2023 MagNet Challenge: An Approach Towards Improved Core Loss Modelling

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***Abstract*—2023 MagNet challenge aims to develop innovative core loss modeling approaches with high accuracy and reduced complexity. The core loss of magnetic materials is governed by complex physics and depends on the material's electrical, magnetic, mechanical, thermal, and other physical properties. An evaluation of state-of-the-art empirical and data-driven approaches for core loss modeling has been done. In our approach we aim to leverage the best of both empirical and data-driven methods, thus coming up with a hybrid modeling strategy. This report summarises the key aspects of the hybrid model and summarizes our team's efforts toward developing the bybrid core loss model.**

I. Introduction

Power magnetics constitutes about 50-60% of the weight and volume of state-of-the-art power converters. Design optimization of power-magnetics is crucial to enable highly efficient and power-dense converters for weight-critical systems.

Magnetics design in itself is a multidisciplinary endeavor. A designer has many choices regarding magnetic core materials, core geometries, and winding options. Typically, several design iterations are needed to arrive at an optimal design. The availability of accurate models (reluctance models, core loss models, copper loss models, thermal models, insulation aging models) can considerably speed up the design life cycle.

The focus of this work is to come up with improved methods for modeling magnetic core losses. The 2023 MagNet challenge has renewed researchers' interest in developing improved core loss modeling methods. The availability of experimental datasets has made it easier to evaluate existing models and benchmark any new models. We target a multi-pronged approach toward modeling the core losses that combines the simplicity of the empirical model and the accuracy of the data-driven approaches. Our approach includes separating the input data based on the excitations (sine, triangular and trapezoidal) and building three hybrid models i.e., we are trying to embed the nature of physics with the neural network. Our approach includes the following:

- Evaluating state-of-the-art empirical models (listed in Table I) using the experimental data set and identifying any underlying trends by analyzing the error data.
- Building hybrid neural networks i.e., modeling three separate physics-informed neural networks (PINN) for each sinusoidal, triangular, and trapezoidal excitations; training them by embedding suitable empirical core loss equations and parameters trends with respect to temperature and frequency into the training process.
- Building a pre-trained model by using the pre-existing material data (previously published 10 materials) for each excitation.
- Fine-tuning and validating the PINN models using the hyperparameters of the models for each excitation for the newly introduced five materials.

II. Our Approach

In this section, the steps taken towards creating the hybrid models are explained in detail.

A. Feature Extraction

First, the single-cycle flux density waveform data is segregated into three datasets based on the excitation i.e., sinusoidal, triangular, and trapezoidal excitations. Several distinct features characterizing each waveform have been extracted and listed below for each excitation type.

- Sinusoidal flux type - peak-to-peak flux density (B_{pkpk}), maximum flux density (B_{max}), minimum flux density (B_{min}), time period (T).
- Triangular flux type - peak flux density (B_{pk}), duty ratio (d), positive and negative slopes (dB/dt)
- Trapezoidal flux type - flux densities (B_1, B_2, B_3, B_4) at the critical points (i.e. instants where there is a slope change), duty ratios (d_1, d_2, d_3, d_4).

In addition to the above quantities, the frequency (f) and temperature (T) data are directly read from the data provided by the MagNet team and have been added as features of the respective waveforms.

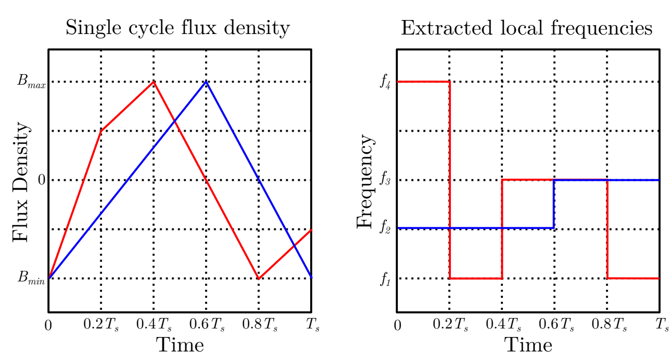

Fig. 1. Composite waveform hypothesis-based extraction of local frequencies [8].

