Review of Data-Driven Artificial Intelligence Applications in Electric Machines and Drive Systems

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Abstract—**It is expected that the continuous advancements in learning algorithms and specialized embedded hardware platforms will establish data-driven artificial intelligence (AI) based techniques as standard tools for automating high-performance modelling, design, optimization and control of electric machines and drive systems. Our research delves into the various AI-based numerical and analytical approaches employed in electric drive systems. Moreover, this review article systematically summarizes the strengths and weaknesses of different algorithms in practical applications. More importantly, valuable insights into fostering the widespread adoption of AI in the automatic industry are further forwarded.**

Keywords—Artificial intelligence (AI), machine learning (ML), deep learning, electric machine drives, design and optimization

I. INTRODUCTION

Electric motors and their drive systems, known for their high energy efficiency compared to internal combustion engines, hold immense importance in both current and future societies. They convert electrical energy into mechanical energy with minimal energy loss, leading to reduced energy consumption and lower greenhouse gas emissions, which can contribute to a cleaner and more sustainable future world. Moreover, they enable efficient conversion and utilization of renewable energy sources, such as solar and wind. On the other hand, ongoing research and development in electric motor technologies have potential to realize comprehensive automation and intelligence, further driving their importance in future societies. These benefits have led to the revolutionary electrification of sectors as diverse as transportation, industrial processes, and residential buildings that rely heavily on electric motors and drive systems, such as electric vehicles (EVs), electric trains, and electric airplanes [1].

However, modelling, design optimization, and control of electric drive systems can be challenging due to several factors. i) Electric drive systems exhibit nonlinear behaviour, especially at high operating speeds and under heavy loads. Nonlinearity makes the modelling and control of these systems more complex, as traditional linear control techniques may not be sufficient. ii) Motors can have complex dynamics with multiple mechanical, thermal and electrical parameters affecting their performance. Accurate modelling of these dynamics requires detailed knowledge of motor characteristic, magnetic field, temperature rising and mechanical interaction. iii) Design optimization of electric drive systems often involves trade-offs between conflicting objectives, such as maximizing efficiency while minimizing cost, size, or weight. Finding an optimal compromise can be complex. iv) High-fidelity modelling and optimization techniques for electric drive systems can require significant computational resources and simulation time [2].

On January 2016, the journal "Nature" featured an article reporting that Google's artificial intelligence robot called "AlphaGo" achieved a remarkable victory of 5:0 against the European Go champion. AlphaGo's exceptional performance sparked significant attention from various sectors of society. In October 2016, the US National Science and Technology Council released the "National artificial intelligence research and development strategic plan". In July 2017, the Chinese State Council also issued the "New generation artificial intelligence development plan. Artificial intelligence (AI) algorithms present novel opportunities for various industries and researchers to address challenging problems, particularly in the electric drive system industry.

AI-based approaches have the potential to help solve many of the challenges associated with modelling, design, optimization, and control of electric machines and drive systems. For example, AI-based control techniques, such as neural networks and fuzzy logic, are well-suited for handling nonlinearities in motor drive systems. They can learn complex relationships between input and output variables, enabling more effective control in nonlinear operating regions [3]. AI can be used for data-driven modelling of motor drive systems. By collecting and analyzing real-world data from motors, AI algorithms can create accurate models that capture the system dynamic behavior and improve control strategies [4]. Reinforcement learning and deep reinforcement learning can be employed to optimize control strategies in motor drives, considering multiple objectives and trade-offs across various operating points [5]. AI techniques, such as machine learning and pattern recognition, can detect and diagnose faults in motor drive systems, enabling predictive maintenance and improving system reliability [6].

Therefore, by harnessing the power of AI, advancements in modelling, design, optimization and control can be realized, leading to more efficient, reliable, and environmental-friendly motor drive solutions.

II. AI-BASED MODELLING APPROACHES

A. *Artificial Neural Networks (ANN)*

The research on artificial neural networks (ANNs) can be traced back to the 1940s with the work of Warren McCulloch and Walter Pitts, where they theoretically demonstrated that artificial neural networks could compute any arithmetic and logical function [7]. The first practical application of ANNs emerged in the late 1950s when Frank Rosenblatt proposed the perceptron network and associative learning rules. However, in the 1960s, due to a lack of new ideas and high-performance computers for experimentation, research on neural networks entered a period of decline. It wasn't until the 1980s that research on neural networks regained momentum with the widespread use of computers and the continuous introduction of new concepts.

