

A white line-art illustration of a large, classical-style building with a central dome and multiple arches, set against a light gray background.

# Data-driven parameter identification of magnetic material models

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University of Technology Graz

April 10, 2026

## 1. Introduction

## 2. ML for Parameter Identification

- Overview
- Example : linear material identification
- Example : nonlinear material identification

## 3. Summary

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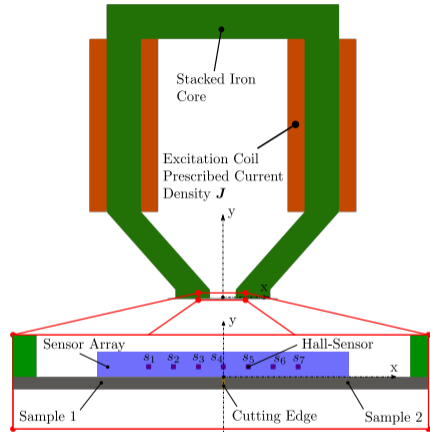
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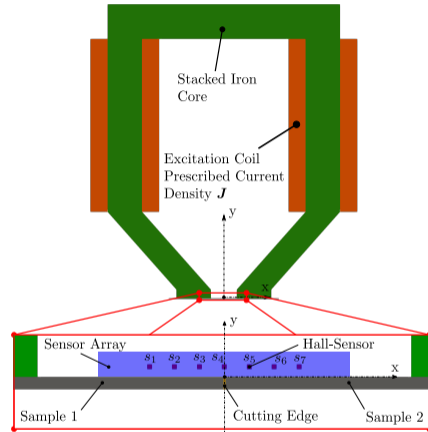
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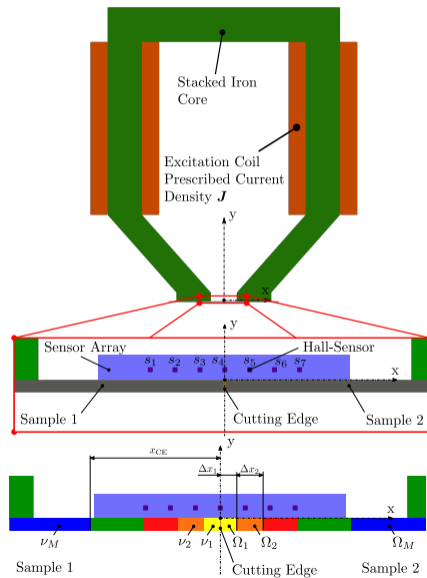
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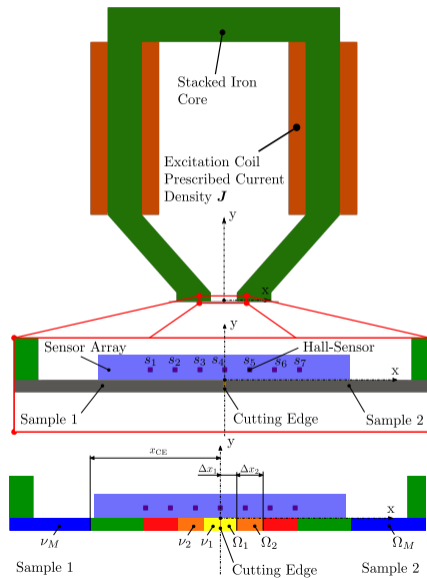
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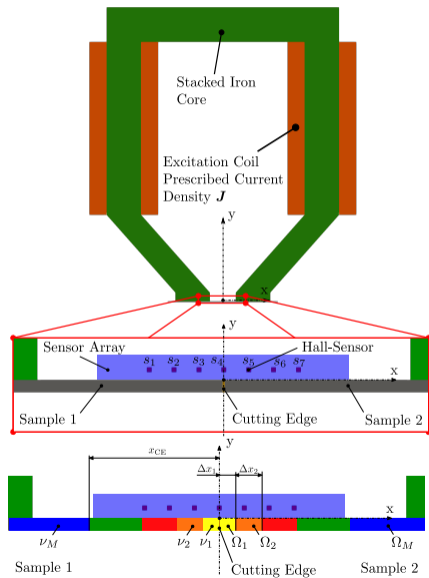


