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Neural-Network-Based Identification of Material Law Parameters for Fast and Accurate Simulations of Electrical Machines in Periodic Regime

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Florent PURNODE, François HENROTTE, Gilles LOUPPE & Christophe GEUZAINE
Department of Electrical Engineering and Computer Science, University of Liège, Belgium

Abstract

Ferromagnetic lamination stacks are ubiquitous in electrical engineering applications. An accurate knowledge of iron losses in such stacks is highly valuable in a design phase, but their explicit modelling is computationally prohibitive. Hence, iron losses are usually neglected in R&D and lossless material laws are used. Here, a lossy homogenized parametric law $\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)$ is used as material law. The parameters pk are identified elementwise, thanks to a neural network, on basis of the local knowledge of the magnetic field. This approach provides designers with a fast and robust model to account for iron losses, with a controlled accuracy and only little overhead compared to a conventional formulation.

New irreversible parametric material law: the p_k law

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

$\tilde{\mathbf{H}}_{an}$ → Reversible (anhysteretic) saturation curve

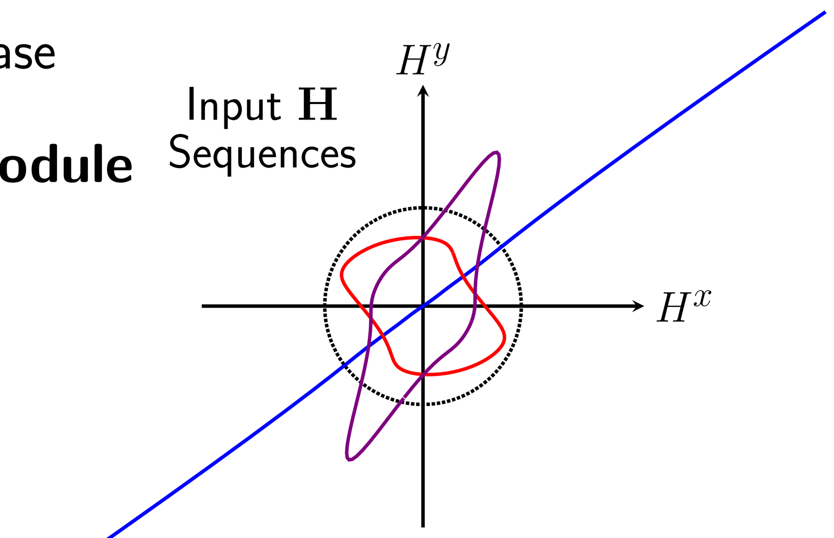
$\tilde{\mathbf{H}}_{eddy}$ → Irreversible dynamic eddy current (viscosity-like) term

