MagNet Challenge 2023 - Politecnico di Torino Proposal

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***Abstract*—A methodology for calculating ferrite core losses is introduced within the context of the 2023 MagNet Challenge. The challenge aimed to explore alternative approaches for estimating losses, emphasizing the use of machine learning methods and generalized Steinmetz methods. Our team aimed to integrate both statistical and physical approaches by incorporating Neural Networks and the Composition Waveform Hypothesis. The final selection was made among numerous approaches based on its simplicity and practical functionality.**

I. Introduction

CHARLES Steinmetz proposed the Steinmetz formula ($P = kf^{\alpha}B^{\beta}$) in the late nineteenth century to calculate time-averaged core losses in soft magnetic materials. The Steinmetz equation represents a straightforward fitting formulation based on three material-depending parameters and two input variables: the magnetic induction peak value and the frequency of the excitation waveform. However, the framework in which the Steinmetz equation was developed is extremely different from the actual application area of magnetics for power electronics converters. Different magnetic materials, such as ferrites, amorphous and nanocrystalline materials, different excitation waveforms, such as triangular, trapezoidal, and PWM waveforms, and even higher switching frequencies require a more detailed approach for the description of the magnetic power losses. The initiative to develop a comprehensive model for predicting these critical losses in various electrical engineering applications gained traction on the centenary of Steinmetz's passing. From early June, our team explored suitable adaptations for modeling ferrite losses. We believed that the machine-learning aspect of the solution should complement a more physics-based approach to the challenge.

II. Modeling Choices

The developed approach for predicting losses in sinusoidal, triangular, and trapezoidal waveforms relies on triangular waveforms as the foundational element. Initially, the data is divided based on each waveform type, and neural networks are employed to compute triangular losses for different input conditions. Sinusoidal losses are derived by scaling the previous results through regression. Additionally, a portion of trapezoidal losses is determined using the Composite Waveform Hypothesis (CWH) [1], by using the predicted triangular losses as inputs. Finally, the remaining trapezoidal signals are examined using a distinct neural network separate from the triangular one. The flow chart of Figure 1 summarizes the workflow of the proposed loss computation procedure.

The project has been entirely developed in Python 3.10 using open-source libraries and packages. Concerning the neural networks, we opted to use Keras [2]. Keras is an efficient tool for creating, training, and using neural networks in the Python environment, and it's well-suited for dealing with the complexities of analyzing different types of waveforms and operating conditions, proper of the MagNet Challenge tasks. Keras simplifies the whole process of working with neural networks, making it easier for us to design and implement our models.

III. Loss computation procedure

A. Waveform Detection

The model starts by dividing the input induction waveforms into four different types:

1) Triangular waveforms.
2) Sinusoidal waveforms.
3) Trapezoidal waveforms, without near-zero derivative segments.
4) Trapezoidal waveforms, with a near-zero derivative segment.

These classifications are established by evaluating the form and crest factors of the induction waveforms and grouping the outcomes accordingly. Sinusoidal and triangular signals are easily discernible since their form and crest values are constant. All the waveforms that do not respect the requirements of sinusoidal and triangular waveforms are considered trapezoidal, and their further sub-division involves assessing the derivative of the signal. The methodology is related to the application of the CWH, in which an equivalent frequency is defined as:

$$f_{\mathrm{eq}} = \frac{\left|\frac{dB}{dt}\right|}{2B_{\mathrm{pkpk}}} \tag{1}$$

If a segment of the trapezoidal signal exhibits an equivalent frequency lower than a predetermined threshold, the signal is placed in the last category. The obtained classification allows the implementation of the proposed framework for the computation of the power losses under different excitation waveforms.

B. Triangular Waveforms

After identifying the triangular signals, calculations are performed to determine key parameters (scalar inputs) for

