A Review of Data-driven Surrogate Models for Design Optimization of Electric Motors

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***Abstract*—Electric motor is one of the core components of electronic propulsion systems and plays an essential role in the industry. The optimal design of an electric motor poses a complex nonlinear problem, often challenging traditional methods to strike a balance between accuracy and efficiency. Achieving accurate analysis and holistic optimization typically entails significant computational requirements, particularly when dealing with massive individuals. As a result, researchers begun to explore the utilization of data-driven surrogate models to resolve this dilemma. This review paper focuses on investigating the leading techniques employed for constructing data-driven surrogate models to assist and facilitate the design optimization process of electric motors. These techniques encompass statistical models, machine learning models, deep learning models, and other artificial intelligence-based technologies. The paper provides a comprehensive survey of the underlying principles and offers detailed examples of studies that have utilized these diverse models. Besides, the performances and potentials of these models are highlighted with comments, shedding light on their respective strengths and limitations. Furthermore, the research challenges that lie ahead and promising avenues for future improvements under this topic are discussed.**

***Index Terms*—artificial intelligence, data-driven models, deep learning, electric motors, machine learning, optimization, surrogate models.**

ABBREVIATIONS

EVs	Electric vehicles
PMSMs	Permanent magnet synchronous motors
IMs	Induction motors
SRMs	Switched reluctance motors
SynRMs	Synchronous reluctance motors
AFPMs	Axial-flux ironless permanent magnet motors
AFIM	Axial-flux induction machine
EMF	Back electromotive force
THD	Total harmonic distortion
DOE	Design of experiments
AM	Analytical models
MEC	Magnetic equivalent circuit
FEA	Finite element analysis
CAD	Computer-aided design
RSM	Response surface model
ML	Machine learning
SVMs	Support vector machines
RF	Random forests
ANNs	Artificial neural networks
DL	Deep learning
MLP	Multilayer perceptrons
CNNs	Convolutional neural networks
GANs	Generative adversarial networks
EMN	Equivalent magnetic network
DoFs	Degree of freedoms
MMF	Magnetomotive force
EAs	Evolutionary algorithms
GAs	Genetic algorithms
EP	Evolutionary programming
DE	Differential evolution
ES	Evolution strategies
PSO	Particle swarm optimization
ABC	Artificial bee colony
ACO	Ant colony optimization
MOEAs	Multi-objective evolutionary algorithms
FSPMM	Flux-switching permanent magnet machine
TL	Transfer learning
DNN	Deep neural networks

I. INTRODUCTION

Electric motors, as one of the core components of the electronic propulsion system, account for approximately 53% of global electricity consumption [1]. As the demand for electric vehicles (EVs) continues to grow in the automotive market in industrialized countries [2, 3] due to their advantages of zero emissions, simplicity, and lower cost [4, 5], more than 57% of the total produced electricity is consumed by electric motors in industrialized regions including US, UK, EU, Turkey, Canada, India, China, and South Africa [6, 7]. Therefore, the performance of electric motors has a significant impact on energy utilization ratio and sustainability.

Electric motors designed for traction purposes usually have requirements on energy efficiency, power density, and speed

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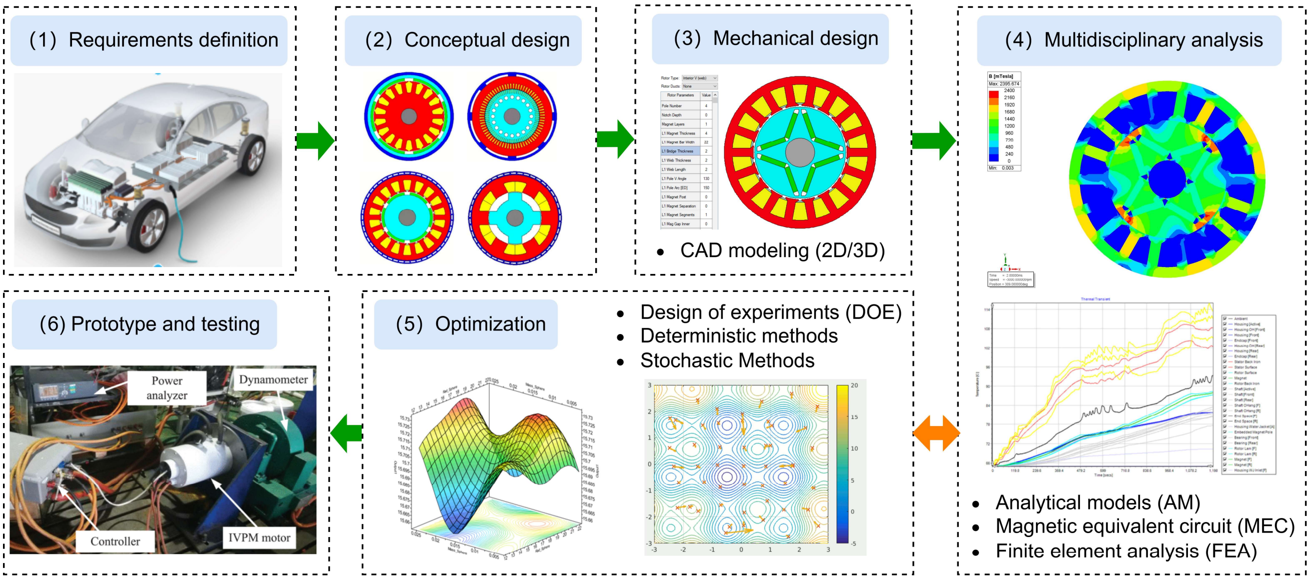

Fig. 1. Common process of designing an electric motor and conventionally applied techniques [10, 19-21].

range [8]. The most popular choices in traction applications are permanent magnet synchronous motors (PMSMs), poly-phase induction motors (IMs), switched reluctance motors (SRMs), synchronous reluctance motors (SynRMs), axial-flux ironless permanent magnet motors (AFPMs), axial-flux induction machine (AFIM) [9-11]. To satisfy the requirements mentioned before and other specifications [12-14], the optimal design of these electric motors becomes a complex nonlinear multi-objective problem involving not only the highest efficiency, lowest cost, and minimum weight of active materials but also electromagnetic, mechanical and thermal aspects [15].

The design and optimization of electric motors aim to approach a practical scheme that meets specific performance requirements while minimizing cost and environmental impact. This involves a multidisciplinary analysis considering motor structures, topologies, materials, and dimensions. The design and optimization process typically involves several vital tasks:

1) Requirements definition: This step involves identifying the critical stationary and dynamic performance requirements for the electric motor, such as operating conditions, average torque, torque ripple, speed, efficiency, and costs. Specific applications, such as EVs or other industrial types of machinery, may drive these requirements.
2) Conceptual design: Based on the performance requirements, designers create a conceptual design of the motor that includes specifications such as motor principles, size, weight, topologies, and materials [16].
3) Mechanical design: Mechanical design ensures the motor's durability and strength. It includes factors such as the type and quality of the applied materials, the geometric structure of the stator and rotor, dimensions, and the specific dimensions.
4) Multidisciplinary analysis: Implementing multi-physics analysis incorporating disciplines such as electromagnetics, structural mechanics, and thermal analysis is essential. The electromagnetic field analysis is used to obtain the electromagnetic parameters such as core loss, inductance, and back electromotive force (EMF) of the motor to evaluate the performance including torque and efficiency. The thermal analysis is used to determine the temperature distribution in the motor and identify areas of potential overheating. It helps to design an effective cooling system that maintains the motor at the desired operating temperature [17].
5) Optimization: Based on the analysis and design, optimization techniques are used to find the optimal design parameters that meet the performance requirements while minimizing cost and energy consumption. This may involve sample selection based on design of experiments (DOE) and applying advanced computational techniques, including deterministic methods and stochastic algorithms [15].
6) Prototype and testing: Once the optimal design has been identified, a motor prototype is built and tested to evaluate its performance and identify any areas for further improvement [18].

The typical process and conventionally applied techniques for the design and optimization of electric motors can be summarized in Fig. 1 [19-21]. With the advancement and widespread availability of sophisticated computer-aided design (CAD) software, it has become convenient to generate detailed 2D or 3D models of motor components, making the process's core job lies in the combination of motor performance analysis and optimization.

Traditional methods for analyzing motors' performance primarily include analytical models (AM) [22-25], magnetic equivalent circuit (MEC) models [25-28], and finite element analysis (FEA) [29-32]. Different approaches are normally preferred at specific design stages. Over the years, FEA has emerged as a highly accurate simulation method with the advantage of great geometric flexibility. Still, it is computationally expensive and time-consuming, especially when it comes to optimization stages because the evaluation of multiple individuals is required [33]. In this case, many researchers have begun to explore suitable data-driven methods with comprehensive capabilities that can partially or entirely replace the design tasks 3-5 shown in Fig. 1 to accelerate the process and attend to both computational cost and accuracy.

