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Application of Artificial Intelligence Techniques on Computational Electromagnetics for Power System Apparatus: An Overview

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ABSTRACT This paper provides a review of the most recent advances in artificial intelligence (AI) as applied to computational electromagnetics (CEM) to address challenges and unlock opportunities in power system applications. It is intended to provide readers and practitioners in electromagnetics (EM) and related applicable fields with valuable perspectives on the efficiency and capabilities of machine learning (ML) techniques used with CEM tools, offering unparalleled computational advantage. The discussion begins with an overview of traditional computational methods in EM, highlighting their strengths and limitations. The paper then delves into the integration of AI techniques, including ML, deep learning, and optimization algorithms, into CEM frameworks. Emphasis is placed on how AI enhances the accuracy and efficiency of EM simulations, enabling rapid analysis and optimization of power system components and configurations. Case studies and examples illustrate the successful application of AI-based CEM in solving practical challenges in electrical machine modeling, condition monitoring, and design optimizations in power systems. This paper conducts a comprehensive assessment of AI-based CEM techniques, critically evaluating their merits, addressing open issues, and examining the technical implementations within the context of power system applications.

INDEX TERMS Artificial neural networks (ANN), deep learning, finite difference time domain (FDTD), finite element method (FEM), machine learning (ML), method of moments (MoM), partial element equivalent circuit (PEEC), power system equipment modeling, power system simulation, transmission line modeling (TLM).

I. INTRODUCTION

RCENT research conducted by integrating computational electromagnetics (CEM) and artificial intelligence (AI) has witnessed significant advancements and promising outcomes. CEM can be defined as a branch of electromagnetics (EM) that relies on a digital computer to derive numerical outcomes. There are various traditional CEM techniques such as the finite difference time domain (FDTD) method, the finite element method (FEM), the transmission line modeling (TLM), the method of moments (MoM), and the partial element equivalent circuit (PEEC) method which significantly contribute to the understanding and analysis of EM phenomena. However, the inherent complexity and computational demands of the EM problems and the inherent limitations of the above techniques to overcome these barriers have prompted researchers to explore new approaches.

The development of AI has witnessed rapid progress and a transformative impact across various domains, including CEM [1]. AI has evolved from its beginning to encompass a diverse range of techniques and algorithms that mimic human intelligence. The synergy between increased computing power and the availability of large datasets has fueled the successful implementation of these technologies across various domains. There are three main machine learning algorithms (MLA), such as supervised learning (SL), unsupervised learning (UL), and reinforcement learning (RL), which have become increasingly popular [2]. SL algorithms learn from labeled data sets to make predictions or classify new data. UL algorithms, on the other hand, uncover hidden patterns and structures within unlabeled data. RL algorithms interact with an environment, receiving feedback in the form of rewards or penalties to optimize decision-making and behavior [3].

This comprehensive review provides details of the recent advancements in AI-based CEM techniques with the aid of recent publications. It discusses the principles of different AI algorithms and their applicability for solving specific electromagnetic problems in power system applications. Furthermore, this review highlights the advantages of AI-based CEM techniques over conventional methods, such as reduced computational cost, faster convergence, and the ability to handle large-scale problems. It also highlights the limitations associated with the adoption of AI in CEM, including the data requirements, model interpretability, and generalization capabilities.

This survey will serve as a comprehensive guide to the latest AI-based CEM techniques, offering a foundation for researchers to explore and harness the potential of AI in advancing the field of CEM. Section II provides an overview of the traditional CEM techniques, stating their methodology, merits, and demerits. Some AI techniques are briefly discussed in Section III while Section IV provides an overview of the AI-based CEM applications reviewing recent publications.

II. COMPUTATIONAL ELECTROMAGNETICS-AN OVERVIEW

Over the years, various techniques have been utilized for simulating power system apparatus, incorporating both differential and integral methods. Differential techniques, such as FDTD, FEM and TLM are applied in the modeling of power systems, with FEM playing a major role due to its ability to handle complex geometries and ensure higher accuracy. Integral methods such as MoM and PEEC have gained prominence in solving electromagnetic problems due to their ability to solve the domain effectively by addressing only the discretization of magnetizable regions. These methods have been combined with AI for various applications, and the subsequent sections will provide a comprehensive overview of these methods, including their detailed techniques and latest developments.

A. FDTD

The FDTD method was introduced in 1966 to solve electromagnetic boundary value problems numerically [4]. It approximates partial derivative terms in Maxwell's equations using a set of finite difference equations while operating on a mesh called the Yee grid, where electric and magnetic field components are discretized. Initially, the method was applied to wave propagation applications [5], and later it was extended to various classes of electromagnetic domains, including antenna design, optical devices, medical devices, digital circuits, and power systems.The FDTD method approximates the continuous derivatives in the governing equation of the system by employing discrete finite difference formulas in both the spatial and time domains, and they are accurate up to $\mathcal{O}(h^2)$ (where h is the grid size), and even higher-order accuracy can be achieved by increasing the nodes in the finite difference formula. Among the power system applications, the FDTD method has been widely used for static geometry-based applications, such as transformers and transmission lines, with transmission line modeling being the most common application. This theory has been successfully employed in the transient analysis of lightning surges [6], the modeling of lossy transmission lines [7], and the investigation of transient phenomena in underground cables [8].

