

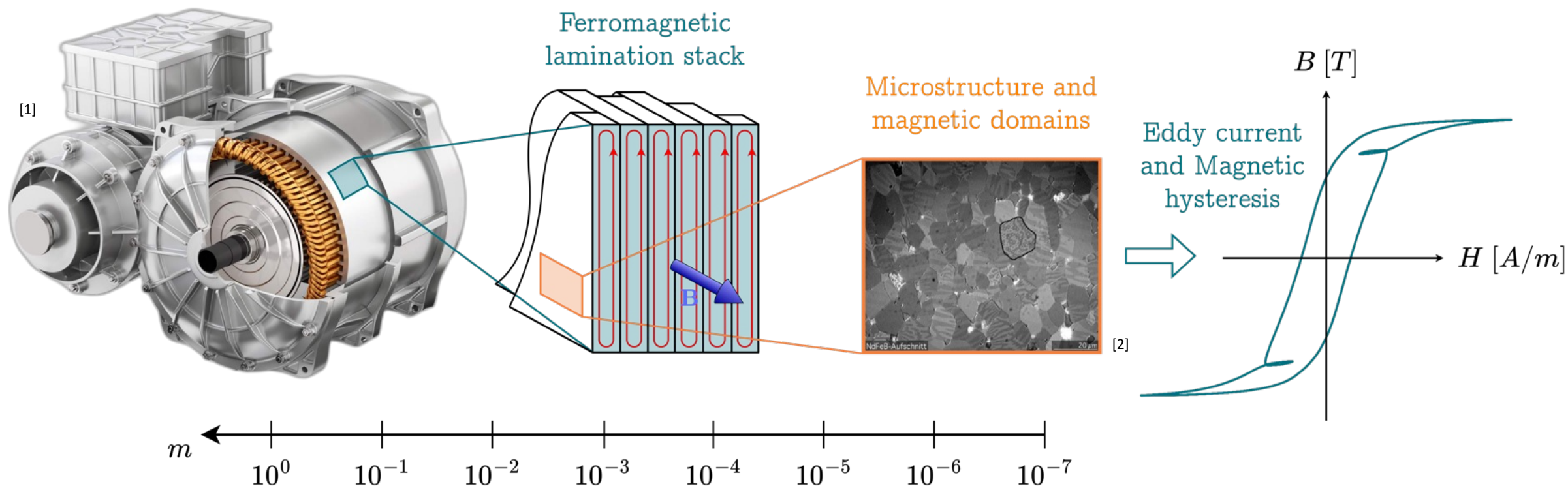


Fast and accurate Neural-Network-based Ferromagnetic Laminated Stack Model for Electrical Machine Simulations in Periodic Regime

Florent Purnode, François Henrotte,
Gilles Louppe and Christophe Geuzaine

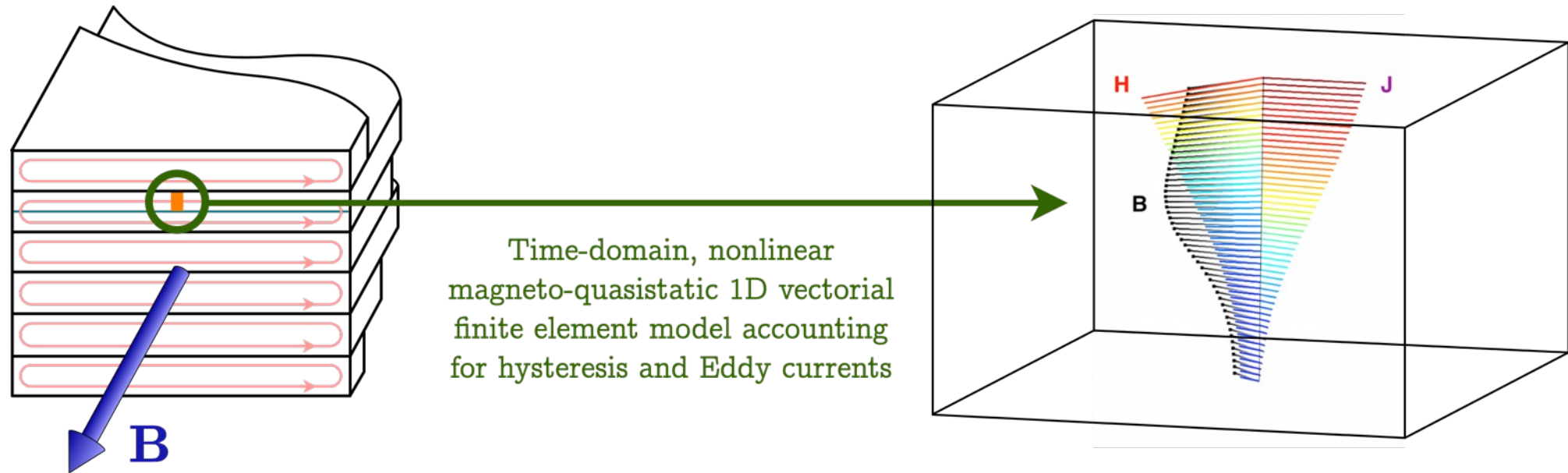
Université de Liège, Institut Montefiore
B-4000 Liège, Belgium