TABLE I
LITERATURE SUMMARY

Loss Models	Highlights	No. of Parameters
Jiles-Atherton model [1]	Accurate phenomenological model describing the hysterical behavior of the magnetic materials. A thorough understanding of magnetic domain walls and other microscopic behavior is required for accurate macroscopic hysteresis loss modeling.	5
Steinmetz equation [2]	A simple power law equation-based empirical model, which is suitable for sinusoidal excitations only.	3
Modified Steinmetz equation (MSE) [3]	First empirical model to identify the effect of induction change-rate $\frac{dB}{dt}$ on core-loss and introduction of an equivalent-frequency concept.	3
Improved Generalized Steinmetz Equation (iGSE) [4]	Influence of peak-to-peak flux density on core loss rather than the instantaneous value of flux density is discussed.	3
Improved Steinmetz Equation (ISE) [5]	A composite waveform hypothesis (CWH) based model where the effect of waveform duty ratio is incorporated. It is similar to the Steinmetz equation, where frequency and flux density are the main variables.	up to 6 for triangular and up to 12 for trapezoidal excitations
MagNet core loss model [6]	A two-stage machine learning for magnetic core loss modeling. The complex behavioral attribute of magnetic material can be captured using a machine learning approach.	upto 50,000
Meta-material core loss model [7]	Introduced a new core loss model for estimating eddy current core loss based on the meta-material modeling approach of material parameters and wave equations; when combined with state-of-the-art hysteresis model can predict accurate estimation of overall core losses	11

B. Empirical Models

State-of-the-art empirical loss models that are available in the literature are evaluated.

In our approach to hybrid modeling, we have used the Improved Steinmetz equation (ISE) [5] based empirical loss equations. It reduces to the Steinmetz equation for sinusoidal data. The ISE has been extended for trapezoidal excitations by applying the composite waveform hypothesis (CWH) [8] as shown in Fig. 1.

Further, the coefficients used in the ISE based models have been made adaptive with respect to frequency and temperature rather than keeping them as constants for improved accuracy.

C. Proposed Hybrid Model

Our approach to hybrid modeling includes the following innovative aspects.

Three separate models

Three different hybrid models have been developed, one for each excitation. The hybrid modeling approach is inspired by physics-informed neural networks, wherein the empirical equations governing the core loss are incorporated into the neural network. The incorporation of the empirical loss model into the neural network is shown in Fig. 2.

Creating separate models allows the flexibility to embed separate empirical core loss functions suitable for each excitation. Table II shows the architecture of the neural network for each excitation type. It is to be noted that these three models are used for training data for a single material.

Learnable parameters

The coefficients of the empirical loss models have been made adaptive with respect to temperature (T) and frequency (f). Therefore, they are expressed as functions of T, f, and some constants. These constants are defined as the learnable parameters of the neural networks. This enhances the capacity of the neural network to learn meaningful patterns and generalize its learning. This will help to predict the results for data that has not been encountered while training. Also, the coefficients in the empirical core loss models exhibit wide variations across different grades of ferrite materials. Thus, including these coefficients as the learnable parameters seemed like an interesting and wise option.

Also, these meaningful patterns can further be utilized to understand the core loss trends for each material, for which obtaining an empirical fit is challenging.

Customized training loss function

In our training process, a custom loss function is defined. This function ensures that the output of the neural networks, i.e., core loss of the given ferrite material, closely follows the defined empirical equation. The custom loss, $Loss_{custom}$ is defined as:

$$Loss_{custom} = \lambda \times MSE(P_{pred}, P_{act}) + MSE(P_{pred}, P_{emp}) \quad (1)$$

where P_{pred} is the core loss predicted from the neural network, P_{emp} is the core loss from the empirical loss model (based on ISE with adaptive coefficients), and P_{act} is the measured core loss as given for each waveform in the training dataset.

The MSE indicates the mean-squared error; here, λ is again a hyperparameter set by employing the grid-search algorithm. This hyperparameter, λ, when fine-tuned, helps balance out the contribution from data loss and physics loss and aids in the proper training of the neural network.