B. FEM

FEM is a differential equation-based numerical modeling technique, and it has widely been utilized due to its capability to describe the geometry of the given problem with higher flexibility. FEM employs triangular elements to create a finer mesh of the geometry and assigns a global basis function to each node. The Galerkin's FEM method [9] is then applied, integrating the system's governing equations to construct a global matrix system for solving the problem. FEM solutions can be expressed in both the frequency-domain and the time-domain based on the solution requirements [10]. Time-domain solutions are primarily employed in power system simulations to analyze transient behavior. FEM has been coupled with the FDTD method [11] and the TLM method [12] to provide accurate and efficient time-domain solutions. Despite the method's complexity, the matrix solution can be massively parallelized using the TLM method [13]. FEM has been particularly valuable in the analysis of shielded underground cables [14], transient modeling of transformers [13], modeling of induction motors [15], and the study of eddy current losses in wind generators [16]. The primary advantage of the FEM is its ability to derive comprehensive models, including power loss calculations, thermal analysis, and field distributions. As illustrated in Fig. 1, FEM has dominated the number of publications over the past two decades, displaying a consistent increase in publications each year.

C. TLM

The TLM method [17] was originally developed to address wave propagation problems, and it utilizes the connection between network laws and Maxwell's equations to derive a lumped circuit model, which can be numerically approximated using loss-less transmission lines [18]. Ultimately, the inductors and capacitors in the circuit represent energy storage in magnetic and electric fields. Though frequency-domain solution is available [19], TLM is widely used for

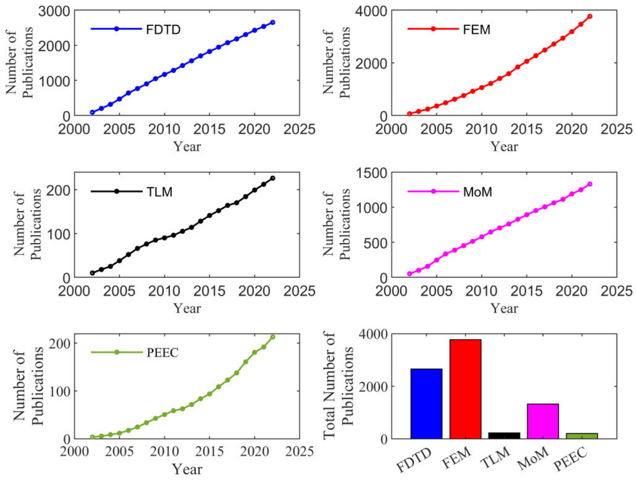

FIGURE 1. **Number of journal publications in IEEE Xplore from 2003 to 2023 having index terms "FDTD", "FEM", "TLM", "MoM" and "PEEC".**

solving time-domain electromagnetic problems. The TLM model is typically solved in the time domain using scattering and gathering phenomena in transmission lines. At the initial time-step, incident voltage pulses will be assumed and reflected voltage pulses will be calculated using reflection coefficients of each transmission line. The reflected voltage pulses then serve as the incident voltage pulses for the respective neighboring nodes at the next time-step. The TLM method has been used to facilitate real-time FEM simulations by enabling parallelized calculations within the emulation time-step [12]. The time-stepped eddy current analysis of induction motors conducted using the TLM method is more efficient compared to traditional approaches [20]. Hence, the TLM method represents an efficient approach for addressing electromagnetic problems and can be easily integrated with other methodologies to further enhance its efficiency.

D. MoM

The MoM has been proven to be a powerful integral-based numerical method for the computation of electromagnetic fields in various applications. The MoM was developed decades ago [21], and different variations can be obtained by using different basis functions, weighting functions, and discretization procedures. The most frequently used procedure is based on surface current approximation. In this approach, the electromagnetic problem is discretized using either triangular or rectangular elements, and unknown electrical currents or magnetic currents are defined for each element using basis functions. The governing integral equation is approximated using Green's functions, and a matrix system is formulated to obtain the unknown currents. In antenna analysis and scattering problems, accurately modeling the current distribution on the surfaces of the structure is essential. MoM provides a natural way to model this current distribution and is widely used in antenna and scattering problems. The MoM offers a more accurate approximation for the DC distribution in AC power systems [22], the electric field induced by power lines [23], and the analysis of lightning-induced voltage in overhead lines [24].