ANNs are a class of machine learning algorithms inspired by the structure and functioning of the human brain. ANNs consist of interconnected nodes, also known as artificial neurons or perceptrons, organized into layers. These networks process and learn from input data, allowing them to make predictions, classify objects, recognize patterns, and perform other complex tasks [8]-[9].

For electric driver applications, in [10], a generalized regression neural network (GRNN) was utilized within the design process of a 3-phase 12/8 switched reluctance motor (SRM). GRNN belongs to the category of probabilistic ANNs with a straightforward structure and rapid convergence. It exhibits superior generalization capabilities compared to Backpropagation Neural Networks (BPNN), particularly when dealing with relatively small training datasets, and it avoids converging to local minima. Notably, GRNN achieves its outcomes without requiring an iterative process, leading to notably shortened training times [11]. Drawing similarities with the Radial Basis Function (RBF) method [12], GRNN features an RBF layer within its structure along with a distinctive linear layer. Moreover, GRNN features only one tunable parameter, referred to as the spread parameter, which governs its generalization prowess. This parameter necessitates careful optimization to bolster the precision of motor performance predictions. In [13], the authors proposed a strategy for speed tracking of brushless DC motors using neural networks, employing a dual neural network control approach consisting of an identification network and a control network. The authors contend that this method can be realized as long as the desired velocity trajectory is provided. By harnessing the inherent robustness of neural networks, the system's disturbance rejection capabilities are improved, which aids in suppressing instability and significant tracking errors stemming from variations in system parameters. However, this approach is hindered by its high computational demand and low sampling frequency, which limit its proximity to practical applications. In [14], authors reported a sensorless control method for brushless DC motors based on radial basis function neural networks (RBFNN) by analyzing rotor position detection principles. This approach establishes a dynamic RBFNN model. The initial network parameters are obtained by offline training using the K2-means clustering method and recursive least squares algorithm. The online training involves correcting errors using a gradient descent-based approach to update network parameters. Through mapping motor terminal voltage and phase currents, the motor commutation signals are derived.

ANNs offer a powerful, versatile framework for solving complex problems by mimicking the brain's interconnected neuron structure. ANNs excel at capturing intricate nonlinear relationships in data, automatically extracting relevant features, and adapting to new information through training. Their parallel processing ability accelerates data processing, while their robustness in handling noisy or incomplete data enhances reliability. ANNs' ability to generalize from training to new data enables accurate predictions, and their adaptability to various data types makes them applicable across diverse domains. While ANNs have numerous advantages, they also have certain challenges, such as the need for large amounts of data for training, potential overfitting, and the complexity of tuning their parameters.

B. Fuzzy Logic

In 1965, Prof. Zadeh of the University of California, Los Angeles, first introduced the theory of fuzzy logic. In 1974, Prof. Mamdani of University of London successfully applied this theory to the control of steam engines, providing the initial validation of its efficacy [15]. Fuzzy logic is a computing approach that deals with uncertainty and imprecision by allowing degrees of truth to be expressed rather than strict binary values (true or false). It is a mathematical framework that aims to model and simulate human reasoning, which often involves vague or ambiguous information. In fuzzy logic, variables and statements can take on values between 0 and 1, representing the degree of truth or membership. This allows for more nuanced and flexible decision-making in situations where information may be incomplete or subject to interpretation. Fuzzy logic systems use linguistic variables and terms, along with membership functions, to define relationships and rules. These rules can then be used to make decisions or control processes based on the input data's fuzzy characteristics. So far, fuzzy logic has found applications in various fields, including control systems, artificial intelligence, decision-making, image processing, and pattern recognition. Its ability to handle uncertainty and approximate reasoning makes it valuable for modelling complex and real-world situations where crisp binary logic might fall short.

Reference [16] combines fuzzy selection with a multi-reference model, building upon the proposed multi-control-input adaptive algorithm. They present a brushless motor adaptive algorithm using a fuzzy multi-reference model, where the system parameters are utilized to categorize system states through fuzzy rules and select reference models for controller adjustment. An adaptive weight correction method is employed to adjust the connection weights between the fuzzy loop and the PI loop. Simulation results demonstrate minimal overshoot and rapid control convergence in the system. A master fuzzy controller was proposed in [17] to replace the feedback controller in traditional model reference adaptive control. The fuzzy inverse model was combined with an adaptive adjustment algorithm to substitute the intricate conventional adaptive rules of the fuzzy adaptive controller. This fuzzy adaptive mechanism consists of a fuzzy inverse model and an adaptive law generation mechanism. The fuzzy inverse model employs the discrepancy and rate of change of discrepancy between the output of the reference model and the system as inputs, generating a corrective term through fuzzy logical reasoning. This corrective term is then utilized to adaptively adjust the output control signal of the fuzzy controller. The study achieves consistency between the system output and reference model output by dynamically adjusting the proportional factor online.

