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Magnetic Field Estimation for Electromagnetic Devices Using Physics-Informed Deep Learning: Methods, Challenges and Future Directions

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Abstract – As performance demands on electromagnetic devices (EMDs) intensify, the need for high-precision magnetic field estimation techniques becomes increasingly critical. Physics-informed neural networks (PINNs), which integrate physical laws with deep learning, have recently emerged as a powerful approach for tackling complex electromagnetic problems, offering superior computational efficiency and generalization. Compared to traditional numerical methods, PINNs can effectively handle heterogeneous media and complex boundaries, while maintain high prediction accuracy even with limited data, thus garnering significant global research interest. However, the application of artificial intelligence to magnetic field estimation is still nascent, and a systematic survey of existing methods, especially those involving the solution of Maxwell's equations, has not yet been conducted. This paper provides a comprehensive overview of physics-informed deep learning approaches for magnetic field estimation, summarizes general computational procedures, identifies key challenges, and discusses future directions. Using inverters and permanent magnet machines as representative examples, practical magnetic field estimation processes are outlined and how post-processing of predicted fields is analyzed, which can facilitate the design optimization of EMDs.

Keywords: Deep Learning, Electromagnetic Devices (EMDs), Maxwell's Equations, Magnetic Field Estimation, Physics-Informed Neural Networks (PINNs)

1. Introduction

Increasing performance demands on electromagnetic devices (EMDs) necessitate high-precision magnetic field estimation methods [1]-[4]. Decades of research have been dedicated to developing fast numerical solvers for design analysis of EMDs [5]-[7]. However, as device structures grow in scale and complexity, nonlinear effects cause the computational cost of electromagnetic field simulations to rise sharply. Traditional numerical methods, such as finite element analysis, involve large-scale computations, resulting in slow calculating speeds that struggle to meet the real-time demands of modern design and optimization [8]-[9].

On the other hand, although surrogate models offer a faster alternative, they are typically problem specific and describe systems with very few parameters, limiting their adaptability to arbitrary design changes [10]. Additionally, machine learning methods have introduced effective alternatives for mode recognition and complex regression, and much of the research in this area currently focuses on developing data-driven methods specifically to augment simulation-based approaches for magnetic field estimation, offering a path beyond the limitations of prior techniques [11]-[12]. However, machine learning approaches predominantly rely on statistical patterns learned from data, which might lack rigorous adherence to the governing physical laws. This limitation can compromise their predictive accuracy and generalizability, particularly in scenarios beyond the training datasets.

Recently, physics-informed deep learning, like physics-informed neural networks (PINNs), which integrate physical laws with deep learning, have demonstrated superior computational efficiency and generalization capability in complex electromagnetic field problems [13]-[14]. Compared to traditional numerical methods, PINNs can effectively handle multiple media and complex boundaries, and maintain high prediction accuracy even with limited data, thus attracting increasing worldwide attention [15]-[17]. However, PINN-based magnetic field estimation still remains in its early stages, and a systematic survey of existing methods, especially those involving the solution of Maxwell's equations, has not yet been conducted.

Therefore, this paper provides a comprehensive review of PINN methods for magnetic field estimation in EMDs. It summarizes general computational procedures, evaluates key technical aspects, including boundary condition problems, sampling methods, network architectures and loss functions, identifies current challenges, and discusses future research directions. Using inverters and permanent magnet machines as case studies, we demonstrate a practical

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workflow for magnetic field estimation, analyze post-processing techniques for the predicted fields, and discuss their application in EMD performance evaluation. By directly linking theoretical advances to industrial practice, this work illustrates how these techniques enhance device performance, ultimately facilitating the development of high-performance EMDs that meet the stringent demands of next-generation intelligent manufacturing.

2. Literature Survey

PINNs, as a deep learning approach that embeds physical laws such as partial differential equations and boundary conditions into the training process, have attracted increasing attention in electromagnetic field computation in recent years. Existing studies have attempted to apply PINNs to the solution of static, low-frequency, and multi-material electromagnetic field problems, exploring their potential in forward modeling, parametric design, and inverse problem solving.

