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Application of Artificial Intelligence-Based Technique in Electric Motors: A Review

Wangde Qiu, Xing Zhao, *Senior Member, IEEE,* Andy Tyrrell, *Senior Member, IEEE* , Suresh Perinpanayagam, *Member, IEEE,* Shuangxia Niu, *Senior Member, IEEE* and Guojun Wen

***Abstract*—Electric motors find widespread application across various industrial fields. The pursuit of enhanced comprehensive electric motors performance has consistently drawn significant attention, prompting extensive research in this domain. With the rapid and profound integration of artificial intelligence (AI) technology into diverse sectors, an increasing array of AI-based methodologies are being employed in electric motors research. This review aims to comprehensively delineate the applications of AI within the realm of electric motors, specifically focusing into three pivotal stages: electric motors design, drive control and health maintenance, covering a full-cycle research and development of electric motors. The review commences by outlining the elucidation of the fundamental principles and components of AI. Subsequently, the encompassed input signals, characteristic methodologies and AI techniques are reviewed and analyzed as demonstrated by pertinent research cases. Furthermore, a synthesis of the distinctive attributes characterizing various techniques is presented. Conclusively, this paper offers an unprecedented review of AI-based technology throughout the entirety of the electric motors research cycle. Considering the existing body of knowledge, this paper stands as the pioneering endeavor to encapsulate the expansive domain of AI's influence in electric motors research.**

***Index Terms*—artificial intelligence, design, drive control, maintenance, electric motors.**

I. INTRODUCTION

Amidst the remarkable advancements in modern industrial technology, electric motors have gained widespread utilization across various domains of industrial systems, offering indispensable power support for the advancement and progression of contemporary society [1-8]. Functioning as pivotal energy conversion devices, electric motors find extensive application within industrial production realms [6], encompassing manufacturing, transportation [2], energy generation [8], and more. Their application is pervasive, ranging from minute household appliances [9-10] to expansive industrial machinery [11-12]. A striking illustration lies in the surge of electric vehicles [7], propelling motor technology to unparalleled pinnacles, necessitating revolutionary strides in performance, efficiency, and reliability. Furthermore, the pervasive adoption of renewable energy sources, exemplified by wind turbines [13-16], has precipitated an augmented demand for electric motors. However, despite the notable strides in fundamental principles and design of electric motors over recent decades, the relentless cadence of technological innovation and the escalating intricacy of societal dynamics has concurrently elevated the requisites for mot or performance and efficiency. Paramount are the attributes of efficiency, precision in control, and adeptness in fault diagnosis. In response to this burgeoning demand and the emergence of novel challenges, electric motors research perpetually seeks pioneering avenues, among which AI technology emerges as a potent vanguard propelling the realm of electric motors research.

While conventional approaches to motor design, control, and maintenance have yielded significant progress in the past, their efficacy is progressively constrained when confronted with the intricacies of contemporary production environments [17-25]. This backdrop has paved the way for the integration of AI technology, ushering in novel prospects and avenues for electric motors research. AI, as a technology simulating human intelligence, has exhibited significant potential across various domains, including autonomous driving [26-27], image recognition [28-30], speech synthesis [31-32], and intelligent robotics [33-34]. Its capacity for data-driven learning and autonomous decision-making offers numerous compelling applications within the realm of electrical machine research. From motor design [35] and control [36] to maintenance [37], AI technology introduces fresh perspectives and methodologies distinct from conventional approaches. Through the utilization of techniques such as big data analytics, machine learning, and deep learning, researchers gain an enhanced understanding of the performance characteristics, operational parameters, and potential failure scenarios of electric motors. These advancements not only facilitate parameter optimization during the motor design phase but also enable more precise monitoring

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Wangde Qiu, Xing Zhao, Andy Tyrrell, Suresh Perinpanayagam are with the School of Physics, Engineering and Technology, University of York, United Kingdom, York, YO10 5DD, U.K. (e-mail: wangde.qiu@york.ac.uk, xing.zhao@york.ac.uk, andy.tyrrell@york.ac.uk, suresh.perin@york.ac.uk,).

Shuangxia Niu is with the Department of Electrical Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China. (e-mail: eesxniu@polyu.edu.hk).

Wangde Qiu, and Guojun Wen are with the School of Mechanical and Electronic Information, China university of Geoscience (Wuhan). Wuhan, 430074, China. (e-mail: 13026108709@cug.edu.cn, wenguojun@cug.edu.cn.

and real-time response during operation and maintenance. With the continuous advancement and innovation of technology, electric motors research is undergoing a transformative evolution. From traditional motor design and control to modern intelligence and autonomy, the field of motor research has transitioned from mechanical focus to intelligent exploration. Historically, electric motors research primarily concentrated on enhancing efficiency, reducing energy consumption, and optimizing performance. However, the emergence of AI technology has instigated a paradigm shift, steering electric motors research towards data-driven methodologies, thereby enabling more sophisticated design and control strategies [38-39].

Throughout the complete research cycle of electric motors, spanning from the initial design phase to subsequent control and maintenance stages, AI emerges as a robust pillar of support. During the design phase, AI exhibits the potential to greatly enhance engineering efforts, enabling more precise and efficient designs through the analysis of extensive historical data and simulation outcomes. Moving on to the control stage, the infusion of AI technology empowers real-time adjustment of motor parameters, thereby enabling the adaptation to diverse operational conditions and requirements, ultimately resulting in heightened performance optimization. In the realm of maintenance, AI assumes the pivotal role of identifying potential issues through continuous monitoring of motor operational data. This, in turn, facilitates proactive measures to rectify problems in advance, consequently mitigating production interruptions and curbing repair expenditures.

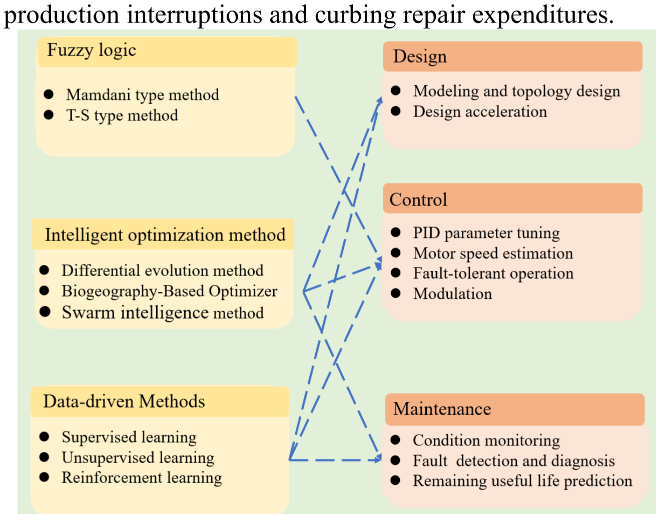

Fig. 1. Application of AI in the life-cycle of electric motors.

AI holds tremendous potential in the realm of electromechanical research. However, it also grapples with a multitude of challenges and limitations. These encompass concerns related to data privacy, algorithm interpretability, and robustness amidst intricate operational conditions. We have identified several existing literature reviews related to this topic. In [40], a review of motor optimization design is presented, covering analytical methods, finite element methods, and artificial intelligence algorithms for data-driven motor optimization. However, it fails to categorize and discuss specific tasks based on optimization or accelerated design, focusing solely on issues related to motor model establishment. [41] provides a review of machine learning algorithm applications in switched reluctance motor (SRM) modeling and optimization design, predominantly discussing supervised learning methods. [42] explores research progress in motor design and control optimization for axial flux permanent magnet synchronous motors, emphasizing traditional model-driven approaches. Although it presents specific motor design and control cases, there is minimal discussion on AI-driven optimization methods. [43] primarily discusses recent advancements in optimal design methods for electromagnetic devices, concentrating on machine learning algorithms with limited case studies on motor research. [44] reviews motor design and control methods, yet predominantly focuses on design aspects, with a shorter discussion on control methods. Finally, [45] examines various options for motor control system solutions, but lacks comprehensive coverage of AI methods due to time constraints.

Motor maintenance encompasses condition detection, fault diagnosis, and Remaining Useful Life (RUL) prediction. [46] presents the latest advancements in motor fault diagnosis, primarily focusing on rolling element bearings. [47] reviews research progress in status detection and fault diagnosis of asynchronous motors, primarily analyzing vibration and current signals. Notably, there is currently no dedicated review paper on motor-related research pertaining to RUL prediction. The existing literature reviewed lacks a comprehensive examination of artificial intelligence algorithms and their applications in motor research. This review seeks to bridge this gap by meticulously studying relevant research from a lifecycle perspective, thereby delineating the trajectory of artificial intelligence development in the electric motor research domain. It further delves into its applications encompassing motor design, control mechanisms, and health maintenance, scrutinizing its role in enhancing motor performance and efficiency across diverse phases. The exploration will predominantly center on the gamut of AI techniques, encompassing fuzzy logic, intelligent optimization algorithms, data-driven algorithms. Through an exhaustive analysis of existing research endeavors, this review unearths how AI can act as a catalyst for innovation in the field of electric machines. Additionally, it deliberates on the potential of AI in surmounting electric machine predicaments and optimizing their performance.

The rest of this article is organized as follows. Section II provides an overview of the AI methods employed in studying the entire life cycle of electric motor. The applications of AI in design, control, and maintenance are discussed in Sections III–V, respectively. The outlook on the AI applications for electric motors is put forward in Section VI. Finally, Section VII concludes this article.

II. Functions And Methods Of AI

Fig. 1 illustrates the methodologies, functionalities, and applications of AI within the realm of electric motors systems.

It is apparent that AI is extensively employed throughout three pivotal stages in the lifecycle of motor systems: design, control, and maintenance. In the comprehensive life cycle research of electric motors, AI methods play a pivotal role, encompassing fuzzy logic, intelligent optimization algorithms, and data-driven approaches. Each of these will be discussed individually below.

A. Fuzzy Logic

Fuzzy Logic is a reasoning method based on fuzzy set theory, designed to address uncertainty and fuzziness. Traditional logic processing methods primarily rely on binary logic, distinguishing between true or false. In contrast, fuzzy logic introduces the concept of "fuzziness," enabling variables to possess continuous membership degrees beyond the binary 0 or 1. This characteristic makes fuzzy logic particularly adept at handling vague, uncertain, and complex problems. It proves to be an invaluable tool for addressing system uncertainty and handling noisy measurements [48]-[50].

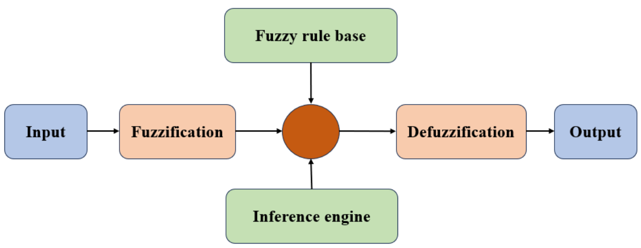

Fig.2. Flowchart of fuzzy logic algorithm

In typical applications, fuzzy logic methods typically comprise four fundamental components [51]: fuzzification, rule-based reasoning, knowledge base, and defuzzification. Fig.2 illustrates the flowchart of the entire fuzzy logic calculation process. In the context of fuzzy inference systems, the predominant synthetic operation formula is as follows:

$$R \circledast S \leftrightarrow \mu_{R \circledast S}(x,z) = \bigvee_{y \in Y} \left(\min\left(\mu_R(x,y), \mu_S(y,z)\right)\right) \tag{1}$$

Fuzzy reasoning relies on a set of fuzzy rules that incorporate fuzzy logic operations, with the Mamdani [45] and TS-type [52] being commonly utilized. The selection between the Mamdani and TS-type hinges on the specific problem's characteristics and requirements. Situations demanding enhanced interpretability and greater tolerance for ambiguity make the Mamdani type more suitable, such as the Mamdani complex fuzzy inference system (Mamdani CFIS) to improve performance of the classical FIS and complex FIS [53]. On the other hand, the TS-type may be more appropriate in cases where there are heightened deterministic requirements for the output and the system model is relatively straightforward, such as a TS-type maximizing-discriminability-based recurrent fuzzy network (MDRFN) that can classify highly confusable patterns [54].

B. Intelligent Optimization Algorithm

In terms of formation principles, intelligent optimization methods can be classified into three categories: those based on evolutionary mechanisms (e.g. genetic algorithms (GA) [55], differential evolution algorithms (DE) [56], Biogeography-Based Optimizer (BBO) [57], etc.), those grounded in physical principles (e.g. simulated annealing (SA) [58], Gravitational Search Algorithm (GSA) [59], Curved Space Optimization (CSO) [60]), and those rooted in swarm intelligence (e.g. Particle Swarm Optimization algorithm (PSO) [61], Ant Colony Optimization (ACO) [62], Bat-inspired algorithm(BA) [63], etc.). Fig. 3 provides an overview of the most common intelligent optimization algorithms. Due to belonging to the same category of algorithms, different intelligent optimization algorithms often share certain similarities. Firstly, they all possess the capability to escape from local optimal solutions, a fundamental requirement for this type of algorithm, typically achieved through the incorporation of random functions. Secondly, manual configuration of all hyperparameters is necessary, with variations in the number of hyperparameters depending on the algorithm type. Generally, intelligent optimization algorithms based on evolutionary mechanisms and physical principles tend to have fewer hyperparameters. Thirdly, a trade-off must be struck between global exploration and local development. Unrestricted global exploration may result in algorithmic failure to converge, while exclusive focus on local development may lead the algorithm to a local optimal solution. Therefore, striking a balance between the two is an imperative step.