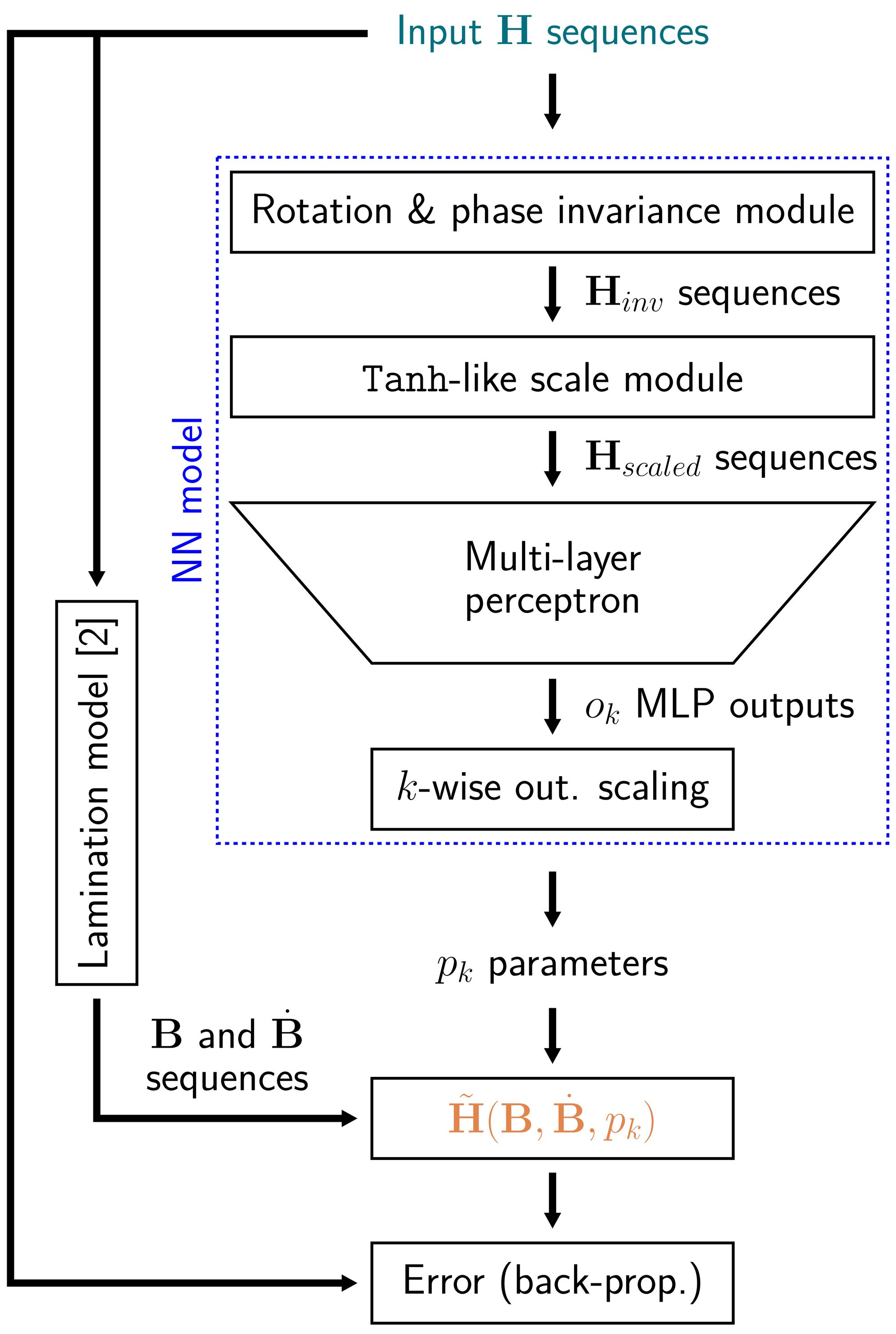
$\tilde{\mathbf{H}}_{hsyt.}$ → Irreversible hysteresis (dry friction-like) term

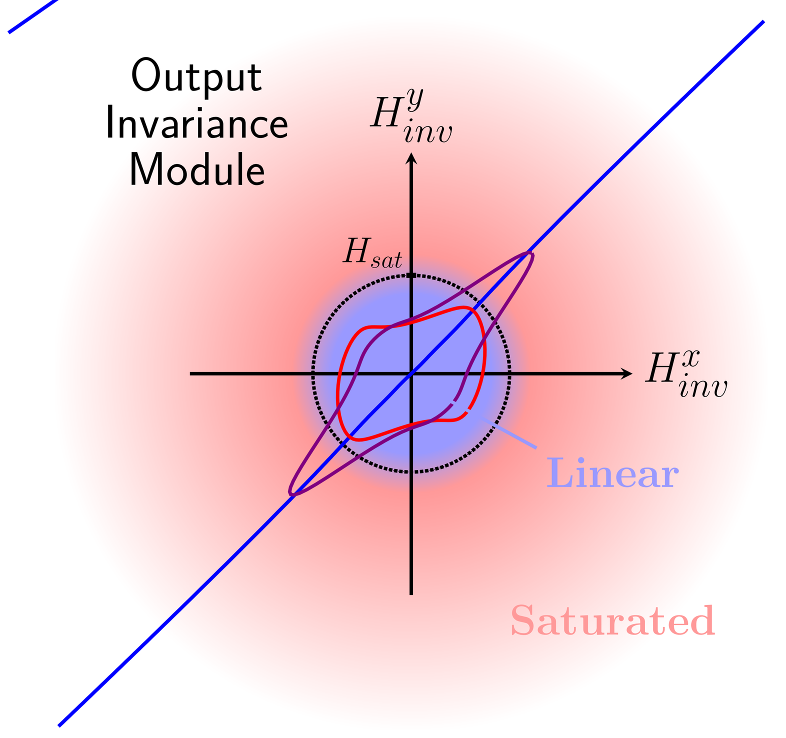
p_k Identification with a Neural Network: Architecture and Learning

