output moving force hammer method is used for the modal test of the wound core. To reflect the geometry of the wound core and obtain its mode shape, the surface of the wound core is uniformly meshed, and seventy-six hammering points and three triaxial acceleration transducers are set up. The test platform is shown in Fig. 15.

The modal frequencies and mode shapes of the wound core are obtained by testing, as shown in Fig. 16. As shown in Table III, compared with the test values, the maximum error of the modal frequency of the anisotropic model is 8.17% when taking the mode shape consistency as the criterion. In comparison, the maximum error of the isotropic model is 99.26%. The structural parameters of the silicon steel sheet are used for the isotropic model.

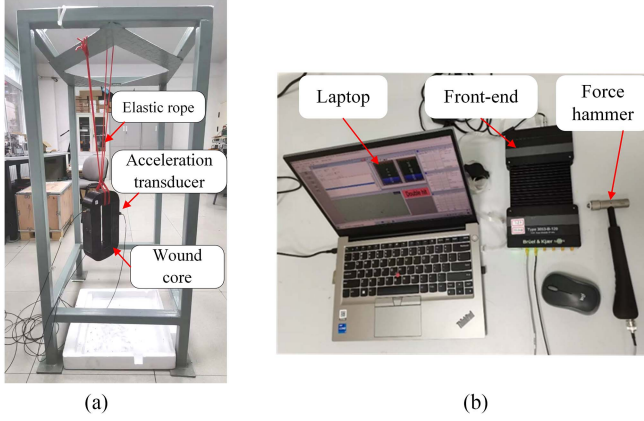


Fig. 15. Modal test. (a) Wound core. (b) Front-end and force hammer.

TABLE III
COMPARISON OF MODAL FREQUENCIES

Modal order	Test values /Hz	FEM values (isotropic model) /Hz	Relative error /%	FEM values (orthotropic model) /Hz	Relative error /%
First	1278	2455.9	92.16	1249	2.27
Second	1532	2908.8	89.87	1571	2.55
Third	1726	3028.8	75.48	1782	3.24
Fourth	2265	3054.5	34.85	2450	8.17
Fifth	2580	5140.9	99.26	2661	3.14
Sixth	3167	4389.5	38.60	3381	6.76
Seventh	3394	5408.1	59.34	3243	4.45
Eighth	3935	7446.6	89.24	4027	2.34

Although the stacking coefficient of the wound core is as high as 97%, the insulating varnish with a volume fraction of 3% causes a significant impact on the mechanical performance of the core. In this article, the anisotropic homogenization method is used to establish the structure model of the wound core, which can accurately and conveniently reflect the mechanical characteristics of the wound core.

C. Electromagnetic-Structural Coupling Modeling

Fig. 17 shows the flow chart of the electromagnetic-mechanical coupling vibration modeling method for the wound core, including the electromagnetic field, MSS-CM, and structural field models. In the electromagnetic field model, an anisotropic hysteresis model is used to characterize the magnetic field distribution inside the core accurately. The structural field is established based on the anisotropic structural parameters of the wound core. The electromagnetic and structural fields are coupled by the MSS-CM to calculate the core vibration response. In this section, the MNNM-TD is used to realize the “Magnetic flux density-Strain” transformation.

The key to realizing the electromagnetic-structural coupling modeling is the MSS-CM. First, the magnetic field is partitioned according to the core structure and magnetic field distribution characteristics, and the vector magnetic field in the global coordinate system is transformed into the local coordinate system of each partition. Second, based on the principle of constant magnetostrictive strain during the analysis process

