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Deep Investigation of Machine Learning Techniques for Optimizing the Parameters of Microstrip Antennas

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Abstract

This paper presents a deep investigation and analysis of the recent advances in optimizing the parameters of microstrip antennas based on machine learning techniques. This investigation explains the numerical and traditional methods necessary for understanding the insights in designing microstrip antennas. Contemporary machine learning techniques employed in parameters optimization are then discussed for emphasizing the various approaches used in antenna synthesis. In addition, the regression methods in machine learning are highlighted in terms of the mathematical description and implementation of parameters optimization. Various methodologies and algorithms used to produce the design parameters of microstrip antennas based on antenna specifications and desired radiation are also described in this paper. Moreover, the recent research publications that target the design and optimization of microstrip antennas using machine learning are discussed in this paper to supply readers with the essential understanding of the recent methods required for applying the presented approaches in related tasks and projects.

Disciplinary: Computer Science (Machine Learning), Wireless Communication (Antenna Parameters Optimization).

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1 Introduction

Machine learning (ML) has been widespread in automating routine activities and providing revolutionary insights across all the fields of science and engineering. ML practitioners have altered the basis of several businesses and disciplines of study. Design and optimization of microstrip antennas are one of the most recent disciplines. Considering the world's current big data age, ML has gotten significant attention in this sector. ML offers considerable potential in the design and prediction of antenna behavior that allows for substantial acceleration while retaining high accuracy [1].

Microstrip antennas, because of their complicated forms, seldom have closed-form solutions. Maxwell's equations are used in computational electromagnetics (CEM) to describe the role of electromagnetic fields in the pace of antennas design. A set of approximate solutions can be typically utilized to get a physical insight into the antenna's design. For instance, to solve linear antennas using advanced numerical techniques, integral equations can be utilized. Later, as computer technology advanced, Maxwell's equations could be solved using solvers of differential and integral equations [2].

Numerical techniques and high-frequency methods are the two most commonly used CEM approaches in the microstrip antennas design. The method of moments (MoM), finite element method (FEM), and the finite difference time domain (FDTD) are three methods usually used in simulating and testing antenna parameters. In addition, the physical optics approximation approach can be used to calculate the radiation field of high-frequency reflector antennas. Most antenna simulation work entails utilizing computers to solve tasks with defined boundary conditions and entails partial differential equations [3].

Machine learning has been fully examined as a complementary approach to CEM in optimizing and designing a wide range of antenna types for numerous advantages due to their intrinsic nonlinearities. ML is considered a significant subset of artificial intelligence (AI) that focuses on extracting usable information from data, which explains why it has been frequently linked to statistics and data science. Machine learning's data-driven approach has enabled researchers to create systems, bringing the world closer to genuinely autonomous systems that can equal, compete, and occasionally surpass human talents and intuition. On the other hand, the quality, amount, and availability of data, which can be difficult to come by in some circumstances, is critical to the success of ML techniques [4].

There is no standardized dataset available for microstrip antennas, such as those accessible for computer vision, for instance. This dataset must be obtained, if it is not already available, from an antenna design standpoint. This may be accomplished by utilizing CEM simulation software to simulate the desired antenna over a broad range of values. The dataset may be constructed and separated into three parts: training, testing, and cross-validation. These parts are used to train and verify the ML model's ability to generalize to new inputs. It is up to the designer's foresight and skill at this stage to figure out how to check the model and enhance its generalization. Plotting learning curves and checking bias and variance values are two standard procedures to take in this respect. Typically, the designer's intuition plays a significant role in optimizing the performance of a model [5].

