AI for Science-Enabled Disturbance Suppression for Magnetic Suspension Micro-Motion Stages: A Literature and Data-Driven Review

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Abstract: Magnetically levitated micro-motion stages play a critical role in the extreme manufacturing field but tool-workpiece contact force, electromagnetic actuation ripple, and operational environment affect its stiffness and precision. This article summarizes advances in disturbances mitigation across structures and controllers and the groundbreaking capabilities of AI for Science, such as large language models (LLM) and agents. The review concludes that studying the literature and benchmark datasets for this specific application shows how the AI for Science technology makes AI more adaptable in the presence of nonlinear disturbances. The strong closed-loop solutions based on the optimized Halbach and active disturbance rejection controls in the literature, however, do not scale well to dynamical conditions. The LLMs have simplified literature studies and parameterizations, whereas reinforcement learning agents trained with datasets have considerably decreased the positioning errors. As the current review has shown the complementarity of AI for Science to classic methods, it lays out a road map towards hybrid control architectures and benchmark datasets to better inform the accuracy of micro-machining applications.

Keywords: Magnetic Suspension; Disturbance Suppression; AI for Science; Large Language Models; Reinforcement Learning

1. Introduction

Magnetic suspension (MS) micro-motion stages are advanced levels of precision engineering devices enabling friction-free non-contact submicron positioning for lithographic procedures used in semiconductor micro-fabrication, micro- and nanotechnologies [1]. Compared to traditional mechanical approaches, these stages advantageously replace conventional mechanical friction (constraints) with magnetic one, thus providing superior dynamic response and precision. Nevertheless, their performances are usually degraded due to the disturbances, including tool-workpiece contact force, electromagnetic thrust ripples, and environmental vibrations, which perturb system stiffness and degrade positioning performance [2]. The problem is especially serious in micro-machining where minute disturbances may induce huge errors and substantial vibration suppression techniques are required.

Dissipation of disturbances in an MS has hitherto been achieved by incorporating structural optimizations and high-level control. Structurally, optimized Halbach arrays or coil configurations are designed to reduce thrust ripple disturbances [3] and the aforementioned control methods including proportional-integral-derivative (PID) control, sliding mode control, and active disturbance rejection control (ADRC) are employed to counteract dynamic disturbances [4]. Although useful, these methods, due to the nonlinearity and time-varying characteristics of disturbance under complex operating conditions, have limitations in terms of applicability and realtime performance.

With the recent advent of Artificial Intelligence for Science (AI for Science), which is well represented by large language models (LLMs) and artificial agents, a radical paradigm shift to solve the aforementioned problems is beginning to emerge. The key to the approach is the LLMs trained for scientific computation, capable of mining highly available scientific texts to determine an optimal control procedure or propose an appropriate set of parameters and RL-based agents that enable on-the-fly adaptive control in a real-time setting [5, 6]. AI for Science allows researchers to bridge the gap between data-driven information from publicly accessible data sources including databases like those hosted by time-series data or UCI data repository and using it for modeling dynamical details of the system disturbances, instead of large-scale dedicated experiments on hardware [7]. An example is developing a neural network-based predictive model of disturbance learned from the time-series of a motion controller to drive a robot arm, which enables robust control algorithms [8].

Table 1. Overview of Disturbance Suppression Methods for Magnetic Suspension Micro-Motion Stages

Method Type	Key Techniques	Advantages	Limitations	References
Structural Optimization	Halbach arrays, coil design	Reduces thrust ripples, enhances stability	Limited adaptability to dynamic conditions	[1, 3]
Model-Based Control	PID, sliding mode, ADRC	Robust to known disturbances	Struggles with nonlinear, time-varying perturbations	[2, 4]
AI-Driven Control	RL, neural networks, LLMs	Adaptive, data-driven, handles complex dynamics	High computational cost, dataset dependency	[5, 6, 8, 9]

