Physics-informed Neural network-based estimation of magnetic losses in ferrites using physical parameters

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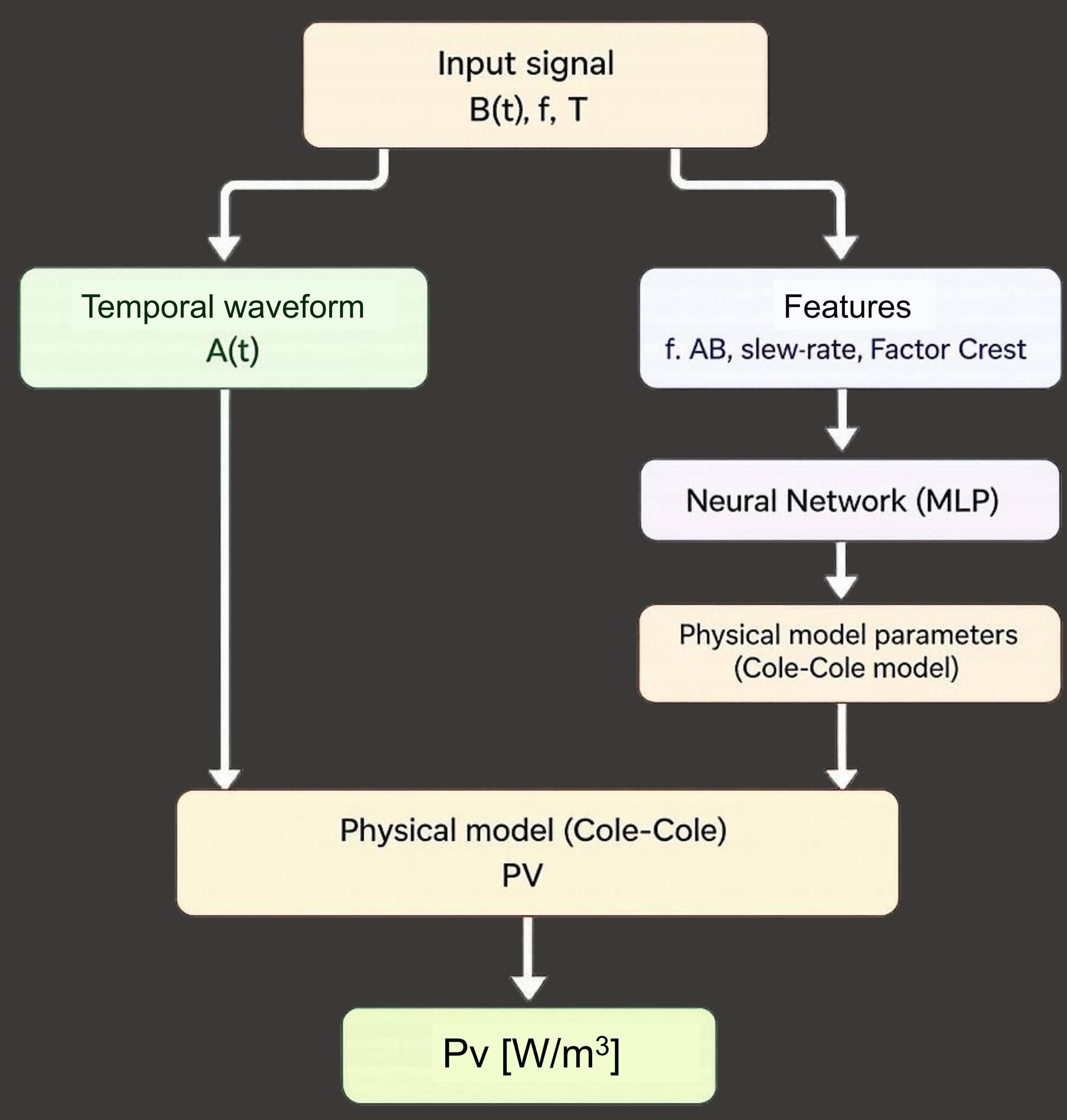
1. Introduction

Magnetic losses in ferrite cores constitute one of the main limiting factors for the efficiency and power density of modern switched converters. The Steinmetz equation and its extensions- such as the improved Generalized Steinmetz Equation- provide compact and widely used formulations; however, they exhibit a systematic degradation in accuracy when the excitation departs from sinusoidal waveforms. Trapezoidal and triangular waveforms with high slew rates, typical of power electronic converters, produce losses that are significantly underestimated by the classical model.