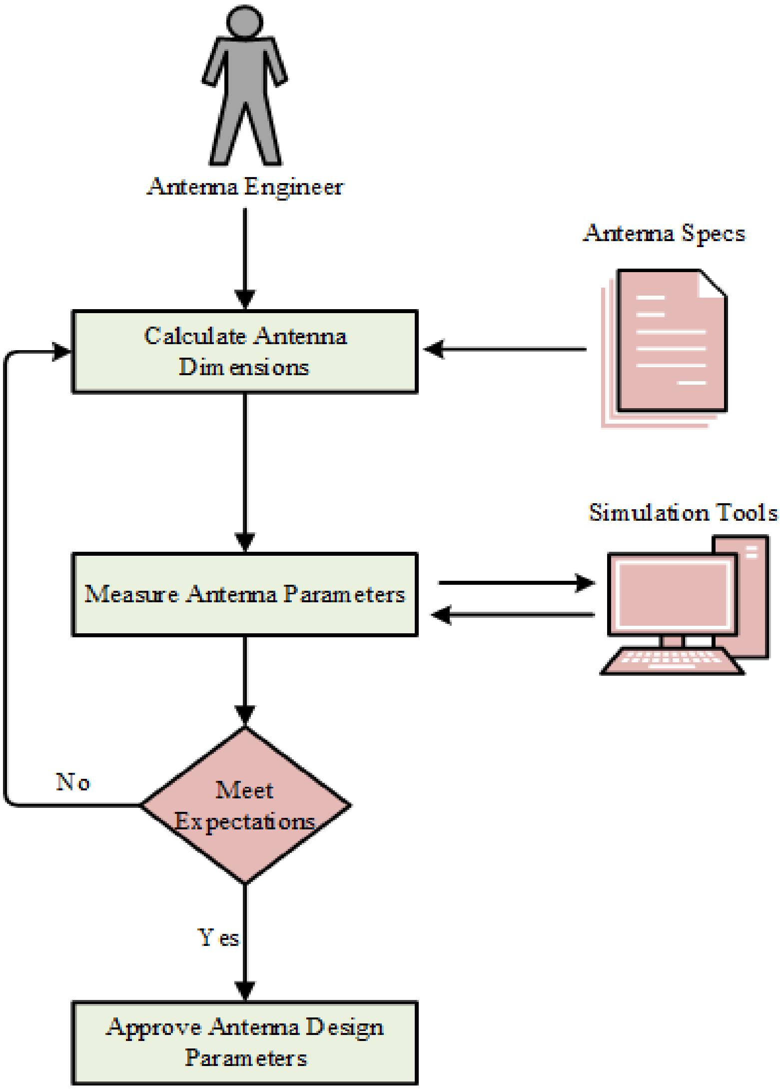

Figure 1: The traditional approach of antenna parameters optimization

The integration of machine learning in the optimization of antenna parameters greatly speedups the design process. As shown in Figure 1, the traditional approach of getting optimal parameters for specific antenna design usually takes a too long time using current simulation tools. However, a close approximation of these parameters can be obtained quickly if machine learning is employed to perform the parameter optimization process. Because of this advantage, there are many research efforts done by researchers in the literature that focuses on embedding machine learning models in the design of antennas. The work that has been done in this regard is presented in this section, along with the achieved results.

This study introduces and examines the application of ML in antenna design and optimization and provides a deep investigation of the most common antenna designs discovered in the literature that employ various ML approaches. This paper is intended to guide antenna researchers with little or no knowledge of machine learning who want to use it in their study. The many antenna design articles studied are organized to make it easier for researchers to learn more about the optimization and design of microstrip antennas using machine learning to get started.

This paper is organized as follows. An overview of machine learning is presented in Section 2. In addition, a detailed review of the regression methods is discussed in Section 3. Moreover, an analysis of the current approaches used in antenna parameters optimization is presented and discussed in Section 4. Finally, the conclusions of this work are presented in Section 5.

2 Machine Learning Overview

The concept of machine learning dates back to the 1950s; there has been an unexpected interest in ML techniques in recent years. This has been sparked by the abundance of data available in the world's digital era and access to high-performance computation and improved mathematical formulation and grasp of learning approaches. ML innovations, such as generative adversarial networks and deep reinforcement learning, have changed many sectors of study and industry. Although some forms of ML algorithms, particularly deep neural networks, are considered "Black Box" technologies, they could achieve good performance in practice [6].

Artificial neural network (ANN) is one of the most common machine learning techniques that can be used in conjunction with traditional CEM approaches to reduce the energy function. In addition, the stability of ANNs results in achieving solutions to MoM. Based on the current distributed computing developments, neural networks may be utilized to effectively solve large and complicated tasks due to their capabilities from the distributed and parallel processing perspectives. ANNs were also employed with FDTD to speed up EM issues, and they proved to be effective. For instance, a global modeling method for Millimeter-Wave Circuits and Microwave design can be achieved by a considerably quicker global modeling than the usual FDTD approach [7-9].