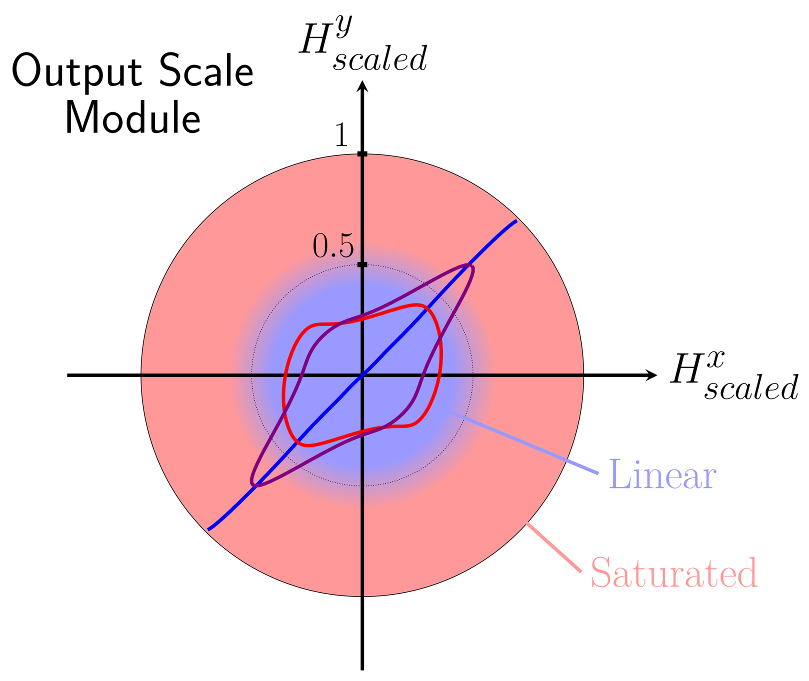
Assuming periodicity, the parameters p_k can be determined using a neural network:

- **Auto-encoder-like learning** [1], the p_k law is the decoder
- Sequences image of each other by a phase shift and/or a rotation are equivalent → **Rotation & phase invariance module**
- Material exhibits saturation → **Saturation-like input scaling**
- Parameters vary on different scales → **k-wise output scaling**



