A Hybrid Data-Driven Approach in Magnetic Core Loss Modeling for Power Electronics Applications

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***Abstract*—The accurate magnetic core loss estimation in power electronics applications, which is crucial for designing efficient converters, is a highly challenging task. Traditional methods like the Steinmetz equation and its evolutions fail to describe various operating conditions accurately. This paper presents a hybrid approach to address these challenges, proposing a workflow that integrates machine learning concepts with the physical understanding of magnetic phenomena for accurate and fast magnetic core loss predictions under various operating conditions, offering a promising path for effective loss models in power electronics applications.**

I. Introduction

The demand for effective magnetic core loss estimation methods is continuously growing in the field of power electronics, driven by the goal of ensuring the design of highly efficient and power-dense converters. Nevertheless, it is still challenging to obtain an effective and accurate loss prediction that can cover a wide range of operating conditions, and that can be easily integrated into the design stage of magnetic components or circuit simulations of power converters [1]. The adoption of conventional methods, such as the classical Steinmetz equation or its evolutions proposed in the last decades, are not able to address the variety of waveform shapes, frequency range, and temperature conditions typical of the operation of magnetic components in power electronics converters [2]–[5]. These methods require a fast computational task and the tuning of a very tiny set of parameters determined on the basis of the described magnetic material and the range of the operating conditions. However, the accuracy can be significantly far from the real loss values. On the other hand, the physical description of the different loss mechanisms involved in soft magnetic materials can lead to more accurate results but can also require a huge set of specific measurement data, not usually available to the designer [6]. In addition, the range of applicability of these methodologies can be limited due to their basic assumptions.

Nowadays, interesting perspectives appear on adopting machine learning methodologies for describing physical phenomena [7], [8]. New design tools and modeling methods can be employed to accurately estimate the power losses of magnetic components in power electronics converters by enabling cooperation between the physical understanding of the magnetic phenomena and the statistical and numerical concepts behind the machine learning methodologies.

The demand for new and standardized procedures for the accurate core loss predictions of magnetic components in power electronics emerged in the context of the MagNet Challenge, an international student competition with the aim of developing innovative and efficient uses of measurement data for modeling power magnetics [9]. Our team from Politecnico di Torino was involved in this competition, and this paper describes the workflow we proposed for the computation of magnetic losses under different magnetic flux density waveforms.

II. Model overview

The first remarks regard the nature of the provided dataset for developing the models in the MagNet Challenge context. A huge amount of measured magnetic core loss data for ten commercial soft ferrites is available on the MagNet website [9]. Figure 1 summarizes the proposed magnetic flux density waveforms, represented by sinusoidal, triangular, and trapezoidal magnetic flux density waveforms, sampled with 1024

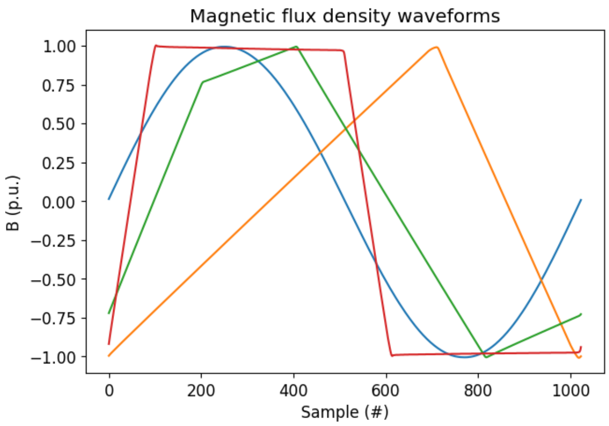

Fig. 1. Different magnetic flux density waveform shapes available in the MagNet database.

TABLE I
MAGNET CHALLENGE DATASET RANGE

	Min	Max
B_{pkpk} (mT)	21.05	561.43
f (kHz)	49.95	446.69
θ (°C)	25	90
δ	0.1	0.9

points. The variety of the proposed waveforms describes a wide range of applications in power electronics. Also, the variety of operating conditions, in terms of the amplitude of the magnetic flux density, frequency, temperature, and duty cycle (for triangular waveforms), is considerable, as described in Table I, which reports the data range for the N87 ferrite.