Ferromagnetic stacks are multi-scale



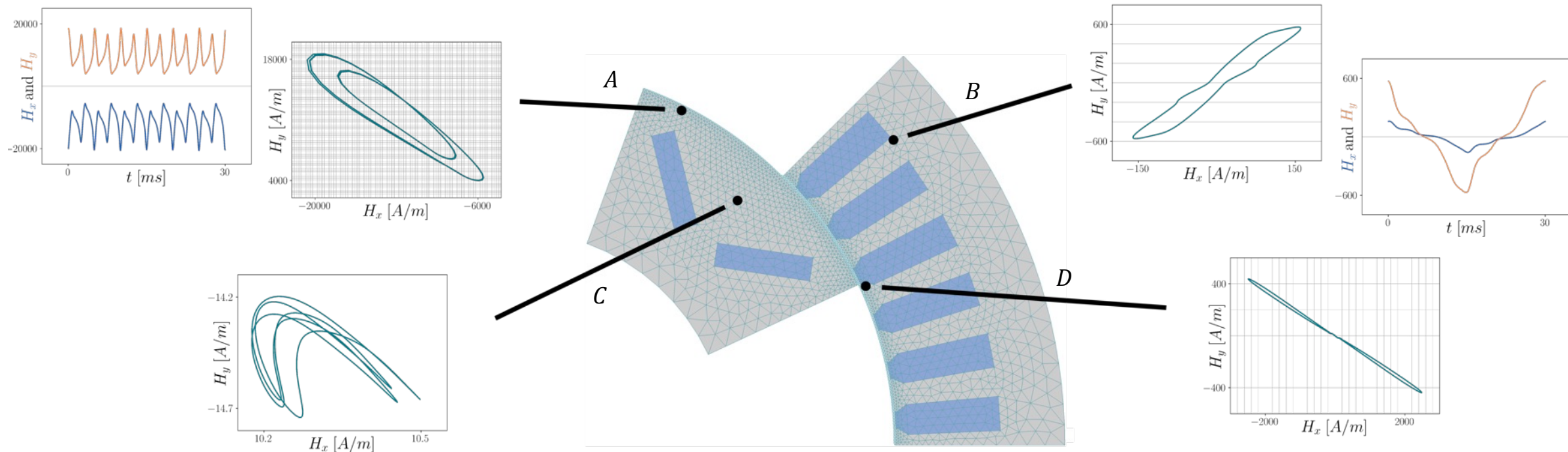
- Ferromagnetic materials exhibit eddy currents and hysteresis
- Both phenomena induce losses

What happens inside a ferro lamination



- The response of a lamination accounting for hysteresis and Eddy currents is very complex (Magnetodynamics, skin effect, vector hysteresis coupled together)
- 3D simulation is way to expensive → **Homogenization** is required
- Invoking the homogenized lamination model in each element of a 2D model is also too slow
- Hence, **2D conventional approaches often disregard hysteresis and Eddy currents**

$\mathbf{H}(t)$ excitation varies from place to place



- Local magnetic fields $\mathbf{H}(t)$ are very different from place to place
- To account for hysteresis and Eddy currents, one has to compute the lamination response to every local $\mathbf{H}(t)$
- We introduce a new parametric homogenized irreversible $\tilde{\mathbf{H}}(\mathbf{B})$ material law extended to account for the ferromagnetic behaviour

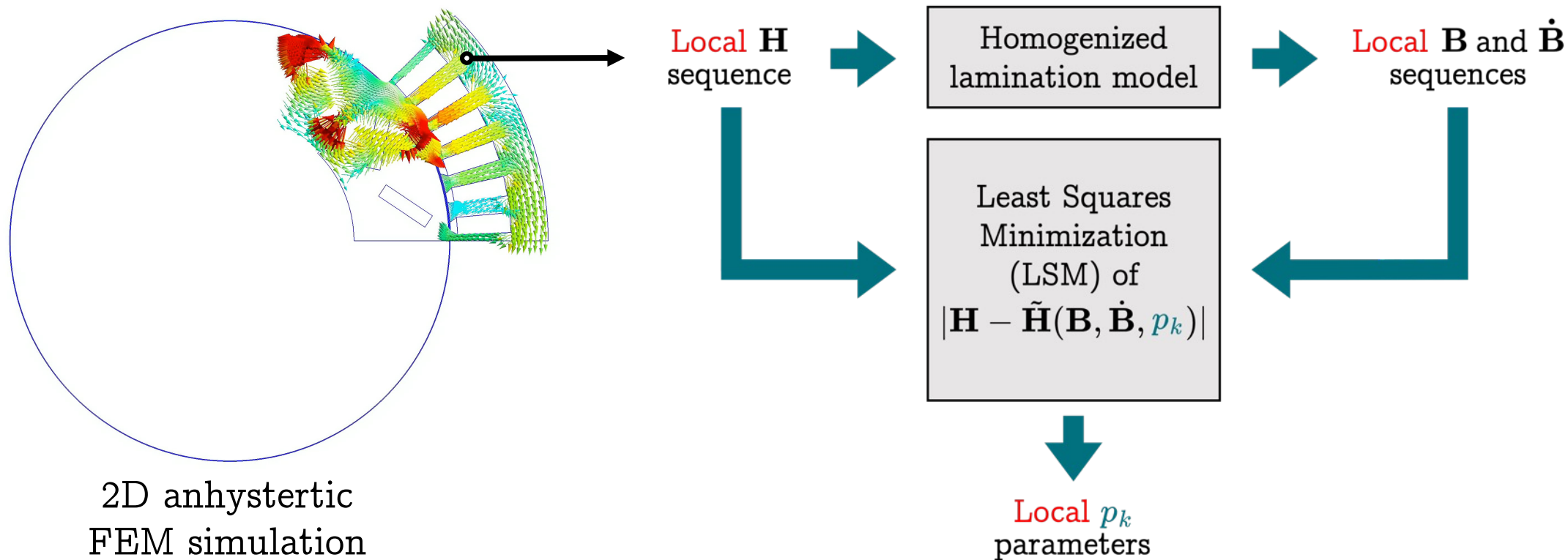
$$\tilde{H}(\mathbf{B}, \dot{\mathbf{B}}, p_k) = \mathbf{B} (p_0 + (p_1 |\mathbf{B}|^2)^{p_2}) + p_3 \dot{\mathbf{B}} + \frac{p_4}{\sqrt{p_5^2 + |\dot{\mathbf{B}}|^2}} \dot{\mathbf{B}}$$

Reversible (anhysteretic)
saturation curve

Irreversible dynamic eddy
current (viscosity-like) term

Irreversible hysteresis
(dry friction-like) term

- Local p_k parameters to adapt to the local fields
- How to identify the right p_k 's? Identification per region or per element?

