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Antenna Optimization using Machine Learning Algorithms and their Applications: A Review

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Abstract

Antenna optimization using machine learning is a rapidly evolving field that leverages the power of artificial intelligence to design and improve antenna systems. Antenna optimization is a process of modifying antenna parameters to achieve desired performance metrics, such as gain, bandwidth, radiation pattern, and impedance matching. This paper presents a review of the most advanced development in antenna design and optimization by using machine learning techniques. The aim of this survey is to focus on different machine learning optimization techniques and their optimization capability with efficiency challenges. A deep outline from literature survey on optimization of antennas using machine learning are presented and listing various optimization algorithms and procedures that are applied to produce desired antenna characteristics and specifications. Firstly, a brief introduction of machine learning and its algorithms, later a quick explanation of antenna optimization process followed by an arranged introduction of different types of printed antenna designs using machine learning algorithm are reported. The methods emphasized in this survey have probably an effect on the imminent advancement of antennas for a variety of wireless applications.

Keywords: Microstrip Antenna, Optimization, Machine Learning, Evolutionary Algorithm, Wireless Communication.

1. Introduction

In modern wireless communication systems, design of antenna arrays and their optimization, integration, and fabrication are turn into more complication. Traditionally, antenna optimization has been done through multiple approaches. One of them has trial-and-error approach, where engineers manually tweak antenna parameters until the desired performance has been achieved. This approach is time-consuming, resource-intensive, and often limited by human expertise. Nowadays, a huge requirement of compact, multiband, and wideband for higher data rate with low loss antenna for advanced applications of wireless communication. To design and analyze of desired antennas in [1], few methods are applied for numerical validations specifically: finite difference time domain (FDTD) [2,3], finite element method (FEM) [4,5], and method of moments (MoM) [6,7]. A modified FDTD method is applicable for thorough analysis of more than one dielectric interfaces [8]. The method of moments needs accurate computation of the impedance matrix for calculating precise values of currents, impedance, and resonance frequency of the rectangular shaped and nonrectangular shape patch antennas [9]. Antenna design and simulation are widely preferred easily available commercial Computational Electromagnetics (CEM) software such as Advanced Design System (ADS), high-frequency structure simulator (HFSS), Computer Simulation Technology (CST), and Integral Equation Three-Dimensional (IE3D). All CEM software tools are very efficient, but due to absence of few significant features, limited performance achieved. For example, ADS have lack of 3D structures modelling, IE3D have no facilities of structures modelling with finite details, and the expanded structure of antenna simulation takes large time in HFSS and CST. The fullwave electromagnetic simulation for antenna design and optimization is very time consuming and leads to various limitations. Now days efficiency and optimization ability of existing antenna optimization techniques is the main limitation to report an extensive background of antenna design challenges. To overcome the limitation, different algorithms of machine learning (ML) have been considered for optimizing various parameters of antennas for different applications [10-13]. Machine learning offers a more efficient and effective way to optimize antennas by leveraging data-driven models and algorithms. Machine learning can automatically learn from large amounts of data and find patterns and correlations between antenna parameters and performance metrics. This enables engineers to design better antennas in less time and with fewer resources. Machine learning algorithm for antenna optimization has been broadly presented to step up the design procedure of antennas and arrays for different applications. Various ML techniques, such as Gaussian Process Regression (GPR), Support Vector Machine (SVM) and Artificial Neural Networks (ANNs), have been employed to develop alternate models of antenna to predict quick outcomes. In [14] a model is generated by using variable-fidelity electromagnetic (EM) simulations and co-Kriging. A genuine approach of combining sampled accurate EM data and densely sampled coarse-discretization in one model has been applied to design low-cost antenna. Another approach has been proposed for low optimization cost with little updated responses of antenna [15]. In [16], a multi objective model of an antenna has been designed by using kriging interpolation of coarse-discretization simulation data and known as multi-objective evolutionary algorithm. A complete performance evaluation of various miniature UWB

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antenna based on optimization techniques has been studied in [17].

In recent decades, many literatures reported various ML optimization algorithm such as ANNs, SVM and GPR have been developed for optimization of antenna parameters. The implementation and complex problems are easily handled by gaussian process (GP) than ANN and SVM. As per definition, deep learning algorithms and Convolutional Neural Network (CNN), includes convolutional calculations and a deep structure. Literature [18] presented a deep GP model by combining the structural CNN with GP. In this paper design parameters can reduce to decrease the training sample data and increase the designing efficiency with steady accuracy. Letter [19] presents a huge shaped-beam reflectarray design by using a new technique based on SVR. This technique used to find reflection coefficients for fast designing of reflectarray for direct broadcast satellite application. Paper [20] reported a multi-objective optimization model of antenna by using nested kriging algorithm with effective. To overcome the limitation of optimization efficiency for the designing of electromagnetic (EM) device and machine, a new technique named parallel surrogate model-assisted evolutionary algorithm has been proposed in [21] by using mutation operators in a parallel computing environment. In [22] various ML algorithm have been employed to analyse and optimize the performance of different antennas. A nano antenna has been optimized in [23] to achieve minimum loss and maximum radiation efficiency. To analyse aperiodic array with uniform excitation, a novel multi-objective optimisation technique known as non-dominated sorting and local search (NSLS) has been proposed [24,25]. To improve efficiency a three stage multi-fidelity-simulation-model assisted antenna design optimization outline has been presented in [26]. This outline is employed on SADEA and creating SADEA-II. A brief study in literature [27,28] demonstrates various printed antenna designs by utilizing ANN and other machine learning approaches. Paper [29] proposed a technique utilizing neuro-fuzzy networks to evaluate the antenna's resonance frequency of. A new type of ANN has been described in [30] for the analysis of antenna parameters. A dual band H-shaped patch microstrip antenna has been designed by applying machine learning techniques [31] to achieve compactness. An evolutionary algorithm known as Particle Swarm Optimization (PSO) has been used to design stacked patch antenna in [32] with the neural networks approach for the application of satellite communication.