ANN models, in general, have positive properties that aid in the solution of EM tasks. An essential property of ANNs is their ability to approximate the mappings of nonlinear input-output data by maximizing the relationship between input and output data. On the other hand, the adaptability of ANN to the changes in the training environment is another significant property of it. One of the key benefits of machine learning is that it reduces the computation time observed in CEM approaches. This benefit is obvious when optimizing several parameters or when it is needed to build a large model structure. The geometries of microstrip antennas, particularly complicated geometrical antennas, or the new model structures are still challenging to be handled efficiently using the established theories of antennas. This can be shown when given some of these geometries have low accuracy. In real-time, machine learning may be used to model and forecast scattering problems as well as evaluate and improve antennas performance [10–12].

ANNs can be easily implemented on high-performance computers using a variety of frameworks, and they can simulate electromagnetic structures efficiently and in considerably reduced time and computing resources along with insignificant error factors. As the closed-form solutions are still challenging to find, in the context of antenna design, ML can be the efficient approach for reducing the time needed in trial-and-error experiments conducted for getting the optimal values of geometrical parameters based on a set of predefined design requirements, such as the characteristics of the desired radiation [13, 14].

2.1 Types of Machine Learning

2.1.1 Supervised Learning

In this type of machine learning, the generalization of a model can be achieved on a collection of pairs of labeled input-output to predict unknown input. In supervised learning, there is a separation between datasets used in training and testing. The training set samples are usually linked with targets or labels, but the samples of the test set lack these labels. It is possible to break the tasks of supervised learning into the following sections. 1) Classification: The objective of classification is to classify data using a limited number of categories. Multi-class classification usually includes a set of more than two classes, whereas binary classification is based on a collection of two classes. 2)Regression: The objective of regression is to predict the label of real values for data that has yet to be seen. Some of the regression techniques available are support vector regression (SVR) [15], kernel ridge regression (KRR) [16], linear regression (LR) [17], and least absolute shrinkage and selection operator (LASSO) [18].