The huge variety of measured data for different operating conditions allows the adoption of suitably trained data-driven methodologies, such as neural networks. In this framework, our approach was based on using scalar input and scalar output models, such as the feedforward neural network. In this case, the different operating conditions can be described by a set of scalar variables, such as the frequency, the peak-to-peak magnetic flux density, the temperature, and the network output is a scalar value, such as the energy or the power loss. The workflow proposed by our team follows the strategy of supporting the development of straightforward scalar-to-scalar data-driven models with useful physical insights based on the core loss phenomena involved for the considered magnetic materials. With this in mind, the first goal is to find the lowest number of scalar inputs that can fully describe the behavior of the magnetic core losses. While sinusoidal and triangular magnetic flux density waveforms can be fully described by a few scalar values, such as the temperature, the frequency, the peak-to-peak flux density value, and the duty cycle for the triangular case, trapezoidal waveforms require more information related to the slope and the flux density change of each time interval. Thus, the definition of a generalized model for the loss prediction of the entire dataset that involves sinusoidal, triangular, and trapezoidal waveforms can lead to an extremely complex and wide neural network, increasing the efforts of the training phase and reducing the computation efficiency. On the other hand, it is well known in the literature that magnetic losses under different magnetic flux density waveforms exhibit theoretical relations [10]–[13]. To this end, our team was motivated to use a neural network-based model for the prediction of the magnetic losses for triangular magnetic flux density waveforms under different temperatures, frequencies, duty cycles, and amplitude values and then extend the achieved results to sinusoidal and trapezoidal waveforms. This task, described in detail in the next sections, is implemented with a Support Vector Regression (SVR) for the sinusoidal waveforms and with the Composite Waveform Hypothesis (CWH) for the trapezoidal ones.

The first task for the model is to recognize and classify the different waveforms, and it is approached with the computation of the form factor and crest factor of each magnetic flux density waveform. Sinusoidal and triangular waveforms are easily discernible since their form and crest factors are constant. All the waveforms not classified as sinusoidal or triangular are labeled as trapezoidal.

The results presented in the following section refer to the N87 ferrites, but the procedure has been tested on all the available materials in the MagNet database, giving comparable performances. For the N87 material, a dataset of 40616 measured samples (Dataset A) is adopted for the training phase of the models, while a further dataset of 5000 samples (Dataset B) is used for testing the performances.

III. TRIANGULAR WAVEFORM MODEL

Once the triangular flux density waveforms dataset is defined, the procedure for building the neural network model can be determined. The goal of the model for triangular waveforms is to describe the power loss P as a function of the peak-to-peak magnetic flux density, frequency, temperature, and duty cycle (B_{pkpk}, f, θ, δ). The selected structure of the model is a feed-forward neural network implemented in Python by adopting Keras [14]. We selected the energy loss per cycle W as the neural network output since the power loss can be easily determined by multiplying the energy loss by frequency. This choice will be useful for reconstructing the sinusoidal and the trapezoidal losses, as reported in the following sections.

Since the dependence of the energy loss on the amplitude and the frequency of the magnetic flux density follows a power law, the logarithm operation is applied to the B_{pkpk} and f inputs and the output W. The available data from Dataset A are shuffled and divided into training, validation, and testing sets (60%, 20%, 20%). Then, the inputs are standardized to obtain compatible dimensions for all the different quantities. The mean and standard deviation of the training dataset are used for standardization.

The neural network structure has been preliminary determined by using a random search optimization, leading to a Sequential Network in Keras described by Table II.