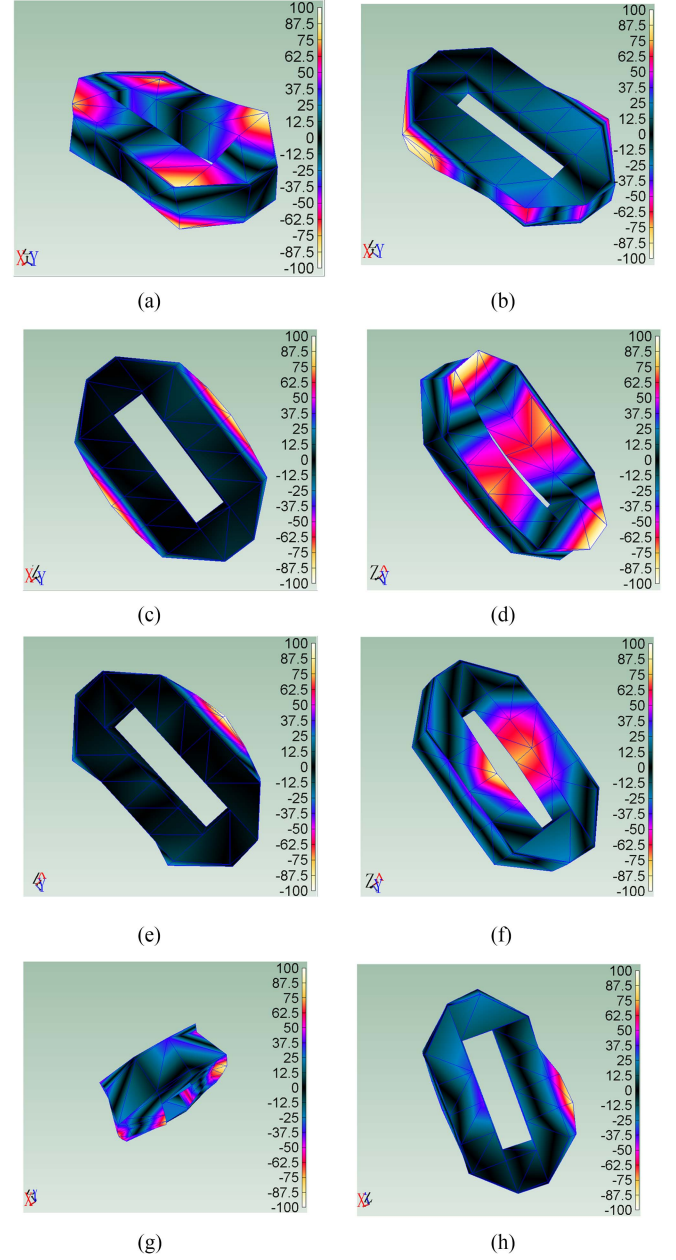


Fig. 16. First eight-orders modal frequencies and mode shapes. (a)–(h) First eighth order mode. (The number of legend color bar is the per-unit value of the displacement deformation).

from monolithic to core, the time-domain waveform of the whole-period flux density is extracted at a point in the partition. The flux density waveform is input into MNNM-TD to compute the magnetostrictive strain time-domain waveform, realizing the “Magnetic flux density-Strain” transformation. Finally, the strain time-domain waveform is loaded into the structural field, and the “Strain-Stress” transformation is realized by the generalized Hooke’s law. The vibration analysis is driven by stress, which is the excitation of the structural model.

It is worth mentioning that the effect of stress on the magnetic field is negligible, and the difference in the hysteresis curve between 10 MPa and 20 MPa is minimal [32]. In this article, the