For solving forward problems, in [18], the authors applied PINNs to direct numerical analysis of electromagnetic fields and verified their feasibility for solving problems with relatively simple structures. In this approach, the constraints of partial differential equations are embedded by automatic differentiation, thereby avoiding the dependence on mesh reconstruction required in traditional numerical methods. However, the convergence and accuracy of this method in multi-material region or under complex boundary conditions still require further improvement. To ensure the performance of electromagnetic field solutions, enhanced PINNs were developed, incorporating techniques such as mesh-assisted sampling [19], multi-network fusion [20], and physics-constrained hard constraints [21]. These innovations refine core components of conventional PINNs, namely sampling methods, network architectures, and loss function design, thereby boosting solving accuracy and efficiency.

In terms of parametric design and inverse problem solving, in [22], the authors proposed a PINN framework for parameterized magnetic problems, which enables the network to simultaneously learn the influence of multiple design parameters on the magnetic field distribution during the training process. This method demonstrates significant advantages in structural optimization; however, the training process is sensitive to the distribution of sampling points and may encounter convergence difficulties when multiple parameters are strongly coupled. In [23], a hard-constraint mechanism that directly embeds boundary conditions into the network architecture was reported, through which the stability and accuracy of inverse problem solutions were improved. But its adaptability to complex geometries still requires further investigations. In [24], temporal dimension was directly embedded into the network input for time-varying electromagnetic field problems, in which automatic differentiation was utilized to compute temporal and spatial derivatives, avoiding the time-stepping scheme of traditional numerical methods as well as realizing fast transient field estimation. This improved method retains the mesh-free and parameter-independent advantages of traditional PINNs, and effectively mitigates the problems of slow convergence and poor sampling robustness.

Traditional numerical methods are often hindered by computational efficiency in high-dimensional parametric electromagnetic design and real-time field monitoring. In response, the improved PINN framework addresses the key limitations of conventional PINNs in electromagnetic applications while retaining their core advantages, making itself as a promising alternative for electromagnetic field computation in modern device design, online monitoring, and inverse optimization [25]-[26]. The application progress, advantages, and drawbacks of PINN-based methods for electromagnetic field estimations are summarized in Table 1.

Table 1. Advantages and disadvantages of various PINNs for electromagnetic field estimations

Methods	**Advantages**	**Disadvantages**
Traditional PINNs	i) Mesh-free, no complex discretization ii) Low dependence on labeled field data iii) Unified forward/inverse/parametric design solutions iv) Adaptable to multi-medium complex boundary domains	i) Slow convergence for strong nonlinear/high-frequency problems ii) Prediction accuracy sensitive to collocation point sampling iii) Gradient vanishing/explosion in PDE residual training iv) PDE and BC loss imbalance without rational weighting
Improved PINNs (Mesh-assisted Sampling)	i) Retains all traditional PINN advantages ii) Significantly improves key field region prediction accuracy iii) Reduces collocation points while maintaining accuracy iv) Enhances training stability for multi-medium EM problems	i) Requires lightweight geometric preprocessing ii) Sampling strategy geometry-specific, poor generalization iii) Limited improvement for time-varying/3D high-dimensional EM problems
Improved PINNs (Network/Loss Optimization)	i) Enables fast transient EM field computation ii) Improves BC accuracy and training convergence speed iii) Adaptable to multi-physics coupling EM problems iv) High-precision EM inverse design with limited data	i) Complex network/loss design, high engineering threshold ii) High computational cost for 3D large-scale EM devices iii) Hyperparameter tuning dependent for different EM field types
PINNs Combined with Data-Driven DL	i) Integrates PINN physics consistency with data-driven fast inference ii) Reduces training cost with small-sample labeled data iii) Enables real-time EM estimation for in-service devices iv) Strong adaptability to unmeasured conditions	i) Requires partial labeled field data (FEA/experiment) ii) Inference degrades for out-of-distribution conditions iii) High hardware requirements for large-scale device real-time computation

3. General Workflow and Challenges

3.1 General Workflow of PINN-Based Magnetic Field Prediction

PINNs leverage the integration of physical laws into deep learning to deliver efficient and high-precision magnetic field estimation for EMDs, even with limited data, a capability that addresses significant challenges faced by traditional numerical methods in handling heterogeneous media and complex boundary conditions [16]. As illustrated in Figure 1, a general PINN-based magnetic field estimation framework typically follows six key steps.

