Magnetic Properties Simulation of Electrical Steel Sheet Based on Recurrent Neural Network

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In this work, a Play model based on recurrent neural network (RNN) is proposed to predict hysteresis characteristics of electrical steel sheets under complex excitation conditions. The proposed model combines the neural network with the Play hysteresis operator, replacing the distribution function in the hysteresis model with the trained neural network parameter structure. An automatic selection method for neural network hyperparameters based on genetic algorithm (GA) is suggested, which improves the prediction accuracy. Comparing the experimental with the model prediction results, the proposed model can accurately predict the hysteresis characteristics of materials under sinusoidal and harmonic conditions.

Index Terms— **Hysteresis model, machine learning, magnetic characteristic measurement, recurrent neural network (RNN).**

I. Introduction

THE hysteresis characteristics and eddy current effects of the core materials are significant factors contributing to energy loss in electrical equipment. However, analyzing the energy loss in actual operation is challenging due to the presence of complex harmonics in the excitation current of electrical equipment [1]. Therefore, it is essential to develop an accurate model that represents the hysteresis characteristics of the core materials in order to improve the efficiency of electrical equipment [2].

Numerous hysteresis models have been proposed to describe the hysteresis properties of magnetic materials. Among these models, the Preisach model, Jiles–Atherton (JA) model, and the Play model are commonly used. The JA model is often preferred over the Preisach model due to its greater physical significance, although it requires a detailed understanding of the physical properties of the material being modeled [3]. In contrast, the Play model is a simple and efficient hysteresis model that is mathematically equivalent to the classical Preisach model [4], [5]. However, identifying the model parameters presents the main challenge in implementing the Play model, since empirical methods make the procedure problem-dependent [6]. In most cases, the function can be identified using measured data and applying a numerical approach, which can involve a specific formulation or conventional methods such as the Everett integral or Gaussian/Lorentzian functions. Other black-box identification techniques, such as genetic algorithms (GAs), fuzzy models, and neural networks (NNs), are also used in conjunction with the Play model [7], [8], [9].

In this article, a Play model was implemented using a recurrent neural network (RNN) to predict the hysteresis loop of electrical steel sheets under complex excitation conditions. The experimental results indicate that the improved model possesses high identification accuracy, fast convergence speed, and a high success rate. The proposed method is a promising approach for accurately modeling hysteresis behavior under complex excitation conditions, with potential applications in areas such as electric machines.

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II. Experimentation

In this study, a single sheet tester (SST) was employed to measure the magnetic properties of B27R090 grain-oriented electrical steel. The dynamic hysteresis loops under sinusoidal excitations are measured to identify the parameters of the proposed model.

According to Ampere's law, the magnetic field strength H can be expressed as follows:

$$H(t) = (N_1 \cdot I)/l_m \tag{1}$$

where N_1 is the number of turns in the primary coil. l_m is the effective magnetic path length. I is the excitation current that requires the application of a voltage $u(t)$ with harmonics at the primary coil terminal. It can be defined as follows:

$$u(t) = U_{1m}\sin(2\pi tf) + U_{km}\sin(2k\pi tf + \theta_k) \tag{2}$$

where U_{1m} and U_{km} represent the amplitudes of the fundamental voltage and kth harmonic voltage, respectively. While the magnetic hysteresis loops are measured at different fundamental frequencies, the added harmonic frequencies are an integral multiple of 50 Hz.

Magnetic flux density $B(t)$ is calculated from $U(t)$ as follows:

$$B(t) = -\frac{1}{N_2 S}\int_0^t u_2(t)dt \tag{3}$$

where N_2 represents the number of turns in the secondary coil, $u_2(t)$ is the induced voltage across the secondary coil, and S is the sample cross-sectional area. The main parameters of the magnetic measurement system used in the experiment are shown in Table I.

III. Hysteresis Model Based on RNN

A. Recurrent Neural Network

RNN is a type of neural network model that can process and predict sequential data. Compared to traditional feedforward neural network (FNN), RNN increases the temporal interactions between neurons, allowing the neural network to handle sequential data with inter-dependencies between inputs.

