LIÈGE université
Sciences Appliquées

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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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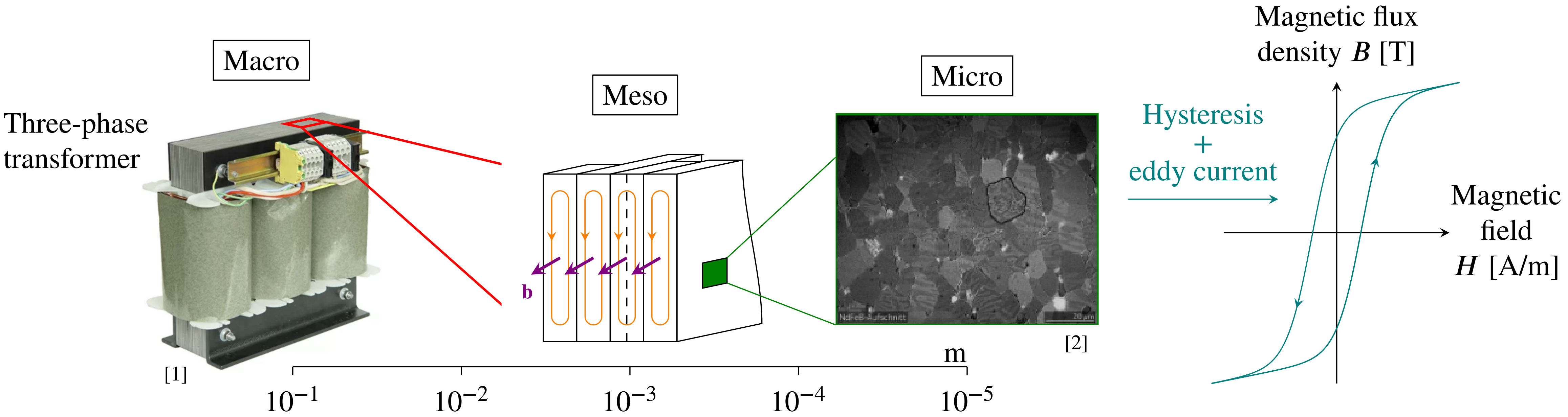
Ferromagnetic stacks are multi-scale



- When subjected to a variable magnetic field $\mathbf{H}(t)$, ferromagnetic materials exhibit **eddy currents** and **hysteresis**, both inducing losses
- These phenomena occur at a **scale much smaller** than the electrical machine scale

[1] www.indiamart.com, [2] Photomicrograph of NdFeB (Wikipedia – Magnetic domain)

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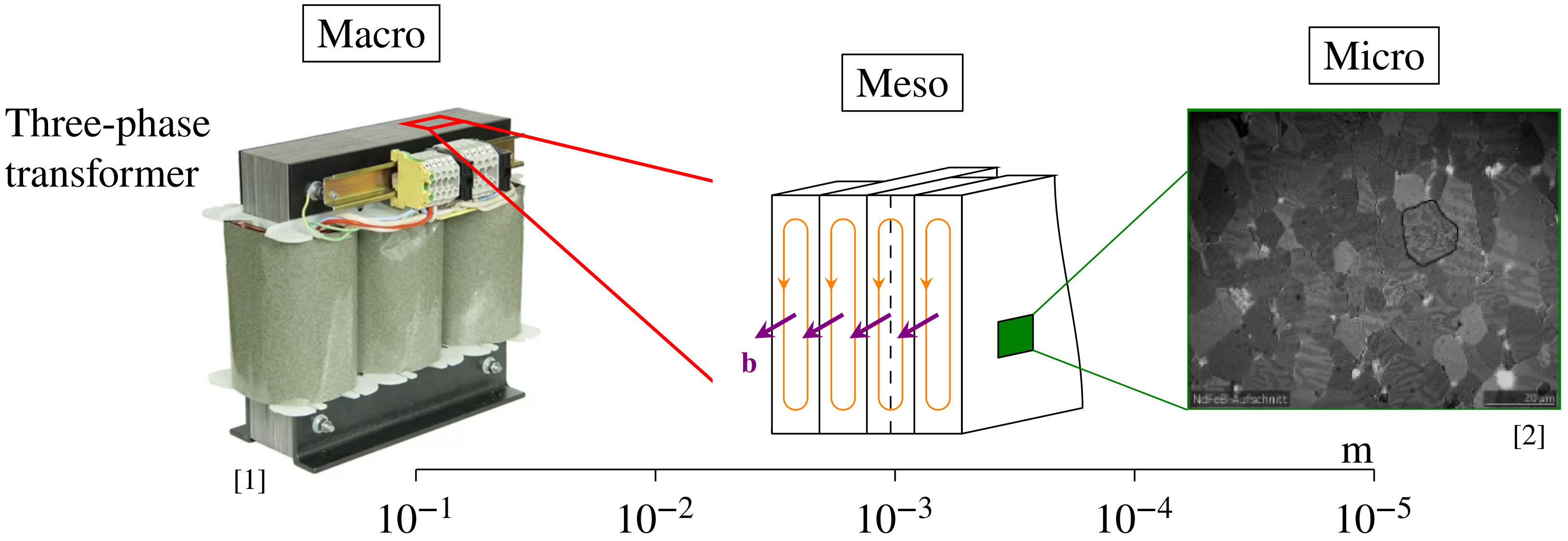