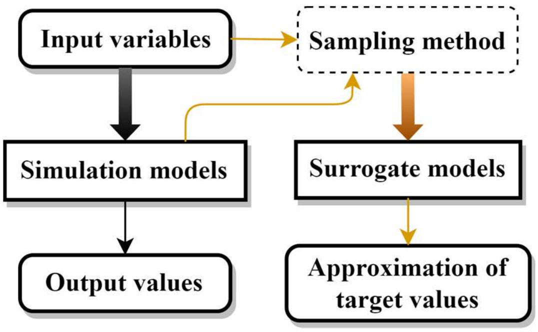

Fig. 2. Difference between applying FEA and surrogate models.

Data-driven surrogate models employ algorithms to discern the relationship between input and output variables, providing alternative means to assess outcomes of specific inquiries, diverging from traditional methodologies. The main difference between applying FEA and surrogate models can be illustrated as Fig. 2. These models offer computationally efficient substitutes to simulations by learning from data to predict new outcomes. The models explored in this paper, applied to the optimization of electric motor designs, span the last decade's developments in three major categories: 1) statistical models methods like response surface model (RSM) and kriging model; 2) machine learning (ML) models like support vector machines (SVMs), boosting algorithms, random forests (RF), and artificial neural networks (ANNs); 3) deep learning (DL) models like multilayer perceptrons (MLP), BP neural network, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs). This paper reviews the studies concerned with data-driven surrogate models for accelerating the design optimization of electric motors and provides a critical analysis of each model's capabilities and limitations.

II. Conventional Methods for Electric Motors' Design and Analysis

As highlighted in Section 1, successful motor design and optimization necessitate the integration of robust design and analysis models, alongside effective optimization techniques. This section focuses on discussing and comparing commonly employed design and analysis models for electric motors, including analytical models (AM), magnetic equivalent circuit (MEC) models, and finite element analysis (FEA).

A. Analytical Models

AM is a numerical evaluation technique widely used in motor design and analysis. It is a versatile and representative approach that allows designers to reach a principle-level understanding of the motors' mechanism and to visualize how changes in input parameters will affect the output motor performance. The significant advantage of AM is that it offers quick and efficient analysis due to its simplicity. In AM, the magnetic field is often approximated as being uniform in the air gap and laminations, and the resulting characteristics are calculated based on the average magnetic field.

Fundamentally, analytical models are constructed based on formal solutions of the classical Maxwell equations in constant permeability regions. Take permanent magnet synchronous motors (PMSM) as an example, and the governing field equations can be expressed as follows [25]:

$$\begin{cases} \nabla^2 A_{slots} = -\mu_0 J \\ \nabla^2 A_{air-gap} = 0 \\ \nabla^2 A_{magnents} = -\mu_0 \nabla \times M \end{cases} \tag{1}$$

where A_i is the curl of magnetic vector potential of the corresponding magnetic field, J is the armature current density, μ_0 is the permeability of the vacuum, and M is the magnetization vector. The permeability of permanent magnets is assumed to be equal to the permeability of air, and the permeability of all ferromagnetic parts is assumed to be infinite.

Generally, AM can be used for the calculation of electromotive force [34, 35], inductances (self and mutual) [36], forces and torques [22, 37, 38], and electromagnetic losses [23, 39, 40]. The simplification of AM allows for more straightforward calculations and analysis, but these assumptions make it difficult to account for local saturation effects, which may lead to significant inaccuracies [41-43]. Therefore, when developing AMs for electric motors, researchers normally seek ways to reduce this effect and use experimental methods or precise analysis techniques such as FEA to verify the model's accuracy [22, 24].

Even though, concerns related to saturation effects have driven the exploration of analytical methods designed to accurately incorporate these influences. Diverse strategies have emerged to address this problem, including: 1) Representation through a saturation factor, effectively simulating an augmented air-gap length [44, 45]; 2) Utilization of nonlinear subdomain models [46-48] that account for the permeability of stator teeth and rotor poles; 3) Implementation of an equivalent magnetic network (EMN) to compute of permeance at distinct sections of the iron core [49, 50]; 4) Hybrid models that integrate EMN models with slotless flux density models [51, 52]; 5) Hybrid models that combine subdomain models and EMNs [53-55]. However, these methodologies are frequently explored and suggested within the context of specific motors, rendering them challenging to universally apply. The geometric flexibility of AM is quite low compared to FEA. Additionally, the pursuit of heightened accuracy often comes at the expense of increased computational costs.

B. Magnetic Equivalent Circuit

MEC is an ideal modeling tool commonly used for building equivalent mapping of magnetic fields. As defined by E.R. Lwithwaite [56], MEC models are based on the concept of an electrical equivalent circuit but with magnetic elements, including reluctances, inductances, and magnetomotive forces to represent the decomposition of magnetic field into flux tubes and the magnetic characteristics of the device. For example, the resistance–reluctance model, often known as Hopkinson's law, in MEC is functionally similar to Ohm's Law in electrical circuits written as:

$$\mathcal{F} = \Phi \mathcal{R} \tag{2}$$

where $\mathcal{R}$ is the magnetic reluctance, $\mathcal{F}$ is the magnetomotive force (MMF), the analog of electromotive force (EMF). MMF can be interpreted as the force driving the magnetic flux through magnetic equivalent circuits, which can be defined as (3). As in (4), Φ is the magnetic flux analogous to the current in electrical circuits. Therefore $\mathcal{R}$ can be computed as (5), where μ is the material's permeability, and S is the cross-sectional area of the circuit with the length $\mathrm{d}l$.

$$\mathcal{F} = \oint \mathbf{H} \cdot \mathrm{dl}, \tag{3}$$

$$\Phi = \iint_S \boldsymbol{B} \cdot d\boldsymbol{S}, \tag{4}$$

$$\mathcal{R} = \int_L \frac{\mathrm{d}l}{\mu(l)S(l)}. \tag{5}$$

MEC models are developed by dividing the magnetic system into smaller sections and applying the laws of magnetic circuits to each section with saturation considered [26, 28, 57]. MEC provides a simple and efficient way to represent the magnetic behavior of electric motors since the number of elements (flux tubes) implemented is much less than FEA, especially in 3D models. Peyman and Heidary [58] conducted a comparative analysis of the application of MEC, 2D-FEA, and 3D-FEA in modeling and analyzing a new type of permanent magnet flux-switching linear motor (PM-FSLM). The results showed that MEC improved 78% efficiency compared to 2D-FEA and 97% to 3D-FEA.

MEC has been proven to be one of the fastest modeling and analysis methods even compared with AM models based on classical Maxwell equations. And relative studies [25, 40] showed that coupling MEC and AM can improve the accuracy to computational time ratio and the estimation of loss calculation. However, MEC has two major defects: 1) It is difficult for MEC to consider eddy current effects as there are no geometric properties expressed in the scalar equations applied for the model; 2) The geometric flexibility of MEC could be even worse than AM models. MEC can be very accurate and efficient when predicting the performance of an electric motor before putting it into production. Still, it is not competent for mass optimization as the model often need to be adapted significantly if the geometric feature changes [26, 59].

C. Finite Element Analysis

FEA is a powerful numerical method that can simulate the magnetic field distribution in the motor by discretizing the motor geometry into a finite number of small elements, such as triangles or tetrahedra, and solving the governing equations on each component, which can be assembled into a system of linear equations to calculate various motor performances such as torque, induced voltage, and magnetic flux density [11]. Besides, it can be used to analyze the mechanical performance of the motor, such as stress and deformation due to mechanical loads. Over the decades, FEA has become one of the most popular tools for motor analysis due to the distinctive advantages of 1) its applicability to problems with complex boundary shapes or boundary conditions and containing complex media; 2) the ability to solve nonlinear problems; 3) the ability to standardize the analysis process making many commercialized calculation programs with high analytical accuracy available [60]. Additionally, FEA has evolved to accommodate multi-physics field solving, allowing for the concurrent analysis of multiple physical phenomena influencing motor performance. This capability enables the assessment of interactions between electromagnetic, thermal, structural, or acoustic aspects, providing a comprehensive understanding of complex systems [61-63]. This integration of multi-physics considerations within FEA enhances its effectiveness in predicting real-world motor behavior under varying operating conditions. However, if 3D fluxes and eddy-current distributions are required or in scenarios involving mass individuals, the computational cost of FEA would increase significantly.