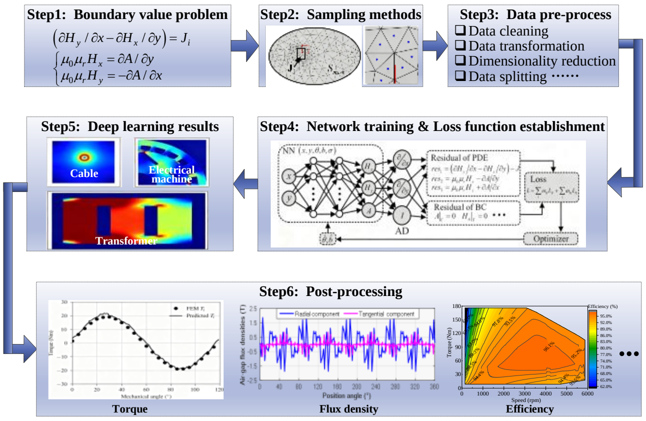

Fig. 1. General procedure for magnetic field estimation using PINNs

First, the electromagnetic issues are formulated as a boundary value problem derived from Maxwell's equations, where the governing equations and boundary conditions define the physical constraints of the model [17]. Second, spatial collocation points are generated within the computational domain, for instance through mesh-based or adaptive sampling techniques to enforce these constraints during training, ensuring robust coverage of critical regions and boundaries. Third, the sampled data may undergo basic preprocessing like cleaning, transformation, dimensionality reduction, and splitting to enhance the training stability, computational efficiency, and model generalization. Subsequently, a neural network with appropriate network parameters is constructed to approximate the target magnetic field variables such as H_x, H_y representing the components of the magnetic field intensity along the x-axis and y-axis, and A for vector potential. In this step, a composite loss function is also established, which penalizes residuals of the partial differential equations, violations of boundary conditions, and discrepancies with measurement data. The network is then trained to minimize the physics-based loss, enabling the prediction of magnetic field distributions [27]. Finally, the predicted fields can be used for engineering analysis. The practical applications of the proposed framework and the corresponding data post-processing procedures will be discussed in detail in the following Sections 4.1 and 4.2.

3.2 Open Challenges

Despite the promising advantages of PINNs in magnetic field estimation, several critical challenges remain to be addressed before large-scale engineering applications.

i) Strict enforcement of complex boundary conditions and interface constraints is difficult due to the soft-constraint nature of loss functions [28].

ii) The precise integration of non-linear material properties and hysteresis effects into loss functions presents a significant challenge for high-fidelity modeling [29].

iii) Moving boundary problems caused by rotor rotation and the complex coupling of multi-physics fields, such as thermal and mechanical stress, significantly limit the large-scale industrial application of PINNs [30].

iv) The inherent stochasticity and sensitivity of PINN training to hyperparameters often lead to inconsistent predictions, failing to meet the rigorous reliability and reproducibility standards required in engineering design [31].

v) PINNs grapple with a fundamental trilemma involving poor convergence of physics-driven models, high costsof data acquisition, and low robustness in sparse-data scenarios, which hinders their transition to practical industrial applications [32].

4. Practical Applications and Future Directions

To validate the proposed PINN framework for magnetic field estimation in EMDs with complex multi-medium structures, two representative electromagnetic devices are selected as case studies, i.e. an E-shaped transformer [33] and an interior permanent magnet synchronous motor (PMSM) in authors' lab [34].

4.1 Case study with an E-shaped transformer

The two-dimensional (2D) computational domain of the E-shaped transformer is constructed by exploiting geometric symmetry and only half of the structure is modeled along the O-y symmetry axis. The domain consists of a magnetic core with a relative permeability of μ_r=100 and a coil carrying an impressive current density of J_i =1000 A/cm^2. To truncate the unbounded air region, a large air hood is introduced, with dimensions approximately four times those of the main transformer body. This sizing follows the inverse-square-law decay of the magnetic field and is validated through numerical experiments. Appropriate boundary conditions are applied on the air hood and the symmetry axis, specifically, constraints on the magnetic vector potential and the normal magnetic field intensity, to ensure the model accurately reflects the physical behavior of the magnetic field distribution [33].