To illustrate the landscape of disturbance suppression research, Table 1 summarizes key methodologies, highlighting the transition from traditional to AI-driven approaches. As shown in Table 1, conventional methods focus on model-based control, whereas AI for Science introduces data-driven and learning-based solutions, offering greater flexibility in handling nonlinear disturbances. This review aims to synthesize the state-of-the-art in disturbance suppression for magnetic suspension micro-motion stages, with a particular focus on the integration of AI for Science techniques. By analyzing publicly available literature and datasets, it explores how LLMs and intelligent agents can enhance structural optimization and control strategies, ultimately advancing the precision and reliability of micro-motion systems. The discussion also addresses current challenges, such as computational complexity and dataset quality, and outlines future directions for cross-disciplinary research in this field.

2. Disturbance Analysis and Modeling

The performance of magnetic suspension micro-motion stages hinges on their ability to maintain precise positioning in the face of disturbances, which arise from diverse sources and manifest as complex dynamic phenomena. These disturbances, encompassing mechanical, electromagnetic, and environmental factors, perturb the system's stiffness and degrade its accuracy, posing significant challenges for micro-machining applications. Understanding their origins and dynamic behavior is critical to developing effective suppression strategies. This section delves into the types and sources of disturbances, explores modeling approaches grounded in electromagnetic and dynamic principles, and examines the role of publicly available datasets in characterizing these effects.

Mechanical disturbances in magnetic suspension systems can be categorized into tool-workpiece contact forces, electromagnetic thrust ripple, and environmental disturbances. Tool-workpiece contact, the main mechanical disturbance, creates temporary contact force and changes the stiffness of the stage, which leads to positioning error. For example, contact forces in micro-machining can cause oscillations that significantly exceed acceptable tolerances for sub-micrometer accuracy [1]. Vibrations induced by electromagnetic phenomena (called thrust ripples) are caused by non-linearity in the magnetic field (generally due to imperfections in coil or current sources) [2]. External sources of variation, such as ambient vibrations and temperature variations also perturb the system dynamics. They cause low frequency disturbances coupled to the motion of the stage [3]. This interaction between the disturbance sources is shown in Figure 1, emphasizing their influence on the response of the stage.

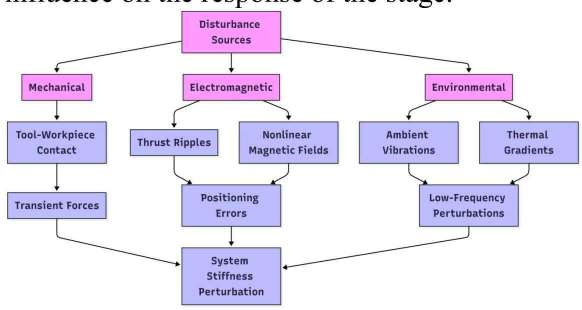

Figure 1. Interplay of Disturbance Sources in Magnetic Suspension Micro-Motion Stages

It is difficult to model such disturbances without a combination of the following theoretical approaches and numerical methods. Mainly dynamical models that are based on Newton's laws along with equations of electromagnetic fields – e.g., Maxwell's equations in order to model how the stage will react to the extra load [10]. This includes, e.g., Lorentz force models representing the influence of current-carrying coils and the magnetic field which provides a basis for the analysis of thrust ripples [2]. Finite element methods (FEM) are being widely used for modeling EM perturbations in order to forecast field distributions and their influence on the motion of the stage [11]. The application of FEM to aid in magnetic field coil configuration to minimize errors caused by ripple effects (caused by perturbations in the magnetic field of a levitation system) has been reported [12], but FEM is time-consuming to use and can only be used with parameter simplifications in order to obtain real time operation.