D. Summary

In general, AM offer a versatile and representative approach for understanding motor mechanisms and visualizing the impact of input parameter changes on performances. Its simplicity allows for quick analysis, but it is hard for AM to take local magnetic saturation into account. Although some novel AM models attempt to address this, increased accuracy often results in higher computational costs. And these models are often tailored to specific motors, limiting their universal applicability. In contrast, MEC can account for saturation effects, but their geometric flexibility may be limited. FEA has emerged as a widely adopted tool, celebrated for exceptional accuracy and geometric flexibility. FEA excels in complex motor designs and multi-physics field optimization, offering insights into both electromagnetic and mechanical behaviors. However, the computational expense of applying FEA, especially in scenarios involving numerous individuals, remains a challenge. Balancing geometric flexibility, accuracy, and computational cost is a hard goal to reach, and no single method can simultaneously address all these aspects effectively.

III. Intelligent Optimization Algorithms

In the past decades, intelligent optimization algorithms, also referred to as stochastic optimization techniques or population-based optimization, have gained increasing prevalence and influence as pivotal tools for optimizing electric motors. Their widespread adoption is rooted in their remarkable capacity to navigate complex design spaces and potential of addressing multiple objectives. Notably, these algorithms excel in facilitating a gradient-free search for solutions, offering an essential advantage when dealing with intricate motor design challenges [64, 65]. As previously discussed, compared to AM and MEC, FEA stands out for its flexibility, owing to its principle of dissecting the solution domain. With standardized calculation procedures, FEA facilitates batch analysis of new models with varying geometric topologies, dimensions, and materials. This inherent flexibility enables FEA to seamlessly integrate with intelligent optimization algorithms. This integration aims to enhance the performance and reliability of electric motors by systematically exploring and optimizing diverse design possibilities. This section delves into the features and applications of noteworthy intelligent optimization techniques, providing insights into the motor design and optimization process.

A. Evolutionary Algorithms

Evolutionary algorithms (EAs) are optimization techniques inspired by the principles of natural selection and genetics. These algorithms work by iteratively evolving a population of potential solutions to a problem [66]. Genetic algorithms (GAs) stand out as representative examples of evolutionary algorithms applied to motor optimization. These optimization algorithms draw inspiration from the natural selection process in evolution and are widely employed in solving complex problems of identifying optimal solutions within expansive search spaces [67]. In GAs, a population of potential solutions is created. It evolves through a process of selection (choosing the fittest individuals in the population to reproduce and produce new offspring), crossover (combining the genetic material of two individuals to create new offspring with characteristics from both parents), and mutation (randomly changing the genetic material of an individual to introduce new genetic variation into the population) [68]. This iterative process repeats across multiple generations until a satisfactory solution is identified or a predefined stopping criterion is met. The evaluation of each individual's fitness, particularly in terms of motor design, typically involves assessing its performance through FEA [24, 69]. For example, [70] combined GA and FEA to optimize the dimensions of an axial-flux permanent magnet (AFPM) motor concerning the highest possible power density.

Apart from GAs, there are other popular EAs widely used for motors' optimization, such as evolutionary programming (EP) [71-73], differential evolution (DE) [74-76], and evolution strategies (ES) [77]. These algorithms, while sharing the fundamental principles of genetic evolution, introduce unique strategies for selection, crossover, and mutation. EP emphasizes self-adaptation of mutation parameters [72], DE focuses on differential operators for candidate generation [78], and ES employs self-adaptation and covariance matrix learning [79]. These diverse algorithms contribute to the versatility of evolutionary approaches in addressing the intricate challenges of motor optimization.

B. Swarm Intelligence

Swarm intelligence algorithms are inspired by the collective behavior of decentralized, self-organized systems in nature, such as flocks of birds or colonies of ants. These algorithms involve a population of agents that interact with each other and their environment to find optimal solutions [80]. Particle swarm optimization (PSO) is one of the most popular swarm intelligence methods introduced by Kennedy and Eberhart in 1995. The algorithm is based on a social metaphor of a group of birds or fish moving in a search space to find the best location for survival [81]. In PSO, a population of particles moves through the search space, and the movement of each particle is guided by its own experience and the experience of the other particles in the population. At each iteration, the position and velocity of each particle are updated based on the best place it has visited so far and the best position found by the entire swarm. The revised formula for the velocity of the ith particle is given by:

$$V_i^d(t+1) = wV_i^d(t) + c_1 r_1\left(P_i^d(t) - X_i^d(t)\right) + c_2 r_2\left(P_t^d(t) - X_i^d(t)\right) \tag{6}$$

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \tag{7}$$

where $V_i^d(t+1)$ and $X_i^d(t+1)$ is the velocity and position of the ith particle at time t, $P_i^d(t)$ is the best position visited by the ith particle so far, $P_t^d(t)$ is the best position found by the entire swarm, w is the inertia weight. c_1, c_2, r_1, and r_2 are the cognitive and social learning factors and random numbers between 0 and 1.

Concerning electric motors, PSO has been used to optimize electric motors' geometry and winding layout to improve their performances. For example, in [29], PSO was applied to search the global optimum design of a PMSM to minimize torque ripples.

In tandem with PSO, various swarm intelligence optimization algorithms, sharing similar mathematical principles, have been harnessed for motor optimization. This includes artificial bee colony [82] (ABC) and ant colony optimization (ACO) [83]. ABC is inspired by the foraging behavior of honeybees. In motor optimization, artificial bees search for optimal solutions, mimicking the exploration and exploitation strategies observed in natural bee colonies [23, 84-86]. In [23], a novel method aimed at enhancing the dynamic performance and efficiency of a PMSM was introduced. The approach involved an analytical model targeting the reduction of both electrical and mechanical time constants. Subsequently, the ABC algorithm was employed to optimize motor design, considering efficiency, mechanical, and electrical time constants as optimal objectives and related motor parameters as optimal variables. Within the broader scope of motor optimization, swarm intelligence algorithms emerge as valuable tools, each contributing distinctive strengths to the pursuit of optimal motor designs. However, it is noteworthy that ACO algorithms are frequently employed for the optimization of motor control strategies [87-90]. The collective intelligence and path-finding capabilities inherent in ACO contribute to its effectiveness in finding optimal solutions for motor control, enhancing the overall performance and efficiency of motor systems.

C. Multi-objective Optimization Algorithms

Multi-objective optimization is of paramount importance in the field of motor design as it addresses the inherent conflict between diverse and conflicting design objectives. Single-objective optimization methods often fall short in capturing the intricate trade-offs required in motor design [65]. To tackle these challenges, multi-objective optimization algorithms play a crucial role, considering multiple conflicting objectives simultaneously, providing a diverse set of trade-off solutions known as the Pareto front that represents a balanced compromise between competing design criteria [91].

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TABLE I
COMMON INTELLIGENT MULTI-OBJECTIVE OPTIMIZATION ALGORITHMS

Paradigms	Technique	Name
Pareto-dominance based MOEAs	NSGA-II [92]	Non-dominated sorting genetic algorithm II
	NSGA-III [93]	Non-dominated sorting genetic algorithm III
	SPEA2 [94]	Strength pareto evolutionary algorithm 2
	NSDE [95]	Non-dominated sorting differential evolution
	PESA-II [96]	Pareto envelope-based selection algorithm II
	PAES [97]	Pareto archived evolution strategy
	ε-MOEA [98]	ε-dominance based multi-objective evolutionary algorithm
Indicator-based MOEAs	IBEA [99]	Indicator-based evolutionary algorithm
	SMS-EMOA [100]	S-metric selection evolutionary multi-objective algorithm
	HypE [101]	Hypervolume estimation evolutionary multi-objective optimization algorithm
	MOMBI [102]	Many-objective metaheuristic based on Indicators
Decomposition-based MOEAs	MOEA/D [103]	Multi-objective evolutionary algorithm based on decomposition
	MOEA/DD [104]	Multi-objective evolutionary algorithm based on decomposition with dominance
	GDE3 [105]	Generalized differential evolution 3
Multi-objective swarm intelligence	OMOPSO [106]	Optimized multi-objective particle swarm optimization
	SMPSO [107]	Speed-constrained multi-objective particle swarm optimization
	NSPSO [108]	Non-dominated sorting based multi-objective particle swarm optimization
	MOABC [109]	Multi-objective artificial bee colony
	MOFA [110]	Multi-objective firefly algorithm

Existing multi-objective optimization algorithms can be broadly classified into two main categories: multi-objective evolutionary algorithms (MOEAs or EMOAs) and multi-objective swarm intelligence [111]. Within the realm of MOEAs, a more nuanced breakdown reveals three primary paradigms: pareto-dominance based MOEAs, indicator-based evolutionary algorithms (IBEAs), and decomposition-based MOEAs [65, 112]. Table I presents an integration of common intelligent multi-objective optimization algorithms along with their classifications into the specified paradigms. While this categorization provides a conceptual framework, it is imperative to note that these distinctions are not absolute, and some techniques may exhibit hybrid principles or intersect in their approaches.