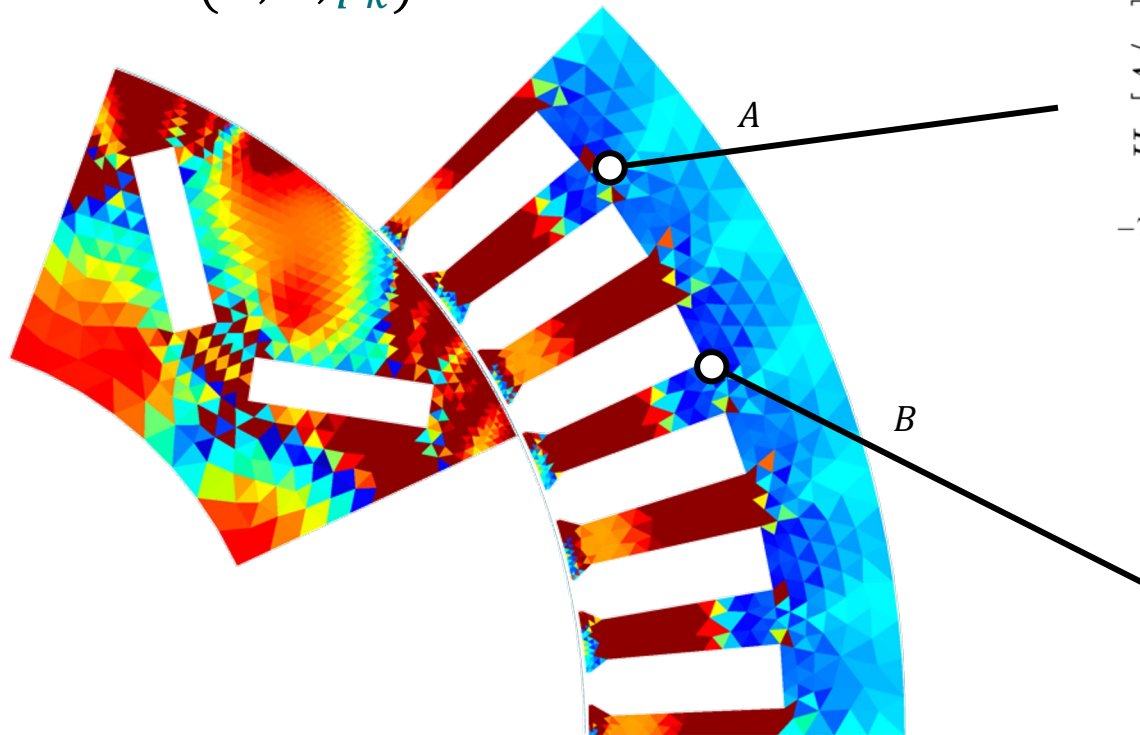


- One has to first perform a 2D anhystertic macro simulation to generate local $\mathbf{H}(t)$ sequences
- Homogenized lamination model: Any efficient code that solves Magnetodynamics, skin effect and vector hysteresis coupled together to obtain the corresponding $\mathbf{B}(t)$
- Least Squares Minimization (LSM) of the error $|\mathbf{H} - \tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)| \mapsto p_k$ (e.g. python `scipy.optimize.leastsq`)

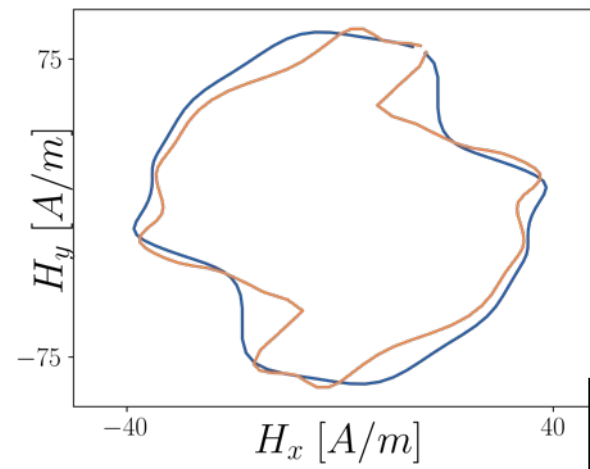
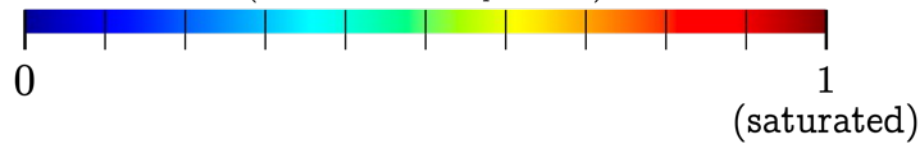
p_k identification, per element or region?

$$\text{LSM of } |\mathbf{H} - \tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)| \mapsto p_k$$