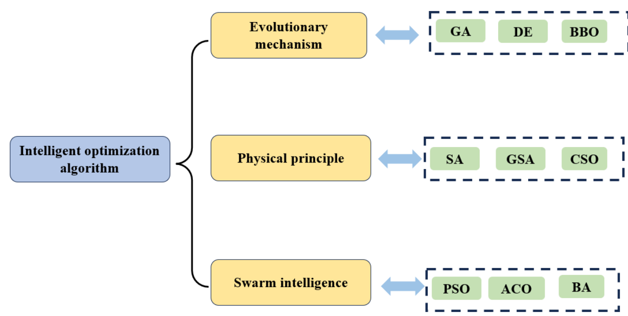

Fig.3. Intelligent optimization algorithm classification

Due to the diverse origins of these algorithms, their strengths and weaknesses exhibit variations. Notably, strategies for balancing global exploration and local development differ. In the PSO, the direction and step size are determined collectively by the original speed of the particle, the local optimal direction of the particle, and the global optimal direction of the particle. In the GA, the direction is determined solely by part of the dimensions, and the step size can be considered as 1. The calculation formula for the most classic particle swarm optimization algorithm is as follows:

$$\begin{aligned} v_i^{t+1} &= w \cdot v_i^{\,t} + c_1 \cdot r_1 \cdot (pbest_i - x_i^{\,t}) \\ &\quad + c_2 \cdot r_2 \cdot (gbest - x_i^{\,t}) \end{aligned} \tag{2}$$

$$x_i^{t+1} = x_i^{\,t} + v_i^{t+1} \tag{3}$$

Equation (2) defines the formula for updating the optimization speed. In this equation, v_i^{t+1} represents the speed of particle i at the (t+1)-th iteration, w is the inertia weight, and c_1 and c_2 are acceleration coefficients signifying the impact of individual experience and group collaboration, respectively.

Both r_1 and r_2 are randomly generated numbers within the range [0,1]. Moreover, $pbest_i$ denotes the best position that particle i has ever reached, which corresponds to the group's optimal solution, while $gbest$ denotes the best position achieved by the entire group, representing the global optimal solution. Lastly, $x_i^{\,t}$ denotes the position of particle i at the t-th iteration. Equation (3) is employed to update the optimized position, where $x_i^{\,t+1}$ represents the position of particle i at the (t+1)-th iteration. This equation elucidates the movement process of particles within the solution space. Utilizing information derived from individual experience and group collaboration, particles endeavor to discover superior solutions. During each iteration, the velocity and position of the particle are updated in accordance with (2 & 3) until the iteration termination condition is met.

Owing to the distinct advantages and disadvantages of the three types of intelligent optimization algorithms, most motor optimization tasks (e.g. electric motors structure topology optimization [39]) are presently addressed using group-based methods. These swarm intelligence-based optimization algorithms enhance motion optimization tasks, evolving and maturing through inspiration drawn from various aspects of nature. Of course, the crux of research lies in selecting the most suitable intelligent optimization algorithm based on specific research tasks, a topic that has also become a research focus.

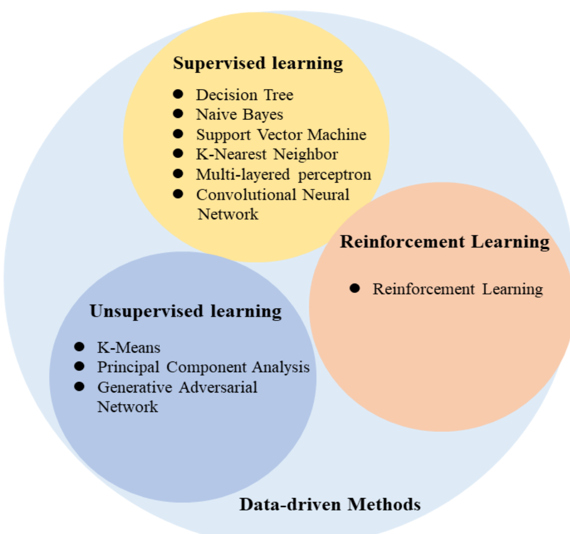

Fig.4. Data-driven method construction

C. Data-driven Methods

Data-driven methods aim to automatically uncover principles and laws through the analysis of collected data, replacing the formulas traditionally derived from mathematical equations. In the context of electric motors applications, this field is primarily categorized into three subdomains: supervised learning, unsupervised learning, and reinforcement learning. Fig. 4 illustrates all the types of data-driven approaches.

1) Supervised Learning

Supervised learning encompasses a variety of functional algorithms designed to map inputs to desired outputs [64]. This approach has proven to be particularly valuable in the field of electrical machines, where formulating accurate system models can be a challenging task. Typically, supervised learning is employed for addressing classification and regression problems. In the realm of motor research, a common classification task involves motor bearing fault diagnosis [65], which entails identifying fault types based on input fault signals. Conversely, a typical regression task is to predict the remaining useful life (RUL) of motor bearings [66].

Supervised learning methods can generally be categorized into three major types: probabilistic models, decision-based methods, and neural network methods. The most typical probabilistic model is the probability graph method, illustrated in Fig.5. The probability graph employs a graphical structure to depict the conditional independence among multivariate random variables, providing valuable insights for those investigating high-dimensional spaces (paying attention to the concept of conditional independence). Probabilistic models offer significant convenience, with one of its most typical applications being Bayesian networks [67].

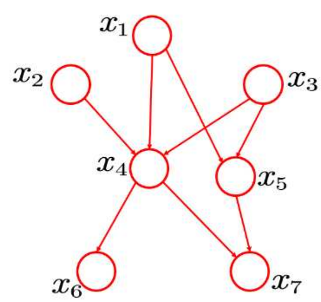

Fig. 5. The structure of probabilistic graph algorithm

Decision-based methods are primarily employed to address nonlinear problems. The fundamental concept underlying these methods is to map input data to a high-dimensional feature space using a technique known as a "kernel function," rendering the problem linearly separable or more manageable in this space. Its most classic application is the support vector machine (SVM), depicted in Fig. 6. In motor applications, it finds utility in the process of predicting motor b earing life [68]. The formula of SVM is as follows:

$$\min_{wb} \ \frac{1}{2}||w||^2 \qquad (4)$$
$$s.t.\ y_i(w\cdot x_i+b)\geqslant 1,\ i=1,2,...,N$$

This problem is a convex quadratic programming issue with inequality constraints. The dual problem can be derived through the Lagrange multiplier method. Kernel functions are generally used for high-dimensional transformation to reduce computational load. Equation 5 gives the Gaussian kernel function formula:

$$K(x,z)=\exp\left(-\frac{||x-z||^2}{2\sigma^2}\right) \qquad (5)$$

After optimization, the basic SVM structure can be described as

$$f(x) = sign\left(\sum_{i=1}^{N} \alpha_i^{*} y_i \exp\left(-\frac{||x-z||^2}{2\sigma^2}\right) + b^{*}\right) \quad (6)$$

In the current era of big data, neural network methods have become widely prevalent. The neural network comprises node layers, including an input layer, one or more hidden layers, and an output layer [69], as illustrated in Fig. 7 and Fig. 8. As highlighted in the preceding discussion, the neural network method is applied across the entire motor research cycle. This encompasses streamlining the design time in motor design [70], achieving intelligent motor control through neural networks in motor control [71], and utilizing neural networks for motor fault detection [72] and Remaining Useful Life (RUL) prediction during the maintenance phase [66].

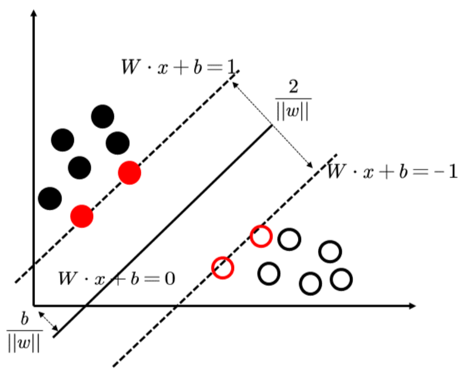

Fig.6. Basic principle of SVM

2) *Unsupervised Learning*

Unsupervised learning encompasses algorithms capable of independently learning to perform a given task without explicit guidance. In unsupervised learning, the program endeavors to identify similarities among objects and group them based on shared patterns, forming clusters. One prevalent method among unsupervised algorithms is k-means clustering, depicted in Fig. 8, commonly employed to discern discrete health states in continuous degradation data [73].

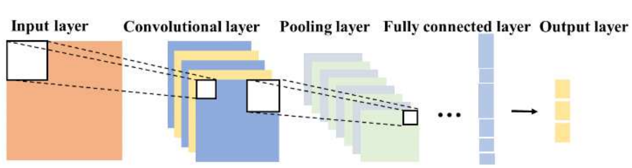

Fig. 7. The basic process of convolutional neural network (CNN)

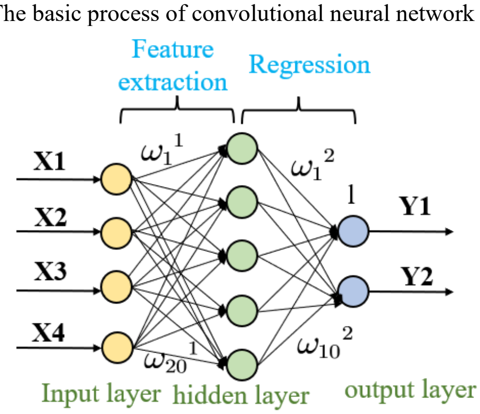

Fig.8. The diagram of multilayer perceptron (MLP)

Principal Component Analysis (PCA) stands out as another frequently used unsupervised method. Its notable advantage lies in the independence of its components, resulting in a reduction in training time. Numerous studies in the literature leverage unsupervised algorithms for analyzing high-dimensional datasets. For instance, in [74-75], the author applies PCA to high-dimensional non-equilibrium fault diagnosis data, enhancing classification performance in rolling bearing fault diagnosis. In [76], researchers utilize PCA-based methods to monitor nonlinear processes.

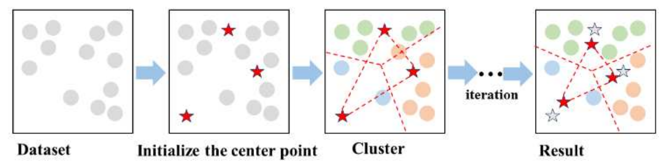

Fig. 9. The process of K-means clustering algorithm

Additionally, Generative Adversarial Networks (GAN), as illustrated in Fig. 9, a deep learning model introduced by Ian Goodfellow and colleagues in 2014, play a crucial role in generating realistic data. The GAN formula is as follows:

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[1 - D(G(z))] \quad (7)$$

Establishing an adversarial process. The generator update formula is as follows:

$$\min_G V(D,G) = E_{z\sim p_z(z)}[\log(1 - D(G(z)))] \quad (8)$$

The objective of the generator is to minimize the likelihood that the output is identified as generated data. The discriminator update formula is as follows:

$$\max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_{(z)}(z)}[\log(1 - D(G(z)))] \quad (9)$$

The objective of the discriminator is to optimize the combined probability of correctly classifying real data and the generator's output. In electric motors research, GANs prove invaluable in scenarios with insufficient data, where they supplement datasets for model training, yielding improved algorithmic results [77].