Regarding the PINN training configuration, the network is implemented using the DeepXDE package with a PyTorch backend, adopting a fully-connected neural network as the base architecture. To ensure training stability and convergence, a two-stage optimizer strategy is employed. The Adam algorithm is first applied for 26,000 training epochs, followed by the limited-memory Broyden–Fletcher–Goldfarb–Shanno algorithm for an additional 300,000 epochs. The weighting factors in the composite loss function are calibrated to maintain consistent orders of magnitude across all residual norms, thereby eliminating imbalances among contributions from partial differential equation residuals and boundary condition residuals [33].

A core focus of this case study is the comparative analysis of three collocation point sampling strategies to evaluate the improvement of the proposed mesh-assisted non-uniform sampling method on PINN performance.

i) Uniform sampling: Collocation points are generated across the entire computational domain using the Hammersley sequence method, with no regional differentiation in sampling density.

ii) Subdomain sampling: The computational domain is partitioned into a key subdomain Ω where the magnetic field is concentrated, and an air subdomain Ω_{air}, with distinct Hammersley sequence sampling densities applied to each.

iii) Mesh-assisted non-uniform sampling: The computational domain is discretized using an adaptively refined finite element method (FEM) mesh, with higher resolution near material boundaries where the magnetic field varies sharply. Collocation points are then placed at the centers of the triangular mesh elements to inherently avoid sampling across element interfaces and the associated risk of solution discontinuity. The final training set integrates FEM-derived and subdomain-sampled points.

This E-shaped transformer case study validates that the proposed PINN framework can effectively solve magnetic field problems in electromagnetic devices with multiple magnetic media, maintaining high prediction accuracy and numerical stability. More importantly, it demonstrates the significant superiority of the mesh-assisted non-uniform sampling method over traditional uniform and simple subdomain sampling strategies. By incorporating geometric a priori information from FEM meshes and adaptively densifying collocation points in regions of high field variation, the method optimizes the distribution of training points, thereby improving both the utilization efficiency of computational resources and the prediction accuracy in functional regions.

The results offer practical guidance for applying PINNs to the field estimations in electromagnetic devices. They demonstrate that integrating geometric information from traditional numerical simulations with physics-informed deep learning effectively enhances the performance of PINN frameworks in engineering applications [33]. This approach proves particularly valuable for complex electromagnetic devices with irregular geometries and heterogeneous material distributions, where traditional uniform sampling methods often fail to achieve a satisfactory balance between accuracy and computational efficiency.

4.2 Case study with an interior PMSM

To further evaluate the capability of PINNs for magnetic field estimation in rotating electromagnetic devices with complex geometries and nonlinear material properties, an interior PMSM is selected as the second case study [34]. The proposed framework follows a three-stage methodology, as illustrated in Fig. 2. First, an enhanced analytical iron loss model is developed that simultaneously considers spatial harmonics, carrier harmonics, temperature effects, and mechanical stress. Using co-simulations with Simplorer and ANSYS, magnetic flux density, temperature, and stress profiles are generated across diverse operating conditions, producing comprehensive iron loss datasets. Then, a neural network is designed to learn the complex nonlinear relationships between operating parameters and iron losses. Finally, the model undergoes a training including the pre-training on simulated data followed by fine-tuning with limited experimental measurements, ensuring both physical consistency and adaptability to real-world conditions.

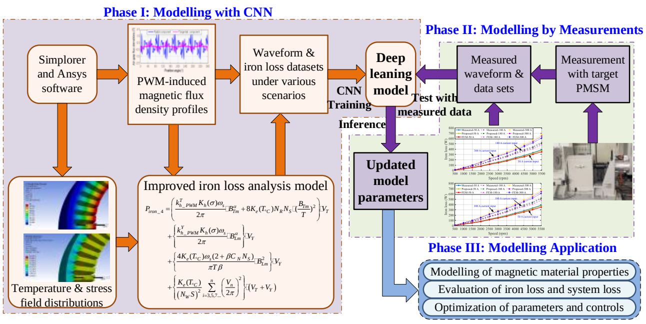

Fig. 2. Framework of the PINN modelling methods [34]

