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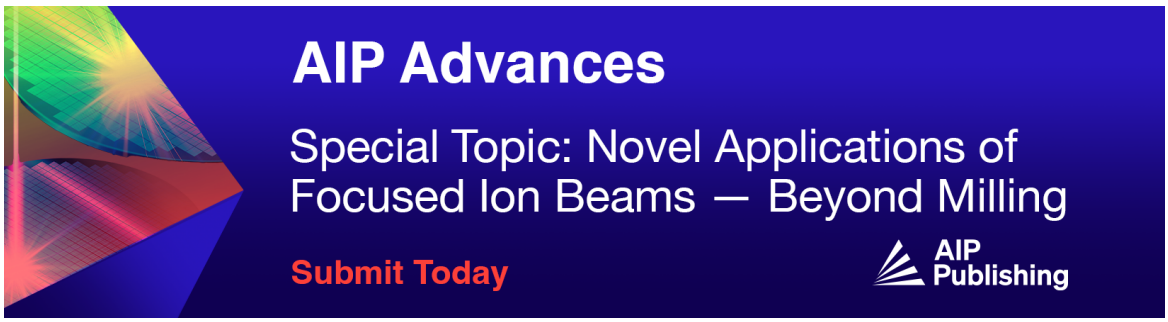
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ABSTRACT

The variation of temperature modifies the magnetic behavior of ferromagnetic cores which may affect the performance of electrical equipment. Therefore, it is imperative to develop a temperature-dependent hysteresis model to precisely calculate electromagnetic characteristics of electrical equipment. In this paper, a Temporal Convolutional Network (TCN) in combination with the Play operator is developed. The proposed model incorporates the temperature-dependent spontaneous magnetization intensity as the model input to introduce the temperature effect. To enhance the accuracy of model training outcomes, the Bayesian optimization approach for automatically selecting network model parameters is provided. The results show that the proposed model can accurately predict the hysteresis characteristics of materials under varying temperature and frequency conditions.

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I. INTRODUCTION

Electrical equipment is influenced by complex operating conditions, and therefore exhibits different operating characteristics.[1] The influence of ambient temperature to magnetic materials is inherent. The loss of heat is generated due to eddy current in the presence of dynamic magnetic field.[2] Therefore, it is crucial to study the hysteresis and loss characteristics of materials under different temperature conditions for the efficient operation of electrical equipment.

The application of J-A model in the magnetization process has garnered significant attention within the scientific community, owing to its potential to incorporate the influences of temperature of external magnetic fields.[3,4] However, the classic J-A model is a static model and cannot be applied to simulate dynamic magnetic property. The Play hysteresis model is not rate dependent, but a history-dependent. Similar to the Preisach model, it has the capability to be combined with neural network, thereby transforming into a dynamic model.[5–10]

In this paper, a Temporal Convolutional Network,[11,12] incorporating the Play hysteresis operator, is employed to predict the variation of magnetic properties of materials with temperature. First, in accordance with the Weiss theory of magnetic materials, we construct input features for the model to reflect the influence of temperature. Then, the magnetic properties data of ferrites under various temperature conditions were trained by TCN, with network parameters replacing the distribution functions in classical hysteresis models. By comparing the results of experiment and prediction, the proposed model based on the Play hysteresis operator can accurately predict the hysteresis phenomenon of materials with variable temperature.

II. METHOD

The purpose of establishing a hysteresis model is to obtain the mapping relationship between magnetic field strength H and magnetic flux density B. In this study, convolution operations in neural networks are used to construct nonlinear mapping relationships. The future magnetic behaviors can be predicted by the model utilizing the historical magnetization features of ferromagnetic materials. This approach can effectively integrate neural networks with the Play hysteresis model that has historical dependencies.