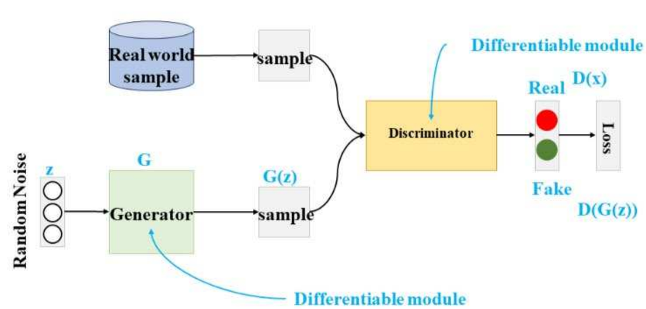

Fig. 10. Basis structure of GAN

3) Reinforcement Learning

Reinforcement learning (RL) [78], as the third fundamental data-driven approach alongside supervised and unsupervised learning, involves learning through interaction with an environment. Unlike supervised algorithms, it does not necessitate labeled data pairs. Reinforcement learning primarily seeks a balance between an unfamiliar environment and existing knowledge. The general algorithm for reinforcement learning is illustrated in Fig. 10. Reinforcement learning primarily centers on the agent's learning to achieve a specific goal while interacting with the environment. The formula of Q-learning reinforcement learning is as follows:

$$Q(s,a) = Q(s,a) + \alpha\left(R(s,a) + \max_{A} Q(s',A) - Q(s,a)\right) \quad (10)$$

Its loss function is:

$$\begin{aligned} &L(\theta) = E[(TargetQ - Q(s,a;\theta))], \\ &TargetQ = R(s,a) + \max_{A} Q(s',A,\theta) \end{aligned} \quad (11)$$

In reinforcement learning, an agent observes feedback from the environment by executing various actions and adjusts its behavior based on this feedback to maximize expected long-term rewards. This process mirrors the way humans learn new tasks, refining behavior through trial-and-error experiences. Further theoretical details can be found in [78]. Noteworthy applications of reinforcement learning in comprehensive motor research cycles include using reinforcement learning (RL) to have an agent learn electric drive control from scratch merely by interacting with a suitable control environment [79]. Reinforcement learning derives experience from interactions between systems rather than relying on existing datasets. Consequently, it proves advantageous in situations where the system is less understood, or its model is challenging to formulate.

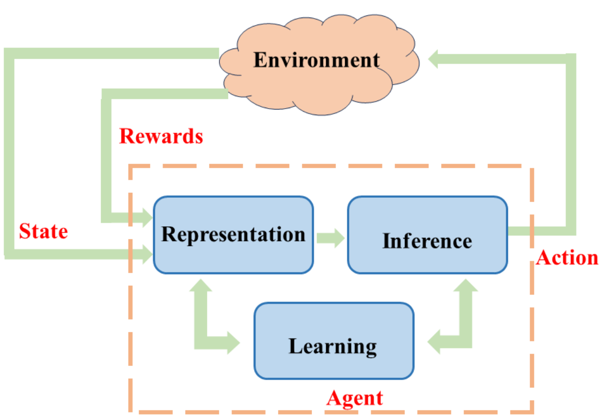

Fig. 11. The structure of reinforcement learning

III. Model Design And Optimization

Electric motors play a crucial role in contemporary industry and everyday life, finding extensive applications across manufacturing, transportation, energy, and more. To enhance the performance, efficiency, and reliability of electric motors, optimal design has emerged as a pivotal area of research. The motor's performance parameters and structural design exert a direct influence on its efficiency, power density, reliability, and other critical aspects. Traditional motor design methods often necessitate extensive trial-and-error, along with a significant amount of experience. This makes it challenging to achieve optimal performance, especially under intricate and ever-changing working conditions. Hence, the importance of optimal motor design becomes evident. The objective of optimal design is to identify the most suitable design parameters within specified constraints. However, the process of achieving the optimal design for motors is fraught with challenges such as multiple objectives, numerous constraints, and high dimensions.

AI technologies, including machine learning, deep learning, and intelligent optimization algorithms, introduce novel concepts and approaches for the design of motors. This section introduces the utilization of traditional AI algorithms in the context of motor optimization design.

A. Topology Design

Motor topology design involves the systematic design of a motor's structure and parameters while adhering to design constraints, with the aim of achieving optimal motor performance in terms of attributes like torque, power density, and loss. This process commonly employs methodologies such as EA, GA, or PSO to explore the design space and identify the optimal motor parameters that meet predefined performance objectives. Fig. 11 shows the application of AI algorithm in motor topology optimization.

An increasing number of novel intelligent optimization methods, grounded in AI, are being proposed and applied within the realm of motor topology design and parameter optimization. Among these methods, Mahmoudi [80] introduced a hybrid approach that combines the genetic algorithm with finite element analysis to optimize the dimensions of axial flux permanent magnet motors, thereby achieving the highest power density for the motor. Similarly, Lee [81] presented an intelligent optimization algorithm based on the particle swarm optimization algorithm. This approach was employed to optimize both the geometry and winding layout of permanent magnet synchronous motors, effectively attaining the objective of minimizing torque ripple. Furthermore, Hong [82] drew inspiration from the artificial bee colony algorithm. They formulated motor efficiency, mechanical and electrical time constants as the optimization objectives, while identifying pertinent motor parameters as the adjustable variables for conducting comprehensive motor design optimization. A comparative analysis, utilizing finite element simulation, was performed between the motors before and after optimization. The results validated the superiority of the proposed methodology.

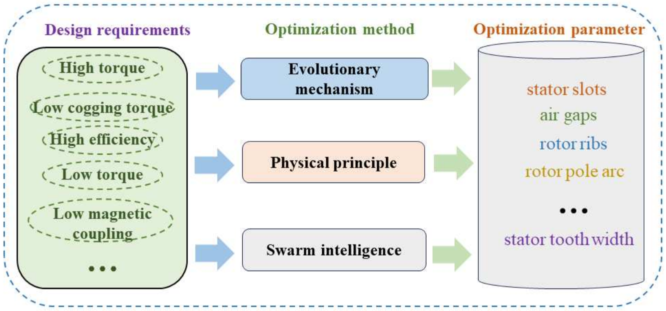

Fig. 12. AI algorithm for electric motors topology optimization

Park [83] proposed a method for designing synchronous reluctance motors aimed at optimizing torque ripple through the establishment of a Response Surface Methodology (RSM) model. By optimizing various parameters such as stator slots, air gaps, rotor ribs, and flux barriers, a significant reduction in torque ripple was achieved, amounting to a 95.8% reduction in total variation. The application of the RSM model in motor design has also been explored in [84] and [85]. These studies utilized the RSM approach to optimize cogging torque and torque ripple in brushless DC motors, as well as to enhance power factor and overall efficiency.

These cases collectively underscore the profound advantages of employing intelligent optimization algorithms in the domains of topology design and parameter optimization. It is, however, discernible from the overview of these methods that the design parameters and optimization objectives tend to be relatively simplistic and unidimensional in nature. Consequently, they might not be well-suited to address the intricate demands of complex multi-objective variable optimization scenarios. To address this limitation, Kwon [86] introduced an innovative algorithm that amalgamates the Kriging model with the MOGA (Multi-Objective Genetic Algorithm) to effectively optimize a trio of objectives: cogging torque, torque ripple, and average torque. The algorithm's inputs encompass essential parameters such as rotor pole arc and stator tooth width. Through experimentation, the algorithm's efficacy has been empirically validated, confirming its proficiency in addressing intricate optimization challenges.

From the aforementioned review, it is evident that the collaborative research between Finite Element Analysis (FEA) and intelligent optimization algorithms has laid a solid foundation and represents a promising avenue for achieving efficient motor design to meet the evolving industry demands. Furthermore, certain commercial software packages such as ANSYS and COMSOL have integrated preliminary optimization algorithms, facilitating users in swiftly conducting motor design optimization. However, employing FEA for motor simulation is a computationally intensive process, particularly for multi-objective optimization and three-dimensional motor simulations. Consequently, the current optimization designs primarily prioritize accuracy, making it challenging to simultaneously consider computational costs. Therefore, the development of more flexible and novel models emerges as a significant research trend for the future.

B. *Design Acceleration*

If the evaluation of design objectives involves computationally intensive tasks, there is a need for enhancing the formulation of these objectives. One notable application of AI methods lies in the utilization of surrogate models within the framework of objective formulation to alleviate computational burdens. Surrogate models replicate the same behavior as numerical computation methods, such as finite elements or finite differences, which are known to be challenging or demand extensive computational resources for characterization. The adoption of AI-based surrogate models can substantially mitigate the computational workload encountered during iterative design processes. Fig. 12 shown the flowchart of AI models in design acceleration.

In the realm of magnetic field acceleration estimation, Arbaaz [70] pioneered the application of a deep learning algorithm based on the Unet network structure for accelerating magnetic field estimation in the IPM motor design process. The neural network model, trained on a carefully constructed dataset, swiftly yields motor magnetic field distributions with accuracy on par with those obtained through finite element analysis. Additionally, Arbaaz [87] introduced an innovative approach employing deep learning to predict motor drive efficiency maps. Recognizing the time-intensive nature of incorporating the complete efficiency map into the design optimization process, the article proposes two deep learning network frameworks for rapid and precise efficiency map prediction. Comparative analysis against finite element results substantiates the advantages of this approach, including heightened prediction accuracy and reduced computation time. Similarly, Sami [88] devised a method to expedite motor torque acquisition by training convolutional neural networks on finite element analysis data, thus significantly curtailing the overall computational time required for the optimization process.

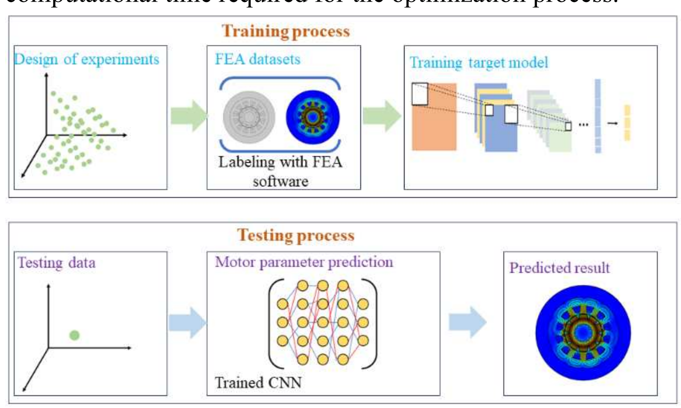

Fig. 13. The flowchart of AI models in design acceleration

Another example of accelerated motor optimization is given in [89]. Asanuma proposes a method to reduce the computational cost of motor topology optimization based on GA through transfer learning. Through transfer learning of a small sample dataset, accurate inferences can be made regarding the average torque and torque ripple values. This method is capable of reducing the computational cost to less than 15% of the traditional topology optimization method. In

TABLE I
STUDIES ON TOPOLOGY DESIGN AND DESIGN ACCELERATION FOR ELECTRIC MOTORS

Functions	Reference	AI algorithm	Input	Accuracy	efficiency
Topology design	[74]	GA	• inner to outer diameter ratio; air-gap length;machine outer diameter • stator and rotor core flux density	THD 2.5%； Peak cogging torque 40% reduction;	91.5%
	[75]	PSO	• rotor core • rotor teeth	THD 2.35%; Torque ripple 2.93%	--
	[76]	ABC	• inner diameterof stator • length of air gap	Mechanical time constant reduced 68.6%	increased 1%;
	[77]	RSM	• slot of stator • air gap • rib of rotor • flux barrier	Torque ripple 63.8%	--
	[78]	RSM	• Permanent magnet shape • length of air gap	Cogging torque reduced 89.9%; Average torque incresed 16.66%;	79%
	[79]	RSM	• Length from PM slot to shaft • Slot angle of side PM segment • Air duct gap	Torque ripple reduced 40%	92.37%
	[80]	GA	• Rotor pole-arc • Stator tooth width	Cogging torque reduction 89%; Torque ripple redcution 72.4%	Back-EMF 3% less;
Design acceleration	[64]	CNN	• image of magnetic field	MSE 0.1%-1%	2-3s
	[81]	RNN	• image pair of motor and efficiency map	RMSE 0.75-1.5%	2-3s
	[82]	DNN	• SyncRM geometry image • magnetic image	MAPE 7.54%	Accelerate up to 20×
	[83]	Transfer learning	• cross-sectional image of motor	Correlation coefficient 0.993	Reduced to 15% and 13%
	[84]	DNN	• cross-section of EM consists geometry information of one full pole rotor and stator.	MRE less than 5%	PCC close to 1
	[91]	Deep transfer learning	• image pair of 2D motor and magnetic image. • image pair of 3D motor and magnetic image.	MSE Less than FEA	faster than FEA
	[92]	RL	• Motor geometry image. • Magnetic image.	T_{avg} 3.34-3.4N.M	Reduce time by 70%-90%
	[77]	Pix2pix CycleGAN StarGAN	• Motor geometry image with hole. • Stress diagram of the motor stator	80% similaritar to the FEA	15s
	[93]	PI-GAN	• image pair of motor and magnetic image.	MAE 3.16%	40× faster than FEA

his research, Vivek [90] emphasized that quantifying and evaluating motor design using key performance indicators (KPIs) and optimizing all KPIs across different domains by altering specified parameters within the extensive design space is a time-consuming process. Therefore, a meta-model based on deep learning is proposed to predict motor KPIs, thus expediting the optimization process and lowering its computational burden. Through experimental comparisons, the proposed method demonstrates high prediction accuracy and the ability to significantly minimize optimization time. Additionally, Korean scholar Soo-Hwan [91] introduced an agent modeling approach based on deep transfer learning to reduce the computational cost associated with calculating three-dimensional finite element motor parameters. This method leverages a large dataset of motor parameters based on two-dimensional finite elements alongside a smaller dataset of motor parameters based on three-dimensional finite elements. By identifying size-related variables that adhere to the required specifications, accurate predictions regarding motor characteristics can be made. This approach has been validated through three-dimensional finite element analysis and experimental testing, confirming its effectiveness.

