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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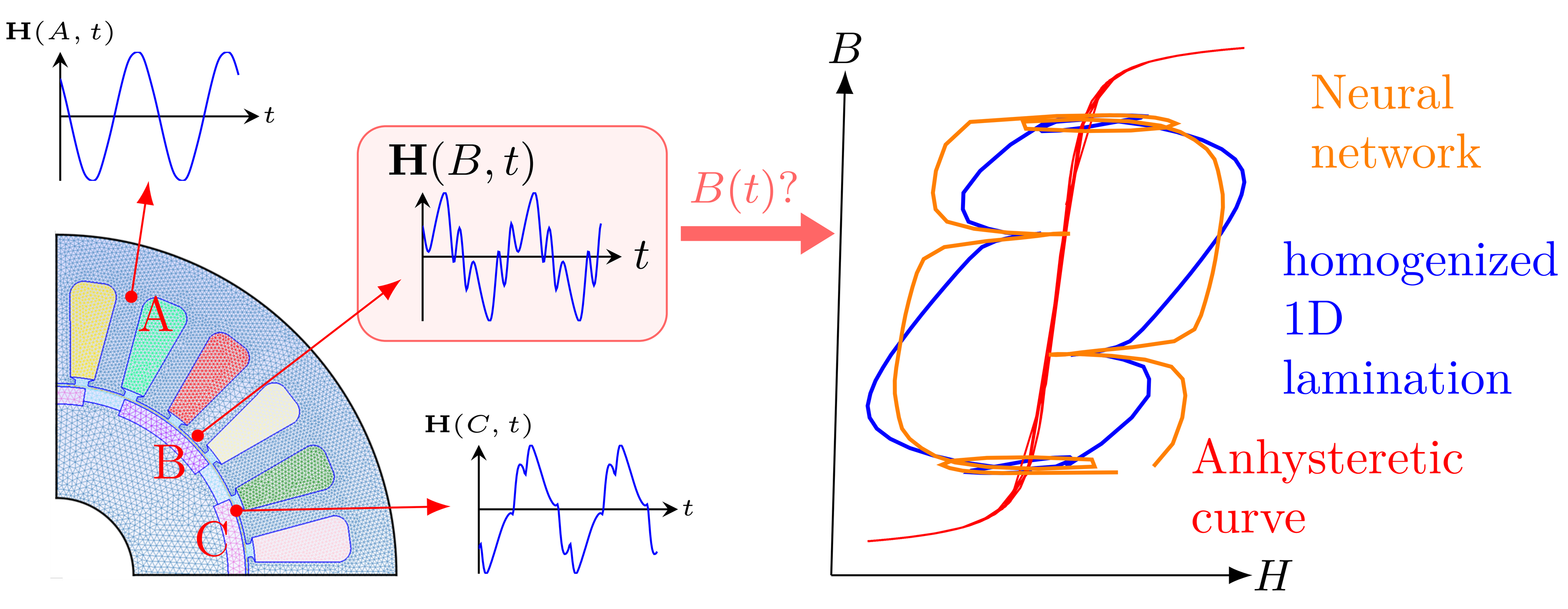
Abstract

Eddy currents in ferromagnetic laminated cores are usually outright disregarded in conventional simulations and **magnetic losses** are only evaluated a posteriori, by means of a Steinmetz like empirical formula. The conventional approach yields however **seriously inaccurate** computed fields and losses whenever the operating frequency increases, or in the presence of higher harmonics, which is an issue in industrial R&D. A much more accurate approach based on **homogenization** and **neural networks** is here presented. The $\mathbf{H}-\mathbf{B}$ relationship is approximated by a macroscopic $\mathbf{H}(\mathbf{B},\dot{\mathbf{B}},p_k)$ material law where the local values of the p_k parameters at a point P in the macroscopic model depend on the local time evolution of the $\mathbf{H}(P,t)$ field over one period. The mapping $\mathbf{H}(P,t)\mapsto p_k$, required to assemble the macroscopic FE system, is efficiently handled by a specifically trained neural network. The method can be rather easily implemented in a standard FE package.