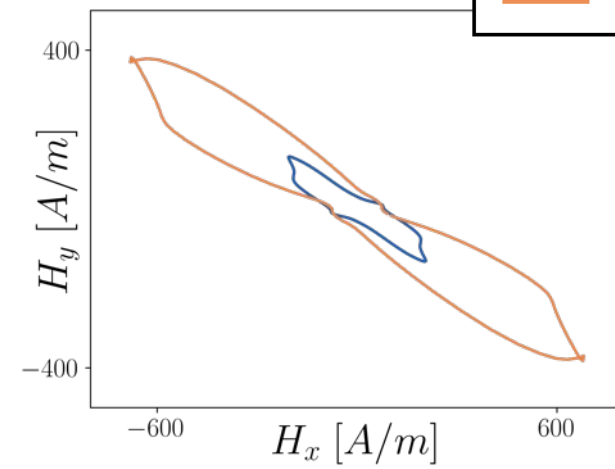
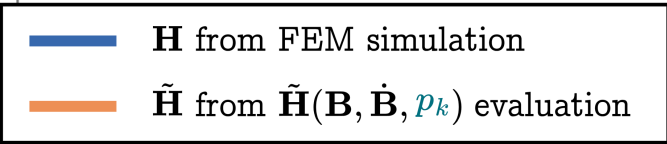
$$\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k) \mapsto \tilde{\mathbf{H}}$$



$|\mathbf{H} - \tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)|$
(Root relative mean square error)

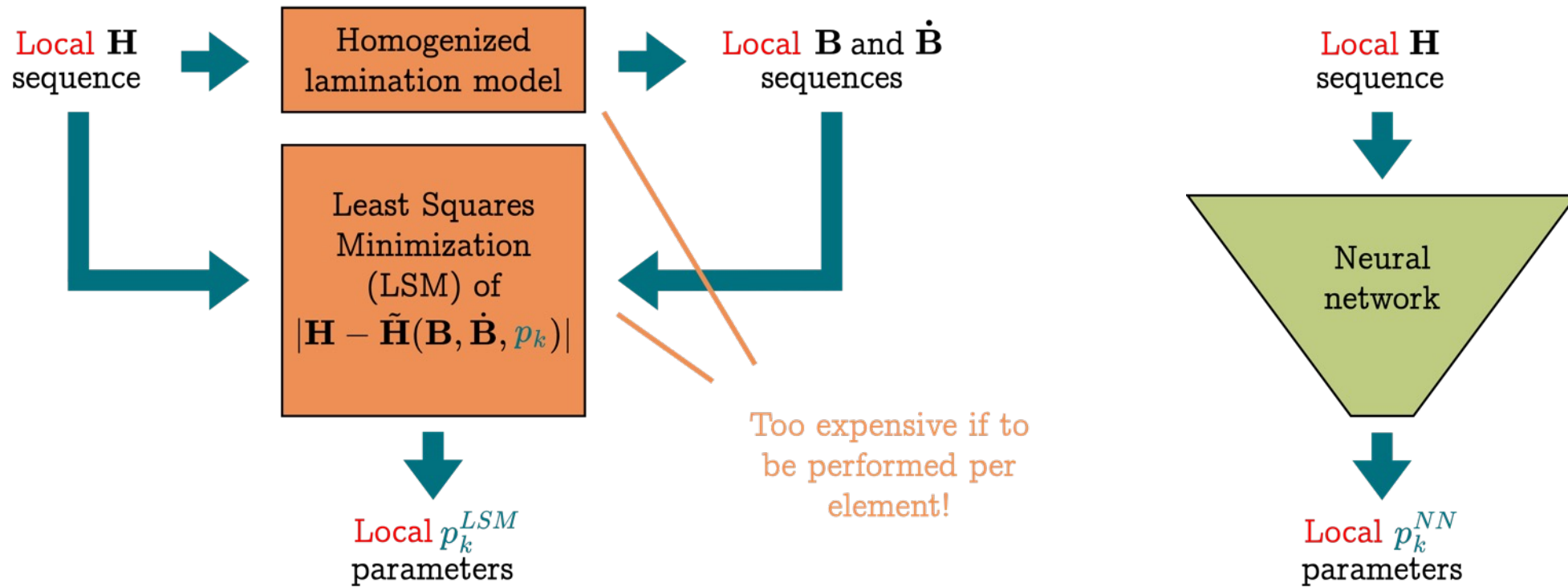


After LSM identification of the p_k for one local element, the $\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)$ law captures the essential features of the corresponding local fields