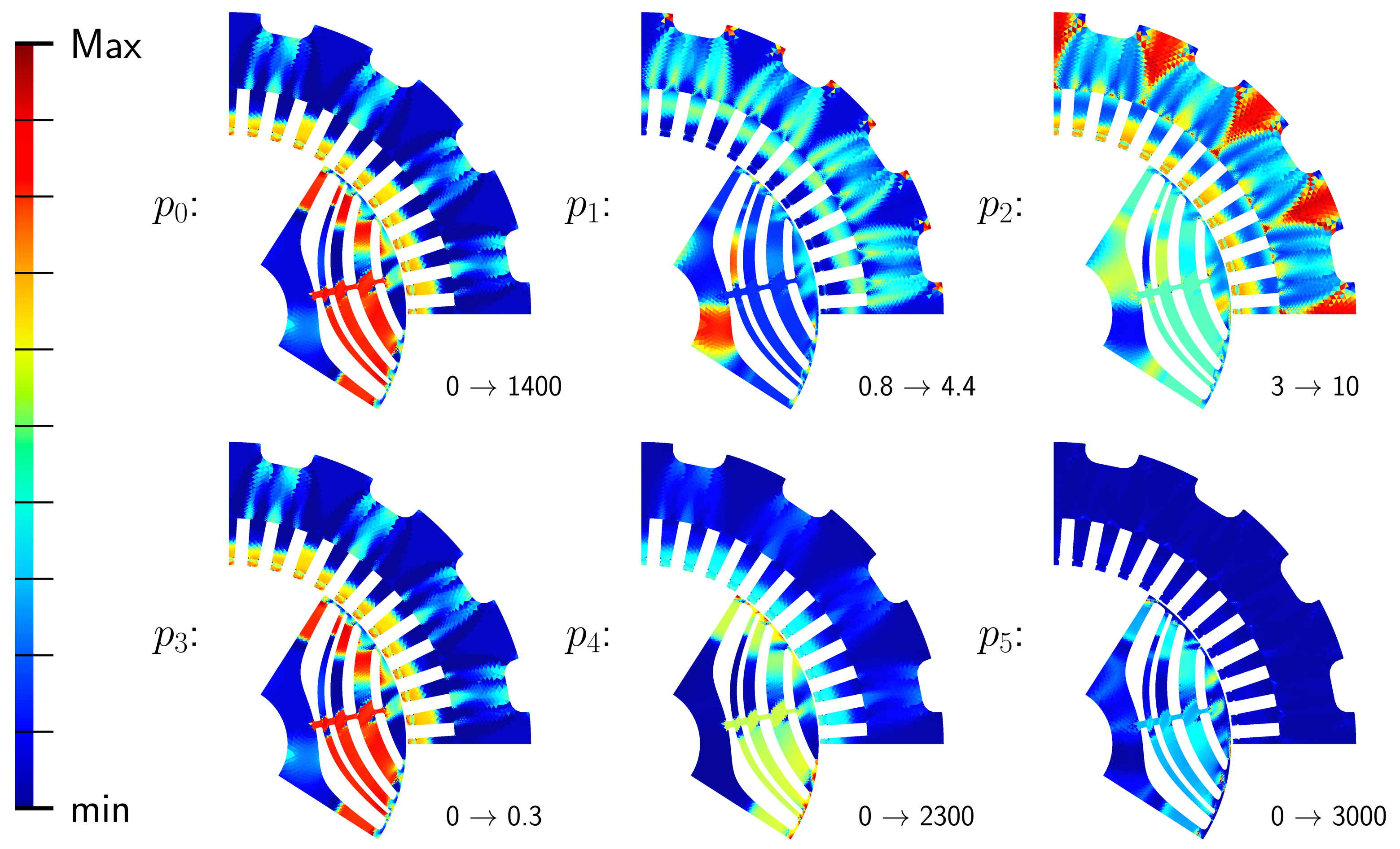




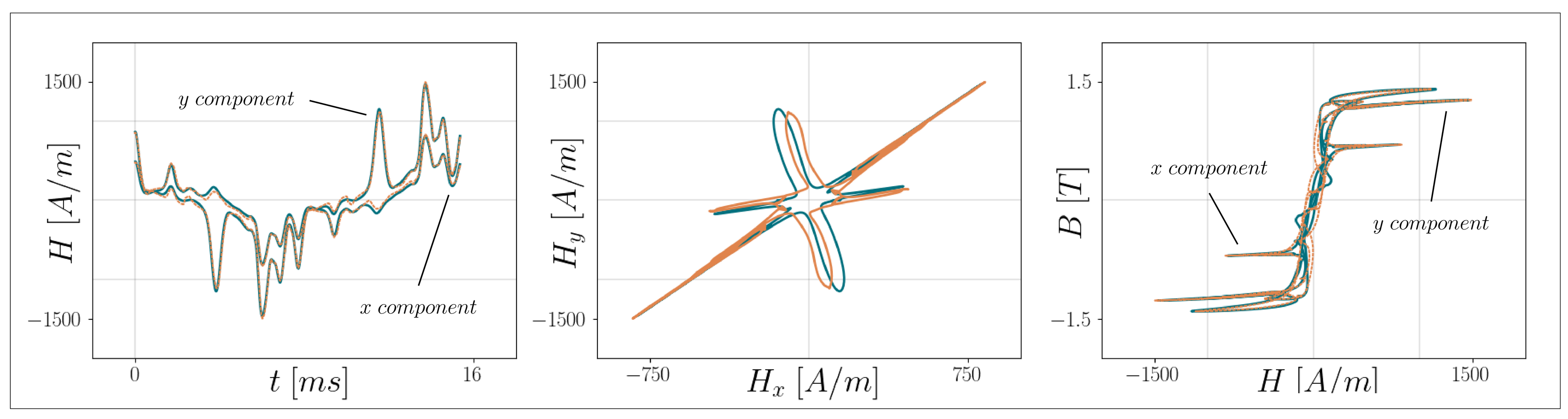


Results

NN computed distribution of the p_k parameters in a switched reluctance motor:



Error distribution and Input $\mathbf{H}$ Sequences vs. $\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)$ curves:

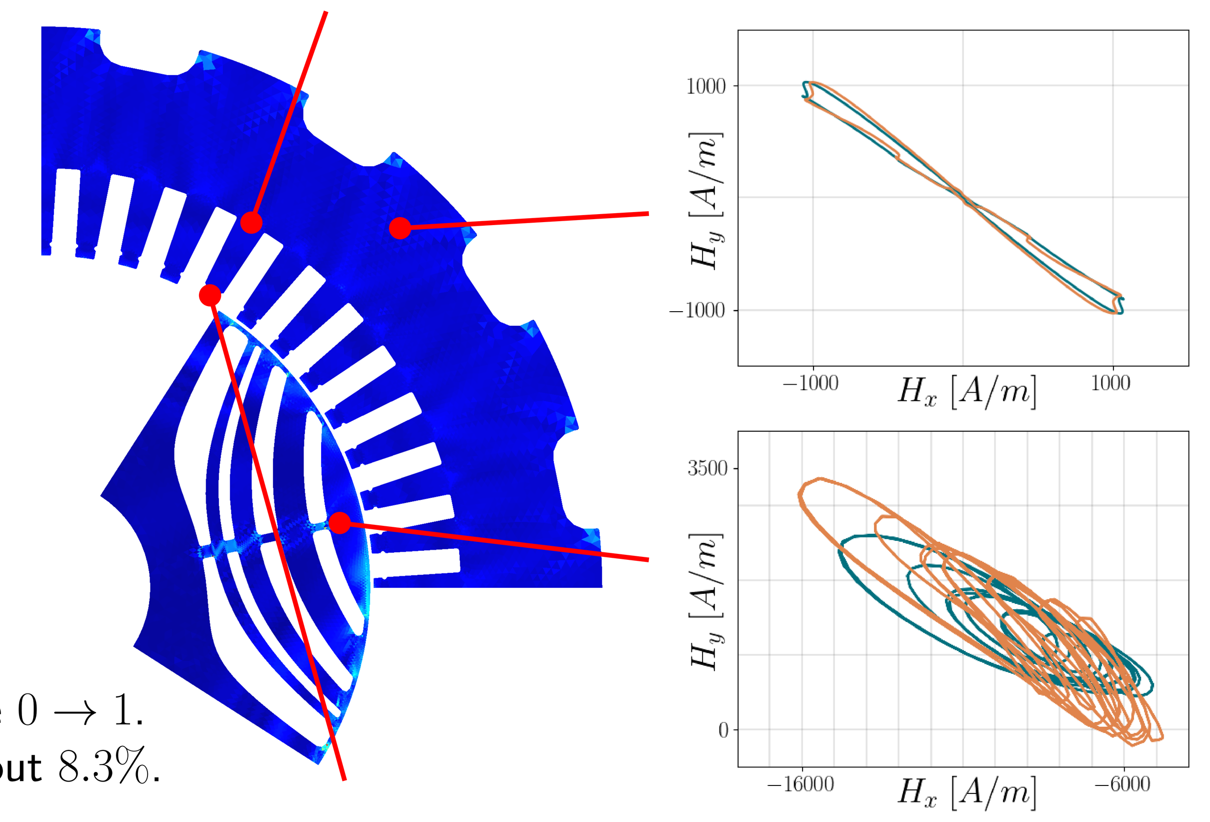


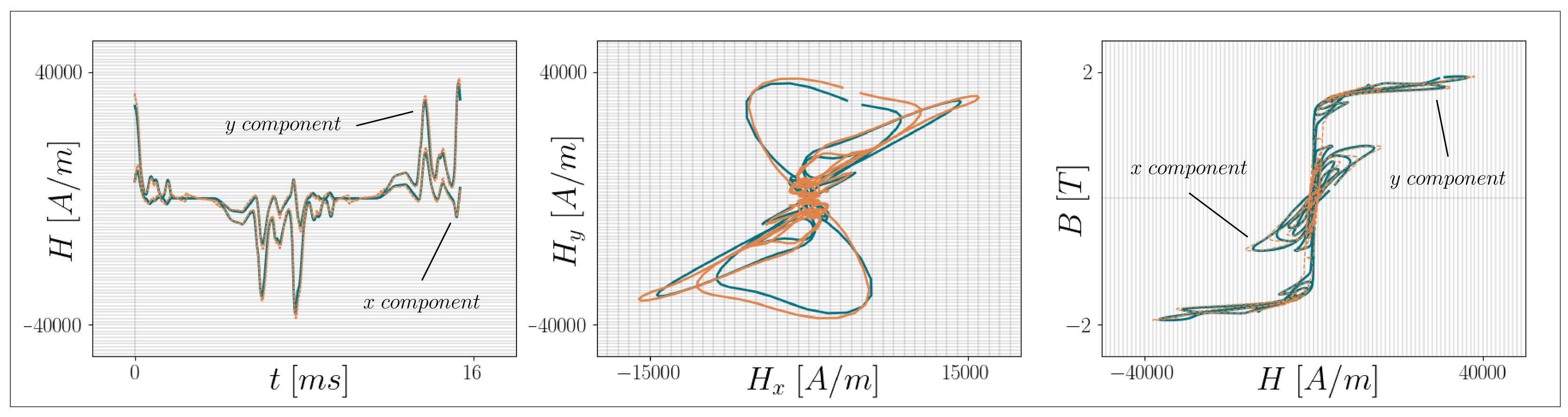
Legend:
Input $\mathbf{H}$ seq.
$\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)$

For the above distribution of p_k's, the distribution of the error