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TABLE I
PARAMETERS OF THE MAGNETIC MEASURING SYSTEM

Parameter name	Values
Magnetic flux density B(T)	0.01~1.9
Magnetic field strength H(A/m)	1~10000
Frequency f(Hz)	5~500
Turn ratio	188:198

Hysteresis is also a phenomenon of historical dependence, and the current magnetization state depends on the historical magnetization trajectory. Therefore, in this article, RNN is chosen to construct a hysteresis model.

The output of RNN can be represented by the following equations:

$$h_t = f\left(W_{xh}^i x_t + W_{hh}^i h_{t-1}\right) \tag{4}$$

$$y_t = \sum_{i=1}^{n} W_{yh}^i h_t \tag{5}$$

where W_{xh}^i, W_{hh}^i, and W_{yh}^i represent the input, hidden, and output weight parameter matrices, respectively. x_t, h_t, and y_t represent the input value, hidden layer node value, and output value of the neural network. $f(\cdot)$ is the activation function, which introduces nonlinearity into the neural network system. The overall structure of RNN is shown in Fig. 1.

B. Classical Play Model

The classical Play model is history-dependent and rate-independent [10], [11]. In comparison to the Preisach model, it can describe the static hysteresis with simple calculations. The Play model can be expressed as follows:

$$y(t) = \int_0^{+\infty} g(r, P[u(t)])dr. \tag{6}$$

Which can be discretized to n play operators as follows:

$$h(t) = \sum_{j=1}^{n} \phi_j P_j[u](t) \tag{7}$$

where ϕ_j represents the density function of the jth play operator, which has to be identified. The play operator can be defined as follows:

$$P_j[u](t) = \max\left(u(t) - r_j, \min\left(u(t) + r_j, P_j[u](t-1)\right)\right) \tag{8}$$

$$P_j[0] = \max\left(u(0) - r_j, \min\left(u(0) + r_j, k_0\right)\right) \tag{9}$$

where k_0 is the initial condition of the operator and r_j represents the memory depth as follows:

$$r_j = \frac{j-1}{n}[\max(u(t)) - \min(u(t))] \tag{10}$$

where $j = 1, 2, 3, \ldots, n$.

The Play model is rate-independent and only suitable for calculating static magnetic hysteresis. As shown in Fig. 2, the area of the hysteresis loop is closely related to the rate of excitation variation under complex excitation conditions. The rate-independent model cannot accurately predict changes in losses. However, the Play model is a history-dependent model. By combining with RNN, a rate-dependent dynamic magnetic hysteresis model can be constructed.

C. Dynamic Hysteresis Model With RNN

The nonlinear dynamic hysteresis model of a neural network consists of three layers: the input layer, the hidden layer, and the output layer. The self-feedback of the hidden layer is similar to a first-order difference equation. The output layer is the weighted sum of the output of hidden layers. This NNs hysteresis model is the Play-RNN (P-RNN), which is described as follows:

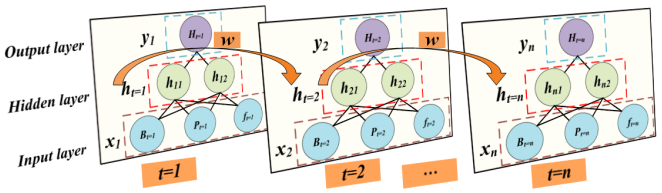


Fig. 1. RNN structural schematic.

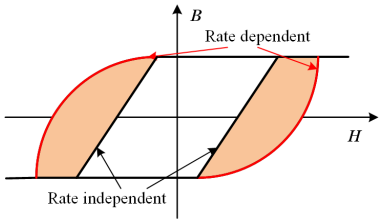


Fig. 2. Rate-dependent and rate-independent hysteresis loops.

$$R_j(t) = W_j^1\left[\alpha D_j(t-1) + (1-\alpha)S_j(t)\right] \tag{11}$$

$$D_j(t) = W_j^2 f\left(R_j(t)\right) \tag{12}$$

$$y(t) = \sum_{j=1}^{n} W_j^3 D_j(t) \tag{13}$$

where W_j^1, W_j^2, and W_j^3 are the input weight, recurrent weight, and output weight, respectively, which are similar to W_{xh}^i, W_{hh}^i, and W_{yh}^i in (4) and (5). f represents the activation function tanh, n is the number of neurons in hidden layers, and α ($0 < \alpha < 1$) is the adjustable factor. $S(t)$ is a matrix composed of the Play operator P_t, magnetic flux density B_t, and magnetic field strength at the previous time step H_{t-1}, which constitutes the input of P-RNN.