Recently, Arbaaz [92] introduced a novel approach based on deep reinforcement learning to train neural network-based agents for the optimization of synchronous reluctance motors' topology. When compared to the optimization method relying on GA, this approach substantially reduces computation time by 70%-80%. Addressing concerns related to vibration and noise suppression in motor optimization, Zhang [77] proposed an innovative technique rooted in deep learning as a replacement for conventional finite element analysis. This methodology not only attains the same level of precision as the finite element method but also boasts absolute timeliness as a distinct advantage. In a similar vein, Wu [93] directly presented the PIGAN method, which supplants finite element analysis for modeling and simulating linear motors. In contrast to finite element analysis results, this proposed method not only offers a substantial level of accuracy but also accelerates computation by a factor of 40.

The aforementioned literature review provides a chronological overview of recent research examples on accelerating motor design through AI algorithms. In the field of motor design acceleration, AI models have become an increasingly prominent research trend due to their computational efficiency and satisfactory predictive capabilities. These models are characterized by their simplicity while offering excellent predictive performance. Table I summarizes the AI-based methods for motor design discussed in this section.

Compared to traditional FEA methods, AI models excel in creating accurate vector-to-vector mappings. This ability enables them to handle optimization tasks involving high-dimensional datasets more effectively. In essence, AI models can extract relevant features from complex input data, thereby achieving more accurate and efficient performance predictions. By harnessing the power of AI models, researchers aim to overcome the computational challenges associated with motor topology optimization. To overcome the laborious nature of manual feature definition, some deep learning models, including CNNs and GANs, have emerged as promising techniques. CNNs are particularly suitable for extracting features directly from images, providing more comprehensive and representative information for performance prediction. Similarly, GANs offer the potential to generate synthetic data samples that capture the underlying distribution of motor performance features, thereby enhancing predictive capabilities. Furthermore, considering the research across different motor types, transfer learning algorithms can save model training time and quickly yield accurate models. The advancements made by these AI-based methods have the potential to revolutionize the design and optimization simulation of electric motors.

IV. Motor Control Strategies

Effective control of electric motors stands as a critical process in ensuring their optimal and precise functioning. The primary objective is to achieve anticipated performance and operational benchmarks by meticulously regulating parameters such as motor current, speed, and torque. While conventional motor control methods primarily rely on classical approaches like PID controllers, their ability to handle intricate nonlinear operational contexts and dynamic load variations is limited. Furthermore, challenges persist, encompassing uncertainties, time lags within the motor system, and the inability of traditional techniques to adequately surmount these hurdles. The advent of AI technology has introduced novel concepts and methodologies to motor control, enhancing the adaptability of motor systems to intricate and fluctuating environments. This section elucidates the integration of AI algorithms into motor control strategies. For the AI-related methods in control applications, it is organized in terms of fuzzy logic, neural networks and reinforcement learning.

A. Fuzzy Logic Controller

Fuzzy logic-based methods have been widely applied to the control of electric motors systems, as illustrated in Fig. 13, e.g., speed control [94]. This article employs PID controllers and fuzzy logic controllers to regulate the speed of a DC motor. PID controllers necessitate a mathematical model of the system, whereas fuzzy logic controllers are grounded in experiential rule-based knowledge. Designing a fuzzy logic controller involves numerous decisions, including those related to rule bases and fuzzification. The FLC encompasses two inputs: speed error and the change in speed error. For the fuzzy logic controller, 49 fuzzy rules have been devised. Defuzzification is achieved using the centroid method. The fuzzy logic controller adopts the Mamdani system, employing fuzzy sets in subsequent stages. In contrast to traditional PID controllers, fuzzy controllers exhibit superior performance in both transient and steady-state responses. They boast more favorable dynamic response curves, shorter response times, smaller steady-state errors (SSE), and higher precision. Notably, the PID controller determines parameters through a trial-and-error approach. Fig. 14 shown the flowchart of fuzzy logic controller.

In [95], a novel adaptive Takagi-Sugeno-Kang (TSK) fuzzy controller (ATSKFC) is proposed to regulate the speed of a switched reluctance motor (SRM). The controller comprises two components: the TSK fuzzy controller and the compensation controller. The TSK fuzzy controller serves as the primary controller, approximating the ideal control law, while the compensation controller is designed to address the approximation error between the TSK fuzzy controller and the ideal control law. Robustness of the proposed scheme is ensured by considering parameter changes in the SRM driver and external loads. The parameters of the ATSKFC are adjusted using an online tuning method based on Lyapunov, ensuring the stability of the control system. Three control schemes—ATSKFC, fuzzy control, and PI speed control—were experimentally studied, and each scheme was evaluated using the performance index root mean square error. The results demonstrate that ATSKFC outperforms the other comparison schemes. Similarly, the TS controller has been employed in [96] and [97], both focusing on motor speed control. In comparison with traditional PID control, they have exhibited favorable results.

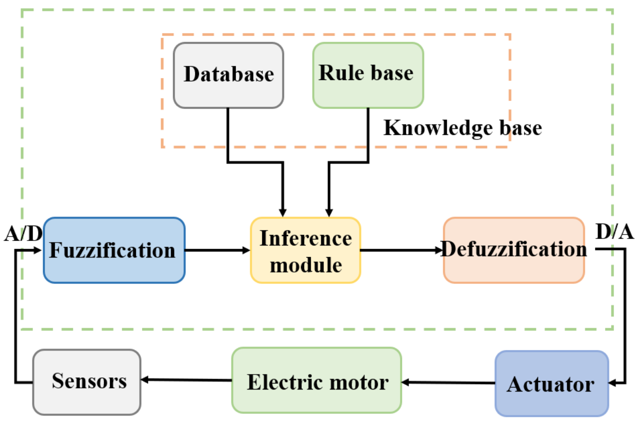

Fig. 14. Flowchart of fuzzy logic controller

B. Neural network Controller

In recent years, neural networks have gained popularity in control research due to their notable advantages, primarily showcased through their robust nonlinear modeling and adaptability. Neural networks excel in capturing complex nonlinear relationships within a system, making them particularly effective in addressing highly dynamic and uncertain control problems. Their distributed representation learning, and end-to-end training methods empower neural networks to autonomously glean features and control strategies from data without the explicit definition of a system model. This adaptability allows neural networks to demonstrate flexibility and robustness when confronted with real, complex systems, changing environments, and unknown dynamics.

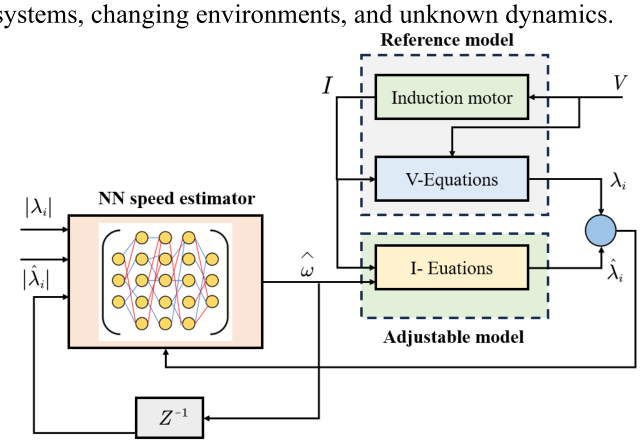

Fig. 15. Neural network block diagram for parameter estimation

In [98], an innovative self-tuning PI control system based on neural networks was proposed to enhance the robustness of the fixed gain PI controller. In this novel approach, a trained neural network dynamically adjusts the gains of the PI controller according to each identified operating condition pair (torque, angular velocity, and position error). Both computer simulations and experimental results demonstrate the superiority of this newly developed dynamic PI method over the fixed PI scheme in terms of rise time, precise positioning, and robustness, thereby achieving more accurate motion control for PMAC motors.

Additionally, in [99], the author recognized that many practical problems involve the control of a nonlinear system using a known structural controller under parameter uncertainty. However, there are instances where certain state variables cannot be directly measured. To address this challenge, the control requirements, originating from induction motors, are met through the application of neural network-based observer techniques. These techniques aim to estimate state variables while compensating for unknown parameter changes. Extensive simulations conducted by the author affirm the effectiveness of this approach in motor control scenarios.

To estimate the speed of electric motors using neural networks, models of rotor magnetic flux based on voltage and current need to be specified. Fig. 15. presents a schematic of a motor speed estimator using a neural network. The reference model is defined by a voltage equation without parameter $\hat{\omega}$, while the adjustable model is defined by a current equation with parameter $\hat{\omega}$, and is identified as the output of the ANN. If the estimated speed does not match the measured speed, an error will occur between the fluxes of the reference and adjustable models. This error prompts an online adjustment of the neural network weights to minimize it, followed by backpropagation into the ANN. Subsequently, the output of the neural network seeks to match the actual speed [100]. [101] introduces an effective method for speed estimation of a magnetically controlled three-phase induction motor using a time-sequence neural network. This approach utilizes D-axis and Q-axis voltages, electromagnetic torque, and rotor magnetic flux data from the SVPWM inverter as inputs for the neural network. Compared to model-based reference adaptive systems (MRAS), this method offers reduced computational complexity and improved results due to the neural network's approximation capabilities. [102] proposes a novel approach to estimate rotor and stator resistance in real-time using an artificial neural network. This technique employs a feedforward neural network to estimate rotor resistance, while a dual-layer neural network with a variable learning rate is used to assess stator resistance. Consequently, accurate resistance estimation enhances the performance of sensor-driven induction motors. Both simulation and experimental results validate that the neural network estimates align closely with the actual motor speeds, with minimal error in resistance estimates. [103] discusses estimating equivalent circuit parameters using a method that integrates model reference adaptive systems (MRAS) and a

TABLE II
STUDIES ON AI-BASED CONTROLLER FOR ELECTRIC MOTORS

Function	Reference	AI control algorithm	Input	Accuracy	efficiency	Contributions
Fuzzy logic-based controller	[94]	Fuzzy logic	• Current	Overshoot 0.0082%	Settling time 0.76s	• Better dynamic response curve, shorter response time, small steady state error (SSE) and high precision
	[95]	TSK-fuzzy logic	• Motor speed	RMSE 4.5586	--	• Superior tolerance capacity for parameter variations
	[96]	TSK-fuzzy logic	• Motor speed	Overshoot 0%	Settling time 0.042s	• The performance of the controller is much better than that of conventional controllers
	[97]	TSK-fuzzy logic	• Motor speed	Overshoot 2.577%	Settling time 12.4ms	• The combined TSK-GA-FLC mechanism has better performance compared to the fixed fuzzy rule mechanism controller.
NN-based controller	[98]	NN	• Torque, angular velocity, and position error	--	Settling time 40ms	• The proposed neural-network-based self-tuning PI control technique was demonstrated to be superior to the conventional PI control
	[99]	NN	• Voltage	--	Shorter settling time Training time:--	• Precise control can also be achieved when some parameters cannot be accurately measured
	[100]	ANN	• Voltage	RMSE 2%	--	• A high level of accuracy in the low speed range
	[101]	ANN	• Voltage • Torque	Nearly zero error	--	• Provided accurate speed estimation
	[102]	ANN	• Current	2%	--	• The proposed method is more accurate
	[103]	FMLP	• Voltage • Current	7%	--	• A high level of accuracy
	[104]	BPNN	• Motor speed	Smaller overshoot	Shorter settling time Training time:--	• Fast response, small overshoot and short recovery time.
	[105]	BPNN	• Voltage	Tracking error 0.04	Settling time 0.05s Training time:--	• Two neural networks have been adopted for system identification (NNI) and control (NNC), respectively.
	[106]	RBFNN	• Speed	Speed fluctuation 25.8 rpm	Settling time 0.05s Training time:--	• Applied to other control systems with uncertain parameters and complex load disturbances.
	[107]	CNN	• Current	Overshoot decreased by 2.5%	Settling time 0.5s Training time:--	• Obustness against external torque load changes.
	[108]	RNN	• Current	Better steady performance	Settling time:faster Training time: 36.5us	• Not require the knowledge of the motor parameters, avoiding therefore the influence of parameter variations.
RL-based controller	[109]	RL	• Motor speed.	Error decreased by 40%	Faster speed response Training time:--	• Improve the robustness against load disturbances and high performance of the PMSM speed control system.
	[110]	RL	• Motor speed.	--	100 us Training time:900s	• The controller maintains the character of its response independently to the changes in the object’s moment of inertia.
	[111]	RL	• Motor speed.	Error 0.41	1min and 53s Training time:10min and 35s	• Short training time and inference time as well as minimal computational load

rotor magnetic flux observer. A multi-layer feedforward neural network (FMLP) acts as a state filter to estimate rotor magnetic flux, while motor speed is determined using rotor slot harmonic or eccentric harmonic techniques. This method requires only current and voltage signals and motor nameplate information to accurately estimate all motor parameters continuously and non-invasively online.