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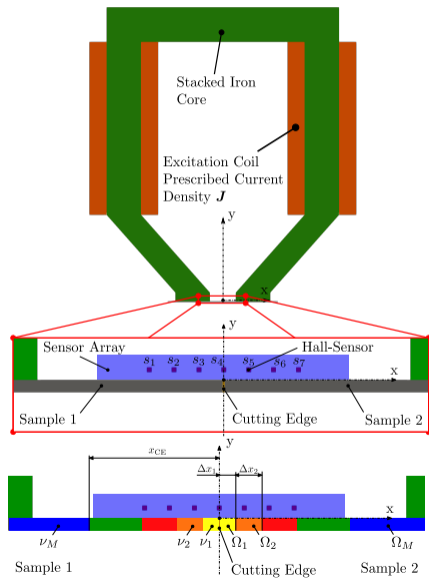
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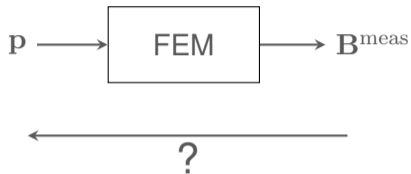
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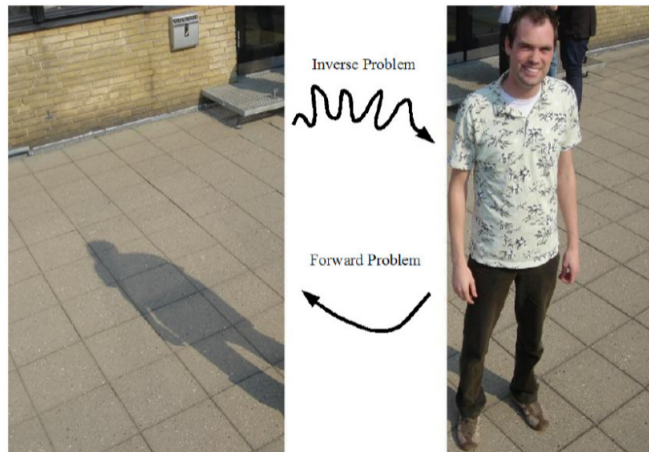
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## Goal

Identify parameters  $\mathbf{p}$  from measurements  $\mathbf{B}^{\text{meas}}$ !



[Kjøller, Master Thesis, DTU Lyngby, 2007]

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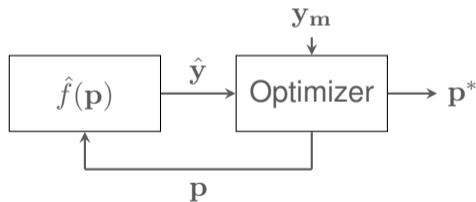
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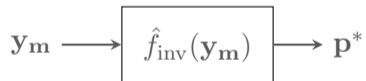
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3. **Equation discovery** : [11, 12]

- ODE/PDE in loss function
- Optimize the PDE parameters along with NN

$$g = u_t + p_1 u u_x - p_2 u_{xx}$$

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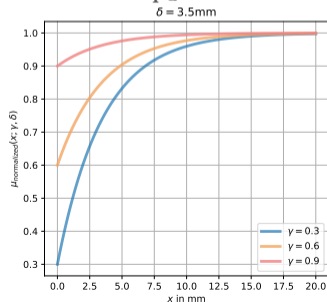
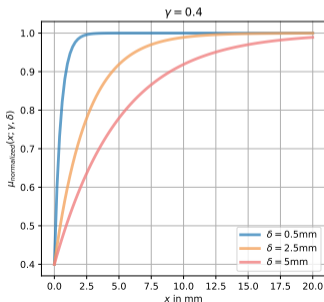
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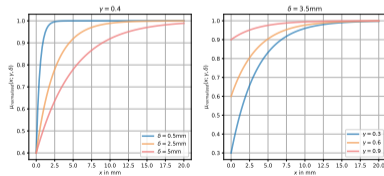
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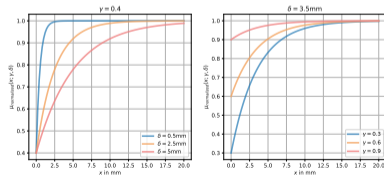
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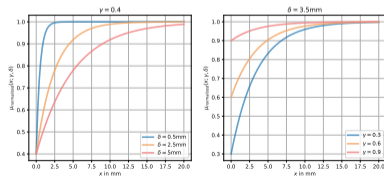
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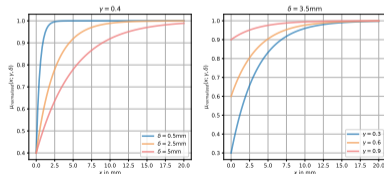
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- Fit the surrogate to the data