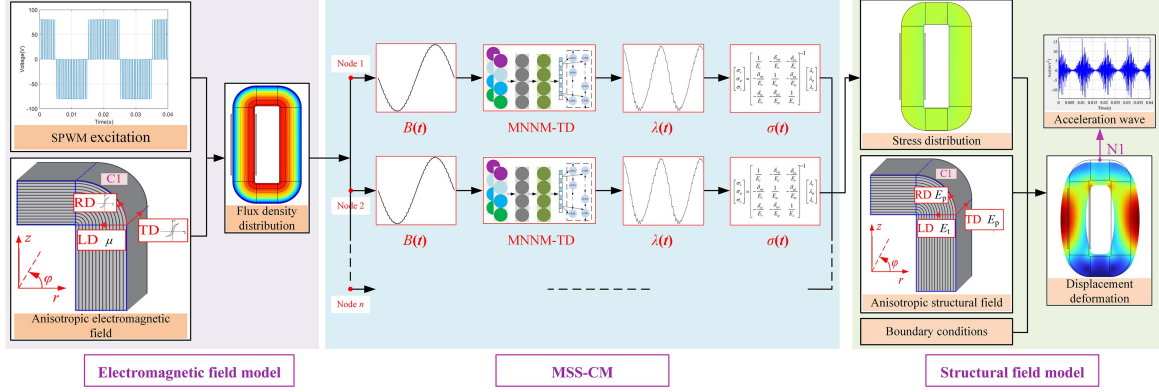


Fig. 17. Flowchart of electromagnetic-mechanical coupling vibration modeling.

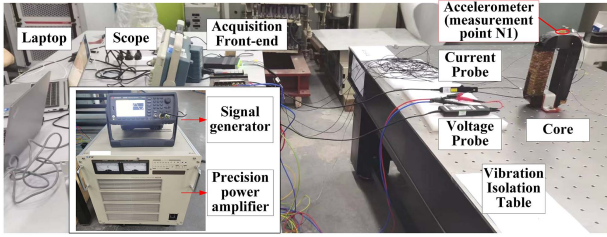


Fig. 18. Experimental platform.

TABLE IV
BASIC PARAMETERS OF THE WOUND CORE

Parameters	Wound core
Turns number	50
Core section	50mm*56mm
Window width	56mm
Window height	190mm
Weight	13.3kg
Stacking coefficient	0.97
State	Annealed

effect of applied external force is not considered, and the effect of stress from magnetostriction on the hysteresis curve of the core strip is neglected.

IV. EXPERIMENTAL VERIFICATION

This section takes the wound core as the research objective. The core vibration test platform is built to verify the accuracy of the vibration model of the wound core.

A. Experimental Platform

As shown in Fig. 18, the core electromagnetic vibration test platform is built. This section takes the rectangular cross-section wound core as the tested objective, and the basic parameters are shown in Table IV. The main parameters of the front-end system, acceleration sensors, and the laser vibrometer are detailed in Table V.

TABLE V
MAIN PARAMETERS OF VIBRATION TEST EQUIPMENT

Test equipment	Type	Main parameters
Front-end acquisition system	Brüel & Kjær 3053-B-120	Channel number: 12; Frequency range: 0-25.6kHz.
Acceleration sensors	Brüel & Kjær 4533-B-001	Weight: 8.6g; Sensitivity at 159.2Hz: 91.61mV/g; Frequency range: 0.2Hz-12.8kHz; Mounted resonance frequency: >38kHz; Measuring range: $\pm 70g$ peak; Residual noise level: 130 μ g.
Laser vibrometer	Optomet LDV-S-N	Working distance: 240mm-100m; Measurement laser: 1550nm; Sense-speed velocity decoder: 1MHz, 12m/s; Length*width*height: 450*224*180mm; Weight: 12kg.

B. Single-Frequency Excitation

To further illustrate the prediction accuracy of the MNNM-TD proposed in this article under different flux densities, the MNNM-TD is compared with the J-A-S model. In this section, the acceleration level AccL is used to evaluate the vertical direction vibration of the measurement point N1, the definition is as follows:

$$\text{AccL} = 20 \log \frac{a_{\text{rms}}}{a_0} \quad (15)$$

where a_{rms} is the acceleration rms value, a_0 is the base acceleration, $a_0 = 1\text{e-}6 \text{ m/s}^2$.