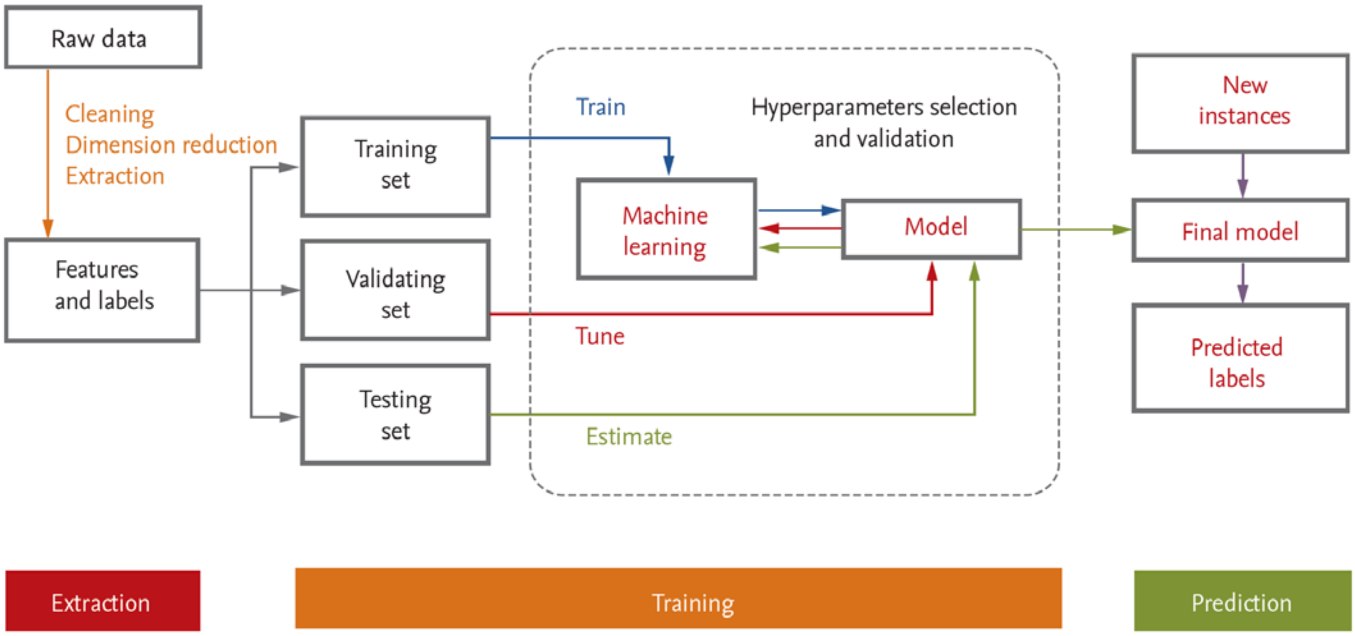

Figure 2: Workflow to develop a supervised machine-learning-based predictive model [14]

The workflow of supervised learning is depicted in Figure 2. This figure starts with preprocessing the raw data by cleaning, dimension reduction, and feature extraction. Then, the preprocessed features are split into training, validation, test sets, along with their target labels. The machine learning algorithm is applied to the training set with the help of a validation set to improve the generalization capability of the trained model. Finally, the resulting model is stored to predict the labels of the new unseen test data.

2.1.2 Unsupervised Learning

In this type of machine learning, specific labels for fresh data can be predicted after obtaining an unlabeled dataset. Unsupervised learning, unlike supervised learning, does not distinguish between train and test data. Two applications/tasks of unsupervised learning are presented in the following. 1) Dimensionality reduction: This task involves decreasing the number of dimensions in which data is represented by preserving the original representation's key characteristics. 2) Clustering: This task involves finding the areas or groups within big datasets based on the similarity of their characteristics.

2.1.3 Reinforcement Learning

This type of machine learning involves an agent that engages actively with the environment used to learn this agent to attain a target objective. This paradigm, which is used in cognitive sciences, optimization, and control theory, is based on the concept of incentives provided to the agent in quantities proportionate to the agent's successes, which he wants to maximize. Markov decision processes (MDPs), which describe the interactions and their working environment, are a frequently used model in this subject. This model is called Markovian since the reward probabilities and transitions are based on the present state of the model rather than its whole history [19].