Fuzzy logic provides a valuable framework for handling uncertain or imprecise data, allowing it to excel in scenarios where information lacks clarity. Its linguistic approach lets experts articulate rules in natural language, enhancing interpretability, while its ability to manage continuous variations supports more nuanced decision-making. Moreover, the fuzzy logic gradual membership concept makes it robust against noise and outliers in data. Despite its strengths, fuzzy logic can become intricate when dealing with numerous variables and rules, leading to potential complexities in system design and fine-tuning. Constructing accurate membership functions and rule sets demands domain expertise and can be a time-intensive process. Furthermore, subjectivity in determining optimal settings may result in variations in performance based on different expert opinions. Finally, the computational load of fuzzy logic calculations, particularly in systems with multiple inputs and rules, might impact real-time applications.

C. Genetic Algorithm

Genetic Algorithm (GA) is an algorithm built upon the foundations of Darwin's theory of biological evolution and Mendel's principles of genetics. It emulates biological genetics and evolutionary principles, incorporating stochastic statistical theories. At its core, GA is an iterative process. Specifically, i) A population of potential solutions, known as individuals or chromosomes, is randomly generated; ii) Each individual's fitness, representing how well it solves the problem, is evaluated using a fitness function specific to the optimization problem; iii) Individuals are selected based on their fitness scores using various selection methods (e.g., roulette wheel selection, tournament selection) to become parents for the next generation; iv) Selected individuals undergo crossover, where parts of their genetic information (encoded solutions) are exchanged to create new offspring. Crossover introduces diversity and allows promising traits from different parents to be combined; v) Occasionally, individuals in the population undergo mutation, where small changes are introduced into their genetic information. Mutation helps explore new regions of the solution space; vi) The new offspring, along with selected individuals from the previous generation, form the new population; vii) The process continues for multiple generations, with each iteration improving the overall fitness of the population. Termination occurs when a predefined condition is met, such as reaching a maximum number of generations or achieving a satisfactory solution [18].

GAs are advantageous in solving complex problems with multiple variables and non-linear relationships, where traditional optimization methods might struggle. They can explore a vast solution space efficiently and often find satisfactory solutions, though not necessarily the absolute best solution. GAs have been successfully applied in various fields, including engineering, economics, machine learning, etc.. For example, in [19], a GA was employed for the control of brushless DC motor systems to achieve position control objectives. This paper applied an adaptive genetic algorithm to search for optimal parameters of a fuzzy sliding mode controller in the context of brushless DC motor systems. Through online control parameter adjustments, this approach ensures precise position output response for the brushless DC motor.

GAs offer a powerful optimization technique that excels in exploring complex solution spaces, particularly when traditional methods struggle. Their ability to search diverse solution regions and handle non-linear relationships makes them versatile for various problems. GAs can find satisfactory solutions even in cases with multiple variables and intricate fitness landscapes. However, GAs have some drawbacks, including their stochastic nature, which might lead to different outcomes in different runs; they can also be computationally intensive, especially when dealing with large populations and complex fitness functions. Additionally, GAs may not always guarantee finding the global optimal solution, but rather provide a good approximation. Careful parameter tuning and selection are essential to strike a balance between exploration and exploitation for effective GA performance.

III. AI-BASED CONTROL AND OPTIMIZATION APPROACHES

A. AI-based Control

Presently, scholars both domestically and internationally have extensively and comprehensively researched control strategies for electric drive systems, proposing a multitude of control approaches. However, due to the inherent nature of this system as a nonlinear, multivariable, and strongly coupled system, fulfilling practical requirements using classical control theories proves challenging. Conversely, intelligent control systems possess attributes such as self-learning, self-adaptation, and self-organization, enabling them to effectively address issues stemming from model uncertainties, nonlinear control, and other intricacies. As a result, the adoption of modern intelligent control strategies is emerging as a prevailing trajectory in development of electric drive systems.