Problem statement

When solving 2D magnetodynamic simulations, the $\mathbf{H}-\mathbf{B}$ relationship has to be approximated. In order to be accurate, eddy currents and hysteresis inside individual laminations must be modelled explicitly:



- Conventional approaches **disregard the magnetic core conductivity** and simply use the anhysteretic curve (red curve).
- If the lamination is large enough with respect to its thickness, the mesoscopic field distribution is accurately resolved by solving a **1D FE magnetodynamic problem**. After **homogenization**, mesoscopic information (blue curve) can be retrieved and given to the macroscopic model. This approach is however **highly time consuming**. Indeed, a 1D FEM problem has to be solved for every element in the macroscopic mesh, since different elements undergo different excitations (Compare $\mathbf{H}(A,t)$, $\mathbf{H}(B,t)$ & $\mathbf{H}(C,t)$).
- The use of a **parametric homogenized material law**, with parameters evaluated with a **neural network**, provides **efficient and accurate approximations** (orange curve).

Homogenized law and neural network

The parametric homogenized law is used in the macro model:

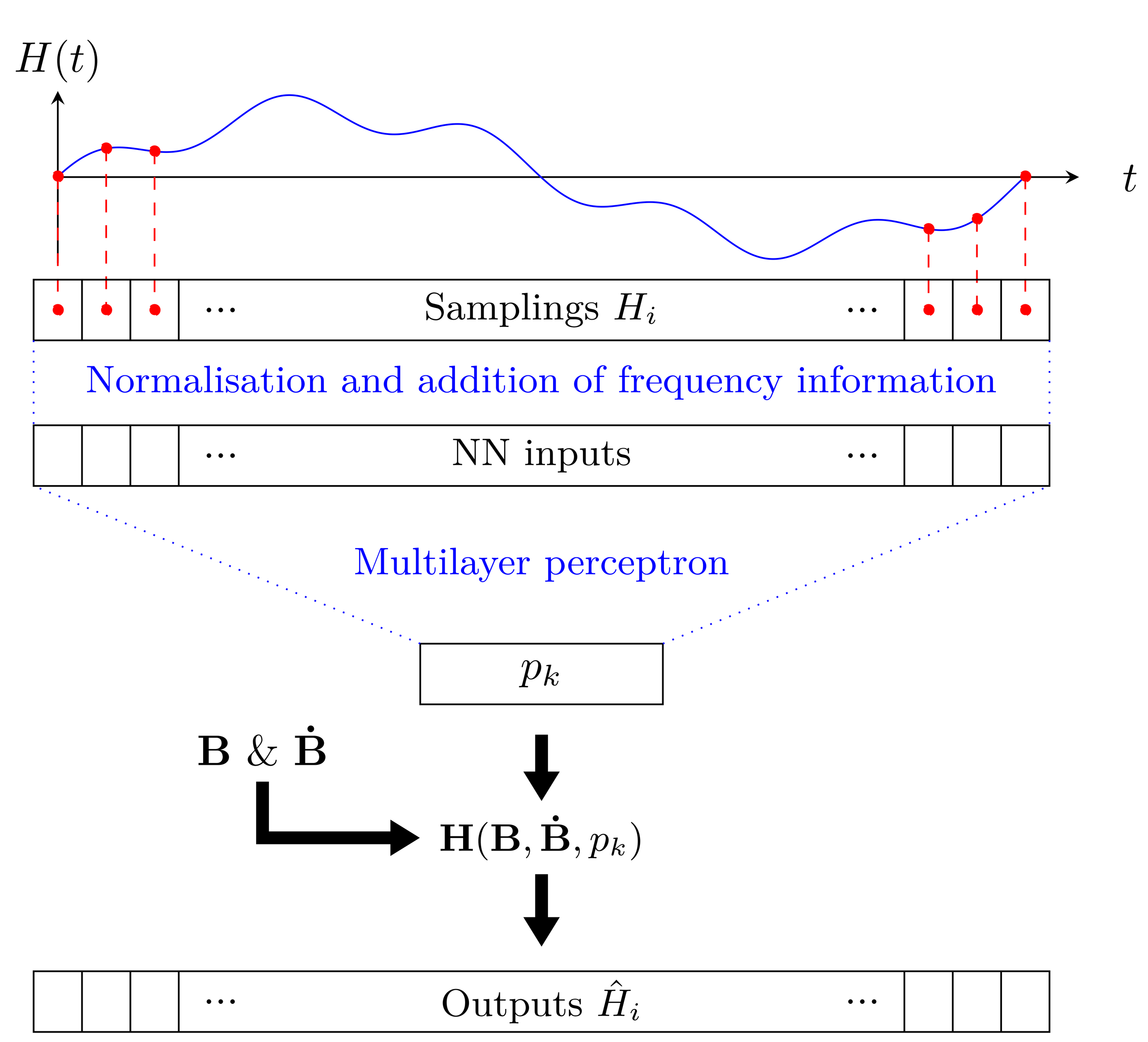
$$\mathbf{H}(\mathbf{B},\dot{\mathbf{B}},p_k)=\mathbf{B}(p_0+p_1\mathbf{B}^{2p_2})+\dot{\mathbf{B}}(p_3+\frac{p_4}{\sqrt{p_5^2+\dot{B}^2}})$$