E. PEEC

The PEEC method is considered an emerging integral-based numerical approach for solving electromagnetic problems by converting field variables into the circuit domain. The PEEC method was initially introduced for conductor systems, and the equivalent circuit was solved using circuit solvers [25]. PEEC models for dielectric materials were introduced, and later they were extended to include linear magnetic materials [26]. Recently, the PEEC method has been further developed for non-linear magnetic materials, introducing non-linear magnetization effects into the circuit model [27]. The domain will be discretized, including conductor, dielectric, and magnetic regions. Partial inductance, capacitance, and resistance will be introduced for each element in the domain to formulate the equivalent circuit. The equivalent circuit model can be solved using a circuit solver technique in either the time-domain or the frequency-domain. The PEEC method has been employed in various areas, such as the analysis of lightning arrestors for power transformers [28], the analysis of air-core reactors for a wider frequency range [29], and the calculation of static leakage inductance in high-frequency transformers [30]. The PEEC method is an efficient approach for solving power systems, particularly when considering air regions or boundary conditions is not necessary. As depicted in Fig. 1, PEEC method demonstrates a continuous growth in the number of research outcomes per year in the last two decades.

III. AN OVERVIEW OF AI TECHNIQUES AND THEIR APPLICATIONS

In the current information technology (IT) industry revolution, AI techniques are rapidly involved in applications in research, engineering, and various industrial sectors [3]. AI is used in the design of computers, robots, and software applications as it possesses the capability to exhibit intelligence on par with human cognitive abilities. Outlined below are some commonly utilized AI methodologies in power system applications [2]:

1) MLA: This can be described as the application of a set of mathematical algorithms to enhance the performance of a specific task over time [31]. It utilizes training datasets as input and uses them as a guide to make predictions without requiring explicit programming for each specific task. MLA primarily can be classified into three main groups as follows [2].
   - SL: A labeled data set that is used in mapping inputs and outputs through a function.
   - UL: An unlabeled data set, patterns are identified to classify the data set.
   - RL: Recognize the method of executing a task through interaction with the surrounding environment.

2) Hybrid methods: Various machine learning (ML) techniques are integrated to address limitations and enhance the outcomes of the application.

Fig. 2 illustrates different types of MLA commonly found in industrial applications. The forthcoming sections will explore several well-known ML methodologies and their applications with CEM in power system applications.

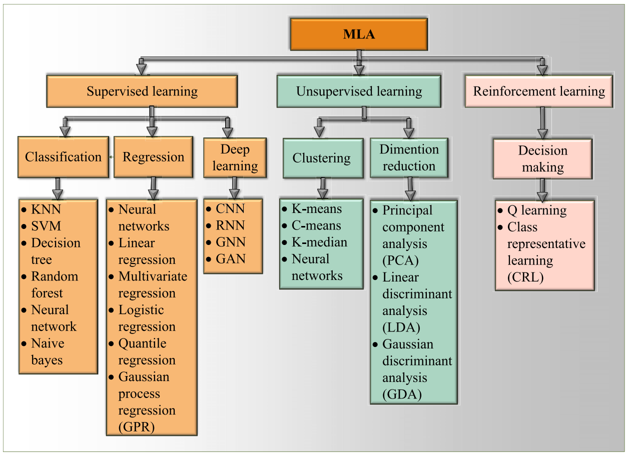

FIGURE 2. Classification of MLA.

A. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are powerful AI algorithms with the ability to discover optimal solutions for a wide variety of complex, non-linear problems. The inherent nonlinearity of ANNs equips them with powerful interpolation capabilities, enabling them to effectively approximate complex nonlinear conductivity distributions [32].

There are internal layers in ANNs, which are called the hidden layers, and the last layer is referred to as the output layer. ANNs with several hidden layers are called deep learning ANNs, and those with only one hidden layer are known as shallow ANNs [3]. The weighting of the interconnections between neurons is determined in the training process of ANNs [33], [34]. This weighting is a crucial aspect of an ANN's architecture and is chosen through the learning process using a provided dataset. The computed output is then compared to the desired or target output from the dataset, resulting in an error value. The error quantifies the discrepancy between the predicted output and the expected output. To minimize this error, the weights of the interconnections are adjusted using optimization techniques such as back-propagation, or gradient descent [34]. This process allows the ANNs to learn the underlying patterns, relationships, and dependencies present in the data, enabling them to make accurate predictions or decisions when presented with new, unseen inputs.

To ensure accurate results from ANNs, it is essential to have an adequate and sufficiently diverse training set. Having a larger training set often helps the ANNs in capturing the underlying trends, reducing the risk of over-fitting and improving their generalization capability to handle unseen inputs effectively [35]. ANNs are frequently employed in the construction of surrogate models and the optimization of pre-existing models for electrical machines. Fig. 3 illustrates an ANN-based inductor model as described in [3]. This model utilizes the classification and regression capabilities of ANNs.

