A Material Law Based on Neural Networks and Homogenization for the Accurate Finite Element Simulation of Laminated Ferromagnetic Cores in the 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. If the lamination is large with respect to its thickness, field and current distributions are accurately resolved by solving a one-dimensional finite element magnetodynamic problem across half the lamination thickness. This 1D model is then able to deliver mesoscocpic information to be used, after appropriate homogenization, in the macroscopic modelling of an electrical machine or transformer. As each evaluation of such a homogenised model implies a finite element simulation at the mesoscale, a monolithic implementation of this method can become very time-consuming. This paper proposes an alternative methodology, assuming a periodic excitation of the system, where the homogenized material law is implemented with techniques of machine learning. The identified law is then used as a conventional constitutive relationship in the 2D or 3D modelling of an electrical machine or a transformer.

***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 2D or 3D electrical machine simulations. 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.

II. One-Dimensional Lamination Problem

The complex interplay between magnetic fields and eddy currents in ferromagnetic laminated cores can be resolved by solving the laws of magnetodynamics with hysteresis inside individual laminations. The hysteresis model used in these numerical simulations is the one described in [1]. The geometrical one-dimensional (1D) approximation is reasonable if the lateral dimension of the laminations is large with respect to their thickness, which is in general the case in the laminated cores of electrical machines or transformers, and in measurement devices such as Epstein frames or single sheet testers. Eddy currents and losses in a ferromagnetic lamination under an arbitrary excitation can therefore be calculated accurately by means of a transient 1D magnetodynamic finite element (FE) simulation, solved across half the lamination thickness [2].

III. Least-Square Parameter Identification

Once the 1D lamination problem is solved, the results in terms of the mesoscale fields, $\mathbf{h}$ and $\mathbf{b}$, can be expressed in

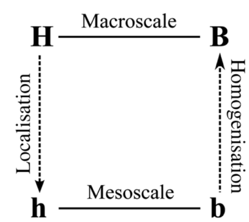

Fig. 1. Macroscale and mesoscale quantities in the homogenization problem.

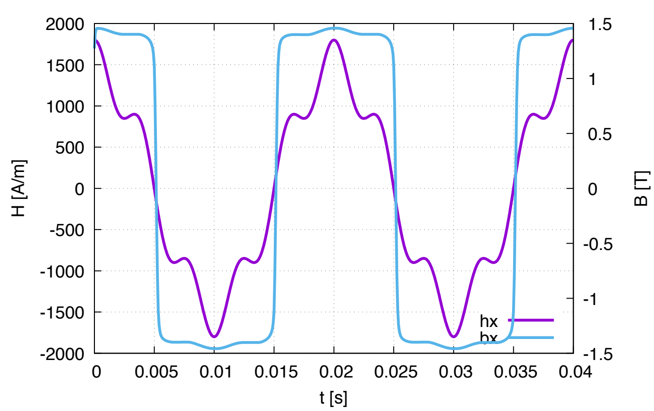

Fig. 2. Outcome of the 1D lamination model in the case of a unidirectional sinusoidal $\mathbf{H}$ field of amplitude $H_0 = 1500$ (A/m) at frequency 50 Hz, superimposed with a fifth harmonic of amplitude $H_0/5$.

terms of the macroscale fields, $\mathbf{H}$ and $\mathbf{B}$, by using the the localisation and homogenisation relationships that are respectively [3]

$$\mathbf{H} = \mathbf{h}(d) \quad , \quad \mathbf{B} = \frac{1}{d}\int_0^d \mathbf{b}(z)\,\mathrm{d}z \tag{1}$$

where d is the half-lamination thickness, see Fig. 1. The computed homogenized fields $\mathbf{H}$ and $\mathbf{B}$ in the case of a unidirectional sinusoidal $\mathbf{H}$ field of amplitude $H_0 = 1500$ (A/m) at frequency 50 Hz, superimposed with a fifth harmonic of amplitude $H_0/5$ are shown in Fig. 2. One sees the homogenized $\mathbf{B}$ field lagging behind the $\mathbf{H}$ field because of the hysteresis effect, as well as the damping of the fifth harmonic in the $\mathbf{B}$ field.

The next step consists in identifying the parameters $\{p_k, k = 0, \ldots, 5\}$ of a generic macroscale consitutive relationship, e.g.,

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

so that the difference between the homogenized response of the 1D mesoscale model and that of the algebric law (2) is minimum in the least-square sense. The first three parameters stand for the reversible saturation of the material, whereas the last three represent the irreversibility of the material, due to both hysteresis and eddy currents in the laminations.