In addressing multi-objective problems in design optimization, MOEAs tend to enjoy widespread preference over multi-objective swarm intelligence algorithms [111]. Notably, NSGA-II and its variants have emerged as highly utilized tools for electric motors' optimization [111, 113].

The availability of the NSGA-II source code, published by Deb and open to the public, has contributed to its widespread use [114]. NSGA-II employs non-dominated sorting and a crowding-distance mechanism, enabling it to efficiently explore the design space. This capability is crucial in motor design, where the search for optimal solutions involves navigating complex and high-dimensional parameter spaces [92, 115-117]. The popularity of NSGA-II is also tied to its continuous evolution. Over the years, researchers and practitioners have contributed to the algorithm's enhancement by proposing novel implementations, tricks, and improvements [118].

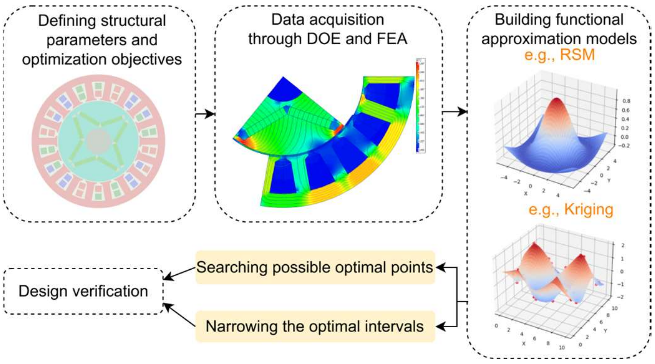

Fig. 3. Working principle of the Functional approximation models.

D. Summary

The synergistic application of FEA and intelligent optimization algorithms signifies a powerful approach in achieving highly efficient and tailored electric motor designs that meet the evolving demands of diverse applications and industries. In addition, some FEA software in the market (e.g., ANSYS Maxwell, JMAG, COMSOL Multiphysics) has integrated a variety of optimization algorithms, including gradient-based optimization and intelligent optimization algorithms to facilitate the user to carry out the motor design optimization conveniently. By harnessing the capabilities of these sophisticated tools, engineers can enhance motor performance and attain desired design objectives. However, although intelligent optimization algorithms can facilitate the search for the optimal design, applying FEA for the modeling and simulation of motors is still a computationally expensive process, especially when it comes to topology optimization, because the number of individuals involved is vast. Each individual needs to be solved by FEA software to obtain an accurate field solution. Therefore, it can be noticed that it is still hard for today's commonly applied optimization procedure to attend to geometric flexibility, accuracy, and computational cost at the same time. This has made researchers try to develop new models with more comprehensive capabilities.

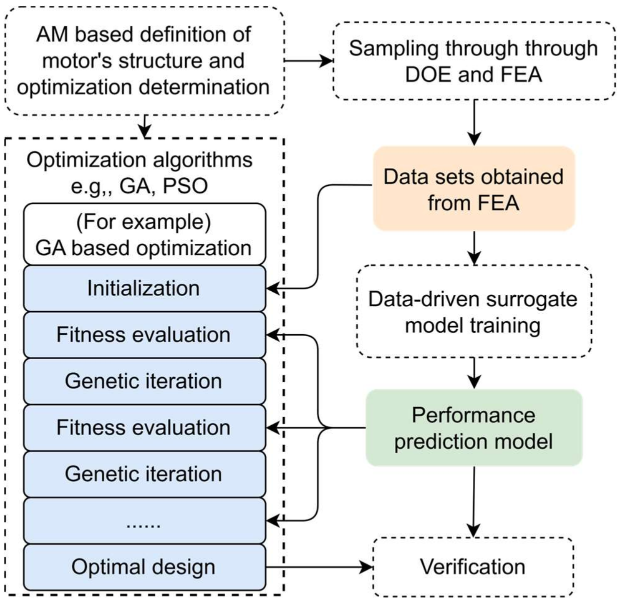

Fig. 4. Working principle of the performance prediction models.

IV. Data-driven Surrogate models

Data-driven surrogate models involve using algorithms to analyze the relationship between the input and output variables to evaluate the results of a particular question through a path different from the original approach. When it comes to designing electric motors, the data-driven models aim to replace or partially replace the techniques used for major tasks in the design phase shown in Fig. 1 [119], so that to address the limitations of traditional procedures mentioned in previous sections. In general, the main purpose of using a surrogate model is to reduce the computational cost required for the optimization process. According to target tasks and working principles, existing studies on data-driven surrogate models for motor's design optimization can be generally divided into two categories:

1) Functional approximation models, as shown in Fig. 3: The data-driven surrogate model is constructed to roughly fit the functional relationship between the optimization objectives and the motor parameters so that to quickly find the optimal solution or narrow the range of the optimal solution.
2) Performance prediction models, as shown in Fig. 4: The data-driven surrogate model is constructed to predict the performance of motors instead of using FEA, and then the model is combined with common optimization algorithms such as GA to find the optimal solution.

By exploring the effectiveness of specific modeling techniques including statistical models, ML models, DL models, and transfer learning (TL), this section will provide valuable insights into their application in motor design and optimization.

A. Statistical Models

1) *Response Surface Model*

Response surface model (RSM) is one of the most frequently used models for functional approximation data-driven surrogate models. RSM is a statistical and mathematical modeling technique usually used to optimize complex systems. RSM involves constructing a mathematical model, known as a response surface, that approximates the second-order functional relationships between input variables and the response or output variable of interest based on a limited number of experimental data points [120]. The general form of a second-order response surface model is given by:

$$Y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \sum_{i \neq j}^{k} \beta_{ij} x_i x_j + \varepsilon \qquad (8)$$

where Y is the response variable, X_i and X_j are the input variables, β_0 is the intercept, β_i, β_{ii}, and β_{ij} are the regression coefficients, and ε represents the random error term.

The response surface is used to predict the system's performance for different combinations of input variables without performing experiments or simulations. Using the response surface, engineers can optimize the system by finding outstanding combinations of input values that lead to the optimal points [121]. The working principle of applying RSM for optimizing motors can also be expressed in Fig. 3. Prior to the optimization phase, DOE with FEA is required to obtain data sets for the regression fitting of the RSM model.

TABLE II
RSM Models for Motor Design Optimization

Reference	Applied machine	Objective	Number of input variables
[121]	IPMSM	• Average torque • Torque ripple • Vibration	5
[122]	SynRM	• Torque ripple	4
[123]	BLDC	• Cogging torque	3
[124]	LSPM	• Power factor • Efficiency	3
[125]	IPMSM	• Back-EMF • Rotor saliency ratio	4
[126]	BLDC	• Cogging torque	7
[127]	PMTFLM	• Machine weight • Motor thrust • Detent force	4

In [122], an RSM model was built to find a synchronous reluctance motor (SynRM) design with the least torque ripple. The input comprises four parameters relating to the geometric features of stator slots, air gap, rib of the rotor, and flux barrier. The second-order regression model could cover 95.8% of the total variation through statistical validation. Similarly, In [123], RSM was used to reduce cogging torque and torque ripple of a Spoke-Type permanent BLDC. This study involves three geometric parameters relating to the rotor pole shape, and the response value is cogging torque. In [124], an RSM model was built to approximate the optimal structure of a two-pole line-start permanent magnet motor (LSPM). The input comprises three design variables (Length from PM slot to shaft, Slot angle of side PM segment, and Air duct gap). The target performances of the motor are the power factor and efficiency of the system. The optimal design determined by the RSM was verified through FEA and physical experiments, and the result showed good agreement. Other design optimization models based on RSM are presented in [125-127] and are summarized in Table II.

From the perspective of the overall process of motor design, applying RSM, to some extent, skips the precise analysis of many motor design individuals. This means the number of experiments needed is much less than the optimization algorithms mentioned in Section 2 [121]. However, RSM assumes a certain level of smoothness and linearity in the response surface and may not perfectly capture complex nonlinear relationships in the data. Besides, it can be seen from Table II that when applying RSM for motor optimization, the number of design parameters and objectives is very limited. Normally, each RSM model is fitted for a particular variable of interest. Therefore, the RSM-based modeling method may not be the preferred choice for surrogate modeling of electrical motors when involving multiple design parameters and objectives.

2) *Kriging model*

Kriging model, also known as Gaussian process regression or spatial correlation modeling, is a statistical modeling technique used to predict the value of a variable based on spatial or temporal relationships within a dataset. The model assumes that the predicted variable is a random function of spatial or temporal coordinates and estimates the unknown values at unobserved locations by combining a weighted average of the nearby observed values. The weights are determined based on the spatial correlation between the observed points, where closer points have more influence on the estimation than those away [128]. The general form of the Kriging prediction equation is given by:

$$Z(x) = \mu + \sum_{i=1}^{k} [\lambda_i(Z(x_i) - \mu)] + \varepsilon(x_i) \quad (9)$$

where $Z(x)$ represents the predicted value at location x, μ is the overall mean, x_i are the observed locations, $Z(x_i)$ are the observed values at those locations, ε is a correlated error term, λ_i are the weights determined, minimizing the estimation variance subject to the unbiasedness constraint, and the summation is performed over all observed locations.