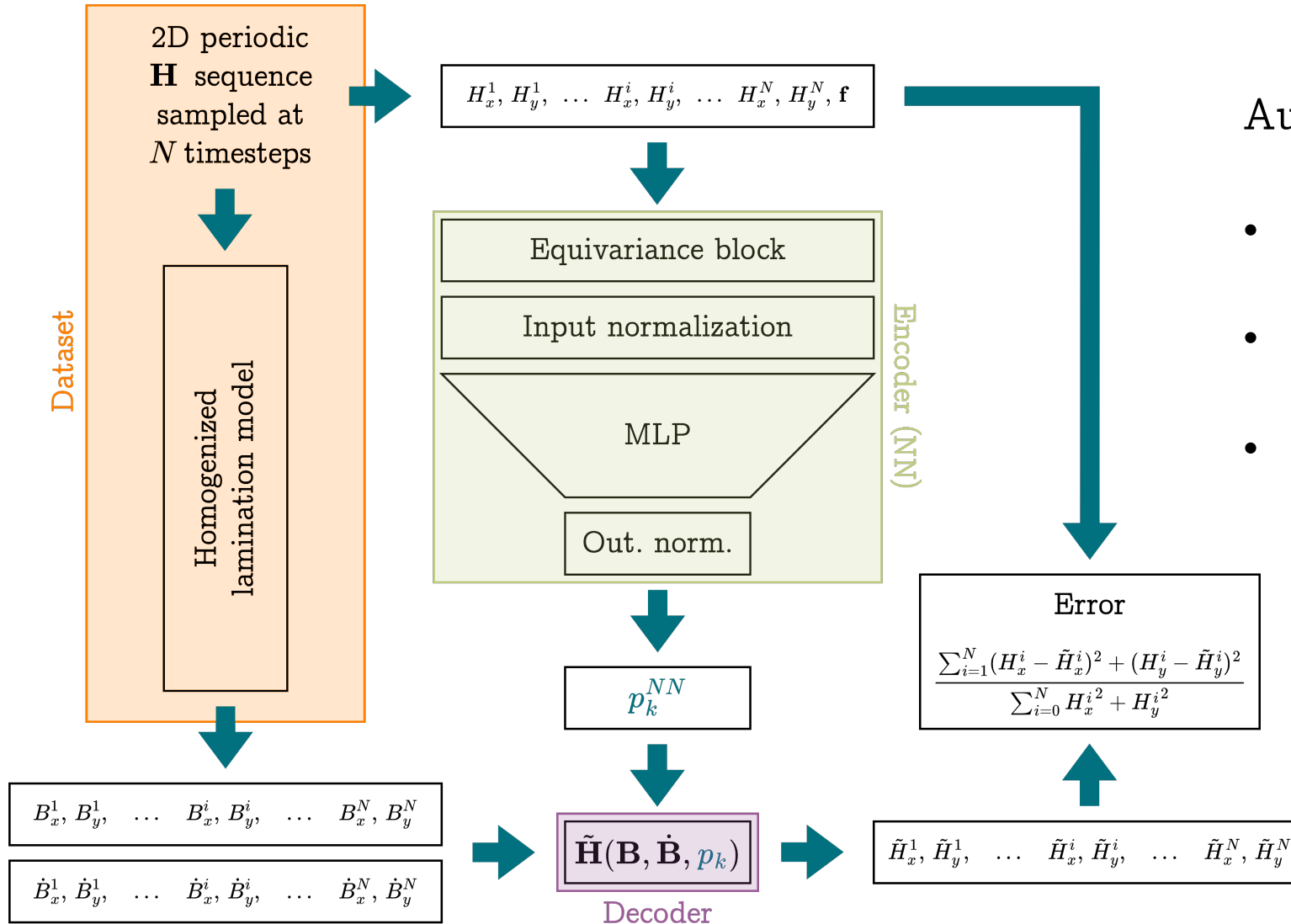


But, using the **same** p_k in other elements leads to **significant errors**

- Better to identify p_k 's per element
- We need an efficient mapping $\mathbf{H}(t) \mapsto p_k$



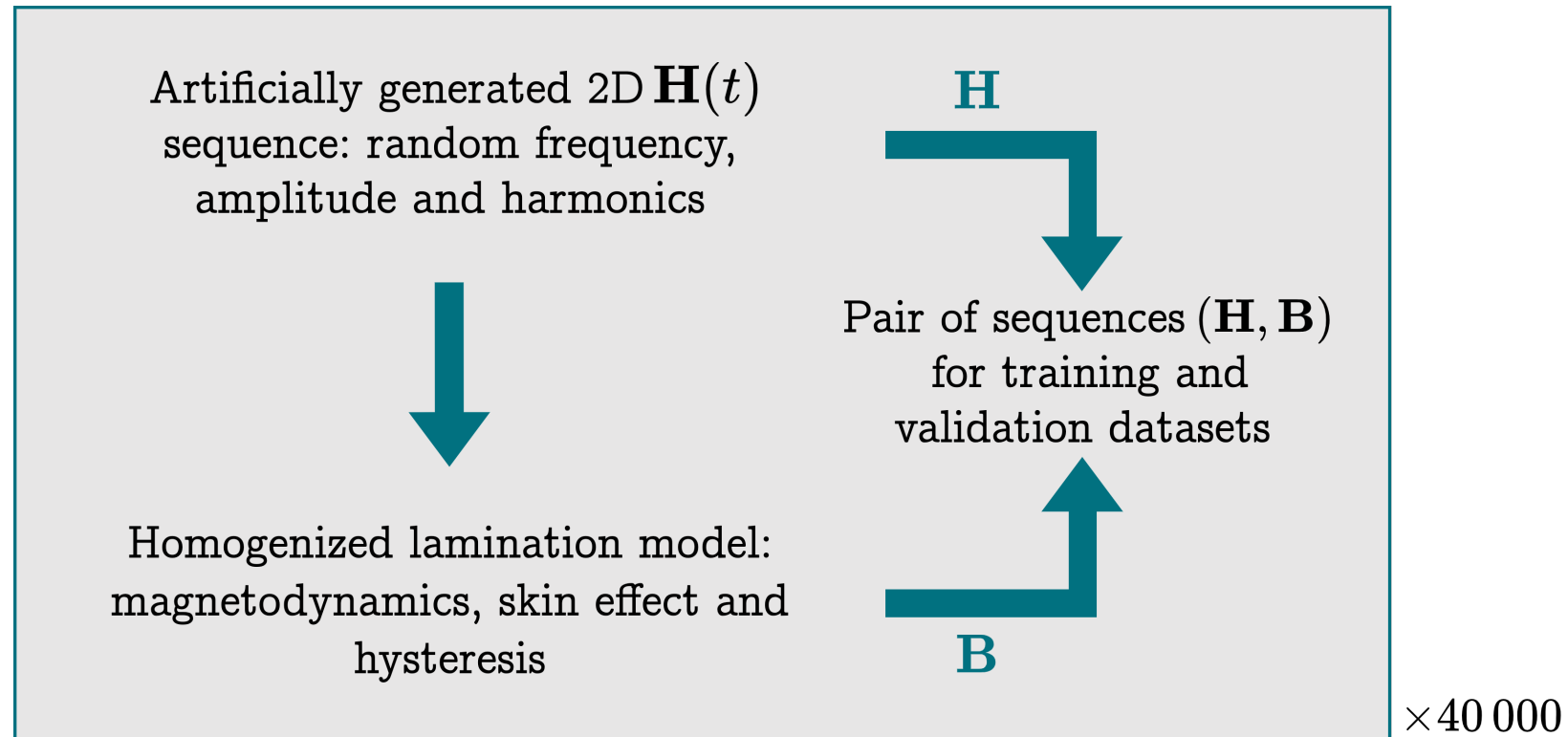
- Neural networks (NN) can efficiently perform regressions
- The dataset generation and the NN training is costly but done only once
- The NN evaluation is much faster
- Considering periodic sequences, the mapping $\mathbf{H}(t) \mapsto p_k$ can be efficiently handled by a neural network



