This article has been accepted for publication in IEEE Transactions on Magnetics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TMAG.2024.3416536

Systematic Optimization of Electromagnet Hardware for Electromagnetic Suspension: A Fusion of Simulation and Multi-Objective Optimization Techniques

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This paper introduces a novel multi-objective design optimization (MOO) framework for enhancing magnetically levitating (Maglev) systems. By integrating finite element method (FEM) simulations and focusing on the dynamic interplay between mechanical, and electromagnetic properties, as well as control system dynamics, our approach addresses the complex challenges of Maglev design, such as variable inductance, force production due to air gap fluctuations, and magnetic saturation. The proposed framework facilitates the development of more efficient, reliable, and adaptable Maglev technologies. Through a simulated implementation, we demonstrate the framework's effectiveness in optimizing electromagnet design for improved system integration and performance, marking a significant advancement in electromechanical system optimization.

***Index Terms*—Multi-objective optimization (MOO), Electromagnetic Suspension (EMS), Design Optimization**

I. Introduction

TRADITIONALLY, electromechanical system design and optimization have relied on manual processes, using finite element method (FEM) simulations, analytical models, and equivalent circuit models to predict and optimize performance. The current trend is moving towards automation, employing optimization techniques to streamline this process. Key performance metrics derived from FEM simulations, such as generated force relative to energy or minimizing weight while maximizing performance [1], are optimized for specific operational points, reflecting static performance expectations typical of conventional applications like motors.

However, this approach has limitations when applied to magnetically levitating (Maglev) systems based on ferromagnetic materials. Traditional electrical machine design targets the upper linear part of the iron's saturation curve to balance weight and remagnetization losses. In contrast, Maglev systems, especially Electromagnetic Suspension (EMS) systems, operate in nonlinear regions where inductance and force production vary significantly with air gap fluctuations, introducing high nonlinearity challenges [2].

Designing Maglev systems to avoid saturation conditions is impractical due to increased weight and energy consumption. Thus, a sophisticated optimization approach that accounts for the wide operational range and inherent nonlinearities is essential. This approach must automate FEM simulations and accommodate the complex interplay of performance metrics within the system's operational envelope.

While our focus is on EMS systems using ferromagnetic materials, superconducting materials present different challenges, particularly in simulations involving both superconducting and ferromagnetic materials [3].

The authors acknowledge the financial support by the Federal Ministry of Education and Research of Germany in the programme of "Souverän. Digital. Vernetzt.". Joint project 6G-life, project identification number: 16KISK002

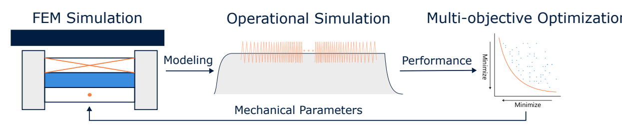

Fig. 1: General sequence of the optimization process involving FEM simulation, model building, levitation simulation, and evaluation using a multi-objective optimization algorithm.

Existing methodologies fall short by failing to provide a cohesive framework for the simultaneous optimization of electromagnets and their control systems, thereby hindering efficient and effective development of Maglev technologies.

Recognizing these challenges, our study explores an alternative approach. We propose a multi-objective design optimization (MOO) framework that concurrently considers both mechanical attributes and control system integration in the early design stages of electromagnets. With the use of FEM simulations, we derive the highly nonlinear inductance and force values of the electromagnet that are crucial for understanding the behavior of Maglev control systems under varying operational conditions. Based on those values, we derive a plant model, and a model-based controller, that is used in simulation to determine the operational performance of a certain mechanical configuration. Utilizing these performance metrics, an MOO algorithm is employed to optimize the mechanical structure of the magnet. This optimization sequence is depicted in Fig. 1.

Our main contributions are the following:

- In IV, we present a comprehensive reference framework employing a MOO algorithm for the design of electromagnets. An overview of this framework is depicted in Fig. 2.
- In V, we provide a detailed explanation of the simulation components that interact within the optimization process.
- In VI, we demonstrate the practical application of our framework through a simulated implementation, show-

casing its efficacy in optimizing electromagnet design for improved integration with control systems.

II. Related Works

In this section, we discuss previous works relevant to our contribution, focusing on A) EMS magnets and B) related electrical machines.

A. Optimal Design of EMS Magnets

In [4] a general flow-chart for the design process of an electromagnetic suspension magnet is outlined, covering system configuration, control requirements, magnet dimensioning, modeling, and evaluation of simulation results. Our approach adheres to this workflow while emphaszising automation to accelerate optimization.

