Magnetization Mechanism-Inspired Neural Networks for Core Loss Estimation

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***Abstract-* Fast, accurate, and cost-effective core loss modelling is critical to achieve the design of high-density high-efficiency power electronics systems. However, conventional core loss modelling methods often demonstrate a significant lack of accuracy, design efficiency and/or cost-effectiveness especially under complex operating conditions. To tackle this problem, this document proposes a new core loss modelling method, Magnetization Mechanism-Inspired Neural Network (MMINN). MMINN is a hybrid data-driven and physics-driven model. It is designed to capture the fundamental magnetization process of magnetic materials at the micro-level. Therefore, MMINN can not only achieve high accuracy and computational efficiency as many other fully data-driven models do, but also enjoy the simplicity (fewer parameters to tune) and generality of a purely physic-driven model. Model training and testing are based on the hysteresis loops of five ferrite materials in the open-source core loss database - MagNet. Experimental results prove the accuracy and the reliability of the proposed model, making it highly applicable for power magnetics design. Additionally, a user interface is provided to visualize model prediction data.**

I. Introduction

Power magnetics often have the largest volume and primary source of power losses, posing significant challenges to high-density and high-efficiency power electronics design [1]-[2]. Modelling of power losses, especially core losses, is a fundamental task of high-performance power magnetics design. The trend of miniaturization of power electronic devices makes fast, accurate, and low-cost core loss modelling imperative. However, modeling core losses is untrivial due to the highly nonlinear nature of the magnetization process of magnetic materials. Steinmetz empirical models are some of the most widely used models in the field of power electronics, which map the relationship between excitation and core losses through a few curve-fitting parameters [3]-[6]. Steinmetz models are simple to use but the key challenge is its lack of accuracy and generality for different core materials and/or operations under different conditions (e.g., variations in frequency, excitation profiles, temperature) [7]-[8]. Thus, it is time to upgrade the Steinmetz equation and advance the entire power electronics society's understanding of magnetization mechanisms.

To this end, extensive research has been devoted to improving core loss modelling by reconstructing the dynamic hysteresis process (i.e., the hysteresis loops of magnetic field strength H and flux density B), which provides deeper physical insights at the material level. Different dynamic hysteresis models can be divided into three main categories:

- ***Fully physics-driven models*** – The models are mainly based on the microscopic (magnetic domain) energy calculation and traditional numerical approaches, where the Preisach model [9] and the J-A model [10] are the most well-documented branches in literature. Such models are physically interpretable and therefore very accurate [9]-[14]. Nevertheless, they still suffer from the following problems: (i) high computational complexity due to iterative calculations and (ii) complex parameter identification process.
- ***Fully data-driven models*** – The models are based on Machine Learning (ML) techniques, especially general-purpose neural networks (NNs) [15]-[19]. Disadvantages of fully data-driven model includes (i) a large dataset which are generally costly and time-consuming to obtain and (ii) a large model size to ensure a satisfactory level of prediction accuracy, thus expensive computational unit for model training. Also, the black box nature makes it (iii) difficult to understand the decisions made inside the model.
- ***Hybrid models*** – Hybrid models combine data-driven and physics-driven characteristics to alleviate their inherent shortcomings. The hybrid model is the most promising method for core loss modelling, owing to (i) significantly reduce the training data requirements, (ii) show a simpler structure, (iii) have lower memory requirements and (iv) provide some physical insights [20]-[22].

In this paper, a hybrid model, Magnetization Mechanism-Inspired Neural Network (MMINN), is proposed for power magnetics design. The proposed model uses separate subnetworks to reconstruct dynamic and static hysteresis components where the static subnetwork adopts the Prandtl-Ishlinskii˘ (PI) stop operator to characterize the material's static magnetic moment changes, and the dynamic subnetwork adopts the idea of ladder network segmentation to account for the dynamic effects within the magnetic material. Based on measurement data from the MagNet database [17], the trained MMINN allows fast and accurate core loss estimation and magnetization process simulation under different operating conditions (temperatures, excitation frequencies, and excitation waveforms). Besides, a user interface (UI) platform is designed to seamlessly integrate with MMINNs, empowering users with a diverse range of interactive possibilities and providing insightful data visualization.

