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TOPICAL REVIEW

Applications of Machine Learning and Deep Learning in Antenna Design, Optimization, and Selection: A Review

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ABSTRACT This review paper provides an overview of the latest developments in artificial intelligence (AI)-based antenna design and optimization for wireless communications. Machine learning (ML) and deep learning (DL) algorithms are applied to antenna engineering to improve the efficiency of the design and optimization processes. The review discusses the use of electromagnetic (EM) simulators such as computer simulation technology (CST) and high-frequency structure simulator (HFSS) for ML and DL-based antenna design, which also covers reinforcement learning (RL)-bases approaches. Various antenna optimization methods including parallel optimization, single and multi-objective optimization, variable fidelity optimization, multilayer ML-assisted optimization, and surrogate-based optimization are discussed. The review also covers the AI-based antenna selection approaches for wireless applications. To support the automation of antenna engineering, the data generation technique with computational electromagnetics software is described and some useful datasets are reported. The review concludes that ML/DL can enhance antenna behavior prediction, reduce the number of simulations, improve computer efficiency, and speed up the antenna design process.

INDEX TERMS Antenna optimization, antenna design, antenna selection, artificial intelligence, deep learning, machine learning.

ACRONYMS

Abbr.	Elaboration
ACLMS	Augmented Complicated LMS.
ADS	Advance Design System.
AI	Artificial Intelligence.
ANN	Artificial Neural Networks.
ARSM	Adaptive Response Surface Method.
AS	Antenna Selection.
BER	Bit Error Rate.
BSPA	Bone Shaped Patch Antenna.
CAD	Computer-Aided Design.
CEM	Computational Electromagnetics.
CNN	Convolutional Neural Network.
CST	Computer Simulation Technology.
CSI	Channel State Information.
D2D	Device to Device.
DEA	Differential Evolution Algorithm.
DLBAS	DL-based Antenna Selection.
DNN	Deep Neural Network.
DQN	Deep Q Network.
DRA	Dielectric Resonator Antenna.
DTR	Decision Tree Regression, Regression Tree.
FDTD	Finite Difference Time Domain.
FEM	Finite Element Method.
FN, IN	Forward Network, Inverse Network.
GPR	Gaussian Process Regression.
GRSM	Global Adaptive Response Surface Method.

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HFSS	High-Frequency Structure Simulator.
IoT	Internet of Things.
k-NN	k- Nearest Neighbor.
LMS	Least Mean Square.
LR	Linear Regression.
LSTM	Long Short-Term Memory.
MGSA	Modified version of the Gravitational Search Algorithm.
MISO	Multiple Input Single Output.
MITH	Maximum Input Tolerance Hypervolume.
ML, UL	Machine Learning, Unsupervised Learning.
MLA	Machine Learning Algorithm.
MLAO	Machine Learning Assisted Optimization.
MLP	Multilayer Perceptron.
MoM	Methods of Moment.
M2M	Machine to Machine.
m-MIMO	massive-Multiple Input Multiple Output.
MOEA	Multi-Objective Evolutionary Algorithms.
MS-CoML	Multistage Collaborative Machine Learning.
NLP	Natural Language Processing.
NBAS	Norm-Based Antenna Selection.
PSADEA	Parallel Surrogate model-Assisted hybrid Differential Evolution for Antenna.
PSO	Particle Swarm Optimization.
RBF	Radial Basis Function.
RSSI	Received Signal Strength Indication.
SDR	Software Defined Radio.
SBO	Surrogate Based Optimization.
SINR	Signal to Interference plus Noise Ratio.
SL, DL	Supervised Learning, Deep Learning.
SNR	Signal-to-Noise Ratio.
SNN	Supervised softmax Neural Network.
SVM	Support Vector Machine.
SVR	Support Vector Regression.
TARC	Total Active Reflection Coefficient.
VFO	Variable Fidelity Optimization.

I. INTRODUCTION

Many cutting-edge technologies, such as the Internet of Things (IoT) and artificial intelligence (AI), have changed the way we live. The IoT has enhanced the Internet's capacity to improve commercial and industrial outcomes, and consequently our living conditions [1]. In recent years, IoT technologies such as machine-to-machine (M2M) or device-to-device (D2D) communication have accelerated the advancement of 5G/6G communications and beyond. For a wireless communication system to operate at its most efficient level, antenna design, optimization, and selection are crucial. As a result, a proper antenna design is required for any type of wireless communication, including WiFi, cellular and satellite communication. Computational electromagnetics (CEM) model the interaction of electromagnetic fields with antennas using Maxwell's equations [2]. The finite difference time domain (FDTD), finite element method (FEM), and methods of moments (MoM) are three numerical analysis approaches widely used in antenna simulation and testing [3], [4], [5]. Physical optics approximation is another well-known antenna design technique. The majority of antenna modeling works involves computer-based solutions of partial differential equations with defined boundary conditions [6].

For constructing an antenna, commercial CEM software like computer simulations technology (CST), integral equation 3D (IE3D), Altair FEKO, high-frequency structure simulator (HFSS), and advanced design systems (ADS) are available. These software programs also lack a number of critical capabilities. ADS, for example, cannot model 3D structures, IE3D cannot simulate structures with finite features, and the execution time of HFSS and CST is considerable and increases with the topology of the antenna structure. As a result, adjusting the antenna parameters using current tools is a complex and time-consuming operation. An antenna cannot emit at its greatest capacity if it is not properly optimized. Currently, researchers are aiming to improve time-saving antenna design performance using machine learning algorithms or deep learning algorithms [7], [8]. Machine learning (ML) has enormous potential in the domain of antenna design and antenna behavior prediction because it allows for significant speeding up while maintaining high accuracy. Figure 1 [9] depicts the link between AI, ML, deep learning (DL), and artificial neural networks (ANN). The quality, quantity, and accessibility of data, which can be challenging to collect in some cases, are critical to the success of ML systems. From the standpoint of antenna design, this data must be gathered, because currently there are not enough standard antenna datasets. The dataset of antennas is accomplished by replicating the intended antenna over a wide range of values with CEM simulation software. Typically, the designer's intuition plays a crucial role in maximizing a model's performance, especially when using neural networks and selecting suitable architecture and hyper-parameters [7], [9]. In this review, we investigate the general concept of ML, how it is gradually used in the design of various types of antennas for wireless communication, and provide a summary of useful ML or DL algorithms for antenna performance optimization. It guides antenna researchers with little or no ML/DL knowledge who want to employ the technology in their work as well as makes it easier for readers to begin research on antenna design, performance optimization, and antenna selection using ML or DL.

Various AI-based research projects are completed for antenna design, optimization, and selection for next-generation wireless communications. Some researchers studied ML and/or DL-based antenna design and optimization, while others focused ML/DL-based antenna selection strategies. To the best of our knowledge, AI-based antenna design, optimization, and selection in a single survey work have not yet been thoroughly investigated and reported. Furthermore, the most difficult step in using the ML or DL concept is to establish a consistent dataset based on an antenna's input and output variables. The issue of dataset inconsistency must be addressed adequately so that researchers understand the

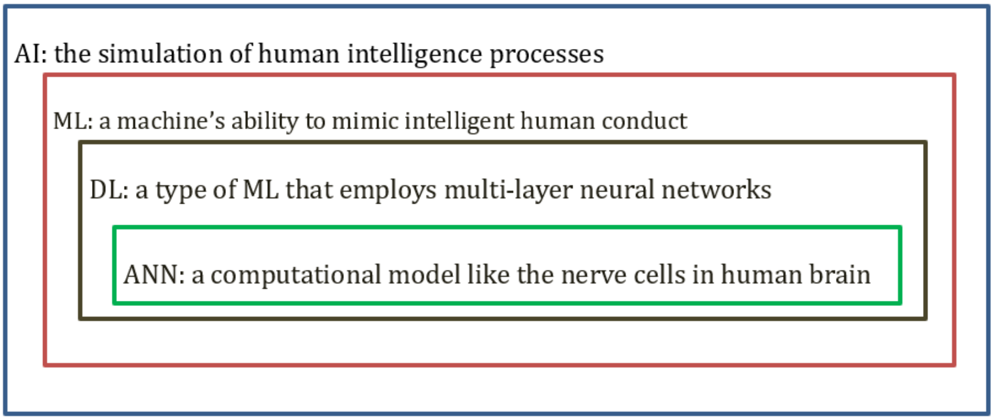

FIGURE 1. Relationship between AI, ML, DL and ANN.

impact of antenna parameters and learn how to choose the appropriate parameter values for successful antenna design, optimization, and selection using ML and/or DL algorithms.

There are several review papers published in the literature that discuss the application of ML/DL in antenna engineering, however, they focus only on a narrow aspect and lack a comprehensive review. On the contrary, this article covers all three important aspects, namely, antenna design, optimization and selection for optimal performance. The concepts of ML and DL are reviewed in [10] for several types of antenna design applications. Various antenna applications such as millimeter wave, body-centric, terahertz, satellite, and beam shaping are studied based on ML and DL algorithms. However, a detailed examination of antenna optimization and selection approaches for ML and DL is out of scope of this work. Another study [11] discusses ML-assisted optimization (MLAO) approaches. Support vector machine (SVM), Gaussian process regression (GPR), and ANN are employed in this study to create a surrogate model for efficient antenna design and sensitivity analysis. There is no discussion of the method for creating accurate datasets using CEM modeling or the idea of DL for antenna design, optimization, and selection. In [12], various ML methods are discussed that have the potential to predict antenna performance characteristics including, resonance frequency, gain, return loss, impedance, and bandwidth. Only microstrip patch antenna performance is predicted, and the model accuracy is measured using mean square error (MSE). The mean absolute error (MAE) and variance score should be handled adequately for a proper inquiry. Furthermore, the studies that use DL models for antenna optimization and selection are not covered in that survey work. The applications of AI in antenna design and computational electromagnetics are reviewed in order to assess the significance of ML or data-driven design in [13]. This survey only discusses the AI-based antenna design features, but does not cover ML and/or DL-based antenna optimization and selection approaches. A survey work on ML for smart antennas is presented in [14]. The limitations of this work are that it solely focuses on smart antennas in terms of ML-based antenna design methodologies. Furthermore, antenna optimization techniques such as surrogate-based optimization and single and/or multi-objective optimization are not covered. In [15], the selection of ML-based antennas and frequency division duplexing multiple input multiple output (MIMO) for multi antenna systems are examined.

The work in [16] gives a survey on AI-based adaptive antenna selection, which includes various ML/DL learning methods. In [17], the DL-based antenna selection (DLBAS) for MIMO software defined radio systems are presented, and its performance is compared to the norm-based antenna selection (NBAS). It can be noted that commercial antennas that explicitly use ML or DL in their design or optimization are not commonly available at the moment. The use of ML/DL in the research of wireless communication antennas is leading to the development of new techniques and architectures. To increase antenna performance, reduce design times, and improve wireless communication systems, researchers are continually experimenting with novel methods. Hence, an up-to-date review of ML and DL-based antenna design, optimization and selection is highly useful.