The total number of trainable parameters for a feedforward neural network dedicated to the loss prediction of triangular

TABLE II
NEURAL NETWORK STRUCTURE FOR TRIANGULAR WAVEFORMS

	Number of neurons	Activation function
Layer 1	10	Tanh
Layer 2	16	Tanh
Layer 3	1	Relu

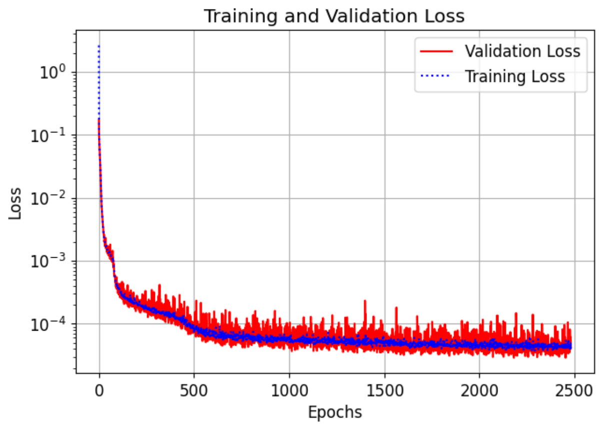

Fig. 2. Evolution of the loss function computed on the training and validation data.

flux density waveforms for a given material is 243. The model training is performed by adopting the Adam algorithm to optimize weights and biases, aiming to minimize the loss function defined as the mean squared error on the validation dataset. Figure 2 illustrates the behavior of the loss function over the training iterations. The maximum number of iterations is 10000, but a stop criterion is defined (300 iterations without improvements on the validation data).

Then, the neural network performances are verified on Dataset B, with the results described by Figures 3 and 4.

The high accuracy of the power loss prediction for triangular

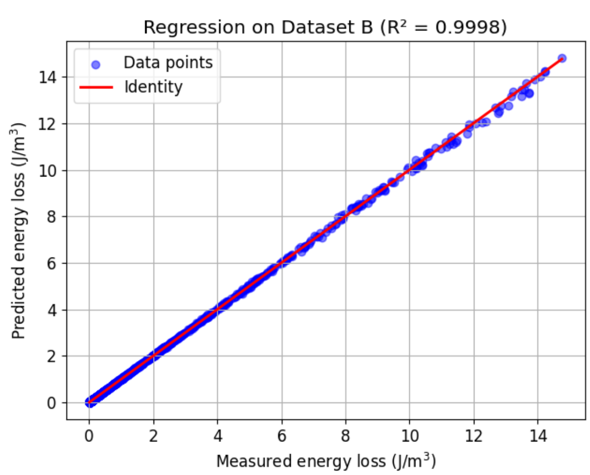

Fig. 3. Correlation between measured and predicted energy losses, for triangular magnetic flux density waveforms of Dataset B.

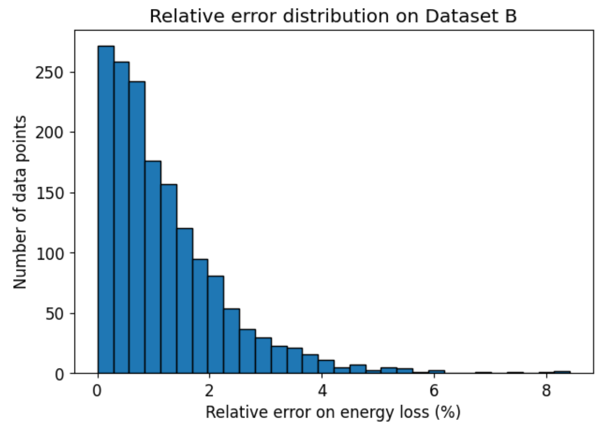

Fig. 4. Distribution of the relative error on the energy loss prediction, for triangular magnetic flux density waveforms of Dataset B.

waveforms is encouraging since it will represent the base for the loss reconstruction under sinusoidal and trapezoidal flux density waveforms.