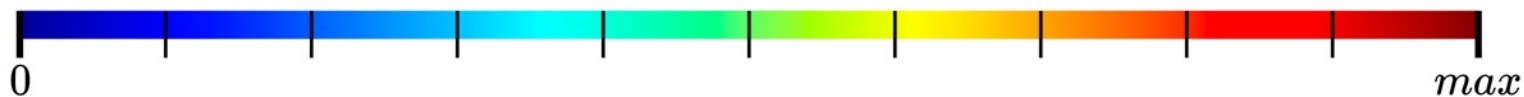
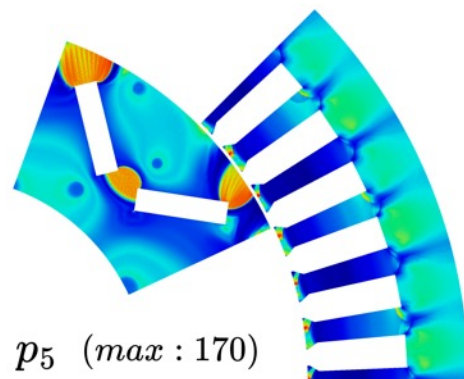
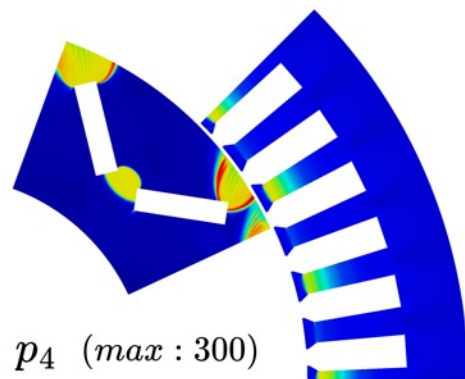
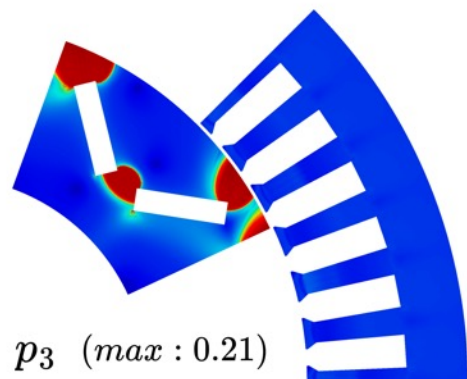
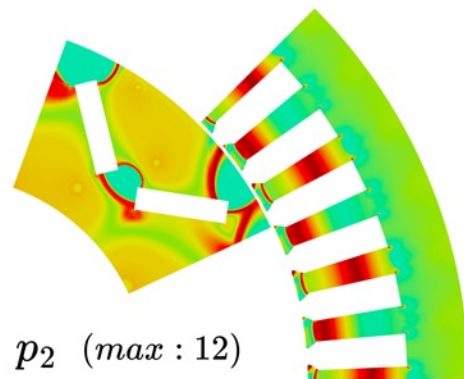
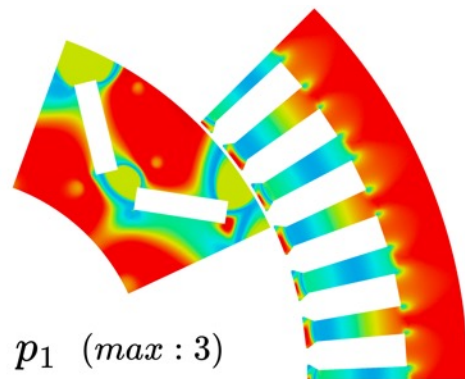
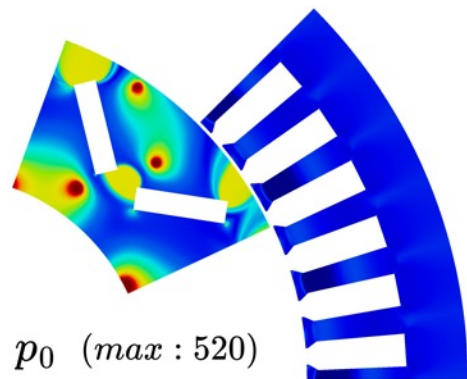
Auto-encoder-like learning:

- Minimization of $|\mathbf{H} - \tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k)|$:
- The p_k law is the decoder
- The p_k^{NN} 's are extracted features

Artificial training dataset



- Training datasets should be populated by a sufficient number of pairs of sequences (\mathbf{H} , \mathbf{B}) similar to those encountered in electrical machine simulations
- I.e., 40 000 artificial sequences are generated for the training and validation datasets