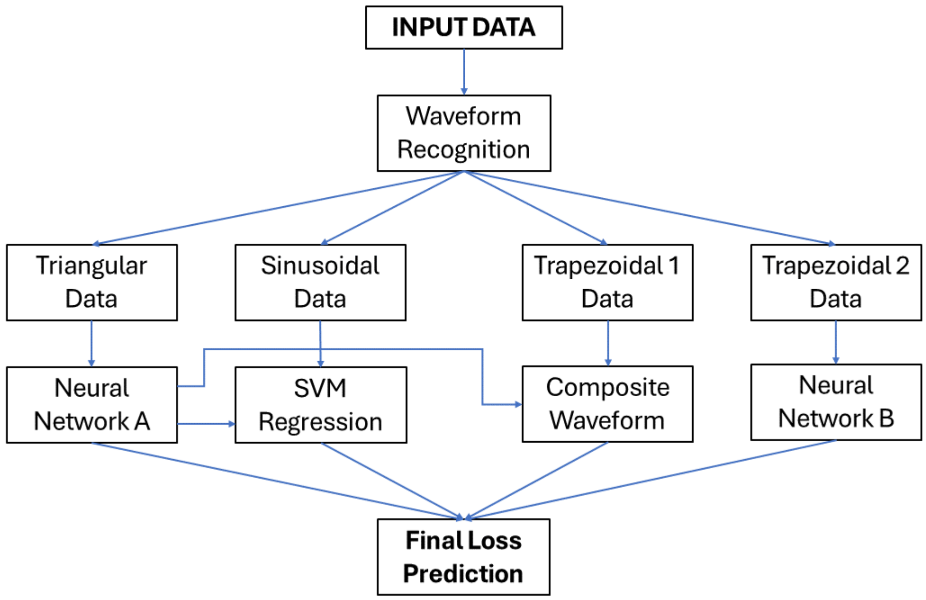

Fig. 1. Flowchart of loss prediction algorithm

predicting losses using the neural network. This involves computing the peak-to-peak induction value and duty cycle for each waveform. Subsequently, a data frame is structured to link each triangular waveform with its peak-to-peak induction, frequency, temperature, and duty cycle (B_{pkpk}, f, T, and δ). This data frame is then used as input for the neural network. The neural network output is the energy loss per cycle. Then, the power loss for each waveform is obtained by multiplying the correspondent energy loss by the frequency. Since the dependence of the energy loss on the induction and the frequency follows a power law, the logarithm operation is applied to these inputs and to the output. Regarding the training phase, performed on the training database of the five final materials, the data are shuffled and divided into training, validation, and testing sets. Then, the inputs are standardized to obtain compatible dimensions for all the different quantities. For all the sets, the mean and standard deviation of the training dataset are used for the standardization. The neural network structure has been preliminary determined by using a random search optimization, defining a Sequential Network in Keras described by Table I.

TABLE I
NEURAL NETWORK STRUCTURE FOR TRIANGULAR WAVEFORMS

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

Every neural network for each material has 243 trainable parameters.

Once the network structure is defined and the other hyperparameters are set, the training of a neural network for each material is performed, with the Adam algorithm for the optimization of weights and biases, in order to minimize the mean squared error on the validation datasets. Then, the neural network output is verified on the testing dataset.

C. Sinusoidal Waveforms

The detected sinusoidal waveforms underwent analysis with a Support Vector Regression (SVR) model. In this case, SVR involves linking the computation of losses from triangular to sinusoidal waveforms. Specifically, an examination was conducted to understand the relationship between symmetric triangular waveforms and sinusoidal waveforms with equivalent peak-to-peak induction, frequency, and temperature values. In fact, it is well-known that the dynamic magnetic loss terms are dependent on the time derivative of the induction $(\frac{dB}{dt})$ [4], [5]. The loss dependence on $(\frac{dB}{dt})$ is influenced by the main loss mechanism involved at a given frequency, peak-to-peak induction, and temperature for a given material. Theoretically, by assuming an energy loss dependence on the square of the time derivative of the induction $(W \propto (\frac{dB}{dt})^2)$, the ratio between sinusoidal and symmetric triangular waveform losses is identified in $\pi^2/8$. However, this ratio is strongly influenced by the operating conditions, determined by the induction, frequency, and operating temperature, and is also dependent on the specific material properties. Figures 2 and 3 give an overview of the behavior of this ratio for the training set of Material B.

Since the dependence of this ratio on the input parameters is not easily determinable theoretically with the available data, our approach is based on modeling the sinusoidal-triangular loss ratio with an SVR. Thus, for a sinusoidal waveform at a given peak-to-peak induction, frequency, and temperature, we compute the correspondent energy loss of a symmetric triangular waveform. Then, we estimate the sinusoidal-triangular ratio by means of the trained SVR model, and finally, we combine the two outputs to obtain the energy losses of the sinusoidal waveforms.

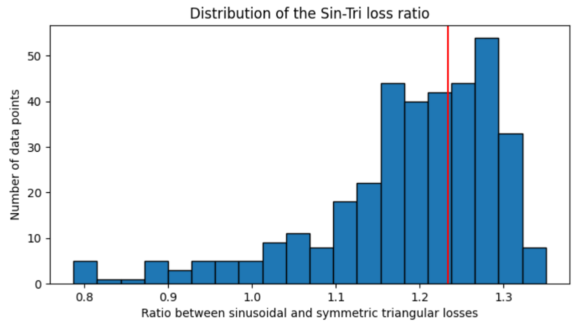

Fig. 2. Distribution of the sinusoidal-symmetric triangular loss ratio for the training set of Material B. The red line represents the theoretical value of $\pi^2/8$

