

Data Driven Parameter Identification of Hysteresis Models for Cut Steel Sheets

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Having accurate material models is crucial for performing high fidelity simulations of electrical machines. Obtaining the parameters of such material models usually requires a high number of simulations to be performed. This is often not feasible due to the complex nature of the underlying models. To this end, machine learning methods, specifically Gaussian Process Regression (GPR) is used to approximate certain relationships obtained from simulation data. In this paper we investigate the application of data driven methods for the parameter identification of magnetic properties in steel sheets. First we show how we apply the methodology to the nonlinear case without the hysteresis and then give an outlook for the final results including the hysteresis models which will be included in the full paper.

Index Terms—Hysteresis, Magnetic materials, Machine learning, Parameter estimation

I. INTRODUCTION

MATERIAL degradation caused by cutting processes [1], [2] introduces complexities in accurately modeling [3] the magnetic behavior of electrical steel sheets. Such degradation significantly influences the material's magnetic properties, particularly near cutting edges. To address this challenge, accurate parameter identification is critical for developing material models that account for these effects. Traditional adjoint-based methods [4], [6] for parameter identification often require extensive computational resources and are difficult to generalize across measurement setups.

In this study, we propose a data-driven approach to parameter identification, leveraging precomputed datasets and machine learning techniques to streamline the process. The key idea is to precompute material parameter datasets, train surrogate models using these datasets, and subsequently apply the models in parameter identification. This approach allows for efficient reuse of simulation data and provides a robust foundation for identifying magnetic properties under various operating conditions. While this work focuses on simulated measurements, future studies will extend the method to real-world data. We present the approach for the case of nonlinear BH-curves and the identification of these. The final paper will show the approach adjusted for the identification of hysteresis model parameters and the results obtained.

II. COMPUTATIONAL MODEL

The proposed setup for parameter identification involves a sensor-actuator system, as shown in Figure II, comprising stacked electrical steel sheets and two excitation coils. This system enables localized magnetization of the steel sheets and precise measurements of magnetic flux density using a Hall sensor array. Measurements are taken at multiple positions above the steel sheets, with a higher density near the cutting edges to capture material variations accurately. To minimize

residual magnetization, the steel sheets are demagnetized between measurements. The steel sheets are divided into M

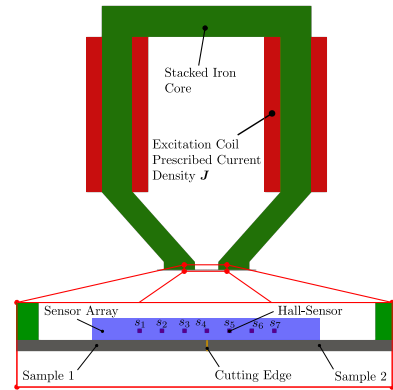


Fig. 1. The sensor-actuator model with two electrical steel sheets, denoted as Sample 1 and Sample 2. All simulations of the system are performed with openCFS [5].

subdomains, Ω_m , as can be seen in Figure II, to account for localized material degradation, which typically extends a few millimeters from the cutting edges. The simulated sample is 32 mm wide and we divide it into $M = 5$ subdomains with the widths of [0.25, 0.5, 0.75, 1.5, 13] mm respectively. Each subdomain is characterized by a BH-curve defined by (1).

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

Where for Ω_m the parameter vector $\mathbf{c}_m$ is expressed by $[c_{0,m}, c_{1,m}, c_{2,m}]$ and the full parameter vector $\mathbf{p}$ consists of M concatenated vectors $\mathbf{c}_m$. In the hysteresis case, for each subdomain Ω_m a hysteresis model is defined. The number of parameters scales with the number of subdomains, allowing for fine-grained characterization of the material's nonlinear magnetic behavior.

III. PARAMETER IDENTIFICATION

The parameter identification pipeline involves multiple stages. These can be separated into four distinct steps.

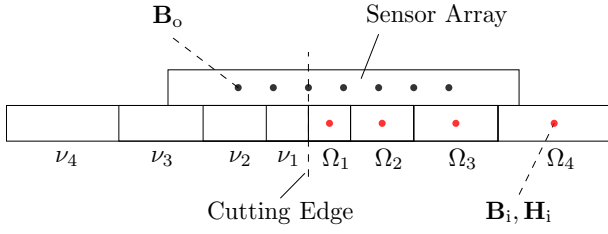


Fig. 2. The magnetic flux values outside the steel sheets, B_o , are mapped onto the magnetic flux values inside the steel sheets, B_i . Variables with subscript "i" are defined where the red dots are located. With the second mapping function $\hat{f}_{H-map}$, we then map B_i to the magnetic field H_i inside the steel sheet. Finally (B_i, H_i) are used within a classic parameter identification approach to obtain p .

First, the high-fidelity finite element simulation is sampled across a wide parameter range. The sampling plan is constructed using latin hypercube sampling [7] to ensure a good coverage of the high dimensional input space. Secondly, two mapping functions are used to map the magnetic flux outside the steel sheets, B_o , onto the magnetic flux inside the steel sheets, B_i . The second mapping function maps the magnetic flux inside the steel sheets, B_i , onto the magnetic field intensity inside the steel sheets, H_i . These mappings bridge the gap between directly measurable external values and the internal field values required for the material characterization. These mapping functions are constructed from data obtained from simulations. We used Gaussian Process Regressors (GPR) [8] to approximate the mappings. All of the models used were implemented with the scikit library [9]. In the third step, a nonlinear least-squares approach [10] is used to obtain the optimal parameters for the material model function (1) for each subdomain. To deal with noisy measurements an ensemble method [11] is used where the prediction of multiple mapping functions is averaged to get a better estimate of the field values.

IV. RESULTS

The robustness of the proposed method was evaluated under noise levels of 5%, 10%, and 15%. Statistical analysis over 100 random noise instances revealed that the approach achieves single-digit relative errors even at the highest noise level. Errors were more pronounced near cutting edges, where subdomains are smaller, and field variations are higher. Figure IV shows an example BH curve identified under 5% noise, demonstrating the method's accuracy in reconstructing nonlinear magnetic properties.

V. CONCLUSION AND OUTLOOK

This study highlights the potential of data-driven techniques for magnetic material characterization. By combining surrogate modeling with optimization, the proposed approach streamlines parameter identification and reduces dependency on high-fidelity simulations. An important part of the approach is that the used simulations are in agreement with the measurement setup. Deviations between these will introduce errors in the mapping functions which will likely lead to wrong identifications. One of the key benefits is that such approaches make it

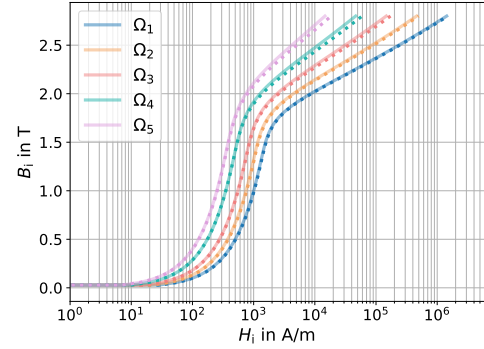


Fig. 3. Example of identified BH-curves for the case of 5% noise level. The full lines correspond to the exact values and the dotted lines correspond to the identified curves.

possible to reuse the whole pipeline for another measurement on the same setup and material type that was covered by the sampling plan. The full paper will include all details regarding the sampling and model setup and will showcase the extended version of the approach to handle hysteresis model identification and the refinement of the excitation levels and parameter ranges. This is key to maximizing the information content of the sparse datasets and improve the accuracy of the mapping functions and the identification process as a whole.

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