IV. SINUSOIDAL WAVEFORM MODEL

This section proposes a model to report the energy losses computed for triangular waveforms under given temperature, frequency, and peak-to-peak flux density conditions to the corresponding sinusoidal cases. The first task is analyzing the relationship between sinusoidal and symmetric triangular waveforms ($\delta = 0.5$). It is well known that the dynamic magnetic loss contributions are dependent on the time derivative of the magnetic flux density $(\frac{\mathrm{d}B}{\mathrm{d}t})$ [12]. For soft magnetic ferrites, the energy loss dependence on $(\frac{\mathrm{d}B}{\mathrm{d}t})$ is influenced by the prevailing role of a specific loss mechanism involved at a given frequency, temperature, and flux density amplitude [13]. As an example, by assuming the energy loss dependence on the square of the time derivative of the induction $(W \propto (\frac{\mathrm{d}B}{\mathrm{d}t})^2)$, the ratio between sinusoidal and symmetric triangular waveform losses is identified in $\pi^2/8$. However, as previously mentioned, in practice, this ratio is strongly influenced by the operating conditions, determined by the amplitude, frequency, and operating temperature, and is also dependent on the specific material properties. Figures 5 and 6 give an overview of the behavior of this ratio for Dataset A.

The dependence of this ratio on the input parameters of the loss prediction is not easily determinable and generalizable for different core materials, and the theoretical description requires additional data from the available database. However, machine learning techniques can effectively tackle the task of modeling the sinusoidal/triangular ratio. Our approach is thus based on modeling the sinusoidal/triangular energy loss ratio with a Support Vector Regression model. We used the Python implementation available in the Scikit-learn library to construct the SVR model [15]. The Radial Basis Function (RBF) kernel is used to effectively deal with the non-linear behavior of the sinusoidal/triangular ratio as a function of the input parameters identified in the peak-to-peak flux density,

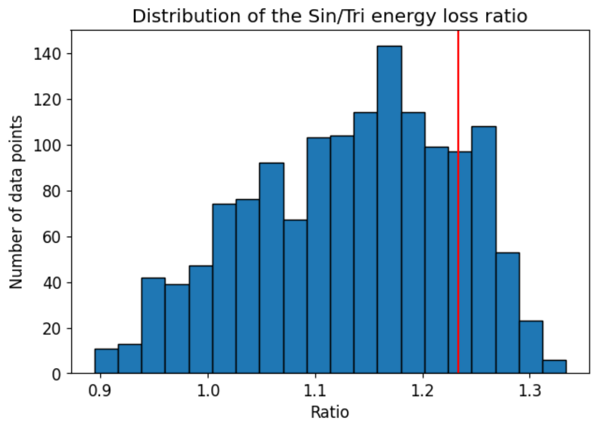

Fig. 5. Distribution of the sinusoidal/symmetric triangular loss ratio for Dataset A. The red line represents the theoretical value of $\pi^2/8$.

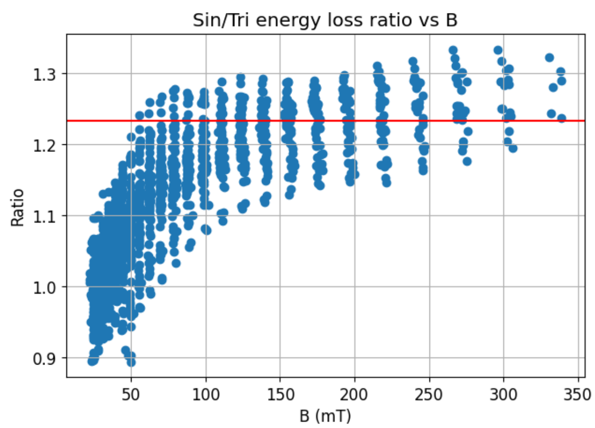

Fig. 6. Behavior of the sinusoidal/symmetric triangular loss ratio as a function of the peak-to-peak magnetic flux density for Dataset A. The red line represents the theoretical value of $\pi^2/8$.

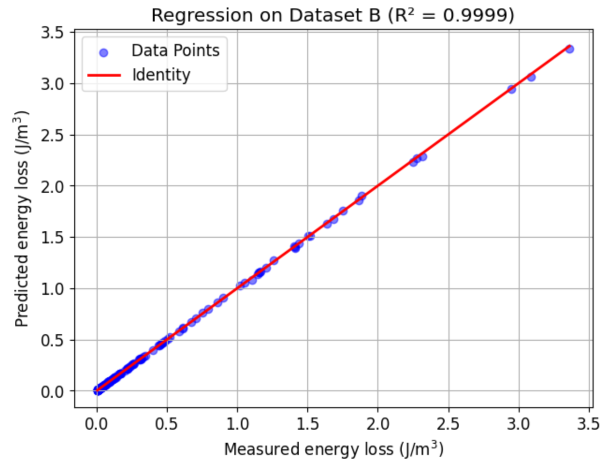

Fig. 7. Correlation between measured and predicted energy losses, for sinusoidal magnetic flux density waveforms of Dataset B.

