

#### Proceedings Article

# Power-Efficient Control of Non-Linear Magnetic Field Generators for MPI

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#### Abstract

The scaling of electrical power constitutes a significant challenge when adapting Magnetic Particle Imaging (MPI) to a human scale. The use of coils incorporating soft-iron cores serves to reduce power usage, but also introduces spatial imperfections and non-linearities in the current-to-field relationship. This study proposes methodologies for the control of the magnetic field output of a system comprising 18 coils, subject to the influence of saturated iron. In particular, we integrate current sequence optimization with neural network-based predictions for field and gradient values, thereby enabling the precise and power-optimal generation of magnetic fields. The proposed framework for controlling non-linear magnetic field generators represents a significant advancement in MPI technology, paving the way for the development of human-scale, power-efficient medical imaging solutions.

#### I. Introduction

The creation of both static and dynamic fields across the entire field of view is essential for Magnetic Particle Imaging (MPI) [1]. Among the field generators, those responsible for producing the static selection field require a significant portion of the system's power. Consequently, power scaling becomes a critical challenge when scaling up to human-sized scanners [2, 3]. One approach to overcome this problem uses soft iron for field amplification, enhancing power efficiency for field generation but introducing spatial field imperfections and non-linearities in the current-to-field relationship [4].

In this study, we explore this approach with an poweroptimized selection field generator consisting of 18 coils [5]. However, due to the non-linear current-tofield dependency including coil cross-talk, achieving precise magnetic field control with minimal power usage is

challenging [6]. We present a framework that provides power-optimal current sequences for generating a predefined selection field sequence. Our framework, which is rooted in an optimization problem, can incorporate both global and local features of the selection field. Finally, we demonstrate a proof of concept using a simplified setup that employs only 8 of the 18 coils, where a neural network approximates the current-to-field relationship, making optimization feasible (see Figure 1).

# II. Methods and Materials

In this context, field control involves determining coil currents that generate a desired field sequence while minimizing power consumption (inverse current problem [7]). The desired field sequence is defined by the trajectory of a field-free point (FFP) and a minimal gradient strength, ensuring that the MPI image resolution



**Figure 1:** A schematic representation of field control is shown. The upper section depicts the coil array with soft iron cores. The 8 coils utilized in this study are highlighted. An exemplary generated field is situated in the center. At the bottom, the optimization process is illustrated. An optimizer adjusts the currents based on optimization goals and constraints, employing neural networks for both field and gradient prediction.

stays above a specified level. Constraints include limits on the maximum magnitude and slew rate of the coil currents. This inverse problem is framed as an optimization problem where the coil currents are variables, and the objective is to minimize system power under these constraints. Instead of the resource-intensive finite element method for calculating fields and gradients [7], we use a fully differentiable model consisting of two neural networks. This approach efficiently computes the desired current sequences using gradient descent methods.

The first network within the field model pipeline approximates the non-linear relationship between the current and the generated magnetic field, which is represented by a spherical harmonic expansion. In particular, the field model proposed by Foerger et al. [8] is employed, which predicts the field coefficients for four coils on one side based on ground truth data from finite element calculations [7]. To obtain the total field, the field is reflected across the plane parallel to the coil boxes and then superimposed. The minimum gradient strength is equivalent to the smallest singular value (SV) of the Jacobian matrix of the magnetic field at the desired FFP position for a given time point within the sequence. To circumvent the computationally expensive process of SV decomposition while maintaining differentiability, a second neural network was trained to predict this SV from the Jacobian matrix.

#### III. Results

As a first step, we consider a simple linear FFP trajectory with a gradient of  $0.1 \text{ T m}^{-1}$  that starts at the center and spans 4 cm along the *x*-axis. It is discretized into 10 FFP positions with current values optimized for each point. After one day of optimization, an average power consumption of 300 mW was achieved. The average error of the FFP positions was about 2 mm and the gradient deviation was around 3 %.

### IV. Discussion and Conclusion

The optimization of current sequences successfully minimizes power consumption while achieving the desired FFP trajectory. Our method integrates current sequence optimization with neural network-based field and SV predictions, thereby enabling the accurate modeling of magnetic fields in a highly non-linear system. This provides a proof of concept for our novel approach to optimal control of our 18-coil magnetic field generator system, and has the potential for application to similar non-linear magnetic field generators.

#### Author's statement

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## References

- B. Gleich and J. Weizenecker. Tomographic imaging using the nonlinear response of magnetic particles. *Nature*, 435(7046):1214–1217, 2005.
- [2] C. Bontus, B. Gleich, B. David, O. Mende, and J. Borgert. Concept of a Generator for the Selection and Focus Field of a Clinical MPI Scanner. *IEEE Trans. Magn.*, 51(2):1–4, 2015.
- [3] J. Rahmer, C. Stehning, and B. Gleich. Remote magnetic actuation using a clinical scale system. *PLOS ONE*, 13(3):e0193546, 2018.
- [4] K. Sajjamark, J. Franke, H. Lehr, R. Pietig, and V. Niemann. Spatial selectivity enhancement in magnetic fluid hyperthermia by magnetic flux confinement. *IJMPI*, 7(1), 2021.
- [5] F. Foerger, M. Boberg, M. Möddel, J.-P. Scheel, M. Graeser, and T. Knopp. Low-power iron selection and focus field generator. *IJMPI*, 8(1 Suppl 1), 2022.
- [6] F. Foerger, N. Hackelberg, M. Boberg, J.-P. Scheel, F. Thieben, L. Mirzojan, F. Mohn, M. Möddel, M. Graeser, and T. Knopp. Flexible selection field generation using iron core coil arrays. *IJMPI*, 9(1 Suppl 1), 2023.
- [7] F. Foerger, M. Boberg, J. Faltinath, T. Knopp, and M. Möddel. Design and optimization of a magnetic field generator for magnetic particle imaging with soft magnetic materials. *Adv. Intell. Syst.*, pp. 2400017, 2024.
- [8] F. Foerger, P. Jürß, M. Boberg, T. Hau, T. Knopp, and M. Möddel. Current-to-field prediction for non-linear magnetic systems via neural networks. *IJMPI*, 11(1 Suppl 1), 2025.