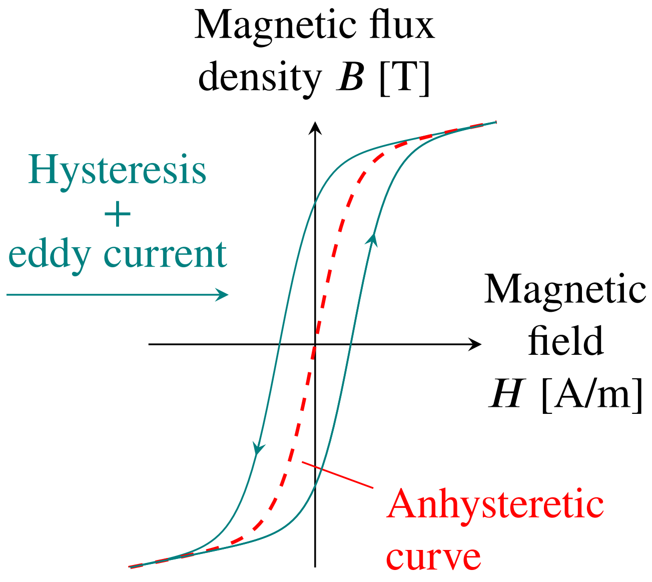

- When subjected to a variable magnetic field $\mathbf{H}(t)$, ferromagnetic materials exhibit **eddy currents** and **hysteresis**, both inducing losses
- These phenomena occur at a **scale much smaller** than the electrical machine scale
- Currently disregarded in R&D due to computational complexity, use anhysteretic approximation

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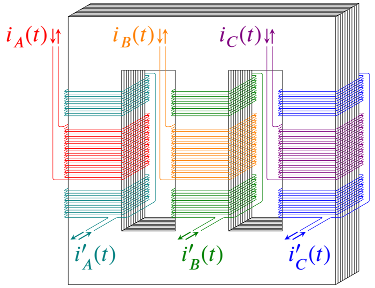
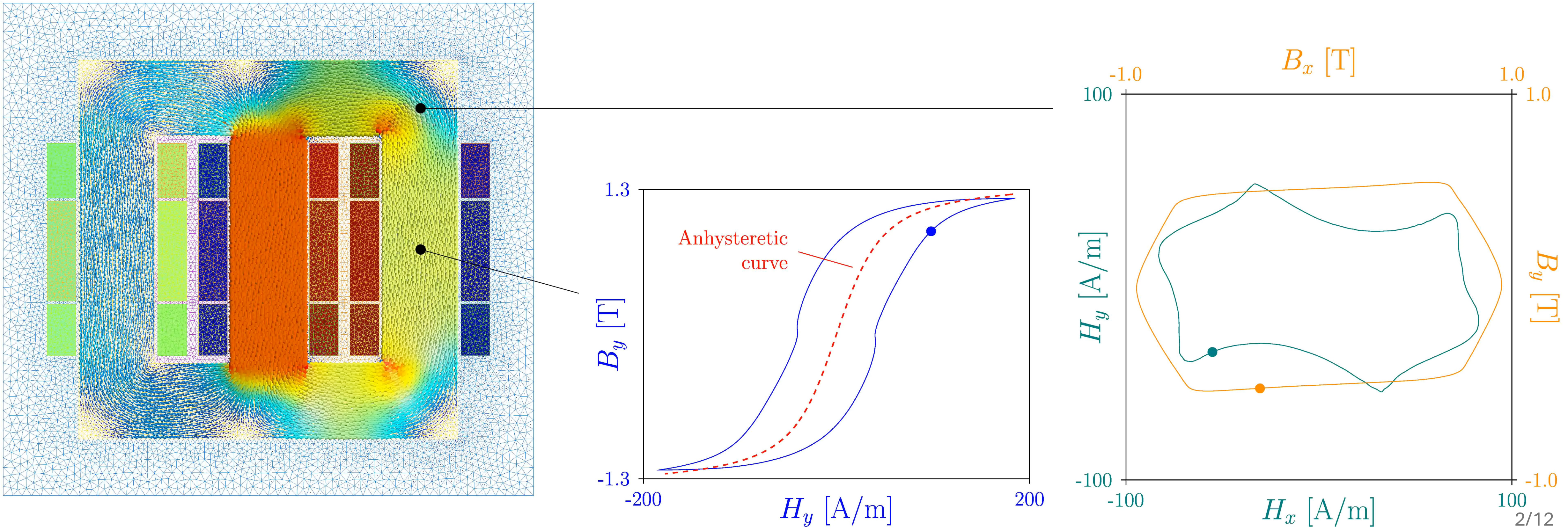
Our working approach



In this presentation we introduce a significantly improved approach combining an **accurate hysteresis model**, **homogenization** and a **recurrent neural network**



Outline

- The “$\boldsymbol{a}$” formulation
- Why using an RNN?
- Dataset generation
- Improving RNN’s predictions
- Validating the RNN model
- Running a FEM simulation

Model at macro scale – The "$\boldsymbol{a}$" formulation

Magnetostatic "$\boldsymbol{a}$" formulation:

$$\nabla \times \mathbf{H} = \mathbf{j}$$
$$\nabla \cdot \mathbf{B} = 0$$

Magnetic vector potential $\boldsymbol{a}$:

$$\mathbf{B} = \nabla \times \boldsymbol{a}$$

Weak formulation of $\nabla \times \mathbf{H} = \boldsymbol{j}$ with vanishing Neumann boundary condition:

$$(\mathbf{H}(\mathbf{B}), \nabla \times \boldsymbol{a}')_{\Omega} = (\boldsymbol{j_s}, \boldsymbol{a}')_{\Omega_s}, \qquad \forall\, \boldsymbol{a}'$$

Linearize the non-linear $\mathbf{H}(\mathbf{B})$ material law, and solve for $\mathbf{B}_{\mathrm{i}}$ with the Newton-Raphson scheme:

$$\left(\mathbf{H}(\mathbf{B}_{i-1}) + \frac{\partial \mathbf{H}}{\partial \mathbf{B}}(\mathbf{B}_{i-1})(\mathbf{B}_i - \mathbf{B}_{i-1}), \nabla \times \boldsymbol{a}'\right)_{\Omega} = (\boldsymbol{j_s}, \boldsymbol{a}')_{\Omega_s}, \qquad \forall\, \boldsymbol{a}'$$

We need a $\mathbf{H}(\mathbf{B})$ model **BUT** hysteresis models are naturally $\mathbf{B}(\mathbf{H})$!