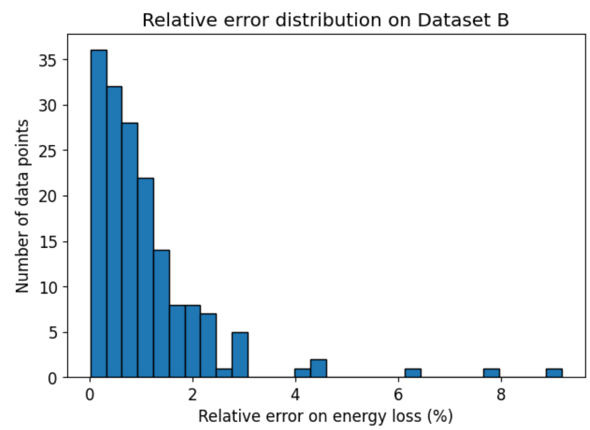

Fig. 8. Distribution of the relative error on the energy loss prediction, for sinusoidal magnetic flux density waveforms of Dataset B.

frequency, and temperature. The data from Dataset A are shuffled, divided into training, validation, and testing sets, and then standardized as in Section III. The optimization of the model hyperparameters is performed, and the model is trained on each material to define the suitable support vectors. The number of trained parameters that define the support vectors for the considered materials is 349.

Once the model is trained, the procedure for computing the magnetic losses can be divided into two phases: in the first phase, for a sinusoidal flux density waveform at a given peak-to-peak amplitude, frequency, and temperature, we compute the corresponding energy loss of a symmetric triangular waveform, by means of the neural network model described in Section III. Then, the trained SVR model is used to estimate the sinusoidal/triangular energy loss ratio. By combining the two model outputs, we obtain the energy loss for a sinusoidal flux density waveform at a given peak-to-peak amplitude, frequency, and temperature.

An overview of the achieved results evaluated on Dataset B is reported in Figures 7 and 8.

V. Trapezoidal waveform model

Our approach to the loss prediction for the trapezoidal magnetic flux density waveforms follows the idea of adopting the model for the triangular case as the building block. To pursue this goal, we implemented a method known in the literature as the Composite Waveform Hypothesis [10], [11]. The method, applied to trapezoidal waveforms, assumes that the energy loss can be computed as the sum of the loss associated with each waveform segment. In particular, a trapezoidal waveform can be decomposed into many symmetrical triangular waveforms, and the core loss can be computed as the sum of the loss associated with each triangular waveform. The link with the previously proposed loss prediction workflow is that we can estimate the losses of the symmetrical triangular waveforms required for applying the CWH with the previously trained neural network model. Going more into the details of the implementation of the CWH, the first task is the computation of a time-varying local equivalent frequency:

$$f_{\mathrm{eq}} = \frac{\left|\frac{\mathrm{d}B}{\mathrm{d}t}\right|}{2B_{\mathrm{pkpk}}}. \tag{1}$$

The equivalent frequency is computed for each sample of the trapezoidal waveform. Thus, for each sample, we compute with the neural network model an energy loss value of a correspondent symmetrical triangular waveform at the computed equivalent frequency under the same peak-to-peak amplitude and temperature of the trapezoidal one. Then, the total energy loss of the trapezoidal waveform is computed as the sum of the contribution of all the samples as

$$W = f \sum_{i}^{n_{\mathrm{samples}}} W_i(B_{\mathrm{pkpk}}, f_{\mathrm{eq,i}}, \theta)\,\Delta t_i. \tag{2}$$