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A. Classical play hysteresis model

The classical Play model is history dependent and rate independent. It can be represented by the following equation, in which a series of operators are integrated under the action of shape function.

$$H = P(B) = \int_0^{B_S} f_\zeta\left(p_\zeta(B)\right)d\zeta \tag{1}$$

where B_s is the saturation magnetic flux density, f_ζ is rate-independent shape function. p_ζ is play operator, which can be expressed as follows:

$$p_\zeta(B) = \max\left(\min\left(p_\zeta^0, B+\zeta\right), B-\zeta\right) \tag{2}$$

where ${p_\zeta}^0$ is the value of the previous moment.

The Play model is rate independent and designed for static magnetic hysteresis calculations. Such a rate-independent model struggles to predict the dynamic loss accurately. However, the history-dependent Play model integrated with TCN is transformed into a dynamic, rate-dependent magnetic hysteresis model. Meanwhile, it can be observed from (1) that the Play model is temperature-independent. In Section B, the parameters related to temperature are introduced into the proposed model.

B. Temperature-dependent TCN model

To accurately describe the impact of temperature on the magnetic characteristics of materials, we incorporated the temperature data of the material into the input features of the neural network. The Weiss theory for ferromagnetic materials enables us to derive an approximate expression for the spontaneous magnetization strength in materials operating below the Curie temperature.[13] This following expression reveals the variation of the spontaneous magnetization strength with temperature.

$$m(T) = m_s(T_0)\left(\frac{T_c - T}{T_c - T_0}\right)^n \tag{3}$$

where T_0 represents room temperature (25 °C). T_c is the Curie temperature of the magnetic material, and the corresponding Curie temperature varies for different materials. $m_s(T_0)$ is the spontaneous magnetization strength of the material at room temperature. $m(T)$ is the magnetization strength at temperature T. The critical exponent n is a coefficient related to the magnetic material. When the material is determined, n is a constant value.

Additionally, the effect of temperature on the magnetic permeability of the material is also considered. A temperature coefficient α_T for the initial magnetic permeability has been proposed, which is described as follows:

$$\alpha_T = \frac{\mu_2 - \mu_1}{\mu_1} \cdot \frac{1}{T_1 - T_2} \tag{4}$$

where μ_1 and μ_2 are the relative magnetic permeabilities measured at T_1 and T_2 respectively.

C. Dilated convolution and residual block

In research that employs neural networks for time series prediction, more historical data often enhances the accuracy of the prediction. It is a challenge to both ensure the accuracy of the hysteresis model prediction and incorporate more historical information simultaneously. The dilated convolution is employed in this paper to address this issue. Fig.1(a) is the schematic diagram of TCN. A time series composed of the magnetic field strength H_t, the hysteresis operator P_{jt}, the spontaneous magnetization strength m_{Tt}, and the temperature coefficient of initial magnetic permeability α_{Tt}, is used as the input of the TCN. Thus, given filter function f with size k, the dilated convolution F for time series input V is defined as follows.

$$F(s) = \left(V *_d f\right)(s) = \sum^{k-1} f(i) \cdot V_{s-d\cdot i} \tag{5}$$

where s is the element of the sequence, d is the dilation parameter. The superscript of $*d$ represent the dilated convolution operator to distinguish from the classic convolution operation, which is reduced into a classic convolution in the case of $d = 1$.

The more historical information can be incorporated by selecting a larger parameter d. However, as d increases, the correlation between the historical information features extracted by the model and the original data reduces. To deal with this problem, the residual block is utilized. The composition structure of the residual block is shown in Fig. 1(b). The output of the residual can be expressed as

$$\hat{y}_t = f\left(\mathrm{Conv}(\hat{y}_{t-1}) + H_2[H_1(\hat{y}_{t-1})]\right) \tag{6}$$

where $\mathrm{Conv}(\hat{y}_{t-1})$ represents the convolution operation. It can reduce the dimensionality of the input data. $H_2[H_1(\hat{y}_{t-1})]$ is the data feature extracted by two hidden layers of TCN. f (.) is an activation function of neural network. By adding residual block, the gradient vanishing can be prevented effectively during neural network training. As a result, it allows for a more stable enhancement of the model performance by increasing the number of TCN layers.