In [20], a BPNN was employed to model a 12/8 1.5-kW SRM. The network architecture featured an input layer with two input variables: targeted average torque and rotor position. The BPNN comprised two hidden layers, each containing 12 neurons utilizing the Hyperbolic Tangent Sigmoid activation function. Conversely, the output layer employed a linear activation function to estimate output current. An experiment setup was established to collect a training dataset depicting torque versus rotor position at varying current levels. In [21], the self-learning capability of Radial Basis Function (RBF) neural networks is employed for online system identification, leading to the approximation of the system model and enabling online tuning of Proportional-Integral-Derivative (PID) parameters. Simulation results demonstrate that this control approach not only enhances the system's dynamic and static characteristics but also improves its adaptability and disturbance rejection capabilities. In [22], Parsa *et al.* introduced an ANN-based speed controller incorporating a radial basis function network. This network is dynamically trained online to accommodate system uncertainties. The discrepancy between the desired speed and the actual measured speed is input to the ANN-based controller, which undergoes real-time training to adjust its weights and biases.

B. AI-based Optimization

Optimization in electric drive systems offers significant advantages by enhancing efficiency, performance, and energy utilization. It enables the fine-tuning of control algorithms, leading to optimal torque, speed, and power output, thus minimizing energy consumption and losses. Additionally, optimization aids in reducing wear and tear on components, extending their lifespan. Moreover, it facilitates the design of compact and lightweight systems, making them suitable for various applications while ensuring safety and reliability.

In [23], a genetic algorithm-optimized fuzzy controller was proposed. Genetic algorithms are utilized to optimize the fuzzy controller, generating optimal fuzzy control rules.

Subsequently, the fuzzy controller is implemented on a digital signal processor, enabling online adjustment of the fuzzy controller parameters. This method overcomes the limitations of inadequate online adjustment effects observed in traditional fuzzy controllers, significantly enhancing controller performance. In [24], a bidirectional recurrent neural network (BRNN) was introduced to attain an optimal design for a single-barrier synchronous reluctance motor. In [25], research was conducted on the optimization problem of brushless DC motors using an adaptive genetic algorithm based on constructing adaptive genetic factors. Addressing the nonlinear combinatorial optimization problem of brushless DC motors, this study develops novel adaptive genetic factors. Verification of the constructed genetic factors is performed using the two-dimensional Schubert function. This study utilized three types of operators for solution: basic genetic algorithm, adaptive genetic algorithm, and an improved adaptive genetic algorithm, to verify that the performance of the constructed adaptive operators surpasses that of the other two operators.

Global optimization design methods, such as genetic algorithms, simulated annealing, and tabu search, encompass all uncertain factors within the optimization objective. However, the establishment of specific objective functions is notably complex, demanding extensive computational resources and prolonged computation times. On the other hand, local optimization design methods, including finite element methods, magnetic network methods, compound shape methods, simplex methods, and hill-climbing methods, offer deterministic approaches. While these local optimization methods demonstrate excellent convergence for single-objective optimization, they are incapable of achieving multi-objective optimization design.

IV. CONCLUSION AND FUTURE WORK

This paper provides a comprehensive state-of-the-art review of AI-based solutions focused on modelling, design optimization and control of electric drive systems. Although there has been ongoing advancement in relevant publications within this domain, several outstanding matters remain unaddressed and merit attention in forthcoming research endeavors.

1) Artificial intelligence technology still lacks theoretical support: Although data-driven artificial intelligence technologies, particularly those centered around deep learning, offer advantages in terms of intelligence and accuracy over traditional state analysis models, these technologies essentially represent black-box models and lack robust mathematical theoretical foundations. As a result, the underlying generic operational mechanisms and expert insights of electric drive systems are yet to be adequately incorporated within artificial intelligence models. Therefore, further research is necessary to explore methodologies that integrate the operational mechanisms, physical laws, and expert knowledge of equipment into artificial intelligence algorithms, thereby achieving a profound fusion of knowledge analysis and data mining.

2) Dataset issues: At the core of data-driven artificial intelligence technology lies the process of exploration and learning of data features and underlying patterns within extensive datasets through training. This approach places significant demands on both the scale and quality of the data involved.

a) Data quality is difficult to guarantee: During data transmission, occurrences of data duplication, anomalies, and omissions due to communication interference are not uncommon. These instances of "dirty data" can significantly impair the accuracy of equipment state analysis outcomes and escalate the complexity of data cleansing procedures.

b) Difficult to share data: The data structure is intricate, encompassing a wide array of types and spanning significant time scales. Moreover, data transfer formats vary across different platforms, making it challenging to achieve seamless cross-platform data interchange and sharing.

c) Data is difficult to classify and balance: Artificial intelligence algorithms centered around deep learning require a relatively balanced distribution of various classes within the training dataset to ensure the learning and generalization capabilities of the deep learning network. However, while electric drive systems are abundant in quantity, samples representing faulty and abnormal states are relatively scarce. Additionally, historical records pertaining to faults and anomalies lack specificity, resulting in an issue of class imbalance within the data training set.

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