In addition to the fundamental neural network controller, the continuous evolution of neural networks and motor control demands has spurred related research. In [104], the author applied the automatic disturbance rejection control (ADRC) to enhance the anti-disturbance capability and tracking accuracy of the speed regulation system for permanent magnet synchronous motors (PMSM). The ADRC was integrated with the backpropagation (BP) neural network, and the process is illustrated in Fig. 16 and Fig. 17. The BP neural network optimizes the parameters of the extended state observer (ESO) through continuous self-learning and weight adjustment, enhancing the estimation accuracy of the summation disturbance in the extended state observer. This results in improved dynamic performance and robustness of the control system. Additionally, [105] acknowledges the strong nonlinear characteristics of servo motors due to factors like excitation input voltage, load torque, and environmental conditions. Deriving a traditional mathematical model expressing both dynamic and steady-state characteristics becomes challenging. To address this, the paper proposes an adaptive control strategy based on neural networks. Two neural networks, one for system identification (NNI) and the other for control (NNC), are employed. The common learning method is modified, using the NNI output as the approximate output of the servo motor during weight training to obtain sensitivity information. The paper also provides rules for selecting the learning rate based on Lyapunov stability analysis. Furthermore, [106] introduces a speed control scheme that combines an adaptive speed controller and a radial basis function neural network (ASC-RBFNN) for regulating the speed of permanent magnet synchronous motors (PMSM). To mitigate the impact of parameter uncertainty and complex load fluctuations on speed control performance, an ASC is proposed. The speed control system (SCS) for permanent magnet synchronous motors, employing ASC, maintains asymptotic stability in the presence of parameter uncertainty and complex load fluctuations. Addressing the uncertainty of complex loads, PMSM parameters, and ASC parameters, RBFNN is utilized to optimize all ASC parameters for achieving optimal speed control performance.

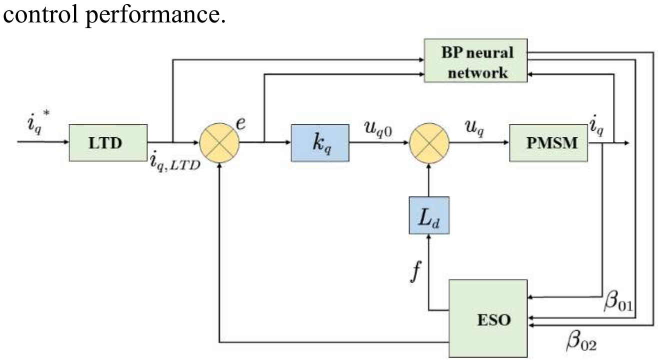

Fig. 16. Block diagram of adaptive ADRC based on BP neural network.

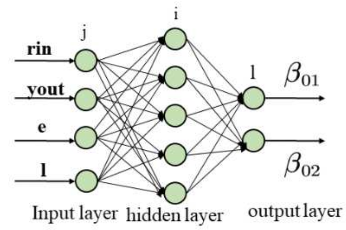

Fig. 17. Structure diagram of BP neural network.

With the onset of the big data era, deep neural networks such as CNN and RNN have become increasingly integral to motor control research. In [107], the authors utilized a full-bridge converter to achieve bidirectional rotation of a PEMFC-powered DC motor. To regulate both the angular velocity of the DC motor and the bus voltage, they proposed an adaptive backstepping sliding mode control (ABSMC) technology integrating a Chebyshev neural network. This neural network estimates system uncertainty through orthogonal basis-Chebyshev polynomials. In the presence of system uncertainty and external disturbances, the CNN estimation method, combined with backstepping sliding mode control, demonstrates a rapid and accurate response. In [108], recognizing that model-based predictive current control (MB-PCC) is highly dependent on system parameters, leading to reduced performance under parameter changes, the authors addressed this limitation. Specifically, for synchronous reluctance motors (SynRM) susceptible to magnetism and inductance changes due to saturation, they introduced a model-free predictive current control method for SynRMs based on recurrent neural network (RNN-PCC). The proposed RNN-PCC relies on the identification of SynRM currents without considering any parameters. Comparing RNN-PCC with MB-PCC, both exhibit outstanding dynamic performance. However, the proposed RNN-PCC achieves superior control performance and reduced tracking error.

C. Reinforcement Learning Controller

The noteworthy advantage of reinforcement learning in control research lies in its capacity to optimize system control strategies through interactive learning between the agent and the environment, obviating the need for an accurate system model. This renders reinforcement learning well-suited for addressing complex, nonlinear, highly dynamic, and uncertain control problems, thereby presenting novel avenues for tackling practical engineering challenges [76]. Its reward-based learning approach empowers the system to continually adjust and enhance control strategies during actual operations, facilitating adaptation to evolving environments and objectives.

One of the pertinent applications of controllers based on reinforcement learning is in the servo speed regulation system of permanent magnet synchronous motors [109]. Specifically, a deep reinforcement learning (DRL) strategy is proposed for the speed control of permanent magnet synchronous motor servo systems, where various disturbances such as load torque and rotational inertia changes are prevalent. The author formulates the speed control problem as a Markov decision process and employs a deep Q network to calculate the optimal adjustment plan corresponding to each speed and error state. In comparison to traditional proportional integral control, the proposed DRL control demonstrates enhanced robustness against load disturbances and high performance in regulating the speed of permanent magnet synchronous motors. In a related study [110], a method for designing neural velocity controllers using reinforcement learning techniques is introduced. The controlled system is an electric drive featuring a permanent magnet synchronous motor with a complex mechanical structure and variable parameters. The study investigates the effects of changes in target parameters and critical behavior of the system based on control error and energy cost. Notably, the proposed approach achieves the desired effect without disabling the adaptive algorithm, ensuring long-term performance stability. Similarly, in another study [111], the authors address the challenge of quickly controlling a DC motor in the presence of disturbances and uncertainties. To tackle this, the study suggests employing sample-efficient reinforcement learning to efficiently learn to control DC motors. Utilizing data collected from real-world hardware interactions, a simulator is developed to experiment with various parameters and learning strategies. Upon identifying the optimal parameters, an effective control strategy is learned in just 1 minute and 53 seconds in simulation and 10 minutes and 35 seconds on the physical system.

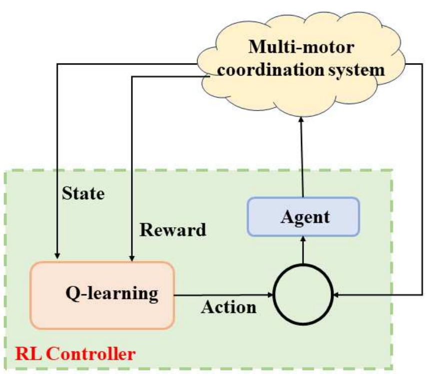

Fig. 18. Block diagram of motor controller based on reinforcement learning.

Overall, these studies highlight the effectiveness of reinforcement learning-based controllers in improving the robustness and performance of motor control systems, particularly in the presence of disturbances and uncertainties.

The aforementioned research on AI-based motor control is organized into three categories: fuzzy logic, neural networks, and reinforcement learning. This categorization is also based on a chronological arrangement. Firstly, it can be observed that AI methods address the limitations of traditional approaches, which require an in-depth understanding of system control principles and are only applicable to steady-state systems, unable to handle parameter variations and rapid transient responses. Fig. 18 illustrates the motor controller structure flow based on reinforcement learning. Table II provides a summary of the AI-based controllers discussed in this section, presenting the test results and contributions of various AI algorithms in motor control applications.

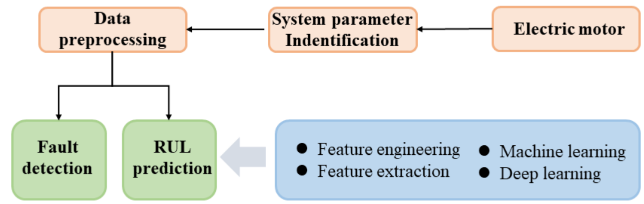

Fig. 19. Flowchart of AI approaches for condition monitoring, fault detection and RUL prediction of electric motor.

It is important to note that the dynamic performance, robustness, and convergence speed of AI algorithms are crucial in control applications. Therefore, the computational cost and data volume of the models need to be considered during the design process. The reviewed research primarily focuses on algorithmic studies. However, in practical online control applications, a comprehensive design should also take into account factors such as control hardware selection, FPGA implementation, and other relevant considerations.

V. Motor Health Maintenance

Although the reliability characteristics of the motor have been carefully considered in the design and control, due to the inevitable effects of temperature, load, vibration, and other factors during long-term operation, performance degradation or failure may occur, or even catastrophic failure may occur. The reliability and safety of motor component control systems are of great significance in practical field applications. In terms of maintenance, preventive activities, such as condition monitoring, fault diagnosis, and Remaining Useful Life (RUL) prediction, are effective methods to ensure the correct performance of expected functions. Traditional maintenance methods typically involve regular inspections or part replacements at scheduled intervals. However, this approach does not provide real-time information about the motor's condition, which can lead to premature maintenance or the neglect of hidden issues. AI technology introduces potentially novel approaches to motor condition monitoring, fault diagnosis, and RUL prediction, enabling more precise detection of potential problems and proactive measures. This section introduces the application of classical Machine Learning (ML) and popular deep learning algorithms in motor condition monitoring, fault diagnosis, and RUL prediction. Fig. 19 summarizes the framework for researching AI methods in the motor maintenance stage.

A. Condition Monitoring

Condition monitoring in motor systems includes system parameter identification, data preprocessing and feature mining. Condition monitoring information is used to discover hidden information, which can serve as the basis for subsequent fault diagnosis.

1) System Parameter Monitoring

Motor current signature analysis (MCSA) [112] is a condition monitoring method used to diagnose motor problems by monitoring the motor's stator current. The fundamental principle lies in the observation that, under various operating

TABLE III

STUDIES ON SYSTEM PARAMETER MONITORING AND FEATURE EXTRACTION FOR ELECTRIC MOTORS

Functions	Reference	Method	Advantages	Shortcoming
System parameter monitoring	[112]	MCSA	• Early fault detection • Non-invasive • High sensitivity • Locate fault location	• Depends on current sensor. • Spectrum interpretation is complex • Unable to detect all types of failures • Environmental impact
	[113]	oil and lubrication analysis	• Early fault detection • Non-invasive • Comprehensiveness • Cost-effectiveness	• Rely on experience. • Limited sensitivity • Not suitable for all situations
	[114]	Vibration analysis	• Early fault detection • Non-invasive • Comprehensiveness • Real-time monitoring	• Complexity. • Equipment cost • Environmental interference • Limited predictive power
	[115]	Acoustic emission analysis	• Real-time monitoring • Non-invasive • Cost-effectiveness • Sensitive to multiple fault types	• Environmental impact • Limited accuracy • Complex fault analysis is difficult • Rely on experience.
	[116-118]	thermal analysis	• Non-invasive • Early fault detection • Comprehensiveness • Wide range of applications	• limited accuracy • Affected by environment • demand for expertise • Higher cost
	[119]	Analysis of air gap or stray flux measurements	• non-invasive • Early fault detection • Real-time monitoring	• Unable to detect all faults • Requires complex equipment a knowledgeable personnel • Demand for expertise
Feature extraction	[120]	FFT	• Frequency domain information extraction • Denoise • Feature dimensionality reduction	• Information lost. • Computational complexity • Sensitive to parameters
	[121]	LDA	• Maximize class separability • Preserves information • Reduces overfitting • Simplifies models	• Assumes Gaussian distributions. • Sensitives to outliers • Linear boundaries
	[122]	Wavelets	• Multi-resolution analysis • Time-frequency localization	• Select wavelet function. • Computational complexity
	[123]	Neural network	• To extract features automatically • Adjustable extraction level	• To find the most suitable network structi difficultly • To be more suitable for image signals
	[124]	HT	• Suitable for non-linear and non-stationary signals • Adaptive	• Modal aliasing problem • Sensitive to noise
	[125]	STFT	• Time-frequency information acquisition • Spectral feature extraction • Suitable for non-stationary signals	• Time-frequency resolution trade-off • Edge effect • High computational complexity
	[126-128]	PCA	• Feature extractiony • Decorrelation	• Information loss • Linearity assumotion
	[129-130]	EWT	• High accuracy and reliability • Reducing signal noise	• After determining the difficult adaptive rob boundary filtering of the EWT segment

conditions of a motor, its current signal manifests distinctive spectral characteristics. Through a thorough analysis of the motor's current signal spectrum, issues pertaining to the motor's operational status can be identified, including concerns such as bearing wear, winding failures, or imbalance. A current sensor at the output records the motor current in the time domain. Motor faults can be diagnosed, and their severity can be verified based on fault characteristics. In addition to MCSA, there are many different condition monitoring methods as follows.