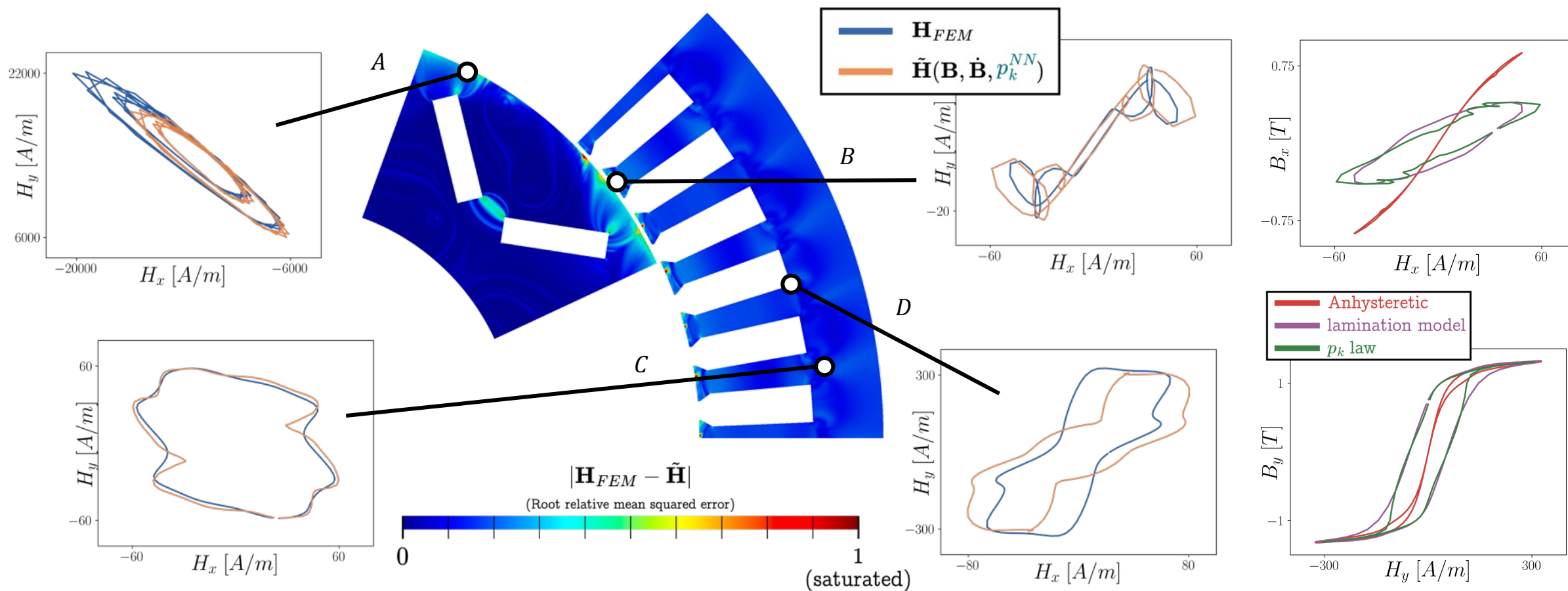
- Run an hysteretic FEM to generate local \mathbf{H}_{FEM} sequences and evaluate the NN:

$$\mathbf{H}_{FEM} \mapsto p_k^{NN}$$

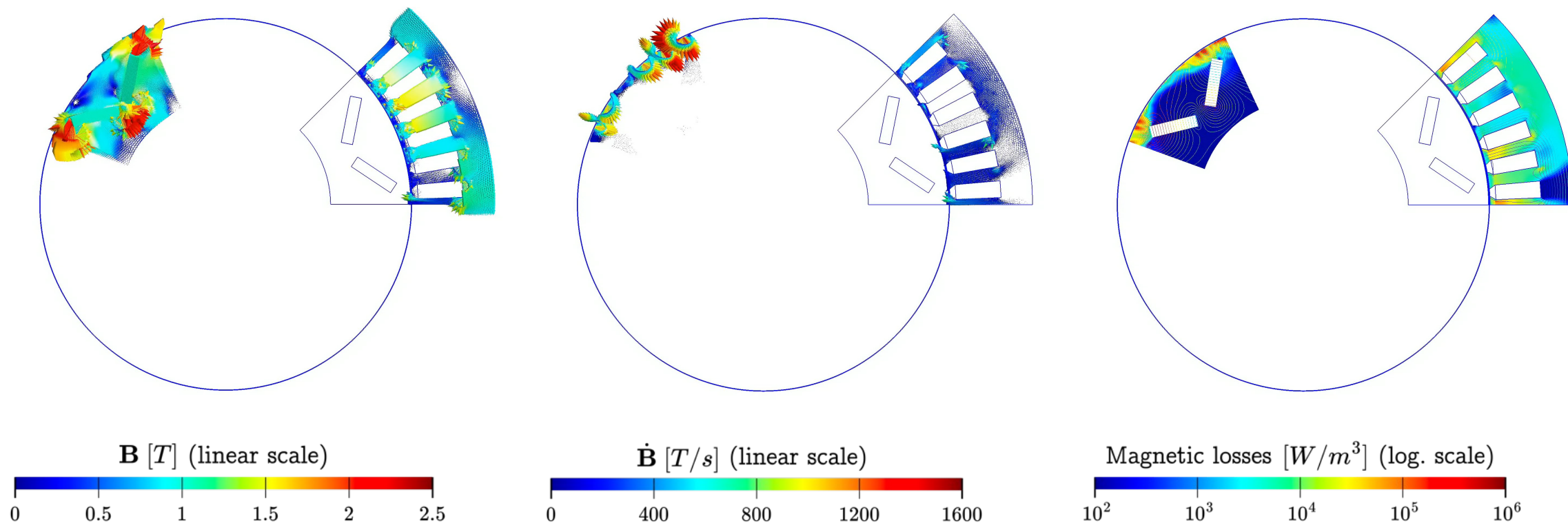
- The identified p_k^{NN} 's are coherent with the physics of the machine
- Despite p_k^{NN} are evaluated elementwise, the spatial distributions are smooth
 → The $\mathbf{H} \mapsto p_k^{NN}$ mapping is well-conditioned