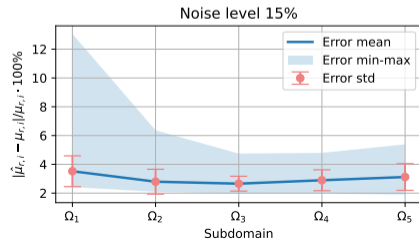
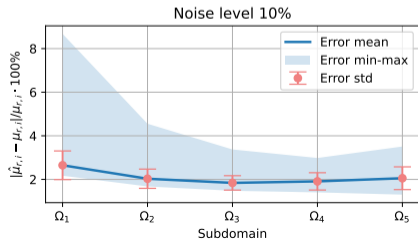
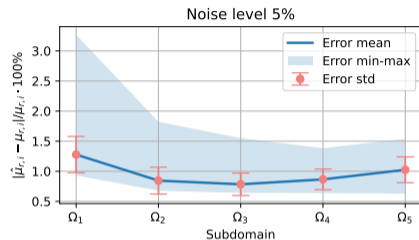
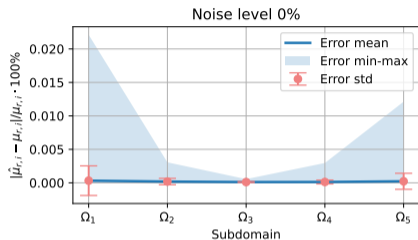
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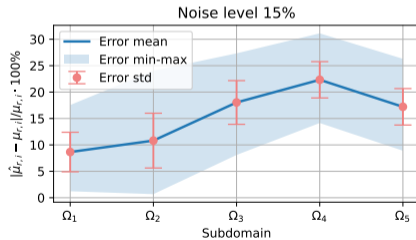
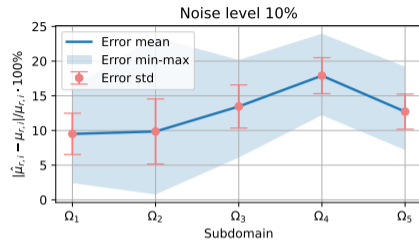
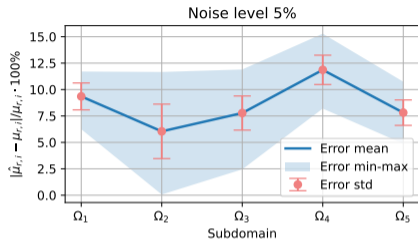
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Sampling plan	$N_\gamma$	$N_\delta$	$N$
$(\mathbf{P}, \mathbf{B})^{\text{Train}}$	50	50	2000
$(\mathbf{P}, \mathbf{B})^{\text{Test}}$	50	50	500



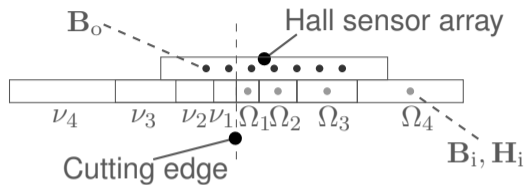


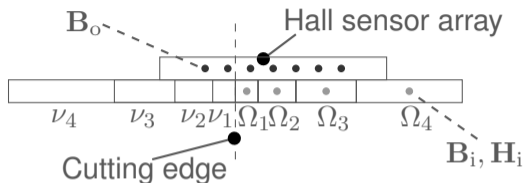
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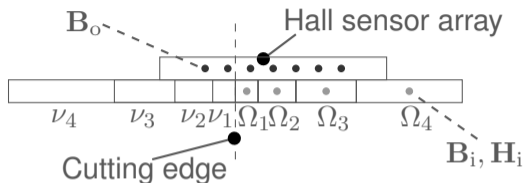
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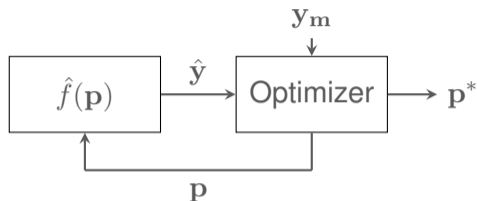
$$\nu(B; \mathbf{c}_m) = c_{0,m} + c_{1,m} B^{c_{2,m}}, \quad \forall B = \|\mathbf{B}\|_2 \quad (5)$$