As shown in Fig. 19, the calculated and measured AccL values of the point N1 under the average peak flux density $B_m = 1.5 \text{ T}$ and $B_m = 1.7 \text{ T}$ of power-frequency excitation conditions are compared (ambient temperature 15°C). Under the $B_m = 1.5 \text{ T}$ condition, the calculation errors of the AccLs of 100 Hz, 200 Hz, 315 Hz (center frequencies of 1/3 octave), and the total level based on the J-A-S model are 1.05 dB, 3.41 dB, 6.16 dB, and 15.10 dB, respectively. The prediction errors of the AccLs based on MNNM-TD are 0.85 dB, 0.40 dB, 0.53 dB, and 0.50 dB, respectively. Under the $B_m = 1.7 \text{ T}$ condition, the calculation errors of the AccLs of 100 Hz, 200 Hz, 315 Hz, and the total level based on the J-A-S model are 2.36 dB, 8.28 dB, 6.18 dB,

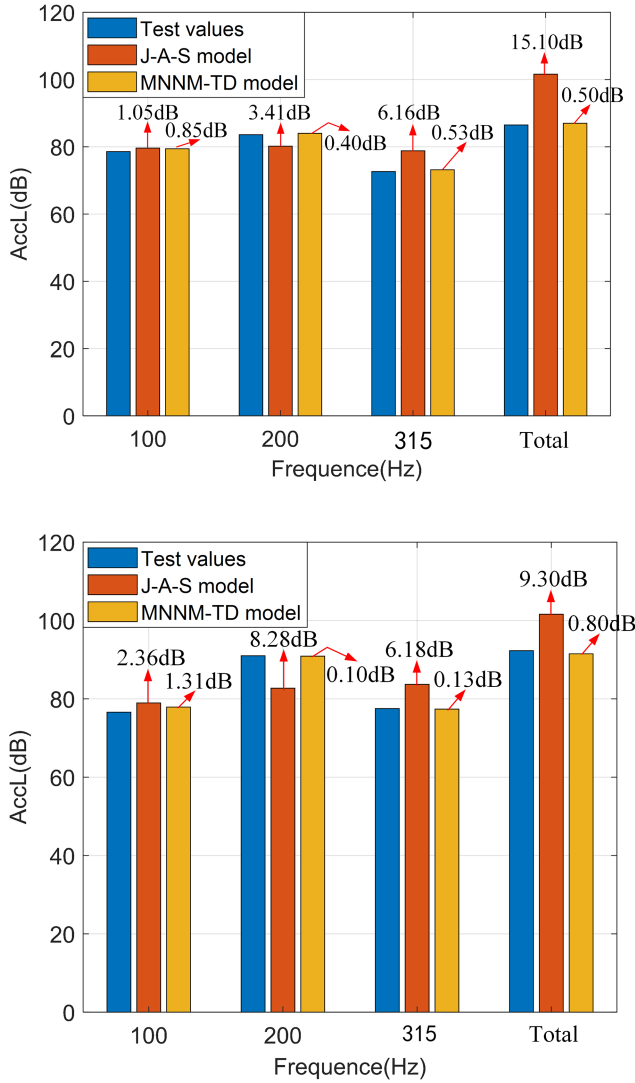


Fig. 19. Acceleration level comparison. (a) $B_m = 1.5T$. (b) $B_m = 1.7T$.

and 9.30 dB, respectively. The prediction errors of the AccLs based on the MNNM-TD are 1.31 dB, 0.10 dB, 0.13 dB, and 0.80 dB, respectively.

The 100 Hz, 200 Hz, and 300 Hz components of the magnetostrictive strain spectrum of the silicon steel sheet are relatively large, which is the root cause of the main components (100 Hz, 200 Hz, and 315 Hz components) of the acceleration spectrum for the wound core. Although the J-A-S model can accurately calculate the peak-to-peak value of magnetostriction, the weak magnetostrictive strain spectrum representation capability of the J-A-S model is the main reasons for the significant errors of 200 Hz and 315 Hz components of the wound core vibration model. However, core vibration prediction based on the MNNM-TD achieves better performance.

