Article:
Li, Zihan, Cheng, Mengyu, Tyrrell, Andy et al. (Accepted: 2025) A Review of Data-Driven Models for Electromagnetic Devices Design and Analysis. IEEE Access. ISSN: 2169-3536 (In Press)

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2025.Doi Number

A Review of Data-Driven Models for Electromagnetic Devices Design and Analysis

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ABSTRACT In recent years, the design and optimization of electromagnetic devices have grown increasingly complex, driven by the demand for higher efficiency, greater power density, and cost-effectiveness. Traditional approaches such as finite element analysis (FEA) offer precise simulations but can be time-consuming and computationally intensive. To address these challenges, data-driven methods have gained traction as efficient alternatives. This review discusses the application of data-driven models in the design and optimization of electromagnetic devices, summarizes the statistical models such as Response Surface Methodology (RSM), and recent popular machine learning (ML) methods in handling multiple variables, as well as the deep learning (DL) models, in predicting various electromagnetic device parameters and optimizing electromagnetic models. This paper highlights the latest advances in DL models for electromagnetic device applications, including motors, transformers, and electrical wires. It discusses their potential to assist FEA to accelerate design and optimization. Future key directions are proposed to improve efficiency and expand the versatility of data-driven models.

INDEX TERMS **Data-driven models, deep learning, electromagnetic device, machine learning, optimization, surrogate model.**

I. INTRODUCTION

Electromagnetic devices have been widely applied in various fields, including biomedical instruments, industrial equipment and systems, as well as household appliances. Examples include artificial hearts, electric vehicles, wireless power transfer systems for electric vehicle battery charging, and household appliances such as air conditioners. These applications impose higher design requirements on devices, such as high efficiency, high power density, and high resource utilization. Consequently, the design and optimization of electromagnetic devices have become an essential part of the industry. Broadly, optimization methods for electromagnetic devices can be classified into multiple categories, such as multi-objective, multi-level, and multidisciplinary design optimization methods [1]-[7]. Although these methods have proven effective in improving the performance of electromagnetic devices, increasing optimization efficiency remains a significant challenge in many design scenarios as the number of design parameters and the complexity of analysis models grow. Multiphysics analysis and high-dimensional parameter optimization are critical aspects of multidisciplinary design optimization. For instance, in the machines and drive systems of electric vehicles, the computational cost of magnetic field prediction and average torque calculations for electric motors is extremely high. Some studies have demonstrated that the optimization of high-speed permanent magnet motors involves numerous design parameters across multiple objectives, along with Multiphysics analyses, including electromagnetic, thermal, and rotor dynamics analyses [8],[9]. Therefore, reducing computational costs and improving optimization efficiency have become core goals in the design optimization of electromagnetic devices. In addition, the diversity of material properties during the manufacturing process of electromagnetic devices can significantly impact their actual performance. To ensure the stability of optimization results, Genetic algorithms (GA) based on reliability and robustness have gained increasing attention in recent years, such as Particle Swarm Optimization (PSO) [10] and Space Mapping Optimization (SMO). Currently, most traditional electromagnetic device design and optimization rely on finite element analysis (FEA). While FEA provides high precision, its computational cost is extremely high, especially when dealing with high-dimensional parameter spaces and Multiphysics analyses. This underscores the need for innovative and efficient optimization methods.

As a result, the introduction of machine learning and deep learning offers a new direction for addressing these challenges. These methods have the potential to handle the complexity of electromagnetic device design in modern applications. This paper reviews the latest advances in the design optimization of electromagnetic devices, focusing on optimization algorithms and the application of machine learning and deep learning in this field. Compared to existing reviews, the contributions of this paper are as follows: First, this review covers a wide range of electromagnetic devices, not limited to electric machines. Second, it not only examines the applications of machine learning in electromagnetic devices but also provides an in-depth analysis of the principles and application scenarios of various models. Third, in addition to summarizing recent developments, this paper highlights the potential future trends of deep learning in the development of electromagnetic devices.

The goal of electromagnetic equipment design is to meet performance requirements while minimizing costs. The design process involves multi-objective analysis of factors such as the model structure, topology, dimensions, and materials. Traditional motor design optimization processes typically involve several steps:

1) Requirements analysis and preliminary design: Determine the application scenario and performance requirements of the electromagnetic device (e.g., power, torque, efficiency, etc.). Select device type (e.g. synchronous motor, induction motor, brushless DC motor) Determine preliminary geometric parameters based on theoretical calculations.
2) Geometric Modelling: Use CAD tools to construct the 2D or 3D geometric model of the electromagnetic equipment. Define the layout and dimensions of the various components and their spatial relationships.
3) Material selection: Select appropriate materials for different components based on their electromagnetic properties, mechanical strength, thermal characteristics, and cost considerations. Define material properties including permeability, conductivity, and loss characteristics.
4) Physical parameters setup: Input key parameters (e.g. material properties, boundary conditions, electromagnetic loss model, etc.) into the FEA software to determine motor operating conditions (e.g. current density, operating temperature and speed range).
5) Electromagnetic simulation: Perform electromagnetic simulation for analysing motor performance (e.g. magnetic flux density, torque), optimize motor design parameters to improve motor performance (e.g. Reduce vibration, maximise torque)

This paper aims to review the applications of deep learning in the design and optimization of electromagnetic devices, with a focus on extending its benefits to electric machine design. figure 1 covered several types of electromagnetic devices including electric motors, transformers, antennas, and electromagnets, electric generators and wireless power transfer.

By examining the successes of deep learning in broader electromagnetic applications, we highlight its potential to revolutionize the field of electric machine design. Additionally, the paper explores the shared methodologies and challenges in both domains, proposing a unified framework for leveraging artificial intelligence in optimizing electromagnetic systems.

The remainder of this paper is organized as follows: Section II reviews traditional design optimization methods for electromagnetic devices. Section III discusses data-driven models for electromagnetic device design and optimization, including gradient-based methods and intelligent optimization algorithms. Section IV explores future scopes of data-driven models for electromagnetic device analysis Finally; Section V concludes with a discussion of future research directions and potential breakthroughs in the field.

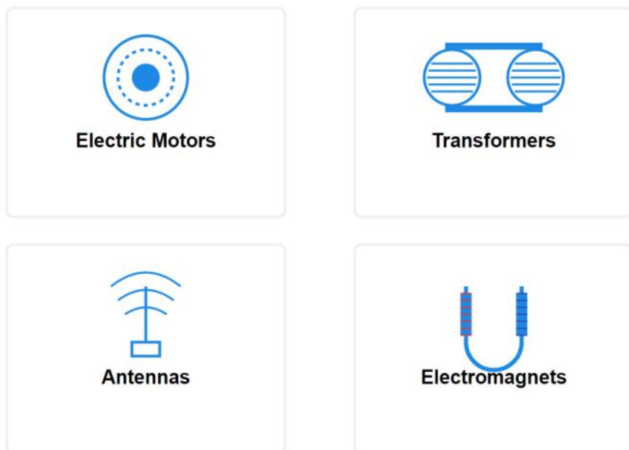


FIGURE 1. Fundamental Electromagnetic Devices in Engineering

II. TRADITIONAL APPROACHES FOR ELECTROMAGNETIC DEVICE ANALYSIS

The main objective of the design stage is to provide multiple feasible solutions for specific application requirements, including exploring various dimensions, materials, motor types, and topologies. It involves a multidisciplinary analysis of the machine's electromagnetic performance, thermal management, structure, and design experience. The outcomes of this stage, such as motor parameter estimation and performance evaluation, serve as inputs for the optimization model in the next stage.

Finite Element Analysis (FEA) has become an indispensable tool in the design and optimization of electric motors. By providing precise computational models, FEA enables engineers to evaluate and enhance the performance of electric motors under different operating conditions, which is critical for the applications of modern electric vehicle (EV)

This section provides a literature review of FEA applications in motor design, covering its role, benefits, and challenges.

A. Role of FEA in Electromagnetic Applications

Finite Element Analysis (FEA) is one of the most widely used techniques in electromagnetic devices design, providing precise simulations to enhance machine performance and reliability. In the electromagnetic domain, such as transformers, electric motors, and antennas. FEA is employed to optimize parameters such as torque ripple and magnetic flux density. For example, modified particle swarm optimization (MPSO) combined with mesh adaptive direct search (MADS) has been applied to improve Permanent Magnet Synchronous Motors (PMSMs) for electric vehicles (EVs) [11]. Additionally, FEA enables multi-objective optimization, balancing efficiency, cost, and thermal performance. This is evident in designs that compare various rotor topologies to achieve higher efficiency and enhanced anti-demagnetization capabilities [12] Furthermore, beyond electromagnetic simulations, FEA extends to mechanical and acoustic analyses. It has been used to predict natural frequencies, surface vibrations, and acoustic noise in high-speed Switched Reluctance Machines (SRMs), providing effective solutions for reducing operational noise without the need for expensive prototyping.[13] Thus, the versatility of FEA establishes it as a cornerstone in modern electric machine design.

Overall, FEA excels in optimizing electromagnetic devices performance, handling complex geometries, nonlinear material properties, and multi-physics simulations. However, despite its numerous advantages, FEA has notable limitations. The comprehensive and precise nature of FEA often results in high computational costs and extended simulation times, particularly for three-dimensional models and coupled multi-physics analyses. These factors underscore the trade-offs associated with its application.

B. Analytical Modelling (AM) for Electromagnetic Devices

Analytical modelling (AM) is also an effective method for predicting machine performance. Generally, AM can be used for the calculation of electromotive force [14],[15], inductances (self and mutual) [16], forces and torques [17],[18],[19], and electromagnetic losses [20],[21],[22]. It calculates important global quantities such as electromagnetic fields, inductance, cogging torque, load torque, and electromagnetic losses to assess machine performance. These parameters form the foundation for machine design optimization and dynamic modelling. Additionally, AM can be coupled with circuit equations to study the behaviour of permanent magnet machines when connected to power converters, enabling the determination of optimization strategies [13],[23]. A substantial body of research shows that in design optimization, the magnetic field plays a crucial role as it reflects key parameters such as speed, efficiency, and torque of the machine. As a result, in most design optimization processes, especially for permanent magnet machines, authors have used analytical magnetic field solutions. Wang et al. used analytical methods to optimize the force capability of a slotless tubular linear permanent magnet structure [24]. Similarly, Zhaoji used analytical field solutions to optimize both the machine and power converter, finding that the power factor significantly affects system efficiency and cost. Chebak et al. also employed analytical modelling to optimize a high-speed slotless permanent magnet synchronous generator, with reduced convergence time in their design approach. They also considered FEA sufficient to validate the analytical modelling approach. Wang et al. used analytical modelling to optimize the design of a linear drive based on a tubular permanent magnet generator, as well as for the design optimization of a tubular linear machine equipped with Halbach magnetized magnets, with experimental verification in both cases [24],[25]. Overall, while analytical modelling offers significant advantages, such as faster convergence and the ability to easily explore design parameters, its limitations should not be overlooked. AM relies on simplified assumptions, making it challenging to capture the complexities of real machine operation, such as nonlinear materials. Therefore, FEA remains essential for validating these models.