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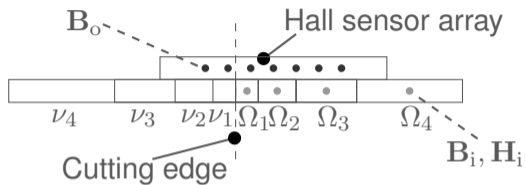
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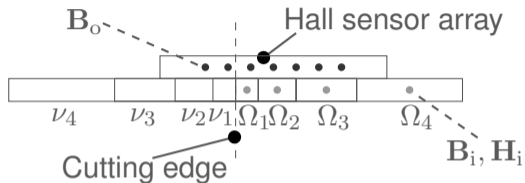


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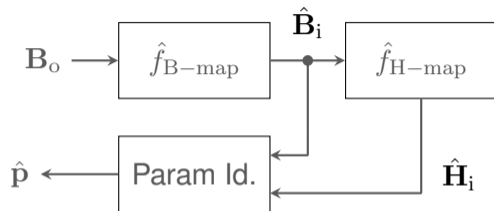
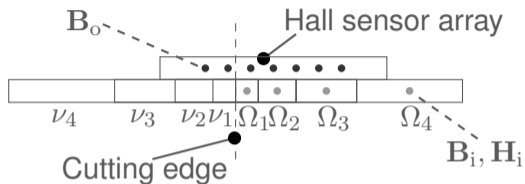




- Introduce mapping functions

$$\hat{B}_i = \hat{f}_{B\text{-map}}(B_o) \quad (7)$$

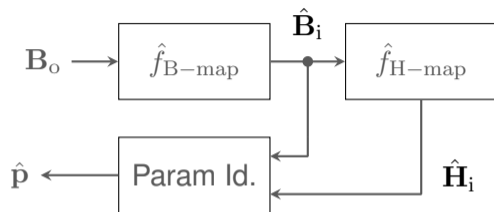
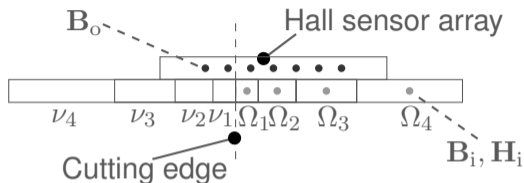
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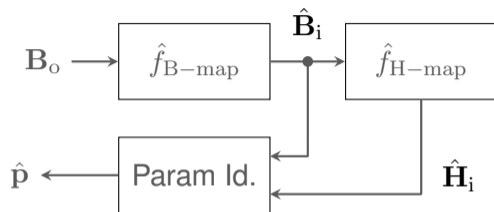
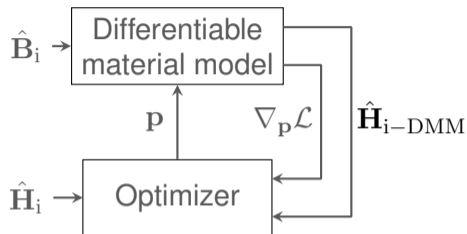
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$$e(\hat{\mathbf{B}}_i, \hat{\mathbf{H}}_i; \mathbf{p}) = (\hat{\mathbf{H}}_i - \nu(\hat{\mathbf{B}}_i; \mathbf{p})\hat{\mathbf{B}}_i)^2 \quad (9)$$