Several limitations of the EM simulations and evolutionary algorithms (high computational cost, low efficiency, and large optimization time) restrict the antenna usages in many applications. To overcome this, an advance method named surrogate model assisted differential evolution for antenna synthesis (SADEA), has been reported in [33]. A new ML technique based on the modified K-nearest neighbour (KNN) algorithm incorporates advanced simulation methods with more features from data sets has been presented in [34]. A reflect array antenna has been analysed through ANN in [35] and a tunnel-based ANN has been developed for the analysis of antenna parameters in [36]. Nowadays many literatures present a thorough survey on the current development in antenna design optimization and emphasized on various methods that include optimization ability and efficiency problems using machine learning [37-43]. It provides a brief note on ML algorithm and various types of microstrip antenna. It also supports to researchers having least expertise in ML in the field of antenna and desire to utilize ML algorithm in study. Literature [44] reported an optimization of microstrip antenna parameters using ANN for X band (8-12 GHz) and Ku band (12-18 GHz) applications. An advanced Machine-learning-assisted optimization method has been reported for antenna optimization with maximum gain 7.4 dBi in [45]. Research paper [46] proposed a new design of isotropic antenna by using machine learning algorithm. Structured supervised learning, which is an alternative of neural networks, proposed in [47] to design patch antenna for the Ku EM band. In [48], ANN has been utilized for the design of multi-slot microstrip antenna and compared with simulated results by using IE3D software. Optimization using ANN of a frequency reconfigurable planar antenna with metasurface superstrate has been reported in [49]. A modelling using the Gaussian Process Regression (GPR) of electromagnetic band gap two-port multiple-input and multiple-output (MIMO) fractal antenna has been presented in [50].

Present study provides a broad report on different optimization process that can be applied on designing of an antenna with desired parameters. This report gives a quick knowledge of different types of ML techniques and types of microstrip antenna. It helps to researchers in optimization of antenna who would like to apply ML algorithm for antenna design. In starting of the paper, a brief overview on ML, types of ML and different literatures on ML are presented. Following section elaborates optimization models, ML algorithms and evolutionary algorithms for efficient computation to design an antenna. To attract the attention of reader, next section includes the in-depth outlines on different printed antenna designs and optimization using ML and organized according to the type of the antenna. Next section investigates another aspect of the literature, where ML has been utilized to improve the optimization characteristics of an antenna for different applications. Concluding explanations has been presented in the last section. All the segments of this paper are briefly expressed and listed with recommended literatures as per requirement. Antenna optimization using machine learning algorithms presents a promising and evolving field with significant scope and opportunities. Machine learning algorithms can optimize antenna parameters to enhance performance metrics such as gain, bandwidth, and radiation pattern. ML algorithms enable antennas to adapt to changing environmental conditions, ensuring optimal performance in dynamic scenarios, like mobile communication or satellite systems. ML can aid in designing multifunctional antennas that can efficiently operate across multiple frequency bands and communication standards. ML algorithms can improve the beamforming capabilities of antenna arrays, optimizing radiation patterns for better signal reception and transmission. It can be applied to mitigate interference in crowded wireless environments, ensuring reliable communication in the presence of competing signals. Antenna optimization is vital for satellite communication systems, and ML can contribute to improving link quality, data rates, and overall system efficiency. With the advent of 5G and future communication technologies, ML can play a key role in optimizing antennas to meet the demanding requirements of high data rates, low latency, and massive device connectivity. There is an opportunity to develop novel machine learning algorithms tailored specifically for antenna optimization, considering the unique challenges and requirements of the domain. Explore the integration of deep learning techniques for more complex optimization tasks, leveraging neural networks to model intricate relationships in antenna design. Develop algorithms that allow antennas to adapt in real-time to changing conditions, providing continuous optimization for improved communication quality. Contribute to the development of standards and best practices for applying machine learning to antenna optimization, ensuring consistency and reliability across different applications. Identify and explore commercial applications of machine learning-optimized antennas, such as in consumer electronics, automotive communication systems, and IoT devices.

2. Machine Learning Overview

Machine learning is the field of computer algorithms combined with dataset, that supports systems to understand automatically and improve from past data. It is a part of artificial intelligence (AI) that allows software applications to analyse the data accurately. Machine learning algorithms permits the computers to process the data and assess autonomously without any human support or program. Such assessment is made by obtaining significant fundamental samples in complex data. Several research have been surveyed on emerging applications of ML, like antenna design and optimization [51-53]. Classification of ML has been done into three basic categories; supervised, unsupervised and reinforcement learning, according to input and output data types to solve the various problems. One other learning methods like Semi supervised [54] has been formed to apply hybrid approach for solving beyond the original observation range. In [55] a brief comparison between Supervised and Unsupervised Learning Algorithms has been explained for Pattern Classification. A review on Feature Selection of Supervised, Unsupervised, and Semi-Supervised has been reported in [56, 57]. A detailed study and analysis of basic learning processes with different ML algorithm are listed in Figure 1 with diagrammatic representation.

Fig. 1. Brief description of various types of Machine Learning

2.1 Supervised Learning
Supervised learning applies labelled data to train the machine [58]. The labelled data indicates, a few input data is used as a training data that provides the accurate output. To resolve the various problems related to real-world such as fraud detection, spam filtering, risk assessment, image classification etc., supervised learning model supported efficiently. Several literatures have been reported different applications analysed by supervised learning algorithm such as, detection of Network Intrusion [59], Recognition of Human Activity in Ambient Assisted Living Environment [60], Earth Science [61] and diagnosis of abnormal voltage [62]. Based on problem types, supervised learning categories in two kinds of algorithms, namely classification and regression. If the output variables are categorical, like positive-negative, yes-no, true false etc. then classification algorithms are employed. Decision trees, logistic regression, random forest and SVM are some common classification algorithms explained in [63]. If there are some relations between input and output variables are exist, then regression algorithms are employed [64-66]. Various common regression algorithms have been explained in literatures like linear regression [67,68], regression trees, non-linear regression, bayesian linear regression, support vector regression [69-71] and polynomial regression.