C. Equivalent Circuit Method (ECM) in Electromagnetic Devices

Equivalent Circuit Model (ECM) play a pivotal role in electric machine design by addressing the structural, thermal, and dynamic aspects of electric machine operation. While electromagnetic performance often takes precedence, mechanical considerations are essential for ensuring the electric machine's reliability, manufacturability, and overall efficiency. The analysis of the Equivalent Circuit Model (ECM) enables the efficient calculation of electric device performance, including relationships between currents and voltages, input and output power, efficiency, and power factor. Traditionally, core loss components are omitted from the ECM, which can compromise computational accuracy and limit its applicability in the design and control of modern high-performance PMSMs. Furthermore, both conventional vector control and the increasingly popular model predictive control of PMSMs rely on the ECM to formulate control strategies. Ignoring core losses in these models can lead to analyses that deviate significantly from real-world operating conditions. In contrast, incorporating core loss predictions into the ECM addresses these challenges, offering more reliable solutions and gaining increasing attention in the field. [26]

To achieve efficient design optimization and precise system-level performance control of electromagnetic devices [26]-[38], there is a growing need for mathematical models that can deliver fast computation without compromising accuracy. Equivalent circuit models (ECMs) are commonly used for such purposes. However, traditional ECMs developed for permanent magnet motors (PMMs) often neglect core loss, which can lead to inaccurate results and suboptimal motor design or operational performance. Therefore, enhanced ECMs that incorporate core loss are essential for effective motor and drive system optimization and control [39], [40].

D. Modified Flux Harmonic Analysis (MFHA) for Field Computation

Magnetic Field Harmonic Analysis (MFHA) is a fundamental method in electromagnetic devices design that evaluates electromagnetic devices performance by analyzing the harmonics of the air-gap magnetic field. Its core principle lies in the application of Fourier series to decompose complex air-gap magnetic fields into harmonic components:

$$B(\theta, t) = B_0 + \sum[\, B_n \cos(n\omega t \pm n\theta + \phi_n)] \quad (1)$$

Where:

- $B(\theta, t)$: Represents the magnetic flux density as a function of spatial position (θ) and time (t).
- B_0: The DC component or the mean value of the magnetic field.
- B_n : The amplitude of the n-th harmonic component.
- n: The harmonic order, which is an integer (1, 2, 3, ...).
- ω: The angular frequency of the fundamental harmonic.
- θ: The angular position around the motor's air gap.
- ϕ_n: The phase angle of the n-th harmonic, indicating its spatial offset.

This method is widely used to predict key electric machine characteristics such as torque ripple, core losses, and electromagnetic noise. It also enables optimization through techniques like winding configuration adjustments and magnetic circuit design. Compared to finite element analysis (FEA), MFHA offers computational efficiency while maintaining acceptable accuracy.

Xu et al. applied harmonic analysis to a magnetic levitation planar motor (MLPM) and established an analytical model for odd harmonics. They measured the actual magnetic field using a Tesla meter and compared it to simulated results. Their study revealed that increasing the odd harmonic order improved the correlation between simulation and measurement, reducing the relative error to 27.639×10^{-4} Tesla when the harmonic order reached 9. This result highlights MFHA's utility in the design of high-precision closed-loop control systems for advanced manufacturing equipment. [41]

Marinova et al. extended the application of MFHA to coaxial magnetic gears, focusing on dynamic torque transmission and magnetic flux density spectra. Using Fast Fourier Transform (FFT), they analysed the harmonic spectrum to minimize torque ripples and optimize gear design. Their study demonstrated how MFHA contributes to improving performance and reducing mechanical vibrations, showcasing its potential in various electromagnetic systems. [42]

Despite its advantages, MFHA has limitations. It struggles with accuracy in highly saturated magnetic circuits and faces challenges when addressing complex geometries or edge effects. To overcome these issues, modern electric machine design often integrates MFHA with other methods such as FEA and equivalent circuit analysis.

Additionally, researchers are exploring the use of artificial intelligence to enhance MFHA’s predictive accuracy while retaining its computational efficiency. These innovations underscore MFHA's role as a vital tool in both traditional and emerging applications of electric machine design, enhanced methods offer a practical means of optimizing electrical machine designs [130-132].

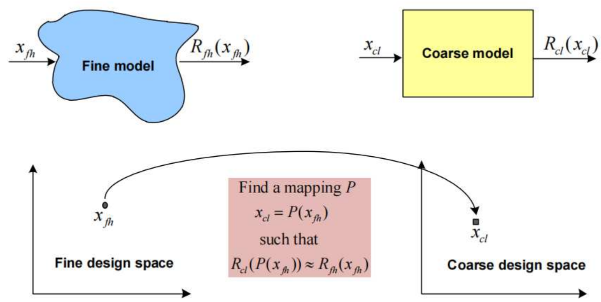


FIGURE 2. Framework of space mapping optimization method [133]

III. DATA-DRIVEN APPROACHES FOR ELECTROMAGNETIC DEVICE ANALYSIS

While proven effective, traditional electric machine design and optimization techniques remain hampered by substantial computational costs, lengthy simulations, and intricate modelling procedures. The rise of artificial intelligence has spurred the widespread adoption of data-driven surrogate models as a superior approach. These AI-powered models directly tackle the shortcomings of conventional methods, such as the accuracy but slow speed of finite element analysis (FEA) for intricate 3D motor designs.

Intelligent computational methods utilize machine learning algorithms to create efficient estimations of the link between design inputs and performance results. This significantly shortens calculation times, quickens the optimization process, and allows for self-learning. Moreover, these techniques, including neural networks, excel at recognizing patterns within data. Trained on existing experimental data, they provide swift predictions of motor performance, eliminating the need for lengthy and resource-intensive finite element calculations.

The design and optimisation of conventional electromagnetic devices still relies on Finite Element Analysis (FEA). However, there are significant limitations of FEA in the analysis of electromagnetic machine design. To address this limitation, researchers have explored data-driven surrogate models that can partially or fully replace the design tasks, accelerating the process while balancing computational cost and accuracy.

A. Framework and Classification of Data-Driven Models

1) Mathematical Formulation Based

Parametric Models: These models, including Response Surface Methodology (RSM) and polynomial regression, employ predetermined mathematical structures with adjustable parameters. They offer computational efficiency but demonstrate less flexibility for complex nonlinear problems.
Semi-parametric Models: Examples include Kriging and Radial Basis Function (RBF) networks, which combine predetermined structures with data-driven components, providing a balance between efficiency and flexibility.
Non-parametric Models: This category encompasses machine learning approaches such as Support Vector Machines (SVM), Random Forests (RF), and neural networks that derive their structure entirely from data, offering maximum flexibility for complex relationships.

2) Target Function Based

Functional Approximation Models: These models establish approximate relationships between optimization objectives and device parameters to efficiently identify optimal solutions. Examples include RSM and Kriging, which require fewer samples but often exhibit limited accuracy with complex, high-dimensional problems.
Performance Prediction Models: Designed to directly predict device performance metrics, these models can substitute for FEA in optimization processes. They require larger training datasets but deliver higher prediction accuracy and better handling of complex, high-dimensional problems. Common methods include SVM, Boosting algorithms, RF, and various neural network architectures.
Field Distribution Models: These specialized models predict complete electromagnetic field distributions rather than isolated performance metrics, enabling detailed analysis of field patterns and local phenomena. Deep learning approaches like Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN) demonstrate effectiveness for this purpose.

3) Learning Paradigm Based

Supervised Learning Models: Trained on paired input-output data, these models learn to map design parameters to performance metrics. Most surrogate models for electromagnetic device design fall into this category.
Unsupervised Learning Models: These focus on discovering patterns and structures within design spaces without labelled outcomes, useful for understanding design variable relationships and dimensional reduction.
Transfer Learning Models: This leverage knowledge gained from one design problem to accelerate learning in related problems, particularly valuable when dealing with limited training data for new device types.
The implementation process for these models typically involves: (1) defining the problem scope and requirements, (2) generating training data through Design of Experiments (DOE) and Finite Element Analysis (FEA), (3) model selection and training, (4) validation and refinement, and (5) integration with optimization algorithms for design exploration. The specific workflow varies according to the model type and application requirements.

B. Model Selection and Challenges

The selection of surrogate models depends on factors such as problem dimension, required accuracy, sample availability, computational resources, and the complexity of optimization objectives. These interrelated criteria significantly influence a model's effectiveness for specific applications. However, surrogate models encounter notable challenges when applied to high-dimensional problems, including the need for extensive training data, increased computational complexity, and potential decreases in prediction accuracy. Machine learning techniques like SVM, boosting algorithms, RF, and ANN are better suited to such tasks due to their ability to handle nonlinear relationships. For more complex applications, such as topology optimization, deep learning methods like Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN) offer further advantages. Emerging models with significant potential include Vision Transformers (ViT), transformer based GAN (TransGAN), which excel at capturing long-range dependencies in electromagnetic field distributions; Graph Neural Networks (GNNs) for handling mesh-based electromagnetic simulations; Physics-Informed Neural Networks (PINNs) that incorporate electromagnetic laws directly into the learning process; and Neural Operators like Fourier Neural Operators (FNO) that can efficiently learn mappings between function spaces for electromagnetic field predictions across different device configurations.

C. Recent Development Trends

Recent advancements in surrogate modelling reflect the increasing complexity of motor design optimization. These include the application of multi-fidelity models that integrate data sources of varying accuracy levels, the development of ensemble methods to enhance predictive performance, and the growing use of deep learning techniques for high dimension problems. Furthermore, transfer learning has

TABLE 1 COMPARISON OF SURROGATE MODELS FOR ELECTROMAGNETIC DEVICE OPTIMIZATION

Model	Mathematical Expression	Form
Response surface model (RSM)	$y = X\beta + \varepsilon$ X: Structure matrix; β: Coefficient matrix	Parametric
Kriging	$y = q(x)'\beta + z(x)$ $q(x)$: Basis function; β:Coefficient matrix; $z(x)$: Stochastic process	Semi-parametric
Artificial neural networks (ANN)	$y_j = f(\sum_{i=1}^{n} w_{ji}x_i - \theta_j)$ w_{ji}: Weighting; θ_j: Neuron's activation threshold; f: Transfer function.	Non-parametric
Support vector machines (SVM)	$y = w \cdot \phi(x) + b$ Φ: A function maps the input space to a higher dimensional feature space; w:Weighting vector; b:Bias term	Non-parametric

emerged as a promising approach to improve model adaptability across different design tasks.

The following sections will delve deeper into the application of statistical models, machine learning, deep learning, and transfer learning in motor design optimization. By analysing the strengths, limitations, and appropriate application scenarios of these methods, this discussion aims to provide practical guidance for surrogate model selection, bridging the gap between theoretical understanding and real-world implementation.

D. Statistical Model for Electromagnetic Device Optimization

1) Response Surface Methodology

Response Surface Methodology (RSM) is an optimisation technique that predicts the optimal point and achieves multi-objective optimisation by constructing a model of the relationship between response values and variables [43] [44]. RSM provides an efficient framework for exploring the effects of multiple factors and their interactions on a desired output. By fitting a response surface to sampled data, it enables researchers to identify local optima and assess sensitivity within a design space.

Compared to global optimisation methods that directly analyse all points, RSM uses a proxy model and a small number of analysis points to significantly reduce computation time [45] [46]. This makes RSM particularly suitable for engineering applications where high-fidelity simulations (e.g., finite element analysis) are costly or time-consuming.

Response surface methodology (RSM) is a combination of mathematical and statistical techniques designed to establish a functional relationship between a target response y and a set of control (or input) variables $x_1, x_{2\ldots} x_{k.}$ Typically, this relationship is unknown but can be approximated by a low-order polynomial model.

$$y = f'(x)\beta + \epsilon \tag{1}$$

Where $f(x)$ is a vector function of p elements that consists of powers and cross-products of powers of $\mathrm{x}_1, \mathrm{x}_{2\ldots}$ up to a certain degree denoted by $d(\geq 1)$. β is a vector of p unknown constant coefficients referred to as parameters, ϵ is a random experimental error.