Figure 1 (c) shows the structure of TCN model combined with Play hysteresis operator. However, the model is static and incapable of describing dynamic hysteresis properties. Based on the historical dependence of the magnetization characteristics of magnetic materials, we introduce TCN structure with the capability of time series prediction into the hysteresis model. It can be used to describe dynamic magnetization process.

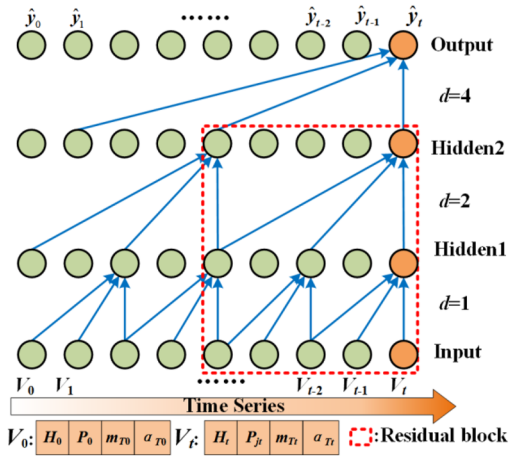
III. EXPERIMENTATION

In this study, the toroidal sample method is employed. It is necessary to consider the influence of sample structure on temperature measurement. The variation in magnetic reluctances arises from the disparity between the inner and outer diameters of the toroidal sample. The magnetic resistance inside the ring-shaped sample is smaller than that outside of the sample, therefore it is easier to reach magnetic saturation, leading to a faster temperature rise. Moreover, there is a temperature difference between the experimental environment and the sample. To minimize the experimental errors arising from the inherent structure of the sample and the temperature difference between the sample and the environment, a thermal tank with a real-time temperature controller is utilized to heat up the toroidal sample.

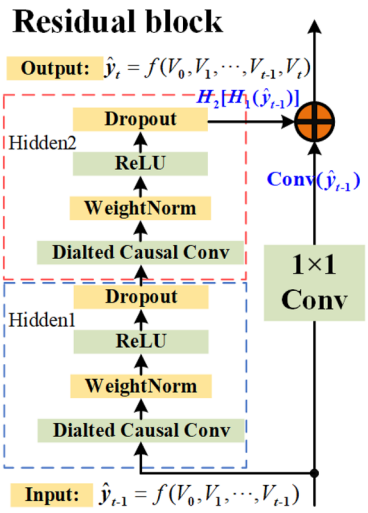
Figure 2 (a) shows the diagram of a magnetic characteristic measurement set-up based on the ring sample method. The magnetic material is the N87 ferrite. Table I provides the detailed

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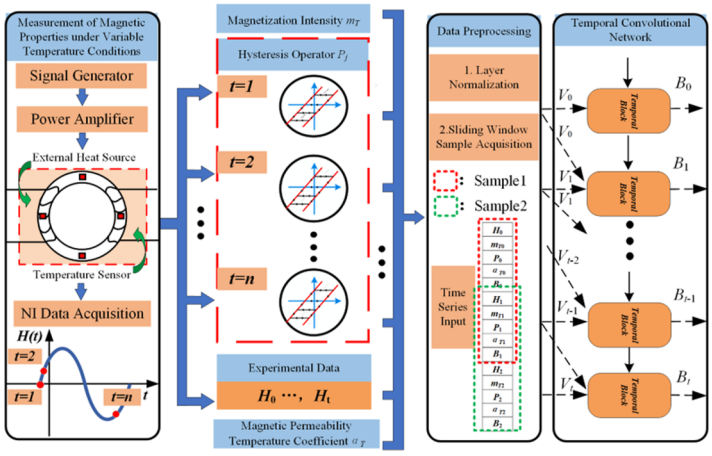
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(a)



(b)



(c)

FIG. 1. Structure of TCN (a) One dimension Dilated Convolution with dilation factors d = 1,2,4. (b) Residual block (c) The structure of TCN model combined with Play hysteresis operator.

