Ferrite Magnetic Characteristic Simulation at Different Temperature Using Recurrent Neural Network Model

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Abstract

The accurate hysteresis characteristics modeling of ferromagnetic materials is crucial to optimally design of electro-magnetic equipment. In this paper, the hysteresis play model is improved to simulate magnetic characteristics of ferrite at variable temperature conditions based on recurrent neural network. The proposed model predicts the magnetic field strength of N87 ferrite with the Mean Square Error (MSE) better than 0.3%. The results demonstrate that ferrite materials can be accurately described by the improved model trained with a limited amount of data.

1 Introduction

The precise electromagnetic simulation of electrical equipment is inseparable from the accurate and efficient magnetic material hysteresis model. The magnetic properties of of ferromagnetic materials change with the variable temperature, however, traditional hysteresis models are incapable of describing the effect of temperature on magnetic properties accurately. Therefore, it is necessary to establish an accurate hysteresis model influenced by temperature effect.

The Preisach model has become the most widely used hysteresis model because of its advantages in considering the influence of magnetization history and easy to numerically simulate. There are amount of numerous identification methods were used. Using Lorentz function to replace the distribution function, G.Finocchio established the derivative relationship between magnetic field intensity and magnetic flux density[1]. Zsolt Szabo used exponential function to approximate the distribution function of the fitted hysteresis model and proposed the Preisach identification method based on the closed from Everett function, which took a new solution to the parameter identification problem of the Preisach model[2].

In this paper, a Preisach model is implemented using a Recurrent Neural Network (RNN), which is able to predict the hysteresis loops of ferromagnetic materials at different temperatures. The results show that the improved model has the advantages of high identification accuracy, fast convergence speed and high success rate.

2 Hysteresis model

2.1 Hystersis Modeling Based on Preisach

The classic Preisach model is expressed using a double integral as:

$$y(t) = \iint_{\alpha \geq \beta} \mu(\alpha,\beta)\gamma_{\alpha\beta}u(t)d\alpha d\beta \tag{1}$$

where $y(t)$ is the model output at time t, $u(t)$ is the model input at time t, while $\gamma_{\alpha\beta}$ are rectangular hysteresis operators with α and β being the up and down switching values. The density function $\mu(\alpha, \beta)$ is a weighting function, which has to be determined from experimental data. Following a change in coordinates $r = (\alpha - \beta)$, $v = (\alpha + \beta)$, it makes (1) rearrange as:

$$y(t) = \int_0^{+\infty} g\left(r, P\left[u(t)\right]\right)dr \tag{2}$$

which can be discretized to n play operators as follows:

$$y(t) = \sum_{j=1}^{n} \phi_j P_j\left[u\right](t) \tag{3}$$

where ϕ_j represents the density function of the j_{th} play operator, which has to be identified. The play operator can be dentified as:

$$P_j\left[u\right](t) = \max\left(u(t) - r_j, \min(u(t) + r_j, P_j\left[u\right](t-1))\right) \tag{4}$$

$$P_j\left[0\right] = \max\left(u(0) - r_j, \min(u(0) + r_j, k_0\right) \tag{5}$$

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

$$r_j = \frac{j-1}{n}\left[\max(u(t)) - \min(u(t))\right] \tag{6}$$

where j = 1, 2, 3, … n.

2.2 RNN with Preisach hysteresis operator

The RNN consists of input layer, hidden layer and output layer. The data in the input layer is a time series composed of *B-H* curves under the influence of temperature. The function of the hidden layer is to extract and save the characteristic value of ferrite sample. The output layer outputs the *B-H* time series of the next moment. Figure 1 shows the schematic diagram of the structure of the recurrent neural network.

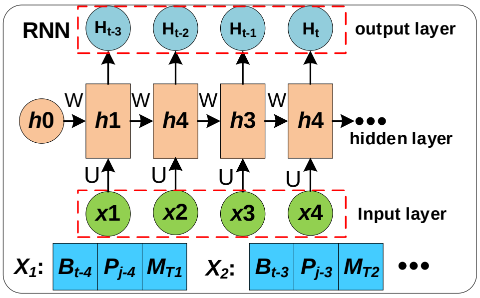

Figure 1: Schematic of the improved recurrent neural network

3 Experiments and Results

3.1 Ferrite Magnetic Properties at Different Temperatures

The hysteresis loop of N87 ferrite measured by the ring sample method from 25℃ to 125℃ is shown in Figure 2. It is obvious from the figure that temperature has a significant effect on magnetic properties of ferrite. The saturation magnetic density of the sample decreases as the temperature increases.

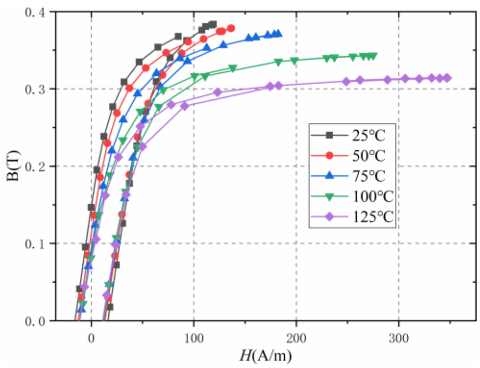

Figure 2: Hysteresis loops of ferrite at different temperatures

3.2 Prediction of the RNN-Preisach model

All hysteresis loops under the temperature of 25 and 50 were selected to be the training set of the neural network for material feature extraction. In order to determine whether the model is overfitting, the validation set of the model takes the measurement data at 75℃ , while the experimental data at 100℃ and 125℃ were used as the test set to test the validation of the model.

Figure.3 shows the comparison between the predicted value of the model and the experimental result at 100℃. As can be seen in Figure 4, the proposed model can achieve accurate predictions with a limited number of training batches.

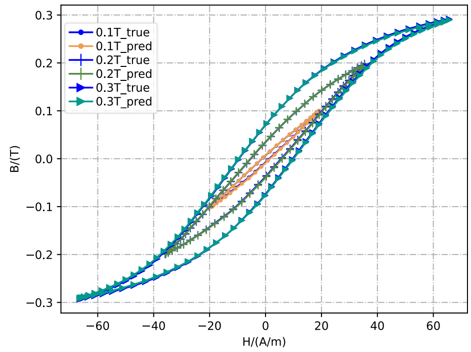

Figure 3: Model predicted value and experimental value of ferrite with different magnetic density at 100 ℃

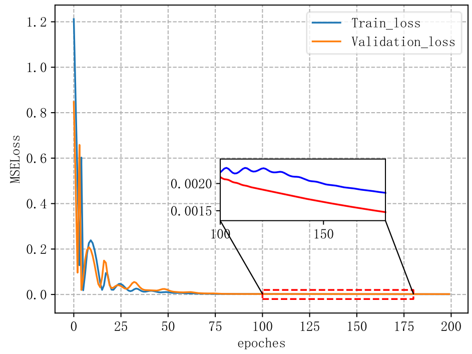

Figure 4: Loss Curve on Training set and Validation set

4 Conclusion

Magnetic characteristic simulation of ferrite based on recurrent neural network can demonstrate the hysteresis characteristics of ferrite effectively at different temperatures. The improved model takes the Mean Squared Error Loss (MSELoss) as the evaluation standard. The MSELoss between predicted value and experimental value is 0.2% and 0.29% at 100℃ and 120℃. Moreover, these results prove that the proposed model has strong scalability to other magnetic materials at different temperature, while it has the potential to predict the magnetization characteristics at complex working conditions.

References

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