Two important models are commonly used in RSM, including the first-degree model $d(= 1)$,

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \epsilon \tag{2}$$

And the second-degree model $d(= 2)$

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} {x_i}^2 + \sum_{i<j}^{k} \beta_{ij} x_i x_j + \in \tag{3}$$

Y : response value (objective function).
β_0: the intercept term.
β_i : the coefficients of the first-order linear term.
β_{ii}: the coefficient of the quadratic (squared) term
β_{ij}: the coefficient of the interaction term
$x_i x_j$: design variables
k: number of design variables
$\in$: the error term, which indicates the difference between the predicted and actual values of the model.

In design of electromagnetic devices, such as the design optimisation of brushless DC motors (BLDC), the design often faces multi-objective balancing, such as reducing the cogging torque and maintaining the inverse electromotive force (EMF) performance [47],[48]. 3D-structured motors can be optimised in a significantly reduced time by using the RSM in combination with the 2D equivalent method due to the high computational complexity [49],[50].

In motor design optimization using Response Surface

Methodology (RSM), a typical approach involves defining two to four key performance objectives [51],[52] to ensure the accuracy of the resulting response surface. For example, in BLDC motor optimization, cogging torque and back-EMF are frequently chosen as objectives [53],[54]. These objectives are influenced by several design variables, including permanent magnet offset, stator offset, and tooth width [43],[44]. To efficiently identify the most significant variables, a multi-factorial full factorial design (often termed Factorial Design) is utilized in the experimental design phase [55], [56]. This helps to filter out less influential factors. The resulting response surface is then constructed using a Central Composite Design (CCD) to accurately capture the often-non-linear relationships between the chosen variables and the desired performance metrics. This two-stage process – first identifying key variables and then fitting a high-fidelity response surface – leads to efficient and accurate optimization.

Response Surface Methodology (RSM) has been widely adopted for the optimization of various electromagnetic devices. Li [57] employed RSM to optimize the shape of permanent magnet poles to reduce the cogging torque in brushless DC motors. Cogging torque is a key contributor to vibration and acoustic noise in electric motors and represents a form of energy loss. Minimizing cogging torque can therefore enhance the overall efficiency of the motor. Their study demonstrated that geometric optimization via RSM led to a reduction of more than 40% in cogging torque, highlighting the capability of RSM to effectively handle specific optimization objectives with minimal computational demand.

For more complex electromagnetic topologies, Jo [58] integrated RSM with two-dimensional equivalent modeling to optimize a three-dimensional brushless DC motor. Traditional 3D modeling approaches in electromagnetic design are computationally intensive. However, by establishing a correlation between 2D and 3D models through RSM, the computational time was reduced by approximately 85%, while the predictive accuracy remained within a 5% deviation from finite element analysis (FEA) results. This indicates that RSM-based surrogate models are well-suited for managing the complexity of advanced electromagnetic structures.

RSM has also demonstrated strong potential in multi-objective optimization scenarios. Park et al. [59] applied RSM to the design of concentrated-winding synchronous reluctance motors. Their method successfully balanced two competing objectives: minimizing torque ripple and maximizing average torque, thereby showcasing the strength of RSM in handling trade-offs among multiple performance indices. Similarly, Si et al. [60] combined RSM with the Taguchi method to concurrently optimize surface-mounted and interior permanent magnet machines. Their approach efficiently managed multiple design objectives within a constrained parameter space.

2) Kriging Method

While RSM employs polynomial models, Kriging provides an alternative statistical approach based on Gaussian process regression. This method offers superior flexibility in modelling complex, nonlinear electromagnetic phenomena by incorporating spatial correlation between sample points. Hawe and Sykulski [61] demonstrated Kriging's effectiveness in electromagnetic device optimization, highlighting its ability to estimate prediction uncertainty alongside expected values. This unique feature enables adaptive sampling strategies that concentrate computational resources in regions of high uncertainty or interest, significantly enhancing optimization efficiency. Their research showed performance improvements of up to 30% with only half the computational budget compared to traditional methods.

For transformer design challenges, Amoiralis et al. [62] implemented Kriging models to predict transformer losses under various operating conditions. Their approach captured the complex interactions between geometric parameters, material properties, and electromagnetic losses with higher fidelity than polynomial models, particularly in regions with steep performance gradients. The resulting surrogate model facilitated comprehensive design exploration while reducing simulation requirements by approximately 70%.

An innovative extension of Kriging was proposed by Gong et al. [8], who integrated Kriging with space mapping techniques to create a hybrid optimization framework for electromagnetic devices. Their Kriging Output Space

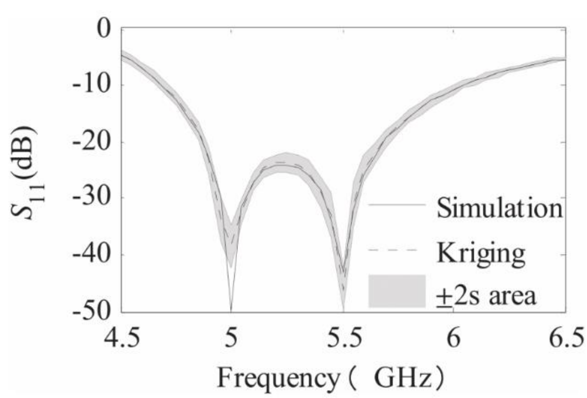


FIGURE 3. The simulated and predicted S11 curves of the optimal design [140]

TABLE 2 APPLICATIONS OF STATISTICAL MODELS IN ELECTROMAGNETIC DEVICES

Reference	Method	Type of Device	Optimized Variable
[43]	RSM	General Electric Motor	Cogging Torque
[44]	RSM	Synchronous Reluctance Motor	Torque ripple, back EMF
[47]	RSM	Interior Permanent Magnet Motor	Rotor rib shape
[47]	RSM	Permanent Magnet Motor	Magnetic pole shape for cogging torque reduction
[48]	RSM	BLDC Motor	Cogging torque reduction
[49]	RSM	BLDC Motor with Magnet Overhang	Cogging torque, back EMF
[51]	RSM	Surface-Mounted and Interior PM Motors	Multi-objective optimization
[134]	RSM	Outer-Rotor BLDC Motor	Magnetic pole torque ripple
[135]	RSM	Spoke-type Permanent Magnet Generator	Overhang coefficient
[57]	RSM	Brushless DC Motors	Permanent magnet pole shape
[59]	RSM	Concentrated-winding Synchronous Reluctance Motors	Torque ripple, average torque
[58]	RSM	3D Brushless DC Motor	3D structure parameters
[60]	RSM	Surface-Mounted and Interior PM Motors	Multiple performance parameters
[61]	Kriging	Electromagnetic Devices	Performance prediction with uncertainty estimation
[62]	Kriging	Transformer	Transformer losses under various conditions
[8]	Kriging	Electromagnetic Devices	Optimization framework combining models of different fidelity

Mapping methodology leveraged coarse models for broad exploration and fine models for accuracy, with Kriging serving as the bridge between these different fidelity levels. This approach proved particularly effective for models with computationally intensive physics, achieving convergence up to three times faster than conventional optimization methods.

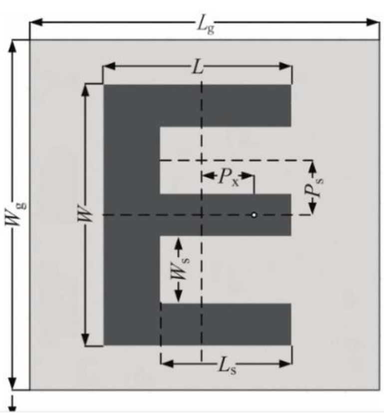


FIGURE 4. E-shaped patch antenna [140]

The Kriging model has also been applied to antenna design and optimization. Chen et al. developed a method that combines Differential Evolution (DE) with the Kriging algorithm to design an E-shaped antenna. As shown in figure 3, six design parameters were optimized: the feed position (Px), slot position (Ps), patch width (W), slot width (Ws), patch length (L), and slot length (Ls). After five runs of the algorithm, the optimal solution was found, as illustrated in figure 4, the predicted parameters closely matched those obtained through simulation. [140]

Table 2 summarizes the application of statistical models in design of electromagnetic devices, including RSM and Kriging models

E. Machine Learning Models

When dealing with high-dimensional problems, data-driven agent models are often used to consider practical applications while ensuring accuracy. Traditional functional approximation such as Response Surface Method (RSM) and Kriging models are often difficult to meet the demands of multi-objective and high-dimensional nonlinear problems in complex motor optimisation tasks.

To solve this problem, in recent years, machine learning (ML) methods such as Support Vector Machines (SVM), Random Forest (RF), and Neural Networks (NN) have been gradually applied to the field of electric motor optimisation, which show stronger feasibility and adaptability. Compared to functional models such as RSM and kriging method, machine learning is more adept at constructing high-precision mapping relations for complex systems, especially in dealing with multi-objective optimisation and complex variables.

Machine Learning (ML) is a crucial component in the field of artificial intelligence, enabling computers to learn and make predictions without explicit programming. ML is closely related to the field of statistical learning, which focuses on directly learning models from provided datasets. These models can capture relationships within data and demonstrate strong generalization capabilities after training.

Over the past decade, ML methods have been widely applied across science, technology, and engineering. ML shares many similarities with computational paradigms such as computational intelligence and data mining. These paradigms involve various techniques and methods to address complex problems in a natural manner. Neural computation, fuzzy logic, bio-inspired and nature-

inspired computing, quantum computing, and general kernel methods—particularly Support Vector Machines (SVM)—are examples of learning paradigms within ML.

In many cases, combining these techniques with each other or integrating them with classical algorithms can lead to new, powerful approaches capable of solving problems with specific characteristics or complexities. As a computational paradigm, the emergence of ML has driven increasing interest and research in related methodologies. In recent years, numerous review and tutorial papers on these methodologies have been published, further advancing the application and development of ML across various fields.

The application of machine learning in motor design continues to expand, not only to effectively deal with complex nonlinear problems, but also to achieve more accurate performance prediction and optimisation under high-dimensional variables, which gradually promotes the enhancement of motor performance and the improvement of design efficiency. [63]

Overall, there is more research carried out on machine learning for improving the runtime of the optimization of electromagnetic devices, as was also shown in Table 3. Different machine learning algorithms, such as SVM, multi-layer perceptron (MLP), Knearest neighbour (KNN), and CNN have been investigated to optimize transformers, antennas, and motors (motors are the majority applications) [64]-[75]. It is noted that deep learning follows promising results when applied for topology optimization of electromagnetic devices, and this topic has attracted much attention recently [75]-[77]. The presented studies confirmed that good optimization results can be obtained by using different machine learning models for optimization.

1) Kernel-Based Methods

a) Support Vector Machines

The formulation of the standard SVM is defined as a maximum margin classifier. As shown in figure 5, the decision function of the classifier is a hyperplane that maximises the separation of different classes of samples, given a labelled training dataset $\{x_i, y_i\}_{i=1}^{n}$, where $x_i \in \mathbb{R}^N$ and $y_i \in \{-1, +1\}$, the SVM method solves the following:

$$\min_{w,\xi_i} \{\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i\} \tag{4}$$

Constrained to:

$$y_i\left(\langle\phi(xi)\rangle, w + b\right) \geq 1 - \xi i \qquad \forall i = 1, \ldots n \tag{5}$$

$$\xi_i \geq 0 \qquad \forall i = 1, \ldots n \tag{6}$$

In this formulation, w and b define a linear classifier in $\mathbb{R}^N$, the input vector xi reside in $\mathbb{R}^N$. ξ_i is slack variable, allow the model to handle classification errors within permissible limits.