The application of the CWH in the proposed workflow for estimating the magnetic losses of ferrite cores under different flux density waveforms has the strength that it does not require a further definition of different models with other trainable parameters but is completely related to the neural network already trained for the triangular waveforms. This aspect reduces the overall size of the model. However, there are two main drawbacks to applying the CWH to compute the energy loss related to trapezoidal flux density waveforms. The first is that the computed equivalent frequency can fall outside the frequency range of the MagNet measurement dataset. An equivalent frequency greater than the upper frequency limit can occur when a trapezoidal waveform segment has a steep slope, while an equivalent frequency lower than the lower frequency limits is caused by segments with a slow variation rate of the flux density. For the first case, our approach still assumes valid (in the hundreds of kHz range) the neural network model extrapolation over the upper frequency limit since it is coherent with the theoretical energy loss dependence on the frequency for the analyzed materials. On the other hand, for equivalent frequencies that are lower than the measured range, we consider the energy losses as independent of the frequency since, typically, for ferrite materials for power electronics applications, the hysteresis loss term is still dominant up to some tens of kHz. The second weakness is related to the CWH inability to consider the relaxation effects [11]. The relaxation effects describe the occurrence of magnetic losses during the phase of constant flux density of waveforms [4]. This issue is well-known in the literature and can introduce troubles in reproducing the energy losses of trapezoidal waveforms with a near-zero flux density derivative segment, as the red waveform of Figure 1.

Conscious of these limitations, we evaluated the performance of the proposed approach to all the trapezoidal waveforms of Dataset B, reaching the results described in Figures 9 and 10.

However, the application of the CWH to the sole trapezoidal waveforms that do not present a near-zero flux density derivative segment can strongly improve the achievable performance of the method, as reported in Figures 11 and 12.

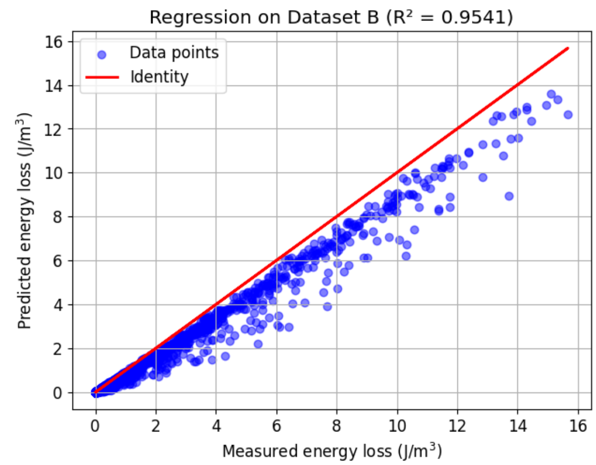

Fig. 9. Correlation between measured and predicted energy losses, for trapezoidal magnetic flux density waveforms of Dataset B.

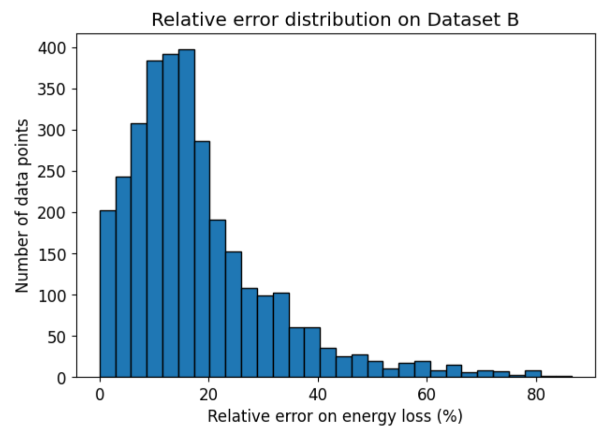

Fig. 10. Distribution of the relative error on the energy loss prediction, for trapezoidal magnetic flux density waveforms of Dataset B.

The distinction between waveforms with or without near-zero flux density derivative segments can be performed by fixing a threshold on the minimum equivalent frequency value, which, for our results, was fixed at 5 kHz.