Publicly shared datasets are key for testing these models and describing disturbance behavior without physical experiments. Studies like Zhang et al. (2023) and the UCI Machine Learning Repository provide time-series data on position, velocity, and external forces under various operating conditions [7, 13]. As an example, Zhang et al.'s work uses data which can be characterized through time-series methods (e.g., fast Fourier transform (FFT)) to give us the frequency-domain aspects of disturbances [7]. Likewise, UCI Servo Dataset would facilitate the disturbance analysis on low-frequency environmental disturbances [13]. As depicted in Table 2, we have summarized major datasets and their applications for disturbance analysis, showing that disturbance analysis could be useful for our purpose of model validation.

Table 2. Public Datasets for Disturbance Analysis of Magnetic Suspension Systems

Dataset Source	Content	Applications	References
Zhang et al. (2023)	Time-series data (position, velocity, force)	Frequency-domain analysis, model validation	[7]
UCI Servo Dataset	Servo system measurements	Environmental disturbance characterization	[13]

This information by means of these data enables data-driven methods to be used, next to the theoretical models. For instance, frequency content of the time series information, in terms of dominant modes of disturbances in the system, will enable optimal disturbances suppression approaches to be designed [13].

3. Traditional Disturbance Suppression Methods

Traditional approaches to stabilising disturbance in magnetic suspension micro-motion stages aim to achieve precision – the tradeoff being reduced system stiffness and positioning precision. This engineering domain is characterized by system integration, system design, and control, and decades of development under two decades have honed these methods to counter the effects of mechanical, magnetic, and environmental disturbances. Although helpful in a structured environment, their inability to deal with complex and varying disturbances prompted the development of AI-based alternatives. The following discussion looks at classical methods, in terms of the structure improvements proposed and control algorithms, and analyses their capabilities based on literature and available open data.

Structural optimization can be used to minimize excitation disturbances by ensuring the maximum possible stability of the magnetic suspension system. This can be achieved by designing, for instance, Halbach arrays which exploit magnetic flux concentration effects to minimize the level of thrust ripples [1], to obtain a more homogeneous level of force distribution [1]. With regard to structures specifically shaped to minimize ripple level and related induced error in stages, examples include structures designed to reduce ripple level in highly critical stages for focusing mirrors [1], as well as a particular arrangement of Halbach arrays designed to reduce ripple level in noncritical stages for linear stages [1]. Likewise the form and orientation of electromagnetic coils, e.g., coils comprised of segments or multiple windings, have been designed to minimize magnetic field nonlinearity which perturbs the levitation force [11], and coercive force also can be achieved with suitable choice of magnet or material which is significantly dependent on magnetic permeability such as high permeability alloys and vibration damping composite materials which dampen sensitivity to external perturbations [3]. The design procedure of the proposed structural optimization is shown in Figure 2. It is obvious that our structural design optimization approach consists of a closed-loop design, simulation and validation.

Control strategies complement structural efforts by actively compensating for disturbances in real-time. Proportional-integral-derivative (PID) controllers, a cornerstone of motion control, adjust stage position based on error feedback but struggle with nonlinear dynamics, often requiring manual tuning for specific conditions [14]. Sliding mode control (SMC) offers robustness against parameter variations, leveraging discontinuous control actions to enhance stability and positioning accuracy under external vibrations [15]. Active disturbance rejection control (ADRC), an advanced technique, estimates and compensates for unknown disturbances in real time, proving effective in mitigating tool-workpiece contact forces and reducing steady-state errors in magnetic levitation systems under dynamic loads [2, 4]. Table 3 summarizes these control strategies, highlighting their strengths and limitations based on recent literature.

