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Accounting for Hysteresis and Eddy Currents in FEM Simulations of Ferromagnetic Laminated Cores using a Recurrent Neural Network

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Abstract

Accounting for hysteresis and eddy currents in finite element simulations of electrical machines with ferromagnetic laminated cores is expensive. These phenomena have however a significant impact on the machine performance. To account for them with a low computational cost, we propose to train a recurrent neural network to serve as material law in 2D finite element simulations.

Key words: FEM Simulation, Hysteresis, Laminated Core, Recurrent Neural Network

1 Introduction

Computing hysteresis and eddy current losses during the design phase of electrical machines remains an open challenge, as traditional multiscale Finite Element Model (FEM) simulations with integrated hysteresis modeling are computationally too demanding. In R&D, hysteresis is therefore often simply neglected during the simulation and losses are evaluated a posteriori. In this work, a Recurrent Neural Network (RNN) is trained to replicate a lamination model, and is integrated into a 2D FEM simulation in order to account for the effect of eddy currents and hystesresis at reasonable cost directly during the simulation.

2 RNN Architecture and Training

Since hysteresis intrinsically depends on the magnetic field history, an RNN, whose hidden state keeps memory of past field values, is a convenient architecture to deal with hysteresis. We use a single-layer gated recurrent unit [1] with a hidden size of 256. Embedding and decoding both use a two-layer feed-forward neural network with `ReLU` and `Linear` activation functions.

The training dataset is populated with magnetic field $\mathbf{H}$ sequences, generated artificially to mimic fields encountered in electrical machines. The corresponding magnetic flux density $\mathbf{B}$ sequences are obtained by solving a 1D magneto-dynamic problem with the energy-based model on a single lamination [2]. All in all, $5 \cdot 10^5$ $(\mathbf{H}, \mathbf{B})$ sequence pairs of 10^3 time steps are generated in about 3 hours on an `AMD EPYC 7763 CPU`. The training is then performed in about 6 hours on a `NVIDIA A100 40GB GPU`.

3 FEM simulation

The RNN is integrated into a magnetic-field-conforming FEM formulation, written in terms of the scalar potential ϕ, with $\mathbf{H} = -\nabla\phi$. At each iteration i of the Newton-Raphson iterative scheme, the following weak formulation is solved for $\mathbf{H}_i$:

$$\left(\mathbf{B}(\mathbf{H}_{i-1}) + \frac{\partial \mathbf{B}}{\partial \mathbf{H}}(\mathbf{H}_{i-1})(\mathbf{H}_i - \mathbf{H}_{i-1}), -\nabla\phi'\right)_{\Omega} = 0,\ \forall\,\phi', \tag{1}$$

where $\mathbf{B}(\mathbf{H}_{i-1})$ is computed in the RNN's forward pass and $\frac{\partial \mathbf{B}}{\partial \mathbf{H}}(\mathbf{H}_{i-1})$ is obtained by reverse-mode automatic differentiation through the RNN. Figure 1 shows **HB** curves obtained on a reference square mesh, with ramped-up sinusoidal source magnetic field. These curves perfectly match with the reference ones, obtained by directly coupling the FEM simulation with the 1D lamination model used to generate the training dataset.

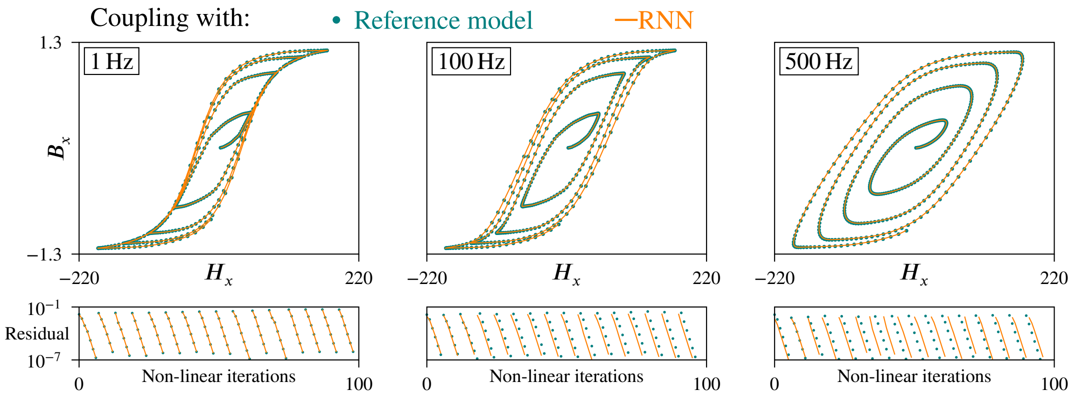

Figure 1: $H_x B_x$ curves from the FEM simulation under loading condition at different frequencies. Coupling the FEM simulation with the RNN provides the same results as a direct coupling with the reference model, which has been used to generate the training dataset. In fact, the root mean squared error between RNN and reference **H** and **B** fields does not exceed 0.2 A/m and 4 mT respectively. In both cases, convergence is also quickly reached.

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