Due to the rather simple and arbitrary choice (2), the match is not be perfect, Fig. 3, but the reconstructed macroscale $\mathbf{B}-\mathbf{H}$ loop is close enough to the mesoscale model to account with a good accuracy for the magnetic losses in the ferromagnetic laminated core. Note that the conventional modelling approach, which consists in assuming the ferromagnetic laminated core saturable and lossless, would correspond with the reversible material law labeled "conventional" in the picture.

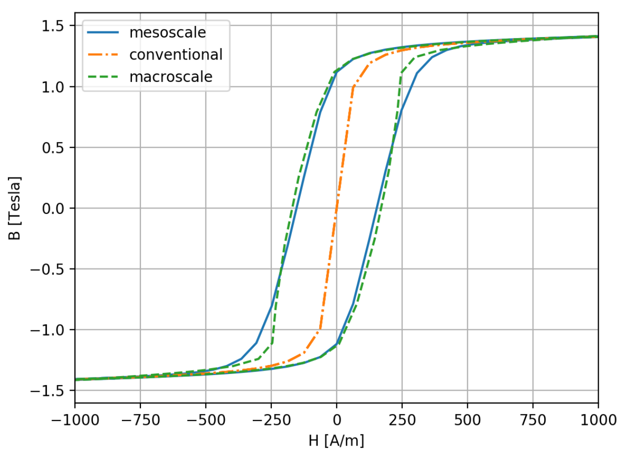

Fig. 3. Comparison between the homogenized response of the 1D model, the algebric law (2), and the conventional lossless approach.

IV. A Machine Learning Approach

The identified p_k parameters depend on the $\mathbf{h}(t)$ field excitation imposed to the 1D lamination model. The above described identification procedure can thus be regarded as a mapping

$$\mathbf{h}(t) \rightarrow \{p_k, k = 1, \ldots, M\}. \tag{3}$$

This mapping is rather abstract and involves quite a lot of input data (the sampling over at least one period of the excitation

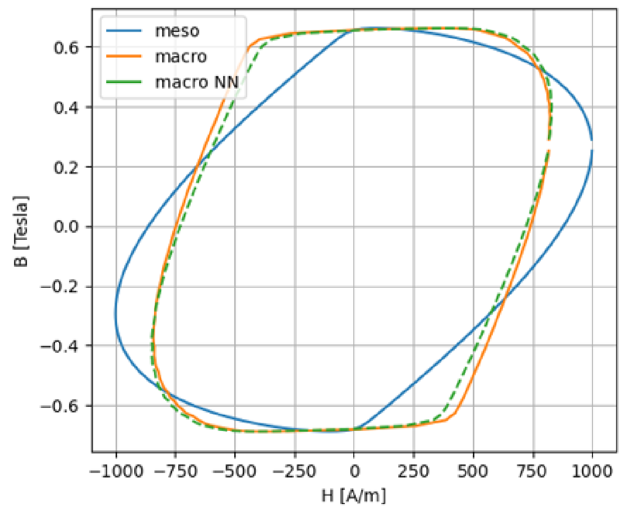

Fig. 4. Comparison of $\mathbf{B}-\mathbf{H}$ loop obtained with the NN identified p_k parameters with the loop obtained with the full homogenization procedure.

$\mathbf{h}(t)$). Its evaluation is expensive as it implies solving and post-processing the 1D FE mesoscale problem. The mapping (IV) is however expected to be smooth and stable because it corresponds to a parabolic dissipative smooth physical problem. These are characteristics for which a machine learning approach based on neural networks (NN) represents an appealing solution [6], [7].

A NN implementation of the mapping (IV) has been realised with the *pytorch* library using rectified linear unit (ReLu) functions as activation functions. The neural network contained 2 internal layers with 60 and 30 neurons, respectively. It was trained with 85% of a set of 9000 simulations done with sinusoidal $\mathbf{h}(t)$ excitations with various amplitudes and frequencies. Training was conducted over 15000 epochs with a learning rate of 10^{-4}. The remaining 15% was reserved as a test set. Fig 4 compares the $\mathbf{B}-\mathbf{H}$ loop obtained with the NN identified p_k parameters with the loop obtained with the full homogenization procedure. A good match is obtained with an evaluation time reduced by several orders of magnitude.

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