Machine learning (ML)-based approaches have demonstrated substantial improvements in loss prediction over datasets such as MagNet. Nevertheless, purely data-driven models require large volumes of samples per material and lack interpretability. The MagNet Challenge 2023 has shown that models incorporating prior physical knowledge achieve better performance with lower data requirements.

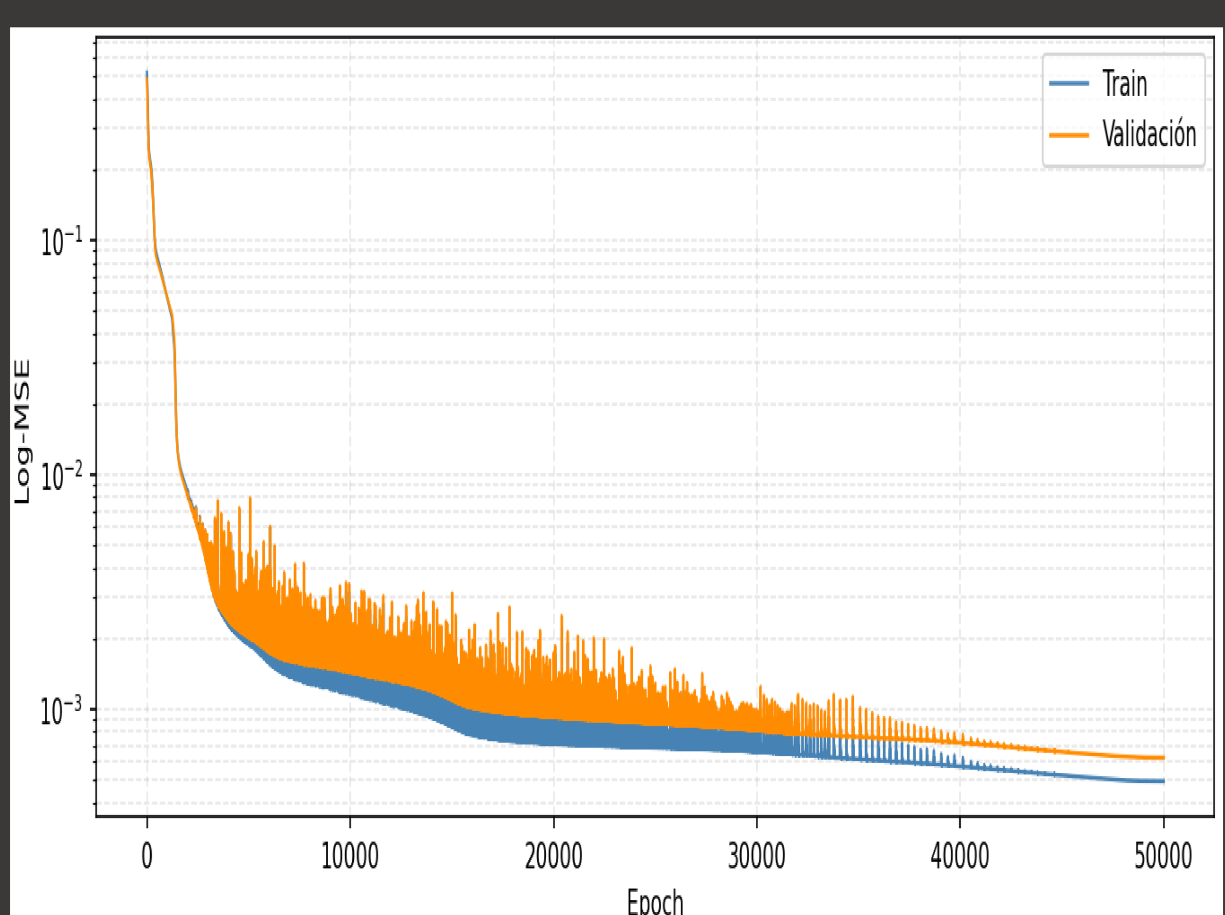
Physics-informed neural networks (PINNs) integrate physical laws into the structure of the neural network. In this work, a PINN model is proposed in which the output layer encodes the material permeability model parameters.