According to (11)–(13), an expression of a first-order difference equation can be obtained

$$y(t) = ay(t-1) + bS(t) \tag{14}$$

where $y(t)$ and $S(t)$ are output and input signal, respectively. The parameters a and b are the part of W_j^i, which can be calculated with autograd in neural network.

Fig. 3 shows the overall structure of P-RNN. The Play model, through a first-order difference equation, becomes sensitive to the rate of change in inputs. This modification transforms it from a static rate-independent model to a dynamic rate-dependent one. In addition, the dynamic hysteresis model combined with RNN benefits from the powerful nonlinear representation ability of NNs and can better represent the hysteresis loop of magnetic materials under complex excitation.

IV. DISCUSSION AND RESULTS COMPARISON

A. Neural Network Inputs Preprocessing

The static hysteresis loops were employed to derive the hysteresis operators in the Play model. This model does not account for the effects of eddy currents, making it frequency-independent in terms of hysteresis. For the training and testing of the dynamic hysteresis model P-RNN, data from

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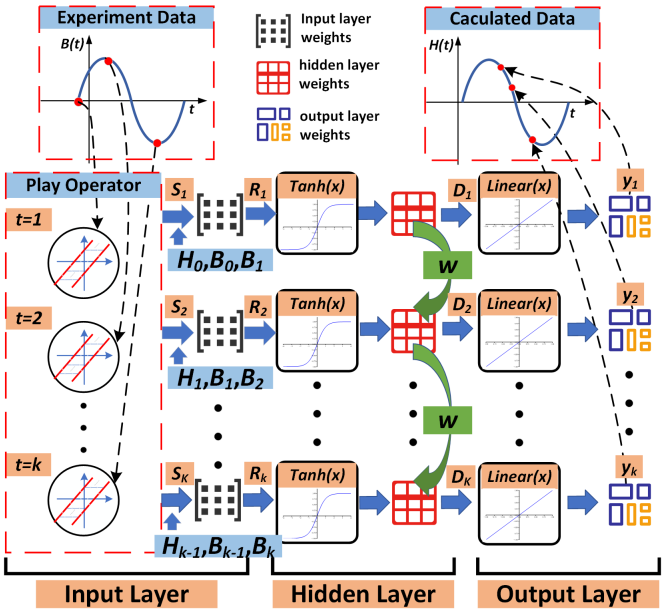


Fig. 3. Overall structure of P-RNN.

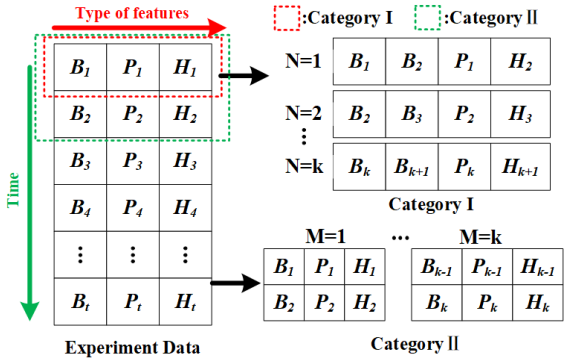


Fig. 4. Methods for constructing sample features under different metric standards.

dynamic hysteresis loops were utilized. The hysteresis data naturally follows a sequential pattern in which the next state is dependent on one or multiple previous states. As shown in Fig. 4, the input features of the neural network from experimental data, vary under different metric standards.