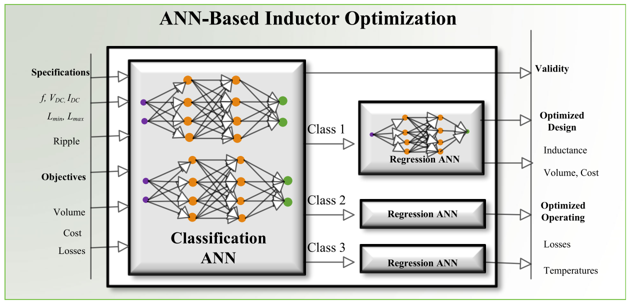

FIGURE 3. Application of ANN for inductor optimization from [3].

B. SUPPORT VECTOR MACHINES

Support vector machines (SVMs) are a prominent supervised ML technique used for analyzing data for both classification and regression analysis. They were originally introduced over two decades ago, these techniques have undergone thorough research and analysis since their inception [37]. SVMs are renowned for their robust theoretical foundations, exceptional generalization capabilities, and adeptness in managing high-dimensional data.

The goal of SVMs is to identify a hyperplane, characterized as a linear decision function, that maximizes the margin between vectors belonging to two distinct classes. SVMs are effectively utilized in [38] and prove valuable for efficiently classifying large datasets into relevant categories within a practical timeframe. The data points that closely align with the optimal hyperplane are referred to as support vectors [37]. This method of classification makes SVMs more appropriate for several applications compared to other ML techniques. SVMs are used in constructing surrogate models based on FEM data in power system applications such as modeling and design optimization in electrical equipment.

C. DEEP LEARNING - BASED ON CONVOLUTIONAL NEURAL NETWORKS

Recent research has employed deep learning to address certain challenges posed by other AI methods in CEM applications [39]. Deep learning methods like Convolutional neural networks (CNNs) demonstrate effectiveness in handling large datasets and they have opened up opportunities for utilizing topological details including the geometric shapes and spatial distribution of various materials within a specific domain, as input data [40]. The CNNs excel in capturing complex patterns and representations from the data, which allows them to generate more accurate and visually pleasing high-resolution outputs compared to conventional techniques.

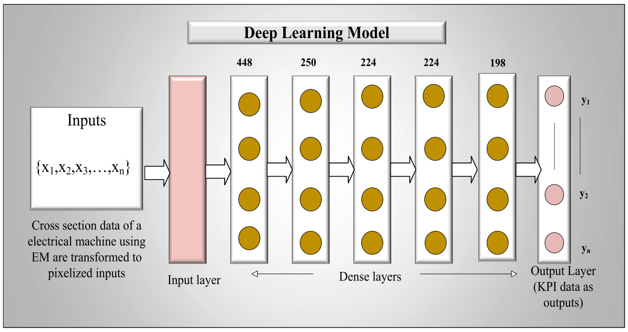

FIGURE 4. A Deep learning model used for KPI prediction in [36].

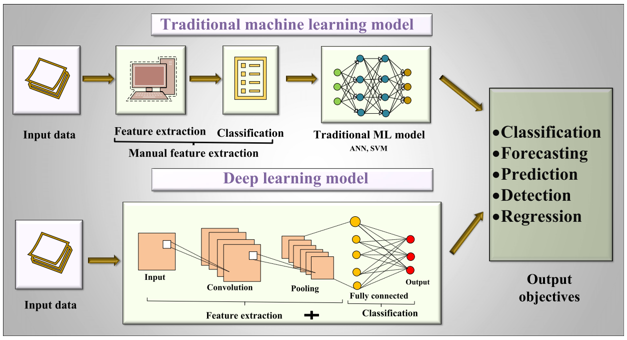

FIGURE 5. Comparison of traditional ML and deep learning methods.

Deep learning is applied in a wide range of applications, including design optimization, where its effectiveness lies in minimizing computational expenses [41]. In [36], a deep learning-based model is employed for key performance indicator (KPI) prediction in electrical machines. The model's representation is illustrated in Fig. 4, where input data undergoes processing through multiple layers to generate the final outputs. Although ANNs have proven effective in modeling and optimizing parameters for electric machines, the process of selecting appropriate image features to construct the input data for the ANNs can be often challenging. In contrast, when employing deep learning for image processing, the image is directly input into the system without the requirement of explicit feature design. This is due to CNN's capability to autonomously learn and extract relevant features directly from the row image data. Fig. 5 demonstrates a comparison between traditional ML methods and deep learning models.

D. REINFORCEMENT LEARNING

RL stands out as a primary ML model capable of interacting with the environment to predict output data. In the context of an RL system, there are four fundamental components: the agent, environment, reward, and action. The decision-making entity within this framework is referred to as the agent, while everything external to the agent is termed the environment [42]. Some of the most widely recognized RL algorithms are Q-learning, state-action-reward-state-action (SARSA), and deep Q Network (DQN) [43].