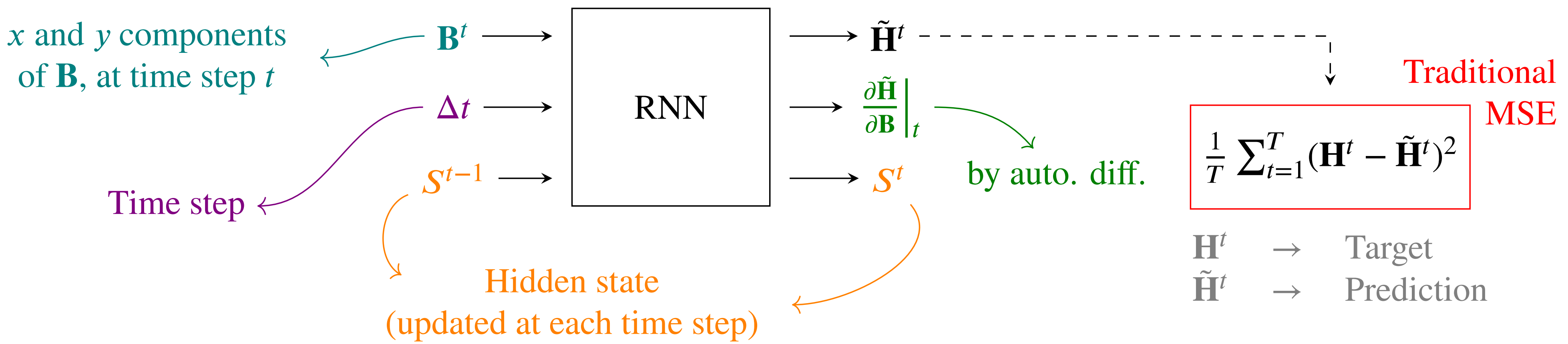
Recurrent Neural Network as $\mathbf{H}(\mathbf{B})$ model

- Required: efficient $\mathbf{H}(\mathbf{B})$ model
- Physics gives $\mathbf{B}(\mathbf{H})$

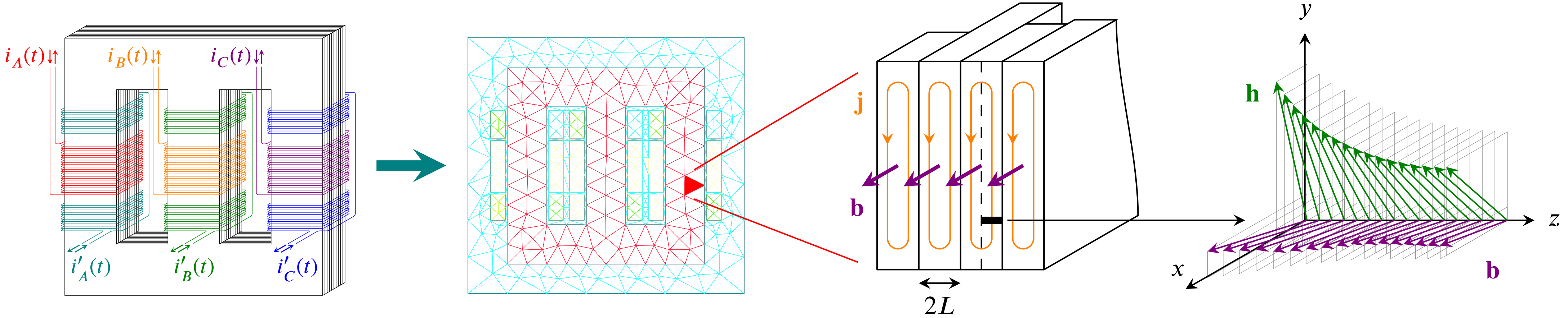
1. Using a $\mathbf{B}(\mathbf{H})$ model, create a dataset of $(\mathbf{H}, \mathbf{B})$ time sequences
2. Train an NN to predict $\mathbf{H}(\mathbf{B})$
3. Inference: $\mathbf{H}(\mathbf{B})$ in forward pass, $\frac{\partial \mathbf{H}}{\partial \mathbf{B}}$ with automatic differentiation

NN requirements:
- Handle sequences
- Accurate
- Fast inference

Recurrent Neural Network (RNN)



Dataset generation – 1D Lamination model

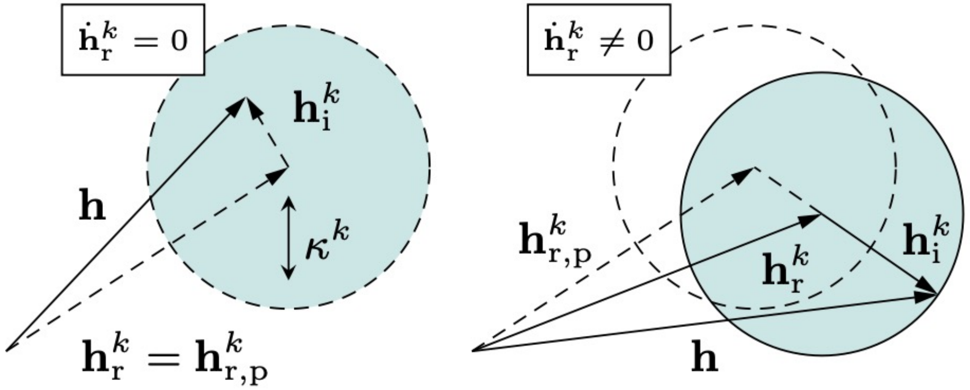


To account for eddy current:

→ 1D magneto-quasistatic problem, driven by the magnetic field $\mathbf{H}$, over half a lamination thickness

To account for hysteresis:

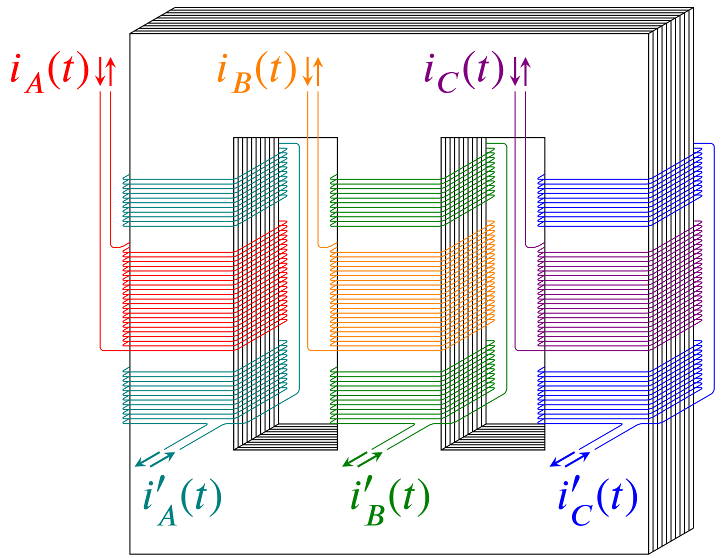
→ Couple each element of the 1D model with the energy-based (EB) hysteresis model



➔ Magnetic flux density $\mathbf{B}$ homogenized across the stack

Dataset generation – $\mathbf{H}$ artificial sequences

$(\mathbf{H}^0, \mathbf{H}^1, \dots, \mathbf{H}^t)$ —Lamination model→ $(\mathbf{B}^0, \mathbf{B}^1, \dots, \mathbf{B}^t)$



Required: $(\mathbf{H}^0, \mathbf{H}^1, \dots, \mathbf{H}^t)$ sequences, **mimicking fields in electrical machines**

Popular approaches:

- Measurements or simulations → expensive, machine specific ☹
- Random walks → unphysical data (wrong resource allocation) ☹
- Sum of random harmonics → easy to build, close to physics ☺

Note: $i_A(t)$, $i_B(t)$ and $i_C(t)$ phase shifted by 120°

→ $\mathbf{H}(t)$ can be decomposed into three identical unidirectional signals, time shifted by 120°, with arbitrary direction

⇨

1. Create a unidirectional signal, with random harmonics and direction
2. Create a replica of this signal, time shifted by 120°, arbitrary rotated
3. Sum them up, with a random scaling factor

In our training dataset:

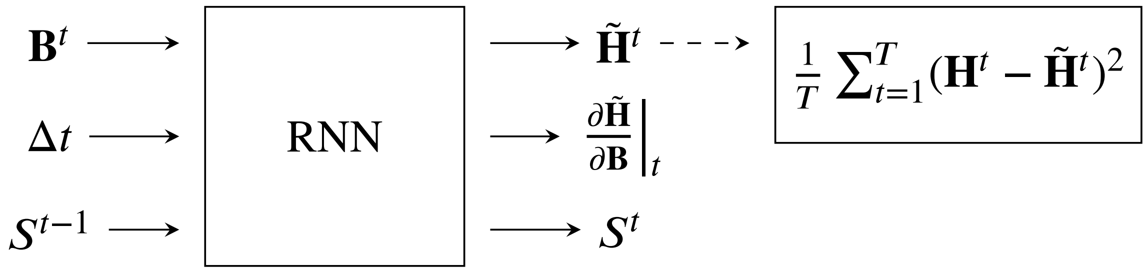
→ Sequences of 1000 timesteps
→ 500 000 training sequences (generated in 3 hours on 1 AMD EPYC 7763 CPU)