VI. Discussion

Table III summarizes the results obtained on the entire Dataset B with the proposed hybrid data-driven approach. The performances achieved on the triangular waveforms with

TABLE III
MEAN VALUE, 95TH PERCENTILE, AND MAX VALUE OF THE RELATIVE ERROR ON THE ENERGY LOSS PREDICTION FOR DATASET B

	N. points	Mean (%)	95 perc (%)	Max (%)
Tri	1625	1.21	3.37	8.42
Sin	167	1.12	2.84	9.19
Trapz (all)	3208	18.1	45.84	86.54
Trapz (reduced)	2478	14.06	31.35	45.22

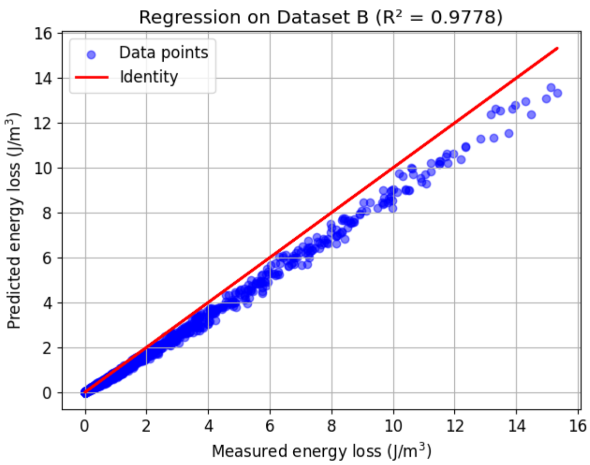

Fig. 11. Correlation between measured and predicted energy losses, for trapezoidal magnetic flux density waveforms of Dataset B without near-zero flux density derivative segments.

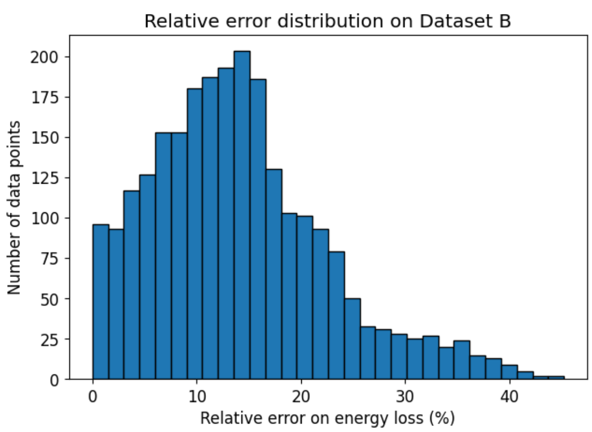

Fig. 12. Distribution of the relative error on the energy loss prediction, for trapezoidal magnetic flux density waveforms of Dataset B without near-zero flux density derivative segments.

a simple feedforward neural network with 243 trainable parameters are extremely satisfying, and they constitute a solid foundation for the reconstruction of sinusoidal and trapezoidal waveforms. Regarding the sinusoidal case, the reconstruction of the sinusoidal/triangular loss ratio performed by means of an SVR also gives interesting results, adding 349 trainable parameters to the model. While the performances on the trapezoidal waveforms appear to be the worst in the context of our loss prediction procedure, the strength of the loss prediction for non-zero derivative trapezoidal waveforms is the adoption of the same neural network of the triangular waveforms and the application of the CWH, without requiring further training phase and further trained parameters. Wanting to enhance performances on trapezoidal waveforms, a suitable model for describing the behavior of the relaxation losses as a function of the time derivative of the magnetic flux density can be implemented.

VII. Conclusion

This paper describes the magnetic core loss procedure defined by the team from Politecnico di Torino that participated in the MagNet Challenge. A workflow for the loss estimation under different magnetic flux density waveform shapes and different operating conditions is proposed, with the aim of obtaining a good compromise between result accuracy, computational time, and methodology simplicity. We tried to define differentiated loss prediction methods for each waveform type with a limited trainable parameter set for the entire model. The results are satisfactory, but there is still room for improvement in the proposed methodology, particularly when looking at the loss prediction under trapezoidal magnetic flux density waveforms.

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