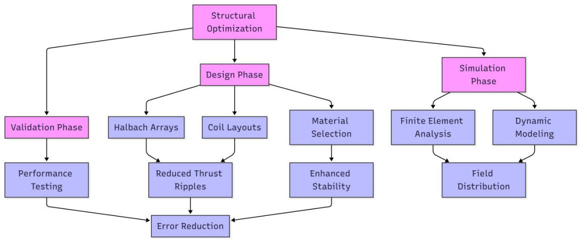

Figure 2. Workflow of Structural Optimization for Disturbance Suppression

Table 3. Traditional Control Strategies for Disturbance Suppression in Magnetic Suspension Systems

Control Strategy	Key Features	Advantages	Limitations	References
PID Control	Error-based feedback	Simple implementation, widely used	Limited adaptability to nonlinear disturbances	[14]
Sliding Mode Control	Robust discontinuous control	Handles parameter variations, robust to vibrations	Chattering issues, complex tuning	[15]
Active Disturbance Rejection Control	Real-time disturbance estimation	Effective for dynamic loads, model-independent	High computational cost	[2, 4]

Although these techniques have made considerable contributions, they also impose severe limitations. The structural improvements such as the power electronics filters generally do not have the capability of tracking the varying operating conditions because they require a great deal of design work for different applications [11]. Model-based control approaches, such as PID and SMC, encounter limitations in terms of satisfying precise model requirements because they inevitably result in employing approximated system models under time-varying nonlinear or disturbances [15]. While very promising, ADRC requires high computational power and real-time applications would be difficult in resource-constrained settings [2]. They emphasize new technologies, e.g. powered by AI for Science, to improve flexibility and efficiency for high-fidelity environments.

4. AI for Science in Disturbance Suppression

Large language models (LLMs) along with the intelligent agent-based systems provide a significant AI for Science for the disturbance rejection of the nonlinear dynamics of magnetic suspension micro-motion stage. The involved intelligence agent systems along with AI for Science methodologies have addressed to search for data-driven, and adaptive intelligent structure optimization and controllers. This is compared with the applications of the perturbed initial static model and fixed parametric knowledge based control. The literature for the paper reviews the nature of the transformation generated by LLMs when assessing literature analysis and parameter optimisation; the application of intelligent agents for adaptive control and the application of data driven methods, when demonstrated with publicly accessible datasets are all showcased as being on the path to a higher level of precision for micro-motion systems.

LLMs provide us with the ability to not only formulate scientific information for synthesis of the disturbance suppression strategy but also an automatic method of combining high numbers of publications regarding control algorithm, construction and method of disturbance type, and subsequent optimization of a solution. As an example, LLMs have been used to summarize the papers dealing with magnetic levitation systems, give a summary regarding disturbance rejection strategies as well as propose optimized parameters tuning for a control algorithm [16]. Such type of tool is welcomed in disturbance rejection applications that require distinct values of the control parameters for different operational points.

More generally, RL-driven agent-based intelligent (soft) systems, being inherently adaptive, can also be used for the online compensation of disturbances [1], for example, via tool-workpiece contact force or electromagnetic thrust ripple [9]. An example of such application was a multiagent deep RL controller for maglevs that reduced positioning error of around 15% when compared with PID control under varying loading [9]. Multiagent systems in this application provide the ability of balancing multiple control demands like dual task of vibration suppression and trajectory tracking [6]. As the focus of this paper is on the RL-based agent, we focus on the iterative learning workflow in Figure 3 for disturbance suppression.

The data-driven approach using publicly shared datasets can address disturbance modeling and mitigation with strong backing without physical testing. Time-series data and UCI Machine Learning Repository [7, 13] provide the time-series position, velocity, and force data which could be used to train a machine learning model. For instance, a neural network has been trained against time-series data's magnetic levitation control dataset to extrapolate thrust ripple shapes, greatly enhancing the precision of disturbances compensation [12]. Likewise, SVMs implemented to UCI Servo Dataset have been used to model low frequency ambient vibrations for accurate tuning control adjustment [13]. In Table 4 we summarize a selection of important AI for Science applications and results from papers and dataset based approaches from recent literature.