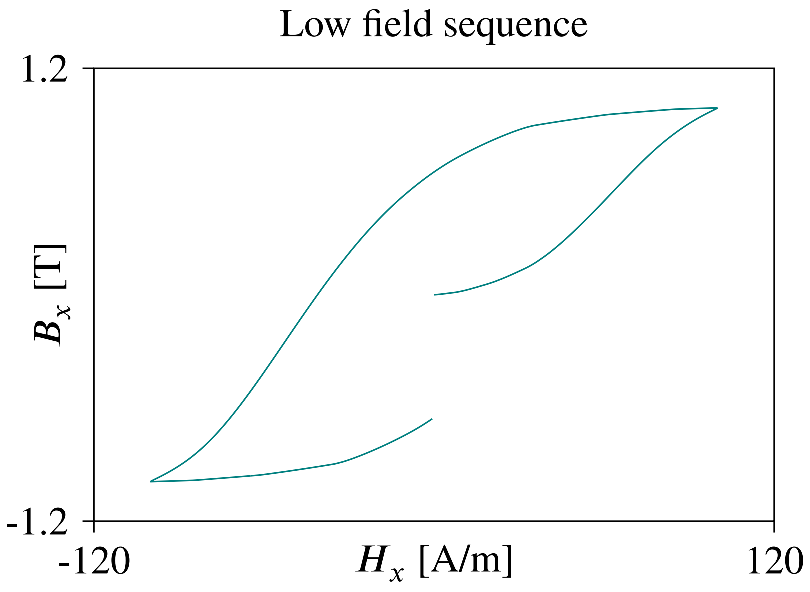
Mean Squared Scaled Loss

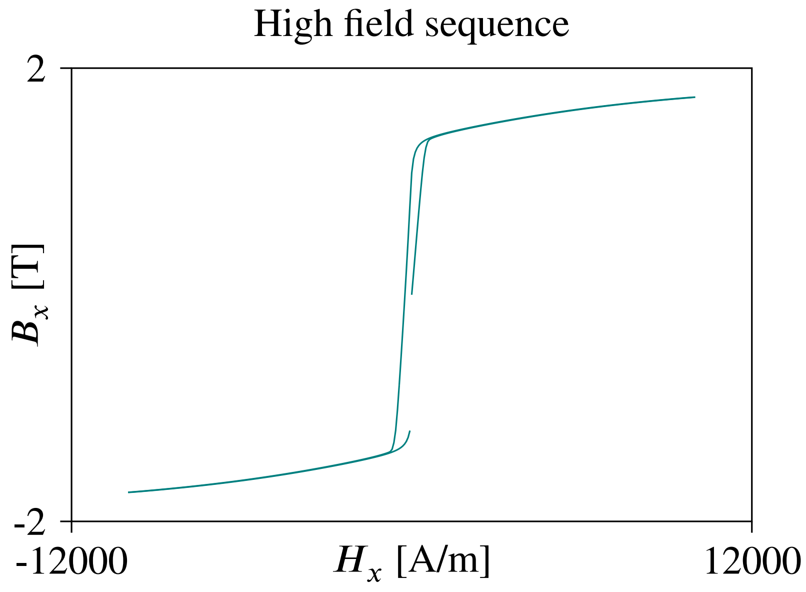
Target sequences

H → **B**

Lamination model







Mean Squared Scaled Loss

Target sequences

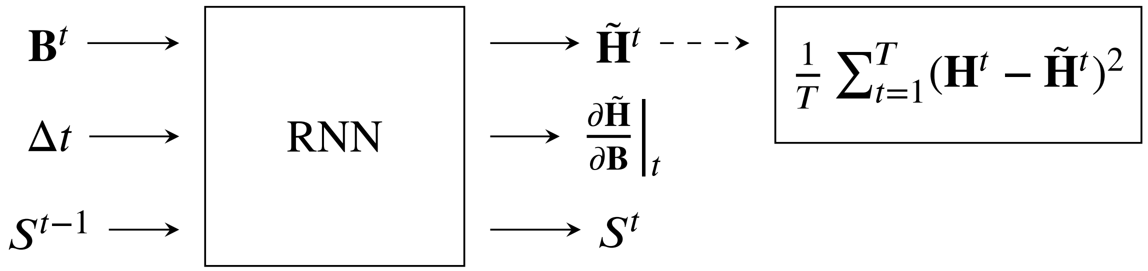
H → **B**

Lamination model

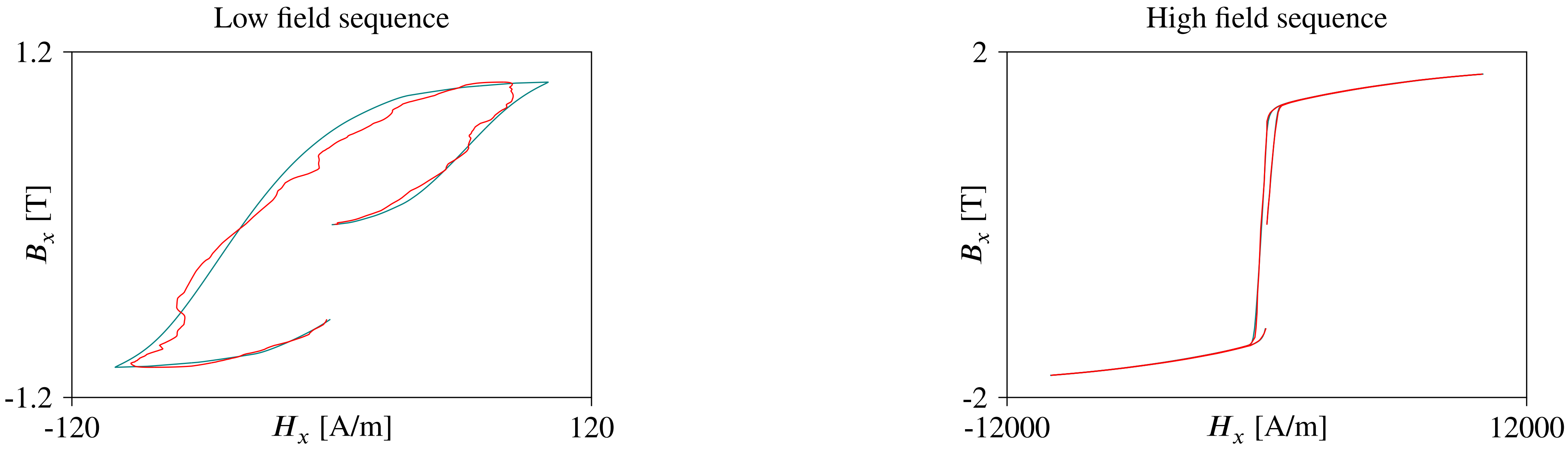
Prediction

B → $\tilde{\mathbf{H}}$

RNN