In [5], Zhang et al. focus on optimizing the cross-sectional dimensions of High-Temperature Superconductor (HTS) coils to achieve desired magnetic levitation forces using FEM analysis. Their aim is to optimize mechanical attributes of HTS magnets for efficient levitation force generation.

Our framework, however employs a MOO methodology that concurrently considers mechanical attributes and control system integration from the early design stages. This holistic approach reduces the iterative design process traditionally seen in EMS system development, where control systems compensate for electromagnet design limitations.

B. Multiobjective Optimal Design of Electrical Machines

The literature is rich of MOO of electrical machines [6]. Whilst most of those MOO approaches follow a similar method of determining the performance directly from the electro-mechanical simulations, our approach constructs the performance through a combination of electro-mechanical simulation and model-based control simulation. We furthermore want to highlight one specific approach to underscore the differences.

For instance, the design optimization of interior permanent-magnet machines (IPMs) has been explored using multi-physics models that integrate electromagnetic, thermal, and structural analyses within a MOO framework [7]. Similar to our approach, the electro-mechanical properties are determined at different operating points for each design iteration. However, our approach significantly diverges in constructing the performance function to drive the optimization.

We derive the performance of the overall system by constructing a controller and plant model from the magnetic model and simulating these to determine the performance of the overall target system of the electromagnet during operation. This holistic method ensures that the dynamic interplay of the mechanical and electromagnetic properties, as well as control system dynamics, is considered. By contrast, the approach in [7] determines the overall performance by averaging of the performance metrics at the individual operation points.

III. Background

This section discusses the theoretical background of A) Multi-objective optimization and B) electromagnet design influences.

A. Multi-objective Optimization

Multi-objective optimization is a mathematical and computational approach used to find the best trade-offs when optimizing multiple, often conflicting objectives simultaneously. This is particularly important in real-world scenarios where improvements in one aspect can lead to compromises in another, such as in engineering design, economics, and environmental management.

In MOO, the goal is to identify Pareto-optimal solutions. A solution is considered Pareto optimal if no objective can be improved without worsening at least one other objective. These solutions form the pareto front, representing the best possible compromises between the conflicting objectives. For example, in the design of an electric vehicle, one might need to balance maximizing battery life against minimizing weight and cost.

Genetic algorithms (GA) such as the NSGA-II algorithm [6] and Surrogate-based MOO, such as Gaussian Process Regression (GPR) are two prominent methods used to tackle these kinds of problems. Both approaches have their unique strengths and weaknesses, particularly in terms of the number of samples required to model a problem and their ability to model complex systems.

Genetic algorithms are a class of evolutionary algorithms inspired by natural selection processes. They are particularly well-suited for solving complex optimization problems with large, non-linear search spaces where the mathematical model is not straightforward. By constrast, surrogate based MOO relies on fitting a surrogate function to the original model, which the optimization algorithm then uses. A common approach combines Bayesian Optimization with GPR as the surrogate model. GPR includes probabilistic information, enabling the system to be represented with a smaller sample size compared to non-probabilistic models [8], making it suitable for expensive models like FEM models.

Recently, a novel theoretical approach was introduced that allows users to target Pareto points with specific properties [9]. This approach, which inherits mathematical guarantees, is particularly useful in scenarios where the black-box function is expensive to evaluate and the user is primarily interested in Pareto points that satisfy certain properties, such as prioritizing specific objectives or meeting minimum constraints.

B. Electromagnet Design Influences on Control

Designing an electromagnet requires careful consideration of multiple factors beyond just the weight of the assembly. Key aspects are the coil's electrical resistance determining energy consumption, static and dynamic magnetic characteristics such as the magnetic force at various currents and air gaps, which affect the levitation system's lifting capacity and suspension stiffness.

Effective control systems must account for current behavior determined by inductance, as current dynamics influence the force required for stable levitation, particularly during disturbances. This calls for a design where current and force dynamics are responsive enough to handle such disturbances.

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Design conflicts arise because both force and inductance depend on the structure's geometry, winding characteristics, and material saturation properties. Adding iron can increase lifting force but also inductance, complicating control due to slower current dynamics. Energy consumption is also a concern, as it depends on lifting force, magnet weight, and coil resistance. For instance, a thicker core can enhance control and lifting force by delaying iron saturation but may shift the operating point due to added weight. The interconnected nature of these parameters underscores the need for a holistic optimization approach.