In [44], Q learning was used to identify the optimal coupling coefficient among transmitting (Tx) and receiving (Rx) coils of a wireless power transfer (WPT) system. The drawbacks of using SL methods include the requirement for a more extensive training dataset and increased computational time. RL methods are incorporated into CEM for power-related purposes, including tasks like topology optimization (TO) and electrical component designs.

E. HYBRID METHODS

Hybrid methods are the integration of two or more AI techniques in order to take advantage of the unique characteristics that each method possesses. When referring to the papers published after 2020, it becomes apparent that the common practice of employing various AI techniques within a single application has increased compared to research conducted in earlier years. In 2021, a method to enhance torque performance in a permanent magnet arc motor (PMAM) was introduced by combining an MLA, extreme gradient boosting (XGBoost) with the non-dominated sorting genetic algorithm (NSGA) [45]. The two methods provided the best results for the application by efficiently combining optimization objectives, structural parameters, and motor performance. The results were validated using FEM, and the developed model demonstrated enhanced torque performance compared to the original motor design.

In [46], an efficient approach is introduced for creating an optimal model of an interior permanent magnet synchronous motor (IPMSM) using generative adversarial networks (GAN) and CNNs. The utilization of CNNs enables the training of the developed model with a more extensive dataset, and GAN contributes to generating a larger dataset with fewer FEM simulations.

IV. ANALYTICAL COMPARISON OF AI-BASED CEM TECHNIQUES IN POWER SYSTEMS APPLICATIONS

The integration of AI with CEM in power system applications holds the promise of significantly enhancing computational efficiency. Fig.6 illustrates the number of journal publications from 1993-2023 for various AI-based CEM implementations. Some of these applications in power systems can be listed as follows.

1) Electrical machine modeling and design optimizations.
2) Topology optimizations.
3) Fault diagnosis and condition monitoring.
4) Electrical impedance tomography.

The forthcoming sections will provide a comprehensive discussion and comparison of some of the most popular applications of AI-based CEM in power systems. Different AI techniques can be compared based on parameters such as accuracy, algorithmic complexity, and the data set requirements. In some applications, several surrogate models are taken into consideration and compared to identify the optimal

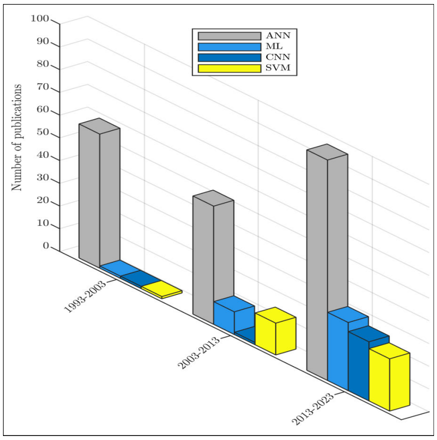

FIGURE 6. Approximate publication popularity of AI-based CEM applications from 1993-2023 (IEEE Xplore).

model that delivers the best performance. The broad classification of popular AI-based CEM includes various techniques such as ANN, SVM, deep learning, MLA, genetic algorithms (GA), recurrent neural networks (RNN), k-nearest neighbors (KNN), and hybrid methods.

In [47], four classes of regression models, namely linear regression (LR), regression tree (RT), SVM, and Gaussian process (GP) are explored for predicting the acoustic noise of electric motors. The comparative analysis of the constructed surrogate models involves evaluating their performance based on metrics such as the size of the root mean square error (RMSE), training time, and sample evaluation speed. However, a larger training set enhances result accuracy, and it concurrently raises the cost associated with training.

A. ELECTRICAL MACHINE MODELING AND DESIGN OPTIMIZATION

The modeling and optimization of designs for electrical machines are crucial, given their pivotal role in power system applications. Conventional machine modeling techniques can be categorized into two groups: analytical methods and numerical methods. Analytical methods rely on mathematical equations, offering speed but sacrificing accuracy. In contrast, numerical methods use parameters derived from numerical field simulations, providing accuracy at the expense of high computational costs [48]. To maintain a balance between accuracy and computational efficiency, MLAs have been incorporated alongside these modeling approaches.

Recent publications highlight some distinct and successful strategies aimed at overcoming the limitations associated with existing methods. The initial attempt to identify synchronous motor parameters was undertaken in [35], employing FEM and ANN. A comparable approach was then adopted in [49] for an induction motor, utilizing a self-organized distributed network (SODN). The primary function of an electrical machine design model is to establish a mapping between the design space and the performance space. In the context of magnetic components, the design possibilities span a wide range, covering various configurations and parameters. However, the performance space, which represents the outcomes and characteristics of these designs, is relatively narrow. In [3], an inductor model has been developed utilizing ANN. In this approach, the first ANN is employed to forecast magnetic properties like inductance, magnetic flux, and magnetic field. Concurrently, a second ANN is employed to predict the thermal behavior of the inductor. This dual-ANN setup allows for a comprehensive modeling approach that accounts for both magnetic and thermal aspects of the inductor's performance. Fig. 7 illustrates the workflow involved in developing a data-driven surrogate model.