The electromagnetic-structural coupling vibration models of the wound core are established based on CNN, BiLSTM, and CNN-LSTM magnetostrictive models, respectively. The spectral comparison of the AccL under the average peak flux density 1.5 T of power-frequency excitation is shown in Table VI. Compared with the test values (ambient temperature 15°C), the

TABLE VI
COMPARISON OF ACCELERATION LEVEL SPECTRA OF THE WOUND CORE UNDER POWER-FREQUENCY EXCITATION

Frequency (Hz)	100	200	315	Total
Test values (dB)	78.57	83.60	72.65	86.50
CNN values (dB)	81.42	80.09	77.88	98.60
CNN errors (dB)	2.85	3.51	5.23	12.10
BiLSTM values (dB)	81.83	86.32	77.40	96.73
BiLSTM errors (dB)	3.26	2.72	4.75	10.23
CNN-LSTM values (dB)	80.35	86.23	76.54	93.24
CNN-LSTM errors (dB)	1.78	2.63	3.89	6.74
MNNM-TD values (dB)	79.42	84.00	73.18	87.00
MNNM-TD errors (dB)	0.85	0.40	0.53	0.50

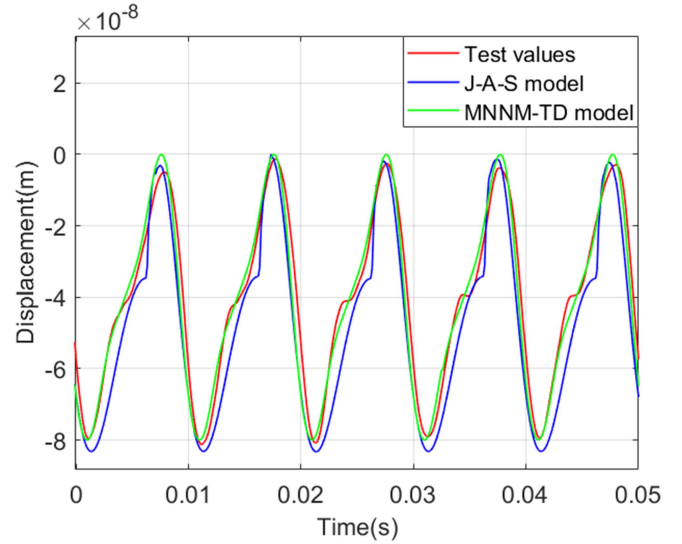


Fig. 20. Comparison of the point N1 displacement.

maximum calculation errors of the 1/3 octave center frequencies of the AccL based on the CNN, BiLSTM, and CNN-LSTM magnetostrictive models are 5.23 dB, 4.75 dB, and 3.89 dB, respectively, which are more obvious than that of the MNNM-TD model. The maximum calculation errors of the total level of the acceleration based on the CNN, BiLSTM, and CNN-LSTM magnetostrictive models are 12.10 dB, 10.23 dB, and 6.74 dB, respectively, which are more obvious than that of the MNNM-TD model.

The velocity of the point N1 is measured by the laser vibrometer, and the displacement is obtained by velocity integration and high-pass filtering. Fig. 20 shows the displacement under the 1.5 T condition. Compared with the test values, the maximum error of the displacement amplitude of the wound core vibration FEM model based on J-A-S model is 8.15%, and the maximum error of the FEM model based on MNNM-TD is 3.04%. The simulated core deformation based on MNNM-TD is shown in Fig. 21.

C. Superimposed Third Harmonic Excitation

Under the fundamental flux density $B_{m1} = 1.5 T$ with the third harmonic flux density $B_{m3} = 0.3 T$ condition, the comparison of acceleration level spectra of the wound core is shown in Fig. 22. Compared with the test values (ambient temperature 15°C), the