The first term generally $MSE(P_{pred}, P_{act})$ corresponds to *'data-loss'* since the output of the neural network is compared against the actual measured core loss values. The second term $MSE(P_{pred}, P_{emp})$ corresponds to *'physics-loss'* or *'empirical-loss'* since the output of the neural network is compared against the empirical equation. Hence, the idea of

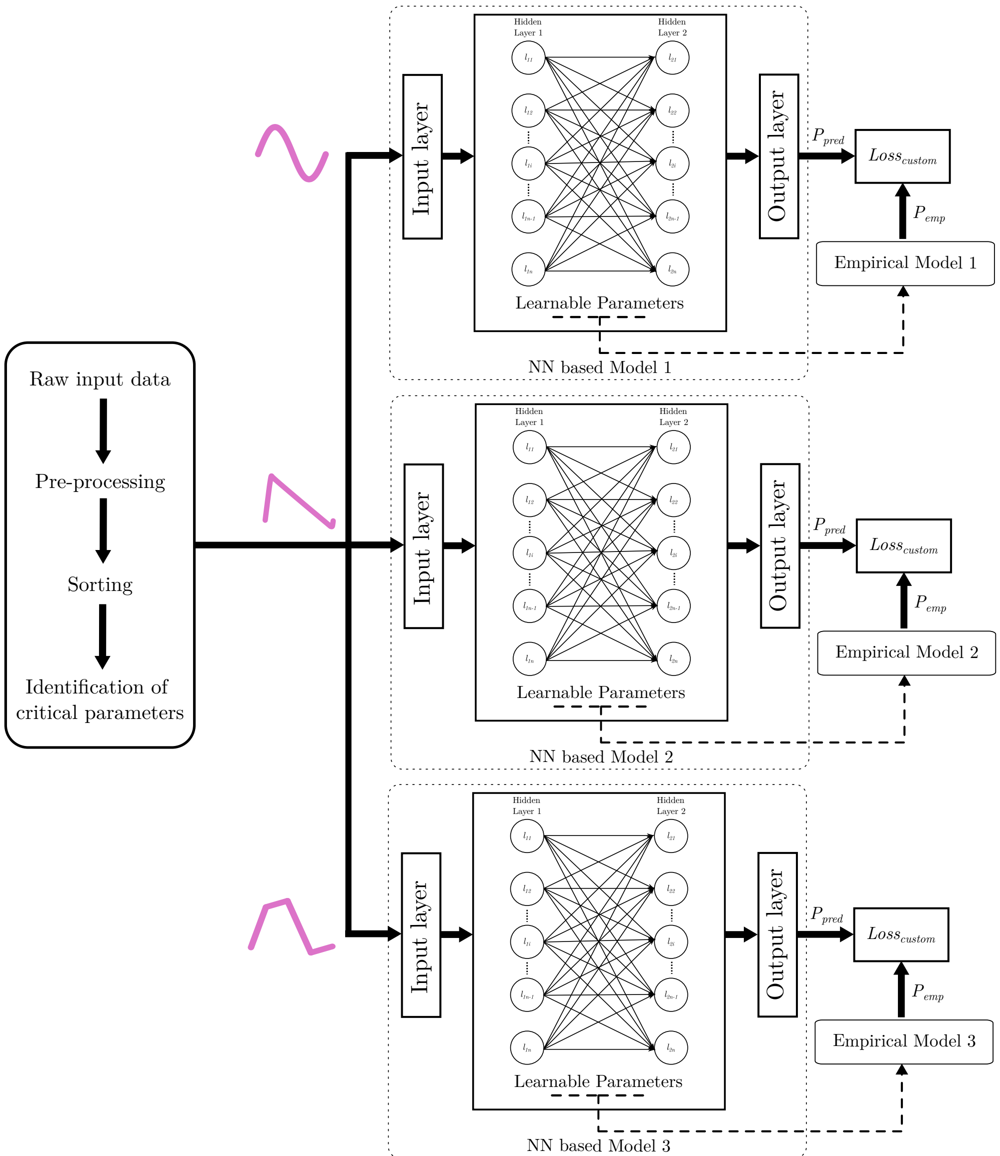

Fig. 2. Implementation of proposed hybrid model.

the hybrid model is inspired by PINN; empirical models are used instead of physics models.