The literature survey of this review work is conducted using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. All the pertinent research papers are searched in the literature. The period of five years is taken to be from 2018 to 2023. Papers written in any other language are ignored, and only documents in English are considered. Initially, 'antenna design', 'antenna optimization', and 'antenna selection' based on 'ML and DL' are used as the primary keywords for searching papers. The two Boolean operators such as 'OR' and 'AND' are used to identify the keywords. The papers are selected based a number of factors about the articles, including the title, keywords, abstract, and conclusion. From various reputed sources, namely IEEE, Elsevier, Wiley, IET, MDPI, and different web portals, a total of 3950 articles are identified. Out of these 3950 articles, 3600 articles are manually omitted because they are not relevant to the core topic of our research.

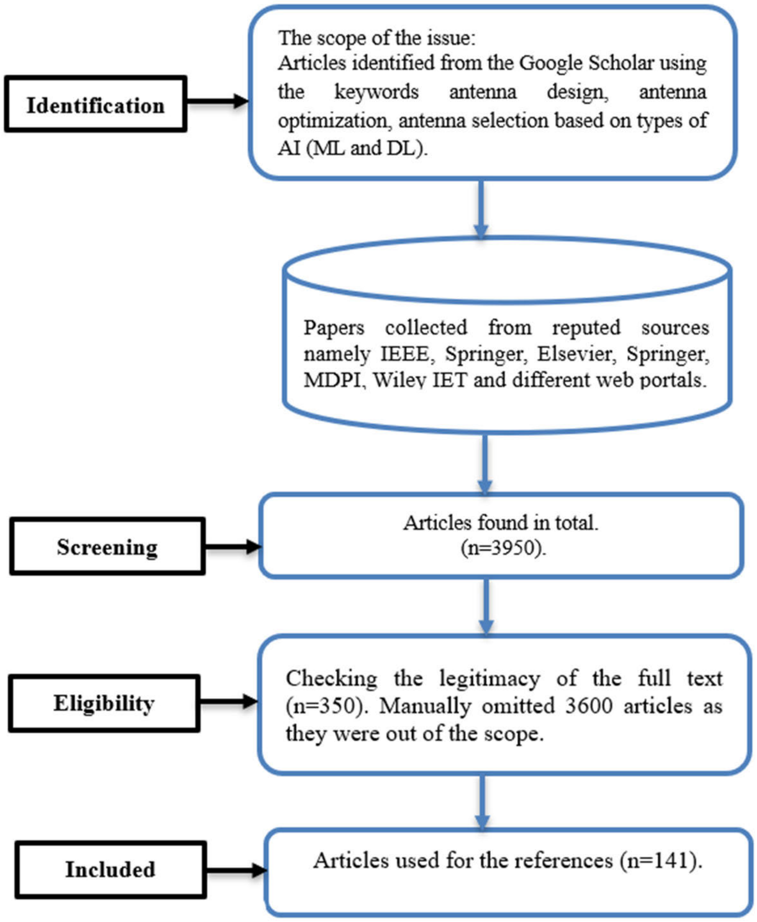

FIGURE 2. Systematic review through PRISMA guideline.

In other words, they do not meet the prerequisites for applying ML and DL in antenna engineering. The remaining 350 articles are given a full-text review before 141 of them are chosen for the study and used as references in this paper. Out of these 141 papers, 120 papers consider ML and DL for antennas as those papers introduce various ML and/or DL techniques as well as datasets and performance results. The remaining 21 papers include research articles, review papers and web portals and these are used for introductory description. The PRISMA guideline for this survey work is shown in Figure 2.

The main contributions of this survey work are summarized as follows:

a) ML and DL-based antenna design procedures of the existing research works are summarized, which also cover RL-based approaches.
b) Various antenna optimization techniques that are suitable for single and multi-objective performance optimization are discussed in detail, with a particular focus on surrogate-based optimization. Moreover, a list of useful datasets on antenna engineering is provided to facilitate readers to conduct research in this field.
c) A discussion is provided on the current ML and DL-based approaches for antenna selection.
d) The current challenges of ML and DL use in antenna engineering and guidance for future efforts to meet those challenges are presented.

The remainder of the paper is structured as shown in Figure 3. The overview of several ML and DL algorithms that can be used for antenna engineering is provided in Section II, and the design flow of an ML-based antenna is described in Section III. Then, in Section IV, various strategies are discussed, including ML approaches for antenna optimization. Section V details ML and DL-based antenna selection. Following that, Section VI presents issues with ML/DL-based antenna design that must be resolved in the future. The concluding remarks are listed in Section VII.

II. OVERVIEW OF ML/DL ALGORITHMS

ML and DL are the subsets of Artificial Intelligence (AI). There are many ML and DL algorithms suitable for antenna design or optimization or selection. The basic ML and DL models are presented in Figure 4. Some of these algorithms are discussed in the following sections.

A. SUPERVISED LEARNING (SL)

In a supervised learning model, the computer learns from a labeled dataset in order to generate predicted responses

Introduction	Overview on ML	Flow chart for ML-based Antenna Design	Antenna Optimization Using ML	ML and DL-based Antenna Selection
i. PRISMA Guideline ii. Research Contribution	i. Supervised Learning ii. Unsupervised Learning iii. Reinforcement Learning iv. Artificial Neural Networks v. Deep Learning	i. ML-based Antenna Design ii. DL-based Antenna Design iii. RL-based Antenna Design and Beamforming iv. Datasets for ML/DL-based Antenna Design	i. Parallel Optimization ii. Single-Objective Optimization iii. Multi-Objective Optimization iv. Variable Fidelity Optimization v. Multilayer ML-Assisted Optimization vi. Surrogate-based Optimization	i. ML-based Antenna Design Challenges ii. Future Direction and Conclusion

FIGURE 3. Organization of this survey work.

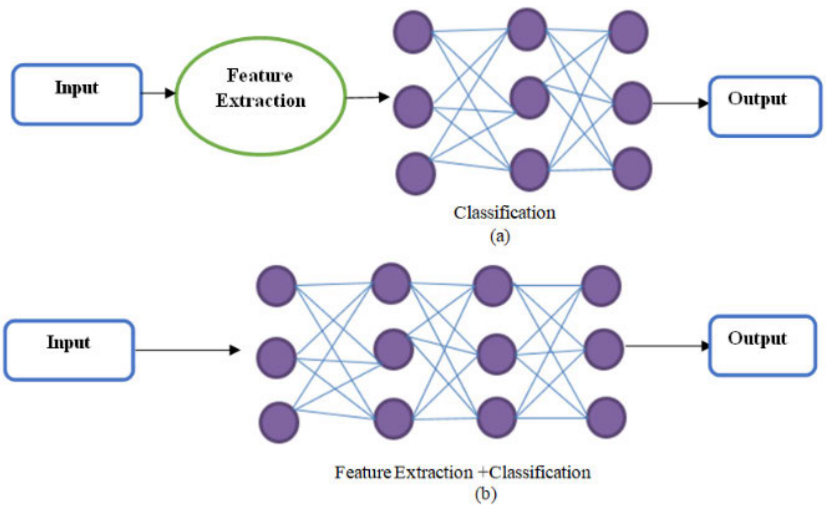

FIGURE 4. The general architecture of (a) an ML model, (b) a DL model.

to new input. Regression and classification are two forms of supervised learning techniques. In the classification task, a model is trained using the learning algorithm on a set of samples and their corresponding labels. Once trained, the model should be able to classify any unseen data into one of the labels. The regression algorithm's goal is to discover the mapping function that will transfer input variables (x) to a continuous output variable (y). There are many supervised learning algorithms proposed in the literature. Figure 5 shows a categorization of supervised learning algorithms along with their suitability for different applications. The graphical representation of the classification and regression algorithm of supervised learning is shown in Figure 6.

B. UNSUPERVISED LEARNING (UL)

An unsupervised learning algorithm uses an unlabeled dataset to train the model, attempting to make sense of it by extracting features, co-occurrence, and underlying patterns in the data. In many cases, the labeling of data may not be available or costly, and unsupervised learning overcomes this issue by learning from data and classifying them without the use of labels. Unsupervised learning is quite useful for detecting patterns in data that are not visible using traditional methods. Figure 7 depicts the clustering of the unsupervised learning algorithms. Various unsupervised learning techniques and their usage in multiple domains are Shown in Figure 8.

C. REINFORCEMENT LEARNING (RL)

Reinforcement learning (RL) is a sort of ML in which a model learns how to behave in a given environment by executing actions and assessing the outcomes. RL method is shown in Figure 9, while various types of RL and their suitable application areas are shown in Figure 10.

D. ARTIFICIAL NEURAL NETWORKS

The ANNs are computational neural networks that are capable of performing the same tasks mimicking the human brain. Based on their learning characteristics, ANN may be grouped into three types. These include the supervised neural network, the unsupervised neural network, and the reinforcement neural network. The block diagram of the

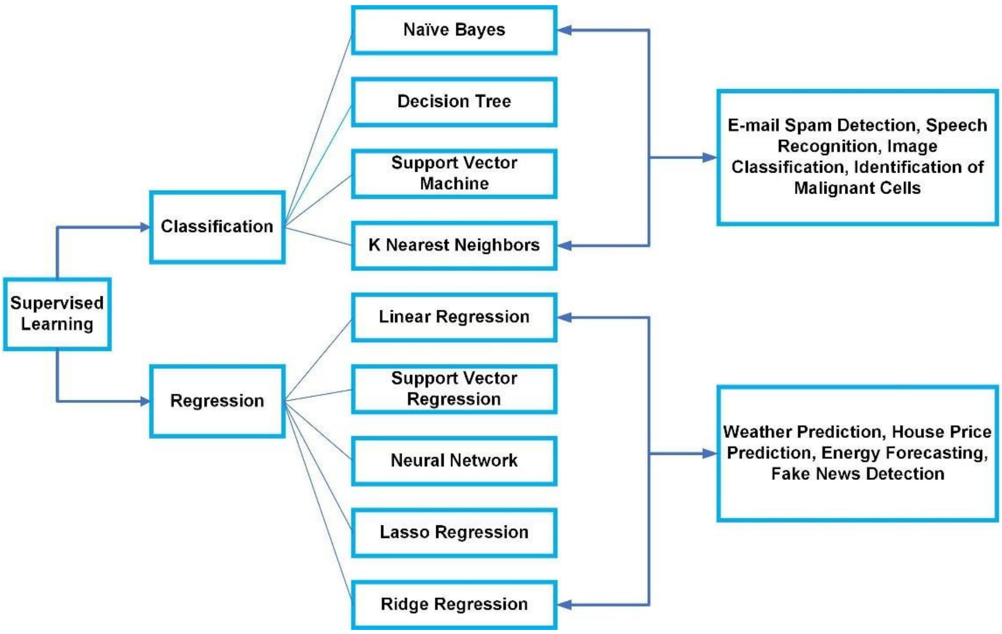

FIGURE 5. Classification of supervised learning.