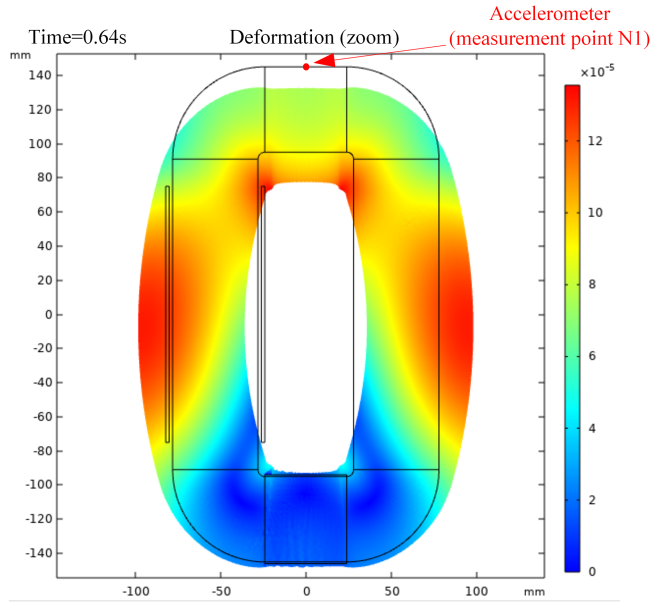


Fig. 21. Wound core deformation. The deformation has been exaggerated 810 000 times for illustration purposes.

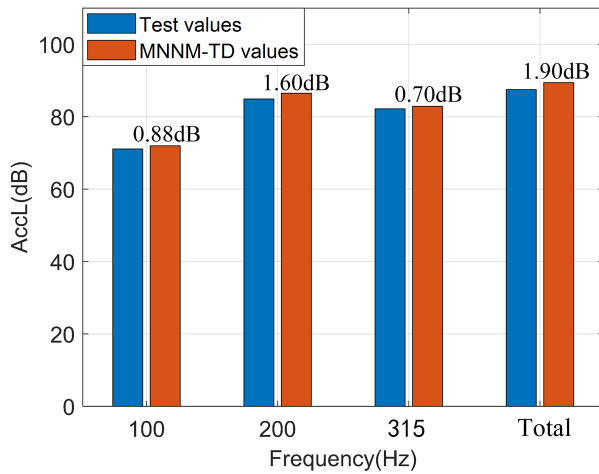


Fig. 22. Acceleration level comparison ($B_{m1}=1.5$ T, $B_{m3}=0.3$ T).

prediction errors of the AccLs of 100 Hz, 200 Hz, 315 Hz, and the total level based on the MNNM-TD are 0.88 dB, 1.60 dB, 0.70 dB, and 1.90 dB, respectively. With the introduction of the third harmonic at the same fundamental flux density, the AccL of 100 Hz component of the wound core decreases, while that of 200 Hz, 315 Hz, and the total level increase.

D. SPWM Excitation

The measured values of the excitation voltage under unipolar double-frequency SPWM with carrier frequency 1 kHz, modulation ratio 0.8, and flux density fundamental component 1.5 T at 50 Hz are shown in Fig. 23. The comparison of acceleration level spectra of the wound core is shown in Fig. 24, and the specific data are listed in Table VII. Compared with the test values (ambient temperature 25°C), the prediction errors of the AccLs of the main components (100 Hz, 200 Hz, 315 Hz, and

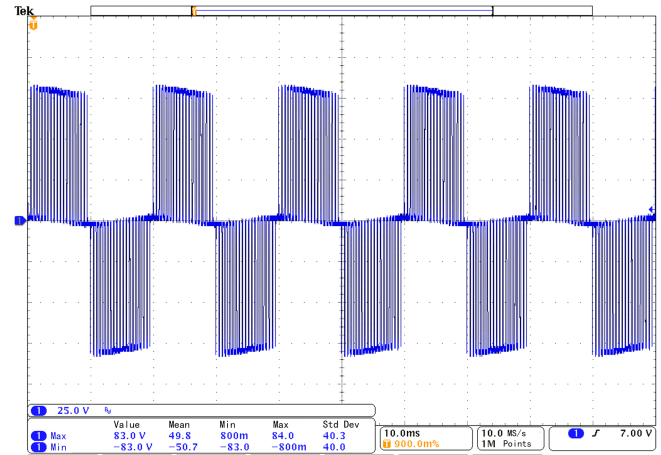


Fig. 23. SPWM excitation (carrier frequency 1 kHz, modulation ratio 0.8).