Kriging has several advantages over other interpolation methods, such as estimating the uncertainty of the prediction, incorporating spatial or temporal dependence in the data, and producing smooth predictions that honor the autocorrelation of the data [129].

Given that the Kriging model features both functional regression and good prediction accuracy, it can be used as either functional approximation model [130] or performance prediction model [66-68] for motor design and optimization. For example, in [130], Adaptive-Sampling Kriging Algorithm (ASKA) was applied to approximate a functional relationship between torque ripple and magnet positions of an IPMSM. Similar to RSM, the model constructed in this study replaces the traditional optimization algorithms, which need numerous FEA solutions, and can effectively narrow the range where the optimal solution is located. In [131], Kriging model and GA were used to optimize the magnet position and barrier shape of an in-wheel interior permanent magnet synchronous motor (IPMSM) to achieve higher efficiency and lower cogging torque. And by comparison, the Kriging model is closer to the actual mapping between input and output than the RSM.

In addition, although each Kriging model is also constructed for a single objective, the accuracy makes them able to cooperate with multi-objective optimization algorithms to accomplish optimization concerning several different variables of interest. In [132], dynamic Kriging was applied to build a data-driven model for predicting the average torque and torque ripple of a switched reluctance motor (SRM). The input is the stator's pole face shape and the rotor's pole shoe. The model showed good accuracy because there is a good correlation between the input variables and output objectives. After modeling, multi-objective particle swarm was applied as the optimization algorithm. In [133], Kriging model was combined with MOGA to minimize the cogging torque of a flux-switching permanent magnet machine (FSPMM). The input of the model contains two variables: the rotor pole arc and stator tooth width, and the output of the model have three objectives: cogging torque, torque ripple, and average torque. The result showed good agreement with FEA verification and prototype experiment.

TABLE III
KRIGING MODELS FOR MOTOR DESIGN OPTIMIZATION

Reference	Applied machine	Objective	Number of input variables
[130]	IPMSM	• Torque ripple • Vibration	2
[131]	IPMSM	• Cogging torque • Efficiency	5
[132]	SRM	• Torque ripple	2
[133]	FSPMM	• Average Torque • Torque ripple • Cogging torque	2

In summary, Kriging models offers significant benefits in terms of higher prediction accuracy. While RSM provide guidance during the optimization process, Kriging models can serve as a viable alternative to FEA by providing motor performance values to designers. However, it is important to note that the accuracy of Kriging models is highly dependent on the correlation between the input and output variables. In Table III, it can be observed that the number of input variables for the Kriging model is relatively small. This is because statistical interpolation methods like Kriging can become computationally expensive as the size of the input data increases.

B. *Machine Learning*

A data-driven surrogate model is usually required to address high-dimensional problems to achieve good accuracy and practicality. This makes the functional approximation models mentioned in the previous part not competent enough for motor optimization tasks. To address this defect, popular machine learning (ML) algorithms such as support vector machines (SVMs), Boosting algorithms, random forests (RF), and artificial neural networks (ANNs) have been explored in this field in recent years and shown better feasibility [119]. Unlike functional models established through methods such as RSM or Kriging, these ML models are designed to construct mapping relationships with a higher degree of accuracy, particularly concerning multiple objectives and high-dimensional variables in complex nonlinear problems. The working flow of these methods should be classified into performance prediction models described in Fig. 4. FEA-assisted DOE is also required for obtaining training samples. However, the optimal point cannot be deduced from the mapping provided by the model directly, so the trained models have to be combined with optimization algorithms to find the optimal solution.

1) *Support Vector Machines*

Support vector machines (SVMs) are a popular supervised machine learning algorithm for classification and regression analysis. SVMs are based on finding the hyperplane that best separates the data points into different classes or predicts a continuous value for regression [134]. In SVMs, the hyperplane that separates the data is chosen to maximize the margin, which is the distance between the hyperplane and the closest data points of each class. The goal of SVM is to find the hyperplane that maximizes this margin while ensuring that the data is correctly classified [135].

For binary classification, SVMs find the optimal hyperplane by solving the following optimization problem:

$$minimize: \frac{1}{2}||w||^2 + C\sum_{i=1}^{n}(max(0,1-y_i(w\cdot x_i-b)))^2 \tag{10}$$

$$subject\ to: y_i(w\cdot x_i - b) \geq 1-\xi_i, \xi_i \geq 0 \tag{11}$$

where x_i represents the input features, y_i is the corresponding class label (-1 or 1), w is the weight vector perpendicular to the hyperplane, b is the bias term, and ξ_i are slack variables that allow for misclassified or margin-violating samples. Parameter C controls the trade-off between maximizing the margin and minimizing the classification errors.

SVMs employ a kernel function that maps the input data into a higher-dimensional feature space, allowing for the separation of nonlinearly separable classes. The most commonly used kernel functions are Linear Kernel (12), Polynomial Kernel (13), and Gaussian Radial Basis Function (RBF) Kernel (14):

$$k(x,x_i) = x\,x_i \tag{12}$$

$$k(x,x_i) = (\gamma(x\,x_i)+r)^2 \tag{13}$$

$$k(x,x_i) = \exp\left(-\gamma \parallel x-x_i \parallel^2\right); \gamma = \frac{1}{2\sigma_b^2} > 0. \tag{14}$$

The advantages of SVMs include their ability to handle high-dimensional data, their effectiveness on small datasets, and their robustness to outliers. However, the large datasets required for training a motor performance prediction model make it lose its edge because SVMs can be computationally expensive for large datasets.

2) *Boosting Algorithms*

Boosting algorithms are ML algorithms that combine multiple weaker models to form a robust predictive model. The idea behind boosting algorithms is to iteratively train a sequence of weak models, where each subsequent model focuses on the errors made by the previous models. The final model is obtained by taking a weighted average of the predictions made by all the models in the sequence[136]. Boosting algorithms have several advantages over single models, including higher accuracy, better generalization, and increased stability. They are particularly effective in situations where the data is complex and noisy and where traditional single models may not be able to capture all the underlying patterns in the data [137].

3) *Random Forests*

Random forests (RF) are an ML algorithm that also belongs to the family of ensemble methods, which combine multiple models to improve the predictive accuracy of the algorithm and are easier to train and configure than boosting algorithms. RF is suitable for both classification and regression tasks [138]. RF works by constructing multiple decision trees and combining their results to produce a final prediction. Each decision tree in the forest is built using a random subset of the training data and a random subset of the features. This randomness helps to reduce overfitting and improve generalization performance [139].

4) *Artificial neural networks*

Artificial neural networks (ANNs) are ML algorithms inspired by the human brain's structure and function. ANNs are composed of interconnected processing nodes or neurons that work together to process input data and generate output predictions [140]. The neurons in an ANN are organized into layers, with each layer performing a specific type of computation. The input layer receives the raw data, which is then processed through a series of hidden layers before reaching the output layer, which generates the final prediction. The connections between neurons are assigned weights, which determine the strength of the connection. During training, the weights are adjusted through backpropagation, which involves iteratively adjusting the weights to minimize the difference between the predicted and actual output [141].

5) *Summary*

In the realm of electric motor analysis and optimization, ML models have gained popularity due to their computational efficiency and impressive mapping capabilities. These ML models are typically characterized by their simplicity, yet they deliver robust performance. A comprehensive summary of studies applying ML algorithms to construct performance prediction models and exploring the impact of different techniques can be found in Table IV [142-148].

Compared to statistical modeling methods, ML models excel in creating accurate vector-to-vector mappings. This capability enables them to handle optimization tasks involving higher-dimensional datasets more effectively. From the projects discussed in the literature, certain trends and conclusions can be drawn.

When dealing with relatively small datasets, SVMs tend to exhibit superior accuracy. SVM is a powerful algorithm that works well in scenarios where the dataset size is limited. However, as the number of input variables increases, boosting algorithms and ANNs showed more satisfactory results.

Boosting algorithms, such as AdaBoost or Gradient Boosting, are designed to iteratively improve the performance of weak learners, thereby producing a robust predictive model. These algorithms are particularly adept at handling datasets with a larger number of input variables, leading to enhanced optimization outcomes.

Similarly, ANNs, inspired by the structure of the human brain, have shown promising results in handling higher-dimensional datasets for electric motor analysis and optimization. The ability of ANNs to learn complex patterns and relationships within the data makes them well-suited for tasks that involve numerous input variables.