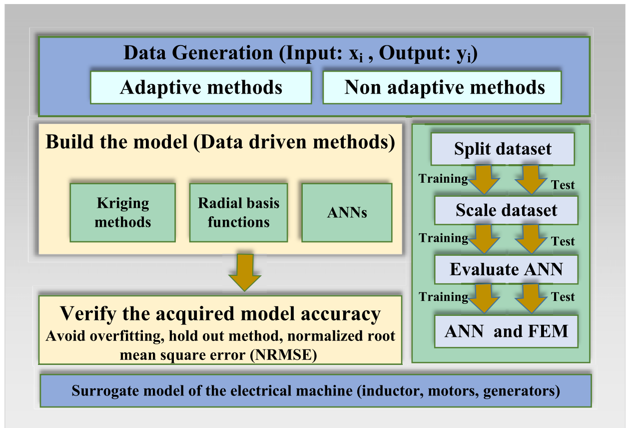

FIGURE 7. Workflow of developing a data-driven surrogate model.

ANNs are frequently utilized in the modeling of electrical devices, including generators, inductors, and industrial motors. This is achieved by using a dataset derived from a traditional method for both training and testing the developed model. Because of the minimal errors observed during model testing, researchers concluded that the developed models have the potential to accurately predict machine parameters based on the provided initial conditions. The primary focal point of consideration revolved around obtaining precise results in a more expedient manner compared to classical methods like FEM. In [35], the authors conducted a comparison between the utilization of ANN and gradient boosting decision trees (GBDT) for modeling the torque characteristics of a permanent magnet synchronous motor (PMSM). The comparison revealed that while the surrogate model employing GBDT exhibited a faster computational speed than the model relying on ANN, it displayed a relatively lower level of accuracy.

The utilization of AI techniques for the design optimization of electrical machines has gained increased popularity in recent years. This trend is driven by the demand for more optimized machines to deliver superior performance across various applications. The optimization can be applied to an analytical model or to a numerical model to enhance its performance in both accuracy and efficiency. Results from FEM simulations are frequently employed to determine intermediate measures, including iron losses, electromagnetic torque,

TABLE 1. Recent Comparative Studies of AI-Based CEM Implementations (↓ - decrease and ↑ -increase).

Ref.	Machine	Method	AI model	Error	Computer cost/findings	Limitations
Electrical machine modeling and design						
[35]	Synchronous machine	ANN	Data: FEM, Inputs: V, I, PF angle, output: d, q reactance	$\leq 2\%$	↓	ANN: Improved complexity, additional data: geometry, material, less ability of prediction due to the black box nature
[49]	Induction motor	ANN	Data: FEM, Inputs: d0, S, W, d1, R0, Outputs: R2, X2	$\leq 3\%$	↓ $\leq$ 1s (FEM: 630s, 3492 nodes)	
[3]	Inductor	ANN	FEM data, Outputs: max. and avg. temp. elevations	$\leq 3\%$	↓ to 50,000 computations per second	
[50]	Air core reactor	SVM	FEM	$\leq 4\%$	↓	
[48]	PMSM	ANN	FEM		↓	
[51]	Turbine generator	DGPR	FEM, 1000 samples, eddy current loss		136h ↓	
[52]	Electric vehicle	ML	Ferrite core design, Tx, Rx, ANSYS, FEM	$\leq 3\%$	volume ↓ 90%	
[44]	WPT	RL	Ferrite core design, Tx, Rx, ANSYS, FEM		↑ performance than GA	
[53]	PMSLM	ELM, GA	Air core PMSLM design tolerance, FEM, thrust data		↓ time, high precision, simple	
[54]	IPM	CNN	bitmap images, magnetic flux density, stator data	↓	↓ 27.3 and 47.5%	
Topology optimization						
[55]	Rotating machines	CNN	Data: Cross-sectional images, CNN and GA, CNN		50 and 30% ↓	CNN: Unreliable with unseen new geometry
[41]	IPM	CNN	Data: FEM		10 and 30%	
[56]	Electric motors	CNN	Data: FEM		15% ↓	
[57]	IPM	CNN	Data: magnetic flux density, current amplitude/ density		95.1% ↓	
[58]	SynRM	RL	Data: FEM		70-90% to GA	
Electrical impedance tomography						
[32]		ANN	FEM, 3195 nodes	↓	similar accuracy with 135 % faster	
[59]	Tactile sensors	ANN	FEM, COMSOL, 364 nodal conductivity values		↑ sensor performance	
Design optimization						
[60]	Induction machine	ML	FEM	$\leq$9%	loss reduction: 12%	ML: Lack of generalizability and depend on the data collection methods, the utilized data set is not bias free
[61]	PMSM	ML	FEM, 2D model using ANSYS Maxwell, 10000		↑ torque, torque ripple	
[62]	PMSM	SVM	FEM	$\leq$1%	Avg. thrust: ↑ 12% , thrust ripple: ↓ 84.78% ,THD: ↓ 47%	
[46]	IPMSM	GAN, CNN	FEM, GAN - 10279500 data from 26209 FEM results, CNN - predict using a large dataset		↓ only 13-15 seconds	
[63]	PMAM	RF, GA	FEM, 529 sample data, output torque, torque ripple, back EMF, Total harmonic distortion (THD)		EMF: ↑ 41.9% Avg. thrust: ↑ 44.4%, thrust ripple: ↓ 67.5%, THD: ↓ 47%	
[64]	PMSLM	KNN	FEM, 1267 samples, Avg. thrust, torque ripple	$\leq$0.6%	Avg. thrust: ↑ 28.4%, thrust ripple:↓ 78%	
[31]	PMSLM	KNN	FEM, Avg. thrust, torque ripple	$\leq$2%	Avg. thrust: ↑ 14.51% , thrust ripple: ↓ 81.71%	
[65]	Permanent magnet vernier machine (PMVM)	SVR	FEM, 6250 cases, optimize spatial distribution uniformity and orthogonality of Latin hypercube design (LHD)	↑	$\leq$2% and 50% and 90%	
[66]	PMSLM	Regression	FEM for accuracy testing	$\leq$1%	502 groups in 247s	
[67]	IPMSM	ML	FEM	↓	$\leq$0.2% time of the FEM simulations	
[51]	PMSM	GPR	FEM	↓	4 % of FEM models evaluations	
Model order reduction						
[68]	PMSM	ANN	FEM, 220 X 61, current x torque,	$\leq$1%	50% ↓	