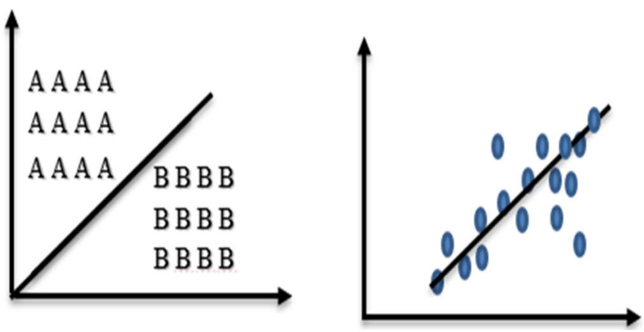

FIGURE 6. Classification and regression of supervised learning.

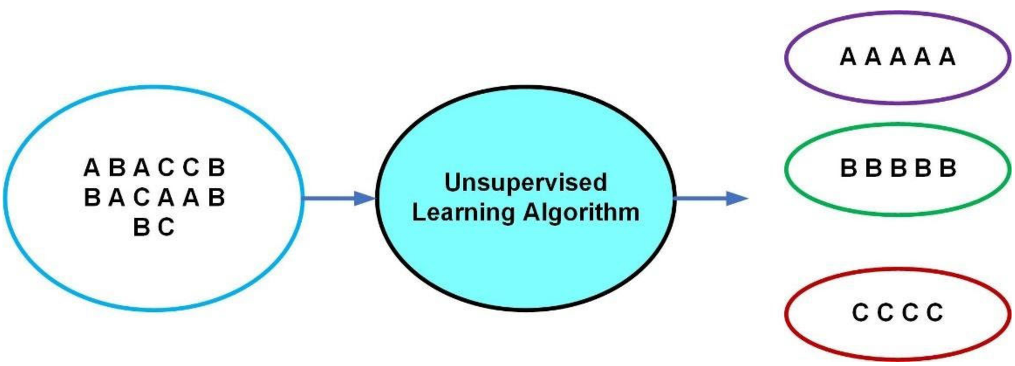

FIGURE 7. Clustering using unsupervised learning algorithm.

ANN model with interconnected nodes and weighted links is shown in Figure 11.

E. DL ALGORITHM

DL is a sort of technology that models the neural network of the brain. Connected layers are utilized to develop DL algorithms. The input layer is the initial layer in DL, whereas the output layer is the last layer. Hidden layers consist of all the intermediate layers. The weight, bias, and activation function all impact the signal strength transmitted to the neuron in the subsequent layers. There are two learning stages in DL. In the first stage, the input data are subjected to a nonlinear transformation, and a statistical model is generated; in the second stage, the model is enhanced via a mathematical

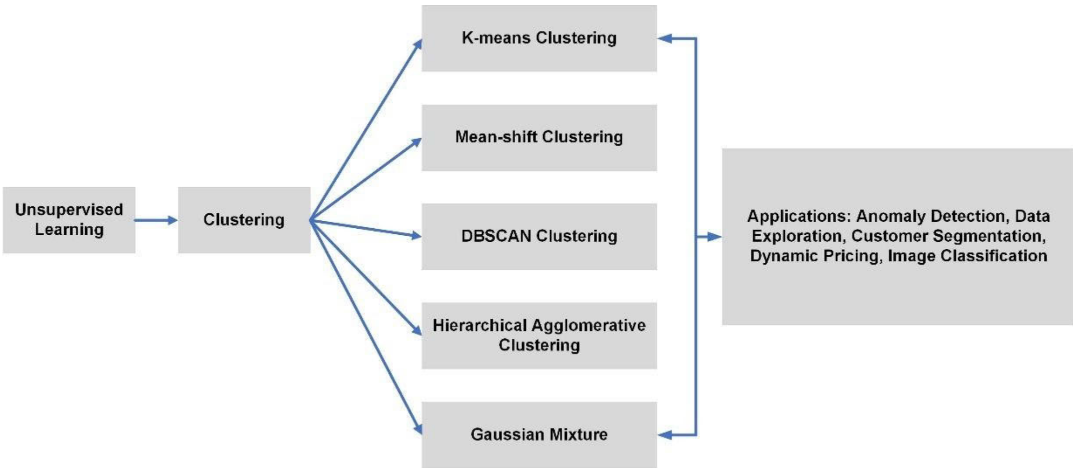

FIGURE 8. Classification of unsupervised learning.

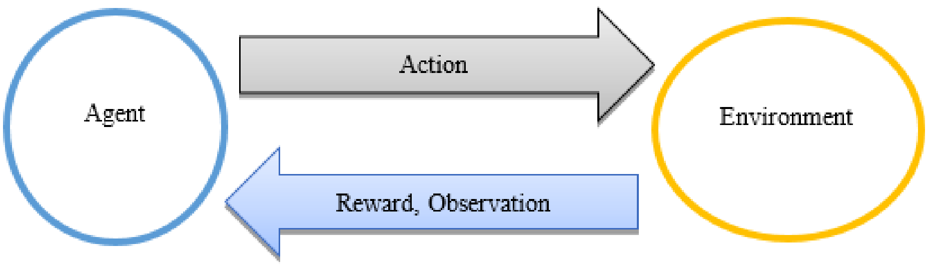

FIGURE 9. Illustration of RL algorithm.

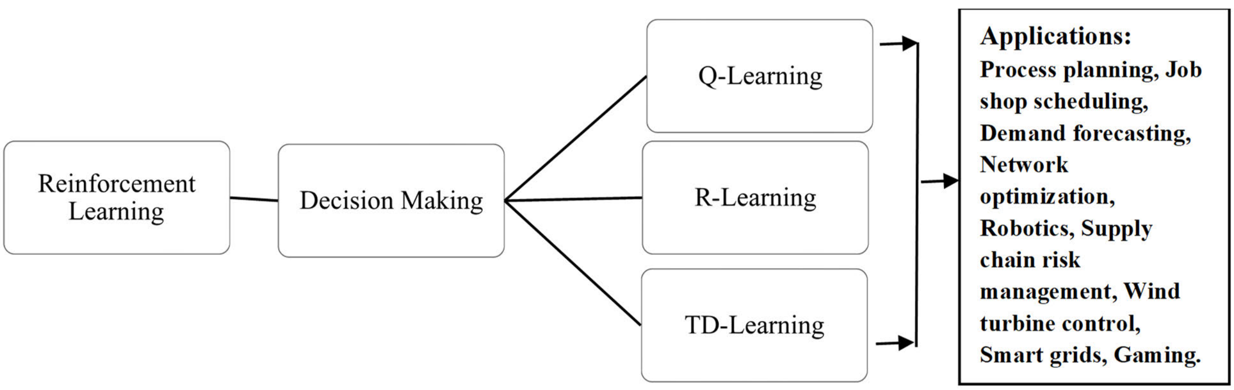

FIGURE 10. Classification of RL algorithms.

process known as derivative. These two procedures are performed hundreds to thousands of times until the neural network reaches an acceptable level of accuracy. This two-phase method is repeated via iteration. The general schematic of a DL model is already shown in Figure 4(b), now the classification of DL is shown in Figure 12.

III. ML/DL-BASED ANTENNA DESIGN

To complete a task and to predict the future, ML follows a flow chart as shown in Figure 13. It aids in improving task performance and productivity. When presented with new data, it incorporates learning and self-correction during training. After a model is built, it goes through a testing phase where the model is evaluated. On deployment, further parameter tuning is possible for even better performance.

Multiple simulations of an antenna using CST, HFSS, IE3D, Altair FEKO, Antenna Magus, and so on are used to generate the required dataset for optimizing antenna performance. Now, we discuss antenna design using different simulators. An antenna can be designed in CAD FEKO and the simulated results can then be observed in the POST FEKO. An antenna can also be designed in FEKO

TABLE 1. ML-based antenna design.

Study	ML algorithm used	EM simulator	Antenna types	Observations
[22]	Bayesian Regularization	CST	PIFA	Calculate gain, bandwidth, radiation efficiency, and resonant frequency with good precision.
[21]	SVM	-	Beam-shaped reflect array	Speed up the design process with accurate results.
[23]	ANN with PSO	IE3D	Patch antenna	Speed up the design process and enhance bandwidth.
[24]	NN-based MLP with SCA and GWO	-	Double T-shaped monopole antenna	Recognize antenna design parameters in an optimal way.
[25]	GP and SADEA	-	Four element E shaped array antenna	3 to 7 times speed enhancement for the antenna design optimization.
[26]	ANN based on Levenberg–Marquardt Algorithm	CST	Elliptical printed dipole antenna	Reduce the simulation time and large computing cluster.
[27]	DT, SVR, RF, ANN	CST	Rectangular patch microstrip antenna	Efficient prediction of the antenna dimension.
[28]	NSGA-II	-	Patch antenna array and Log periodic dual-dipole antenna	Optimize SLL, gain, VSWR, return loss.
[29]	DTR, DFR, ANN	CST	Multiband Rectangular Spiral-Shaped Microstrip Antenna	Improve efficiency and accuracy, also simulated directivity, half-power beamwidth, and VSWR are compared with measured results.

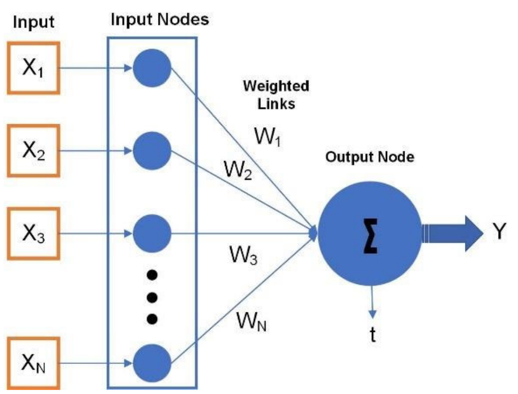

FIGURE 11. The basic block diagram of ANN model.

and connected with the Hyperstudy to produce a superior output. The Altair Hyperstudy supports some advanced ML algorithms such as the adaptive response surface method (ARSM), global response surface method (GRSM), sequential quadratic programming (SQP), method of feasible directions (MFD), and genetic algorithm (GA). Based on these learning algorithms, Hyperstudy provides the expected design parameters such as antenna length, width, slot size, or other desired design parameters to obtain acceptable performance. The flow diagram of antenna design and optimization using Altair FEKO and Hyperstudy is shown in Figure 14.