Thus, electromagnet design requires balancing static and dynamic aspects with control system requirements. For the modeling process, FEM is commonly used to obtain detailed system characteristics. Based on this, it is possible to derive levitation simulations and control using system models such as an electric circuit model [10].

IV. Reference Framework

This section presents our Reference Framework for the MOO of electromagnets, as shown in Fig. 2. The framework integrates an MOO Algorithm with FEM simulation and Maglev simulations to yield Pareto-optimal design parameters by influencing the mechanical attributes of the electromagnet.

The framework includes:

- An FEM simulation module to predict electromagnetic characteristics.
- An electric circuit model, based on those characteristics for developing a responsive and efficient EMS system controller.
- A Maglev system simulation to understand the controller's interaction with the electromagnet in practical settings.
- A performance evaluation module to generate a vector of performance metrics, encompassing system efficiency, reliability, and response characteristics.

The metrics feed back into the MOO algorithm for iterative enhancements, converging towards optimal design parameters. This systematic, data-driven approach ensures comprehensive optimization of electromagnet designs in EMS systems.

V. Homopolar Magnet Modeling and Control

A. Magnet Modeling

Typically, an EMS system consists of a coil wound around an iron core, which, along with the limbs, forms a U-shape with the opening facing towards the rail of the track. Applying current to the coil creates a magnetic flux through the core, limbs, air gap, and rail, generating an attractive force that counteracts gravity and enables levitation. We start with parameters coming from the MOO algorithm defining the magnetic configuration. The parameters involve the thicknesses of the core t_c, limbs t_l, and rail t_r, as shown in the cross-section in Fig. 2 a). Additionally, the number of windings in the coil is defined by their arrangement side by side n_{side} and stacked $n_{stacked}$. The arrangement of the windings, in turn, influences the widths of the core and rail, while the total number of windings sets the coil's electrical resistance.

An electromagnetic FEM simulation in Ansys Maxwell derives the configuration's magnetic properties — force $F_{mag}(s, I)$ and inductance $L(s, I)$. Both are influenced by the electromagnet's air gap s between limbs and rail and the current I flowing through the coil. The magnetic force typically increases initially quadratically with the current I. The simulation incorporates magnetization curves for iron and accurately maps saturation effects and resulting nonlinearities in force and inductance, as depicted in Fig. 3. The results of the FEM simulation have been validated with measurements from our prototype design. Neglecting flux line displacement due to eddy currents is justified, as laminating the rail, a standard Maglev practice, minimizes this effect. Besides the characteristics $F_{mag}(s, I)$ and $L(s, I)$, the chosen parameterization of the coil windings also influences the electrical resistance R_{el} that occurs in the subsequent modeling.

The electromagnet is modeled as an RL circuit, as described in [10] and illustrated in Fig. 2 c). The dynamics of electric current can be formulated by applying Kirchhoff's second law

$$\begin{aligned} U(t) &= R_{el} I + U_{ind} \\ &= R_{el} I + \frac{d}{dt}\big[L(s, I) I\big] \\ &= R_{el} I + \tilde{L}(s, I)\dot{I} + \frac{\partial L(s, I)}{\partial s} I \dot{s}, \end{aligned} \tag{1}$$

where U is the applied voltage, R_{el} is the electric resistance, and $\tilde{L}(s, I)$ is used to abbreviate the expression $\frac{\partial L(s,I)}{\partial I} I + L(s, I)$. In this case, $L(s, I)$ represents the previously derived inductance. Solving (1) for $\dot{I}$ results in the differential equation for the current

$$\dot{I} = \frac{1}{\tilde{L}}\left(U - R_{el} I + \frac{\partial L(s, I)}{\partial s} I \dot{s}\right). \tag{2}$$

The force output of the model $F_{mag}(s, I)$ is obtained using the current output from solving (2) under the common assumption that current and magnetic force share the same dynamics.

B. Controller Design

Based on the system's mechanical properties and the derived magnetic model, an active levitation control system is being designed. The controller consists of an Linear–quadratic regulator for mechanics, influencing body dynamics. It receives the desired air gap, actual air gap measurements, vertical acceleration of the magnet, and current as input variables. The control process accounts for the magnetic force nonlinearities from the FEM model. The resulting reference current I_{Ref} is realized through feedforward control (FFC), considering the magnet's inductance characteristic of the magnet to determine the control voltage U.