The values of the p_k parameters at point P depend on the $\mathbf{H}(P,t)$ field evaluated at the previous period, and a neural network is specifically trained to represent the mapping $\mathbf{H}(P,t)\mapsto p_k$.The training of the neural network then proceeds as follows:

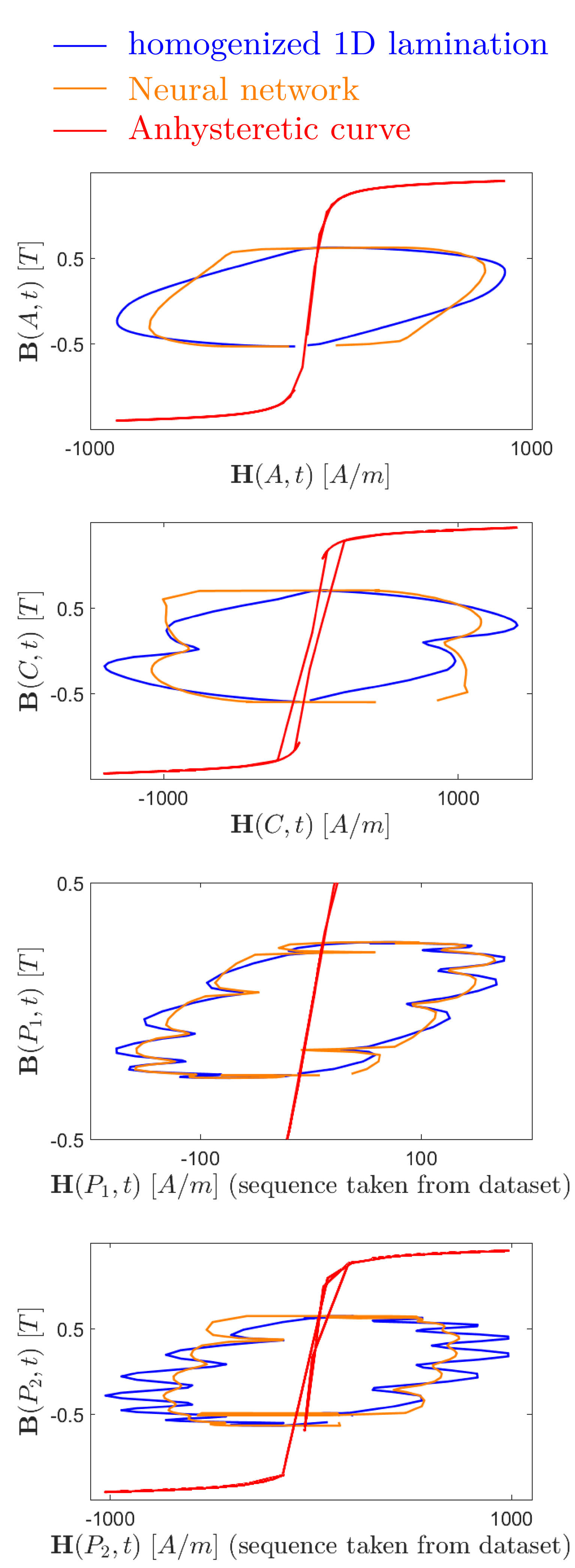
First, a set of 150 000 sequences of sinusoidal $\mathbf{H}(t)$ with harmonics is generated with a 100 points per period sampling. The corresponding $\mathbf{B}$ sequences are obtained by **solving the 1D FE problem**, and the $\dot{\mathbf{B}}$ sequences are finally obtained by a second order accurate finite difference derivation. Each $\mathbf{H}$ sequence is then given as input to the neural network which provides a set of p_k values. This set p_k, together with the $\mathbf{B}$ and $\dot{\mathbf{B}}$ sequences corresponding to the input $\mathbf{H}$ sequence, are **injected into the law** $\mathbf{H}(\mathbf{B},\dot{\mathbf{B}},p_k)$, which returns $\hat{\mathbf{H}}$. The error between $\mathbf{H}$ and $\hat{\mathbf{H}}$ is then computed according to the mean-square-error formula:

$$MSE=\sum_{i=0}^{N=99}(\hat{H}_i-H_i)^2/\sum_{i=0}^{N=99}H_i^2.$$

The error is then back-propagated, enabling the neural network to learn. This kind of neural network is said "physics-informed" since the training of the neural network also explicitly relies on the physics-based material law.



Main results



The gain in accuracy is best assessed in the $\mathbf{H}-\mathbf{B}$ plane. The true homogenized response of the ferromagnetic lamination under an imposed $\mathbf{H}(P,t)$ field is given by the blue curves. This accurate modelling is the reference. The response with a simple anhysteretic $\mathbf{H}-\mathbf{B}$ law is represented by the red curves, whereas the response with the homogenized $\mathbf{H}(\mathbf{B},\dot{\mathbf{B}},p_k)$ law is represented by the orange curves. the latter is clearly much closer to the reality, provided that the values of the p_k parameters are adapted to the $\mathbf{H}(P,t)$ excitation, which is the role of the neural network. The error can be estimated using the same formula as during the neural network training. Doing so, the **mean homogenization error is below 6%.**

On the other hand, the neural network representation of the mapping $\mathbf{H}(P,t)\mapsto p_k$ yields a impressive gain in computation time. It is indeed **30 000 times faster** compared to a direct coupling with 1D FE problem resolution.

The results however show decreased accuracy in the saturation regime (Comparison between the third and fourth plots). Changes in the $\mathbf{H}(\mathbf{B},\dot{\mathbf{B}},p_k)$ law can be made to handle it. Notably, by increasing the number of parameters, identifying saturation regions and adding a saturation-term contribution when saturation is exhibited, improvements are obtained with some preliminary results showing a mean error of 2%.

Conclusions

The physics-informed neural network, combined with the homogenized material law, allows simulating eddy currents and hysteresis in ferromagnetic laminated cores at a low computation price. Magnetic losses can so be truly modelled, with actual field waveforms, and not simply evaluated a posteriori on basis of standardized analytic formulas. **The homogenization error is below 6%**, and the neural network representation is **30 000 time faster** than a direct coupling with the lamination model.