# Fast and accurate Neural-Network-based Ferromagnetic Laminated Stack Model for Electrical Machine Simulations in Periodic Regime

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**Electromagnetic fields and eddy currents in thin electrical steel laminations are governed by the laws of magnetodynamics with hysteresis. Conventional homogenization techniques are however complex and very time-consuming. In consequence, hysteresis and eddy currents in ferromagnetic laminated cores are usually outright disregarded in finite element simulations, considering only saturation, and magnetic losses are only evaluated *a posteriori*, by means of a Steinmetz-Bertotti like empirical formula. This model simplification yields however potentially inaccurate results in the presence of non-sinusoidal B-fields, common in modern electrical devices. Assuming a time-periodic excitation of the system, a more accurate and fast approach, based on homogenization and neural networks (NN), is presented. A parametric homogenized material law is used in the macroscopic model, whose parameters are given element-wise by a NN according to the actual local waveform of the magnetic field. It is shown that, with an appropriately trained NN, this NN-based material law allows computing fields and losses inside ferromagnetic laminated stacks efficiently and accurately.**

*Index Terms*—**Magnetic hysteresis, Magnetic losses, Neural Networks, Nonhomogeneous media.**

## I. Introduction

DESPITE an urgent need in industry, there does not yet exist a practical and accurate simulation method able to account for magnetic losses in ferromagnetic laminated cores in electrical machine simulations [1]. The detailed efficiency analysis of electrical machines is thus still an open problem. The complexity of this question is due to the fact that magnetic losses are the macroscopic outcome of an intricate combination of micro- or mesoscopic level physical phenomena: eddy currents, skin effect, saturation and hysteresis. Those phenomena are strongly influenced by the microstructure of the ferromagnetic material, but also by the laminated structure of the cores. The magnetic losses are thus actually determined at geometrical scales much smaller than that of the electrical machine applications, thus advocating strongly for a homogenization approach. In the proposed approach, the homogenized $\mathbf{H}-\mathbf{B}$ relationship is approximated by a macroscopic $\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)$ law, which is used as a conventional constitutive relationship in a 2D modeling of an electrical machine. Moreover, the $p_k$ parameters in this law are determined locally in each finite element so as to represent at best the material response to the local magnetic field waveform $\mathbf{H}(t)$. Following recent developments introduced by machine learning in multi-scale modeling [2], [3], the mapping $\mathbf{H}(t) \mapsto p_k$, required when assembling the macroscopic finite element system, can be efficiently handled by a specifically trained NN, with a considerable speed-up with respect to a direct evaluation.

## II. One-Dimensional Lamination Problem

As laminations are large with respect to their thickness, fields and current distributions can be accurately resolved by solving a one-dimensional (1D) finite element magnetodynamic simulation across half the lamination thickness [4]. This 1D model is able to generate the relevant mesoscopic information at the inside lamination level. After appropriate homogenization, macroscale $\mathbf{H}$ and $\mathbf{B}$ fields are obtained which could directly be used in an electrical machine simulation, leading to accurate but also highly time-and-memory-consuming results.

## III. The parametric homogenized material law

Rather than directly solving the 1D lamination problem when evaluating the local material law, it is proposed to use an intermediate parametric homogenized material law [4]:

$$\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k) = \left(p_0 + (p_1|\mathbf{B}|)^{2p_2}\right)\mathbf{B} + \left(p_3 + \frac{p_4}{\sqrt{p_5^2 + |\dot{\mathbf{B}}|^2}}\right)\dot{\mathbf{B}}. \quad (1)$$

This law is designed to account for all physical phenomena occurring in ferromagnetic laminations, that is: a reversible anhysteretic saturation curve ($p_0$, $p_1$ and $p_2$), an irreversible dynamic eddy current term ($p_3$) and an irreversible hysteresis term ($p_4$ and $p_5$). The law (1) allows a good approximation of the 1D lamination problem solution, and it can be used directly as a constitutive law in a macroscopic simulation. This nevertheless assumes that the $p_k$ parameters are "wisely" chosen, i.e., that every finite element receives a set of $p_k$ parameters adapted to the local magnetic field variation $\mathbf{H}(t)$ in that element. Adapted $p_k$ parameters could be identified as those that minimize in the mean-square-error (MSE) sense the representation error $||\mathbf{H}(t) - \tilde{\mathbf{H}}(\mathbf{B}(t), \dot{\mathbf{B}}(t), p_k)||$ over one period. In this error, the magnetic field $\mathbf{H}(t)$ is obtained by means of a preliminary macroscopic simulation with a conventional anhysteretic material law, and the field $\mathbf{B}(t)$ is the result of the 1D lamination problem. This approach nevertheless remains slow, as it requires solving the 1D lamination problem and performing a MSE minimization for every element in the mesh. Alternatively, it is proposed in this paper to use a NN to give the adapted $p_k$ parameters as a function of the local waveform $\mathbf{H}(t)$, i.e., to realize more efficiently the needed $\mathbf{H}(t) \mapsto p_k$ mapping.