2.2 Unsupervised Learning
Unsupervised learning applies unlabelled data to train the machine. The unlabelled data indicates, the input data without corresponding output values and applied after finding hidden patterns of dataset. Unsupervised learning is mostly used for complicated problems as compared to supervised learning. Literature [72] reported detection of zero-day attacks using Unsupervised Algorithms. Paper [73] investigates different techniques and applications of Unsupervised Machine Learning in Networking. Some other applications like early fault detection [74], iron mining [75], Network Intrusion Detection [76, 77] and deep convolutional neural networks enhancement [78, 79] have been reported and studied in various papers. Based on dataset types unsupervised learning is classified into two categories: Clustering and Association. In clustering, inherent groups are created from given dataset to predict output. Association is applied to discover the links between variables in the big dataset. Several common unsupervised learning algorithms are neural networks, principal and independent component analysis, K-means clustering, K-Nearest Neighbours (KNN), hierarchal clustering, Apriori algorithm, anomaly detection and singular value decomposition.

2.3 Reinforcement Learning
Reinforcement learning applies feedback based automatically learning technique. During the learning process, an agent learns to perform in a situation by executing the actions and seeing the results either positive or negative rewards for the actions. The main objective of reinforcement learning is to maximize the positive rewards by enhancing the performance. There are two types of reinforcement learning: Positive and Negative. The positive reinforcement learning increases the strength and the frequency of the expected performance. The negative reinforcement learning increases the strength of specific performance that will stop or avoid negative rewards. Reinforcement learning mostly utilized in game-playing and robotics [80,81]. Figure 2 illustrates different machine learning approaches to solve the problems.

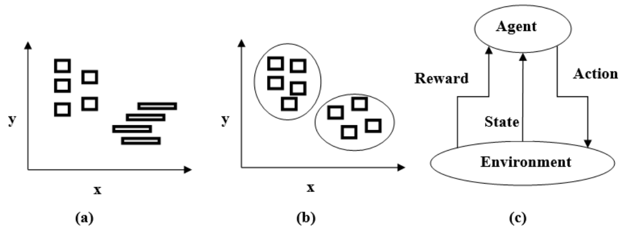

Fig. 2. (a) Supervised Learning Graph, (b) Unsupervised Learning Graph, and (c) Reinforcement Learning Process

3. Machine Learning Algorithms

To predict the output, observe the hidden patterns from dataset and maximize the positive feedback from experiences, machine learning algorithms are applied by programming. Different ML algorithms are used for different problems according to the complexity [82-88]. For example, linear regression can be used for predictions like sales, salary, age, stock market prediction, the KNN algorithm can be used for Text mining, Agriculture, Finance, Medical, Facial recognition, and Gaussian process regression can be used for process monitoring and fault detection. Some trendy Machine Learning Algorithms are listed below.

- Artificial neural network [89, 90]
- Support vector machine [91]
- Gaussian process regression [92-94]
- Linear regression
- Least absolute shrinkage and selection operator [95]
- Kriging regression [96-98]

A neural network is a data processing system contains many simple, highly interconnected processing elements in an architecture encouraged by the brain system. Paper [89] provides a brief discussion on neural networks and defines applications to a variety of real-world problems. Article [90] gives some ANN implementations with basic theory of ANN and its specific applications. Article [91] proposed an effective deep learning approach STL-IDS based on the self-taught learning (STL) framework to reduce the training and testing time. A method has been proposed in [92] by using Gaussian process regression to model spatial functions for mobile wireless sensor networks. An investigation of the Gaussian process approach for classifying multisource and hyperspectral remote sensing images has been reported in [93]. [94] summarize different ML algorithms which are not based on neural networks for the analysis of accuracy of the final model. Paper [95] modify the selection process of LASSO to explicitly leverage combinatorial sparsity models through the combinatorial selection and least absolute shrinkage operator. [96] provides progressive tutorial on regression, kriging, and stochastic kriging. The co-kriging-based antenna structure optimization algorithm has been proposed in [97]. Paper [98] proposed a cost-efficient Gradient Enhanced Kriging modeling of dielectric resonator antenna structures for considerable reduction of the model setup cost.

4. Machine Learning for Antenna Design

The need of antennas for various applications expanding from electromagnetic to thermal going through mechanical or space limits is increased for recent technology development. Printed antennas become a most favourable class of antennas to build an advanced device for communication systems, due to their notable merits such as cost-effective, easy fabrication, compactness, conformable, and adequate gain. Several literatures reported the use of machine learning in the design process of an antenna. The machine learning techniques speed up the design process of an antenna by providing high accuracy, minimum error, less execution time, accurate prediction of the antenna operation, good computational efficiency, and minimum number of required simulations. Following steps are involved in the process of antenna optimization using machine learning:

1. Data collection: The first step is to collect data on the performance of the antenna. This can be done through simulations or measurements of the antenna's radiation pattern, gain, and other relevant metrics.
2. Feature extraction: The data collected in step 1 is then processed to extract relevant features that describe the antenna's performance. These features can include parameters such as frequency, bandwidth, and polarization.
3. Model training: Once the features have been extracted, a machine learning algorithm is trained on the data to learn the relationship between the antenna parameters and the performance metrics.
4. Optimization: With a trained machine learning model, the antenna design can be optimized by using the model to predict the performance of different antenna configurations. The optimization process typically involves exploring the design space using techniques such as genetic algorithms or reinforcement learning.
5. Validation: Finally, the optimized antenna design is validated using simulations or measurements to ensure that it meets the desired performance metrics.

The antenna optimization using machine learning algorithms provides a powerful tool for engineers to design and optimize antennas with improved performance characteristics. To evaluate the accuracy of the machine learning model and the optimization algorithm, it is essential to calculate the error or loss function, which measures the difference between the predicted and actual values of the performance metrics. There are several types of error functions that can be used depending on the nature of the problem and the objectives of the optimization.