TABLE 1. ***(Continued.)*** **Recent Comparative Studies of AI-Based CEM Implementations (↓ - decrease and ↑ -increase).**

Ref.	Machine	Method	AI model	Error	Computer cost/findings	Limitations
Visual results prediction						
[69]	3D objects	CNN	Inputs: Images of surface currents, 500 epochs		7.6h ↓ 18 min, 100 iterations ↓ 4	
Prediticting key performance indicators						
[36]	PMSM	CNN	Dataset 1: Stator parameters (68099), Dataset 2: Image samples (7744)	≤13%, ≤8%	↓, Image-based approach has high flexibility and re-usability	
[70]	PMSM	CNN	FEM data, physics, and data-driven hybrid method, multi-branch CNN	↓	↑ compared to CNN approach, ↓ compared to FEM	
[71]	SRM	Regression	FEM, Ansoft Maxwell, 1000 iterations	↓	↓ compared to ELM and backpropagation	
Fault diagnosis and condition monitoring						
[72]	PMSLM	ELM	FEM, demagnetization faults	↓	↓	
[73]	DC power cables	ML	FEM, series faults, load current measurements	2%		

and flux rates, at various operating points of an electrical machine model [70].

As of the publications available until March 2023, various AI techniques have been employed to optimize different types of electrical machines, including commonly used induction motors in industrial applications. A significant portion of the literature focuses on optimizing PMSMs, switched reluctance motors (SRMs), and interior permanent magnet motors (IPMs) using ML algorithms. These algorithms include SL methods, deep learning, KNN, and RL [31], [40], [44], [56], [60], [61], [66], [71], [74]. The findings of the above research are summarized in Table 1.

In 2022, a hybrid model was introduced to enhance the thrust performance of a permanent magnet synchronous linear motor (PMSLM). This model incorporated deep adaptive ridge regression and an analytical mapping function. The suggested approach demonstrates superior accuracy compared to existing methods, such as extreme learning machines (ELM). FEM was employed to construct a database that captures the mapping relationship from structural parameters to thrust performance. The optimized model exhibited a 28.4 % increase in average thrust compared to the unoptimized initial PMSLM, and the thrust fluctuation was reduced by 78 % [64].

In [61], an optimal design is introduced to address the challenge of choosing a PMSM model that achieves both higher torque density and lower torque ripple. Existing methods, often relying heavily on FEM, are noted for their prolonged computation times.