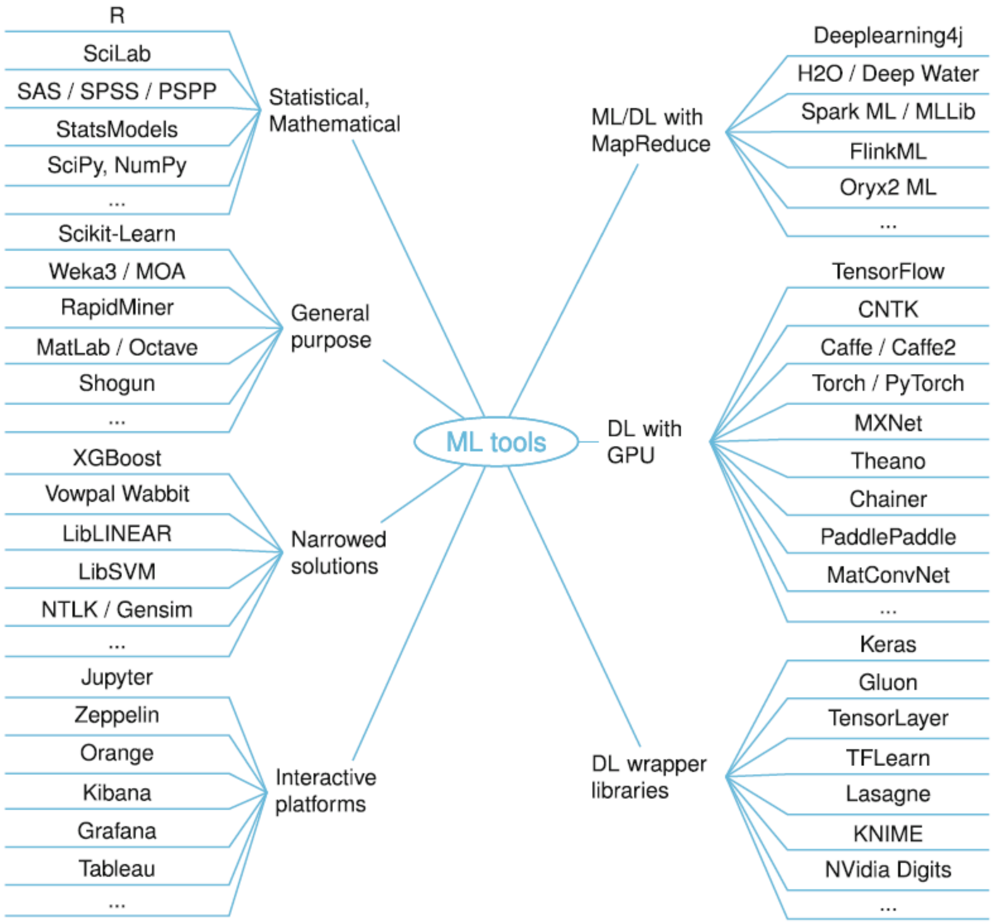

Figure 3: Machine learning tools, frameworks, and platforms [20]

2.2 Machine Learning Frameworks

There is a slew of open-source frameworks available for real-world cases to apply the machine and deep learning ideas. These platforms, built on efficient code implemented in Java, R, Python, etc., provide quick and straightforward access to various methods, making them critical research and development tools. Microsoft CNTK [21], CAFFE [22], Tensorflow [23], Scikit-Learn [24], Apache-Spark [25], and many other tools are some of the libraries currently available, as shown in Figure 3. Additionally, WEKA software is considered one of the most significant off-the-shelf technologies [26], is accessible for professionals with domain-specific experience, without the need for deep expertise in ML. These technologies could provide them with ready-made implementations of gathering data and tweaking hyperparameters, their sole responsibilities.

3 Regression Methods Overview

When it comes to using machine learning in antenna design, regression methods are a must-have. A model describing the non-linear mapping function was created utilizing these methods and a large dataset. The geometrical dimensions and properties of the antenna may be determined using a linear relationship. ANNs and SVR are the most commonly used machine learning techniques for antenna design. LASSO, LR, and Kriging Regression are less commonly utilized regression algorithms. This section offers a mathematical overview of the machine learning techniques used in optimizing and designing microstrip antennas.

3.1 Linear regression

Linear regression (LR) is a statistical technique used to connect certain variables with their corresponding goals, usually represented numerically, in a linear space. It is considered to be one of the simplest regression methods. To develop a model in an uncertain stochastic environment, a set of labeled instances is examined $\{(x_i, y_i)\}_{i=1}^{N}$ to find the parameters w; b of the function

$$f_{\{w,b\}}(x) = wx + b \quad (1),$$

where N is the set size under consideration, x_i is a vector of a dimension D with examples $i = 1, \ldots, N, y_i \in R$ are the numeric values of the goal, w_i is a weight vector in D-dimensional space, and D and b are some real values. The ideal values of b and w must be found for the model to give robust and accurate forecasting of y. To that aim, the cost function in the following is needed to be minimized,

$$l(w, b) = \frac{1}{N}\sum_{i=1}^{N}\left(f_{w,b}(x_i) - y_i\right)^2 \quad (2).$$

Based on this formula, the average loss (or empirical risk) can be determined based on this squared error loss function and after training the model on the available training set. It takes into consideration the average penalty for misclassifying cases $I = 1, \ldots, N$. The cost function is reduced using the gradient descent optimization method (GD). In LR, GD is used to repeatedly discover the function's minimum by progressively moving away from the gradient's negative value.

3.2 LASSO regression

The LASSO method is based on mean-squared error, L1 regularization for modeling linear data. This method is also called Sparse Linear Regression. L1 regularization is applied to produce a sparse solution, with sparsity referring to parameters with a zero optimum value. As a result, the LASSO method may be utilized to pick features. The following equation is used to get the LASSO estimate.

$$\sum_{i=1}^{N}(wx_i + b - y_i)^2 + \lambda \|w\|_1 \quad (3),$$

where $\|w\|_1$ is refers to the L1 norm which can be measured by $\sum_{i=1}^{d}|w_i|$ and λ is the regularization parameter.