The objective function being minimized consists of two distinct components, the total error: $\sum_{i=1}^{n}\xi_i$, and the squared norm of the weight vector $\|w\|^2$. Minimizing $\|w\|^2$ aligns maximizing the margin, that represents the separation between classes. By including the slack variables ξ_i one relaxes the problem, and the solution is called the soft-margin SVM, which minimizes the training error traded off against the margin.

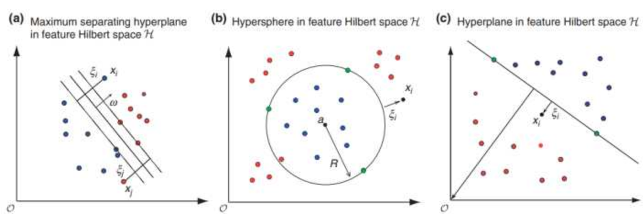


FIGURE 5. (a) Support vector machine (SVM): Linear decision hyperplanes in a nonlinearly transformed, feature space, where slack variables ξ_i are included to deal with errors. (b) Support vector domain description (SVDD): The hypersphere containing the target data is described by radius R.(c) One class-support vector machine (OC-SVM): another way of solving the data description problem [138]

In recent years, least square support vector machine (LSSVM) technique has been adopted for modelling electromagnetic characteristics of SRM. The electromagnetic characteristics model was built based on

LSSVM by employing torque-angle-inductance characteristics. [68]. The flux linkage model and torque model of SRM were constructed based on LSSVM as well. Both methods were proved to be accurate by mathematical verification and experimental tests. [69]
However, the cascade of single-output LSSVM results in accumulation of errors. Moreover, the traditional radial basis function (RBF) kernel functions have poor generalization ability compared with other kernel functions. In this paper, a multi-output LSSVM is proposed to reduce the cascade error, and the kernel function is improved by the combination of modified RBF kernel function and poly kernel function [70]. This shows that while LSSVM has shown promise in SRM modelling, previous implementations had limitations in error accumulation and generalization capabilities that needed to be addressed through multi-output structures and improved kernel functions.

b) Relevance Vector Machines

The Relevance Vector Machine (RVM) is a Bayesian alternative to the Support Vector Machine (SVM), capable of providing probabilistic predictions while yielding significantly sparser models. Unlike SVM, RVM imposes a prior over the model weights governed by hyperparameters, which are estimated through the maximization of marginal likelihood (also known as evidence) [79]. As a result, the final RVM model retains only a small subset of basis functions associated with non-zero weights—referred to as relevance vectors.

In the design and optimization of electromagnetic devices, RVM has demonstrated notable advantages in performance prediction. Wong et al. [80] employed RVM to estimate the magnetic flux density distribution in permanent magnet machines. Their results showed that the prediction time was reduced by approximately 80% compared to finite element analysis (FEA), while maintaining high consistency with FEA results.
RVM has also proven effective in fault diagnosis applications. In the context of power transformer diagnostics, Huang and Chen [81] developed a customized-kernel RVM model based on dissolved gas analysis to detect incipient faults. Their findings indicated that RVM outperformed SVM in both diagnostic accuracy and computational efficiency. This performance gain can be attributed to the Bayesian framework of RVM, which inherently mitigates overfitting without the need for explicit regularization parameter tuning.

The probabilistic nature of RVM further enables uncertainty quantification in electromagnetic performance prediction. Zhao et al. [82] leveraged this feature to devise an optimization strategy for switched reluctance motors, where the predicted confidence intervals guided exploration within the design space. Their study revealed that incorporating uncertainty into the optimization process led to more robust and reliable outcomes compared to deterministic methods.

Despite its benefits, the practical application of RVM in electromagnetic design remains challenged by computational demands in large-scale problems. Recent algorithmic enhancements—such as fast marginal likelihood optimization and incremental training schemes—have partially addressed these limitations, improving the feasibility of RVM for complex electromagnetic modeling tasks [833].

2) Tree-Based Ensemble Methods

a) Random Forest

Random Forest is an Ensemble Learning algorithm that generates final predictions by constructing multiple decision trees and combining their results. It performs well in classification and regression tasks and has strong generalisation capabilities when dealing with high-dimensional data and complex relationships. The core feature of Random Forest is the introduction of randomness to reduce variance and reduce overfitting. Random forests typically have lower Bias and higher Variance than a single decision tree, allowing them to significantly benefit from integrating the results of individual trees by averaging or voting.

During training, each tree is constructed using a random subset of the training set and a randomly selected subset from the features at each node split. This random perturbation effectively increases the robustness of the model while reducing the correlation between different trees, which in turn improves the stability and generalisation of the overall model.

To deeply understand the performance of Random Forest and its working mechanism, key formulas and concepts such as Margin Function, Generalisation Error, Classifier Strength and Correlation need to be introduced. These theories reveal how Random Forests control model error through the accuracy of individual trees and the independence between trees and explain how Random Forests remain stable when the number of trees increases. [70], [72].

(i) Margin Function

The margin function measures how confident the classifier is in the correct category:

$$mg(X,Y) = av_k I(h_x(X) = Y) - \max_{j \neq Y} av_k I(h_k(X) = j). \tag{7}$$

Where $I(.)$ is the indicator function, measures whether the prediction is correct, $h_x(X)$ is the classification result of the kth tree on the input X.

(ii) Generalization Error

$$PE^* = P_{X,Y}(mg(X,Y) < 0). \tag{8}$$

This formula indicates that in the probability that the marginal function is less than 0, i.e., the probability of misclassification, under the joint probability distribution of X, Y.

(iii) Convergence Theorem

When the number of trees in the forest increases infinitely, for almost surely all sequences Θ_1 ... , the generalisation error of the random forest converges to the following equation:

$$P_{X,Y}(P_\Theta(\mathrm{h}\ (\mathrm{X}, \Theta) = Y) - \max_{j \neq Y} P_\Theta(h(X,\Theta) = j) < 0) \tag{9}$$

This shows that random forests do not suffer from overfitting problems as the number of trees increases.

(iv) Upper Bound on Generalization Error

The upper bound on the generalisation error for random forests is given by:

$$PE^* \leq \frac{\overline{\rho}(1 - s^2)}{s^2} \tag{10}$$

Where s is the strength of the set of classifiers, $\overline{\rho}$ is the average correlation between trees. This formula shows that increasing the accuracy of individual trees and decreasing the correlation between trees reduces the generalization error.

(v) Strength and Correlation

The strength of the classifier is defined by:

$$s = E_{X,Y}(mr(X,Y)) \tag{11}$$

And the variance of the original marginal function can be expressed as:

$$var(mr) = E_{\Theta,\Theta'}(cov_{X,Y}(rmg(\Theta,X,Y)rmg(\Theta',X,Y)))$$

This equation indicates how to reduce the error by reducing the correlation between the trees. [76]

Random Forest, as a powerful machine learning algorithm, has a wide range of applications in the field of motor design. It can help engineers make better design decisions by analysing the complex relationship between multiple design parameters (e.g. stator outer diameter, number of slots, number of poles, air gap length, etc.) and performance metrics (e.g. efficiency, temperature rise, loss) of the motor. Due to its good nonlinear feature processing capability and anti-noise performance, it is particularly suitable for dealing with parameter optimisation, performance prediction and fault diagnosis in motor design. By constructing a forest model consisting of multiple decision trees, it can not only predict the performance of the design scheme, but also evaluate the importance of each design parameter, thus providing powerful data support for the optimal design of the motor.

b) Gradient Boosting Models

Gradient Boosted Decision Tree (GBDT) is an efficient, accurate machine learning algorithm. GBDT has achieved efficient performance in many machine learning tasks, such as multi-class classification [72], click prediction [73] and learning to rank [74]. However, with the emergence of big data in recent years, GBDT faces the challenge of balancing accuracy and efficiency. Traditional GBDT needs to scan all data instances for each feature to estimate the information gain of all possible segmentation points. As a result, the computational complexity of GBDT is proportional to the number of features, which makes it very time-consuming and inefficient when dealing with big data.

To solve the problem of GBDT, reducing the number of data instances and features is necessary. There are some studies on sampling data based on weights to speed up training [75],[76],[77]. However, this approach is not feasible for GBDT because there are no sampling weights in GBDT at all. Ke et al. (2017) combined Exclusive Feature Bundling (EFB) and Gradient-based Single-Sided Sampling (GOSS), and the authors found that the instances with larger gradients (under-trained) contribute more to the information gain. To maintain the accuracy of the information gain estimation, instances with smaller gradients can be randomly discarded to focus with instances with larger gradients. Also, the authors reduce the optimal bundling problem to a graph colouring problem (using features as vertices and adding edges to two features if they are not mutually exclusive). This new GBDT algorithm that combines GOSS and EFB is called LightGBM, and it can speed up the training process by a factor of 20 while maintaining almost the same accuracy. [71]

3) Conventional Neural Networks

a) Multilayer Perceptron

Multilayer Perceptron (MLP) is a feedforward neural network consists of an input layer, hidden layers, and an output layer. As shown in figure 6, each neuron in MLP uses a nonlinear activation function to learn nonlinear function mappings.

- Input layer: receives feature input from the original data.
- Hidden layer: extracts and transforms features from the input data.

- Output layer: outputs the prediction results or classification labels.

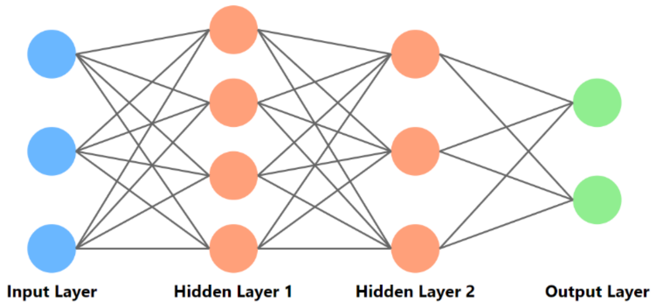


FIGURE 6. Architecture of Multilayer Perceptron Neural Networks

MLP is trained with back propagation algorithm to minimize the error between predicted and target values by adjusting the weights and biases of the network, which plays an important role in the performance prediction of electromagnetic devices, and its mathematical expression is:

$$y_i = f\left(\sum_{i=1}^{n} w_{ji}x_i + b_j\right)$$

- y is the output of the j-th neuron
- f is the activation function
- w_{ji} is the weight connecting the i-th neuron
- x_i is the i-th input
- b_j is the bias of the j-th neuron.

Mahmouditabar et al. [86] used MLP for multi-objective design optimization and sensitivity analysis of flux switched permanent magnet (FSPM) motors. The authors utilized an MLP neural network with one input layer, two hidden layers, and one output layer to investigate the relationship between design variables (internal angle between permanent magnets, rib thickness, and other design geometrical parameters) and performance parameters (torque ripple, average torque). The dataset is generated from finite element analysis and combined with the NSGA-II algorithm to find the most optimal design. This MLP neural network-based optimization algorithm significantly improves the electromagnetic torque while keeping the torque ripple of the motor low.