One of the important condition monitoring methods is oil and lubrication analysis [113]. Oil and lubrication analysis play a pivotal role in the detection of motor conditions. By monitoring oil samples extracted from a functioning motor, valuable insights into the system's health can be collected. Particles, specifically metal particles, and other impurities in the oil, serve as indicators of internal wear and potential motor failure. Additionally, the physical and chemical properties of the lubricant furnish diagnostic information, such as variations in temperature, viscosity, and acid number. These changes can signal abnormal conditions during motor operation, including friction, wear, and oil aging. Regular analysis of the oil allows for the early detection of potential issues, enabling proactive maintenance measures, extending the motor's lifespan, and minimizing downtime. Therefore, oil and lubrication analysis not only constitute an effective means of monitoring motor conditions but also stands as a crucial component of preventive maintenance strategies, offering essential support for enhancing the reliability and performance of motor systems.

Vibration analysis stands as a crucial non-destructive monitoring technique for assessing motor status [114]. Its fundamental principle lies in the rich information contained within the vibration signals generated during motor operation. By scrutinizing the vibration spectrum and amplitude, one can effectively pinpoint internal motor faults, such as bearing wear, imbalance, and poor alignment. Frequency domain analysis of vibration signals unveils characteristic frequencies and harmonics associated with these faults, while time domain analysis reveals the waveform characteristics. Combining these methods establishes features related to different failure modes, enabling precise diagnosis of motor status. Motor vibration analysis finds widespread application in practical scenarios, facilitating early detection of potential faults, enabling preventive maintenance, and enhancing the overall reliability and operational efficiency of motor systems.

The principle of acoustic emission analysis in motor status detection is grounded in monitoring the sound signals generated during motor operation [115]. By scrutinizing the spectrum, amplitude, and time domain characteristics of these sounds, potential faults or abnormal conditions within the motor can be identified. This method proves effective in detecting issues with motor bearings, insulation, gears, and other crucial components. In terms of applications, acoustic emission analysis finds extensive use in predicting motor failures, enabling proactive maintenance, and ensuring equipment reliability. Its merits lie in non-intrusiveness, real-time performance, and sensitivity to various fault types, rendering it an efficient means of motor condition monitoring. However, drawbacks include susceptibility to environmental noise and interference, as well as signal complexity that may arise under specific operating conditions. Addressing these challenges requires consideration of multiple factors to enhance accuracy and reliability.

Temperature rise analysis is a commonly employed method in motor status detection [116]. Its principle is grounded in assessing the temperature elevation resulting from losses attributed to internal resistance, current, magnetic fields, and other factors during motor operation. Monitoring temperature rise during motor operation enables the inference of the motor's working status and performance. In terms of application, temperature rise analysis proves valuable for real-time monitoring of the motor's load condition, thermal effects, and potential faults. By measuring the temperature rise of each motor component, it becomes possible to identify in advance issues such as overloading, insulation failure, or bearing problems, facilitating swift and accurate diagnosis and prediction of the motor's status [117-118]. Advantages of this approach include non-intrusiveness, real-time performance, and high fault sensitivity, rendering it widely applicable in motor condition monitoring. However, notable disadvantages stem from the requisite use of reliable temperature sensors and the complexity involved in modeling the motor's thermal characteristics.

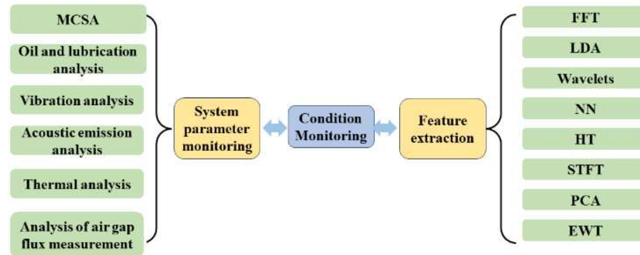

Fig. 20. Block diagram of condition monitoring technology summary

Measurements of air gap or stray flux play a pivotal role in motor status detection, offering valuable insights into the motor's operational condition [119]. This principle relies on the premise that alterations in the motor's air gap or leakage flux convey crucial information about its performance. Monitoring these signals facilitates the assessment of motor health and performance. Fundamentally, detecting changes in magnetic field strength or leakage flux within the motor's air gap enables the acquisition of information related to rotor position, flux distribution, and potential fault conditions. Typically, these measurements are conducted using sensors or sensor networks, with the data transmitted to a monitoring system for comprehensive analysis. In practical applications, air gap or stray flux measurements find widespread use in the realm of condition monitoring and fault diagnosis for motors. These technologies prove instrumental in identifying issues such as rotor fractures, bearing failures, and magnetic flux imbalances, enabling the anticipation of potential failures and consequently reducing downtime and maintenance costs. Nonetheless, this approach has its limitations. Firstly, for small motors, the measurement of air gap or leakage flux may be susceptible to interference from noise, compromising accuracy. Secondly, the implementation of complex sensors and monitoring systems is necessary, thereby increasing system costs. Additionally, high-performance motors may necessitate more intricate algorithms and data processing techniques to effectively extract pertinent information.

The above review summarizes various real-time motor condition monitoring techniques and outlines their advantages and disadvantages. For readers, it is possible to select appropriate monitoring techniques based on the summary of condition monitoring technologies provided in this paper, considering the specific research scenarios. Existing research indicates that MCSA is the earliest and most commonly used monitoring technique. Currently, vibration analysis, MCSA, and thermal analysis are the most prevalent signal acquisition techniques in academic research. Several publicly available datasets also offer a wealth of data collected using these techniques.

2) Data Preprocessing and Feature Extraction

Data preprocessing and feature mining are essential steps in

refining raw data collected, ensuring its optimal utilization in subsequent AI models. For instance, identifying the most effective features for fault detection involves sifting through a myriad of original data features to compress the dimensionality of the feature space, resulting in a more precise fault identification model. The signals gathered in the preceding stages, such as MCSA and vibration analysis,
manifest as current and vibration signals, respectively. These signals, however, may not align with the inputs required for AI model training. Various methods, including Fourier analysis [120], linear discriminant analysis [121], wavelet analysis [122], and neural networks [123], are indispensable for organizing and analyzing the raw data.

Furthermore, the Hilbert Transform (HT) feature extraction method plays a pivotal role in the analysis of original motor data [124]. This method operates by transforming the original data into an analytical signal through HT, followed by the extraction of time-frequency features. Leveraging the properties of HT, this approach effectively characterizes signal features across both time and frequency domains, making it particularly well-suited for analyzing non-stationary signals. In the area of motors, HT feature extraction methods find widespread application in fault diagnosis and condition monitoring. Through the analysis of raw data such as vibration, current, or voltage of the motor, the HT method captures spectral changes, harmonics, and other time-frequency characteristics, enabling the identification of abnormalities or faults in motor operation. Its merits include sensitivity to non-stationary signals, applicability to the analysis of complex vibration signals, and a relatively straightforward implementation. However, drawbacks of the HT method include susceptibility to noise and interference, the necessity for careful parameter selection to ensure accuracy, and potential challenges in phase estimation.

The Short-Time Fourier Transform (STFT), a widely employed method for time-frequency analysis, is commonly utilized in the extraction of features from raw motor data [125]. The underlying principle involves segmenting the signal into brief intervals and applying Fourier Transform to each interval, thereby capturing local information in both time and frequency domains. STFT finds substantial application in motor raw data analysis, particularly in the spectral examination of signals such as motor vibrations, sound, or current. By decomposing the signal into distinct frequency components, it becomes possible to identify characteristics associated with the motor's operational status, including frequency components corresponding to various failure modes.

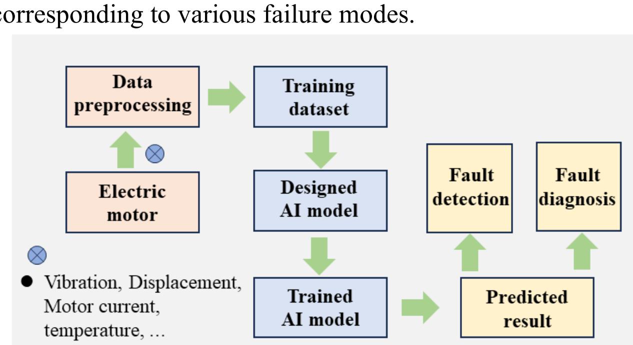

Fig. 21. Block diagram of motor fault diagnosis and fault detection based on AI algorithm

Principal Component Analysis (PCA), as the most prevalent feature extraction method, finds extensive application in the analysis of raw motor data [126-128]. PCA involves the projection of original data onto a new coordinate system through linear transformation, maximizing data variance in this new space. By selecting the initial principal components of this transformed system-representing directions with higher variance-the original data can undergo dimensionality reduction and feature extraction. PCA proves valuable in extracting critical operational characteristics, discerning potential failure modes, and eliminating redundant information within the dataset. Retaining the principal components enables an effective representation of the motor system's status, facilitating fault diagnosis and performance monitoring. An inherent advantage of PCA lies in its ability to reduce data dimensionality, enhance computational efficiency, and unveil hidden structures within the dataset.

For analyzing nonlinear and non-stationary signals, the Empirical Wavelet Transform (EWT) serves as a feature extraction method grounded in the principles of Empirical Mode Decomposition (EMD) [129-130]. In its application to original motor data, the primary objective of EWT is to capture crucial temporal and frequency information embedded in the signals. Through the utilization of EWT, raw motor data can undergo decomposition into a sequence of signal components termed as "Intrinsic Mode Functions" (IMFs). Each IMF encapsulates distinct frequency and amplitude features within the data. This decomposition process facilitates the effective extraction of significant patterns and variations in the motor's operational status. However, it is essential to acknowledge the drawbacks associated with EWT. These include its elevated computational complexity, susceptibility to parameter sensitivity, and limited robustness against noise and interference. These challenges may potentially impede its seamless integration into practical applications. Nevertheless, when considering its overall utility, EWT demonstrates considerable promise in the processing of raw motor data.

The fundamental task of feature extraction is to identify the most effective features for fault recognition from a large set of features, achieving dimensionality reduction in the feature space. In other words, it aims to obtain a concise set of discriminative features with low classification error probability. The above review summarizes various electrical feature extraction techniques and discusses their advantages and disadvantages. Signal processing methods for feature extraction are summarized in Table III. Additionally, Fig. 20 provides an overview of the methods employed for system parameter monitoring and feature extraction.

For readers, it is possible to select appropriate feature extraction techniques based on the characteristics of the collected signal data and the summary of condition monitoring technologies provided in this paper. This selection will facilitate the optimal extraction of data features for further analysis.

B. Fault Detection and Diagnosis

To ensure the consistent and reliable operation of motors, the domains of electric motor fault diagnosis have emerged as critical areas of research. Traditional maintenance methods typically involve regular inspections or scheduled periodic replacement of parts. However, these approaches often fail to provide real-time status information about the motor, potentially leading to premature maintenance or overlooking hidden issues. The emergence of AI technology has introduced novel ideas and methodologies to electric motor fault diagnosis. This advancement enables the motor system to detect potential problems more precisely and proactively implement preventive measures. In this section, the application of classical ML techniques as well as popular deep learning algorithms for electric motors fault diagnosis are considered. The subsequent description of motor faults will be in the following order: Bearing faults; Rotor faults; Stator faults.

1) Bearing Faults

Some new fault identification and fault diagnosis methods based on AI are increasingly being proposed and applied to bearing fault identification. Among them, earlier work includes the CP-select algorithm proposed in 2006 [131], which focused on fault monitoring and classification of multi-category faults through ANN. In this paper, a model-based diagnostic system framework driven by machine learning algorithms for multi-category fault detection in electric drive systems with three-phase induction motors is introduced. The framework comprises an electric drive simulation model implemented using Matlab-Simulink, a machine learning algorithm for intelligently selecting vehicle operating points from the (torque, speed) space. These points are then utilized by the simulation model to generate representative training data. Additionally, a neural network classification system is developed and trained based on signals generated under representative operating conditions for motor fault diagnosis.

According to [132], the author proposed a hybrid motor current data-driven method for bearing fault diagnosis utilizing statistical features, genetic algorithm (GA), and machine learning models. The approach involves extracting statistical features from the motor current signal, using GA to reduce the number of features and select the most important ones from the feature database. Subsequently, these features are employed to train and test three different classification algorithms: KNN, decision tree, and random forest to evaluate bearing faults. In [133], a Gaussian SVM method for machine learning application is proposed. It extracts characteristics of vibration signals collected on-site based on experience to construct a feature space. Features are clustered and classified using different methods to assess electric motors health. The impact of various Gaussian kernel functions (fine, medium, and coarse) on the performance of the SVM algorithm is analyzed. Experimental data validate the performance of various models using datasets from Case Western Reserve University's Motor Bearing Data Center. Additional studies utilizing the SVM method are also found [134-137].