2. Neural Network Diagram

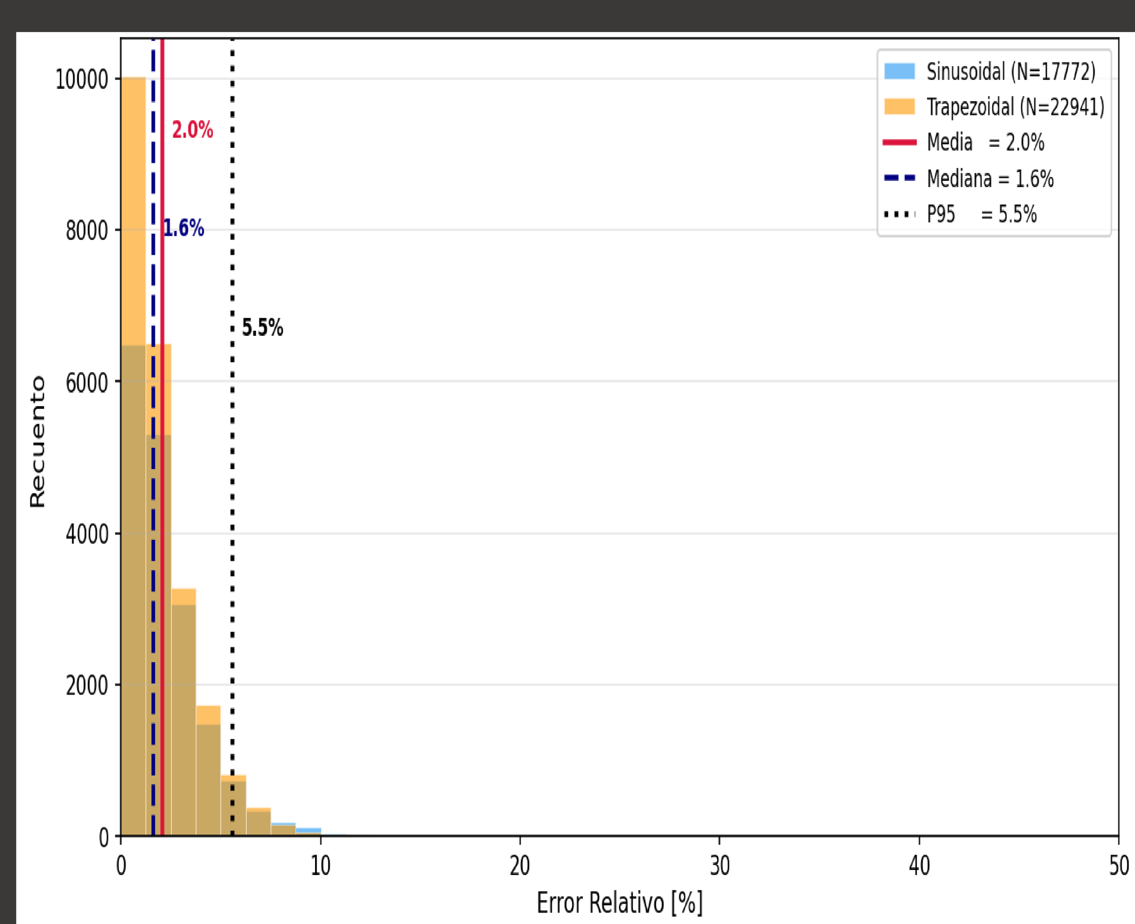


Physical Informed Neural Network diagram

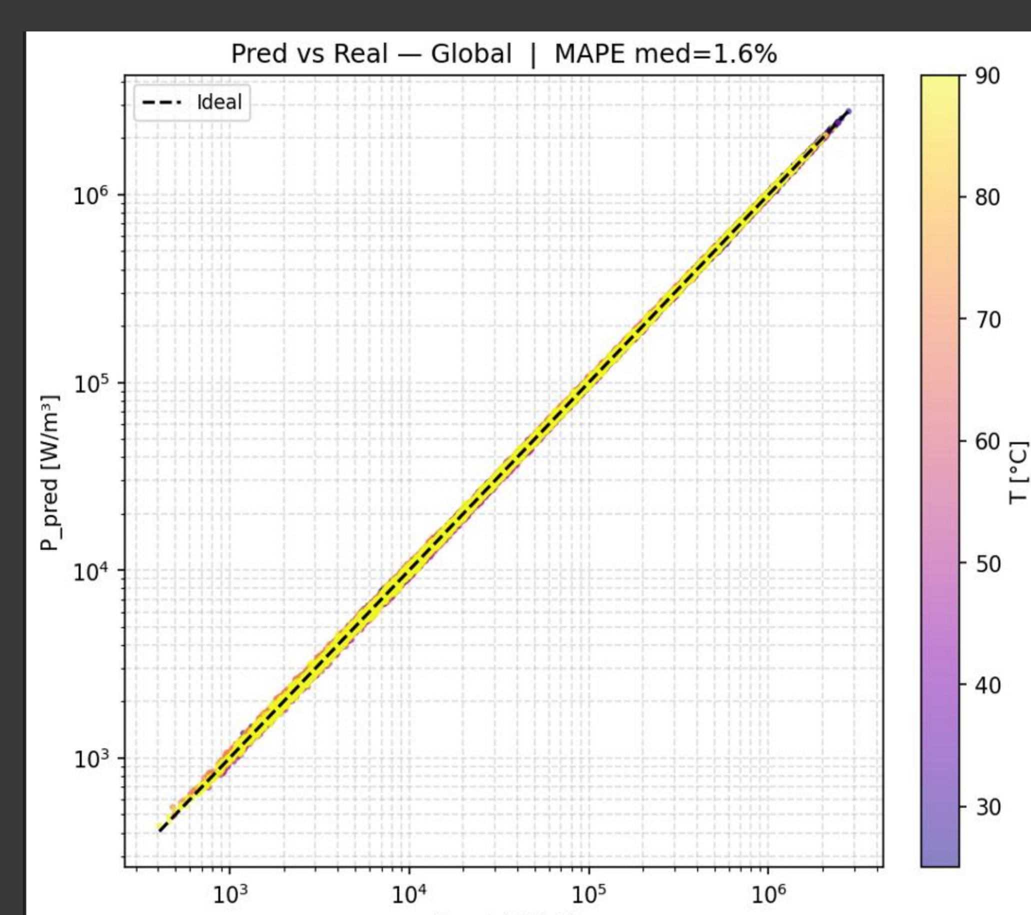
3. Experimental Results



Learning ratio



Relative error histogram with arbitrary waveforms



Predicted vs real losses at different temperatures

4. Conclusions

A physics-informed neural network (PINN) has been developed and validated for the estimation of magnetic losses in ferrite cores under arbitrary excitations. The network learns seven permeability model parameters and computes the dissipated power through a physics-based parametrization. The model achieves a mean error below 5% across the materials in the MagNet dataset, effectively combining the accuracy of machine learning with the interpretability of physical modeling.

5. References

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