A. ML-BASED ANTENNA DESIGN

ML algorithms are useful for antenna design. The antennas are designed by researchers using EM simulation software, and the antenna dimensions are adjusted through a process of trial and error. This is a very time-consuming task due to the large number of simulations required and sometimes the estimated level of accuracy might not be achieved. In this regard, many useful ML methods such multistage collaborative machine learning method (MS-CoML), single output GPR (SOGPR), multi-output GPR (MOGPR), SVR, SVM, ANN. KNN, DTR, DFR and others are used by antenna designers to solve the aforementioned bottleneck [18], [19], [20]. Thus, ML can anticipate antenna behavior, increase computing efficiency, decrease the number of simulations needed, and speed up the antenna design process while maintaining high accuracy, decreasing errors, and saving time. In [9], ML is used to optimize the antenna parameter and enhance evolutionary computation algorithms such as

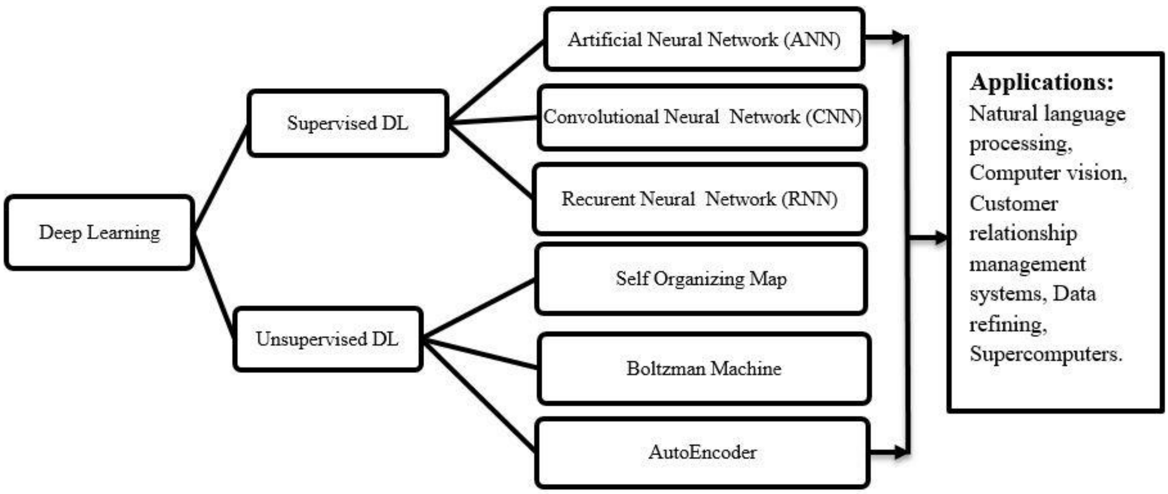

FIGURE 12. Classification of DL algorithms.

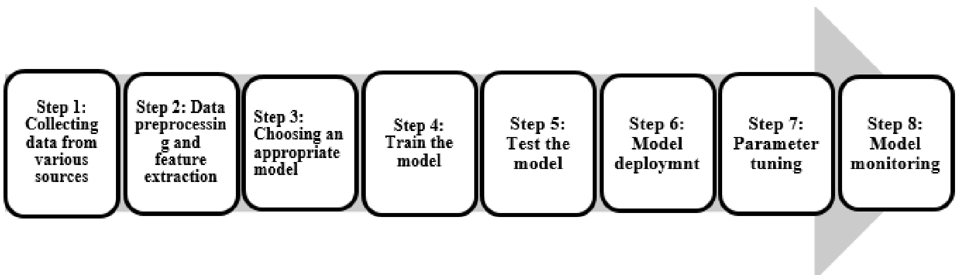

FIGURE 13. ML based antenna design flow diagram.

PSO and differential evolution (DE). PSO and DE algorithms are used to design multiband patch and E-shaped antennas, respectively. Both algorithms ensure a speedy design process by removing unnecessary time-consuming EM simulations. A beam shaped reflect array antenna based on the SVM is presented in [21] where two sets of four parallel dipoles are used and the reflection coefficient matrix is characterized using SVM. In this work, SVM provides high accuracy except for some discrepancies for low levels of the cross-polar pattern due to the tolerances in the manufacturing and measurement process.

Bayesian regularization as the neural network learning process is used for designing planer inverted-F antenna (PIFA) in [22]. An ML model is built to determine the complex permittivity and permeability based on varying particle radius and volume fraction. Moreover, a modified magneto dielectric material is introduced for the antenna substrate. Due to this artificial substrate, the proposed PIFA antenna provides an acceptable performance [22]. An ANN with a PSO-based learning model is used to design a multiband patch antenna with higher bandwidth [23]. The authors report a computer-aided design (CAD) tool that is user-friendly and faster to design stacked patch antennas for the X-Ku band. However, the work only considers estimating the resonant frequencies and bandwidth, without focusing on expected gain, directivity, efficiency and E-field/H-field radiation pattern. A double T-shaped monopole antenna is analyzed in [24] using ANN-based multilayer perception (MLP). For this purpose, the sine-cosine algorithm (SCA) and grey wolf optimizer (GWO) are used to train the ANN. The proposed SCGWO MLP model is shown to be more precise than MLP and KNN models to design and optimize a double T-shaped monopole antenna. A novel surrogate model with SADEA is proposed for antenna design and optimization [25]. Compared to widely used DE and PSO, the SADEA model improves the antenna efficiency and speeds up the design process. In [26], Levenberg–Marquardt Algorithm with ANN is used to design an elliptical printed dipole antenna; however, only 24 data samples are created using EM simulations. An ML approach to predict the dimension of the rectangular microstrip patch antenna is depicted in [27].

To predict the optimized dimension DT, SVR, ANN and random forest algorithms are employed. ML-based dual antenna systems consisting of a four-element patch antenna array and log periodic dual-dipole antenna are discussed in [28]. A multi-objective genetic learning algorithm is used to design and optimize the antenna dimension and performance metrics such as side lobe, gain, standing wave ratio, and return loss. Figure 15 shows the proposed dual antenna system while the overall volume is $500 \times 143.66 \times 8.175\ \text{mm}^3$.

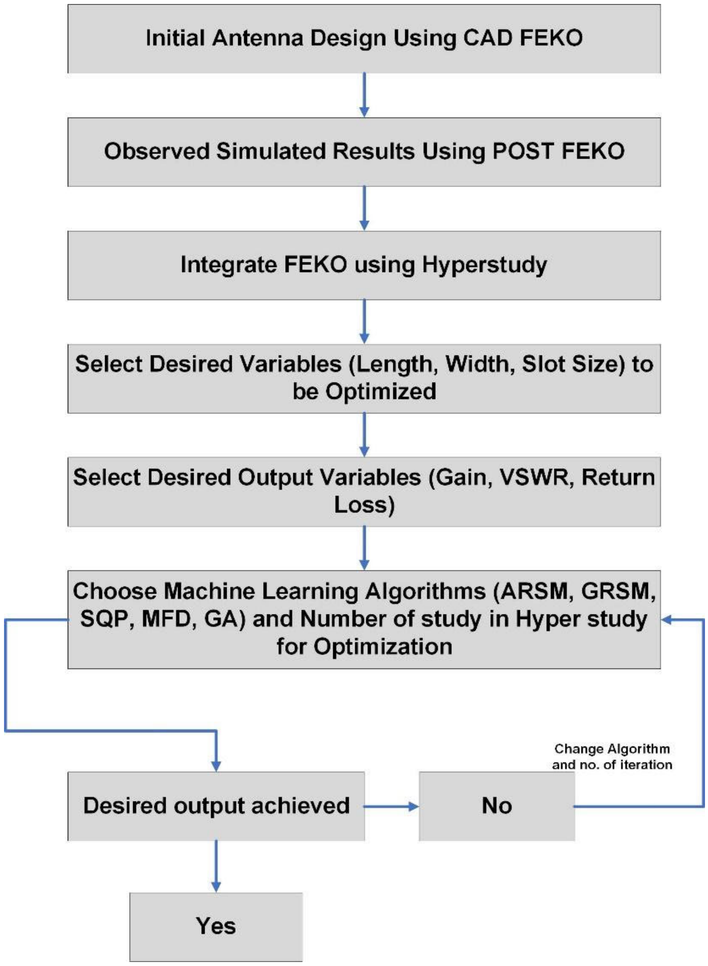

FIGURE 14. Antenna design and optimization using Altair FEKO and Hyperstudy.

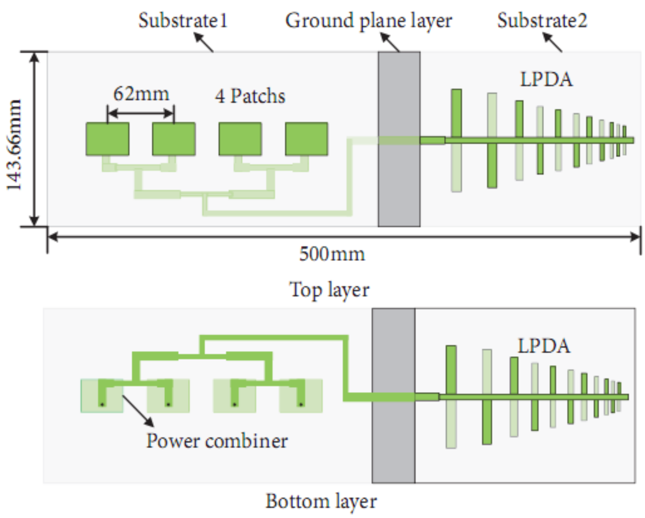

FIGURE 15. The proposed dual antenna system in [28].

Using the proposed multi-objective ML model, the number of side lobes and side lobe level is reduced which improves the directionality. The multi-objective genetic algorithm is used to overcome the limitations of a single-objective genetic

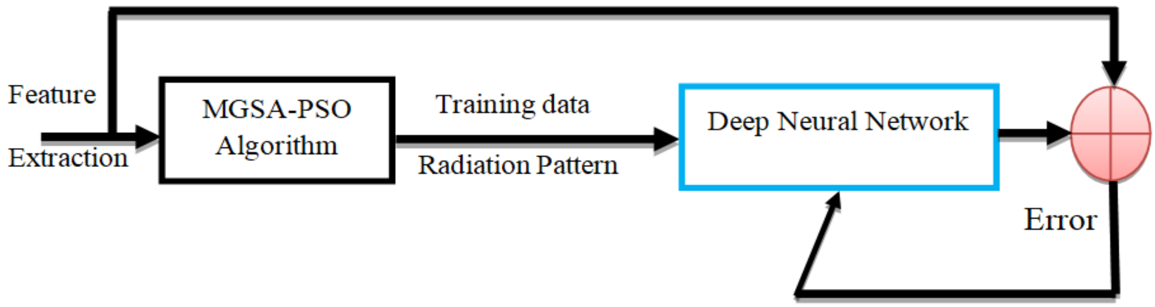

FIGURE 16. **MGSA-PSO algorithm-based DNN training procedure [30].**

algorithm. The single-objective algorithm gives priority to only one parameter, while the multi-objective learning algorithm can optimize multiple parameters as objective functions. One study [29] introduces an EM-driven and ML-based multiband rectangular spiral-shaped microstrip antenna. For modeling and optimizing the antenna, three models: DTR, DFR and ANN are used. To analyze the predicting accuracy, MSE is also calculated. Among these models, DTR performs better than the other two. Table 1 shows the various ML techniques used in antenna design.