3.3 Artificial neural networks

The human brain mainly inspires artificial neural networks (ANN) regarding neurons and their interconnections. These neurons represent the primary computing cells of a neural network. In addition, the generalization based on experimental information forms a robust capability that enables neural networks to perform better when applied to real test cases. One of the main applications of ANN is the regression process, as it can be considered an excellent approach for function approximation. The architecture of ANN is composed of a set of layers, namely the input layer, (zero or more) hidden layers, and the output layer. The computation performed at each neuron is performed in terms of the following function [27].

$$f_l(x) = g_l(W_l x + b_l) \quad (4)$$

where l represents the layer in which the neuron is located, x denotes the input to this neuron. The interconnections to the neuron are denoted by W and the bias of the layer l is represented by b. The activation function of g can be one of the types shown in Table 1 [28].

Table 1: Potential activation functions of a neural network

Activation function	Definition
Logistic function	$g(x) = \frac{1}{1+e^{-x}}$
Hyperbolic tangent function	$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
ReLU Function	$relu(x) = \begin{cases} 0 \text{ if } x < 0 \\ x \text{ otherwise} \end{cases}$

Backpropagation algorithm, a prominent and extensively used training technique, can be used to estimate the cost function's gradient descent of a neural network non-linearly. Backpropagation is an iterative computer technique based on GD that seeks to discover the cost function's local minimum. It is made up of two passes, namely, forward and backward passes. Finally, the output layer's activation functions compute an output that is saved during the forward passes to be used in the subsequent pass [29].

Table 2: Potential kernel functions used in support vector regression

Kernel function	Definition
Radial basis function	$K(X_i,X_j) = \exp(-\gamma \left\|X_i - X_j\right\|^2)$
Polynomial kernel	$K(X_i,X_j) = (-\gamma\, X_i.X_j + r)^d$
Wave Kernel	$K(X_i,X_j) = \frac{x}{\left\|X_i - X_j\right\|} \sin\left(\frac{\left\|X_i - X_j\right\|}{\gamma}\right)$
Sigmoid kernel	$K(X_i,X_j) = \tanh(\gamma X_i.X_j + r)$
Exponential kernel	$K(X_i,X_j) = \exp\left(-\frac{\left\|X_i - X_j\right\|}{\gamma}\right)$

3.4 Support vector regression

Another machine learning technique used in parameter estimation is support vector machines (SVM). This technique is widely used in the literature for classification tasks, but it also can be used for regression tasks and is thus called support vector regression (SVR). The regression task of SVR works similar to the classification task, in which the data points are divided into two sets; points that lay within a margin and other points that lay outside the margin [30, 31]. In support vector regression, the functions of the linear hypothesis are defined as

$$H = \{x \rightarrow w\,.\emptyset(x_i) + b : w \in R^N, b \in R\} \quad (5).$$

The feature mapping is denoted by $\emptyset$ which is referred to by kernel function K. The cost function is then minimized to find out the best values of b and w. The minimization of the cost function can be applied as

$$\frac{1}{2}|w^2| + C \sum_{i=1}^{m} |y_i - (w\,.\,\emptyset(x_i) + b|_\epsilon \quad (6),$$

where $\phi(.)$ is the feature mapping function, which is also known as kernel function K. The most popular kernel functions used in regression tasks are presented in Table 2.

3.5 Gaussian process regression

This type of regression is a special type of a Gaussian stochastic process. It depends on utilizing the available samples to predict the approximate distribution of the new data points. The prediction of a new data point can be measured based on the labeled samples as

$$\hat{y}\,(x^*) = \mu + r^T R^{-1}(y - I\mu) \quad (7),$$

where μ is the distribution mean and I is a vector of ones of dimension $n \times 1$. The correlation between x_i and x_j is denoted by R_i, and r is an array of correlations.

