

# Preisach Operator Intelligent Hysteresis Model for Core Loss Estimation

Ying Jing<sup>1</sup>, Yanli Zhang<sup>1</sup>, and Jianguo Zhu<sup>2</sup>

<sup>1</sup> School of Electrical Engineering, Shenyang University of Technology, Shenyang, China

<sup>2</sup> School of Electrical and Computer Engineering, The University of Sydney, Sydney, Australia

Accurate hysteresis modeling with minimal use of experimental data sets is essential for the design and performance optimization of highly efficient magnetic materials. However, the accuracy of the traditional Preisach model is often inadequate, especially under complex excitation conditions. To solve this challenge, a Preisach operator intelligent hysteresis (POIH) model is proposed in this paper. By combining Preisach operator with backpropagation neural network, the model combines the simplicity of traditional physical model with the high precision and flexibility of modern data-driven model. Based on the experimental data of 30Q130 silicon steel, the model is trained and tested under the conditions of stress and temperature. The experimental results show that the model has advantages in accuracy, efficiency, and universality.

**Index Terms**—Preisach model, Preisach operator intelligent hysteresis (POIH) model, Preisach operator, backpropagation neural network.

## I. INTRODUCTION

Magnetic materials (such as silicon steel sheets) play a crucial role in electrical equipment, especially in motors and transformers. To accurately analyze the magnetic fields in these devices, it is essential to establish a reliable hysteresis model [1]. The Preisach model describes the hysteresis behavior of magnetic materials by simplifying the complex magnetic domain flip into the collective switching of numerous magnetic dipoles. The magnetic dipoles in the model are defined as Preisach hysteresis operators, which flip under the influence of an external magnetic field [2]. Moreover, the distribution function of Preisach hysteresis operator determines the calculation accuracy of the model. The model shows the behavior of these hysteresis operators through the distribution function. Since each magnetic dipole can simulate the magnetic domain rotation process of single-domain particles, the microscopic magnetic domain motion can be associated with the macroscopic magnetization characteristics, but the distribution function is very difficult to determine. A neural network can learn arbitrarily complex distribution functions by adjusting the weights without presupposing their form.

In recent years, neural networks have gradually become an effective tool for modeling hysteresis behavior. Although the neural network model has excellent performance in accuracy, it lacks internal physical mechanism support and relies on a large number of experimental data for training, which limits its practical application to a certain extent. Therefore, this paper proposes a method that integrates physical constraints into neural networks, takes hysteresis operators as input to neural networks, and optimizes network performance by randomly initializing weights.

## II. THE CLASSICAL PREISACH MODEL

The Preisach model describes the hysteresis characteristics of magnetic materials composed of numerous independent magnetic dipoles, each having a unique coercivity and state. Under the influence of an external magnetic field, the magnetic

dipoles flip at specific thresholds, forming complex hysteresis loops. The Preisach hysteresis operator captures the microscopic behavior of the magnetic dipoles by using a simplified rectangular hysteresis operator. Through statistical analysis of the Preisach hysteresis operators, this model can effectively describe the macroscopic magnetic characteristics of materials, such as permeability and hysteresis behavior. Therefore, the Preisach model has clear physical significance.

The model assumes that each magnetic dipole can only flip forward or backward, and the magnetization state of its Preisach hysteresis operator is represented by  $\gamma_{\alpha\beta}$ , which can only take values of "+1" or "-1". The Preisach diagram is divided into a positive magnetization region  $S^+$  ( $\gamma_{\alpha\beta}=1$ ) and a negative magnetization region  $S^-$  ( $\gamma_{\alpha\beta}=-1$ ), as shown in Fig. 1.

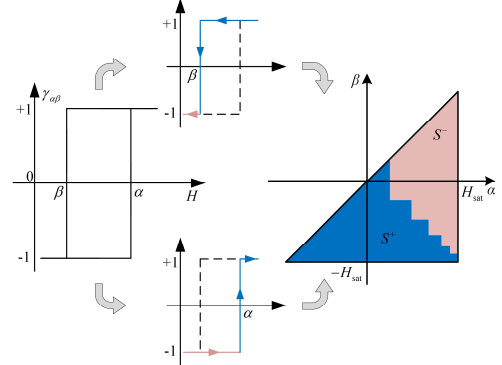


Fig. 1. Preisach hysteresis operator and Preisach diagram

## III. PREISACH OPERATOR INTELLIGENT HYSTERESIS MODEL

### A. Construction of the Magnetization State Matrix of the Preisach Hysteresis Operator

Each hysteresis loop corresponds to a triangular element on the Preisach diagram. Specifically, through the  $2N$  reversal points of  $N$  hysteresis loops, the Preisach diagram is non-uniformly discretized into  $N(2N+1)$  units, with each unit representing a Preisach hysteresis operator, as shown in Fig. 2. In the discrete unit coordinate system, the horizontal and vertical axes are numbered according to the magnetic field

intensity reversal points of each hysteresis loop. Based on the correspondence between the hysteresis loops and the Preisach diagram, the numbering starts from the reversal point of the negative saturation magnetic field of the limiting hysteresis loop and increases sequentially. The reversal point of the magnetic field strength of any hysteresis loop can be obtained by the initial magnetization curve.