You [87] also applied MLP to the multi-objective optimal design of electric motors, but for the optimal design of permanent magnet synchronous motors (PMSMs) for electric vehicles. The authors used an MLP that includes hyperparameters such as automatic selection of the number of hidden layers, neurons, and activation functions to maximize the predicted performance parameters of the motor. The MLP in the article uses seven hidden layers with 2-5 neurons per layer and a hyperbolic tangent activation function, while the THD prediction model uses one hidden layer with three neurons per layer and a sigmoid activation function. The MLP-based optimization model significantly improves the average torque of the permanent magnet synchronous motor (PMSM) by 2.2% compared to the conventional Kriging models. However, the conventional Kriging models only improved by 1.3%, showing excellent predictive performance. The method also demonstrates superb computational efficiency, with the model convergence time reduced from 27 seconds to 22 seconds.

b) Back-Propagation Neural Network

Back-Propagation Neural Network is a training method for multilayer perception. It adjusts network weights through the backpropagation algorithm to minimize output errors. figure 7 illustrates the principle of BP neural networks. The weight update process follows:

$$w_{ij}^{new} = w_{ij}^{old} - \eta \frac{\partial E}{\partial w_{ij}}$$

w_{ij} is the weigh connecting neuron i and j
η is the learning rate
$\frac{\partial E}{\partial w_{ij}}$ is the partial derivative of the error with respect to the weight

[87] describes the application of BP neural networks for flux-linkage estimation in permanent magnet synchronous motors (PMSMs). The researchers trained the network to predict complex nonlinear relationships between various motor parameters and the resulting flux linkage. This approach achieved significant computational efficiency compared to conventional FEA methods, enabling more effective control strategy development for PMSMs in applications like electric vehicles.

Qiu et al. [89] developed a BP neural network model for prediction of build-up rate in electromagnetic manufacturing processes. Their approach incorporated genetic algorithms to optimize the network structure and hyperparameters, enhancing prediction accuracy while avoiding local optima issues common in traditional BP training. This hybrid approach demonstrated superior performance compared to conventional numerical methods.

He et al. [90] employed BP neural networks to predict losses in vehicle permanent magnet synchronous motors. Their research captured the complex relationships between motor design parameters, operating conditions, and various loss components. The model enabled more effective thermal management and efficiency optimization during the motor

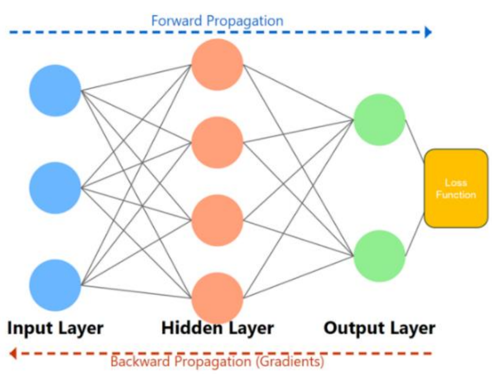


FIGURE 7 Architecture of Back-Propagation (BP) Neural Network

4) Application of Machine Learning in Electromagnetic devices

From the comprehensive analysis presented in Section 2, it becomes evident that machine learning methods have emerged as powerful tools for addressing two fundamental challenges in electromagnetic device optimization. The first challenge lies in the computational burden of accurate Multiphysics analysis, particularly in applications like high-speed PM motor design that require intensive FEA calculations. The second challenge involves developing highly accurate surrogate models capable of capturing the inherent nonlinearity in electromagnetic device performance prediction.

Traditional parametric and semi-parametric models often struggle to accurately capture the complex nonlinear relationships between design parameters and device performance. For instance, conventional polynomial-based approaches like Response Surface Methodology (RSM) may fail to adequately model the relationship between a PM motor's dimensions and its efficiency. Machine learning techniques offer promising solutions to these limitations through their ability to automatically construct analytical models and capture complex nonlinear relationships using various neural network architectures. As a subset of artificial intelligence, machine learning has demonstrated effectiveness in handling multiple input-output relationships without requiring predetermined mathematical structures.

The application of machine learning in electromagnetic device optimization has primarily manifested in two key areas: performance prediction/field distribution estimation and surrogate model development for optimization purposes. Various algorithms have been employed, ranging from artificial neural networks (ANN) and support vector machines (SVM) to more advanced approaches like extreme learning machines (ELM), random forest (RF), and deep learning (DL). Deep learning, implemented through deep neural networks (DNN), represents a particularly sophisticated subset of these methods, offering enhanced capabilities through its multi-layered neuronal architecture.

Table 1 provides a systematic comparison of surrogate models used in electromagnetic device optimization, categorizing them into three main groups based on their parameterization approach:

- Parametric models (including RSM and RBF)
- Semi-parametric models (exemplified by Kriging-based approaches)
- Non-parametric models (encompassing ANN, SVM, and ELM)

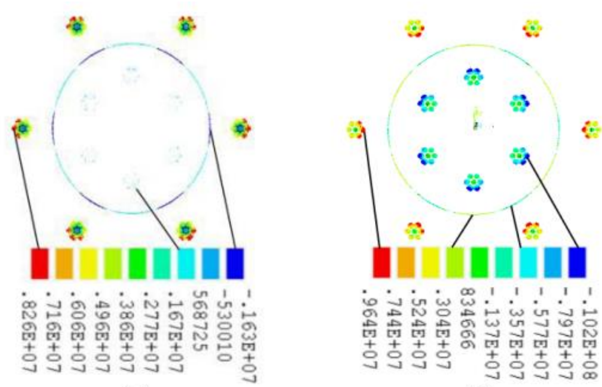
Traditional neural networks exhibit numerous performance peaks, which will not be discussed in detail here. Instead, the focus is placed on their practical applications in electromagnetic devices.

a) Application of ANN in electromagnetic devices

Artificial Neural Networks (ANNs) have been widely applied in transformer fault diagnosis [144][145]. Modeled after the structure of biological neurons, ANNs possess powerful parallel information processing capabilities, strong fault tolerance, and self-learning abilities. Among them, the Backpropagation Neural Network (BPNN) is the most commonly used ANN in diagnostic applications. Numerous studies in the literature have adopted ANN-based approaches to address transformer fault diagnosis problems. One study employed a feedforward variance network with two hidden layers, trained using real-world data from 59 transformers. The results showed that 97% of the test samples were accurately classified into three diagnostic categories [146]. Similar methods have also been utilized in other studies [102], [103].

Li et al. proposed a method that combines artificial neural networks (ANN) with finite element methods (FEM) to simulate and optimize transformer design. They developed an integrated computational design environment for high-frequency coaxial transformers (HFCTs). This system incorporates material and winding structure databases and employs ANN to optimize transformer parameters.

Experimental validation demonstrated that the 8 kW coaxial transformer designed using the ANN-FEM hybrid approach exhibited high accuracy. As shown in the figure 8, an integrated design platform that combines Artificial Neural Networks (ANN) with Finite Element Method (FEM) enables automated modeling, simulation, and optimization of transformer designs. By intelligently recommending materials and winding configurations, the ANN eliminates tedious manual calculations and learns the complex relationships between input and output parameters, offering engineers accurate design guidance. In the 8 kW coaxial transformer case study, the ANN-assisted selection of a 21-strand twisted wire winding configuration achieved high efficiency (>99%), and the FEM simulation results closely matched experimental measurements, with a leakage inductance deviation of only 0.7 μH. [136].



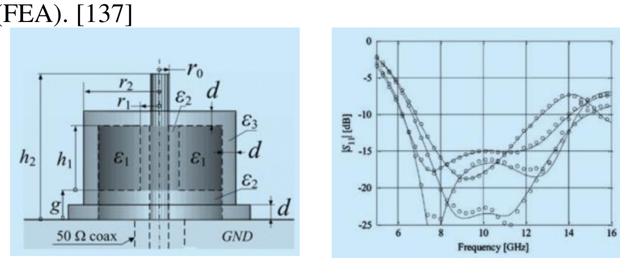
(a) (b)

FIGURE. 8 Eddy-current distribution of the 8 kW HFCT. (a) Open Circuit. (b) Short Circuit. [136]

Wu et al. proposed a Machine Learning Assisted Optimization (MLAO) approach to accelerate the design and optimization processes of electromagnetic devices. MLAO integrates Gaussian Process Regression (GPR), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) to construct surrogate models. It learns the mapping between inputs (design parameters) and outputs (performance metrics) from a limited set of training data, enabling the prediction of the performance of new design points.

In the optimization of UWB monopole and Yagi antennas, the MLAO method demonstrated exceptional computational efficiency. For instance, in the case study involving the optimization of a broadband hybrid dielectric resonator antenna, MLAO built an accurate co-Kriging surrogate model using only 50 high-fidelity evaluations and 400 low-fidelity evaluations.

As shown in figure 9, the prediction error of the surrogate models less than 1.5% compared to the high-fidelity solutions, while the prediction speed was approximately 500 times faster than that of conventional finite element analysis (FEA). [137]



(a) (b)

FIGURE 9. (a) antenna structure (b) responses of fine results (-) and co-Kriging surrogate (o) at selected test points [137]

b) Application of KNN in electromagnetic devices

Cui et al. developed a novel machine learning approach based on a modified K-Nearest Neighbors (KNN) algorithm. This method utilizes Euclidean distance to evaluate proximity and employs a neighbor count of k=5 to balance accuracy and computational efficiency, significantly reducing the amount of required training data.

They applied KNN, along with Artificial Neural Networks (ANN), Gaussian Process Regression (GPR), and Conjugate Gradient (CG) methods, to optimize a frequency-programmable (FP) resonator antenna. As illustrated, the KNN method required only 20 iterations to converge, whereas ANN required 100 iterations, GPR required 94, and CG required 658 iterations.

The KNN algorithm exhibited strong predictive capability across various antenna parameters: the median relative error for the S_{11} parameter was 5.3%, for the real part of impedance Re(Z) was 0.03%, and for the bandwidth (BW) was 1.3%. These results demonstrate that the KNN approach can achieve sufficiently high predictive accuracy even with a limited amount of training data.

Figure 10 illustrates the geometry and parameters of the antenna. The labeled variables, including w1 (feed width), l1 (feed length), sl2 (slot length), and sw2 (slot width), are the key design variables targeted in the optimization process. These parameters collectively determine the antenna's performance characteristics and serve as the objective variables for the optimization algorithm. Figure 11 compares the S11 curves obtained using the improved KNN-based optimization method, the engineer's design, and the original model. Within the operating frequency range of 1.6 to 3 GHz, the antenna designed using the improved KNN method shows a lower S11 value, indicating better impedance matching and higher operational efficiency.

It's worth noting that while RF and DL models demonstrate significant potential, their complex mathematical structure precludes their inclusion in the comparative table. The implementation of these methods has been further enhanced through various network architectures, such as backpropagation and radial basis function networks in ANN, and specialized deep learning variants including CNN, RNN,

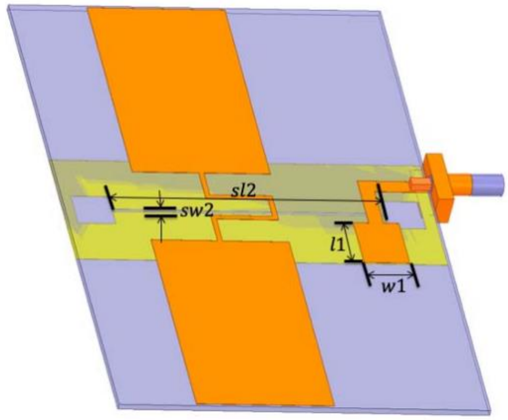


FIGURE 10. Geometry of the dipole element [88]

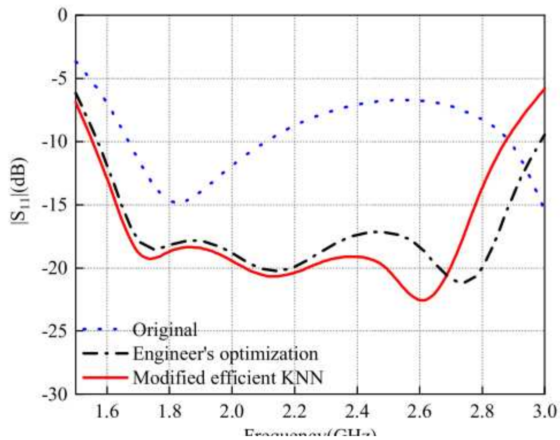


FIGURE 11. Comparison between modified efficient KNN, engineer's optimization, and the original model [88]

and GAN. Table 3 presents selected studies showcasing the application of these various machine learning approaches in electromagnetic device optimization.