B. DL-BASED ANTENNA DESIGN

Deep neural network (DNN) is utilized mostly for image processing, natural language processing (NLP), and speech recognition. Due to the extensive demand for data capacity in the field of wireless communications, such as radar communication, satellite communication, telemedicine, MIMO systems, and radio astronomy, researchers are now motivated to improve algorithms that support large data capacities. In this situation, the design of an efficient antenna for wireless communications is a challenge. To construct an effective antenna taking into account all the antenna properties, neural networks (NN) may be employed [30]. Using EM simulations, only 150 data samples are created by the authors in [30] by varying antenna geometry and electrical properties. The dataset is split into 135 and 15 for training and testing the DNN model, respectively. The proposed DNN model is suitable for resonant frequency prediction and also is a suitable alternative for costly measurement and simulations. Nowadays, researchers are exploiting many techniques to design antennas based on the DNN. The k-nearest neighbor (k-NN) concept is used for the DNN-based antenna design because less training and testing data samples are required [31]. The benefit of this method is that it can generate important data samples during the training process ensuring its high efficiency. Some advanced DL algorithms such as deep CNN (DCNN), and deep recursive neural networks (DRNN) may be applicable in the future for antenna design, optimization, and radar image synthesis.

In [32] the radiation pattern of non-uniform linear arrays of high superconducting microstrips antennas is modified based on the radial basis function (RBF) NN. A total of 80 data samples are used to train and test the model. The model performance shows that the side lobe levels are acceptable and useful for designing arrays with superconducting antennas. An array antenna is proposed based on the backpropagation NN, while a phased array antenna is introduced based on Taguchi NN [33], [34]. Taguchi NN is easy to implement and useful for optimizing electromagnetic applications because of solving a high degree of complexity with a lesser number of experiments [34]. Although ANN/DNN provides very accurate results, the drawback is that there is no general rule to define the architecture of NN [34]. The DNN is used in the research of radiation pattern synthesis with a 4×1 array of patch antenna with 0.28λ spacing (among the array elements) [35]. The radiation pattern of an antenna is used as the input for a DNN model, and the output is the amplitude and phase of the antenna elements. The proposed DNN is trained with a large number of radiation model samples and is shown to be capable of synthesizing radiation patterns [35]. The measurement result of the bone-shaped patch antenna (BSPA) operating in the frequency span of 28 GHz-38 GHz is tested and verified with DNN-based results [30]. Figure 16 shows a hybrid approach that is adopted in that work that combines the strengths of PSO and a modified version of the gravitational search algorithm (MGSA-PSO) to improve the framework and hyper-parameters of the DNN model during the training phase. The MGSA-PSO algorithm is used to train the model using a collection of input-output data pairs [30]. For input-output generation, the input vector is first formed for testing input samples, and the corresponding output vector is generated when input is presented to the neural networks [30]. Simulations with various shapes and electrical characteristics are used to generate a dataset containing the resonance frequency of 150 BSPAs [30]. The data samples are divided into 135 and 15 samples for training and testing the model, respectively. The reported DNN model is utilized to predict the resonant frequencies with the highest level of accuracy, making it a practical and cost-effective substitute for expensive simulations and testing. The beam-steering radiation pattern of the planned antenna array is then applied using the DNN model [30]. A four-layer DNN is used to design a metasurface unit cell antenna at a resonance frequency of 5.8 GHz with a dimension of

TABLE 2. DL-based antenna design.

Ref.	Number of layers in NN	Number of hidden layers	Number of neurons per layer	Algorithm	EM simulator	Antenna Types
[30]	5	3	Neuron in the input layer: 18 hidden layer: 30 output layer: 16	MGSO-PSO, Backward Propagation model	CST	Bone Shaped Patch Antenna
[36]	Forward network (FN): 10 Inverse network (IN):6	FN:8 IN:4	For FN- Neuron in the input layer: 4 hidden layer: 50,50,50,50,50,50,50,20 output layer: 2 For IN- Neuron in the input layer: 2 hidden layer:100,100,100,20 output layer: 4	Forward and backward network with a random search algorithm	HFSS	Transmissive Metasurface Antenna
[32]	3	1	-	Radial basis function (RBF), k- means and least mean square	Galerkin method	Superconducting array antenna, Array elements:20×1
[33]	3	1	Neuron in the input layer: 15 hidden layer:50 output layer: 10	Taguchi neural network and back propagation algorithm	Taguchi's code	Phased antenna array, Array elements:10×1
[34]	3	1	Back propagation network1: Neuron in the input layer: 1 hidden layer:8 output layer: 5 Back propagation network2: Neuron in the input layer: 3 hidden layer:12 output layer: 5	Multilayer back propagation and RBF network		Array antenna, Array elements:10×1 and 8×1
[35]	5	3	Neuron in the input layer: 181 hidden layer: 150, 100, 80 output layer: 6	DNN	HFSS and MATLAB	Array patch antenna, Array elements:4×1

TABLE 2. *(Continued.)* **DL-based antenna design.**

[38]	8 (Four convolutional layers and four fully connected layers)	3 hidden layers for each fully connected layer	Neuron in the hidden layer: 2048, 1024, 16	CNN	HFSS	Phased antenna array, Array elements:8*8
[39]	5	3	Neuron in the hidden layer: 5	Feedforward-Backpropagation neural network	WPT	Antenna impedance matching
[37]	12	10	-	DNN	HFSS	Antenna impedance matching

TABLE 3. **Summary of major works on RL-based antenna design.**

Refs.	Adopted technique	Antenna structures	Freq. range	Major contributions	Remarks
[40]	Domain knowledge-informed RL and IL	Slot filtering antenna	3.5 GHz, 6 GHz	-design process is fast. -high performance in terms of adaptability and efficiency	-requires multiple stages (IL, RL, and deployment stages) to achieve desirable performance.
[41]	RL and DNN surrogate model	1×2 and 1×4 array	3.5 GHz	-contributes to the fully automated design of EM systems. -manual training data preparation is not required to automate the EM design process.	-the used double- layer rectangular patch as a metamaterial unit may not be a suitable choice for other forms of array antennas.
[42]	DRL	-1×8 planner antenna array -1×8 Conformal phased array antenna	2 GHz	-acceptable beam steering performance is achieved.	-Deep Q-network is required to train and regulate the phase distribution for the array antenna.
[43]	Twin delayed deep deterministic policy gradient (TD3) algorithm	Conformal phased array antenna	3.1-5.3 GHz, 6.5-11.2 GHz	-high-flexibility of beam scanning within $\pm 50^0$ around 6 GHz. -efficient (10 dB) radar cross-section reduction.	TD3 has higher complexity and requires more computing resources compared to GA and PSO.
[44]	Deep Deterministic Policy Gradient Algorithm (DDPG)	1×17 Conformal Phased Array Antenna	2 GHz	-fast beam steering is achieved within $\pm 150^0$. -DDPG can handle nonlinear problems and high-dimensional data space efficiently.	DDPG is more complex and requires more computing resources compared to GA.

$\lambda/4$ [36]. The target metasurfaces are implemented based on the inverse network and data augmentation by a forward network and a random search algorithm [36]. Using the two DNNs (one inverse and one backward network), the average transmittance of the unit cells is improved by roughly 0.024 compared to the unit cells created using the traditional technique. The DNN is very useful for antenna impedance matching without any mathematical reasoning of matching methods [37]. A traditional inverted-F antenna is used for impedance matching with a gamma-matching circuit composed of a series capacitor and a parallel capacitor. The matching circuit's element values are used to obtain the antenna's input impedance S_{11} magnitude for learning purposes. A total of 66 validation samples and 377 training samples altogether are collected [37]. The results indicate that the reported DNN model is suitable for impedance matching and resonant frequency prediction, even if the antenna structure is physically complex. The summarized results of DL based antenna are presented in Table 2.

C. RL- BASED ANTENNA DESIGN AND BEAMFORMING

In this section, the applications of RL in antenna design and beamforming are presented. By integrating domain knowledge-informed imitation learning (IL) with RL, the authors in [40] offer a novel technique for automating antenna design. Learning the RL process can be challenging and time-consuming. This is avoided by employing IL to retrain the decision-making network in the RL algorithm. IL with RL uses domain knowledge to initialize the antenna settings. As a result, the antenna design procedure is more expedited than

TABLE 4. Summary of works on RL-based beamforming.

Refs.	Adopted technique	Major Contributions
[45]	RL-based beamforming for MIMO systems.	-ensures optimal power usage and minimal co-channel interferences
[46]	DRL-based beamforming in massive MIMO	-ensures fast and efficient beamforming for highly mobile communications. -proposes a low-complexity federated DRL-based beamforming.
[47]	DRL-based coordinated beamforming	-ensures considerable sum-rate capacity for highly mobile mmWave communications.
[48]	Deep-Q learning-based beamforming for massive MIMO systems.	-ensures optimal beamforming that increases the beamforming rate.
[49]	DRL-based adaptive beamforming	-ensures an excellent system sum rate and reduces the possibility of malicious jamming.

traditional RL using techniques such as deep deterministic policy gradient (DDPG). RL and surrogate model based fully automated 1×2 and 1×4 array antenna design methodology is introduced in [41]. Advanced RL with DNN-based surrogate model is also a powerful tool to boost the efficiency of EM devices [41]. The double-layer rectangular patch as a metamaterial unit may not be a good choice for other types of antenna arrays. A specialized antenna known as a cognitive antenna for intelligent spectrum sensing and beam steering capability is presented in [42] and [43]. The intelligent beam steering capability of the cognitive antenna is achieved through deep reinforcement learning (DRL) or the twin delayed deep deterministic policy gradient (TD3) algorithm. DRL-based cognitive 1×8 planer antenna array (CAA) and a 1×8 conformal phased array antenna show satisfactory radiation performance for various beam scan angles [42]. However, to achieve acceptable beam steering, a deep-Q network is required to train and regulate the phase distribution of the array antenna. The TD3 technique is a revolutionary array optimization approach for stealthy CAAs that combines the advantages of DL and RL [43]. Although $\pm 50^0$beam scanning around 6 GHz is obtained, the TD3 algorithm is computationally more complex compared to GA and PSO.