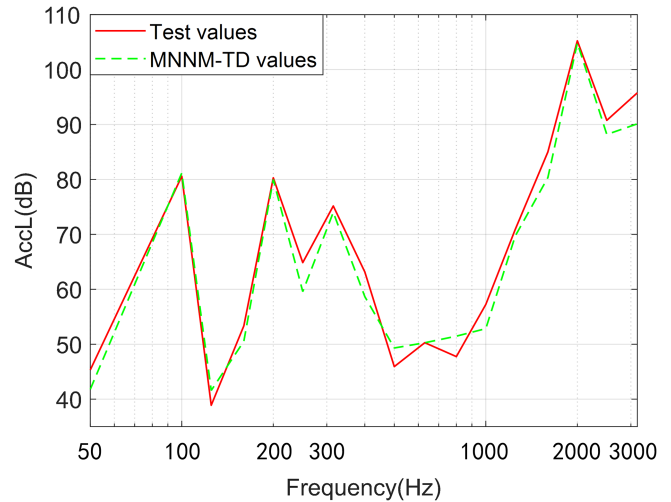


Fig. 24. Acceleration level spectra comparison (SPWM).

TABLE VII
COMPARISON OF ACCELERATION LEVEL SPECTRA OF THE WOUND CORE UNDER SPWM EXCITATION

Frequency (Hz)	100	200	315	2000
Test values (dB)	80.58	80.30	75.17	105.24
FEM values (dB)	81.17	79.99	73.52	105.46
Relative error (dB)	0.59	0.31	1.65	0.22

2 kHz) based on the MNNM-TD are 0.59 dB, 0.31 dB, 1.65 dB, and 0.39 dB, respectively. At the same fundamental flux density, compared to the single-frequency excitation, the AccL of the 200 Hz component of the wound core decreases, and the AccLs of 100 Hz and 315 Hz increase under SPWM excitation.

V. CONCLUSION

The modeling and analysis of transformer core vibration considering hysteresis and magnetostrictive effects are challenging multi-physical problems. In this article, the MNNM-TD under complex working conditions is proposed; considering the physical characteristics of the core's electromagnetic and structural

anisotropy, the core vibration model that simultaneously considers core saturation, hysteresis, and magnetostriction is proposed. This article realizes the modeling, calculation, and experimental verification of the wound core vibration under SPWM excitation. The main conclusions are drawn as follows.

- 1) The MNNM-TD of core strips is proposed based on time-domain characteristics. Compared with the test values, the magnetostriction curves predicted by the MNNM-TD generally agree with the test values under the excitation condition of unipolar double-frequency SPWM with carrier frequency 1 kHz, modulation ratio 0.8, and flux density fundamental component 1.5 T at 50 Hz. Specifically, the RMSE and MAPE are 0.0087 and 7.94% lower than the J-A-S model.
- 2) Aiming to improve the narrow application scope of the parameters of the traditional J-A hysteresis model, this article establishes a SNVP J-A model and adopts the simplified Newton's method to realize the convergence calculation. In the case of FEM simulations under the condition of average peak flux density 1.5 T, at the node of local flux density peak 1.6 T, the $H_{\max}$ error of the SNVP J-A model is 9.5%, and that of the fixed-parameter model is 31.2%, which indicates that the accuracy of the SNVP J-A model is significantly higher than the fixed-parameter model.
- 3) The wound core vibration test is carried out. Under single-frequency excitation ($B_m = 1.5$ T and $B_m = 1.7$ T), the prediction errors of the AccLs of 100 Hz, 200 Hz, and 315 Hz based on the MNNM-TD are less than 1.31 dB, and the error of the total level is less than 0.80 dB.
- 4) Based on the proposed model, the core vibration under superimposed third harmonic excitation is analyzed. Under the condition of the flux density fundamental frequency 1.5 T with the third harmonic 0.3 T, the prediction errors of the AccLs of 100 Hz, 200 Hz, 315 Hz, and the total level based on the MNNM-TD are 0.88 dB, 1.60 dB, 0.70 dB, and 1.90 dB, respectively.
- 5) Under unipolar double-frequency SPWM with carrier frequency 1 kHz, modulation ratio 0.8, and flux density fundamental component 1.5 T at 50 Hz, compared with the test values (ambient temperature 25°C), the prediction errors of the AccLs of 100 Hz, 200 Hz, 315 Hz, and 2 kHz based on the MNNM-TD are 0.59 dB, 0.31 dB, 1.65 dB, and 0.22 dB, respectively. At the same fundamental flux density, compared to the single-frequency excitation, the AccL of the 200 Hz component of the wound core decreases, and the AccLs of 100 Hz and 315 Hz increase under SPWM excitation. The proposed model has engineering utility capacity in the analysis of electromagnetic vibration of the wound core under SPWM excitation.