F. Deep Learning Models

The above machine learning (ML) models demonstrate the ability to effectively predict motor performance by analysing the inputs to the motor geometry parameters. However, there are several issues with machine learning in predicting the parameters of EM devices:

- Feature engineering dependency: ML requires experts to manually design and select features, which is very difficult for complex systems such as EM devices. The choice of features has a direct impact on model performance.
- Difficult to deal with high-dimensional nonlinear relationships: There are complex nonlinear coupling relationships between the parameters of electromagnetic devices, and traditional machine learning methods (e.g., SVM, Random Forest, etc.) are difficult to fully capture these relationships.
- Generalisation ability: When facing new operating conditions or equipment states, the prediction accuracy tends to drop dramatically.

Therefore, deep learning has emerged as a potential solution. Deep learning typically employs multi-layer artificial neural networks to extract local features from high-dimensional input data, covering a wider range of design degrees of freedom. [91] In the field of motor performance prediction, deep learning

models that have been widely used are classified into two categories: supervised learning and unsupervised learning.

1) Supervised Learning

Due to the popularity of deep learning in recent years, there have been many studies applying supervised deep learning to motor prediction. Deep Learning Networks (DNN), Backpropagation (BP) Neural Networks Convolutional Neural Networks (CNN), Multilayer Perceptrons (MLP) [90]-[92] and Recurrent Neural Networks (RNN).

a) Deep Neural Networks

Deep neural network is a multi-layer artificial neural network capable of extracting features from high-dimensional data. Compared to traditional neural networks, DNNs have more hidden layers to capture more complex nonlinear relationships, which has significant value in the design of electromagnetic devices. Fig. 12 illustrates the architecture of a DNN, which has more hidden layers in addition to the same output layers, hidden layers, and output layers as a traditional neural network. The input layer accepts the design parameters (e.g., material properties, geometric dimensions, etc.), which are then nonlinearly transformed by a nonlinear activation function based on ReLU and other nonlinear activation functions, and ultimately a linear activation function is used in the output layer to generate performance predictions.

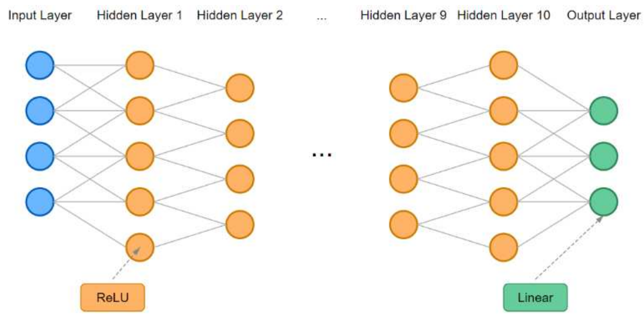


FIGURE 12. Architecture of Deep Neural Networks (DNN)

Based on this unique network structure of DNNs, Poudel and Amiri used DNNs to optimize the design of hybrid permanent magnet motors. The author's DNN model consists of an output layer that is a hidden layer and an output layer. The DNN uses ReLU as the hidden layer activation function and a linear activation function for the output layer. DNN was trained using 10,000 sets of parametric data, 70% as a training set and 30% as a test set to ensure the generalization ability of the model, and the tests showed that DNN was able to accurately predict the performance of the motor for any combination of geometrical parameters. The air gap flux density predicted by DNN was highly consistent with the results of the FEA simulations, with the minimization of the flux harmonic content and the cogging torque as the objective function for the permanent magnet motor. The optimization successfully reduces the total harmonic distortion (THD) from 36.57% to 23.66% while reducing the cogging torque by 58.7%. [92]

The researchers proposed a multi-objective optimization algorithm combining Thompson Sampling Efficient Multi-Objective Optimization (TSEMO) with deep neural networks to determine the optimal design parameters of antennas. figure 13 shows the optimized antenna. A bottom-up optimization (BUO) approach was employed to configure the antenna shape and determine the feeding point. In figure 14, the experimental results demonstrated that the broadband antenna designed using this method achieved a maximum gain of 7.13 dB in the 8.8–10.1 GHz frequency band and 7.8 dB in the 11.3–13.16 GHz frequency band. [141]

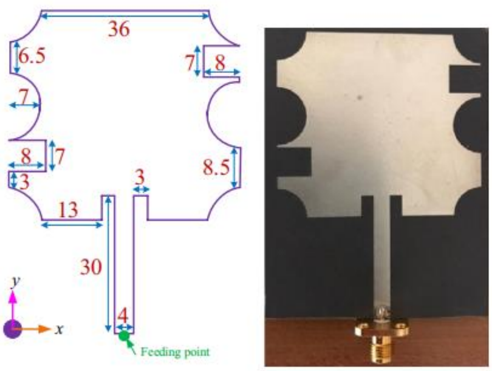


FIGURE 13. Optimized antenna-2 simulated (left) fabricated (right). Unit mm [141]

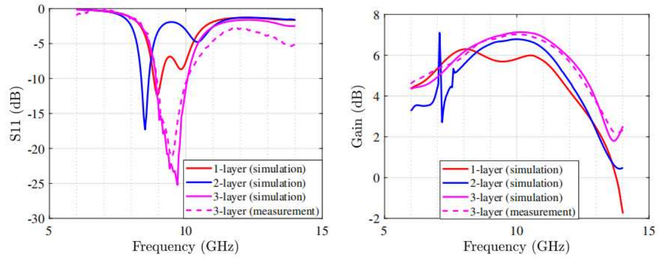


FIGURE 14. S11 parameter of antenna-2 (left); gain of antenna-2 (right).[141]

Jiménez-Navarro proposed a novel deep learning neural network for transformer oil temperature prediction, named Smoothed Residual Convolutional Network (SRCNet). Their approach builds upon a dual-stacked structure and introduces a smoothed residual stacking mechanism, which is combined with residual connections in convolutional layers. SRCNet decomposes the problem into multiple sub-problems, capturing different representations of the time series data. These representations are then integrated to produce the final prediction. The network achieved impressive results on the Electrical Transformer Temperature (ETT) dataset, outperforming state-of-the-art architectures with a 13% improvement in Mean Squared Error (MSE) and a 57% boost in overall performance. [142]

b) Convolutional Neural Networks

Among the supervised deep learning neural networks, CNN is the most widely used deep learning model in various domains such as image segmentation and image classification in computer vision, audio recognition, video processing, and other domains. These supervised deep learning models require the construction of a paired training dataset containing inputs and outputs to define the mapping relationships between the input and output variables, which is more extensive than the number of parameters analysed by machine learning models.

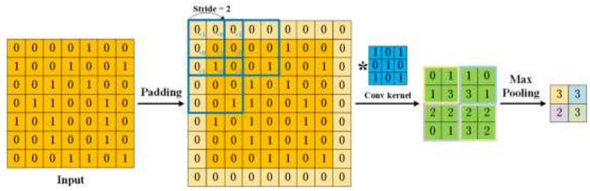


FIGURE. 15. Principle of Convolutional Neural Networks [138]

Supervised learning is a machine learning approach where a model learns to map inputs to outputs using labelled data. As shown in figure 16, it involves training the system with input-output pairs, allowing it to infer a function that predicts outputs for new inputs. During training, the model compares its predictions to the known outputs, adjusts its weights using gradient descent, and minimizes the error between the predicted (S_A, Actual signal) and actual values (S_T, Target signal). For instance, to classify images of birds and cats, the algorithm is trained on labelled examples of these categories. Once trained, the model can predict labels for new, unseen images. [93]

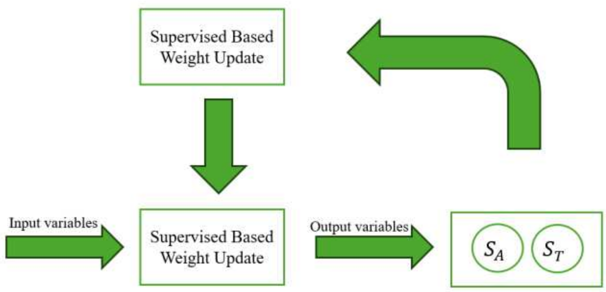


FIGURE 16. Supervised Learning Process

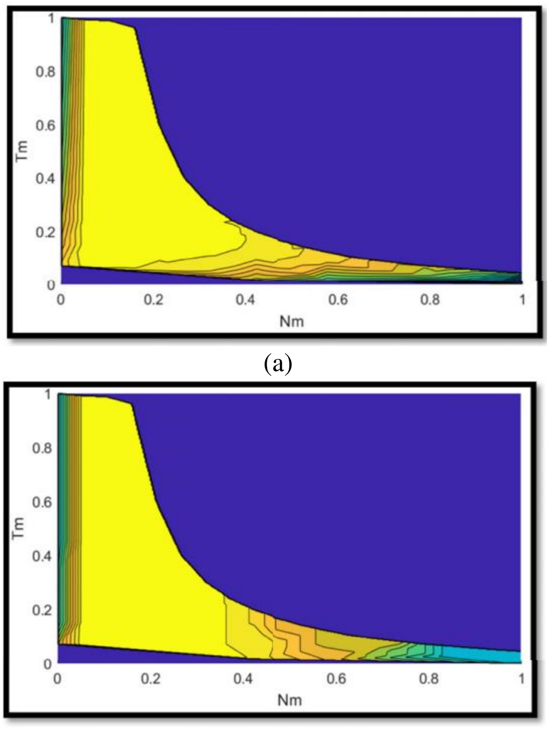
These supervised deep learning models have been widely applied to electromagnetic instruments. For instance, research [92] employed a DNN model with one input layer, one output layer, and 10 hidden layers to predict the airgap magnetic properties of a standard surface-mounted permanent magnet motor (SPM) across 360 mechanical angles. The output results can be optimized for various SPM motor geometric parameters, such as cogging torque and magnetic flux. Similarly, some studies have used BP neural networks to predict motor losses in permanent magnet synchronous motors (PMSM). Other research has utilized MLP models to predict the average torque and back electromotive force (EMF) of PMSMs.

Convolutional Neural Network (CNN) is a deep feedforward neural network particularly suited for extracting features directly from high-dimensional data, thereby providing more comprehensive information for performance prediction. CNN uses convolutional layers to filter input images for detecting specific features and patterns. As illustrated in figure 15, CNN performs convolution operations by sliding filters across images, enabling the network to detect the location of these features. The pooling layers downsample the output of convolutional layers, reducing the dimensionality of feature maps and thus enhancing the network's generalization capability for new inputs [205].