B. TOPOLOGY OPTIMIZATION

TO is a computer-aided design process used to create efficient designs determining optimal material distribution to satisfy predefined performance objectives and constraints [57]. When optimizing electrical machines, such as electric motors, it is essential to take into account various properties. This includes objectives such as minimizing torque ripple, maximizing average torque, and controlling losses and forces. These considerations are crucial for achieving the optimal and efficient performance of the electric machine. TO using FEM may need to be replaced with more advanced techniques owing to the elevated computational costs associated with FEM simulations. Certain techniques, like the response surface method and the kriging method, have been explored to mitigate computational time. However, their effectiveness is notable mainly when the degree of freedom (DoF) within the design space is less than ten [41]. In general, DoF in many real-world images is higher, rendering the aforementioned methods inadequate. Recognizing these drawbacks, research has been conducted to apply ML techniques in TO applications.

Considering the prior publications, ML techniques were integrated with TO after the year 2019, starting with ANN techniques and progressing to deep learning techniques. There are merits and demerits of employing SL techniques like ANN compared to deep learning techniques in TO. ANNs can operate with raw data but are hindered by a limitation in generalizability. On the other hand, deep learning techniques possess the capability to automatically extract features from input data. However, the models generated may have inaccuracies when applied to new geometries. In [58], the author discusses significant drawbacks associated with the use of SL methods in TO of a synchronous reluctance motor (SynRM) and suggests an RL-based approach. This new method aims to achieve independence from existing optimal designs. While the training time requirement may be relatively high, once trained, the computational cost of the proposed method becomes very low. Additionally, it provides an optimal solution compared to traditional methods.

C. FAULT DIAGNOSIS

Fault detection and condition monitoring in electrical apparatus is a vital requirement for the reliable operation of power systems. FEM is regarded as more applicable in fault diagnosis because it has the capability to address below drawbacks present in traditional methods, such as current analysis [75].

1) Unavailability of detailed data sets on the field measurements.
2) Inability to observe the severity of the fault.

Hence, it is comprehensible that the integration of AI and FEM is a recommended approach for fault detection. AI addresses the limitations of FEM, enhancing overall computational efficiency in the process. In [72], the focus is on the PMSM, which is widely acknowledged in the industry. The investigation in this study centers around the identification and classification of demagnetization faults in the PMSM. ELM has been introduced as the classifier in fault feature analysis for the classification of fault positions, sides, and severity types to derive unique fault type labels. A comparison of the performance of probabilistic neural networks (PNNs), backpropagation neural network (BPNNs), and ELM indicates that ELM outperforms in terms of accuracy and efficiency indexes. Turbine generators play a pivotal role in power generation. Hence, regular condition monitoring is crucial to ensure the ongoing smooth operation of turbine generators. For large turbine generators, eddy current analysis is often necessary. In [51], a method for predicting eddy current loss is introduced, employing deep Gaussian process regression (DGPR) and relying on FEM data. The outcomes of the tests demonstrated the effectiveness of the DGPR method in accurately predicting eddy current losses. The research initiated in this stream is relatively limited compared to the extensive literature available on other implementations of AI-based CEM.

D. OTHER APPLICATIONS

There are also less popular applications in power systems. Some examples are electrical impedance tomography (EIT), surface current estimations, and model order reductions. The above-mentioned research areas have limited literature available, indicating that these are emerging within the domain of AI-based CEM in power systems. It suggests the potential opportunities for further research and development in these specific areas.

In [59], an investigation was conducted to implement a tactile sensor based on EIT as it was recognized as a valuable solution for constructing flexible and comfortable tactile sensors. Based on the results, it is evident that the reconstruction using ANN has enhanced the sensing performance compared to commonly used reconstruction methods such as L2 regularization and Newton's one-step error reconstructor (NOSER).

PMSM is known in the industry for its high performance in power density and efficiency. In [68], a reduced-order model using ANN is developed and presented to capture the essential dynamics of the PMSM. Here, two ANNs were developed for current and torque prediction, demonstrating an enhanced capacity to fit the data extracted from FEM in accordance with the applied data reduction methods.

V. CONCLUSION

This article represents a review of the AI-based computational electromagnetic (CEM) simulations for power system applications. The initial part of the article provides a discussion on the significance of CEM techniques and their key characteristics. These approaches are employed for precise modeling of electrical machines and the optimization of their design procedures. However, a drawback associated with these methods is the extended computational time they require. Consequently, efforts were initiated to explore alternatives and address the limitations associated with traditional approaches. Then, a brief overview of common AI techniques was presented stating their major functions. These AI methods possess their own advantages and disadvantages, which are thoroughly discussed within the context of their respective applications. Next, the applications of AI-based CEM in power system applications were discussed. The literature review shows that the use of AI models for different CEM approaches in the power sector is increasing due to their advantages compared to conventional methods. The outcomes of the introduced models demonstrate similar accuracy and superior efficiency when compared with the existing methods. The research findings have been succinctly summarized in Table 1, outlining the applications and the corresponding techniques employed. It is expected that this overview will motivate further research and new knowledge generation in the exciting field of AI-enhanced CEM for various application domains.

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