One common error function used in antenna optimization is the mean squared error (MSE), which is the average of the squared differences between the predicted and actual values of the performance metrics. The MSE is a widely used metric in machine learning because it is differentiable, convex, and easy to interpret. The Mean Squared Error is calculated as:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}(y_i - \widetilde{y}_i)^2}{n} \tag{1}$$

Where y_i: Actual value for the i^{th} observation
x_i: Predicted value for the i^{th} observation
n: Total number of observations

Another popular error function in antenna optimization is the mean absolute error (MAE), which is the average of the absolute differences between the predicted and actual values of the performance metrics.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}\mathrm{abs}(y_i - x_i)}{n} \tag{2}$$

Where y_i: Actual value for the i^{th} observation
x_i: Calculated value for the i^{th} observation
n: Total number of observations

The MAE is more robust to outliers than the MSE and is less sensitive to small changes in the predicted values. Other error functions that can be used in antenna optimization include the cross-entropy loss, the hinge loss, and the KL-divergence. These error functions are often used in classification and regression problems and can be adapted to the antenna optimization problem by encoding the constraints and objectives of the problem in the loss function. Overall, the choice of error function depends on the specific problem and the objectives of the optimization. The error function should be chosen carefully to balance accuracy, robustness, and computational efficiency.

This section focuses on optimization process, conventional and evolutionary optimization algorithm of machine learning for antenna design. The papers reviewed in this section are categorized in three area: optimization modelling methods, machine learning optimization techniques and evolutionary computation algorithms.

4.1 Optimization of Antennas

Machine learning based antenna optimization prefers specific and evolutionary algorithm which are based on the optimization characteristic, efficiency, simplification, and robustness. There are various modelling methods are used to optimize the design of an antenna with good optimization outcomes. Some models namely, Single-objective optimization, multi-fidelity optimization, multi-objective optimization and yield-driven optimization that are used for different antenna optimization problems. Antenna optimization modelled as single-objective optimization problems to maximization of the isotropic gain has been presented in [99]. To enhance optimization efficiency of an antenna, multi-fidelity optimization is used to model the problem of antenna design. This technique uses high-fidelity expensive and precise models and to remove unwanted solutions, low-fidelity, imperfect and inadequate models [100]. In [101], a conventional multi-objective optimization problem has been illustrated and studied. This paper reported a design of compact planar antenna with low value of reflection coefficient in desired operating bands using multi-objective optimization. Paper [102] depicts statistical analysis-based yield-driven optimization for the analytical evaluations of deviations. Due to this probability of assumed and nominal design performance specifications of a fabricated prototype is increases.

4.2 Machine Learning Optimization Techniques

Design of an antenna must have some important parameters like implementation, usability, and cost-efficient. Optimization is the process of making a model as good as it can be. Optimization using machine learning is one of the important methodologies to get improved results of designed model by comparing various solutions using iteration. Optimization process, design a model with minimum production cost and maximum production efficiency. Antenna optimization consists proper range of functions, design parameters, variables, and limitations. There are several approaches to using machine learning for antenna optimization, including reinforcement learning, genetic algorithms, and neural networks. Reinforcement learning involves training an agent to make decisions based on feedback from the environment. Genetic algorithms mimic natural selection to evolve antenna designs over multiple generations. Neural networks use deep learning techniques to model the relationship between antenna parameters and performance metrics. Several literatures are discussed antenna optimization using machine learning for different applications. There are different ML techniques are illustrated which can optimize an antenna design parameter:

- Gradient descent [103]
- Adaptive moment estimation
- Levenberg-Marquardt algorithm [104]
- Bayesian regularization [105]

4.3 Machine Learning Evolutionary Algorithms

An optimization process is required to calculate nearest optimal values of design parameters of antenna. Use of evolutionary algorithms are new approach to applying machine learning in antenna design. Evolutionary Algorithms play an important role in computing sciences. It allows to achieve nearest solutions to optimization problem and implicated in real selection. To improve the performance characteristics of an antenna for space communication and faster computations, evolutionary algorithms are effectively employed in machine learning techniques. Figure 3 illustrates block diagram of antenna optimization process using ML algorithm.

Some standard evolutionary algorithms like, particle swarm optimization and differential evolution, covariance matrix adaptation evolution strategy, genetic algorithms and simulated annealing have been explained in [106]-[112] for antenna design and optimization.

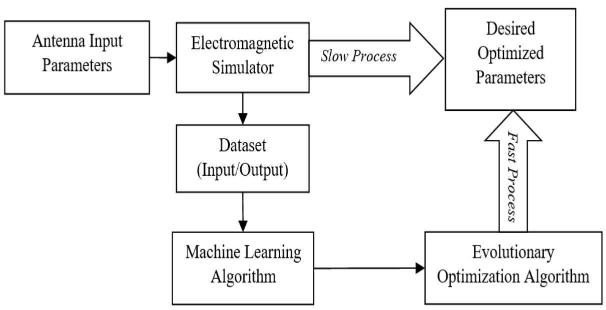

Fig. 3. Antenna optimization process using ML algorithm.

5 Printed Antennas Using Machine Learning

This section provided a comprehensive survey of several papers on antenna design using machine learning. An antenna fabricated by using lithographic methods on a printed circuit board is known as Printed antenna or microstrip antenna. It has several advantages like mechanical durability, conformability, small sizes, and low manufacturing costs. They are generally used at microwave frequencies for both the military and commercial applications. There are various size and shapes of printed antennas are available which are optimized using different optimization techniques of machine learning. Some common types of printed antennas are rectangular patch, circular patch, fractal, slotted, MIMO, Dipole, ultra-wide band, multiband antennas etc. In following section some of the printed antenna types, design, and optimization based on literature survey are described in brief. Figure 4 listed various printed antenna types, shapes, feeding techniques and their applications in different fields.