Table 3: Machine learning model optimization algorithms

Algorithm	Features
Gradient descent [32]	It is slow as the parameters optimization is done after calculating the gradient of the dataset. While training, it may stuck in the local minima. However, it is considered the simplest algorithm for parameter optimization.
Adaptive moment estimation [33]	It is faster than gradient descent and efficient in solving optimization problems. In addition, it can deal with models with a large number of parameters and a large training set.
Levenberg-Marquardt algorithm [34]	This algorithm is used to find the function's local minimum based on batch form trust-region optimization. For small and medium-sized sample sets, this algorithm is efficient and fast.
Bayesian regularization [35]	This algorithm is usually used as an alternative to the backpropagation algorithm for training neural networks. The neural network based on this algorithm is very efficient for the perspectives of overfitting and overtraining.
Evolutionary algorithms [36]	The evolutionary theory of creatures forms the basic idea of this set of algorithms; which includes particle swarm optimization (PSO), differential evolution (DE), and genetic algorithms (GA).

3.6 Optimization algorithms

The performance of a machine learning model depends mainly on the algorithm used to train and optimize it. A set of training algorithms can be used with the previously mentioned machine learning regression models. The most common optimization algorithms used in learning the parameters of antennas are described in Table. 3. In this table, the most common algorithms are presented along with the features of each algorithm. The choice from this list of algorithms depends on the task at hand and the dataset available for training the machine learning model.

4 Antenna Optimization Overview

In the literature, many research efforts employed machine learning models for optimizing the parameters of microstrip antennas. The most commonly used model to perform this optimization is the neural network. However, the antenna structure determines the number of geometrical parameters needed in the optimization process, and as this number increases, it becomes hard for the model to derive a better relationship among these parameters. Table 4 presents the recent approaches employed for optimizing the parameters of microstrip antennas. As shown in the table, it can be noted that the most common method in parameter optimization is neural networks in the form of MLP or SVR with the help of other approaches. In addition, most of the parameters targeted by parameter optimization are the resonance frequency based on the geometrical information of the microstrip antenna. Moreover, the table shows the achievement of each approach in optimizing the target parameters.

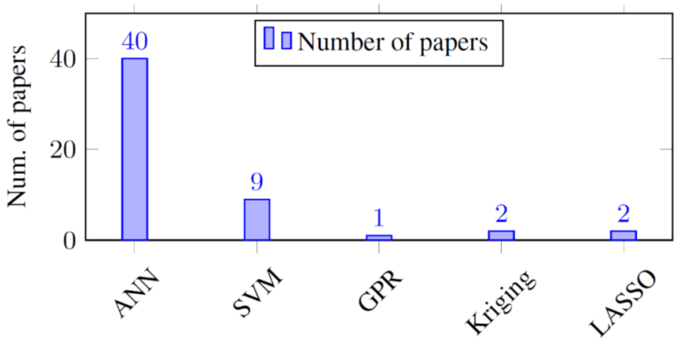

Figure 4: Number of research papers based on the machine learning approach.

Table 4: Recent approaches for optimizing the parameters of microstrip antennas

Paper	Approach	Input	Output	Results
[37]	RBF	Patch's radius, and substrate's permittivity and height	Resonant frequency	Error = 2 MHz
[38]	MLP	Substrate's resonant frequency, thickness, and relative dielectric constant	Radius, effective radius, and directivity of the patch	MSE was 9.7^{-4}, 9.80×10^{-4}, and 7.76×10^{-4} for the respective inputs
[39]	Standard SVR	Height and length of the rectangular patch	Input impedance Rn, bandwidth (BW), and resonant frequency fr.	Percentages of error are 1.21% for fr , 2.15% for BW, and 0.2% for Rn
[40]	SVR + Gaussian kernel	Patch's width and length	Voltage standing wave ratio (VSWR), gain, and resonant frequency	NA
[41]	SVR + different kernel configurations	Patch's height and width	Resonant frequency	Error = 3dB
[42]	MLP + feed forward back propagation, resilient backpropagation, LM, RBF	Patch's length and width, and substrate's dielectric constant r and thickness	Resonant frequency	Error = 3.5×10^{-14}
[10]	NN + PSO	Patch's height and resonant frequency, and substrate's permittivity	Width and length of the patch	MSE = 0.104
[43]	NN + GA	Patch's length L, width W, and Substrate's dielectric constant r	Resonant frequency	Error = 0.013545 GHz
[44]	SVM	Substrate's thickness, radius, and dielectric constant	Resonant frequency	Error percentage = 0.35%
[45]	MLP	Substrate's permittivity, height, and radius	Resonant frequency	Error percentage = 0.10721%
[46]	RBF	Patch's eccentricity and substrate's permittivity, resonance frequency, and height	Resonant frequency	Error percentage = 0.006%