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Xinsheng Zhang received the B.S. degree in electrical engineering and automation from Shandong University, Jinan, China, in 2015 and the M.S. and Ph.D. degrees in electrical engineering and automation from Naval University of Engineering, Wuhan, China, in 2017 and 2022, respectively.

His research interests include design and analysis of magnetic components in power electronics converters.



Ruitian Wang received the B.S. degree in automation from Huazhong University of Science and Technology, Wuhan, China, in 2008 and the M.S. and Ph.D. degrees in electrical engineering from Naval University of Engineering, Wuhan, China, in 2010 and 2014, respectively.

In 2015, he was a Lecturer with the Naval University of Engineering, where he was promoted to an Associate Professor in 2018. His research interests include medium-voltage large-power dc-dc converter and multiobjective optimization of magnetic components.



tronics converters.

Beichao Yang received the B.E. degree in civil engineering from China University of Geosciences, Wuhan, China, in 2016 and the M.S. degree in electrical engineering from Naval University of Engineering, Wuhan, China, in 2021. He is currently working toward the Ph.D. degree in electrical engineering with the National Key Laboratory of Science and Technology on Vessel Integrated Power System, Naval University of Engineering, Wuhan, China.

His research interests include modeling and optimal design of magnetic components in power electronics converters.



Xuexin Fan was born in Zhejiang, China, in 1977. He received the B.S. and M.S. degrees in electrical engineering from the Naval University of Engineering, Wuhan, China, in 2000 and 2003, respectively.

From 2003 to 2013, he was a Lecturer with the Naval University of Engineering, where he was promoted to Associate Professor in 2013. His current research interests include independent power system and medium-voltage large-capacity dc–dc converter.



Fei Xiao was born in Hubei province, China, in 1977. He received the B.S. and M.S. degrees from the Naval University of Engineering, Wuhan, China, in 1999 and 2001, respectively, and the Ph.D. degree from Zhejiang University, Hangzhou, China, in 2012, all in electrical engineering.

From 2003 to 2009, he was a Lecturer with the Naval University of Engineering, where he was promoted to an Associate Professor in 2009 and to a Full Professor in 2012. His current research interests include renewable energy generation, modeling and

control of power electronics system, and high-voltage large-capacity power electronics equipment.

Dr. Xiao is currently the Committee Member of the Department of Energy and Transportation, China Ministry of Science and Technology.



Guisheng Jie received the B.S. and M.S. degrees in ordnance engineering from the Naval University of Engineering, Wuhan, China, in 1998 and 2001, respectively, and the Ph.D. degree in electrical engineering from the Naval University of Engineering, Wuhan, China, in 2005.

From 2005 to 2008, he was a Lecturer with the Naval University of Engineering, where he was promoted to an Associate Research Fellow in 2008 and to a Research Fellow in 2014. His current research interests include large-power inverters and electric vehicle drives.



Haolan Shen was born in Hunan, China, in 1997. He received the B.S. degree in electrical engineering from Zhejiang University, Hangzhou, China, in 2019, and the M.S. degree in electrical engineering in 2021 from Naval University of Engineering, Wuhan, China, where he is currently working toward the Ph.D. degree in electrical engineering.

His research interests include power electronics, fault diagnosis, and fault tolerant control.



Luyuan Song received the B.E. degree in electrical engineering from the Hefei University of Technology, Hefei, China, in 2021. He is currently working toward the M.S. degree in electrical engineering with the School of Electrical and Electronic Engineering, Huazhong University of Science and Technology, Wuhan, China.

His research interests include modeling and optimal design of magnetic components in power electronics converters.