DDPG, also known as deep RL algorithm [44], is used to synthesise the pattern of the 1×17 conformal phased array antenna (PAA). At 2 GHz, $\pm 150^0$ beam scanning is achieved. In the case of an array and MIMO antenna, RL is a useful tool for beamforming. RL-based intelligent beamforming capability for array antenna and mmWave massive MIMO is presented in [45], [46] and [47]. The efficient beamforming and optimal power usage techniques can reduce co-channel interference, and improve the sum rate capacity for mmWave mobile communications [45], [46], [47]. However, the optimal beamforming for large antenna arrays is a big challenge at the mmWave band. To overcome this problem, deep Q-learning is reported in [48] that maximizes the beamforming rate. The hybrid beamforming for large antenna arrays is yet to be done and needs to be explored in the future. DRL-based adaptive beamforming technique is presented in [49] to prevent malicious jamming when the expected signal is transmitted by multiple antenna arrays. It is reported that anti-jamming algorithms may prevent malicious attacks for large-scale dual-polarized antenna arrays [49]. Summarized information on RL-based antenna design and beamforming technique is presented in Table 3 and Table 4, respectively.

The above discussion indicates that RL can help with antenna design and beamforming techniques, improving communication coverage and effectiveness.

D. DATASETS FOR ML/DL-BASED ANTENNA DESIGN

To apply ML/DL algorithms to predict any attributes or design parameters, a valid dataset is mandatory. Various EM simulation software such as CST, HFSS, FEKO, and IE3D are useful tools for dataset generation. A brief description of some of the available datasets used in ML/DL studies in antenna engineering is presented in Table 5. It can be seen that the datasets have different numbers of samples and attributes.

IV. ANTENNA OPTIMIZATION USING ML

This section discusses the application of ML in antenna optimization. The term optimization refers to the process of trying to identify a combination of inputs to an objective function that would either produce the highest possible function evaluation or the lowest possible one. This challenging task provides the foundation for a wide variety of ML algorithms, including those for fitting logistic regression models and those for training ANNs. The development of novel and sophisticated electromagnetic devices that are competitive in terms of performance, serviceability, and cost-effectiveness is the objective of antenna optimization. Selecting suitable objective functions, design variables, parameter values, and constraint conditions are all part of this method. Traditional methods of designing antennas are laborious and provide no assurance that they will provide satisfactory outcomes. This is due to the complexity of modern antennas in terms of their topology and performance standards. Although experience-based rules of thumb can be useful to antenna designers, they are not always appropriate for use with relatively simple small antenna structures, and adopting them can result in less-than-ideal designs. As a direct consequence of this, optimizing a multilayer, multiband sophisticated antenna is a process that is not only difficult but also time-demanding. In most cases,

TABLE 5. Summary of datasets for ML/DL-based antenna design.

Refs.	Size and attributes of the dataset	Applications	Data generation tools
[8]	Data samples: 86 The total number of attributes is 8. Major attributes such as antenna length, width, thickness, substrate, and S-parameter were used to generate this dataset.	Predicting resonance frequency of microstrip patch antenna	CST parameter sweep
[27]	Data samples: 215 Total number of attribute is 5. Resonant frequency, S-parameter, bandwidth, length, and width of the antenna patch were used to generate this dataset.	Predicting rectangular patch microstrip antenna dimension	CST
[50]	Data samples: 141 Mjaor attributes such as Yagi antenna length of reflector, length of director, thickness, resonance frequencies, S-parameter, and gain were used to generate this dataset.	Gain and resonance frequency prediction of mid band 5G Yagi antenna	CST parameter sweep
[51]	Data samples: 80 Total number of attribute is 2. Slot length and slot width were used to generate this dataset.	Designing rectangular microstrip patch antenna	IE3D
[52]	Data samples: 573×13 Total number of attribute is 13. Major attributes such as antenna length, width, gain, bandwidth, S-parameter, and VSWR used to generate this dataset.	Designing microstrip antennas with metamaterials.	CST-MATLAB-API-master
[53]	Data samples: 1267×6 Total number of attribute is 6. Major attributes such as patch length, patch width, slot length, slot width, frequency, and signal strength were used to generate this dataset.	Predicting signal strength	CST

the solution to the aforementioned bottleneck can be found in procedures involving trial and error as well as the fine-tuning of the properties of materials [54].

Another useful technique for optimizing an antenna is sweeping multiple parameters at a time. However, it is also a very lengthy process and there is no guarantee for desired results. As a result, design automation through optimization is necessary. Local and/or global numerical optimization approaches are commonly used to improve antenna performance through optimization [56]. Although numerical optimization is superior to experience-driven parameter sweeping, there are still certain obstacles to overcome. A good initial or starting point is required in local optimization technique, while in global optimization technique, it is not mandatory [19]. However, in Global optimization techniques, a large number of electromagnetic (EM) simulations are required to achieve desired results. To overcome the aforementioned limitations in traditional antenna optimization methods, researchers are exploiting ML-based antenna optimization. ML-assisted optimization (MLAO) for antennas is gaining research interest. Multiple research works are carried out to optimize antenna performance based on MLAO. In [25], [55], [57], [58], [59], [60], [61], [62], and [63] Gaussian process regression (GPR), surrogate-based optimization (SBO), ANN, support vector machine (SVM), and master-apprentice board learning system (MABLS) are discussed. Different aspects of the current MLAO antenna design methods can be categorized, such as whether they are offline or online, local or global optimization, single or multi-objective optimization, or parallel optimization [25], [55], [57], [58], [59], [60]. The MLAO can be used for antenna design not only in the optimization stage but also for sensitivity analysis (SA) and resilient design [64], [65].

Although many optimizing techniques are available, the following sections focus on parallel optimization, single objective, multi-objective, and variable fidelity (VF) optimization, where ML can assist in achieving the desired objectives. The following subsections provide the details of ML-based and surrogate-based optimization.

A. PARALLEL OPTIMIZATION

At present, parallel optimization or computation is a very prominent method for sensitivity analysis, performance analysis, and resilient design of an antenna. The CPU, memory, and computational capabilities of the cloud can be used to speed up the optimization method by including parallel computation into the MLAO algorithms [55], [60]. In [55], a dielectric resonator antenna (DRA) and Yagi-Uda antenna are designed using parallel surrogate model-assisted hybrid differential evolution for antenna (PSADEA) optimization using GPR. It compares the convergence trends of PSADEA with sequential mode, parallel mode, SADEA,

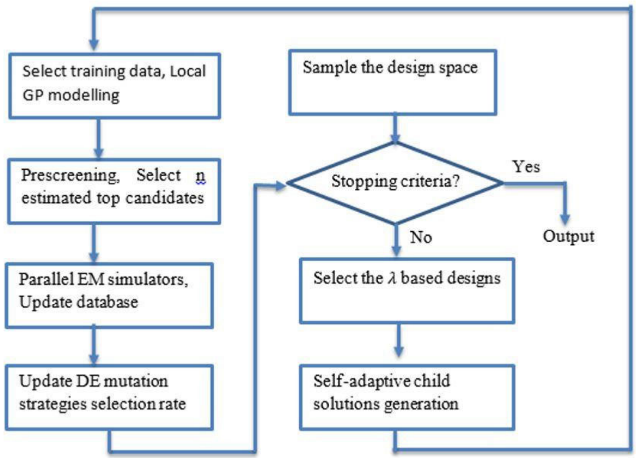

FIGURE 17. Flow diagram of the PSADEA method [55].

parallel differential evolution algorithm (DEA), and parallel PSO. It reveals that PSADEA is much faster (about 20 times) than the other optimization algorithms such as parallel DEA, parallel PSO, and parallel surrogate model-aware evolutionary search. Moreover, in terms of efficiency and optimization capacity, the proposed method outperforms conventional methods. In the future, PSADEA-based EM simulation tools will be developed and the performance of PSAEDA will be evaluated for high-order clusters. The flow diagram of the PSADEA-based antenna design and optimization is shown in Figure 17.

B. SINGLE OBJECTIVE OPTIMIZATION

A single-objective optimization issue is one in which the goal is to identify the optimum solution for a single criterion or metric, such as execution time or performance. Indeed, single-objective optimization problems are frequently used to mimic antenna optimization difficulties. In [56] the isotropic gain is used as the single objective optimization example of an antenna. Antenna optimization problems are typically limited optimization problems. This is because antenna specifications are frequently represented mathematically as two or more objective functions. In most constrained optimization situations, a weighted sum of the constraints and the objective is used to generate a penalty function, which then becomes the single objective function value for the optimization. The penalty technique [12] is a popular method for aggregating various needs in antenna issues. In recent times, for single objective or single constrained antenna optimization, multiple SBO methods are introduced [66], [67], [68]. Many SBO methods require a large number of training datasets to obtain acceptable efficiency, i.e., multiple EM simulations are needed to optimize the antenna efficiency. For this reason, a good balance is needed between the SBO model and antenna efficiency which is called SBO model management. To properly address this challenge some other methods are proposed. In [69] space mapping optimization and trust region (TR) search-based SBO models are adopted. A multi-stage optimization approach using large-scale sensitivity analysis and local optimization routines can improve the convergence speed, lower the dimensionality of the search space, and optimize the initial point of the TR gradient search [68], [69]. A class of SBO methods that offer a good balance between the quality of the surrogate modeling and the efficiency of the optimization are proposed in [25], [55], and [62].

C. MULTI-OBJECTIVE OPTIMIZATION

The multi-objective optimization problem is a field of mathematics that deals with optimization problems containing two or more objective functions that must be maximized or minimized simultaneously. Multi-objective optimization, which generates a set of non-dominant (Pareto) solutions from which a compromise process design can be chosen, has recently become an important tool for decision-making. Much effort has been put into solving the actual industrial challenges with numerous goals in mind. Recent studies are focusing on multi-objective optimization techniques for optimizing the results of an antenna [70], [71]. Based on the multi-objective optimization techniques in [72] a multiband planer antenna is optimized in terms of minimizing reflection coefficient within multiple bands and antenna dimension. Based on the decision-making process, multi-objective optimization methods can be categorized into priori and posteriori [70]. In priori methods, prior information from the decision maker is required while posteriori methods do not rely on prior information from the decision maker. Alternatively, the posteriori methods generate several well-representative best trade-off candidate solutions for a decision maker to check on a Pareto front (PF). In [73], a large number of EM simulations are required to optimize an antenna using traditional multi-objective which consumes significant time. Furthermore, when the designer preferences are strong and just one final design solution is chosen and employed after a successful run, the set of alternative design solutions created by the Pareto front is typically redundant [74].