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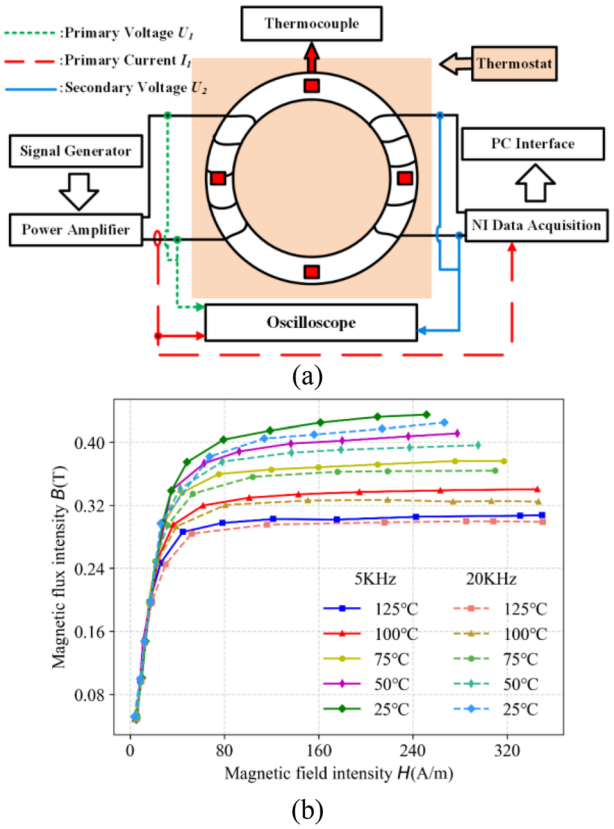


FIG. 2. (a) Schematic diagram of a Magnetic Characteristics Measurement Set-up based on the Ring Sample Method. (b) Saturation magnetization curve of ferrite at variable temperature.

TABLE I. Parameters of N87 ferrite magnetic ring.

Parameter name	Values
Initial magnetic permeability μ_i (25°C)	2200
Saturation magnetic flux density B (mT)	490 (T=25°C); 390 (T=100°C)
Coercivity H (A/m)	21 (T=25°C); 13 (T=100°C)
Curie temperature T (°C)	210
Sample density ρ (kg/m^3)	4850

parameters of the experimental samples. The magnetic properties of the N87 ferrite were measured within a temperature range of 25 °C to 125 °C and a frequency range of 5kHz to 20kHz. The partial experimental results are illustrated in Fig.2 (b). It is shown that temperature variations significantly impact the magnetic properties of ferrites. Consequently, the establishment of a hysteresis model related to temperature is meaningful.

IV. DISCUSSION AND RESULTS COMPARISON

A. Data preprocessing and performance indicator

To reduce the error, all magnetic measurement data is normalized to the range of [-1,1]. The play operator outputs are subsequently calculated based on the normalized magnetic field signal. The other parameters are calculated with the same method.

The performance indicator employed in this study to quantify the error between the model and experimental measurements is the Normalized Root Mean Square Error (NRMSE).

$$\mathrm{NRMSE}(y,\hat{y}) = \frac{1}{\max(y) - \min(y)} \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})_i^2} \quad (7)$$

where y is the measurement value. $\hat{y}$is the prediction value of the model. N is the number of iterations. By normalizing the root mean square error, the errors can be scaled relatively to the range of the measurement, thus allowing an appropriate comparison across different conditions.

B. Model validation

The process of model validation involves selecting the suitable model hyperparameters and making sure that the model is robust to new data. The Bayesian optimization algorithm is employed to optimize the hyperparameters in this work.

The hyperparameter optimization results and network structure parameters of TCN are shown in Table II.

C. Results

Following the model training and validation results in the previous section, we employ the model with the most appropriate hyperparameters to predict the magnetic properties of ferrite at different temperatures.

Figure 3 (a) and (b) show the predicted and experimental values of the hysteresis loop for the ferrite at various temperatures. Meanwhile, Figure 3 (c) provides experimental and predicted core loss of ferrite N87 under temperature variations. These results indicate that the proposed model can accurately predict the hysteresis characteristics of the material under various temperature and frequency conditions.

TABLE II. Parameters of TCN.