As a conventional machine learning algorithm, the random forest is frequently employed in fault diagnosis. In [136], the author extracted statistical, characteristic, and nonlinear features from collected motor vibration signals. Recursive feature elimination techniques were then applied for feature reduction. Subsequently, the dimensionality-reduced top-ranked feature vectors were inputted into a random forest classifier to categorize vibration signals, enabling the automated detection of bearing faults in induction motors.

With the surge in data volume and the advancements in AI, deep neural networks are increasingly applied in motor fault diagnosis research. Networks such as CNN, RNN, LSTM, GAN, and others have been explored. In [139] and [140], CNN networks were utilized for motor bearing detection. A notable feature of this approach, compared to the machine learning method mentioned earlier, is its requirement for substantial training data, resulting in improved model efficacy. Additionally, leveraging the Long Short-Term Memory (LSTM), a representative RNN for processing time series, in [141], the author extracted fault features from the current signal. Redundant frequencies in the signal were filtered, followed by the use of wavelet packet decomposition (WPD) to extract eight features in the time and time-frequency domain from the filtered signal. These features, combined with the well-established deep learning algorithm, an LSTM network was employed for classifying bearing faults, achieving an accuracy exceeding 96%. Similar studies can be found in [142] and [143].

With the emergence of GAN networks, the challenge of insufficient data has been addressed. Therefore, in [144], the authors acknowledged that in practical fault diagnosis scenarios, the cost and time required to amass sufficient training data often result in data scarcity and imbalance. This inevitable consequence leads to a high misclassification rate in traditional CNN models. To tackle this, a data-enhanced GAN-based early and low-speed fault diagnosis method for rolling bearings is proposed in [144]. Acoustic emission (AE) serves as the monitoring signal. In this method, the generator, discriminator, and fault classifier models are concurrently trained with the proposed parameter update strategy to circumvent the vanishing gradient problem, demonstrating superiority over traditional methods. Similarly, in the study conducted by [145], the application of GAN networks for motor fault diagnosis with limited data was explored, yielding promising results.

The aforementioned studies were conducted primarily in an offline setting. With the increasing demand for online monitoring, research on online network models has emerged. In [146], a method based on Online Sequential Extreme Learning Machine (OS-ELM) is proposed to address the issue of deep learning-based equipment fault diagnosis models being unable to automatically identify new fault categories based on updated fault data. Compared to other incremental single-class models, this method demonstrates excellent fault recognition and diagnostic capabilities. Considering the growing importance of online anomaly detection and identification in Industry 4.0 applications, [147] proposes a method based on syntactic

TABLE IV
STUDIES ON FAULT DETECTION FOR ELECTRIC MOTORS

Function	Reference	Technique	Input	Accuracy	Highlights
Bearing faults	[131]	FDNN	• Voltage • Torque	$\geq$ 98%	• Detecting multiple types of faults is very effective
	[132]	GA KNN	• Current	$\geq$99.5%	• Using only simple statistical features has considerable accuracy and requires less computational complexity than other methods
	[133-137]	SVM	• Vibration	$\geq$94%	• The connection uses the original signal as input to achieve end-to-end diagnosis.
	[138]	RF	• Vibration	98.24%	• RFE technology is used to sort the features
	[139-140]	1D-CNN	• Vibration	88.4% / 93.9%	• Utilize multiple sensor data channels simultaneously using the multi-channel 1D CNN architecture
	[141-142]	LSTM	• Vibration	96%	• The LSTM network was able to show excellent results with a classification accuracy of 96%
	[143]	AutoEncoder	• Vibration	99.11%	• The autoencoder is superior to the OCSVM algorithm.
	[144,145]	GAN	• acoustic emission signal	99.79%	• Achieves high precision and fast convergence • Solve the problem of less data sample
	[146]	OS-ELM	• Vibration	99.62%	• Online fault diagnosis can be realized
	[147]	PST	• Vibration	98.33%	• Work completely online
	[148]	OVO-SVM	• CTUDC test data	98%	• Works offline and online
	[149]	ANN	• Vibration • Current	97.15%	• online monitoring
Rotor faults	[150-152]	SVM	• Current	97%/error(0.26%)/98.78%	• New features such as harmonic curve area and harmonic wave peak Angle are extracted
	[153]	RF	• Motor current	98.8%	• The diagnostic accuracy was 98.8%.
	[154-158]	CNN	• Vibration	100%/98.7%/99%/97.37%/99.3%	• Achieve 100% training and test accuracy.
	[159-161]	GAN	• Current	97.99%/98.33%	• Solve the problem of data imbalance.
	[162]	Transfer learning	• Vibration	99%	• The knowledge learned from labeled data under constant working conditions is transferred to unlabeled data under changing working conditions.
Stator faults	[163]	SVM	• Stator current.	--	• SVM is superior to MLPNN, RBFNNs and ELM in diagnosing IM health status.
	[164-165]	RF	• Stator current.	99.3%/$\geq$90%	• Effectively detect short circuit between turns.
	[166]	RF XGBoost	• Stator current.	99%	• Effectively diagnose stator short circuit and air gap eccentricity compound fault.
	[167-169]	CNN	• Stator current.	99.3%/99.89%/97.87%	• It can be used for online fault detection.
	[170]	SDAE-GAN-LSTM	• Stator current.	98.92%	• The average fault identification accuracy reached 98.63%
	[171]	DCGAN	• Stator current	95.4%	• Achieves high precision and fast convergence • Solve the problem of less data sample
	[172]	VGG16 Transfer Learning	• Stator current.	96.7%	• Accurately diagnose different degrees of inter-turn short circuit fault
	[173]	Fuzzy-logic	• Stator current	99.7%	• Online monitoring of motor
	[174]	Fuzzy C-means clustering	• Stator current	Error$\leq$\mp 3A	• Works offline and online

pattern recognition to detect and identify online anomalies in electric motors. By employing Variable-Order Markov Model and Probabilistic Suffix Tree, unsupervised and supervised methods are applied to cluster motion conditions and diagnose them. In addition to interpretability, the proposed diagnostic method is fully online and suitable for parallel computing, making it a favorable approach to be used in sync with physical testing systems. In [148], a multi-fault mode detection method for P2 diesel HEVs is studied using Support Vector Machine (SVM). By utilizing experimental data under the Chinese Typical Urban Driving Cycle (CTUDC), a physical model of HEVs is established and validated. The effectiveness of the detection algorithm is verified through offline and online testing. Similarly, in [149], an alternative method based on Artificial Neural Network is proposed for classification and detection of bearing faults in three-phase induction motors directly connected to the grid. The performance and effectiveness of the proposed fault detection method are evaluated and validated through online experimental testing using a personal computer and embedded digital signal processor.

2) Rotor Faults

As the primary component of motors, there has been a growing body of research on fault diagnosis related to rotors, encompassing various studies and methodologies. SVM, a quintessential machine learning classification algorithm, has been employed for rotor broken bar fault diagnosis in motors as documented in [150]. The approach involves utilizing Fast Fourier Transform (FFT) to extract novel features such as harmonic curve area, harmonic wave peak angle, and harmonic amplitude from the Power Spectral Density (PSD) of the stator current under steady-state conditions. Experimental results validate the efficiency of this method in detecting rotor breakdown faults in asynchronous motors. Similar studies are also evident in [151] and [152].

Random Forest (RF), another prevalent classification algorithm, is frequently employed for rotor fault diagnosis. In [153], 13 statistical time-domain features were extracted from the starting transient current signal, and these features were utilized to train and test random forests to ascertain whether the motor was operating under normal or faulty conditions. Comparative analysis with decision trees, naive Bayes classifiers, logistic regression, linear ridge, and support vector machines revealed that Random Forest consistently achieved higher accuracy, reaching 98.8%.

Moreover, with the escalating volume of data, neural network methods are gaining prevalence in rotor fault diagnosis research. Ronny proposed a Convolutional Neural Network (CNN) incorporating Short-Time Fourier Transform (STFT), a time-frequency feature map, to extract comprehensive information from vibration signals [154]. The method involves recording vibration signals in the time domain to obtain the STFT response. Subsequently, a CNN is trained to diagnose and predict faults, considering the STFT as the sole input. Results demonstrate the efficacy of the proposed method in accurately identifying various faults, with similar studies documented in [155-158].

In addressing the challenge of insufficient actual fault data, similar to bearing fault diagnosis, GAN algorithms are becoming more prevalent in rotor fault diagnosis research. In [159], the authors recognized a significant imbalance between normal and faulty data, leading them to design a deep neural network for fault detection and diagnosis. The study compared oversampling using GAN with standard oversampling techniques, revealing that, under given conditions, the GAN's oversampling performance is noteworthy. The designed deep neural network demonstrated high accuracy in classifying faults in induction motors, with similar studies documented in [160-161].

Considering rotor fault diagnosis across different types of motors, transfer learning is widely employed. In [162], an adaptive motor fault diagnosis using deep transfer learning is proposed to enhance performance by transferring knowledge learned from labeled data under constant operating conditions to unlabeled data under changing operating conditions. A CNN serves as the foundational framework for extracting multi-level features from the original vibration signal. Additionally, a regularization term of Maximum Mean Difference (MMD) is incorporated during the training process to impose constraints on CNN parameters, reducing the distribution mismatch between features in the source and target domains. Results indicate that, compared to other methods, this scheme achieves higher diagnostic accuracy for unlabeled target data and exhibits applicability in bridging differences across diverse fields.

3) Stator Faults

The stator, as an integral component of motors, encompasses various fault types, including turn-to-turn faults, dynamic eccentric faults, current sensor faults, insulation faults, open circuit faults, and short circuit faults. This paper investigates the application of Support Vector Machine (SVM) in the effective detection and localization of inter-turn short circuit faults (ITSC) in three-phase asynchronous motors (IM) [163]. Extracted features from phase shift analysis between stator current and corresponding voltage serve as SVM inputs. Results demonstrate the superior diagnostic capability of SVM compared to MLPNN, RBFNNs, and ELM, particularly in early detection scenarios under low-load conditions.

In [164-165], a novel method utilizing random forest is proposed for detecting stator winding short-circuit faults in Park's Vector squirrel-cage asynchronous motors. The technique assesses imbalance in current and voltage waveforms, coupled with Park's Vector of current and voltage. Similarly, [166] introduces a diagnosis method employing random forest and XGBoost for composite faults arising from stator inter-turn short circuits and air gap eccentricity. The approach involves using current as a diagnostic signal, applying the Savitzky-Golay filtering method to reduce signal noise, wavelet packet decomposition for feature extraction, and PCA for optimizing high-dimensional features. The combination of random forest and XGBoost proves effective in detecting

TABLE V
STUDIES ON RUL PREDICTION FOR ELECTRIC MOTORS

Functions	Reference	AI algorithm	Signal	Accuracy	Contributions
RUL	[66]	Autoencoder-based DNN	•Vibration signal	(RMSE) 12.61	• satisfactory RUL prediction performance even with a relatively small amount of available data.
	[175]	Fuzzy BPNN	• Stator current • Rotor speed • Condition of the bearing	Error ≤3%	• Avoiding the disadvantages of individual AI approaches.
	[176]	ANN	• Vibration signal	Error 3.4%	•The proposed ANN method can produce satisfactory RUL prediction results.
	[78]	SVM	• Vibration signal	95%	• The applications of SVM to RUL prediction are still limited to the prognosis of bearings and batteries.
	[177]	SVM Decision tree	• Vibration signal	RAE 1.5%	• This method that was tested with the bearing life data can also be horizontally deployed for predicting the remaining life of all other critical components
	[178]	Regression model BPNN	• Vibration signal	RMSE 0.05	• The BPNN has better performance than the regression model

composite faults.

Recent research trends favor Artificial Neural Networks (ANN) and CNN over traditional machine learning algorithms. In [167], a method for early fault detection in PMSM stator windings is presented, employing direct signal analysis and CNN. Similar studies can be found in [168-169]. Addressing challenges of insufficient data samples and imbalanced data types, [170] proposes a fault diagnosis method for a three-phase PMSM drive system smart inverter. This approach mitigates imbalanced fault data samples and enhances fault classification accuracy. Additionally, the article introduces a LSTM model based on the second discriminator of GAN for fault diagnosis. Similarly, in the study conducted by [171], the application of GAN networks for motor fault diagnosis with limited data was explored, yielding promising results. Considering diverse motor types, [172] proposes a fault transfer learning. The study establishes a two-dimensional finite element model for inter-turn short circuit faults in PMSM and conducts simulation experiments. The fault characteristic signal is chosen as three-phase current, and a transfer learning-based fault diagnosis method is designed. The inter-turn short circuit fault of PMSM is diagnosed and verified using the transfer learning VGG16 model.

In the context of online monitoring tasks for induction motors, [173] introduces a reliable and non-intrusive technique that avoids interruptions in the manufacturing process, facilitates maintenance tasks, and reduces the downtime of induction motors. This new technology does not require computationally demanding operations as it only performs arithmetic calculations for detecting and locating short-circuit faults in the stator winding of induction motors. The method relies on vector analysis and the root mean square value of the line current, combined with a set of simple if-then rules for diagnosing and identifying stator winding faults. This approach is capable of effectively identifying and locating early and late-stage defects in the winding insulation. Similarly, [174] utilizes neural competitive learning techniques in fuzzy logic. The algorithm takes two PMSM current and torque signals under normal and faulty conditions as inputs and can detect faults in different domains. It is flexible enough to be used for offline and online identification.