Many researchers are exploiting a number of solutions to properly address the challenges [72], [74], [75], [76]. To minimize the computational complexity, offline surrogate modeling, and backward propagation neural networks are introduced in [72]. To easily find out the local optimum and to obtain better convergence speed surrogate model is employed in integration with hybrid real binary PSO optimization algorithms that promote the capability of global optimization [77]. An improved population set in the optimization process is generated using the local search method in one study [75], which is the main difference from conventional optimization. The classic non-dominated sorting approach [78] as well as the farthest-candidate method [33] are utilized to produce the improved population set for successive iterations. Surrogate modeling and variable fidelity EM models are proposed to reduce computational complexity and accelerate the convergence of multi-objective

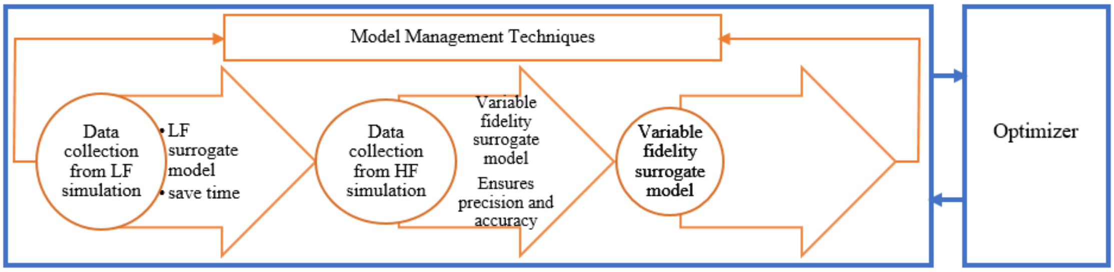

FIGURE 18. Variable-fidelity optimization method.

optimization antennas [74], [76]. To serve this purpose, gaussian interpolation process with standard multi-objective optimization using MOEA is used in one research work [79].

D. VARIABLE-FIDELITY OPTIMIZATION

The variable-fidelity optimization (VFO), also known as multi-fidelity optimization, is a technique for optimizing a process by combining the benefits of high- and low-fidelity models. The high-fidelity (HF) model ensures solution precision, while the low-fidelity (LF) model saves time and money. The VFO technique is shown in Figure 18. The approximation management framework (AMF) algorithms provide the mathematical robustness necessary for VFO [80]. In VFO, LF models are used to find out non-promising and inexpensive solutions while accurate HF models are used to filter out the promising solutions obtained by the LF model. Based on the optimization framework, VFO models could be surrogate and/or EM models [81], [82], [83]. To serve this purpose, surrogate models and antenna or EM models are incorporated into a single optimization framework to verify fidelities or accuracies [84].

The primary challenge in ML-assisted VFO antenna optimization models is to ensure efficient parameter extraction from the LF design space to the HF design space. Several research investigations are carried out to overcome this limitation in [82], [84], [85], and [86]. Conjunctive use of varying-fidelity models with data-driven surrogate models is introduced [85] in which space reduction technique is employed. In the space reduction method, LF EM model design space is used to determine the lateral spread of the solution, while a few HF EM models are used to validate LF design space. A new technique is introduced in [82] to enhance the speed of convergence of the VFO. In this model, several coarse models with increasing discretization levels are used. The coarse models are considered for the iterative construction of a series of local surrogate models through polynomial interpolation. The correlation between the present surrogate model and the corresponding model is essential for updating the size of the local region.

A multistage SBO technique with data mining and a local search mechanism is suggested in [84] based on the algorithmic framework in [87] to reliably address model differences in multi-fidelity antenna optimization while assuring high efficiency and better convergence speed. In [88], a new VFO method is proposed to model the input characteristics of an antenna based on domain confinement and two-stage GPR surrogates. The high CPU cost of the extensive simulations required by parametric optimization, uncertainty quantification, or robust design processes is the primary constraint in EM-driven antenna design. The nested kriging (method of interpolation based on Gaussian process governed by prior covariances) approach and two-stage GPR are leveraged in this research work to mitigate the bottleneck of the EM-driven robust antenna design. A low-cost antenna modeling technique based on variable fidelity EM simulations is proposed in [61]. The main advantage of this technique is the limited number of HF data points required to model an antenna accurately compared to the conventional approximation technique. The computational cost of this model is greatly reduced than the conventional models without sacrificing the accuracy of the model.

E. MULTILAYER ML-ASSISTED OPTIMIZATION

In one research work [89], a series-fed microstrip antenna array (SMAA) is proposed based on multilayer MLAO for robust and efficient design. ML approaches are incorporated into various stages of the robust design process, including worst-case analysis (WCA), maximum input tolerance hypervolume (MITH) searching, and robust optimization, resulting in a significant speed-up of the entire process. To assure reliability, the WCA is performed using a genetic algorithm based on a surrogate model mapping between design parameters and performance. The MITH of the provided design point is then determined with the use of an MLAO-based framework. Following that, correlations between the design parameters and the MITH are learned using the training set generated by MITH searching. Surrogate models for both performance and MITH are used in the robust design, and these models are updated online using the ML-MLAO technique. When the input tolerance is known, many approaches such as worst-case analysis (WCA) [90], [91] are presented to find the output tolerance. Innovative techniques are developed to achieve efficient MITH searching and resilient antenna design optimization; these range from a global search algorithm combined with iterative input tolerance hypervolume (ITH) shrinking [90] to a sampling

TABLE 6. Summary of works on surrogate model-based antenna synthesis.

Refs.	Adopted technique	Antenna Structures	Freq. Range	Major Contributions	Remarks
[93]	Surrogate model based on gradient-enhanced kriging.	Triple band unipolar dipolar antenna and Quasi_Yagi antenna.	(1.5-2.5) GHz, (2.5-5) GHz	-enhances model reliability and accuracy than conventional models	may be affected by typically high nonlinearity of antenna responses
[94]	Surrogate model based on a nested kriging framework.	Microstrip-fed ring slot antenna.	2.5 GHz, 4.5 GHz, 6.5 GHz	-reduction of training data set size without sacrificing parameter ranges. -Accuracy increased by 20% without increasing data samples.	-the performance of the model depends based on whether some prior design information is already available or not.
[95]	ML-based generative method.	Dual resonance antenna.	(0-8) GHz	- simplified geometric model reduces efforts on antenna design and optimization. -incorporates discriminators and integrators to expedite antenna design and optimization efficiency	-only S_{11} is used to build up the model without considering efficiency gain and radiation pattern.
[96]	DL-based surrogate model (Used modified multilayer perceptron model).	Pyramidal-Shaped 3-D Reflectarray antenna.	11 GHz	-less number of data samples is required. -first approach to design 3-D 20×20 reflectarray antenna at acceptable optimization speed and accuracy.	-antenna substrate should have lower permittivity and higher thickness -the unit cell should have at least 360^0 phase characteristics.
[97]	Inverse surrogate model.	20×20 3-D Reflectarray antenna.	10 GHz	-ensures low weight and low fabrication cost of the Reflectarray. -ensures lower computational cost than EM analysis.	-the method is based on unit element characterization of reflectarray elements; hence, effects like mutual coupling cannot be incorporated.
[98]	Knowledge-based domain-constrained DL surrogates.	-coplanar-waveguide-fed dual-band dipole. -microstrip-fed ring-slot antenna. -quasi-.agi antenna with a parabolic reflector.	1.5-6 GHz	-suitable for wide ranges of antenna parameters, frequencies, and substrate parameters. -reducing the cost of surrogate model setup.	-high-quality design may be challenging if the parameter space is enormously large. -experimental validation is not provided.
[99]	ML-basedsurrogate-assisted PSO.	-SIW cavity-backed slot antenna. -four-elements linear array antenna. -sequential rotation feeding network.	23-30 GHz	-less number of EM simulations are required for antenna synthesis -able to solve the synthesis problem of sequential rotation feeding network.	-need to improve optimization efficiency.
[101]	Surrogate-assisted defected ground structure (DGS).	2×2 microstrip antenna array.	2.45 GHz	-suppress mutual coupling by 10 dB between E- and H-plane.	-the improvement of envelop correlation coefficient is not satisfactory.
[103]	Surrogate model.	Frequency reconfigurable UWB pyramidal antenna.	3-11 GHz	-proposed model is feasible, effective, and precise to design reconfigurable antennas.	-the proposed model is shown to be suitable only for multiband antennas.

strategy mixed with surrogate modeling [92]. However, these techniques have some limitations such as the parameters should be identified in advance and cannot be changed during iterations. These limitations are solved in [89] using multilayer MLAO with MITH searching that provides the desired output.

F. SURROGATE-BASED OPTIMIZATION

This section introduces the most recently reported works in antenna optimization based on surrogate models such as pyramidal deep neural networks, fully automated regression surrogates, and other related works. Surrogate modeling is proposed as a solution to alleviate the computational overhead of CPU-intensive EM simulations for tasks such as parametric optimization and uncertainty quantification. This model has gained popularity in the field of antenna design and optimization to address the high cost associated with electromagnetic simulations. The necessity for reliable design of contemporary antenna structures using full-wave electromagnetic analysis is presented in some studies [93], [94]. The effectiveness of the surrogate technique compared to traditional approaches is illustrated by two antenna examples, and practical case studies involving antenna optimization are investigated [93]. To achieve arbitrary antenna shapes and effective optimization, one study [95] proposes an ML-based generative method that enables automated antenna design and optimization. The performance of the proposed method in dual resonance antenna design is better than the other competing algorithms. The limitation of this research work is that only reflection coefficient is used to build the model. To overcome this issue, the gain, efficiency, and radiation pattern should be in consideration for more accurate performance.

The 3-D reflectarrays which offer pencil-beam radiation patterns based on the DL-based surrogate and inverse surrogate models are reported in [96], [97], respectively. Both techniques are useful to reduce the optimization cost significantly and outperform benchmark techniques. In [96], with only 500 data samples, the MAE is only about 5 (phase error), which is significantly (by a factor of 10) lower than that for the ensemble learning model and other conventional models. Inverse surrogate-based antenna design and optimization is significantly faster (almost 200 times) than the full wave-EM design approach [97]. DNN and/or DL-based surrogate models are introduced in [41] and [98] to automate the antenna design, aiming to relieve human engineers, and enhance productivity. Constructing a reliable data-driven surrogate model is difficult as it requires a wide range of geometry and material parameters for practical antenna design and optimization. To address this limitation, a knowledge-based domain-constrained DL surrogate model is used to design three microstrip antennas with high efficiency and low cost [98]. Another popular technique for antenna design and optimization is to integrate the surrogate model with the PSO technique [99], [100]. ML-based surrogate-assisted PSO is used in [99] while deep convolutional auto-encoder (DC-AE) based surrogate-assisted PSO is used in [100]. Both methods provide desirable results with a less number of EM simulations than the conventional methods. The method proposed in [99] is suitable for solving the synthesis problem of sequential rotation feeding networks.

For a 2×2 microstrip array antenna, the surrogate-assisted defected ground structure (DGS) can be used to reduce coupling between the E- and H-planes by 10 dB at 2.45 GHz [101]. To achieve this performance, ML is applied to find the optimal performance of the DGS structure. However, the envelop correlation coefficient has not increased considerably, which is a limitation of this study. Multisurrogate-assisted optimization framework for mmWave array antenna at 28 GHz is proposed in [102]. The framework comprises three stages for initial parameter optimization, side lobe level (SLL) optimization, and beamforming-focused optimization using an improved array factor formula and the space mapping technique [99]. The proposed method is suitable for reconfigurable antenna design and cognitive radio systems. Moreover, the surrogate modeling approach is a very promising technique for frequency reconfigurable antennas and tolerance optimization of antenna structures [103], [104]. A summary of surrogate model-based antenna synthesis is presented in Table 6.