C. *Deep Learning*

The aforementioned ML models have demonstrated their effectiveness in predicting motor performance by analyzing input vector of a limited number of parameters representing motor geometries. However, their applicability for topology optimization is constrained due to the considerably larger design's degrees of freedom (DoFs) that extend well beyond a few geometric parameters. To address this challenge, deep learning (DL) models, a specialized category within ML that often employ multi-layered artificial neural networks, have emerged as a potential solution due to their capability extracting local features from high-dimensional input data, which can cover a broader design DoFs, and learning representations with multiple levels of abstraction [149]. In the domain of electric motor performance prediction, DL models that have been employed to build performance prediction models can be generally categorized into supervised learning and unsupervised learning.

1) *Supervised Deep Learning*

Existing studies on applying supervised DL models for motors' performance prediction are mainly deep neural networks (DNNs) including backpropagation (BP) neural networks [150-152], multilayer perceptrons (MLP) [148, 153-155], convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Similar to the aforementioned cases of applying ANNs, these supervised DL models endeavor to construct a training dataset that consists of input-output pairs, aiming to implicitly define the mapping relationship between input and output variables but the analyzable parameters could be more extensive compared to ANNs. For example, one study [156] trained a DNN with 1 input layer, 10 hidden layers and 1 output layer to predict the air-gap flux density at 360 mechanical angles of a standard hybrid surface mounted PM (SPM) machine, and then the output can be used to optimize the 7 geometric parameters with consideration on flux harmonics and the cogging torque. Similarly, in [148] a MLP model was trained to predict the average torque and THD of the back EMF of a PMSM. Another study [151] employed a BP neural network to predict the motor losses of a PMSM. Although the number of variables was expanded in these works, the input data still consisted of manually defined geometric features.

To overcome the laboriousness of manual feature definition, convolutional neural networks (CNNs) have emerged as promising techniques. As one of the most representative DL algorithms, CNNs are a kind of deep feedforward neural

TABLE IV
STUDIES ON ML MODELS FOR ELECTRIC MOTORS

Applied Machine	Applied algorithm	Objective	Number of input variables	Results
SRM [142]	SVM ANN	• Dynamic current • Dynamic torque	3	• SVM has better generalisation ability • SVM has less time consumption
IM [143]	Kringing model SVM ANN	• Power factor	3	• SVM shows better performance
IPMSM [144]	SVM XGBboost	• PM flux linkage • D-axis inductances • Q-axis inductances	11	• XGBoost has a higher accuracy for predicting the d-axis inductance
FRPMAN [145]	SVM AdaBoost GBDT CatBoost	• Back-EMF amplitude • Back-EMF THD • Average torque • Torque ripple	12	• The CatBoost method provides accurate, efficient and robust prediction of the surrogate model
PMSM [146]	SVM RF	• Dynamic torque • Rotor temperature • Winding temperature	5	• Both SVM and ANN showed satisfactory
PMSM [147]	ANN	• Back-EMF RMS • Back-EMF THD • Cogging torque • PM volume	12	• The overall accuracy of the prediction model reached 97%
PMSM [148]	ANN	• Average torque • Back-EMF THD	2	• Optimal design obtained successfully through proposed method

network that is particularly well-suited for extracting features directly from high-dimensional data like images or audio, which can provide more comprehensive and representative information for performance prediction. CNNs normally work by analyzing input images in a hierarchical manner, where the first layers detect basic features like edges, corners, and colors, and subsequent layers combine these features to identify more complex patterns like shapes, textures, and objects [157, 158].

The key feature of CNNs is utilizing convolutional and pooling layers. Convolutional layers apply filters to the input image, which can detect specific features or patterns. By sliding the filters over the image and performing convolution operations, the network can detect the presence and location of these features, even if they appear in different parts of the image. Pooling layers down sample the output of the convolutional layers, reducing the dimensionality of the feature maps and increasing the network's ability to generalize to new inputs [149]. A significant advantage of CNNs is that they can automatically extract the feature of the target, discover the intricate structures of high-dimensional data (normally in the form of multiple layers of arrays), and avoid time-consuming manual feature extraction [159].

In [160], a motor performance prediction model was built based on CNN. In a standardized rule, the input data is designed to be RGB (bitmap) images expressing the cross-sectional geometry parameters of a specific type of interior permanent magnet motor (IPM). Based on the ratio of the average torque relative to the original model, they divided the output into eight categories. Later in [161], they trained another network using 10000 samples concerning torque ripple. However, only 81% of the testing results have an error range within 0.1, and the total accuracy is only about 47.6%. Through a parallel principle, Shuhei Doi *et al.* [159] trained a CNN with 6000 IPM motor samples to classify the input into seven categories of average torque and torque ripple results. Through testing 700 new data, the accuracy of the predictions for these two objectives is 92.40% and 81.30%, respectively. These two studies show that the accuracy of both models in predicting the torque ripple of IPM motors is significantly lower than the average torque. Shuhei Doi *et al.* attributes this to the relatively weak correlation between material distribution, expressed by the input images, and torque ripple. Under a similar vein, [162, 163] also trained CNNs with cross-sectional images of a IPMSM for performance prediction and applied the network to different topology optimization job. The computational cost of the optimization work was reduced by more than 50% in both cases by using the proposed surrogate models.

Another related work is the study conducted by Arbaaz Khan *et al.* [33]. They tested the feasibility of using a convolutional neural network trained with data obtained from FEA to predict the field distribution of low-frequency electromagnetic devices. The input data and different parameters (geometry, material, excitation) of the three model types (simple coil, transformer, and permanent magnet motor) are also expressed through uniform structured RGB images. The network has an encoder and a decoder, with the encoder taking spatially related features from the input and the decoder projecting these onto the input space to obtain magnetic field distribution maps for the models. The accuracy of the network can reach up to 97%. Then, through testing different network configurations, they found that the accuracy could be improved significantly by increasing the number of layers and adding dilated filters in each layer. Similarly, in [164], Arbaaz Khan *et al.* trained a CNN-RNN network to predict the efficiency map of an IPM motor. The result showed an accuracy of 98%.

TABLE V
CNN MODELS FOR ELECTRIC MOTORS

Ref.	Sample scale	Objective	Applied machine	Accuracy
[160]	4000	•Average torque	•IPMSM	84.80%
[161]	10000	•Torque ripple	•IPMSM	47.60%
[159]	6000	•Average torque •Torque ripple	•IPMSM	92.40% 81.30%
[162]	9030	•Average torque •Torque ripple	•IPMSM	82.90%
[163]	5222	•Average torque •Torque ripple	•IPMSM	90.65% 96.69%
[33]	30000	•Field map	•Simple Coil •Transformer •IPMSM	97.95% 98.02% 97.68%
[164]	2900	•Efficiency map	•IPMSM	98.50%

The differences and effects of these CNN models are summarized in Table V. Normally, the accuracy of the model is higher when the scale of training samples increases. However, the validation samples of these models are commonly selected within a close range to training samples. Although the predictions brought by CNNs can replace FEA in optimization work to a certain extent, if there are only a few thousand training samples, CNNs may still exhibit mediocre accuracy.

2) *Unsupervised Deep Learning*

It can be seen from the investigated studies that the sensitivity and accuracy of CNNs for predicting a specific machine's performance are limited. Furthermore, supervised learning, which relies on human supervisors to provide output examples for each input example, often requires millions of training examples to surpass human or conventional computing performance even though a human could learn to perform the task adequately with just a few examples. To address the problem, unsupervised DL modeling methods like autoencoder [165] and generative adversarial networks (GANs) [166] have been examined.

As shown Fig. 5 in GANs work by training two neural networks concurrently: a generator network and a discriminator network. The generator network takes in random noise or designed data and generates new data that should resemble the training data. On the other hand, the discriminator network takes in both actual training data and generated data from the generator network and is trained to differentiate between the two [167]. The goal of GAN's training process is to find a balance between the generator and the discriminator so that the generator can produce data realistic enough to fool the discriminator but not so like the training data that the discriminator can distinguish it. As both the generator and the discriminator improve, the generated data becomes increasingly realistic and difficult to differentiate from real data. This unsupervised approach reduces the need for extensive human supervision and large numbers of training examples [168].

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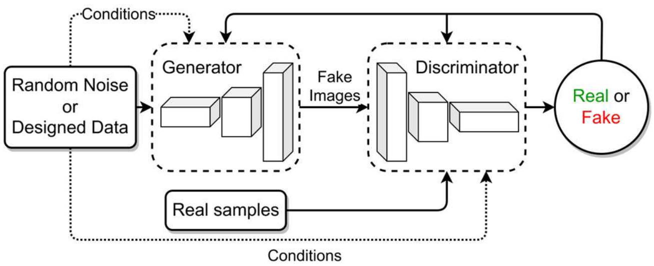

Fig. 5. Basic structure of GANs.

