HYSTERESIS MODEL OF FERROMAGNETIC MATERIAL BASED ON THE DEEP OPERATOR NEURAL NETWORK

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Abstract

In this digest, the deep operator network (DeepONet) is used to model the nonlinear hysteretic behaviour of ferromagnetic materials. We first generate a set of *BH*-curves (with *H,* the magnetic field and *B*, the magnetic flux density) by means of the Jiles-Atherton model to train, validate and test the deep neural operator network. The constructed model is validated by comparing the predicted *B* values and the hysteresis losses with reference values. Attention is paid to feasibility and accuracy.

1 Introduction

The design and analysis of electrotechnical devices (rotating electrical machines, transformers, inductors) requires an accurate loss computation, accounting for the losses in nonlinear ferromagnetic materials, and in particular the hysteresis[1]. Traditionally, there are two widely used phenomenal hysteresis models: Preisach model [3] and Jiles-Atherton (J-A) model [4]. The Preisach model provides good accuracy even for minor loops, but it is computationally expensive. In the contrary, the J-A model calculates the magnetization by solving ordinary differential equation considering sign of derivative of the magnetic field, which makes it easier to implement and computationally cheaper [2].

With the advent of machine learning, some recurrent neural network (RNN) based hysteresis models are proposed considering that the inherent memory-based characteristics of RNN aligns with the hysteresis characteristics. By combining the RNN with Preisach play operator, the trained RNN can also perform well on predicting hysteresis loops with random ramp-rates [5]. However, RNN based models are only accurate under certain circumstances, limited to loops for which training has been performed [7].

Based on the universal operator approximation theorem, the operator neural network is proposed. It allows mapping an infinite function space to another infinite function space. There are mainly two types of neural operator: Deep operator network (DeepONet) [8] and Fourier neural operator (FNO) [9]. DeepONet can employ any type of neural network architectures in the branch net whereas FNO has a fixed architecture, hence DeepONet is more flexible than FNO in terms of problem settings and datasets [10]. These neural operators have successfully been applied to complex problems in fluid dynamics, heat transfer problems, but rarely in electromagnetics. In this digest, neural operator specifically the DeepONet is used to model the hysteresis of ferromagnetic material.

2 Methods and results

2.1 Deep operator network

Let $\mathbb{G}$ be an operator taking as input function u, with $\mathbb{G}(u)$ being the corresponding output function. For any point y in the domain of $\mathbb{G}(u)$, the output $\mathbb{G}(u)(y)$ is a real number. Hence, the network takes inputs composed of two parts: u and y. and outputs $\mathbb{G}(u)(y)$.In DeepONet, there are two networks: the branch net and the trunk net. The trunk network takes y as the input while $[\,u(x_1), u(x_2), u(x_3) \dots u(x_n)]$ with n the number of training data are the inputs for the branch network. The outputs of these two networks are then merged to approximate the output functions [8].

2.2 Generating the training data

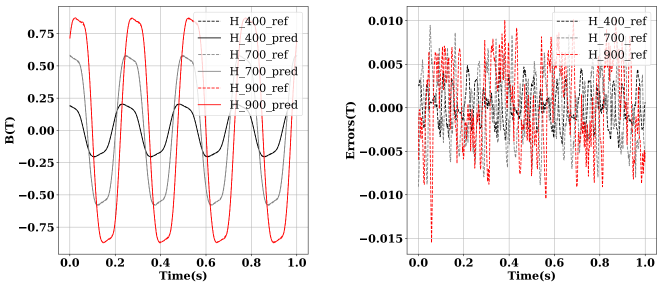
With the effect of hysteresis, under the excitation of *H* with different peak values and phase shifts, the corresponding *B* are different. To learn the nonlinear relation between *B* and H, a group of *B-H* curves are generated by means of the classical J-A model [4]. Five hundred sinusoidal *H* with amplitude ranging in [1,1000] A/m and random phase shift within $[0,2\pi)$ for four periods are used as the excitation to J-A model to calculate the corresponding *B*. The frequency effect is not considered in this study, so the frequency is always set as 1 Hz. The timestep is kept constant as 125 steps per period so there are totally 4x125 = 500 timesteps for function.

For training the model, *n* = 500 functions of *H* are the inputs to branch net as $[\,u(x_1), u(x_2), u(x_3) \dots u(x_{500})]$and the discretized time space are the inputs to trunk net as y. The corresponding *B* for each *H* are used as the references for $\mathbb{G}(u)(y)$. The loss of the model is calculated by the mean square error (MSE) between the predictions and the reference outputs.

2.3 Results

After 50000 iterations, the loss is decreased as around 1e^{-5}. Then, the sinusoidal shape of *H* with random phase shift and peak values as 400, 700 and 900 A/m are used to test the model. All the test data are outside of the training data.

The predictions from the trained neural operator model and the reference values are plotted in Figure 1(a). The results almost overlap with the corresponding references. Figure 1(b) shows the errors, which are mainly less than 10 mT and the mean error is 3.9 mT. The corresponding hysteresis loops are shown in Figure 2. , from which, the hysteresis losses are calculated as the areas of loops. Table1 lists the losses from predictions and references.



(a) Predictions (b) Errors

Figure 1. Magnetic flux density from DeepONet and reference values.

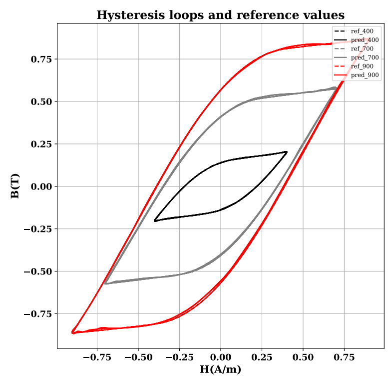


Figure 2. Hysteresis loops from DeepONet and reference.

	Reference (J/m³)	Predictions (J/m³)	Relative error
H400	140.32	140.02	0.21%
H700	686.30	688.39	0.30%
H900	1196.10	1185.40	0.89%

Table 1. Hysteresis losses calculated by DeepONet and reference.

3 Conclusion

In this digest, a deep operator neural network is built to model the hysteresis of ferromagnetic materials with different peak values and phase shift. The established operator model can predict *B* with sinusoidal excitation of *H* outside of the training data very accurately with error less than 10 mT. Besides, the relative error between the predicted and reference hysteresis losses is less than 1%, which shows the great ability of established model for capturing magnetic hysteresis. In our future work, the model would be expanded as the dynamic hysteresis model considering the effect of frequency and eddy currents.

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