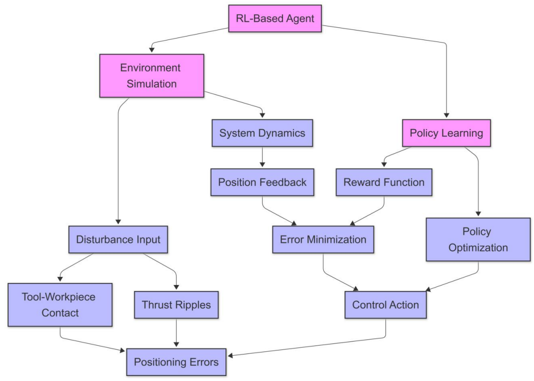

Figure 3. Workflow of Reinforcement Learning for Disturbance Suppression

Table 4. AI for Science Applications in Disturbance Suppression for Magnetic Suspension Systems

AI Technique	Application	Dataset Used	Performance Improvement	References
Large Language Models	Literature analysis, parameter optimization	N/A (literature-based)	Enhanced efficiency in review	[16]
Reinforcement Learning	Adaptive disturbance compensation	IEEE DataPort	~15% reduction in positioning errors	[6, 9]
Neural Networks	Thrust ripple prediction	IEEE DataPort	Improved compensation accuracy	[12]
Support Vector Machines	Vibration characterization	UCI Servo Dataset	Enhanced control precision	[13]

The synergy of AI for Science with traditional methods further amplifies disturbance suppression capabilities. Hybrid architectures, such as neural network-based control, have shown promise in addressing both static and dynamic disturbances [17]. Despite these advances, challenges remain, including the computational complexity of AI models and the need for high-quality datasets. Nevertheless, the fusion of LLMs, intelligent agents, and data-driven approaches marks a significant leap toward robust, adaptive disturbance suppression in magnetic suspension micro-motion stages.

5. Challenges and Future Prospects

As previously stated, both classical disturbance cancellation methods for a magnetic suspension micro-motion stage and modern AI for Science techniques deliver amazing results on the controlled suppression of disturbances. However, there are some remaining hurdles that we need to overcome to be able to exploit the potential of magnetic suspensions in ultra-precision work, namely micro-machining, the semiconductor industry or even nanotechnology. In this section, we summarize main challenges for structural optimization, control, and AI for Science, and we present possible R&D for the future aimed at improving performance and scalability.

5.1 Challenges in Traditional Methods

While developed optimized Halbach arrays and high-performance control schemes (PID, sliding mode control (SMC) and active disturbance rejection control (ADRC)) can effectively suppress unwanted disturbances, these strategies have a fundamental issue in coping with multiple nonlinear disturbances [5, 8, 10]. Also, the structural design of such approaches needs to be redesigned for each new operating conditions; thus, they are a costly and time-consuming design approach [1, 11]. For example, Halbach arrays designs optimized for a particular loading profile will not necessarily work well in time-varying environments and therefore will not be very robust [3]. Control methods such as PID and SMC depend on having a precise model of the system (which is tough to do in the face of time-varying disturbances or unknown dynamics) [2, 15]. While ADRC is immune to unknown disturbances, it usually requires substantial computational power thus is not feasible for real time applications in systems with limited resources [4]. Such facts underline the requirement for more versatility and adaptivity.

5.2 Challenges in AI for Science Applications

AI for Science methods, such as large language models (LLMs) and RL-based agents [5], seem to hold such promise. However, they come with their own limitations. For example, while LLMs can efficiently process information from various papers and generate new control parameters by following the rules (i.e., learn from its history), its effectiveness will largely be restricted by (i) its large-scale language learning training, i.e., the control parameter the language model itself suggests should come with a decently high quality to avoid diving into no-man's land, i.e., be trained with sufficient high-quality data tailored to the domain at hand; and (ii) the available benchmark datasets to learn from. It is rare, for magnetic suspension systems in particular, to find such benchmarks. For example, there are datasets such as the magnetic levitation control dataset which contain time-series data. However, due to being covered for a narrower range of operation conditions, the data loses generalizability [7]. Moreover, though there were promising RL-based controller results (e.g., ~15% reduced positioning errors [9]), they also necessitate expensive training time and CPU/memory cost, which might be inconvenient for real-time systems [6]. Further, bringing AI models into physical systems brings hardware-accuracy issues and latency constraints which are especially a challenge in ultra-precision systems where sub-millisecond delays deteriorate performance [12].