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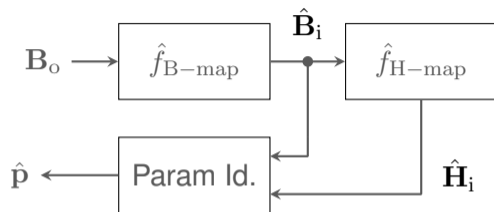
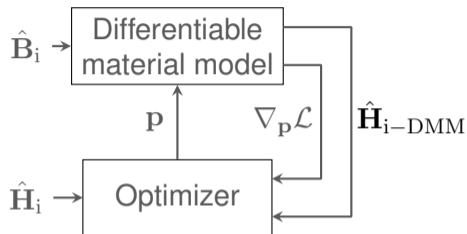
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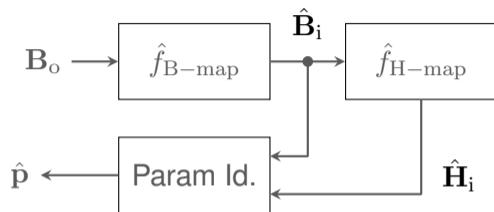
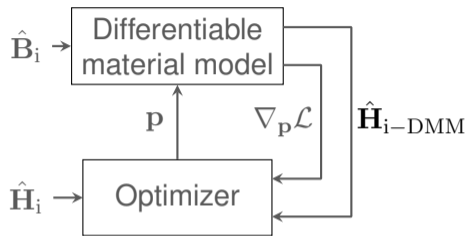
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## Advantages

- Material model acts as regularizer

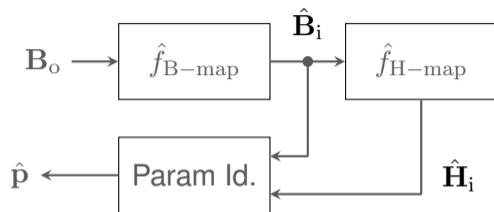
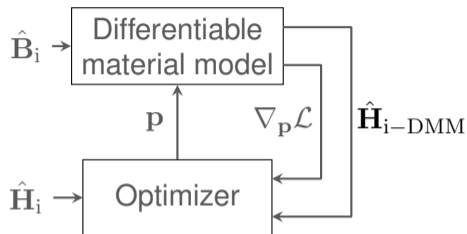
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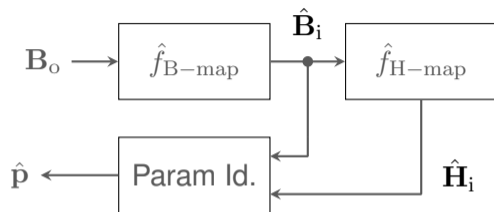
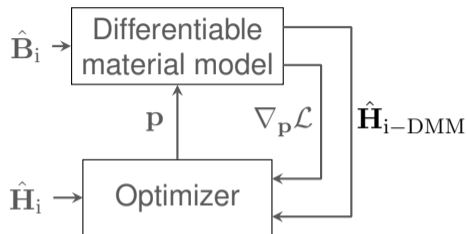
- Material model acts as regularizer
- Can use complex material models

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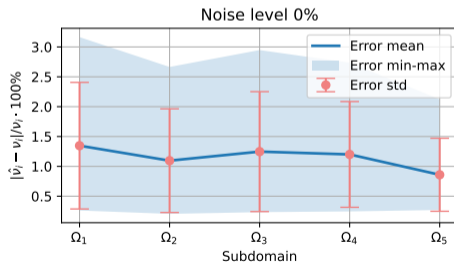
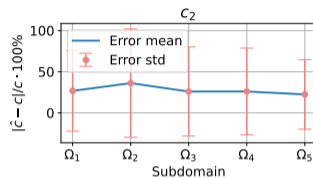
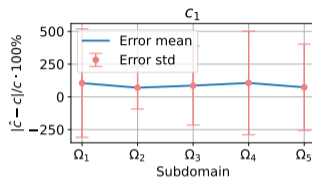
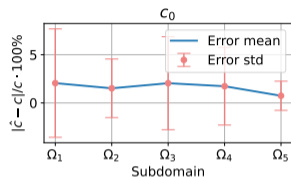
- Material model acts as regularizer
- Can use complex material models
- Independent of FEM simulation