Pre-training with pre-existing data of materials

The hybrid models have been pre-trained with the pre-existing data of 10 materials available on the MagNet Database. The pre-training of the neural network helps capture common core loss trends across the different materials. This boosts the learning of the neural network from the previous ten materials. It helps the models for the new material to achieve faster convergence and also prevents overfitting in the case of the materials where the number of data points in the training dataset is less.

Fine tuning and loss prediction

The pre-trained models and the learnable parameters are loaded into each neural network, thus initializing the weights and biases to trained values rather than random values. The hyperparameters of the models are then fine-tuned for each material for the best training. A final model for each excitation type is saved for testing.

III. Model Summary

Table II lists the architecture of the three models as shown in Fig. 2. The total number of parameters including the learnable parameters for each model is listed. These same models are used for different excitations of each of the 5 new materials.

Table III lists the 95^{th} percentile error numbers for each excitation of the 5 new materials based on the training dataset provided. Table IV lists the final tuned hyperparameters for each of the models.

TABLE II
MODEL SIZE AND PARAMETERS FOR EACH EXCITATION AND MATERIALS

Model	Sinusoidal	Triangular	Trapezoidal
Size	One input layer: (7,16) Two hidden layers: (16,256), (256,16) One output layer: (16,1)	One input layer: (8,16) Two hidden layers: (16,256),(256,16) One output layer:(16,1)	One input layer: (12,16) Two hidden layers: (16,256), (256,16) One input layer: (16,1)
Parameters	8609	8625	8689

TABLE III
95TH PERCENTILE ERROR AFTER PRE-TRAINING AND FINE-TUNING OF THE MODELS WITH FULL 100% TRAINING DATASET

Material	Sinusoidal	Triangular	Trapezoidal
A	2.30 %	4.71 %	3.42 %
B	2.08 %	1.55 %	2.55 %
C	4.90 %	3.55 %	3.72 %
D	3.68 %	4.73 %	2.76 %
E	2.75 %	4.55 %	4.25 %

TABLE IV
THE FINAL TUNED HYPERPARAMETERS FOR EACH OF THE MODELS

Models			
Material	Sinusoidal	Triangular	Trapezoidal
Hyperparameters			
A	LR_INIT = 5.6e-3 EPOCHS = 8000 BATCH SIZE = 128 λ = 215	LR_INIT = 5.6e-3 EPOCHS = 11000 BATCH SIZE = 128 λ = 215	LR_INIT = 5.6e-3 EPOCHS = 11000 BATCH SIZE = 128 λ = 215
B	LR_INIT = 5.5e-3 EPOCHS = 8000 BATCH SIZE = 128 λ = 460	LR_INIT = 5.5e-3 EPOCHS = 8000 BATCH SIZE = 128 λ = 460	LR_INIT = 5.6e-3 EPOCHS = 4000 BATCH SIZE = 128 λ = 460
C	LR_INIT = 6.5e-3 EPOCHS = 20000 BATCH SIZE = 256 λ = 80	LR_INIT = 6.0e-3 EPOCHS = 4000 BATCH SIZE = 128 λ = 132	LR_INIT = 5.5e-3 EPOCHS = 4000 BATCH SIZE = 128 λ = 132
D	LR_INIT = 3.0e-3 EPOCHS = 4000 BATCH SIZE = 64 λ = 193	LR_INIT = 3.0e-3 EPOCHS = 7000 BATCH SIZE = 64 λ = 193	LR_INIT = 3.0e-3 EPOCHS = 10000 BATCH SIZE = 64 λ = 193
E	LR_INIT = 5.5e-3 EPOCHS = 5000 BATCH SIZE = 128 λ = 1000	LR_INIT = 5.5e-3 EPOCHS = 7000 BATCH SIZE = 256 λ = 1000	LR_INIT = 5.5e-3 EPOCHS = 15000 BATCH SIZE = 256 λ = 1000

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