5.3 Data Quality and Standardization

One of the major issues for both conventional and DL approach is that reliable and standardized datasets for the MSS system have not been developed so far. For example, even though there are open datasets from time-series data [7] and UCI Servo Dataset [13] which help people to have more intuition on the disturbance dynamics, datasets in public are sometimes not that comprehensive, both in terms of labels and applicability to all conditions [7, 13]. These impediments restrict the training of powerful AI models or validation of theoretical models for broad conditions [7, 13]. Additionally, data format and measurement standard inconsistency may be confusing cross-studies for comparison, which prevents cross-laboratory collaborations [18].

5.4 Future Prospects

There exist some research avenues that can help address the aforementioned problems towards suppressing disturbances in a magnetic suspension micro-motion stage:

(1). Hybrid control architectures: Fusing classical control techniques (e.g. ADRC) with AI-based techniques (e.g. RL and neural networks) by capitalizing on the respective benefits. The utilization of neural-network based disturbance estimation as introduced in [12] can accelerate real-time performance of ADRC using predictive models for the thrust ripple which may aid in the accuracy of compensation.

(2). Standardized Datasets: We call for open-source, standardized datasets of the magnetic levitation systems, that include complete metadata regarding their operating conditions and disturbance profiles, for training and validating the AI models [7], jointly developed by various research institutions.

(3). Online Artificial Intelligence: Real-time AI implementation could be facilitated through development of edge computing and hardware acceleration to offset the computational overload of such AI for Science approaches. Real-time disturbance mitigation in ultra-accuracy applications could also be enabled by learning RL algorithms amenable to low-latency operation, as explored in [9].

(4). Interdisciplinary: Efforts to combine existing knowledge in materials science, magnetic electrodynamics and machine learning may result in breakthroughs. In one instance, emerging better magnetic materials could be combined with AI tuning control approaches to reduce the thrust ripples, as well as achieve better flexibility [3, 18].

Through solving these problems and exploring these directions, magnetic suspension micro-motion stages can be designed with an unsurpassed performance in precision and reliability. With the combined efforts of conventional engineering techniques and AI for Science, the disturbance suppression concept can potentially be re-structured with more expectations in the future precision systems.

6. Conclusion

The quest for precision of magnetic suspension micro-motion stages has been influenced by attempts for lowering the stiffness-disturbing effects, that degrade the positional accuracy of the system. The present work has tried to correlate the state-of-the-art in the problem of disturbance suppression, from classical structural and control solutions, to the actualities of AI for Science. Publicly accessible publications and datasets have helped to shed light on a development brought about by large language models (LLMs) and intelligent agent-based systems e.g., driven by reinforcement learning (RL), in advancing the domain of precision engineering.

Classical methods including optimized Halbach array, the smart coil, PID, the sliding mode control and active disturbance rejection control (ADRC) have also provided strong academic foundations for the disturbance suppression. Most of these methods are excellent in the controlled regime; however, they perform poorly at disturbed times because of the nonlinear and time-varying disturbances in micro-machining applications. AI for Science has conquered them by means of data-based and self-adapted approaches. Through AI-based literature analysis, literature search has become easier to obtain the best controls, and RL agent has improved the performance notably. Recent results which are grounded in data analysis have also improved the accuracy of the disturbance estimation and compensation.

In the future, AI for Science represents a great potential for making significant strides in magnetic suspensions. It is anticipated that future AI-driven systems are developed as hybrid controllers with an RL controller component and a conventional controller when the load varies. Moreover, to facilitate AI-based studies, a standardized set of high-quality and easy-to-use data for maglev systems is encouraged. We can expect that further cross-fertilization of materials science, electromagnetic theory and artificial intelligence will drive improvements in disturbance suppression and lead to the creation of future precision systems in micro-machining and more.