Based on CNN's advantages in automatically extracting target features and discovering complex structures in high-dimensional data, numerous studies have applied CNN to predict electromagnetic device performance. Among them, [100] used a CNN trained on a dataset of 10,000 samples to predict motor torque ripple. However, only 81% of the predictions in the test results had errors less than 0.1, with overall accuracy below 50%. In other similar studies, [107] authors trained a CNN using 6,000 Interior Permanent Magnet (IPM) motor samples, with outputs for seven categories including average torque and torque ripple parameters. The prediction results achieved 92.4% and 81.3% accuracy respectively, indicating that CNN's capability in predicting IPM motor average torque significantly exceeds its ability to predict torque ripple. Similarly, [96] also used IPM motor cross-sectional image datasets for CNN to predict IPMSM performance, reducing computational costs by over 50% in the motor optimization process using the proposed surrogate model. Other researchers tested CNN trained on datasets obtained from finite element analysis software to predict magnetic field distribution in low-frequency electromagnetic devices, with input data, geometric parameters, material parameters, and excitation parameters represented as RGB images. The network structure includes an encoder and decoder, where the encoder extracts spatially correlated features from inputs, and the decoder projects features onto the input space. This neural network structure achieved 97% accuracy. Moreover, through testing different network structures, they found that increasing the number of CNN convolutional layers can significantly improve accuracy, though at the cost of slower training speeds as the number of convolutional layers increases.

Maeurer *et al.* [5] explored the applications of Convolutional Neural Networks (CNNs) in the fields of electromagnetics, antennas, and propagation. CNNs account for approximately 75 % of the research in this area. In antenna-related applications, CNNs have been utilized for both forward scattering problems—where they help accelerate computations—and inverse scattering problems, focusing on parameter inversion. In direction-of-arrival (DoA) estimation, CNNs demonstrate higher prediction accuracy compared to traditional methods like the MUSIC algorithm. Furthermore, in synthetic aperture radar (SAR) image classification, CNNs have enabled highly accurate automatic target recognition.

Torque and efficiency are key parameters for most electromagnetic machines. They are also complex to calculate, requiring multiple finite element solutions, which can be time consuming for some types of machines. Motor Efficiency Map (EMP) is a two-dimensional contour map showing the efficiency distribution of a motor at different operating points, which can help designers to optimise the motor control strategy by assessing the operating efficiency of an electromagnetic device under real operating conditions. However, the cost of finite element simulation is very high, so it takes a lot of time to calculate the efficiency map of a motor. In this case replacing the finite element simulation with neural network can be used to obtain the efficiency map estimation at the early stage of the design in the shortest possible time. The authors of [102] used an internal permanent magnet (IPM) machine to generate a large machine performance dataset to predict flux. The inputs to the neural network were the device geometry, current and advance angle. As shown in figure 17, the authors' prediction results using CNN on a dataset of 3000 images have an error of less than 1.5%. Also, the neural network was 500 times faster than finite element simulations. All the above articles demonstrate the high accuracy and generalisability of CNNs in predicting the performance parameters of electromagnetic devices.



(a)

(b)

FIGURE 17. (a) the efficiency map generated by a FEA system, (b) the neural network prediction of the efficiency map. [102]

c) Recurrent Neural Network

Recurrent Neural Networks (RNNs) are neural networks that specialize in processing continuous data. RNNs could form directed loops of connections, and unlike traditional feed-forward neural networks, RNNs retain a "memory" of previous inputs. This memory capability makes RNNs suitable for tasks involving sequential or time-series data. Figure 18 illustrates the structure of an RNN across time steps. At each time step (t), the network receives an input x(t) and produces an output y(t), while maintaining a hidden state h(t) to capture the current and previous inputs. This hidden state is passed on to the next time step, thus forming a recursive connection that allows the network to "remember" past information.

Kirchgässner predicted the temperature of a permanent magnet synchronous motor using an RNN. The authors solved the problem of vanishing gradients in traditional RNNs with LSTM (Long Short-Term Memory) units. They trained the network using time-series data of motor operation, 80% of which was training data and 20% validation data. The RNN model accurately predicts motor temperatures under various operating conditions with an error of less than 5 degrees Celsius. Compared to finite element modeling, this RNN model greatly reduces computation time and successfully captures the temporal dynamics of click heat transfer

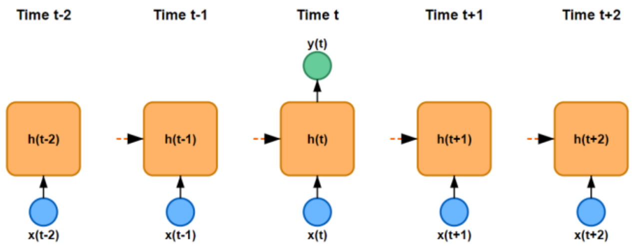


FIGURE 18. Architecture of Recurrent Neural Network (RNN)

2) Unsupervised Learning

Research has shown that CNNs have limited sensitivity and accuracy in predicting specific machine performance. In addition, supervised learning relies on human supervisors to provide labelled output examples for each input, which usually requires a large amount of training data, up to millions of training samples to surpass traditional computing capabilities.

To overcome this limitation, people have explored unsupervised deep learning methods as an alternative. Unsupervised learning is a machine learning task that is characterized by the fact that the training data has no labels or predefined outputs. In this learning method, the model looks for hidden structures or patterns from the input data without relying on any known output information. In unsupervised learning, the algorithm discovers the intrinsic relationships in the data by analysing the characteristics of the data. For example, clustering algorithms divide the data set into different groups, each containing similar samples, while dimensionality reduction algorithms look for low-dimensional representations of the data to simplify and visualize the data. [78]

As shown in figure 19, unsupervised learning relies on local facts and internal mechanisms, and the system learns by learning and becoming familiar with the key information in the input data. At the input layer, a set of training data is provided to the neural network, and the network association weights are adjusted through competition between the nodes in the output layer, where the nodes with the highest values become the final candidates. Unsupervised learning is mainly used for clustering and association algorithms. Recent research results show that clustering in unsupervised learning of feedforward neural networks is hampered by problems such as low speed and low accuracy. Clustering plays an important role in machine learning and medical research.

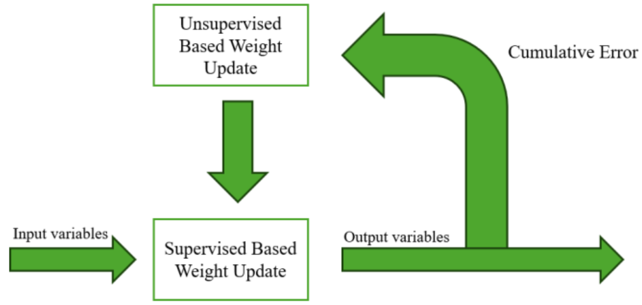


FIGURE 19. The workflow of unsupervised learning

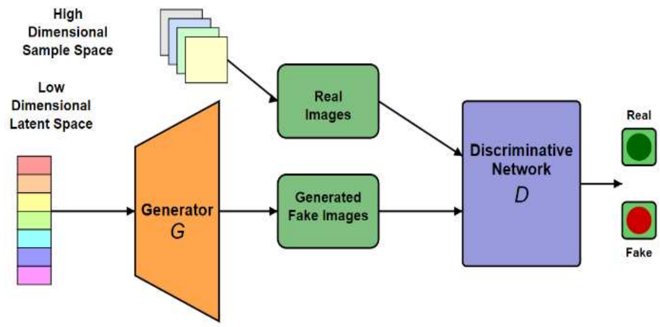


FIGURE 20. Working principle of GAN

a) Generative Adversarial Networks

At the same time, many studies have also applied unsupervised learning networks to the design and optimization of electromagnetic devices. In electromagnetic devices, particularly electric motors, accurate magnetic field prediction is crucial for performance evaluation and optimization. While traditional methods like finite element analysis (FEA) provide accurate results, they are extremely time-consuming and computationally intensive.

On the other hand, analytical methods require fewer computational resources but suffer from limited generalization ability. These limitations have motivated researchers to explore artificial intelligence-based alternatives for magnetic field prediction.

In the field of unsupervised learning, several representative neural networks stand out, including Autoencoders, Generative Adversarial Networks (GANs), K-means Neural Networks, and Deep Belief Networks (DBNs). Among these, Generative Adversarial Networks (GANs) have demonstrated significant impact across various domains in recent years. Introduced by Ian Goodfellow et al. in 2014, GANs leverage a unique adversarial training mechanism involving a generator and a discriminator, effectively addressing challenges in generative modeling. This breakthrough has positioned GANs as a revolutionary technique in deep learning, showcasing exceptional capabilities in tasks such as image generation, style transfer, and data augmentation.

The fundamental principle of GANs, illustrated in figure 20, involves two key components: the generator and the discriminator. The generator takes random noise or design parameters as input and produces "fake" data resembling the real dataset, while the discriminator simultaneously processes real and fake data, learning to distinguish between the two. The training objective of GANs is to optimize the generator to produce data that can deceive the discriminator into classifying it as real. Through iterative adversarial training, the generated data increasingly approximates the real data distribution. This unsupervised learning approach significantly reduces the reliance on large, labelled datasets and manual supervision, enhancing the efficiency of training and data generation.

GANs have given rise to numerous variants, such as Conditional GANs (cGANs), where additional conditional inputs guide the generator to produce more realistic outputs. cGANs combine the advantages of GANs' unsupervised learning capabilities with the targeted guidance of supervised learning. In the domain of electromagnetic device design, cGANs have been widely applied, particularly in optimizing electric vehicle motors. For example, cGANs have demonstrated the ability to predict electromagnetic performance parameters, such as air-gap flux density and torque, with moderate computational costs. Unlike analytical methods, GAN-based models provide a complete magnetic field distribution across the design space, enabling comprehensive analysis. Moreover, incorporating physics-based loss functions into GAN training ensures alignment between predicted outputs and key performance metrics.

Wu et al. [108] successfully employed cGANs to predict the magnetic field distribution of coaxial magnetic gears (CMGs). The network used RGB-formatted geometry images of CMGs generated from finite element analysis (FEA) software as input, and the cGAN architecture generated electromagnetic field density maps as output. These maps were subsequently processed to calculate essential performance metrics, such as air-gap flux density and average torque. In figure 21, the generated results

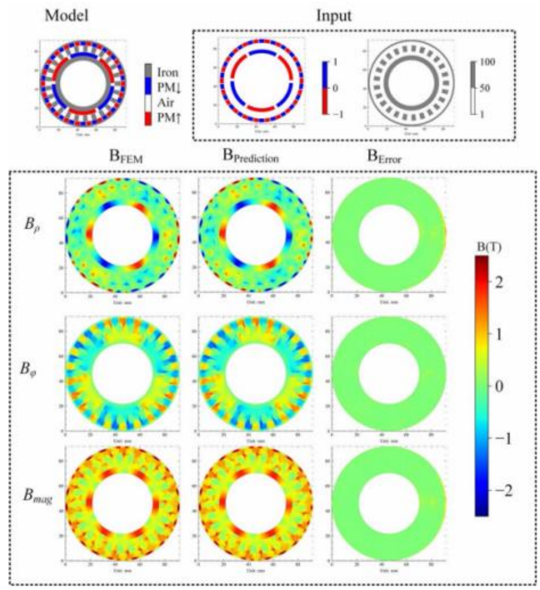


FIGURE 21. Qualitative analysis on magnetic field prediction in the experimental, 2-D setup with a generator network. The input and the predicted magnetic field B_ρ, B_ϕ, B_{mag} are presented. [108]

exhibited less than 1% error compared to FEA simulations. Additionally, the prediction speed of the neural network was approximately 200 times faster than FEA simulations, highlighting the efficiency of GAN-based methods.