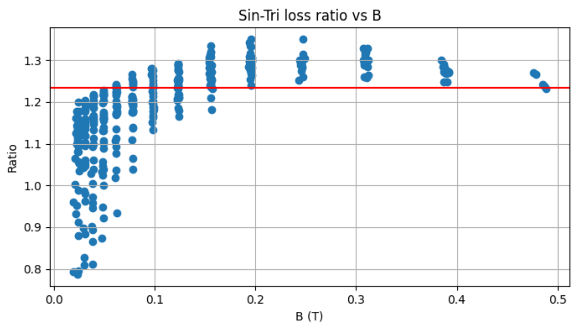

Fig. 3. Behavior of the sinusoidal-symmetric triangular loss ratio as a function of the peak-to-peak induction for the training set of Material B. The red line represents the theoretical value of $\pi^2/8$

For the SVR implementation, the Scikit-learn library has been used [3]. The Radial Basis Function (RBF) kernel is selected to deal with the non-linear nature of the regression problem. The inputs of the regression model are the peak-to-peak induction, frequency, and temperature. Even in this case, the training data are shuffled and divided into training, validation, and testing sets. Then, the inputs are standardized. An SVR model was trained for each material by computing the sinusoidal-symmetric triangular ratio on the training dataset under the same input conditions and using it as the target of the regression model.

The number of parameters required for defining the support vectors for each material model are reported in Table II.

TABLE II
NUMBER OF PARAMETERS OF THE SVR FOR EACH MATERIAL

	A	B	C	D	E
N. parameters	138	288	276	228	138

D. Trapezoidal Waveforms

In this case, trapezoidal waveforms were additionally differentiated depending on the presence of a segment with zero derivative. When examined with CWH, these segments display an equivalent frequency of zero, leading to non-physical losses. Hence, a distinct solution is required for this specific type of waveform.

1) Without near-zero derivative segments: These signal types were addressed by employing CWH and scaling the outcomes derived from triangular waveforms. The equations and procedures utilized align with those detailed in [1]. Notably, the distinction lies in the continuous execution of CWH across samples instead of the linearization of discrete segments. While this minimizes relative errors, it necessitates a longer computation time. Thus, the equivalent frequency is computed for each waveform sample, and for each, an energy loss value of a correspondent symmetric triangular waveform is computed by the previously trained neural network (under the same induction and temperature of the trapezoidal waveform). Then, the energy loss of the trapezoidal waveform is computed from the contributions of all the samples as

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

A possible weakness of the CWH is that the computed equivalent frequency can exceed the frequency bounds of the training dataset. In this case, our approach consists of considering the energy losses independent of the frequency under the lower bound of the dataset since, typically, for the soft ferrites, the hysteresis loss term is still dominant up to some tens of kHz. On the other hand, for equivalent frequencies that exceed the upper bound of the dataset, we still take into account the output of the neural network, even if not trained in this frequency range, since it seems to be coherent with the typical physical behavior of the energy losses of ferrite materials below the MHz range. Despite the described limitations and the worst behavior 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.

2) With a near-zero derivative segment: A different approach was taken when identifying trapezoidal induction waveforms with a near-zero derivative. As CWH proved incapable of estimating losses within these segments, an additional neural network was constructed to tackle this issue. The input parameters for this neural network include the peak-to-peak induction, frequency, temperature, and the RMS value of the induction time derivative (B_{pkpk}, f, T, and $(\frac{dB}{dt})_{\text{RMS}}$). The procedure followed for the definition of the network structure is the same as adopted for the triangular networks. The obtained Sequential Network in Keras is described by Table III.

TABLE III
NEURAL NETWORK STRUCTURE FOR TRAPEZOIDAL WAVEFORMS WITH NEAR-ZERO DERIVATIVE SEGMENTS

	Number of neurons	**Activation function**
Layer 1	12	Tanh
Layer 2	12	Tanh
Layer 3	1	Relu

Every neural network for each material has 229 trainable parameters.

As for the networks for the triangular waveforms, the logarithm operation is applied to the peak-to-peak induction, the frequency, and the energy losses. The training data are shuffled and divided into training, validation, and testing sets. Then, the inputs are standardized to obtain compatible dimensions for all the different quantities. For all the sets, the mean and standard deviation of the training dataset are used for the standardization. The Adam algorithm is adopted for the optimization of weights and biases in order to minimize the mean squared error on the validation datasets. Then, the neural network output is verified on the testing dataset.

A remark is required for the trapezoidal induction waveforms with a near-zero derivative of Material D. Since just eight samples are available for the training phase, the neural network for the trapezoidal waveforms for this material cannot be trained. Thus, the CWH is also applied to the trapezoidal waveforms with a near-zero derivative for Material D.

IV. Total number of parameters

Table IV reports the total number of parameters required for the estimation of the power losses for each material by considering all the models adopted for the different waveform types.