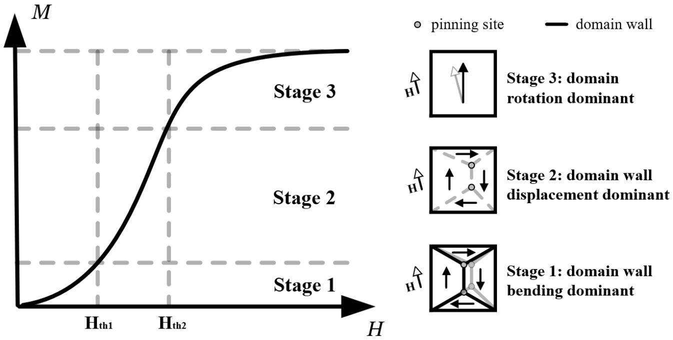
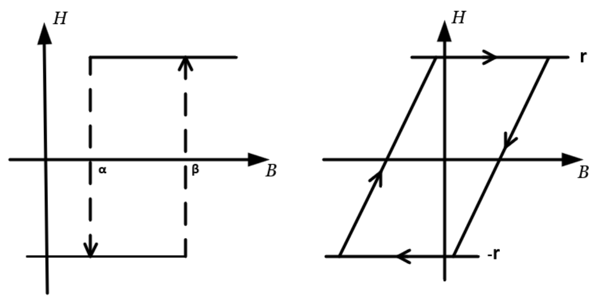


Fig. 1. Magnetization process (a) M-H curve of soft magnetic materials (b) Cubic soft magnetic material magnetization schematic.



(a) (b)

Fig. 2. (a) Preisach model: Relay hysteresis operator (b) PI model: Stop hysteresis operator.

This paper is organized as follows. Section 2 reviews underlying magnetization mechanisms and some physical models to simulate magnetization process. Section 3 introduces MMINN concept. Section 4 presents the research results for the MagNet Challenge 2023. Section 5 concludes the paper.

II. MAGNETIZATION MECHANISMS

The dynamic magnetization process of soft magnetic materials can be constructed through a B-H loop, and the core loss W can be expressed by the enclosed area $\int HdB$ as:

$$W = V(f\int HdB), \tag{1}$$

where V denotes the magnetic component's effective volume and f denotes the operating frequency. According to the loss separation theory [23]-[24], the core loss can be decomposed into the sum of a static hysteresis contribution W_h and a dynamic contribution W_{dyn}. Subsequently, in the dynamic hysteresis modeling, the magnetic response of the material to changes in external magnetic flux density is also composed of two parts. The overall magnetic field strength H can be equivalently interpreted as:

$$H = H_h + H_{dyn}. \tag{2}$$

A. Static component modeling – PI model

The hysteresis contribution H_h is considered a static term because it is independent of excitation frequency. Fig.1(a) illustrates the static magnetization process of a magnetic domain through the magnetization characteristic curve. Magnetic domain, the smallest unit showing magnetic characteristics, undergoes magnetic domain wall movement (stage 1: bending and stage 2: displacement) and magnetic domain rotation (stage 3) during the magnetization process as shown in Fig.1(b) [25]. The static magnetization characteristics of magnetic domain in different materials are dominated by these two magnetization mechanisms. And the B-H loop of a magnetic material is an aggregation of the magnetization status of each individual wall domain inside the material.

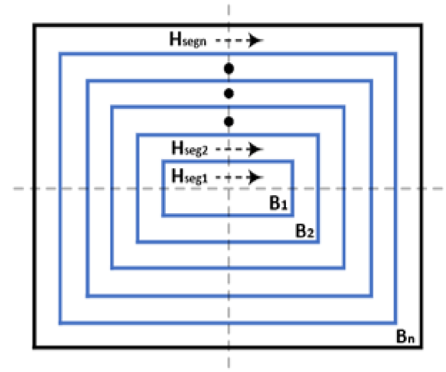


Fig. 3. Core cross-section with hypothetical eddy current paths.

The hysteresis operator is often used to mimic/characterize the static magnetization process of a magnetic domain shown in Fig.1 (a). [26]. The relay hysteresis operator is a typical example having a rectangular hysteresis loop with two thresholds (α, β), as depicted in Fig.2(a). It can be seen as a rough description of domain rotation (stage 3) but does not account for the intermediate transition process (stage 1 and stage 2) [27]. To include all magnetization mechanisms and improve model accuracy, Prantl [28] introduced the stop hysteresis operator S_r, guaranteeing the continuity of B-H mapping (see Fig.2(b)). Physically, it provides an acceptable description of reversible and irreversible components of hysteresis. Its corresponding static B-H hysteresis model is called the PI model, which can be interpreted by:

$$H_h(B) = \sum_{r=1}^{n} \mu_r(f,T)S_r(B). \tag{3}$$

where n is the number of operators. Each stop operator S_r is characterized by a saturation level r, and the corresponding weight function μ_r represents its distribution proportion.