High field data dominates the training process



Mean Squared Scaled Loss

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H → **B**
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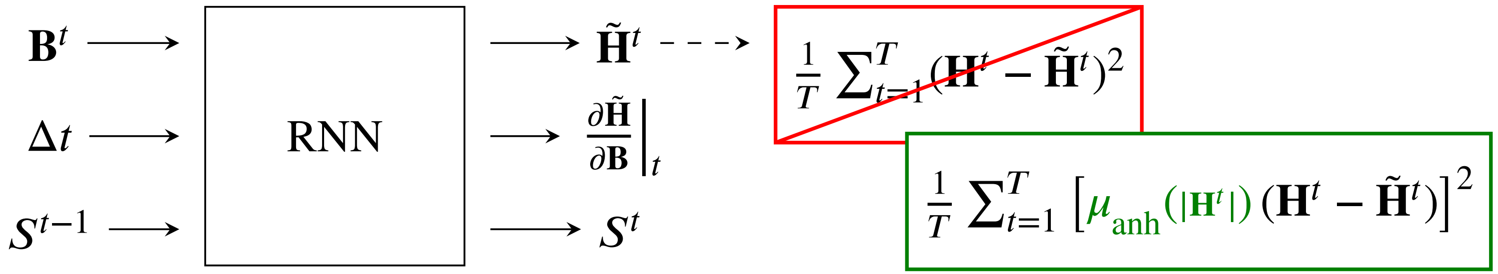
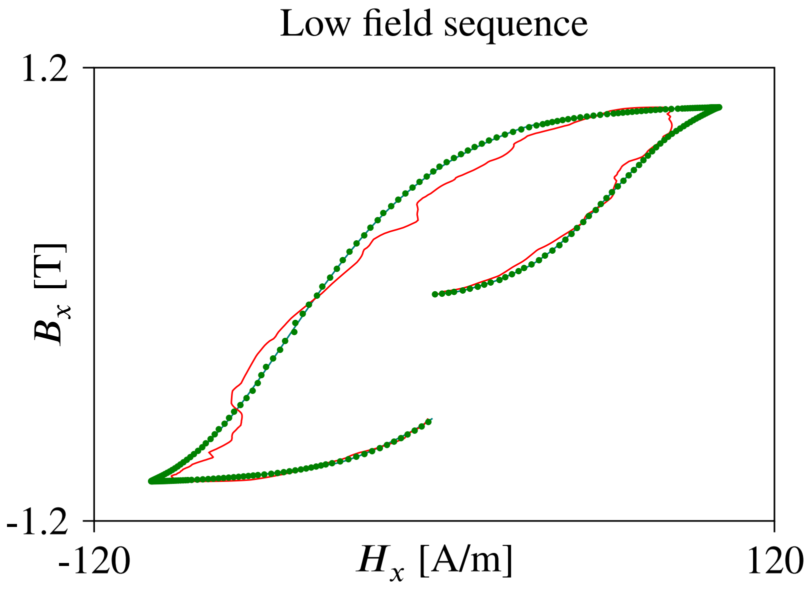
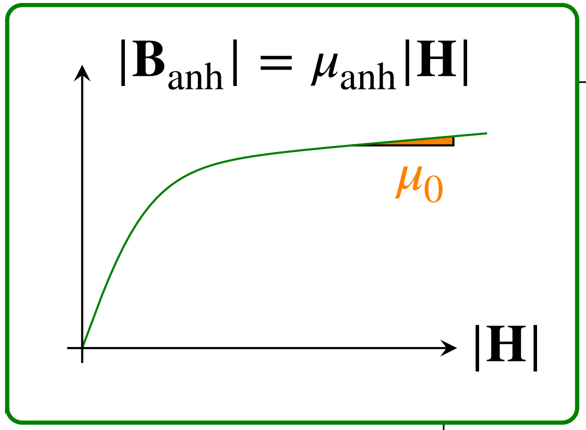
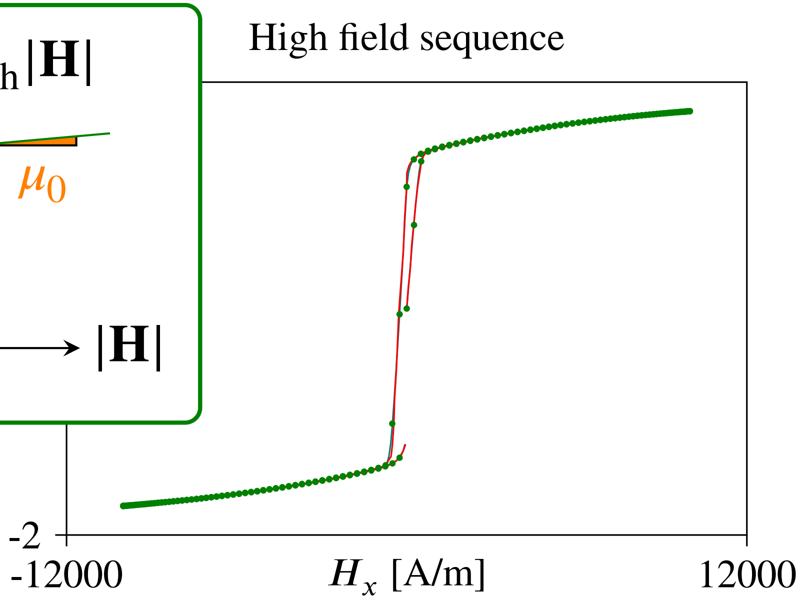