The proposed PINN method was validated using an interior PMSM experimental platform. Iron losses were measured under various speed and load conditions using the dummy rotor method to separate mechanical losses [35]. Fig. 3 presents a scatter plot comparing predicted and measured iron losses. The strong overlap between the two symbol types demonstrates excellent agreement between predictions and measurements. Fig. 4 summarizes the error analysis results in which Fig. 4(a) shows that normalized residuals remain consistently small across all operating conditions. Fig. 4(b) reveals high kurtosis near zero residual in both the histogram and kernel density estimates. This indicates that the residuals are concentrated and closely follow a normal distribution, thereby validating the robust predictive capability of the model. Fig. 4(c) provides a box plot summary, showcasing the maximum residual of 5.59%, minimum -5.29%, median 0.13%, with 25th and 75th percentiles at -1.22% and 1.55% respectively. These results confirm that the proposed PINN-based model achieves satisfactory accuracy and stability for PMSM magnetic field estimation and iron loss prediction.

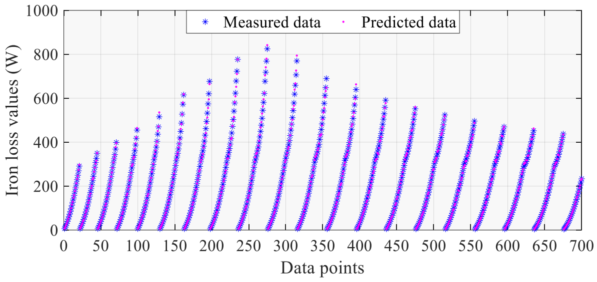

Fig. 3. Validating results of the iron loss model predicted using the proposed PINN approaches [34]

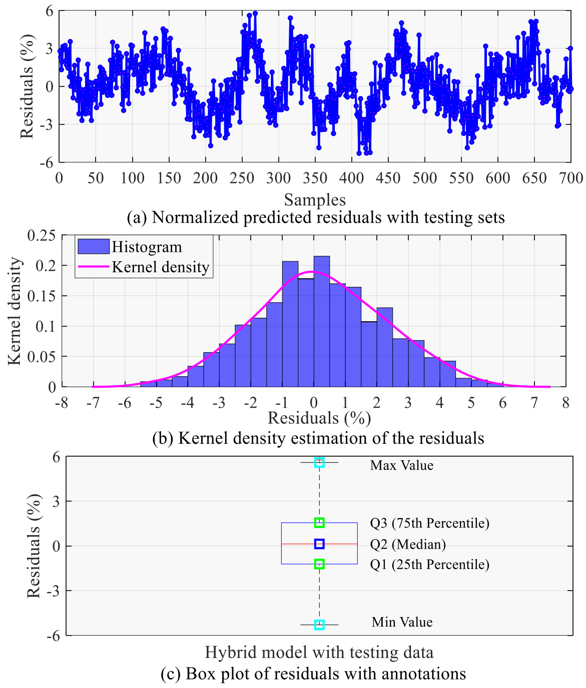

Fig. 4. Error analysis of the predicted results [34]

This case study demonstrates that the proposed PINN-based hybrid model can effectively learn complex magnetic field distributions and iron loss characteristics in multi-material, geometrically intricate electromagnetic devices, delivering fast and accurate predictions across design variations within the training parameter space. The two-stage training strategy, combining physics-based pre-training on simulated data with fine-tuning using limited experimental measurements, ensures both physical consistency and adaptability to real-world conditions. Furthermore, this work lays the foundation for future advancements, such as graph convolutional networks for unstructured meshes and semi-supervised learning to reduce labeled data requirements, which aim to address the current bottlenecks of structured grid dependence and high demand for training data.