The challenge of PI models is computing the distribution function. Conventional methods include formulation of the Everett function and particle swarm optimization [29]-[30]. However, these methods are time-consuming and cannot guarantee model's reliability. Therefore, the proposed model introduces a feed-forward neural network (FNN) to represent μ_r of the PI model and ultimately describes the static component of the magnetization process (see Section III).

B. Dynamic component modeling – Core loss ladder network

The static hysteresis models will produce large core loss prediction errors at high frequencies [26], [31]. At this point, the dynamic hysteresis contribution H_{dyn} should be considered, which mainly originates from electromagnetic induction. Maxwell's equations can be theoretically applied to compute

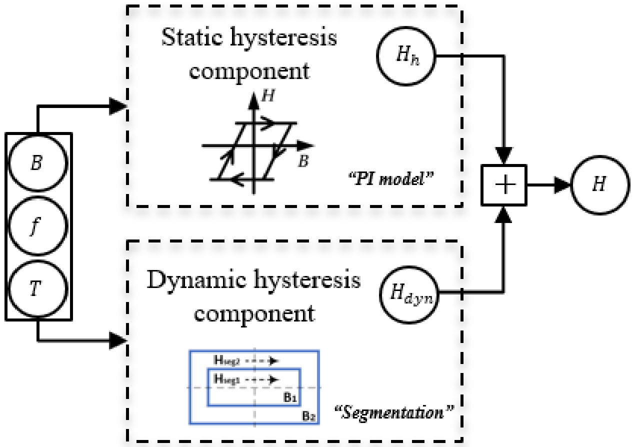


Fig. 4. Physical core loss model schematic diagram.

the overall magnetic field strength. However, in practice, there are differences between the calculated and measured magnetic fields. The differences are caused by anomalous loss behaviors, including localized eddy currents near the magnetic domain wall, spin damping, internal friction, and dimensional resonance effects [32]. These phenomena will lead to spontaneous magnetization vector rotation and circulating currents around the magnetic domain walls. Thus, Bertotti [23] separated H_{dyn} into classical eddy current losses and anomalous losses, as follows:

$$H_{dyn} = C_{cl}\frac{dB}{dt} + C_a\left|\frac{dB}{dt}\right|^{0.5}. \quad (4)$$

where C_{cl} is the classical eddy current coefficient and C_a is the anomalous loss coefficient. Both loss coefficients depend on the material and the component dimensions. Under low-medium frequency excitation, both loss coefficient can be treated as constant and identified by the core loss separation procedure [34]. However, under high frequency excitation, they become multiple factors dependent, including temperature effect, dimensional resonance, and skin effect [35]. Consequently, dynamic magnetization components computation at high frequencies become a popular research topic.

Zhu et al. [14] proposed a ladder network for magnetic cores to generalize the hysteresis model to high-frequency applications. This model regards the skin effect of magnetic field inside the magnetic core as the main reason for the non-uniform flux density in the high frequency environment. To account for the skin effect, the cross-section of the magnetic core is subdivided into several theoretical paths for eddy currents in this model (see Fig.3). The magnetic flux in each segment is regarded as uniformly distributed, so that Eq. (4) can be applied to describe the dynamic hysteresis effects of each segment. The idea of segmentation enables the dynamic magnetization process to be parameterized over a wide frequency range. Hence, the proposed model will apply an RNN to mimic section segmentation, where each hidden neuron reflects the dynamic effect of each hypothesized eddy path (see Section III).