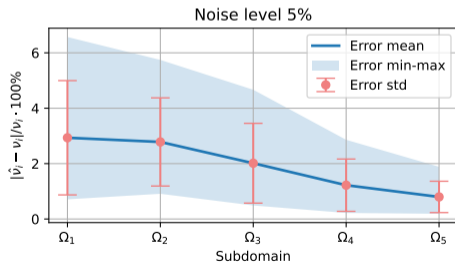
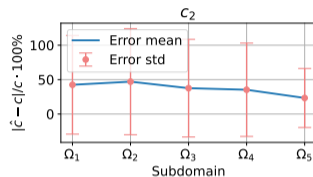
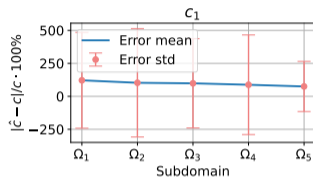
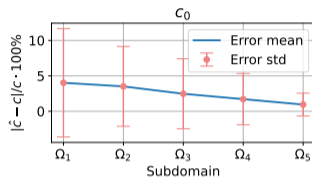
$$\hat{\mathbf{B}}_i = \hat{f}_{B\text{-map}}(\mathbf{B}_o) \quad (7)$$

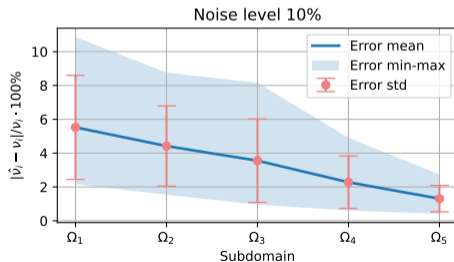
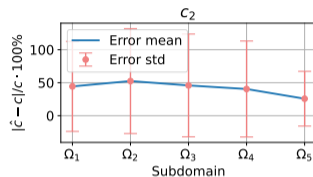
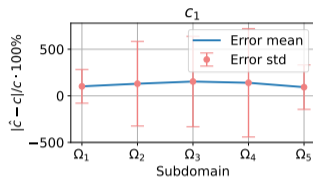
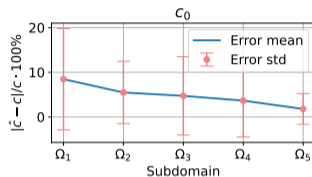
$$\hat{\mathbf{H}}_i = \hat{f}_{H\text{-map}}(\hat{\mathbf{B}}_i) \quad (8)$$

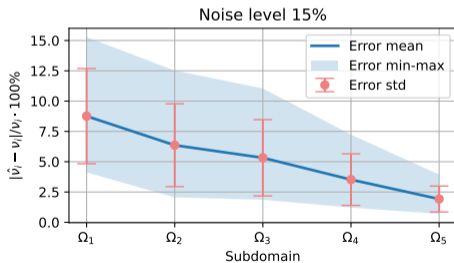
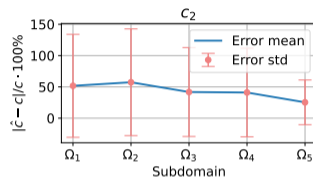
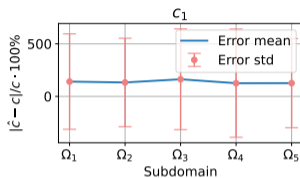
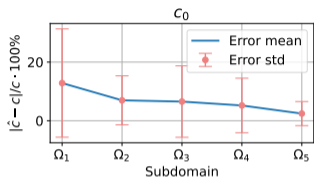
$$e(\hat{\mathbf{B}}_i, \hat{\mathbf{H}}_i; \mathbf{p}) = (\hat{\mathbf{H}}_i - \nu(\hat{\mathbf{B}}_i; \mathbf{p})\hat{\mathbf{B}}_i)^2 \quad (9)$$

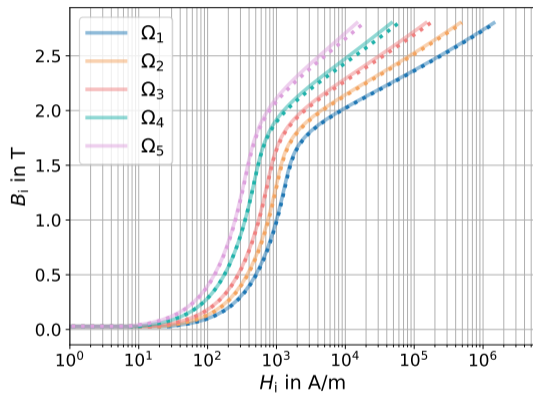
$$\mathbf{p}^* = \arg \min_{\mathbf{p}} e(\hat{\mathbf{B}}_i, \hat{\mathbf{H}}_i; \mathbf{p}) \quad (10)$$











- Data generated via openCFS and pyCFS

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- Parameter ranges are crucial

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Thank you for your attention!

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