$$\sqrt{\frac{\int_T (H_x - \tilde{H}_x)^2 + (H_y - \tilde{H}_y)^2}{\int_T H_x^2 + H_y^2}}$$

is plotted in the range $0 \to 1$.
The mean error is about 8.3%.





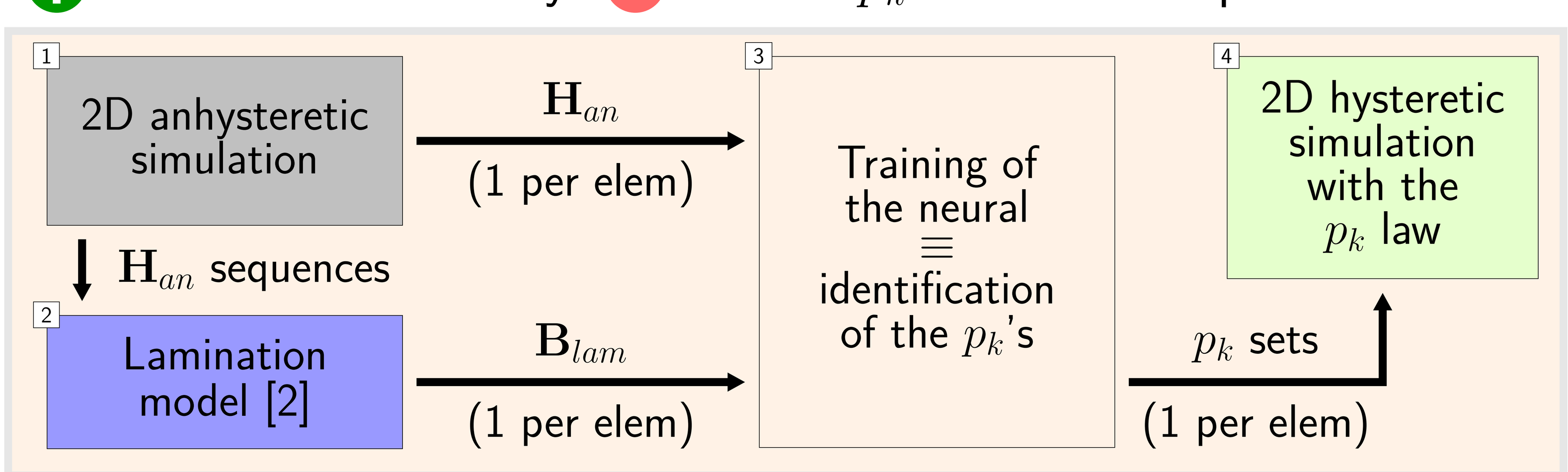
A NN trained in an auto-encoder fashion, with appropriate pre-and-post processing modules, is a fast and accurate way to evaluate the parameters of the p_k law.
The obtained p_k law is a realistic lossy material law for steel lamination stacks.