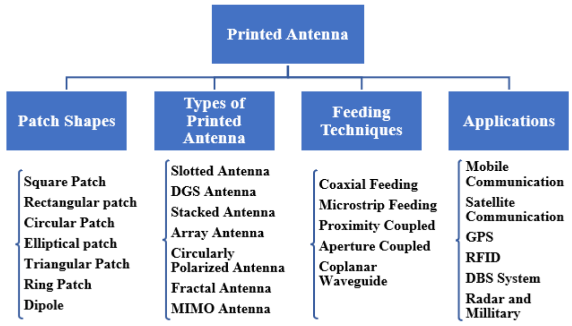

Fig. 4. Printed antenna types, shapes, feeding techniques and applications.

5.1 Rectangular Patch Antenna

The most utilized printed antenna is a rectangular patch antenna as shown in figure 5 that appears like a truncated microstrip transmission line. A CAD model of square shaped patch antenna is designed by using Neural network in [113]. To obtain and analysed the exact resonant frequency of a rectangular patch antenna, ANN has been used in paper [114,115]. Another research based on ANN technique has been reported in [116] include calculation of the rectangular shaped patch length and width of an antenna by training through Bayesian Regularization and Levenberg Marquart algorithms. Particle Swarm Optimization (PSO) optimization process has been studied in [117] for the designing of ANN based printed antenna. To calculate the size of slots and air gap of an antenna, an ANN based synthesis model has been presented in [118]. Radiation patterns of an antenna has been analysed in [119] by using a tunnel-based ANN. In [120], an analysis of an antenna has been done by using both ANN and SVM algorithm. A brief comparison between the results of two advanced nonlinear ML algorithms depicts superiority of SVM over the ANN. To calculate the resonant frequency of rectangular shaped patch antenna designed by ANN in [121], uses various algorithm like feed forward back propagation, resilient back propagation, Levenberg Marquardt and radial basis functions.

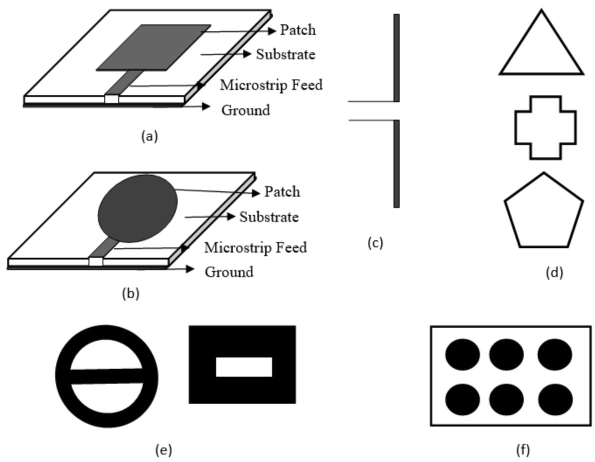

Fig. 5. (a) Rectangular Patch Antenna, (b) Circular Patch Antenna, (c) Dipole, (d) different shaped patch, (e) Slotted Patch and (f) Array Structure.

5.2 Circular Patch Antenna
A multilayer circular microstrip antenna has been optimized using training algorithm named Levenberg - Marquardt to train the Multi- Layer Perceptron Neural Networks in [122]. In paper [123] delta-bar-delta, extended delta-bar-delta, quick-propagation, directed random search and genetic algorithms have been utilized to train the Multi- Layer Perceptron Neural Networks. This paper proposes electrically thin and thick circular printed antennas by evaluating the resonant frequency, characteristic impedance and the effective permittivity using only one neural model. Another paper [124] developed multilayer perceptron based on neural network for circular patch antenna design to determine feed position. A circular patch antenna model has been optimized in [125] by using Quasi Newton model of Artificial Neural Network. To determine all performance constraints like S11, Voltage Standing Wave Ratio (VSWR), resonant frequency, impedance bandwidth and antenna gain of circular patch antenna a Neuro-Computational approach has been applied in [126].

5.3 Dipole
An input impedance of dipole antenna has been optimized using synthesis ANN with FDTD method in [127] for practical applications. This ANN model employs a hetero-associative memory on input and output data for the computation of fault toleration. In addition, a latest randomization method for the optimization of antenna parameters has been reported. Another new SYNTHESIS-ANN model in [128] has been generated for solving the intensive problems and optimization of microwave devices.

5.4 Fractal Antenna
An ANN based method has been applied and projected in [129] to design a double band fractal antenna by calculating return loss, resonance frequency and antenna gain. Paper [130] developed, an advanced square shaped fractal antenna using Advanced C and optimized by ANN. A quasi-fractal patch antenna model efficiently synthesized by using multilayer perceptrons ANN with one hidden layer and resilient backpropagation training algorithm in [131]. A PSO based ANN has been developed in [132] by utilizing hybridized algorithm to optimize a miniaturized circular fractal antenna resonate at 2.45 GHz. Another custom-made fractal antenna illustrated in [133]. In this article, proposed antenna has been designed by using ANNs and PSO technique. For the biomedical applications, a miniaturized giuseppe peano and cantor set fractals-based hybrid fractal antenna reported in [134]. Also, a relative analysis of three different ANNs has been done to assess the truly excellent kind of ANN for the evaluation of proposed antenna.

5.5 Various Shaped Patch Antenna
A deep neural network has been applied in [135], to compute the resonance frequency of a printed antenna with E–shaped resonating patch. Paper [136] proposes a small size microstrip antenna radiated in frequency range from 0.4856GHz to 7.8476 GHz. In this article a regression-based machine learning has been employed to calculate resonant frequency, slot dimensions and patch dimensions at dominant mode. A Gaussian process regression-based method developed in [137] for the precise computation of resonant frequencies of proposed dual-band microstrip antennas. In [138], optimization of a designed antenna has been described by using Gaussian process regression with a genetic algorithm (GA) structure. To achieve desired performance parameters of a dual-band double T-shaped monopole antenna, some modern ML techniques including least absolute shrinkage and selection operator, ANNs, and KNN have been used to optimization process in [139].