Category I indicates the features contained in the input data. As the feature dimension increases, the magnetic information of the material captured becomes richer, leading to more accurate prediction results from the model. Category II signifies that the features at any given moment match those of the previous moment, effectively capturing the memory aspect of the magnetic properties of the material

$$X_{\text{norm}} = \frac{X - X_{\text{mean}}}{X_{\max} - X_{\min}}. \tag{15}$$

It is necessary to preprocess the input data. The magnetic field strength H and magnetic flux density B have different physical units, while the magnetic hysteresis operator P is dimensionless. There is a significant difference in their data distribution, which poses a significant challenge to the automatic differentiation of gradient calculations in NNs. According to (15), the data distribution is scaled to ± 1, thus allowing more possibilities for the activation function on the output layer.

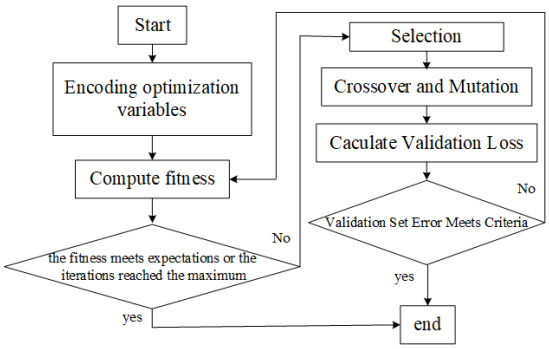


Fig. 5. Flowchart of GA optimizing network hyperparameters.

TABLE II
P-RNN PARAMETERS

Parameter name	Values
Number of data points	32000
Ratio of the dataset (train:validation:test)	8:1:1
Active function	tanh
Loss function	MSE
Train epoches	200
Number of hidden layers	2
Number of hidden nodes	512
Learning rate	0.001

B. Parameter Identification

There are two key factors that need to be considered when building the proposed model. First, the input, hidden, and output weights matrices are calculated. According to the stochastic gradient descent (SGD) shown in (16), the weights matrices can be obtained following neural network training:

$$W_{j+1}^{i} = W_{j}^{i} - \eta \nabla_{w} J\left(W_{j}; \mu_{i}\right) \tag{16}$$

where W^i denotes the model parameter discussed in (11)–(13) and $J(W_j; \mu_i)$ is the loss function of the model on the ith sample. η is the learning rate. $\nabla_w J(W; \mu_i)$ is the gradient of the loss function, indicating the rate of change of the loss function with respect to W_j at W. The formula calculates the gradient on each sample μ_i and then updates the parameters.

Second, selecting the appropriate hyperparameters for a neural network is challenging. It is vital to both the training time and prediction accuracy of the model. Artificially selecting model hyperparameters through experience is inefficient. In this study, GA is used to optimize the hyperparameters of the model.

The flowchart of neural network hyperparameters optimization combined with GA is shown in Fig. 5. It starts by defining the network structure and hyperparameters. Then, the data are partitioned into training, validation, and test sets. Once the model is trained, perform validation on the validation set to calculate the loss using mean square error (mse). Finally, mse is employed as the objective function for a GA to autonomously search for the optimal network hyperparameters. The detailed parameters for the P-RNN are presented in Table II.

C. Modeling Results

In Section II, the static and dynamic hysteresis loops data were measured. The network was trained by data of different frequencies corresponding to each type of excitation

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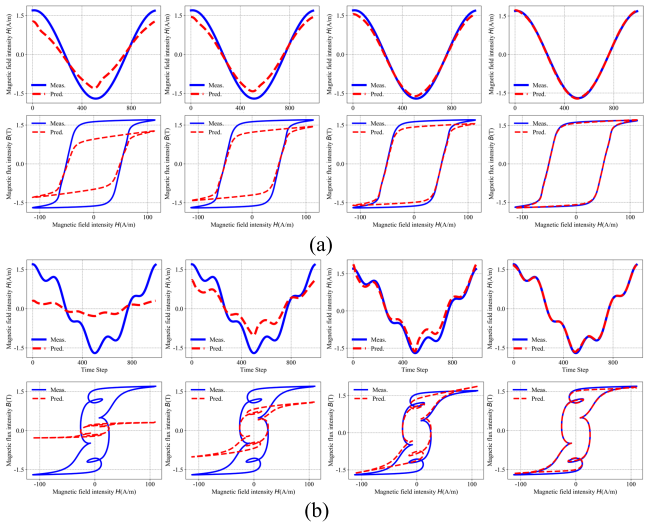


Fig. 6. Accuracy increases as training proceeds (from left to right). (a) Static hysteresis loop data for model training. (b) Dynamic hysteresis loop data for model training.