There are typically two types of input to a GAN, random noise or designed conditional information. In normal GANs, the generator takes random noise as input, resulting in generated images that are random and unpredictable. This lack of control over the output makes it challenging to steer the network towards producing a specific target, thus hindering precise generation goals. To overcome this limitation, conditional GANs (cGANs) were introduced. In cGANs, additional conditional information is provided as input to both the generator and the discriminator. This conditional information serves as guidance for the generator to generate images that align with specific conditions or requirements. The generated images can only pass the discriminator's evaluation if they meet the conditions and exhibit a realistic quality at the same time. This additional conditioning ensures that the generated images align with specific requirements, resulting in improved controllability and purposefulness within the network. As a result, cGAN retains the benefit of requiring a relatively small number of training samples, while also incorporating the advantages of supervised learning.

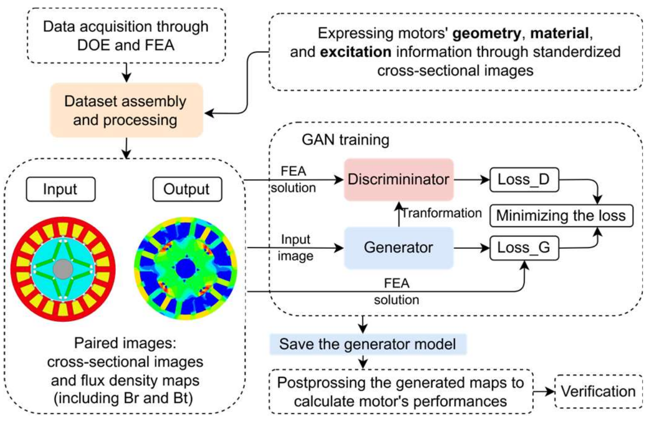

Fig. 6. Working principle of building a performance prediction model through cGAN [166].

In [166], a conditional generative adversarial network (cGAN), Pix2Pix, was applied to build a fast magnetic field approximation model for the magnetic field of coaxial magnetic gears (CMGs). The working principle is described in Fig. 6. This network's input and output are bitmaps. The input is the RGB image representing the geometric structure of the magnetic gear generated by standardized modeling, and the output is the gear's corresponding electromagnetic field density distribution map. The generated bitmaps undergo post-processing to compute CMG performance metrics, including air gap flux density and transmission torque. Notably, the training samples are derived from experimental data obtained through FEA software, necessitating the adherence to the same density color distribution rules for processing the output image. In this particular case study, the Pix2Pix model demonstrated significant concordance with the corresponding outcomes obtained through FEA. Similarly, Zhang et al. [169] tested three different GAN configurations (Pix2pix, CycleGAN, and StarGAN) for predicting the stress diagram of a PMSM's stator through input motor geometry images. The results showed that Pix2PixHD and StarGAN can guarantee 80% similarity to the FEA results.

Due to the ability of GAN to generate high-quality images, another way to use GAN to speed up the motor design process is to use the trained GAN model instead of CAD to create samples for DL network training or validation. For example in [170], GAN is used to generate IMPSM motor models for DOE with FEA, and the obtained data is used for training a CNN motor performance prediction model. In this case, CAD is no longer needed in the training data acquisition phase. In [171], the DCGAN (Deep Convolutional Generative Adversarial networks) was used to generate fake images of various shapes of an IPM motor that existing methods cannot create. The DCGAN model created motor models (in the form of images) according to the classification of pre-trained CNN. The proposed images are then evaluated through the CNN model, and the predicted performance values are compared to FEA simulation results to validate the study.

3) *Summary*

In summary, DL models can extract relevant features from complex input data, allowing for more accurate and efficient performance prediction. By leveraging the power of DL models, researchers aim to overcome the computational challenges associated with topology optimization for electric motors. To overcome the laboriousness of manual feature definition, some DL models including CNNs and GANs have emerged as more promising techniques. CNNs are well-suited for extracting features directly from images, which can provide more comprehensive and representative information for performance prediction. Similarly, GANs offer the potential to generate synthetic data samples that capture the underlying distribution of the motor's performance characteristics, enabling enhanced predictive capabilities. These advancements in DL-based approaches have the potential to revolutionize the design and optimization of electric motors.

D. Transfer Learning

Although there have been several successful cases of data-driven surrogate models applied for electric motors' design optimization, they all share a common characteristic: the models' effectiveness relies heavily on the specific problem they were trained on. Any change in the data acquisition criteria or the analysis target can significantly decrease the network's accuracy. As a result, addressing a problem with different targets would necessitate a substantial amount of new data to retrain the network from scratch. To overcome this, researchers have turned to transfer learning (TL) to extend the capabilities of pre-trained networks to changed or pristine conditions.

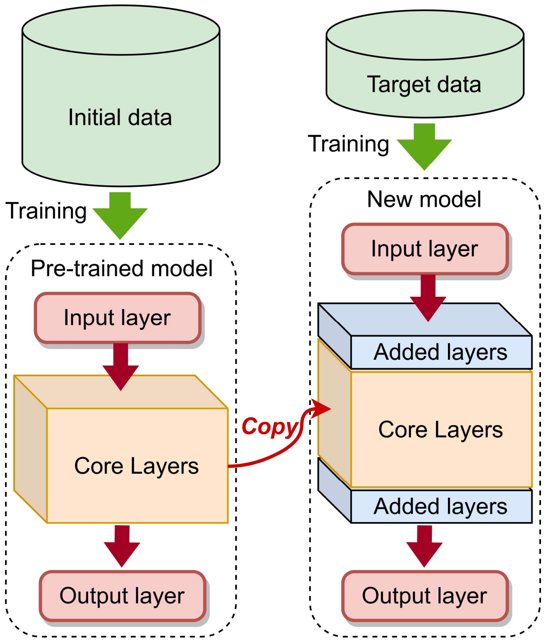

Fig. 7. General principle of transfer learning.

TL is a machine learning technique that leverages "knowledge" gained from solving one case and applies it to a different but related case. As shown in Fig. 7, in TL, a pre-trained model trained on a large-scale dataset is used as a starting point instead of training a model from scratch. In this way, it allows models to transfer learned representations or weights from a pre-trained model to new ones, which can greatly benefit the performance of the new model, especially when the new task has limited samples. Therefore, it can significantly reduce the time and resources required to build a model for new jobs and improve its generalizability [172].

TL can be performed through different methods, such as feature extraction, fine-tuning, and domain adaptation. Feature extraction involves using the pre-trained model as a fixed feature extractor and replacing only the output layer to train on the new dataset. On the other hand, fine-tuning consists in training the entire pre-trained model on the new dataset with a lower learning rate for the output layer. Domain adaptation modifies the pre-trained model's parameters or architecture to fit a different data distribution [173].

The fine-tuning method of TL has demonstrated its effectiveness in improving motor performance prediction across different motor types and analysis scenarios. In a notable example [174], a CNN model trained for predicting the average torque and torque ripple values of a D-shaped IPM motor was then trained by a smaller data set of a V-shaped IPM motor. The new CNN model was proven applicable to both motors and showed much better performance than a CNN model trained by datasets for D- and V-models with the exact sizes of the initial one simultaneously. Similarly, in another study [175], a MLP model trained extensively with a large set of two-dimensional FEA-based samples underwent tuning through transfer learning using a smaller group of three-dimensional FEA-based samples. The tuned network exhibited accurate predictions of motor characteristics, particularly considering size-related variables that satisfied the required specifications while accounting for the axial leakage flux.

E. Challenges and outlook

Table VI summarizes the studies on data-driven surrogate models for motor design optimization that discussed in this section, highlighting the models' functionality categories, input-output forms, major advantages, and encountered limitations. Statistical modeling methods, with their simple structures, are well-suited for single-objective optimization tasks. These models offer a straightforward approach and can provide satisfactory results in such scenarios. However, their accuracy may be insufficient when analyzing new motor designs comprehensively where multiple objectives or complex geometries are involved. Machine learning models, on the other hand, offer higher accuracy and more input variables. They excel at predicting the performance of established motor designs and are particularly suitable for parameter optimization tasks. However, the input of both statistical and ML models is normally at best a dozen predefined dimensional parameters which may make them face challenges when it comes to topology optimization tasks due to the limited number of degree of freedoms (DoFs). In this context, DL models, particularly CNNs and GANs, provide a solution to overcome the limitations of other models in ability of assisting topology optimization. In general, these DL models possess the ability to automatically extract features from images, enabling them to handle a wide range of motor topologies with complex geometries. This allows DL models to bypass the limitations on the number of DoFs encountered in other models. Nevertheless, it is important to note that DL models typically require a significantly larger sample scale and longer training time than other modeling techniques. In addition, although data-driven surrogate models offer great potential for motors' design and optimization, challenges such as accuracy, material inclusion, and generalizability need to be addressed. This Part elaborates on these challenges respectively and discuss about how further research efforts should focus on exploring and refining these models, incorporating material information, and developing techniques that enhance their generalizability to achieve comprehensive motor design optimization.