III. Magnetization mechanism-inspired neural network

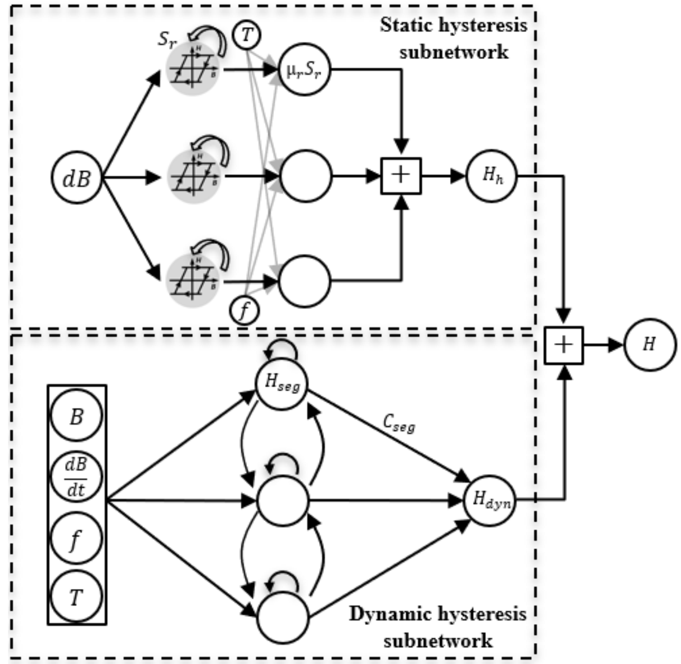


Fig. 5. Magnetization mechanism-inspired neural network.

This paper aims to characterize core loss information of soft magnetic material. The proposed model is inspired by magnetization mechanism and parameterizes the equivalent field strength in the form of $H(B)$ to characterize the dynamic magnetization process. Finally, the core loss prediction is obtained according to Eq. (1).

A. Model architecture

The magnetization process involves the rearrangement of the magnetic moments of the internal magnetic domains, consisting of static and dynamic hysteresis components as in Eq. (2). Based on the physical model introduced in section II, a physical core loss model can be constructed as shown in Fig. 4

Analogously, to build a hybrid model, two sub-neural networks are used to embed the physical models and characterize static and dynamic hysteresis component. Fig.5 depicts the model structure of magnetization mechanism-inspired neural networks.

Static magnetization occurs when the magnetic moments have enough time to respond to an applied flux density. The change in magnetic moment caused by domain rotation and domain wall motion contains reversible and irreversible components. As discussed in Section 2, the PI stop operator can describe reversible and irreversible energy changes, so the static hysteresis subnetwork is constructed based on the PI model and Eq. (3). As shown in Fig. 5, the stop operators' response S_r will be treated as the inputs of the FNN in the static hysteresis subnetwork. Additionally, operating frequency and temperature are auxiliary inputs. Next, the FNN outputs $\mu_r S_r$, that is, the magnetic field strength generated by each type of stop operator (with the same saturation level). From the physical perspective of magnetization, the magnetization of materials is based on the magnetic moment changes of all magnetic domain, where each magnetic domain is modeled by a stop operator. Therefore, we can estimate H_h by summing induced magnetic field strengths of all operators.

The subnetwork used to model the dynamic hysteresis component will adopt the idea of section segmentation in the core loss ladder network, as mentioned in Section 2.3, to transform the complex nonlinear behavior into a combination of linear problems. From Eq. (4), we can rearrange the overall field strength due to the dynamic effects as:

$$H_{dyn} = \sum_{k=1}^{m} C_{seg_k} * g(\frac{dB_{seg_k}}{dt}), \quad (5)$$

where m is the number of the segments, C_{seg} is the dynamic effects coefficient of a specific segment, containing the information of the material property information. $g(.)$ is a nonlinear function with sequential dependency characteristic. We model the dynamic contribution using an RNN, where the number of hidden layer neurons in the RNN represents the number of segments. The neuron hidden state represents $g(\frac{dB_{seg}}{dt})$, which is depicted as H_{seg} in Fig.5. The subnetwork learns C_{seg} from the training data and express it as the weight from the hidden layer to the output. Eventually, the dynamic hysteresis component is the weighted sum of the magnetic field strengths generated in all hypothetical segments.

Mathematically, the operation of MMINN can be written as:

$$\begin{cases} x(t) = {}^1w\,{}^1v(t) \\ h(t) = {}^2w\,{}^2v(t) + {}^hwH_{seg}(t-1) \\ H_{seg}(t) = f_h[h(t)] \\ H_{dyn}(t) = C_{seg}H_{seg}(t) + b \\ H_h(t) = \sum f_h[x(t)] \\ H(t) = H_h(t) + H_{dyn}(t) \end{cases}, \quad (6)$$

where ${}^1w$ and ${}^2w$ are the weight of input nodes of the two subnetworks, ${}^1v(t)$ and ${}^2v(t)$ are the inputs of networks, $x(t)$ is the output of the input layer of the static hysteresis subnetwork, ${}^hw$ is the weight of the hidden nodes, b is the bias of the output node of the dynamic hysteresis subnetwork and $f_h[\cdot]$ is the activation function of the hidden layer. Here we choose sigmoid function as the activation function.