High field data dominates the training process

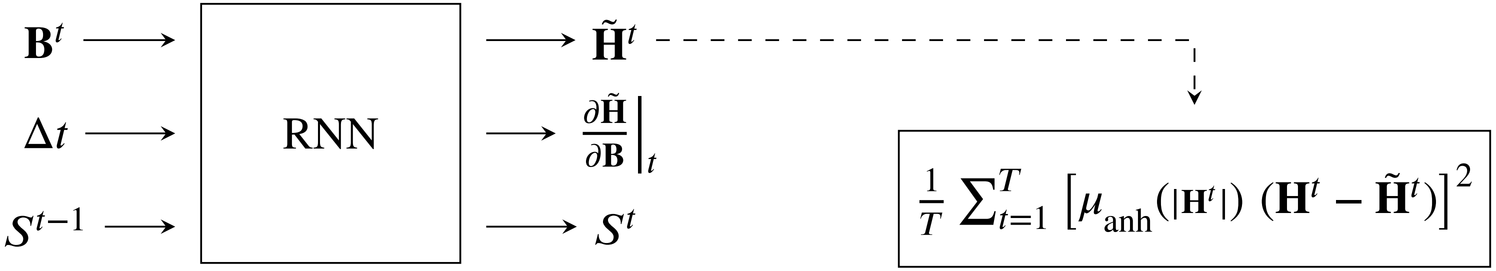
➔ Add a scaling factor in the loss





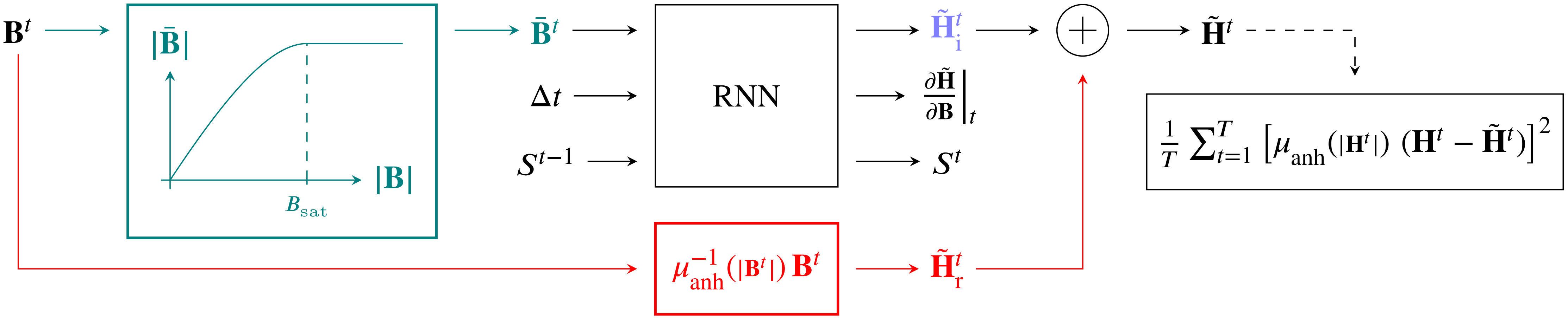


Robustness at high fields



During Newton-Raphson iterations,
possible excursions out of the training range

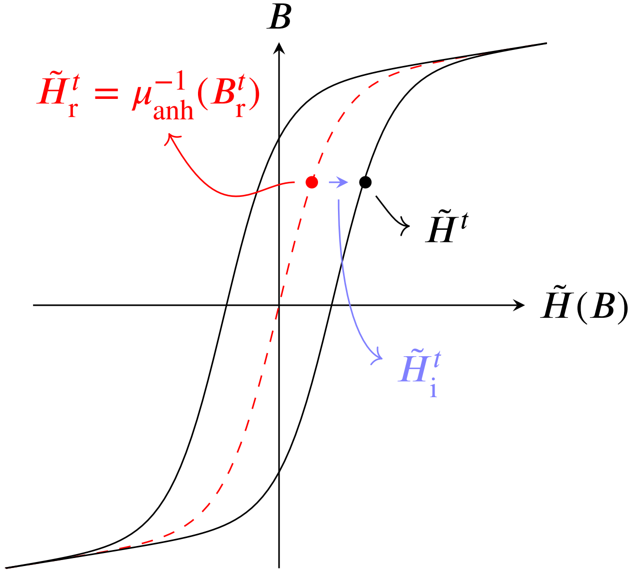
Robustness at high fields

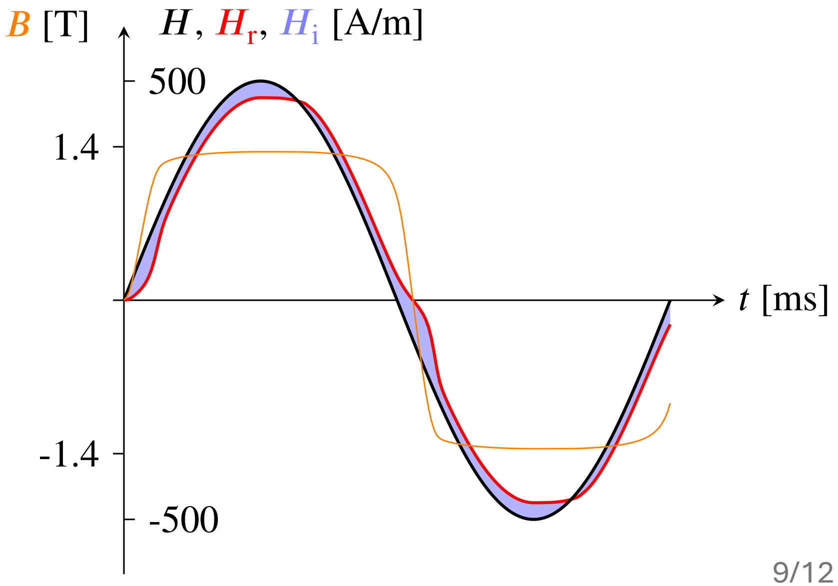


During Newton-Raphson iterations,
possible excursions out of the training range

➔ Analytic anhysteretic extension
  → Exact at high fields
  → NN output is a simple shift $\mathbf{H}_{\mathrm{i}}$