TABLE IV
Number of parameters required for the loss prediction of each material

	A	B	C	D	E
N. parameters	610	760	748	700	610

V. Results

This section reports a brief overview of the result obtained on the Training folder dataset of Material B, highlighting the results obtained for each type of waveform. It should be noted that this dataset also includes the data adopted for the training of the neural network for the triangular waveform, for the trapezoidal induction waveforms with a near-zero derivative, and of the SVR for the sinusoidal waveforms. Table V resumes the main error values obtained for the four waveforms types, while Figures 4, 5 6, and 7 reports the error distribution of the four cases.

	Mean (%)	95 perc (%)	Max (%)
Triangular	0.87	2.19	5.80
Sinusoidal	1.04	2.32	12.11
Trapezoidal CWH	22.6	36.42	40.02
Trapezoidal NN	1.32	3.48	21.02

TABLE V
Mean value, 95th percentile, and max value of the relative error on the loss prediction for Material B (training set)

VI. Conclusion

The report analyzes the solution that the PoliTO team has reached during these months of the MagNet Challenge. Various implementation possibilities have been considered,

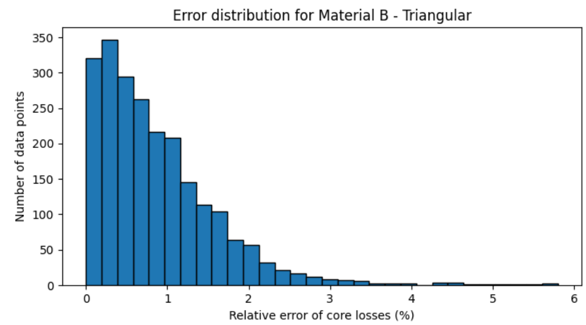

Fig. 4. Error distribution for the triangular waveforms (Material B).

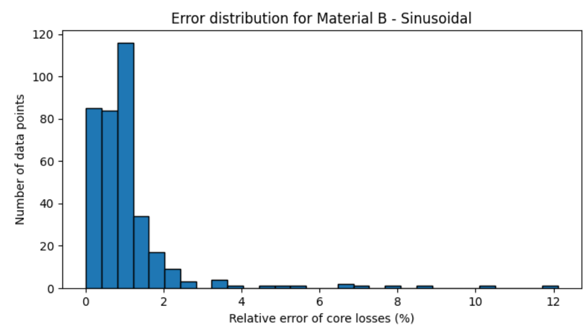

Fig. 5. Error distribution for the sinusoidal waveforms (Material B).

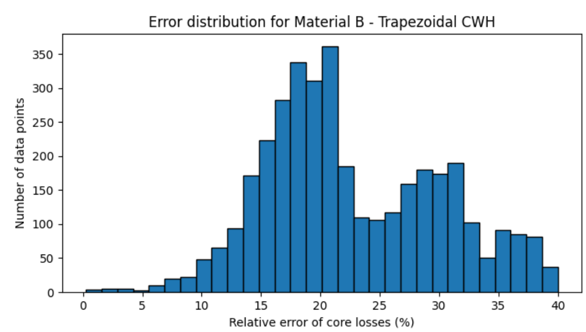

Fig. 6. Error distribution for the trapezoidal waveforms approached with the CWH (Material B).

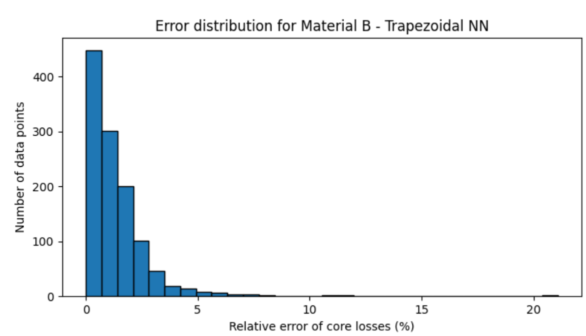

Fig. 7. Error distribution for the trapezoidal waveforms approached with the neural network (Material B).

aiming to strike the best compromise between result accuracy, computational time, and proposal simplicity. The identification of losses in magnetic materials can be significantly improved based on the analysis conducted.

The adopted approach allows for a specific focus on each waveform type, as each presents specific aspects that make it challenging to identify a general method for all waveforms. The objective was to obtain differentiated loss prediction methods for each waveform, but with a limited number of input parameters to the neural networks. Where possible, efforts were directed towards the calculation of losses for a triangular waveform, as the neural network trained for triangular waveforms yielded satisfactory results.

The main challenge to address was the approach to trapezoidal waveforms, where two different paths were chosen depending on the presence of a near-zero derivative segment. Trapezoidal signals are those that exhibit a higher error in loss estimation, particularly for those without a near-zero derivative segment, where the CWH approach was adopted.

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