Mean rel. error $|\mathbf{H}_{FEM} - \tilde{\mathbf{H}}_{FEM}|$ is $\sim 15\%$

Solve lamination model: $\mathbf{H}_{FEM} \mapsto \mathbf{B}$, evaluate p_k law: $\tilde{\mathbf{H}}(\mathbf{B}, \dot{\mathbf{B}}, p_k^{NN}) \mapsto \tilde{\mathbf{H}}$, evaluate error: $|\mathbf{H}_{FEM} - \tilde{\mathbf{H}}|$

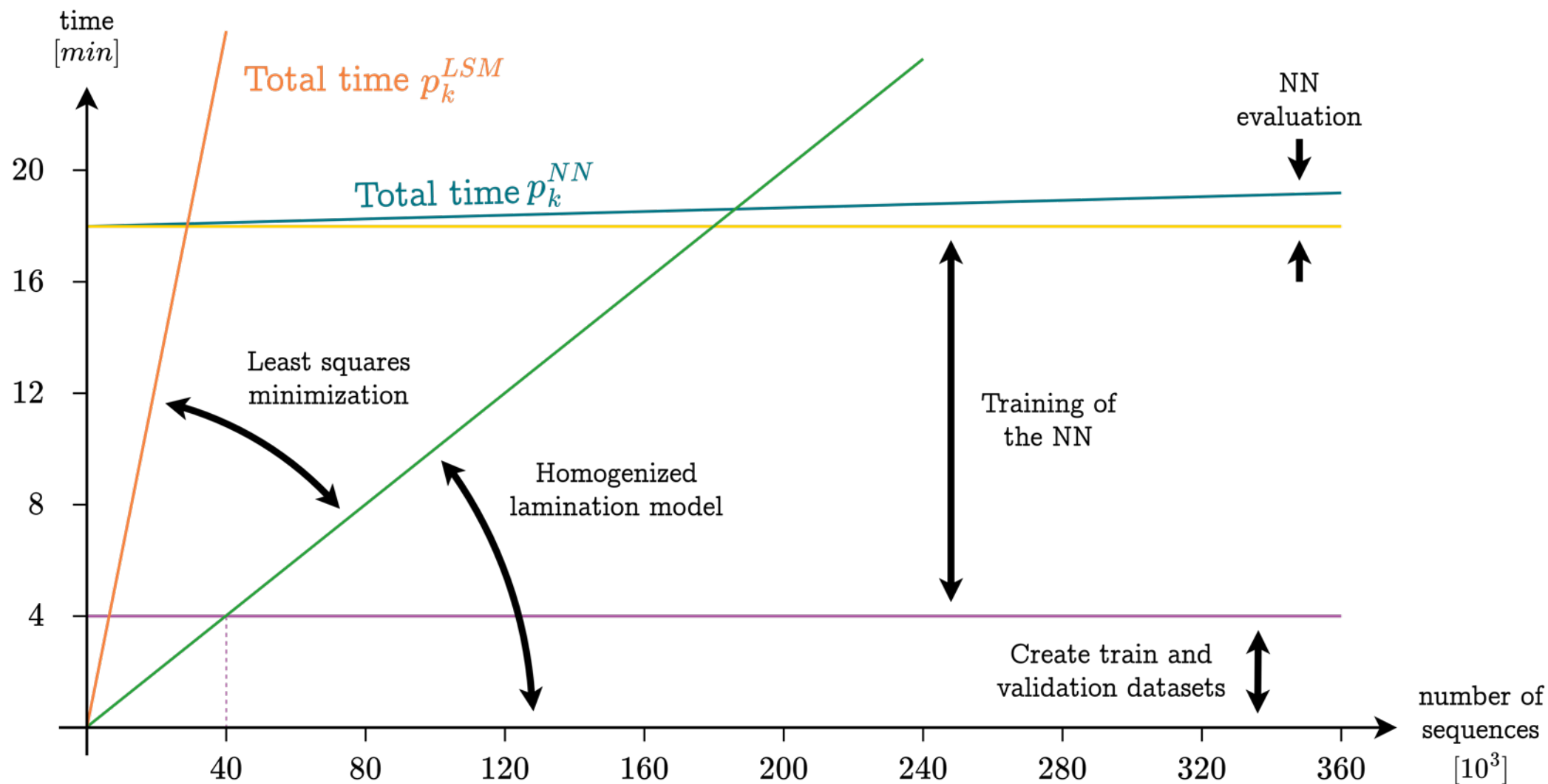


The p_k law captures the essential features of the local fields (compared to the lamination model), with an average error of 15% for the sequences $\mathbf{H}_{FEM}(t)$ issued from the FEM simulation



- The p_k law is differentiable \rightarrow exact Jacobian can be computed \rightarrow non-linear convergence is ensured
- The identified p_k law is used as material law in the FEM model
- Instantaneous iron losses in laminated cores are simulated and can be visualized

Computational time breakdown



- We introduced a new method to include Eddy currents and hysteresis in 2D FEM simulations of electrical machines at a cost similar to a conventional 2D anhysteretic simulation
- The homogenized lamination model, the p_k law and the NN all introduce approximations, but the trade-offs are worth it:
 - The p_k law has an exact Jacobian, it is easily included in a classical Newton-Raphson scheme
 - **The cost is very low** compared to the direct inclusion of a homogenized lamination model in macro simulations
- The method is currently designed for periodic regime, the extension to fully transient is coming