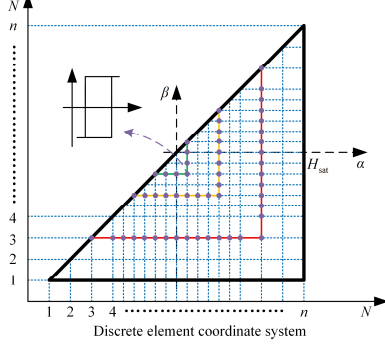


Fig. 2. Preisach triangle discretized by non-uniform loops

### B. Construction of POIH Model

Fig. 3 shows the structure of Preisach operator intelligent hysteresis (POIH) model, which consists of an input layer, hidden layer, and output layer. The input layer contains  $N(2N+1)$  nodes, corresponding to the state matrix  $T_N$  of the Preisach hysteresis operators. The hidden layer has  $M$  neurons, and the output layer consists of a single output node.

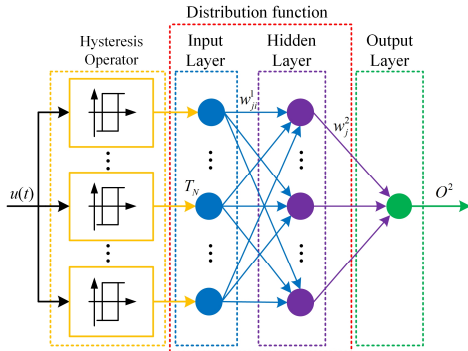


Fig. 3. Structure of POIH model

## IV. THE EXPERIMENT AND SIMULATION

The measurement device adopts the MPG product from Germany's Brockhaus, and the entire excitation loading process adopts closed-loop control. The measurement system diagram and the physical diagram are shown in Fig. 4.

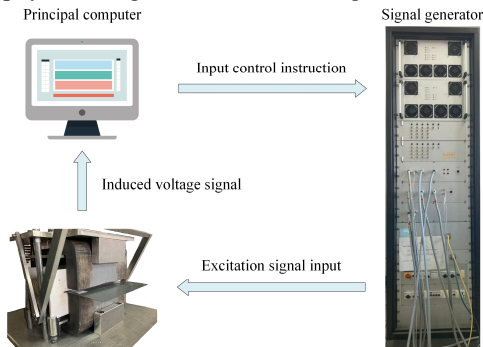


Fig. 4. Experimental device

The hysteresis loops of these two models are compared with those of the limiting Preisach model when  $B=0.7\text{T}$  and  $1.7\text{T}$ , as shown in Fig. 5. The accuracy of the POIH-160 model is better than that of the POIH-40 model, which is consistent with the assumption that the more points in the Preisach diagram, the higher the accuracy of the model. Specifically, the POIH-160 model can more accurately capture the domain flipping behavior during magnetization due to the use of more data points, which significantly improves the prediction accuracy of the model.

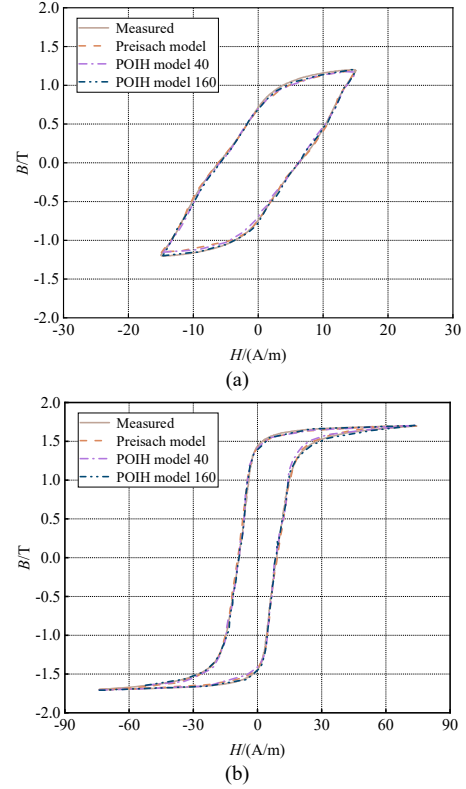


Fig. 5. Comparison of calculated and measured  $B$ - $H$  loops at excitation frequency  $f = 3\text{ Hz}$ . (a)  $B = 0.7\text{T}$ . (b)  $B = 1.7\text{T}$ .

## V. CONCLUSION

Based on the research on the combination of Preisach hysteresis model and neural network, an innovative POIH model is proposed in this paper, which combines the physical mechanism of Preisach model with the nonlinear processing capability of neural network. The experimental results show that the proposed model outperforms the traditional model in accuracy and computational efficiency. In the future, the stress and temperature will be used as input conditions in the full text, and the magnetic properties and core loss of the material will be analyzed in detail.

## REFERENCES

- [1] Yang Li, Jianguo Zhu, Yongjian Li, Lihua Zhu, "A hybrid Jiles–Atherton and Preisach model of dynamic magnetic hysteresis based on backpropagation neural networks," *Journal of Magnetism and Magnetic Materials*, vol. 544, 2022.
- [2] O. Alejos and E. Della Torre, "Improving numerical simulations of Preisach models for accuracy and speed," *IEEE Transactions on Magnetics*, vol. 36, no. 5, pp. 3102-3104, 2000.