p_k Identification on a 2D Model: Synthetic vs. Specific Approaches

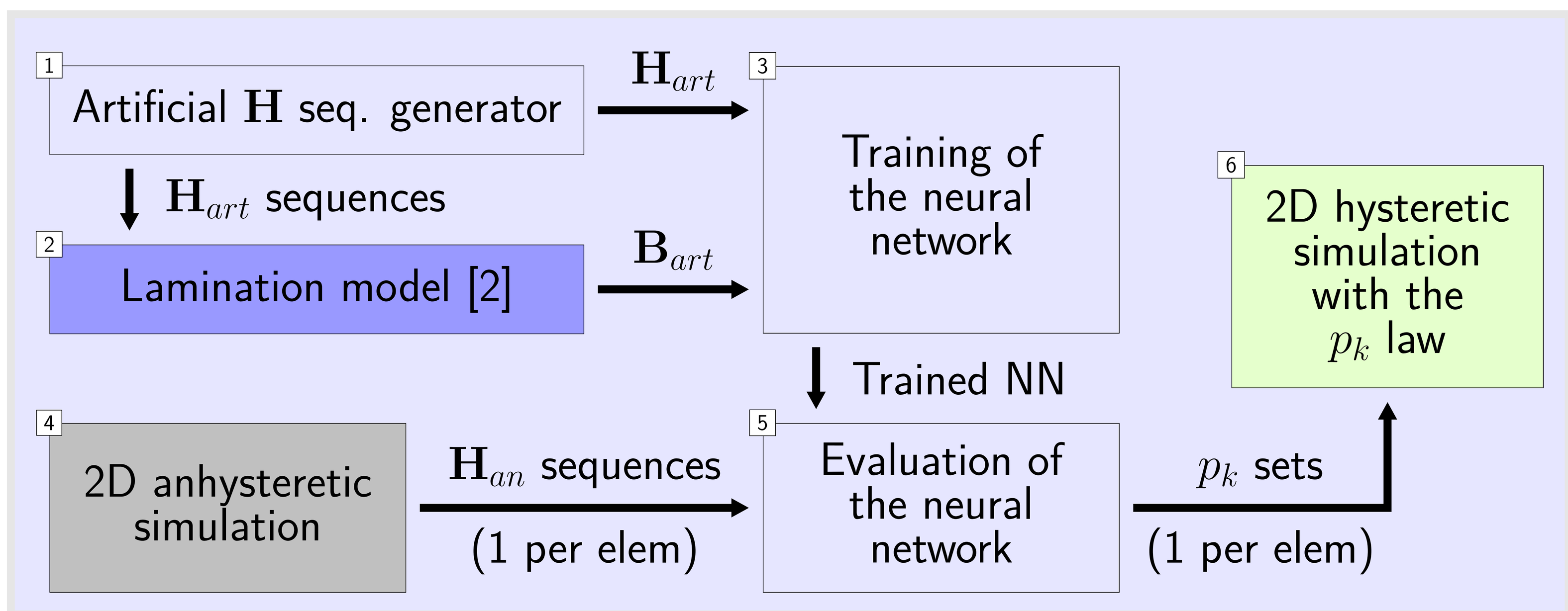
Synthetic approach: Training on a dataset of artificially created $\mathbf{H}$ sequences. NN used for machines with simple harmonic content

Specific approach: Training on the sequences of a specific machine. NN used for that specific machine only

⊕ Measurable accuracy ⊖ Slower p_k identification process



⊕ 1 training, many identifications ⊖ Accuracy depends on dataset



[1] Purnode, F., Henrotte, F., Caire, F., Da Silva, J., Louppe, G., & Geuzaine, C. (2022). A Material Law Based on Neural Networks and Homogenization for the Accurate Finite Element Simulation of Laminated Ferromagnetic Cores in the Periodic Regime. IEEE Transactions on Magnetics. doi:10.1109/TMAG.2022.3160651

[2] Henrotte, F., Steentjes, S., Hameyer, K., & Geuzaine, C. (2015). Pragmatic two-step homogenisation technique for ferromagnetic laminated cores. IET Science, Measurement and Technology, 9 (2), 152-159. doi:10.1049/iet-smt.2014.0201