5.6 Slotted Antenna
Literature [140] depicts a model using neural network for calculating the various performance parameters like; resonance frequencies, antenna gains, antenna directivities, antenna efficiencies for dual-band slotted microstrip antennas. Reported model of neural network has been applicable for all varied dimensions of slot and incorporated air-gap. A knowledge-based neural network model proposed in [141] to obtain desired values of resonance frequency, antenna gain, directivity, and radiation efficiency of a dual-band antenna for accurate prediction of slot-size, that has been presented on the radiating patch. A significant drop in training attempts has been achieved, due to prior knowledge of neural model. In [142], a neural networks prototype developed for calculating the desired size of slot on the patch and air-gap between the ground plane and substrate. A slot loaded rectangular microstrip antenna has been reported in [143] and modelled by using support vector regression method. Article [144] illustrates desired calculation using SVM formulation for evaluating different characteristics of slotted microstrip antenna like resonant frequency, antenna gain, directivity, and radiation efficiency with modified ground plane.

5.7 Ultra-wideband Antenna
A compact monopole antenna with coplanar waveguide feed has been analysed and optimized by using machine learning techniques to speed up the process of antenna design in article [145]. This article approaches to five algorithms for the designing of band-notch antenna named as decision tree, random forest, XGB regression, KNN, and ANN. In paper [146], ANN has been used to analyse and predict the impedance bandwidth and notch frequency of an ultra-wideband (UWB) antenna. A multi-adaptive neuro-fuzzy inference system has been developed in [147] for calculating the impedance bandwidth and notch frequencies of proposed slotted UWB antennas. Article [148] proposes an optimization process that was achieved by utilizing a self-organizing multi-objective genetic algorithm and apply on a ring monopole microstrip antenna design by predicting impedance bandwidth, S11 and central frequency deviation. This antenna is applicable for ultra-wideband operations. To improve a multi-objective evolutionary algorithm, a machine learning application has been reported in [149] that is used to predict the nature of fitness function for the accurate design of UWB antenna.

5.8 Array Antenna
An array antenna is defined as a set of multiple linked antennas that will work simultaneously as an individual antenna. Usually, an array is used to obtain high gain, path diversity characteristics, interference reduction, beam steering, and for radio direction finding. A robust GA along with rapid neural network method has been developed for optimization of a proposed wideband aperiodic linear phased antenna array in [150]. This paper presents a modern nature-based (GA-NN) technique that can design and estimate the performance parameters with desired element positions in given band of operation and scanning range to reduce the element VSWRs and sidelobe levels. A novel beamformer neural networks-based antenna array has been reported in [151]. A new variant of invasive weed optimization known as

modified adaptive dispersion has been used to train the optimized datasets in neural networks training process. In paper [152] a simulation-based Machine Learning method for an antenna optimization has been reported, that provides a large multi-dimensional parameter optimization within an appropriate Time. A brief investigation on different antenna design using machine learning is also listed in Table 1.

Table 1. Different design process of antenna using machine learning and evolutionary algorithm.

Ref.	Antenna Type	ML Algorithm	Results Compared To	Evolutionary Algorithm	Optimization Parameters/ Performance Parameters
[108]	Microstrip antennas and arrays	Differential Evolution (DE)	Simulated and measured results	Self-Adaptive DE, DE, Biogeography-based DE, modified DE, Improved DE, Harmonic Search DE	Antenna parameters
[109]	Log-periodic antenna	--	Evolutionary algorithms	DE, PSO, Taguchi, invasive weed, adaptive invasive weed	Dipole lengths and spacing, dipole wire diameters /Antenna gain, VSWR, front-to-back ratio
[113]	Rectangularpatch antennas	ANN	IE3D electromagnetic simulator	--	Dielectric constant, substrate thickness/resonant frequency
[114]	Rectangular microstrip antenna	ANN	Conventional simulations	Multilayer perceptron modular neural network	Resonant frequency
[115]	Rectangular microstrip antenna	ANN	--	--	Parameters of antenna
[116]	Rectangular patch antenna	ANN	Theoretical value	Bayesian regularization and levenberg marquart	Length and width of antenna
[117]	Rectangular or Circular Microstrip Patch Antenna	ANN	Conventional simulations and measured antenna values	ANN Optimized by PSO Algorithm	--
[118]	Rectangular or circular microstrip patch antenna	ANN	Measured results	--	Slot-Size, Airgap/ Resonance Frequencies, Gains, Directivities, Antenna Efficiencies, and Radiation Efficiencies
[119]	Multi-slot hole-coupled microstrip antenna	Tunnel-based ANN	IE3D software, analytical and experimental results	GA	Radiation patterns, resonant frequency
[120]	Rectangular patch antenna	SVM	Theoretical results and ANN results	--	Resonant frequency, impedance bandwidth and input impedance
[121]	Rectangular patch antenna	ANN	Standard formula and experimental results	--	Dielectric constant, thickness of substrate, patch width and length/resonant frequency
[122]	Multilayer circular microstrip anten na	ANN	Measured and calculated result s	Levenberg – marquart algorith m	Resonant frequency
[123]	Circular patch antenna	Neural models	Experimental results	Delta-bar-delta, extended delta-bar-delta, quick-propagation, directed random search and GA	Resonant frequency, characteristic impedance, and effective permittivity
[124]	Circular microstrip antenna	MLP neural network Radial basis function	Experimental results	--	Feed position
[125]	Circular microstrip antenna	ANN	Experimental results	Quasi newton model	Resonant frequency
[126]	Circular microstrip antenna	ANN	Simulated, measured and theoretical results	Neurocomputational models	Return loss, VSWR, resonant frequency, bandwidth, gain and antenna efficiency
[127]	Printed dipole antenna	ANN	Finite-difference time-domain results	Synthesis ANN	Input impedance
[129]	Elliptical fractal patch antenna	ANN	Simulated results obtained using IE3D software	--	Resonant frequency, return loss and gain
[130]	Square fractal antenna	ANN	Simulated using HFSS	--	Antenna parameters/