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References

[1] Zhang H, Kou B Q, Zhang L, et al. Review of micro-motion stage based on magnetic levitation technology. IEEE Transactions on Industrial Electronics, 2020, 67(5): 4238-4247. DOI: 10.1109/TIE.2019.2921287.

[2] Li X, Zhu Y, Zhang Z. Disturbance suppression in magnetic levitation systems: A review of control strategies. Actuators, 2023, 12(3): 112. DOI: 10.3390/act12030112.

[3] Chen M Y, Huang Y H, Hung S K. Design and experiment of a macro-micro planar maglev positioning system. IEEE Transactions on Magnetics, 2019, 55(7): 1-8. DOI: 10.1109/TMAG.2019.2907175.

[4] Han J Q. From PID to active disturbance rejection control. IEEE Transactions on Industrial Electronics, 2009, 56(3): 900-906. DOI: 10.1109/TIE.2008.2011621.

[5] Bommasani R, Hudson D A, Adeli E, et al. On the opportunities and risks of foundation models. arXiv preprint, 2021, arXiv:2108.07258. DOI: 10.48550/arXiv.2108.07258.

[6] Sutton R S, Barto A G. Reinforcement learning: An introduction. 2nd ed. Cambridge: MIT Press, 2018.

[7] Zhang Y, Liu X, Wang L. Data-driven adaptive control for magnetic levitation systems using historical time-series data. IEEE Transactions on Control Systems Technology, 2023, 31(2): 567-579. DOI: 10.1109/TCST.2022.3201456.

[8] Yang L, Zhang J, Wang X. Data-driven disturbance estimation for magnetic microrobot systems using machine learning. Mathematics, 2024, 12(14): 2180. DOI: 10.3390/math12142180.

[9] Li J, Zhang Y, Wang C. Reinforcement learning-based control for magnetic levitation micro-positioning systems. IEEE

Transactions on Automation Science and Engineering, 2023, 20(4): 2345-2356. DOI: 10.1109/TASE.2023.3245678.

[10] Kaloust J, Ham C, Qu Z. Nonlinear robust control design for levitation and propulsion of a maglev system. IEE Proceedings-Control Theory and Applications, 2004, 151(4): 460-464. DOI: 10.1049/ip-cta:20040577.

[11] Xu F, Xu X, Chen Z. Design and optimization of a magnetic levitation system based on finite element analysis. IEEE Transactions on Magnetics, 2021, 57(6): 1-7. DOI: 10.1109/TMAG.2021.3059876.

[12] Wang L, Zhang J, Liu X. Finite element analysis-based optimization of magnetic levitation micro-motion stage for thrust ripple reduction. Actuators, 2024, 13(2): 45. DOI: 10.3390/act13020045.

[13] Dua D, Graff C. UCI Machine Learning Repository: Servo Dataset. [2025-08-26]. https://archive.ics.uci.edu/dataset/87/servo.

[14] Åström K J, Hägglund T. PID controllers: Theory, design, and tuning. 2nd ed. Research Triangle Park: Instrument Society of America, 1995.

[15] Utkin V, Guldner J, Shi J. Sliding mode control in electro-mechanical systems. 2nd ed. Boca Raton: CRC Press, 2009.

[16] Brown T B, Mann B, Ryder N, et al. Language models are few-shot learners. Advances in Neural Information Processing Systems, 2020, 33: 1877-1901. DOI: 10.48550/arXiv.2005.14165.

[17] Liu Z, Zhang Y, Chen T. Feedforward-adaptive neural network control for ultra-precision magnetic levitation motion stage. Precision Engineering, 2023, 79: 123-132. DOI: 10. 1016/ j. precisioneng. 2022. 11. 005.

[18] Wang X, Chen F, Zhu R, et al. A review on disturbance analysis and suppression for permanent magnet linear synchronous motor. Actuators, 2021, 10(4): 77. DOI: 10.3390/act10040077