In summary, surrogate models offer a useful tool for speeding up the antenna optimization process by drastically lowering the computing effort while maintaining acceptable accuracy.

V. ML AND DL BASED ANTENNA SELECTION FOR WIRELESS COMMUNICATION

Antenna selection (AS) is a signal processing technique that reduces the hardware requirements of multi-antenna systems significantly. AS can reduce the number of radio frequency chains required by activating only a portion of the available antennas in each transmission slot. The computational complexity of the optimal AS, on the other hand, grows exponentially with the size of the antenna array [105]. One possible approach is to use intelligent learning techniques to aid in this process. It is built around an adjustable antenna that employs cognitive learning. It has created the groundwork for adjusting signal strength to improve wireless transmission efficiency [16].

Adaptive antennas, also known as smart antennas, are antennas that use antenna array or beamforming technology to improve antenna gain and other performance metrics to improve signal-to-noise ratio (SNR). Furthermore, the adaptive antenna's radiation pattern can be dynamically changed. The usage of adaptive antennas helps reduce multipath fading concerns such as Rician and Rayleigh fading. On the other hand, high SNR ensures higher data rates on the basis of Shanonn's channel capacity estimation. For the m-element array antenna, this estimation can be modified in a way so that the total SNR is divided evenly among all the antennas [16]. Other advantages of smart antennas

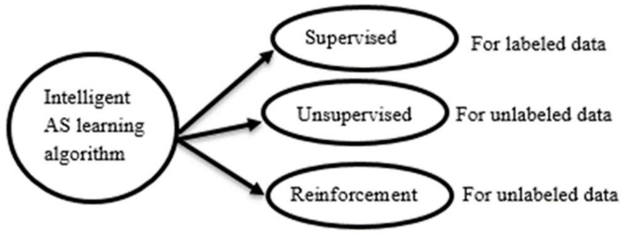

FIGURE 19. Intelligent antenna selection (AS) algorithms.

include increased signal strength, transmission efficiency, enhanced security, and reduced multipath interference. Based on the diversity, phased array, and beamforming, traditional and intelligent techniques are employed to deploy adaptive antennas in wireless networks.

According to recent research, intelligent systems like AI, ML, and/or DL are widely utilized for AS in the modern wireless arena. Typically, supervised learning, unsupervised learning, and RL algorithms are utilized for this purpose. Algorithms such as k-NN, DNN, CNN, SVM, NB, NN, MLP, LSTM, GPR, SNN, ANN, SVR, decision tree (DT), deep Q network (DQN), regression tree (RT), and others are utilized for smart antenna selections. The adaptive AS and estimation accuracy are highly dependent on the various signal data and the proper learning algorithms. Correct feature data extraction is unquestionably necessary for proper modeling of AS selection. This feature data extraction is divided into three categories. These are as follows: i) angle label, such as the direction of arrival (DoA) or angle of arrival (AoA) (ii) data packet or BER label; and iii) antenna element count label. One research work [106] presents the DL and greedy adaptation (GA) based antenna selection for MIMO systems. In [105], authors investigate multi-label learning-based antenna selection for massive-MIMO (m-MIMO). Another study [17] discusses the DL-based AS (DLBAS) algorithm for software-defined radio (SDR) MIMO systems. DLBAS-aided MIMO-SDR system is constructed based on three steps. Firstly, the MIMO-SDR communication system is developed. Then, the DNN framework is adopted to construct a DL decision server to assist the MIMO-SDR. Finally, the DL decision is transformed into multithreading to improve the resource utilization ratio. The DLBAS-aided MIMO-SDR system equally performs with the NBAS and outperforms compared to the MIMO-SDR system without AS.

Some studies [107], [108] show the intelligent AS for wireless communication based on ML and DL algorithms, while [109] shows the DL-based cognitive radar antenna selection technique. In [107], the performance of various ML algorithms for AS is evaluated. The validation of a learning system with realistic channels and an online learning algorithm to track channels with time-varying statistics are interesting areas that warrant further research. In [108], DNN based AS-aided space-time shift keying MIMO system is modeled. Experimental results show that the proposed algorithms are better than kNN and extreme gradient boosting in terms of bit error rate and channel capacity. ML-based power allocation and AS for multiuser MIMO systems is proposed in [110]. This study proposes another interesting aspect which is joint antenna AS and power allocation (JASPA). However, for real-time network applications, JASPA has high complexity due to its double iteration structure. To address this issue, learning-based ASPA is proposed (L-ASPA) and simulation results reveal that learning-based AS can greatly reduce the execution time of JASPA while maintaining higher than 90% of the optimal performance. For AS selection, the learning algorithms are presented in Figure 19. The suitable ML or DL algorithms for intelligent or adaptive antenna selections and the required feature extraction techniques are presented in Table 7 and Table 8.

There are three antenna selection schemes. These are optimal antenna selection, suboptimal antenna selection, and space-time modulation antenna selection scheme.

A. OPTIMAL AS SCHEME

In the optimal AS scheme, the transmit antenna at the source and the receive antenna at the receiver are selected to maximize the SNIR at the receiver which leads to improved BER performance. One limitation of optimal AS is that the exact CSI between a transmitter-to-receiver link and transmitter-to-eavesdroppers link must be needed.

B. SUBOPTIMAL AS SCHEME

In suboptimal AS, the antenna is selected based on the achievable secrecy rate between the transmitter to receiver link, while the CSI of passive eavesdroppers is unavailable. However, the secrecy performance of suboptimal AS is lower compared to optimal AS.

C. SPACE TIME MODULATION SELECTION SCHEME

In this AS method, the space-time coding technique is used to select the antennas when the CSI information of all the links is unavailable. The antenna selection based on the space-time modulation technique is more costly than the optimal and suboptimal AS scheme. Because, in this AS technique, all the available antennas are used.

VI. ML/DL-BASED ANTENNA DESIGN CHALLENGES

As we have discussed in the previous sections, extensive research is being pursued that employs ML/DL algorithms for antenna design, optimization and selection. Although several advantages are realized as a result of the employment of ML/DL, they do have significant limits. Future research should focus on overcoming these challenges. Some of these are as follows:

a) Creating a valid dataset is a difficult task because EM simulation software such as CST, FEKO, and HFSS takes a long time to run a single-element basic antenna. Furthermore, if the antenna design is sophisticated, or if the antenna is MIMO or array, the simulation time

TABLE 7. Intelligent antenna selection techniques with algorithms.

Intelligent Antenna Selection (AS) techniques					
Diversity techniques		Phased array techniques		Beamforming techniques	
Ref.	Algorithm Used	Ref.	Algorithm Used	Ref.	Algorithm Used
[111]	k-NN	[109]	CNN	[112]	CNN
[107]	k-NN, SVM	[113]	ML-based classification	[114]–[116]	DL-based analog and digital parts of beam forming
[117]	k-NN, SVM, NB	[60]	GPR	[118]	RL
[119]	ML-based DT, MLP	[120]	AoA, GP, RT, NN	[121]	DNN
[122]	DQN, deep RL	[123]	LMS, ACLMS, CDU-LMS	[124]	Sparse Bayesian
[125]	Two-step modeling based on ML	[126]	ANN, SVM with DoA	[127]	BR, MLP
[128]–[130]	ML using self-organization	[131]	SVR	[132]	ML-based NN
[133]	RSSI with SVM	[134]	DNN	-	-

TABLE 8. Algorithms for different label and feature data extraction.

Label (Angle, Packet data or BER, Number of antenna elements)								
Angle			Packet data or BER			Number of antenna elements		
Ref.	Algorithms	Feature	Ref.	Algorithms	Feature	Ref. No.	Algorithms	Feature
[109]	CNN, SVM	SINR	[107]	k-NN, SVM	CSI	[134]	DNN	RSSI
[120]	NN, RT, GP	SINR	[122]	DQN	CSI	[135]	SVM	SNR
[112]	DNN	SINR	[136]	BR, MLP	-	[114]	CNN	SNR
[116]	CNN	RSSI	[137]	k-NN, SVM	Tx power, gain	[138]	CNN	CSI
[127]	BR, MLP	-	-	-	-	[139]	DNN	CSI
[140]	CNN	-	-	-	-	[141]	Beamforming NN	SNR

increases significantly. For ML/DL-based antenna design, a large dataset is necessary, and generating such a dataset takes a long time. Moreover, a special type of antenna design may require specific dataset relevant to that type of antenna.

b) Choosing an appropriate ML/DL model to build and optimize an antenna is a critical and difficult issue. Altair Hyperstudy, for example, supports ARSM, GRSM, SQP, MFD, and GA models to maximize antenna performance built by Altair FEKO. However, determining which model is the greatest fit and how many iterations are required to get the necessary performance is not an easy issue.

c) In reality, various application areas require various types of antennas. Additionally, various structures are added to the ground plane and antenna patch to enhance antenna performance. For instance, to accomplish multiband operation, greater gain, and radiation efficiency, defected ground structures (DGS) are employed in the ground plane. Moreover, square, H, E, or circular-shaped slots are created in the patch. Different datasets will be generated while considering different antenna structures or antenna types. The effectiveness of different ML/DL models usually depends on datasets. Many large datasets have to be generated for various antennas to find the appropriate ML/DL model suitable for antenna design, optimization, and selection.

d) The simulation results and experimentally measured results may vary for an antenna. Moreover, the performance of antennas in a real-life scenario may also be different from that in a controlled environment. Hence, the actual performance results of an antenna may vary from the prediction results using the ML/DL model. Innovative learning algorithms and model architecture need to be designed to reduce this difference between the predicted and actual antenna performance.

VII. CONCLUSION

This paper highlights the application of AI in the field of antenna engineering. Various learning algorithms are extensively discussed in this review work for antenna design, optimization, and selection purposes. ML and DL-based antenna design procedures using EM simulators such as CST, HFSS, and FEKO are presented. Moreover, this review article discusses various design optimization techniques of the antenna, such as parallel optimization, single and multi-objective optimization, variable fidelity optimization, and multilayer ML-assisted optimization. Furthermore, applications of ML/DL in different intelligent antenna selection techniques in wireless applications are described. To automate the field of antenna engineering, adequate dataset generation is a must. For this purpose, the complete step-by-step procedure for data generation using FEKO is presented. Moreover, the possible challenges of deploying AI in antenna design, optimization, and selection are discussed in this review. The findings of this review indicate that it is possible to expedite the antenna design process through the use of ML/DL while maintaining high accuracy level, minimizing mistakes, and saving time. Moreover, ML/DL has the potential to predict antenna behavior, improve computing efficiency, and reduce the number of simulations required. The results of this survey work will be highly useful to readers interested in exploring further research on the application of ML/DL concepts in designing, optimizing, and selecting antennas for wireless communications.

CONFLICT OF INTEREST

The authors certify that they do not have an affiliation with any organization in a direct or indirect financial interest in the subject matter discussed in the manuscript.

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