					resonance characteristics
[131]	Quasi-fractal patch antenna	Multilayer perceptrons ANN	Simulated and measured results	Efficient resilient backpropagation algorithm	Thickness and size of antennas
[132]	Circular fractal antenna	PSO based selective ANN	Simulated, desired, and experimental results	--	--
[133]	Custom-made fractal antennas	ANN and PSO	Simulation and experimental results	--	fractal antenna parameters/ operational frequencies
[134]	Hybrid fractal antenna	ANN	Simulated, and experimental results	Firefly algorithm	Feed position
[135]	E–shaped patch antenna	Deep neural network		Deep neuro-computing model	Resonant frequency
[136]	Square patch antenna	GPR	Simulated and measured	--	Slot size and patch dimensions/ resonant frequency
[137]	Dual-band microstrip antennas	GPR		--	Resonant frequencies
[138]	Dual-band CPW-fed slot antennas	GPR	Moment-method-based simulations	GA	Several tunable geometries
[139]	Dual-band double t-shaped monopole antenna	Least absolute shrinkage and selection operator, ANN and KNN	Results obtained from high-frequency structure simulator	--	--
[140]	Slotted microstrip antennas	Neural network model	Simulated, predicted, and measured results	--	Resonance frequencies, gain and radiation efficiencies
[141]	Microstrip antennas	Knowledge-based neural networks model	Measured, and simulated	--	Resonance frequencies, gain and radiation efficiencies
[142]	Microstrip antenna	ANN	Simulated values	--	Slot-size, air-gap/ resonance frequencies, gain and radiation efficiencies
[143]	Rectangular microstrip antenna	Support vector regression	ANN model	--	Slots position, slots-size
[144]	Slotted microstrip antennas	SVM	Simulated and computed values	--	Resonant frequency, gain, directivity, and radiation efficiency
[145]	Band-notched monopole antenna	Decision tree, random forest, XGB regression, KNN, and ANN	ANN	--	Antenna's dimensions
[146]	UWB antenna	ANN	Simulated and experimental results	--	Impedance bandwidth and multi-band notch frequencies
[147]	Slotted UWB antenna	Multi-adaptive neuro-fuzzy inference system	HFSS	GA and PSO	Bandwidth and notch frequencies
[148]	UWB antenna	Multi-objective genetic algorithm	HFSS results with the real prototype antenna	--	Return loss, bandwidth and central frequency deviation
[149]	UWB microstrip antenna	--	Simulated result	Adaptive evolutionary algorithm	Return loss, bandwidth and central frequency deviation
[150]	Aperiodic linear arrays	--	--	Nature-based design technique (includes robust GA optimizer and rapid neural-network estimation procedures)	Optimal element positions
[151]	Antenna array	Neural networks	--	Modified invasive weed optimization (modified adaptive dispersion)	--

A comprehensive survey on various antenna designs by using advanced methods of antenna design through machine learning, deep learning, and ANN listed in table 1 provide better results than conventional methods. After significant work has been done in the field of antenna optimization using machine learning algorithms, researchers can explore several advanced and forward-looking directions to push the boundaries of knowledge and address emerging challenges. Explore the integration of machine learning with other optimization techniques, such as genetic algorithms, simulated annealing, or reinforcement learning. Hybrid approaches may provide synergies that outperform individual optimization methods.

6 Constraints and Overcomes

Table 2 listed various parameters of recently proposed antenna models using different ML algorithm. However, machine learning algorithms have been used to optimize antennas, there are some constraints to this approach. Here are some potential constraints:

1. **Limited Data:** The performance of machine learning algorithms depends heavily on the amount and quality of data used for training. However, for antenna optimization, it may be challenging to collect and label enough data to train the algorithm effectively.
2. **Complexity:** Antenna optimization using machine learning algorithms can be a complex process that requires expertise in both antenna design and machine learning. The algorithm must be carefully designed to account for the various parameters that impact antenna performance, such as resonance frequency, polarization, and radiation pattern.
3. **Computational Cost:** Antenna optimization using machine learning algorithms can be computationally expensive, especially for large and complex antenna designs. This may limit the practical application of the approach in some situations.
4. **Interpretability:** Machine learning algorithms are often criticized for their lack of interpretability. It can be challenging to understand why a particular antenna design is optimal, which can limit the ability to make design decisions based on the results of the algorithm.

Overall, while machine learning algorithms have the potential to optimize antennas, their limitations mean that applied algorithm may not always be the best approach for specific antenna. Other optimization techniques may be more appropriate in some cases. Here are some ways to improve the process of microstrip antenna optimization using machine learning algorithms:

1. **Data Augmentation:** To address the issue of limited data, we can use data augmentation techniques to increase the size of the training dataset. This can be done by generating synthetic data from existing data using techniques such as rotation, translation, and scaling.
2. **Feature Engineering:** Feature engineering involves selecting or designing features that are relevant to the problem at hand. In the case of antenna optimization, this might involve selecting or designing features that capture key antenna parameters such as frequency, radiation pattern, and polarization. Effective feature engineering can help improve the accuracy of the machine learning algorithm.
3. **Ensemble Methods:** Ensemble methods involve combining multiple machine learning models to improve their performance. For example, we could train multiple neural networks with different initializations and combine their outputs to obtain a more robust and accurate solution.
4. **Transfer Learning:** Transfer learning involves leveraging knowledge from one domain to another. In the case of antenna optimization, this might involve using a machine learning algorithm that has been trained on a related problem, such as image classification, and fine-tuning it for antenna optimization.
5. **Explainability:** To improve the interpretability of the machine learning algorithm, we can use techniques such as feature importance analysis and visualization. These techniques can help us understand which features are most important for antenna optimization and how the algorithm is making its decisions.

Generally, by addressing these issues and incorporating these techniques, we can improve the process of microstrip antenna optimization using machine learning algorithms.

Table 2. List of recently optimized antenna model using different ML algorithm.