## IV. Neural network architecture and learning

The NN is developed in the fashion of an autoencoder (Fig. 1). A periodic discretized $\mathbf{H}(t)$ sequence is given at the input of an encoder block designed to predict the $p_k$ parameters. This encoder is made up of different blocks: an equivariance block to consider identically all sequences image of each other by a spatial rotation and/or phase shift;

a normalization layer to facilitate the learning; a multi-layer perceptron (MLP); and an element-wise normalization of the $p_k$ parameters, defining a characteristic range for each $p_k$ independently. The $p_k$ parameters given by the encoder are injected, together with the $\mathbf{B}$ field solution of the 1D lamination problem, into the $\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)$ law to obtain an approximation $\tilde{\mathbf{H}}$ of the input $\mathbf{H}$. An error between $\mathbf{H}$ and $\tilde{\mathbf{H}}$ is computed and back-propagated to perform the MLP learning. This auto-encoder-like learning ensures to directly minimize the error on the $\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)$ law, without need for exact *a priori* $p_k$ values. Using a training and a validation dataset both composed of 20 000 artificial periodic $\mathbf{H}$ and corresponding $\mathbf{B}$ sequences, generated in about 4 minutes, and using the square-root of the training error (see Fig. 1) for evaluation, both the training and validation error fall to 10 % after 5 minutes of training. When testing the neural network on actual $\mathbf{H}$ sequences obtained during a macroscopic simulation using an anhysteretic constitutive law, a 12 % error is obtained.

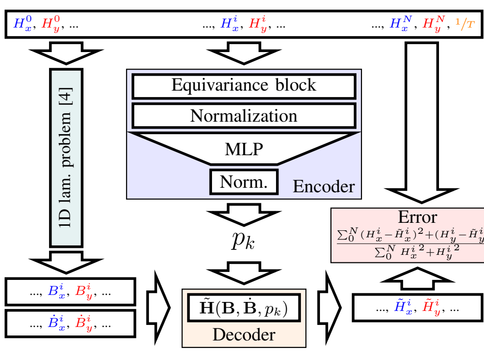


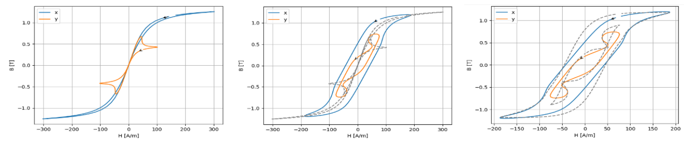

Fig. 1: Autoencoder-like architecture and learning.

## V. Analysis

The parametric homogenized material law with NN-identified parameters provides a good approximation of the 1D lamination problem solution at reduced cost. The encoder can assess $10^5$ sequences in approximately 17 seconds while the direct evaluation would involve solving the 1D lamination problem for each of the $10^5$ sequences (about 10 minutes in total) and performing the corresponding MSE regressions (significant time whatever the algorithm used). It is now possible to rapidly provide every element of a macroscopic simulation with $p_k$ parameters, hence unlocking the use of the $\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)$ law as a constitutive material law and allowing a direct loss computation (see Fig. 2). The distributions of the $p_k$ parameters over the cross-section of a standard interior permanent machine are shown in Fig. 3. Although all elements are evaluated independently, the distributions are smooth and exhibit the expected symmetries.

## VI. Conclusion

The approach presented in this paper is based on two key elements: (i) an accurate mesoscopic model to resolve fields and losses inside ferromagnetic lamination under arbitrary 2D vector magnetic field excitations, and (ii) a macroscopic parametric material law for which an exact Jacobian matrix can be evaluated (ensuring convergence of the Newton-Raphson



(a) (b) (c)

Fig. 2: (a) $H_x - B_x$ and $H_y - B_y$ curves obtained from an initial anhysteretic computation. The two loops have opposite orientations and their areas sum up to zero as the material is non-dissipative. (b) Comparison of the previous curves (recalled in dash lines) with $H_x - B_x$ and $H_y - B_y$ curves obtained with the parametric homogenized material law (1) after identification of the $p_k$ parameters by evaluation of the NN. The loops have now the same orientation and the sum of their areas represent the simulated magnetic losses. (c) Comparison of the $H_x - B_x$ and $H_y - B_y$ curves obtained with the parametric homogenized material law (1) (dashed lines) and with the homogenized lamination model, for the same local magnetic field. The match is not perfect, because the law (1) is only a convenient approximation, but the essential features of the fields are captured.

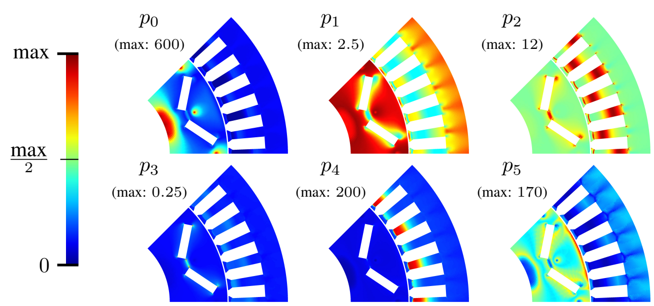



Fig. 3: Element-wise $p_k$ parameters from encoder evaluation.

scheme) and whose element-wise parameters are to be chosen to represent at best the response of the material to the local magnetic field waveform. It is shown that a properly trained NN can achieve this parameter identification orders of magnitude faster than a standard least-square error minimization. At the end, designers dispose of a fast and robust technique to compute fields and losses *a priori* in ferromagnetic laminated cores, with a provable accuracy and accounting for the higher field harmonics.

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