VI. Evaluation

A. Experimental Setup

The experimental setup features the integrated controller as described in Section V-B within a Maglev vehicle model simulation with solely the vertical degree of freedom. This simulation, executed in SIMULINK, runs for 5 minutes to cover the system's complete operational range.

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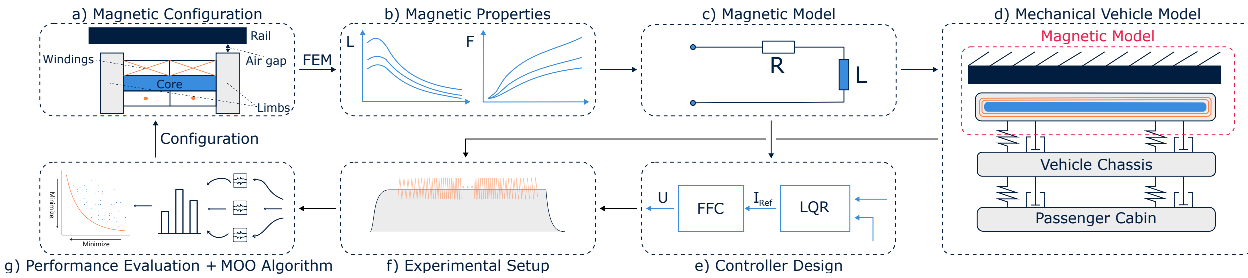

Fig. 2: Reference framework for the optimization process with its individual components and their interaction.

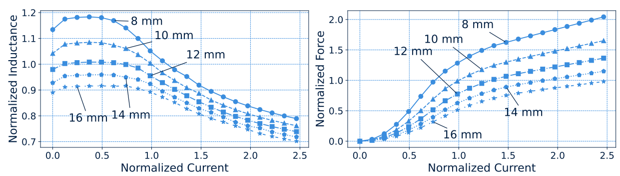

Fig. 3: Exemplary characteristics: normalized inductance $L(s, I)$ (left) and magnetic force $F_{\text{mag}}(s, I)$ (right), both based on air gap s and current I.

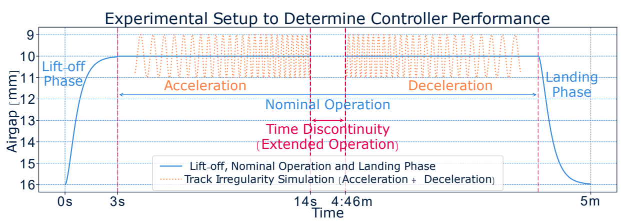

Fig. 4: Experimental setup showing lift-off, landing phase and the nominal operation with track irregularity simulation.

a) Mechanical Vehicle Model: The magnetic model is embedded in the mechanical vehicle model shown in Fig. 2d. The electromagnet is suspended from the vehicle chassis via a primary suspension, with the passenger cabin connected to a secondary suspension.

b) Simulation Operational Setup: The simulation follows an operational graph that mirrors real-world Maglev operations, as shown in Fig. 4.

Lift-off and landing phases: Highlight the system's nonlinearity, particularly the saturation of iron components during lift-off, impacting energy requirements, magnetic field dynamics, and stable control.

Nominal operation and track irregularity simulations: Maintains the target air gap, testing the controller's effectiveness in stable levitation and adaptability to real-world challenges. Using real data from the Transrapid track in Shanghai [11], a 1mm amplitude sine sweep simulates track irregularities, assessing the controller's capability to ensure passenger comfort and system stability.

The overall goal of the system is to minimize the following three performance metrics:

- **Passenger Discomfort (P):** Quantified by the integral of the vertical acceleration a, weighted by the Sperling weighting factor w [12].
- **Controller Deviation (C):** Average of the squared deviations from the target air gap g_{target} (10mm), reflecting controller precision and stability.
- **Energy Consumption (E):** Total power consumed by the electromagnet during the experiment.

In total, this leads to the following optimization model:

$$\min \left(P = \int \left(\mathcal{F}^{-1}\{\mathcal{F}(a) \cdot \mathcal{F}(w)\}\right) dt,\right.$$
$$\left. C = \sqrt{\int (g(t) - g_{\text{target}})^2 \, dt}, \quad E = \int U \cdot I^2 \, dt \right) \tag{3}$$
$$\text{s.t. } n_{\text{side}} \in \{2, 3\}, 120 \le n_{\text{stacked}} \le 200, 20 \le t_c, t_l, t_r \le 40.$$

B. Optimization Algorithm

Executing the FEM simulation along with the controller and model generation, takes approximately 20 minutes per simulation point, making the process highly expensive. This is primarily because the FEM simulation must be performed independently for each airgap s and current I, as shown in Fig. 3. Therefore, it is crucial to minimize the number of required samples. To achieve this, we utilize a surrogate-based model as described in Section III-A. Additionally, we are only interested in specific points on the Pareto front rather than the entire front, allowing us to use the Paref approach [9].