Fig. 21 shown the block diagram of motor fault diagnosis and fault detection based on AI algorithm. Table IV summarizes all mentioned studies on fault detection for electric motors. It is evident that each AI algorithm has its own advantages and disadvantages. The strengths include strong learning ability, adaptability to solve complex classification problems, good portability, and compatibility with required frameworks. However, there are some drawbacks such as the need for a large amount of data, high hardware requirements, and complex model design. The aforementioned literature review is organized chronologically. Based on the timeline, it can be observed that in the beginning, research mainly relied on machine learning methods like SVM due to limited data availability. With the development of data acquisition and AI technologies, some deep learning models (including CNN and GAN) have emerged as more promising techniques to overcome the laborious nature of manual feature definition. CNN is particularly suitable for directly extracting features from images, providing more comprehensive and representative information for performance prediction. Similarly, GAN offers the potential to generate synthetic data samples that capture the underlying distribution of motor fault features, thereby enhancing predictive capabilities. Furthermore, considering the research on different types of motor faults, transfer learning algorithms can save model training time and quickly obtain accurate models. Additionally, with the introduction of online real-time fault diagnosis, there has been progress in related online diagnostic research. The advancements in these AI-based methods have the potential to revolutionize the way motor fault diagnosis is conducted.

C. RUL Prediction

While a motor is assigned a design life during its conceptual phase, the reliability estimates for a specific unit under real-world operating conditions in the field often suffer from inaccuracies stemming from factors such as model calibration errors, manufacturing tolerances, alterations in the operating environment, and varying workloads. Therefore, Remaining Useful Life (RUL) prediction serves as a valuable supplementary tool for mitigating uncertainties in applications where reliability, safety, or availability are of paramount concern. The RUL of electric motors prediction specifically pertains to forecasting the remaining operational life of an individual in-service unit, relying on data gathered from condition monitoring.

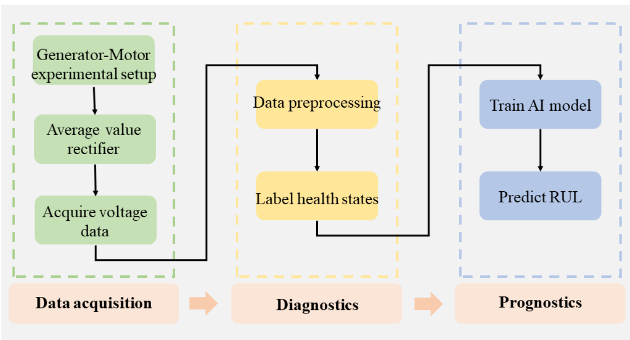

Fig. 22. Flowchart of electric motors RUL prediction based on AI model.

Fig. 22 illustrates the flowchart and steps involved in RUL prediction. The initial step entails the construction of regression models using historical datasets. These models serve as the foundation for estimating the probability density function of degradation levels over specific intervals of monitoring time. It is worth noting that Artificial Intelligence methods frequently underpin RUL prediction by establishing nonlinear regressions between degradation data and corresponding RUL values using training datasets. This approach effectively characterizes degradation patterns. Once these patterns are comprehended, RUL can be directly forecasted based on the established regression model, thus streamlining the prediction of future degradation levels. Consequently, RUL estimation becomes feasible.

Over the past two decades, various AI-based methods for predicting the RUL of electric motors have been developed. In an advancement of AI-based electric motors RUL prediction, Sarma [175] devised a hybrid approach incorporating fuzzy backpropagation networks for diagnosing and estimating the RUL of electric motors bearings. This scholar integrated fuzzy logic and neural networks to create a hybrid technique known as "fuzzy BP" to address the limitations associated with single AI methodologies. This approach utilizes stator current and speed as network inputs and demonstrates superior RUL performance predictions compared to single AI methods.

In 2012, Tian [176] proposed an RUL prediction method for electric motors, primarily focusing on electric motors bearing components. Vibration signals were collected throughout the bearing's degradation process. Their research revealed that constructing a single model during a typical degradation process is challenging due to substantial variations in change patterns at different stages of degradation. Their findings indicated that the ANN-based method yields significantly lower average prediction errors compared to traditional approaches. This method offers more accurate and faster predictions of bearing RUL when compared to conventional methods.

In 2015, Huang [78] proposed the application of SVM for RUL prediction in electric motors. They demonstrated in experiments that vibration signals are crucial features for detecting machine degradation. Their primary focus was on researching and enhancing the SVM method, applying it to RUL studies, such as motor bearings. According to research results, this approach yielded excellent RUL prediction results through data analysis. Similarly, Satishkuma [177] also introduced an SVM-based RUL prediction technique. Likewise, vibration signals were extracted, but what set it apart was the selective consideration of specific characteristic signals. This study similarly indicated that the proposed method exhibited high accuracy and robustness. In 2019, Xia [66] presented a cascade model for predicting bearing RUL. The method comprises two stages: (i) In the first stage, the bearing life was divided into n different stages, and a DNN classifier was employed to categorize vibration signals. A grid search method was utilized to further optimize the classification results for different health stages, thus determining the optimal number of health stages. (ii) In the second stage, the best health stage obtained was employed to estimate the RUL of the bearing. n ANN models were constructed based on optimized health stages, as opposed to utilizing a single ANN model. Experiments proved that this approach resulted in enhanced RUL prediction accuracy. In 2019, Li [178] proposed an ANN model for predicting electric motors bearing RUL. By comparing the performance of the regression model and the ANN model, it was evident that the ANN model outperformed in predicting motor bearing RUL. Furthermore, the output of the regression model was integrated into the ANN model, further enhancing its predictive capabilities.

Table V summarizes the studies on RUL prediction for electric motors. The aforementioned review indicates that most RUL predictions are primarily focused on motor bearings and employ vibration signals. Considering the practicality of real-world scenarios, the proposed models need to possess a certain level of robustness. They should demonstrate consistency between training and testing data. The complexity of actual field conditions (e.g., temperature variations, vibrations, humidity) results in differences between field data and the data used for training the models. Therefore, future exploration of system models should take these factors into account, and advanced deep learning algorithms such as transfer learning and GAN networks should be introduced for in-depth research.

VI. Challenges And Outlook

As AI algorithms are increasingly employed across various phases of electric motor research, it becomes imperative to undertake a series of comprehensive studies to promote further innovation in this area. This can be accomplished by examining instances of AI research across different stages of the electric motor lifecycle, enabling us to clarify the precise application of AI methods at each juncture.

In the realm of electric motors design, numerous decision variables must be ascertained, encompassing factors such as weight, shape, size, and more. This inherently evolves into an optimization task. Currently, intelligent optimization algorithms stand out as the predominant research methods employed to tackle this challenge. Despite their demanding computational requisites, electric motors design tasks are frequently executed offline, mitigating the necessity for rapid algorithmic execution. Moreover, optimization guided by intelligent algorithms generally yields a globally optimal solution. With the escalating demand for electric motors design, expediting the design process has emerged as a focal point in current research, with data-driven methods offering innovative perspectives in this domain. In the realm of intelligent electric motor control, real-time adjustment of control variables such as current and voltage, alongside monitoring output variables like speed and torque, is essential. The emphasis in this domain lies in the real-time responsiveness of algorithms, necessitating swift adaptations to changes in the external environment. In the context of predicting the remaining service life of an electric motors, where the process unfolds over a relatively extended period, real-time responsiveness is not imperative, and an offline mode can be considered. This stage primarily involves offline model training based on the electric motor's processes and subsequent online model predictions.

In the realm of electric motors research, AI has already proven its practical value, yet significant challenges remain. These challenges are mainly in training, data acquisition, and implementation complexity. In terms of training challenges, the primary issue is the insufficiency and diversity of data. The operational environments and conditions for motor systems vary widely, making it challenging to obtain representative and diverse training data in practical settings. Particularly, motor fault modes are difficult to simulate, leading to a shortage of training data. Furthermore, the difficulty in acquiring accurate labels poses a significant hurdle since supervised learning relies heavily on labeled data. For instance, accurately measuring real-time damage or wear in motors often requires halting operations and disassembling, which is impractical in real-world operations.

Another issue is model generalization. Due to differences between various types and sizes of motors, a model trained for one specific motor might not be applicable to another. Therefore, the generalization and scalability of models represent a major research challenge.

Regarding data acquisition requirements, high-quality sensors are essential to capture the operational state of motors, including temperature, vibration, current, and voltage. However, the cost and complexity of installing these sensors may restrict their widespread use. Additionally, data synchronization and integration pose challenges in complex industrial settings where data come from various sources and sensors, necessitating effective mechanisms to ensure data accuracy and consistency.

The practical implementation of artificial intelligence algorithms in the field also involves complexity, primarily due to the real-time demands of motor control systems. AI models, especially deep learning models, may require substantial processing time, making it crucial to optimize models to meet real-time requirements. Furthermore, resource constraints in environments like embedded systems or field-programmable gate arrays (FPGAs) necessitate model compression, quantization, and optimization techniques.

To address these limitations, several solutions have been proposed. Firstly, transfer learning and domain adaptation can utilize models pre-trained in other fields or on similar tasks to reduce the reliance on extensive labeled data and enhance model generalization. Secondly, techniques such as reinforcement learning and semi-supervised learning can be employed to utilize unlabeled data when labels are insufficient. Additionally, reinforcement learning can train models in simulated environments to improve performance and adaptability.

Lastly, edge computing can be implemented to process data and perform model inference on edge devices, reducing dependence on central processing, enhancing system responsiveness, and decreasing communication costs.

As the demands of the future evolve, the potential for further research into the application of AI in electric motors remains significant. The following sections will explore potential future directions for this field.

1) *Multi-source Information Fusion:* Motor systems typically generate various types of data, such as vibration data and current data. Effectively integrating these diverse data sources to enhance the accuracy of status detection and fault diagnosis poses a significant challenge. Future research should focus on the exploration of multi-modal data fusion, enabling more effective combination of information from different sensors. This approach has the potential to significantly enhance the monitoring performance of the system.
2) *Interpretable Model:* In motor design, crucial decisions, such as material selection and structural design, necessitate careful consideration of model interpretability. The opaque nature of deep learning models often results in decisions that are challenging to comprehend. Developing deep learning models with enhanced interpretability for specific decisions in motor design can significantly contribute to improving the credibility and comprehensibility of design choices.
3) *Data Quality and Requirements:* AI algorithms typically demand substantial datasets for effective training. In the realm of motor design, acquiring a high-quality and adequate quantity of data can pose a challenge, particularly in specialized applications or unique operating conditions. The acquisition of top-tier training data, along with precise labels (especially those related to faults), is often problematic, making it challenging to procure a sufficient

number of fault samples in practical applications. Utilizing transfer learning can address the issue of insufficient data, while reinforcement learning enhances the adaptability and intelligence of the system.

4) *Data Model Integration Throughout the Life Cycle:* Current research predominantly focuses on individual stages of design, control, and maintenance, resulting in limited sharing of data and models. However, for enhanced efficiency, data and models can be seamlessly integrated across the entire life cycle, facilitating data exchange and model sharing at each stage. For instance, information gathered during the maintenance phase, such as condition monitoring data, can be seamlessly incorporated into the control phase and subsequently shared across similar motor design phases.

5) *Digital Twin:* The concept of a digital twin involves creating a digital replica of a physical entity and understanding its real-world operations. In the realm of comprehensive motor research, the integration of digital twins is anticipated to offer enhanced insights, monitoring capabilities, and optimization opportunities for motor systems. For instance, digital twin technology enables real-time monitoring of the motor system's operational status, facilitating timely detection of potential faults and thereby improving system reliability and safety. Furthermore, the virtual prototype generated through digital twins can simulate various working conditions of the motor system, reducing the necessity for physical testing and enhancing the efficiency of system design. Leveraging digital twin technology, a virtual motor system can be established to provide engineers and operators with real-time training and education, fostering a deeper understanding of and proficiency in operating the motor system.

VII. CONCLUSION

This article comprehensively reviews the extensive application of AI technology in the complete research cycle of electric motors. Utilizing AI technology in full-cycle motor research can overcome the necessity for precise physical models and parameters, presenting significant implications for advancing intelligent motor research in the future. The key contribution is to categorizing full-cycle research into three stages: design, control, and maintenance, and further provide a comprehensive examination of the application of AI in each stage through real-world applications and case studies. Additionally, it analyzes the prospects and limitations of AI in these stages, offering a valuable summary. The insights gained from this review hold significant implications for future research in motor design, control, condition monitoring, and fault diagnosis. Our review serves as a valuable reference for selecting methodologies in further research endeavors.

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