Parameter	Values
Activation function (hidden layer)	Tanh
Activation function (output layer)	linear
Ratio of dataset (train:validation:test)	8:1:1
Dilation parameter d	2
Size of convolution kernel k	3
Loss function	NRMSE
Algorithm	Adam
Number of epochs	400

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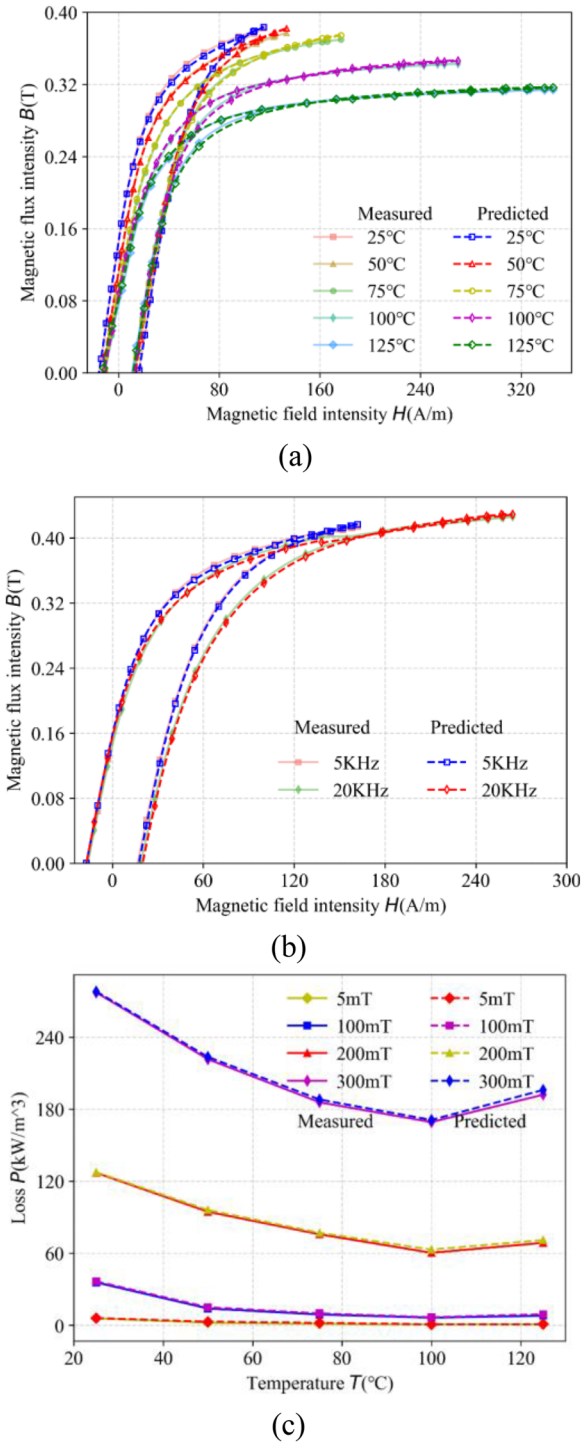


FIG. 3. Predicted and measured dynamic hysteresis loops of ferrite N87 under different conditions (a) 20kHz, from 25 °C to 125 °C (b) 25 °C, 5kHz and 20kHz. (c) Core loss of N87 (20kHz).

V. CONCLUSION

In this paper, we develop a dynamic Play hysteresis model considering temperature effect based on TCN. This model combines the classical Play hysteresis model with the time-sequential predictive capability of the TCN. The model exhibits temperature-dependent characteristics including intrinsic material parameters such as saturation magnetization under varying temperature conditions for neural network training. The developed model accurately predicts the hysteresis properties of ferrites under various temperature and frequency conditions, as the model predictions are in good agreement with the magnetic property experimental.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Author Contributions

Hao Zhang: Writing – original draft (equal). **Qingxin Yang**: Writing – original draft (supporting). **Changgeng Zhang**: Writing – original draft (equal). **Yongjian Li**: Writing – original draft (supporting). **Yifan Chen**: Writing – original draft (supporting).

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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