B. Model training

Before model training, all data needs to be preprocessed, which ensures that network parameters are learned on a similar scale and reduces training complexity. This process includes variable transformation into log scale (frequency) and standardization (all input variables).

For the main model training process, the objective function plays a crucial role in the neural network's performance and defines the direction of model parameters optimization. Here, we use mean square error metric to constrain the predicted field strength H to approximate to the true field strength $\widehat{H}$, as follows:

$$L = \frac{1}{n}\sum_{i=1}^{n}(H_i - \widehat{H_i}), \quad (7)$$

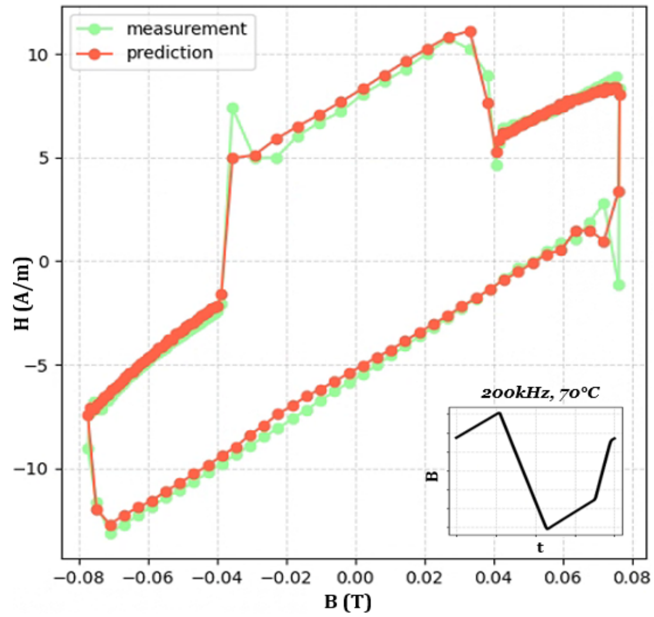


Fig. 6. Magnetization process prediction of material B under a trapezoidal excitation.

Table. 1. Number of parameters of each model.

Material	A	B	C	D	E
Num. of θ	1084	1084	1084	1084	1084
File size	7kb	7kb	7kb	7kb	7kb

where n denotes the number of the training data. Then, the proposed framework applies Adam [36] as the main optimization algorithm, which combines the benefits of adaptive gradient descent and momentum methods. The parameters related to the Adam algorithm will be improved through the performance of the model on the validation dataset.

IV. Results and discussion

The model results and discussions in this section are based on the problem setting of the MagNet challenge 2023. There are five unknown ferrite materials datasets for core loss model development, with each material containing between 580 and 7400 data points including different excitation waveforms, temperatures, and excitation frequencies.

A. Model size

The number of operators and the number of core cross-section segments (i.e., the number of RNN neurons in the dynamic hysteresis subnetwork) are the main factors that determine the performance and generalization ability of the model. They are defined as hyperparameters of the model. For the hyperparameters selection of the following network instances developed, we adopt the Optuna hyperparameter optimization framework, which is an improved version of the grid search technique [37].

MMINN is a hybrid model that naturally has advantages in scale over fully data-driven models. Therefore, instead of focusing on the compactness of the model, the optimization of

Table. 2. MMINN core loss prediction error based on 5 material training datasets.

Material	A	B	C	D	E
Abs. Avg. of Relative Error	3.26%	1.40%	1.73%	1.39%	1.80%
Abs. 95% of Relative Error	8.68%	3.67%	4.68%	3.58%	4.89%
Abs. 99% of Relative Error	14.3%	5.43%	8.29%	4.79%	7.17%
Abs. Max of Relative Error	26.6%	19.0%	24.3%	8.17%	12.9%

hyperparameters should be more focused on making core loss prediction reach the (average) relative error accuracy (<5%) acceptable for engineering applications. We select material A with a relatively suitable amount of data for hyperparameter optimization. Within 1000 training epochs, we found that 30 operators and 30 segments can achieve an average relative error of 5% for core loss prediction. Small adjustments (adding 1-2 neurons) have little impact on model accuracy, but huge adjustments (adding 10 neurons) will double the model size. Thus, we set this set of hyperparameters as the baseline for all material models. Table 1 lists the number of model parameters.