References	Antenna Types	Frequency (GHz)	Dataset	ML Algorithm	Error
[50]	Two-Port MIMO Antenna	2.43–2.50 GHz	125	GPR	RMSE less than 0.0001%
[136]	Square Patch Antenna	0.48–7.84	3822	GPR	RMSE are 0.0087%
[143]	Rectangular Microstrip Antenna	2.15	198	SVR	Average Error 0.40%
[144]	Slotted Antenna	1.75 and 2.50 GHz	198	SVM	Average Error 0.79%
[145]	Band-Notched Monopole Antenna	2.9 and 21.6 GHz	766,413	KNN	Mean Square Error 0.290%
[147]	Slotted RMSA	2–3.17/9.1–14/0–4.84/0–4.39/0–3.51	1195	MANFIS-PSO	Error is >1%
[166]	U-shaped Slotted Antenna	2-10.75	956	ANN	Average Relative Error 1.59%

[167]	Square Patch MSA	5.9206–25-7625	125	GPR	Average Error is 0.400281%

7 Machine Learning for Antenna Applications

Machine learning approaches have been depicting great outcomes in many antenna applications like 5G, biomedical, textile, Global Positioning System (GPS), satellite communication system and smart homes and cities. Its exceptional abilities to process on real problem statements and get hands-on experience with accurate data make it more appropriate for applications. By applying machine learning, the antenna is used for many civilian uses and further wireless applications. Additional, body-centric communication systems also utilize machine learning to improve their capabilities.

7.1 Machine learning for millimeter wave

Machine learning can be used to optimize the design of antennas for wireless communication systems such as 5G, IoT. In electromagnetic spectrum the frequency range of millimeter wave covers 30 to 300 GHz (10 to 1 mm wavelength range). The millimeter wave frequency range are widely used for the data transmission and sensing systems. It provides good flexibility and capability, due to large range of unlicensed bandwidth. Different field of applications uses millimeter wave technology that will come under the millimeter wave range. Nowadays, wireless applications are utilizing millimeter wave antennas designed by using machine learning algorithms to achieve large flexibility. Literatures [153,154] reported optimization of antennas using Machine learning tools for 5G application.

7.2 Machine learning for body-centric communication

Antennas are increasingly used in medical applications such as imaging and wireless sensing. Machine learning can be used to optimize the design of these antennas to improve their performance, such as reducing the power required for wireless sensing. Currently, demand of body-centric communication systems has been increased in different areas and applications such as biomedical, security, identification, sports, smart phones etc. Wearable antennas are the most important elements for the body-centric communication systems. Some of the research papers [155, 156] proposes wearable antennas and experimentally analysed using machine learning algorithms.

7.3 Machine learning for satellite communication

Antennas are critical components in aerospace applications, such as radar systems and satellite communication. Machine learning can be used to optimize the design of these antennas to improve their performance and reduce their size and weight. Satellite communication consist of two main modules: first is the ground portion that contains fixed or mobile transmission/reception system, and supplementary equipment, second is the space portion, that is the satellite. A satellite travels around the Earth in orbit and transferring information from one place to another. Nowadays, machine learning based antennas are designed for satellite communication to deliver signals to a station. Various literatures [157,158] propose different works on satellite applications using machine learning.

7.4 Machine learning for textile communication systems

Demand of wearable antennas in biomedical applications is increases due to its flexibility, durability, and washability. These wearable antennas are fabricated with textile materials and essential for emerging wireless textiles communication systems. In textiles systems, communication has been with the help of wearable antennas with external devices. Several papers [159-162] are focused on sensors and techniques using machine learning that have being more useful to design the flexible textile system.

7.5 Machine learning for global positioning system

Antennas are also important in automotive applications, such as GPS, Bluetooth, and cellular communication. Machine learning can be used to optimize the design of these antennas to improve their performance in challenging environments such as urban canyons and tunnels. The GPS is mostly used to obtain the accurate geographical position in civil and military applications. The microstrip antennas are mostly used in GPS due to compact size and good radiation properties. Due to the requirement of circular polarization property in receiver antennas of GPS, microstrip antennas is needed. The purpose of machine learning in GPS application has been illustrated in [163-165] with detailed explanation.

7.6 Smart homes and cities

Antennas are increasingly being used in smart home applications such as home automation, security systems, and entertainment systems. Machine learning can be used to optimize the design of these antennas to improve their range, data rate, and energy efficiency. Antennas are also important components in smart city applications, such as traffic management, air quality monitoring, and public safety. Machine learning can be used to optimize the design of these antennas to improve their performance in challenging environments, such as urban canyons and high-rise buildings.

In all these applications, machine learning can help engineers optimize antenna designs more efficiently and effectively than traditional methods. By automating the optimization process using machine learning, engineers can save time and resources while also exploring a wider range of design options to find the best antenna configuration for a given application. While the integration of machine learning into antenna applications offers numerous benefits, careful consideration of the associated challenges is crucial. Machine Learning dependent Broadband Millimeter-Wave SIW Cavity-Backed slot antenna has been proposed. But some issues like requirement of substantial amounts of labelled data for training, long duration of development, and the cost. Antenna optimization based on an ANN method for detecting GPS spoofing signals may be faced problem of high error-susceptibility and a lack of capable resources.

8 Conclusion

A thorough discussion on machine learning algorithms in antenna design optimization has been reported in this paper. Due to fast processing speed of the antenna design with minimum errors and high accuracy, machine learning techniques are mostly studied. A concise study has been given on various machine learning types and evolutionary algorithm. In this survey, a thorough investigation has been done on various antenna designs by recently developed machine learning optimization techniques for improved results. This paper has been discussed general approaches to antenna optimization using evolutionary ML algorithm, which are appropriate for antenna parameters with high and multiple specifications. These algorithms are proposed for different modern antenna design due to their simplification, robustness, and optimization ability. Applications of antennas in various fields like telecommunications, aerospace, automotive, medical and textile are explored. In all these applications, machine learning can help engineers optimize antenna designs to meet the specific requirements of smart applications, such as low power consumption, high data rate, and reliable communication.

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