4.3 Future Directions

The future development of PINNs must bridge the gap between computational feasibility and industrial reliability. By advancing in physical fidelity, geometric robustness, and quantified trustworthiness, PINNs are set to transition from theoretical models to essential tools for high-performance electromagnetic device engineering [36]. The future directions will be conducted in the following five aspects.

i) Deep embedding of complex physical mechanisms. Beyond ideal Maxwell equations, future work should enable PINNs to handle strong nonlinearities and multi-field coupling issues directly. This requires incorporating nonlinear material properties such as ***B-H*** curves and hysteresis effects, through specialized neural layers or decoupling algorithms to eliminate non-physical oscillations. Furthermore, developing unified frameworks for transient electromagnetic-thermal-mechanical coupling is essential to address mismatched time scales and complex interfacial terms in high-frequency applications.

ii) Adaptability to complex geometries and multi-scale features. To overcome accuracy limitations in industrial-grade geometries, future research should explore hybrid solvers and geometric adaptation strategies. For example, combining PINNs with FEM allows high-gradient regions such as air gaps to be resolved using either high-resolution sub-networks or conventional numerical methods. In addition, architectural enhancements including Fourier feature mappings and wavelet transforms offer promising ways to capture fine local details while maintaining global low-frequency accuracy.

iii) Enhancement of training convergence and reliability. Building confidence in PINN-based field estimation requires demonstrable improvements in training stability and reproducibility. Adaptive loss-balancing algorithms that dynamically weight Maxwell residuals against boundary conditions are essential for maintaining physical fidelity throughout training. Furthermore, incorporating uncertainty quantification by Bayesian neural networks or ensemble methods provides designers with measurable error estimates, enabling informed decisions based on predicted field distributions.

iv) Synergetic mechanism of data-physics-driven learning. Addressing the challenge of data scarcity calls for progress in transfer learning and domain adaptation. Models pre-trained on standard geometries can be quickly adapted to complex real-world devices, reducing the need for extensive retraining. Meanwhile, physics-guided data augmentation using Maxwell equations to generate high-quality synthetic samples can enrich training datasets, while sparse experimental measurements can be integrated as constraints to align predictions with observed behavior. These approaches collectively enable a deeper fusion of data-driven learning and physical principles.

v) Evolution toward automated artificial intelligence for science platforms. Lowering the barrier to adoption requires the development of end-to-end PINN solvers that automate geometry processing, model configuration, and hyperparameter tuning. In parallel, establishing standardized benchmark libraries, covering static fields, eddy current problems, and permanent magnet machines, will enable fair performance comparisons and accelerate the systematic adoption of PINN technologies in electromagnetic design.

5. Conclusion

This review provides a comprehensive overview of PINNs for magnetic field estimation in electromagnetic devices, systematically summarizing their general computational frameworks, key technical characteristics, and practical application paradigms. As an emerging data-physics hybrid approach, PINNs exhibit distinct advantages over conventional numerical methods in handling complex geometries, multi-material structures, and data-scarce scenarios, opening new avenues for efficient magnetic field computation and design optimization.

Despite these promising capabilities, several critical challenges currently impede the large-scale industrial adoption of PINNs in magnetic field analysis. These include difficulties in rigorously enforcing complex electromagnetic boundary conditions and interface constraints; an inherent sensitivity to data quality that persists despite claims of data efficiency; limited reliability and reproducibility due to the absence of rigorous error estimation and convergence criteria; insufficient capacity for solving multi-scale, high-frequency, and multiphysics problems; training instabilities arising from imbalanced loss terms; restricted generalization across diverse device geometries and operating conditions; inadequate post-processing tools for extracting engineering performance indicators; and a lack of standardized validation frameworks and industrial-grade software toolchains.

To address these bottlenecks, future research should focus on eight key directions: i) developing PINN architectures that embed boundary and interface conditions as hard constraints; ii) advancing toward truly low-data or zero-shot high-precision electromagnetic PINNs; iii) establishing reliable error quantification and reproducibility mechanisms; iv) enhancing capability for multi-scale and multi-physics problems; v) designing adaptive, balanced training strategies; vi) improving generalization across structures and operating conditions; vii) enabling end-to-end prediction of EMD' performance metrics; and viii) building standardized industrial frameworks and toolboxes..

With continued progress in algorithmic innovation, theoretical refinement, and engineering validation, PINNs are poised to evolve from a promising supplementary technique into a mature and reliable numerical method for magnetic field analysis. Such maturation would not only enhance the computational efficiency and design accuracy of EMDs, but also contribute to the broader intelligent transformation of electromagnetic engineering, ultimately supporting the development of high-performance, energy-efficient EMDs.

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