B. Model accuracy

The model accuracy shown in this section is based on the predictions obtained on the training data, as the core loss data of the test dataset is unknown. Table 2 lists the relative prediction errors of each material. It is noticeable that the prediction accuracy on the training dataset can only be used as a reference of model performance and do not fully reflect the generalizability of the model. The final judgment on model performance needs to be based on the model's performance on the test dataset.

C. Model interpretability

The proposed model obtains the core loss by simulating the dynamic hysteresis process and Eq. (1), rather than a simple numerical fitting like the Steinmetz formula. Fig. 6 shows an example of the predicted B-H curve for material B when the excitation is downsampled to 128 points.

Secondly, based on the behavior of magnetic materials under different magnetic field conditions, the model characterizes static hysteresis and dynamic hysteresis components respectively (see Eq. (2)). When capturing the static hysteresis component, the model considers two key magnetization mechanisms (domain rotation and domain wall motion) that cause magnetic moment changes from the magnetic domain level and reconstructs it using the stop hysteresis operator (see Eq. (3)). For the dynamic component, the model mainly focuses on field maldistribution and eddy current effects. Through the method of section segmentation and the powerful learning ability of neural networks, the calculation formula of the dynamic component under quasi-static conditions (see Eq. (4)) is transferred to high-frequency applications. As all modeling formulations rely on the principles of physics (Maxwell's Equations) and phenomenology, the authors are confident that the proposed model possesses adequate physical insights to effectively represent the magnetization process and compute core losses of magnetic material.

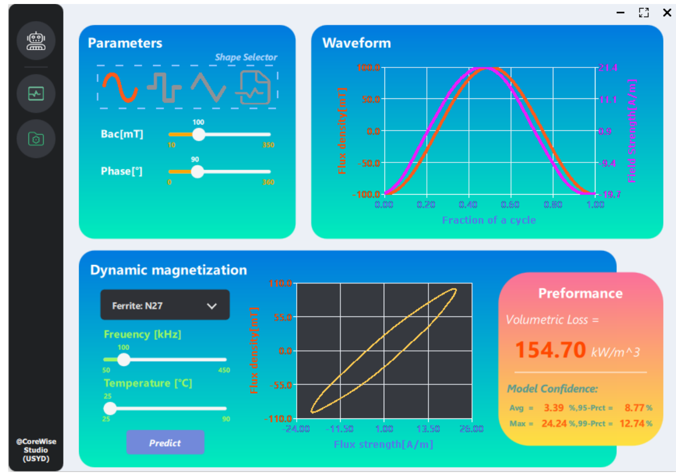


Fig. 7. Main page of the developed UI.

D. Data visualization – QT based user interface

The user interface makes it easy to process and interpret data, ensuring a friendly experience for all users. We developed a UI based on QT design studio (see Fig.7), which contains the following features.

- Sine wave, trapezoidal wave, triangle wave and customized excitation inputs.
- B-H curve prediction and core loss prediction of a single cycle waveform.
- Core loss prediction of a dataset, and prediction data saved as csv file.
- Model accuracy evaluation through the histogram.

V. Conclusion

This paper introduces magnetization mechanism-inspired neural networks, a novel hybrid model capable of encoding underlying loss mechanisms and describing the dynamic magnetization process. More specifically, the proposed model consists of two subnetworks that represent the static and dynamic hysteresis components, respectively, based on the loss separation theory. The concepts of the PI hysteresis model and core loss ladder network segmentation are embedded in the subnetworks to enrich physics insights into the model. The MMINN applies a standard MSE loss function and an optimization algorithm (Adam) to train model parameters. In addition, a UI is designed to make data interpretation a visually engaging experience and help users explore B-H correlations.

Simulations of five materials were performed to verify the effectiveness of the proposed model, where the average 95% percentile error of the core loss predictions for the five materials is 5.1%. Besides, the presented networks have strong physical interpretability and compact size. Such outstanding model performance makes the proposed model suitable for matching with electromagnetic field simulation techniques (e.g., FEM) to drive advances in power magnetics automatic design.

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