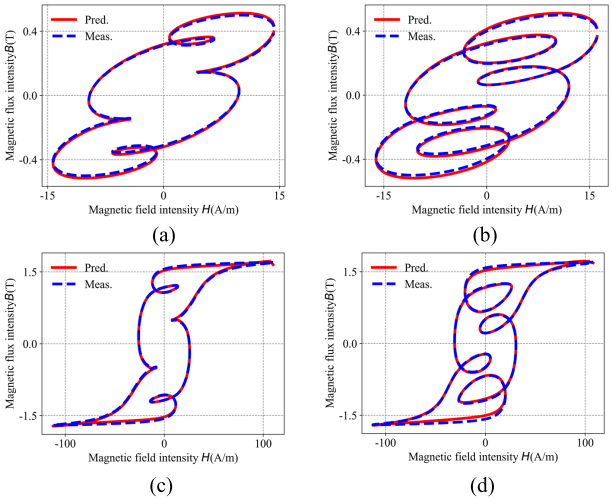


Fig. 7. Predicted and measured dynamic hysteresis loops with harmonic excitations. (a) $B_m = 0.5$ T, $\eta_5 = 20\%$, $\varphi_5 = 90°$. (b) $B_m = 0.5$ T, $\eta_5 = 40\%$, $\varphi_5 = 90°$. (c) $B_m = 1.7$ T, $\eta_5 = 20\%$, $\varphi_5 = 90°$. (d) $B_m = 1.7$ T, $\eta_5 = 40\%$, $\varphi_5 = 90°$.

(sinusoidal and harmonic). In Table II, the data size and the ratio of each dataset are provided.

Fig. 6 shows the predicted results of the neural network model as the training progresses when the static and dynamic hysteresis loops are used as inputs. Obviously, the accuracy of the model increases as training proceeds.

As shown in Fig. 7, the proposed model can accurately predict the hysteresis loop even under complex harmonic excitation. When the excitation waveform contains five harmonic components, the minor loops appear in the hysteresis loop. Fig. 7(a) and (b) show the predicted values of the model and the experimental values at low magnetic fields. Obviously, the proposed model can accurately predict the small hysteresis loops caused by harmonics. By integrating the Play model with the RNN, we obtain the P-RNN model, a rate-dependent dynamic system with robust predictive capabilities. Moreover, it performs well under high magnetic field conditions, evidenced by Fig. 7(c) and (d).

The comparison between the total calculated and experimental loss value of the model under harmonic conditions is presented in Table III. It should be noted that the error is less than 3%, thereby confirming the correctness and effectiveness of the improved model in this article.

TABLE III
COMPARISON OF MEASUREMENT LOSS AND PREDICTED LOSS

Excitations	B(T)	Measured loss(W/kg)	Predicted loss(W/kg)	Error
η_5=20%	0.5	0.0947	0.0935	1.21%
φ_5=90°	1.7	1.4728	1.4956	-1.55%
η_5=40%	0.5	0.1487	0.1477	0.64%
φ_5=90°	1.7	1.7109	1.6664	2.6%

V. CONCLUSION

This article builds a dynamic hysteresis model that simulates the magnetic properties of electrical steel sheets under complex excitation conditions. The model is trained by the hysteresis data of the material with time series prediction ability to develop RNN. The trained network implicitly replaces the density function in the Play hysteresis model, which simplifies the process of model parameter identification. The experimental results show that the proposed model can be applicable to other magnetic materials under different excitation frequencies to predict magnetization characteristics under complex working conditions.

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