To initialize the surrogate model for the Paref framework, we begin by sampling our system 50 times using Latin hypercube sampling [6]. These initial samples help explore the target space and fit the underlying surrogate model effectively.

C. Results

The results are illustrated in Fig. 5, where the three performance metrics are compared pairwise in 2D plots. The original evaluation, characterizing the magnet configuration of our prototype design, is marked by a black star. The initial evaluations are represented as small grey dots. The MOO algorithm, designed to find Pareto points that showcase balanced trade-offs between the three performance metrics, successfully identifies configurations that significantly improve performance metrics compared to the original evaluation. These points are marked in blue in Fig. 5 and are compared with the starting point on a percentage basis in Table I.

Notably, trade-offs between the performance metrics are apparent. Configuration 1 shows a significant reduction in controller deviation but performs poorly in passenger comfort.

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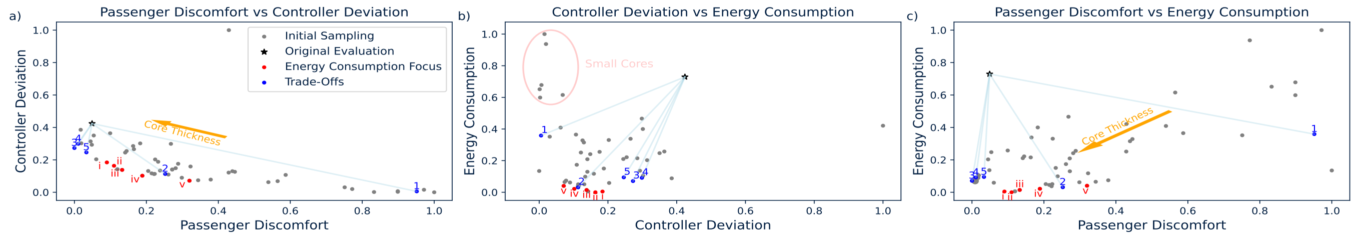

Fig. 5: Simulation results of electromagnet design comparing passenger discomfort, controller deviation, and energy consumption. Lower values in each metric denote higher performance.

TABLE I: Percentage comparison of the evaluations to the original point.

Evaluation	P	C	E
1	367.02%	-25.34%	-40.75%
2	82.68%	-18.81%	-76.75%
3	-19.96%	-9.14%	-72.40%
4	-15.59%	-7.57%	-70.14%
5	-6.42%	-10.77%	-69.81%

Configuration 2 demonstrates the greatest improvement in energy consumption among the presented configurations, yet it does not reduce the controller deviation as effectively. In contrast, Configurations 3-5 prioritize reducing passenger discomfort, although their improvements in the other two metrics are not as substantial as those observed in Configurations 1 and 2.

D. Discussion

Additional trade-offs are significant in meeting the predefined design criteria of the levitation system. For example, when the MOO algorithm prioritizes low energy consumption, the resulting configurations are marked as red dots. Figures 5b and 5c show these configurations have genuinely low energy consumption. Fig. 5a reveals a trade-off between controller deviation and passenger comfort, forming a Pareto edge. Similar trade-offs can be identified when prioritizing other performance metrics.

The results of the optimization can also be interpreted geometrically. Within the pink ellipse, configurations with higher energy consumption are visible. These points correspond to settings with greater saturation of the narrowly parameterized iron core during nominal operation, resulting in an unfavorable force-to-power ratio. The weight savings from the reduced core mass do not compensate for the lack of lift force. The original evaluation exhibits the same issue.

The orange arrows indicate a trend towards configurations with thicker iron core, which consume less energy (Fig. 5c) but lead to greater control deviations (Fig. 5a) due to their inertia.

VII. Conclusion

Our study presents a novel Multi-Objective Optimization (MOO) framework, streamlining electromagnet design in Maglev systems. This innovative approach significantly reduces design time by integrating electromagnet and control system optimization from the start, diverging from conventional methods. While showing improvements in system performance in simulated environments, the framework demands further validation through real-world testing. Our method represents a crucial step towards more efficient and rapidly developed Maglev transportation systems.

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