➔ Clip the input
  → No impact after saturation
  → Never exit training range

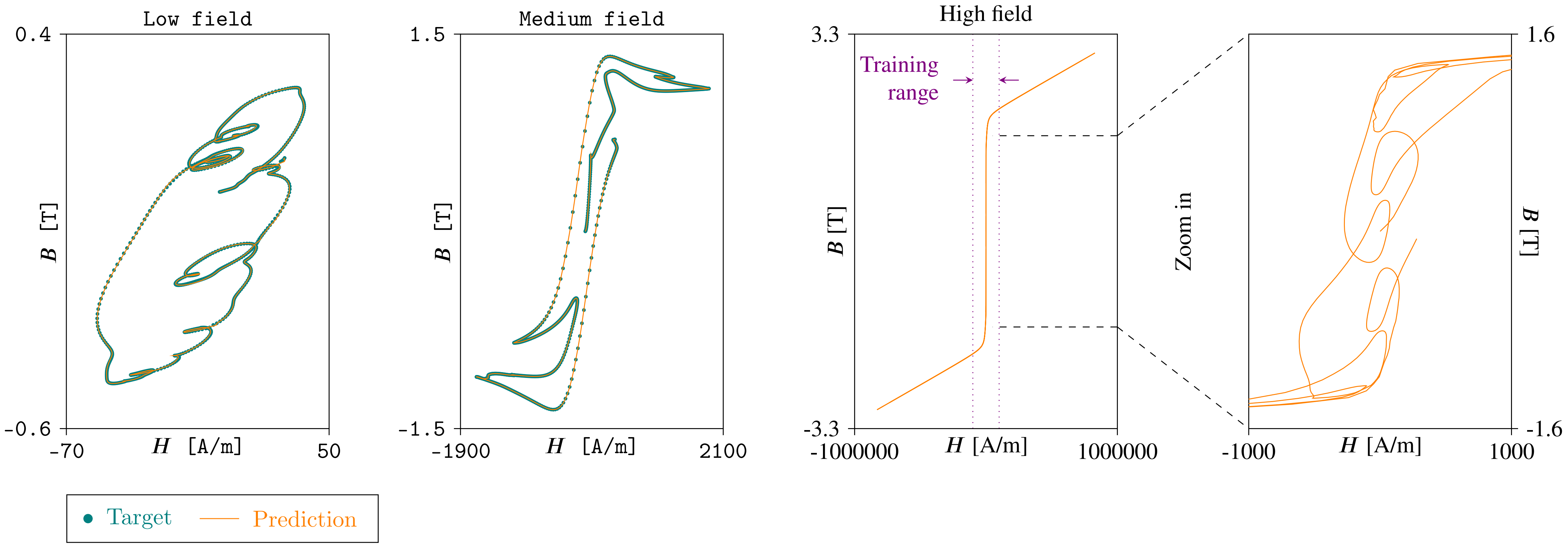




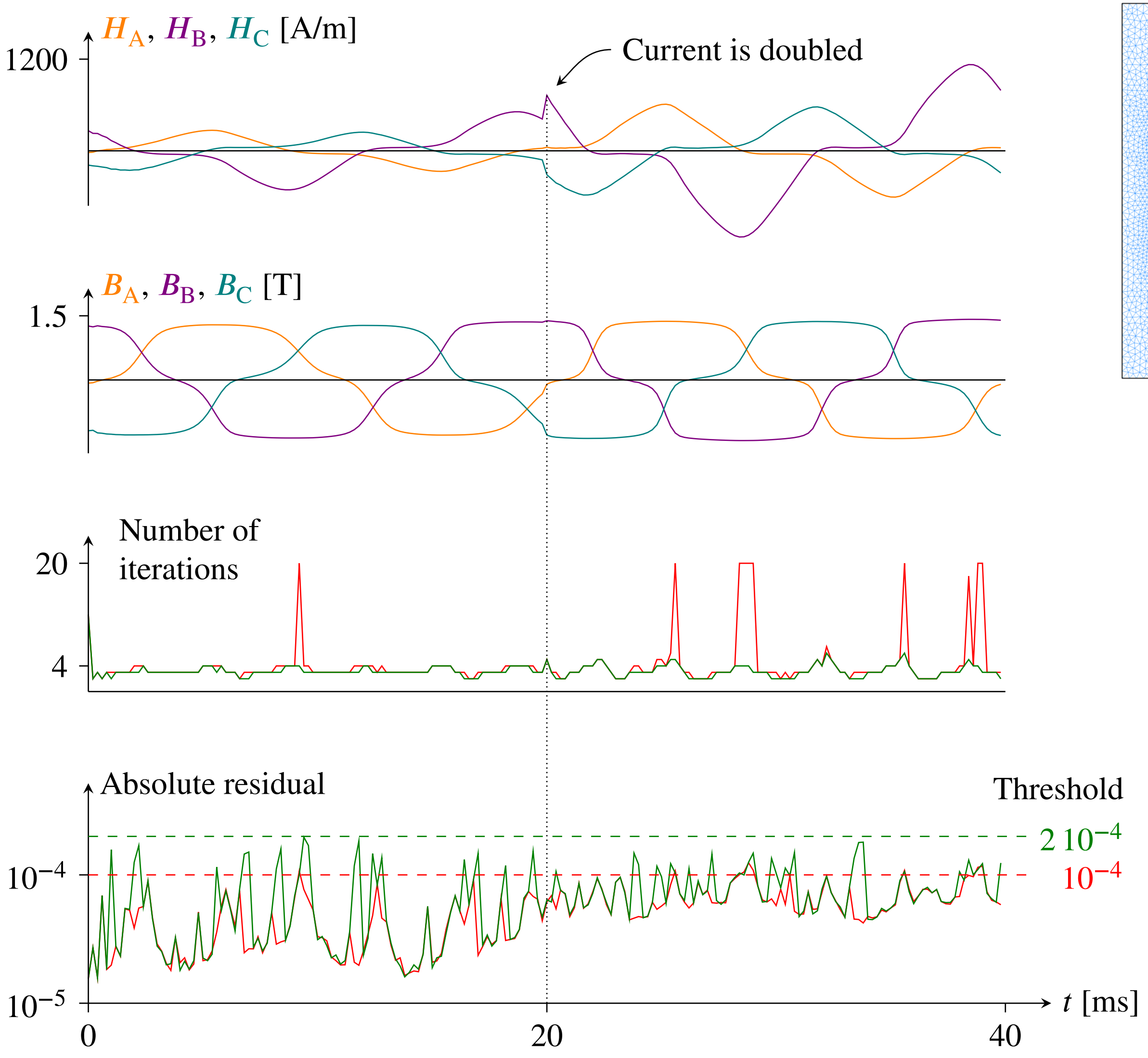
Validation at all field amplitude

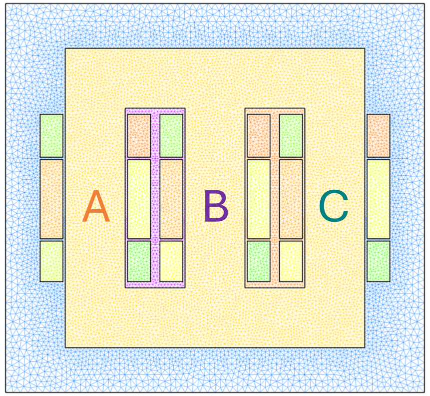
After training (12 H):

- Perfectly handles hysteresis and eddy currents
- Extrapolate out of its training range



Running a FEM simulation





- 25 000 elements
- Imposed 50-Hz sinusoidal currents
- Two periods of 100 timesteps
- Current doubled after one period
- GetDP (calling Pytorch)

- **Robust** – handle the current change after a period
- When saturating, difficulties to reach a 10^{-4} threshold
  Systematically reach a $2\ 10^{-4}$ threshold
- **Fast** – 13 minutes on a laptop computer
  - Anhystertic simulation: 8 minutes
  - Previous implementation [1]: 10 hours

[1] K. Jacques, Energy-Based Magnetic Hysteresis Models - Theoretical Development and Finite Element Formulations, 2018. → Inversion of a hysteresis model, no eddy current, fine Δt, relaxation, on a cluster

Conclusions

The proposed approach accounts for hysteresis and eddy currents in 2D FEM simulations of ferromagnetic cores.

It is:

- **Simple** – Direct coupling in standard "$\boldsymbol{a}$" formulation → easy to add in existing FEM codes
- **Fast** – About twice the computational time of an anhysteretic simulation
- **Portable** – Train the NN once per lamination type, use it in many applications
- **Robust** – Preliminary tests show robust convergence even with abrupt current changes, etc.
- **Lightweight** – Runs on a laptop computer