1) *Accuracy*

Based on the reviewed studies, it can be concluded that as the dimension of input data increases, data-driven models require a larger number of samples to achieve expected accuracy. This presents a similar dilemma to that encountered between FEA and AM methods. Specifically, as highlighted in Section IV, even with thousands of training samples, CNNs may still exhibit mediocre accuracy. In contrast, GANs require fewer training samples due to their training principles based on game theory, potentially achieving higher accuracy by post-processing the output electromagnetic field distribution map instead of relying solely on direct regression on the objectives. GANs leverage the strong correlation between input motor images and their corresponding electromagnetic field distribution, allowing for improved accuracy. The information-sharing scheme between inputs and outputs could greatly improve training effectiveness and efficiency. However, it is essential to note that the existing studies on applying GANs for design optimization in electric motors are still limited, and the

TABLE VI
STUDIES ON DATA-DRIVEN SURROGATE MODELS FOR ELECTRIC MOTORS

Model category	Technique	Input	Output	Highlight
Statistical models	RSM [121-127]	•3-5 dimensional variables	Objective distribution	•To accelerate the optimization process
	Kriging Model [130-133]	•2-5 dimensional variables	Objective values	•To serve as guidance of optimization •To serve as prediction model
Machine learning models	SVMs [142-146]	•2-12 dimensional variables	Objective values	•Good generalization ability •Good time efficiency •limited dataset size
	ANNs [142, 143, 147, 148]	•2-12 dimensional variables	Objective values	•To address higher-dimensional problems •Poor generalization ability
	RFs [146]	•2-5 dimensional variables	Objective values	•Good classification ability •Poor generalization ability
	Boosting algorithms [144, 145]	•2-12 dimensional variables	Objective values	•Better accuracy among ML models •Best overall efficiency among ML models
Deep learning models	MLP [148, 153-155]	•2-10 dimensional variables	Objective values	•More analyzable parameters •Poor generalizability
	BP neural networks [150, 151]	•2-15 dimensional variables	Objective values	•Good accuracy •More analyzable parameters •Poor generalizability
	CNNs [33, 159-164]	•Cross-sectional images of motors	Objective values or performance characteristics maps	•To extract features directly from images •To achieve classification function •To achieve regression function •Large training scale •Time-consuming training •Poor generalizability
	GANs [166, 169]	•Cross-sectional images of motors	Performance characteristics maps	•To extract features directly from images •Less required training samples •To realize image to image translation •Stronger correlation between the input and output

method's feasibility requires further verification through additional research and experimentation.

2) *Material*

Material selection holds significant importance when optimizing motor design, particularly in the context of permanent magnet motors. However, the reviewed studies primarily concentrated on optimizing geometric features and did not adequately consider the inclusion of material parameters as input variables to the models. This limitation was observed across both statistical modeling methods and ML models, where incorporating explicit material information within the input samples posed challenges. Nonetheless, deep DL models present a promising avenue to address this limitation. DL models, such as CNNs, have the capability to capture and learn representations of different materials by utilizing images as inputs for network training. Training the DL model on images exhibiting material variations makes it possible to indirectly learn the relationship between material properties and the resultant motor performance. For example, [176] proposed a method that use three different matrices (one channel images) to express geometry, excitation, and material information of a CI-core respectively and then fed the input data to DL model with designed pre-processing program so that to predict the magnetic flux density map.

However, it is important to note that the inclusion of material information through images in DL models remains an area that requires further exploration. The reviewed studies did not extensively investigate this aspect, and its full potential is yet to be realized. Future research efforts should attend to developing integrated methodologies that effectively incorporate material information into input data, encompassing both geometric features and material characteristics within the modeling, analysis, and optimization frameworks.

3) *Generalizability*

Fig. 8 illustrates the fundamental process followed in existing studies that focus on constructing data-driven models for the design optimization of electric motors. These works primarily aimed to identify an optimal model configuration capable of accurately predicting motor performance. However, after the tolerance test, they showed a common drawback of limited applicability to specific motor types. Consequently, the model's effectiveness significantly diminishes when the target motor changes. This limitation renders the models impractical since extensive analyses of the target machines have already been conducted using FEA prior to training process. Currently, no single model can analyze a wide range of motors with varying topologies, thereby impeding performance prediction for electric motors with arbitrary geometric structures.

Nevertheless, a study [177] has demonstrated the feasibility of integrating GANs and transfer learning for topology optimization. This suggests the potential for utilizing TL to adapt and fine-tune a GAN model proficiently trained with dataset of one specific motor type to analyze different motor configurations effectively. This approach holds promise in addressing limitations on both accuracy and generalizability. It is possible to broaden model's scope to encompass a broader range of motor configurations and topologies for performance prediction and optimization purposes.

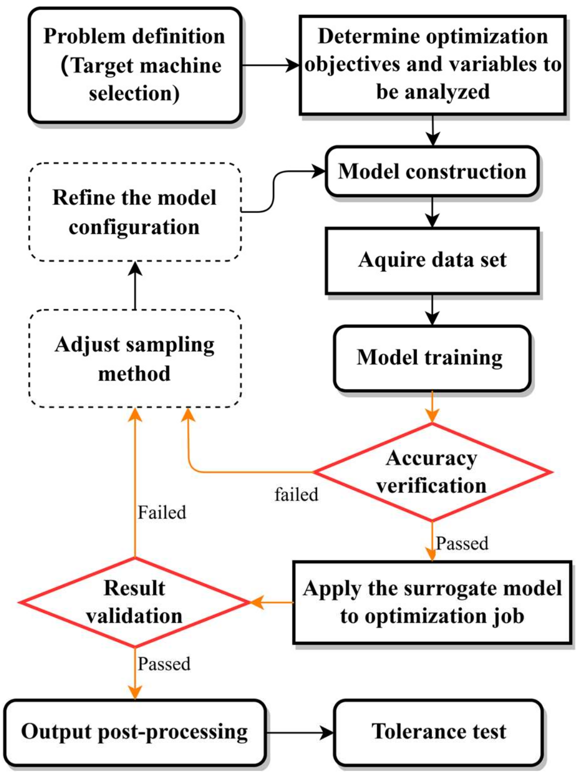

Fig. 8. General methodology of building data-driven surrogate models.

4) *Summary*

As elaborated in this part, key technology trends are shaping the future trajectory of surrogate models for motor design optimization. One prominent trend revolves around the integration of DL models to address the challenges posed by topology optimization and complex motor geometries. The increasing focus on handling higher-dimensional input data and automating feature extraction from images reflects the growing significance of these DL techniques. Additionally, the incorporation of material information within the modeling framework, particularly facilitated by DL models, stands out as a pivotal avenue for future exploration. The roadmap for advancing motor design optimization involves refining existing data-driven surrogate models, addressing challenges related to accuracy, material inclusion, and generalizability. Moreover, the application of TL emerges as a promising strategy to enhance model adaptability and broaden the scope of performance prediction across various motor configurations. Future research endeavors should prioritize the development of integrated methodologies that seamlessly integrate material characteristics, paving the way for comprehensive motor design optimization and further advancing the capabilities of surrogate models in this domain.

V. CONCLUSIONS

This article reviewed the fundamental procedures involved in electric motor design and optimization. The synergistic application of FEA and intelligent optimization algorithms especially EAs has been proven a powerful way to achieve efficient and tailored motor designs that meet the evolving needs of different applications and industries. However, the large number of individual simulations involved in optimization makes this work very computationally intensive. Under this vein, this paper provided an exploration of the studies conducted on data-driven surrogate models to expedite this process. Based on the analysis presented, each data-driven surrogate model examined in this paper possesses distinct advantages and limitations, rendering them suitable for specific requirements within the motor design optimization process.

In summary, the choice of modeling technique depends on the specific requirements of the motor design optimization process. Statistical modeling methods are suitable for simple functional approximation involving relatively fewer design parameters and optimization objectives, while ML models offer higher flexibility for building performance prediction models. Furthermore, DL models improve on ML by increasing the design degrees of freedom that can be analyzed. And it is noteworthy that DL models particularly those designed to handle higher-dimensional data like CNNs and GANs, excel in topology optimization tasks by automatically extracting features from images. Understanding the strengths and weaknesses of each model is crucial in selecting the most appropriate approach, ensuring accurate predictions, and accelerating the motor design optimization process.

Nevertheless, while data-driven surrogate models hold significant promise for the design and optimization of motors, there are inherent challenges that must be addressed. These challenges include ensuring accuracy in predictions, incorporating material considerations effectively, and achieving a high level of generalizability. Overcoming these hurdles is crucial for practical application of data-driven approaches in accelerating motor design optimization.

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