Beyond cGANs, GANs have inspired numerous other architectures in the field of image processing, such as Deep Convolutional GANs (DCGANs), Wasserstein GANs (WGANs), StarGANs, CycleGANs, AttnGANs, and the recent TransGANs, which integrate Transformer architectures. While these GAN variants have achieved remarkable success in image-related tasks, their application in electromagnetic device design remains relatively limited. Shimizu et al. (2023) addressed the challenge of lengthy data acquisition times for interior permanent magnet synchronous motors (IPMSMs) in
FEA simulations. By integrating GANs with CNNs, the authors generated 102,795,000 training data points from 26,209 samples using the generator. The predicted speed-torque characteristics demonstrated less than 3% error compared to actual data, further validating the potential of GANs in optimizing electromagnetic device designs. [99]

With the advancement of deep learning, in addition to the well-known techniques such as Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), more advanced methods have also demonstrated great potential in the optimization of electromagnetic devices. These emerging technologies may offer new approaches in the future to overcome the limitations of traditional methods and conventional neural networks.

b) Transfer Learning

Transfer learning leverages knowledge acquired from one domain to accelerate learning in a related domain. This approach is particularly valuable in the design of electromagnetic devices, where generating large amounts of simulation data for different device types is time-consuming and computationally expensive. The fundamental idea of transfer learning is to train a model on a data-rich source domain and transfer the learned features to a target domain with limited data.

In the context of electromagnetic device design, transfer learning typically involves two main steps. First, a base model is trained on a large dataset from a specific type of electromagnetic device. Then, the pretrained model's parameters are partially frozen, and the remaining parameters are fine-tuned using the limited dataset from the target domain. Asanuma et al. [118] demonstrated the effectiveness of this approach in motor topology optimization. They pretrained a convolutional neural network (CNN) on one motor dataset and successfully transferred the learned features to optimize different motor topologies. Their results showed that transfer learning achieved 95% accuracy using only 20% of the original dataset.

This suggests that transfer learning holds significant potential for broader application in electromagnetic device optimization, supported by the following advantages: (1) Reduced data requirements: By leveraging the knowledge embedded in pretrained models, the number of samples needed for new tasks can be significantly lowered; (2) Faster convergence: With electromagnetic-domain-informed initialization, training time can be substantially reduced.

Topology optimisation, as a powerful design tool, shows great potential in the field of motor design to significantly improve the performance, efficiency and power density of motors. Unlike traditional parametric optimisation methods, topology optimisation optimises the motor structure by manipulating the material distribution, independent of predefined geometries, leading to higher performance design solutions. [110]-[116]In the field of switched reluctance motors (SRMs), researchers have successfully reduced torque pulsations and increased average torque using level-set, density, and ON/OFF methods [117]-[121], and in the design of synchronous reluctance motors (SynRMs), topology optimisation techniques have been used to improve the rotor structure, optimise the flux blocking, improve the torque characteristics, and reduce iron losses [122]-127]. With the continuous and deep application of topology optimisation in motor design, the transfer learning technique is becoming a new direction to improve the optimisation efficiency, which can significantly reduce the amount of simulation data required for a new motor design, accelerate the optimisation convergence speed, and effectively solve

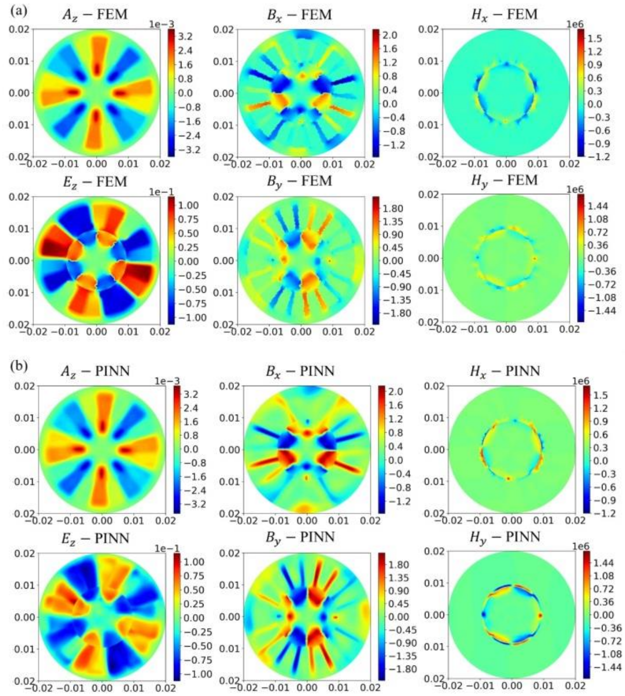


FIGURE 22. Comparison between the reference and estimated results of electromagnetic responses using PINN and ANN under eccentricity fault mode: (a) FEM reference, (b) estimation using PINN [139]

the problem of high computational cost faced by the traditional topology optimisation methods, by transferring the knowledge of one field to the related field, which opens up a new way for the research of motor topology optimisation.

Asanuma presents a method for effective topology optimization using migration learning with CNNs. Migration learning and CNN are combined and adequately trained with relatively small amounts of data. Using the trained CNN, the torque performance of the D-type and V-type motor models can be inferred from the cross-sectional images. The computational cost of topology optimization for D-type and V-type motors is reduced by 15% and 13%, respectively, compared to conventional methods without CNNs. This article validates the feasibility of migration learning for reducing training samples of electromagnetic devices. [128]

c) Physics-Informed Neural Networks

Traditional neural networks often suffer from limited generalization and poor interpretability in motor performance prediction. This is primarily because the relationship between input and output is learned without incorporating underlying physical principles, making it difficult to explain the improvements in prediction accuracy. In contrast, Physics-Informed Neural Networks (PINNs) integrate physical laws into the network architecture, significantly enhancing both interpretability and generalization. For example, unlike conventional data-driven approaches that rely solely on input- output mappings, PINNs incorporate electromagnetic principles—such as

Maxwell's equations—as additional constraints during model training.

$$L_{total} = L_{data} + \lambda L_{physics}$$

In this context, *data* refers to traditional loss modelling based on empirical fitting, while *physics* incorporates constraints derived from Maxwell's equations. The parameter *lambda* serves to balance the contributions of these two components.
In the future optimization of electromagnetic devices, Physics-Informed Neural Networks (PINNs) offer several notable advantages:

- **Improved Prediction Accuracy**: By enforcing physical constraints, PINNs ensure that the network outputs adhere to electromagnetic laws, thus avoiding solutions that violate physical principles.
- **Data Efficiency**: PINNs can achieve accurate predictions even with limited data, addressing the traditional reliance of deep learning models on large datasets.
- **Multi-Physics Integration**: The PINNs framework naturally extends to coupled physical problems, offering a pathway to simultaneously optimize electromagnetic, thermal, and mechanical performance.

A few articles have tried to predict the performance metrics of electromagnetic devices using PINN such as temperature prediction [138], magnetic field prediction [139]. Karl predicted the temperature and power loss of electric motors using PINN. Upon comparison, it was found that the MAE of the PINN prediction of power loss and FEM computation with physical was only 0.09, and the MAE of the winding temperature was 0.27. Compared to the non-PINN model that does not include physical information, the MAE of the prediction of power loss was 0.69, and that of the winding temperature was 0.69. This gap demonstrates the significant improvement in model prediction accuracy due to the inclusion of physical information in the PINN. [129]

Son used PINN combined with Ampere's law to predict the radial and tangential magnetic field of a permanent magnet synchronous motor (PMSM), and the results are shown in figure 22 The neural network combined with physical information predicted the radial field density Bx with an accuracy of more than 99% in comparison with the FEM, and the predicted tangential field density By with an accuracy of more than 98% in comparison with the FEM. The experimental results demonstrate the importance and generality of PINN in magnetic field prediction. [139]

I. FUTURE SCOPE

Tables 3 summarize data-driven models for electromagnetic device design optimization, focusing on their application scenarios and predicted parameters. The article highlights multiple challenges faced by traditional finite element analysis (FEA), which significantly impact the efficiency of electromagnetic device design. Statistical models, such as response surface methodology (RSM), are effective for single-objective optimization but lack accuracy and stability for more complex multi-objective problems. Machine learning (ML) models handle multiple variables with higher accuracy but face limitations due to predefined conditions, making subsequent optimization challenging. Deep learning (DL) models, despite their advantages, are highly data-dependent, requiring large datasets and long training times to ensure accuracy.

Overall, compared to FEA, statistical models, and ML models, DL models are currently more suitable for electromagnetic device optimization. However, DL models still have limitations. For instance, many GAN-based models rely on paired image datasets for performance prediction, often focusing on geometric information while neglecting material properties of electromagnetic devices. Additionally, challenges related to generalizability and training speed remain significant for the future development of DL-based optimization techniques.

Potential solutions include adopting more efficient neural networks while improving dataset quality. For example, several studies have explored transformer networks, leveraging their unique attention mechanisms in combination with various neural architectures to achieve high prediction accuracy. The attention mechanism excels at modelling correlations between arbitrary positions, improving training speed and addressing long-range dependencies, which could be crucial for predicting complex electromagnetic field distributions in device designs. Addressing generalizability issues requires applying neural networks to diverse datasets for training to broaden their applicability.

IV. Conclusion

Data-driven models, especially those based on deep learning, have become revolutionary tools in the design and optimization of electromagnetic devices. They have the potential to replace traditional finite element analysis (FEA) software, addressing issues related to high computational costs and time consumption. Statistical models and machine learning (ML) models can mitigate some of these existing FEA challenges, but their performance is limited when dealing with large amounts of data. Deep learning (DL) models excel in feature extraction
and topology optimization, offering significant advantages in handling complex geometries and nonlinear relationships.

TABLE 3 APPLICATIONS OF MACHINE LEARNING AND DEEP LEARNING NETWORKS IN ELECTROMAGNETIC DEVICES

Reference	Model	Application	Objective
[97]	CNN	Transformer and permanent magnet (BPM) motor	Magnetic field estimation
[100,101]	CNN, RNN	Permanent magnet synchronous motor (PMSMs)	Temperature estimation
[102]	ANN, CNN, RNN	Interior PM motors	Efficiency map and flux-linkage prediction
[103]	KNN	PM synchronous linear motors	Optimization with Differential Evolution algorithm
[104]	Multi-layer perceptron (MLP)	Permanent magnet synchronous motor (PMSMs)	Optimization based on Hybrid metaheuristic algorithm
[105]	R-DNN (deep neural network)	Double secondary linear motor	Cuckoo search algorithm for parameter optimization
[106]	CNN	Synchronous reluctance motor	Optimization via Binary Particle Swarm algorithm
[107]-[108]	CNN	Interior PM motors	Topology optimization, multi-objective optimization
[88]	BP neural network	Permanent magnet synchronous motors (PMSMs)	Flux-linkage estimation
[98]	GAN	Coaxial magnetic gears (CMGs)	Magnetic field estimation
[136]	ANN	High-frequency coaxial transformers (HFCTs)	Design optimization and parameter prediction
[137]	GPR, SVM, ANN (MLAO)	UWB monopole and Yagi antennas	Broadband antenna optimization
[141]	DNN with TSEMO	Broadband antennas	Automated high performance antenna design
[142]	Smoothed Residual CNN (SRCNet)	Power transformers	Oil temperature prediction
[81]	Customized-kernel RVM	Power transformers	Diagnostics based on dissolved gas analysis

Although data-driven models are more efficient than traditional methods for electromagnetic device design and optimization, challenges remain, such as high data dependence, long training
times, and the neglect of material properties. The integration of advanced architectures, such as transformers with attention mechanisms, shows promise for improving accuracy and efficiency. Solving the generalization problem by using diverse datasets and incorporating material information into the model input is crucial for further progress.

Future research should focus on refining DL models, balancing computational efficiency with prediction accuracy, and ensuring their applicability across various electromagnetic devices. By overcoming current limitations, data-driven approaches can significantly enhance the performance, efficiency, and innovation of electromagnetic system.

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