On the other hand, Figure 4 shows the number of papers published in the literature for optimizing antenna parameters is depicted based on the machine learning algorithm. This figure shows that most research efforts are based on artificial neural networks (ANN) followed by support vector machines (SVM). In addition, it Cn be noted that fewer research efforts are based on Gaussian, Kriging, and LASSO regression approaches.

Figure 5 shows the number of recently published papers that optimize the parameters of different types of microstrip antennas. In this figure, the rectangular and reflectarrays are the most popular antenna types attracted researchers in recent years. This is due to the simplicity of the design of these antennas and the efficiency of the machine learning algorithms in optimizing their parameters.

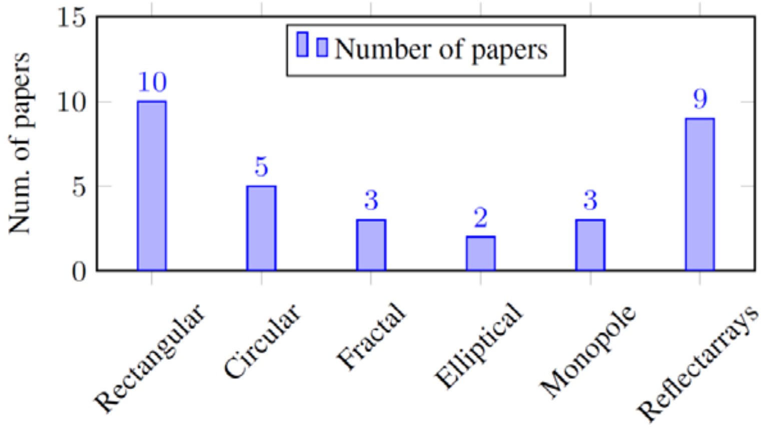

Figure 5: Number of research papers based on antenna types

The results of searching for "antenna machine learning" in both Scopus and Web of Science scientific research databases are shown in Figure 6. In this figure, it is obvious that the number of scientific papers released in the perspective of antenna parameter optimization has recently increased. This makes the application of machine learning in antenna design is promising and attracting more researchers in the coming years.

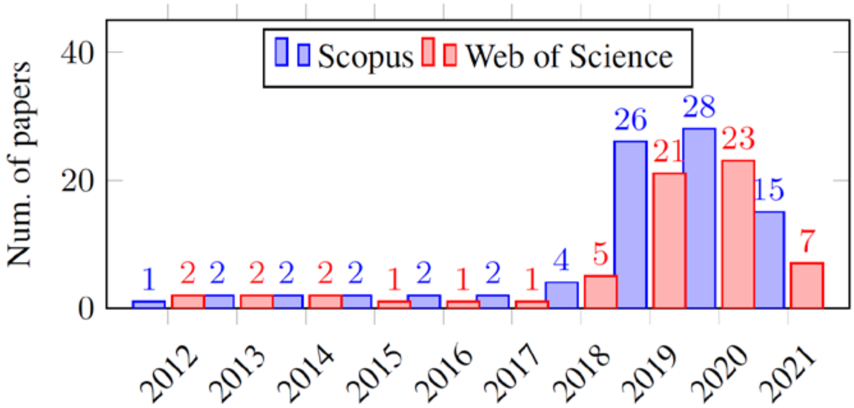

Figure 6: Number of research papers based on antenna types

These figures clearly show that optimizing antenna parameters using machine learning is increasingly attracting more researchers. Meanwhile, the progress in machine learning techniques and approaches can help researchers to achieve this goal more efficiently. On the other hand, it can be noted that the application of deep learning for the task of parameter optimization is not widespread due to the lack of a large dataset that is necessary for training the deep network. However, model transfer approaches can help researchers in this case.

5 Conclusion

When the antenna design and its structure become more complicated, the significance of machine learning in speeding up the design process becomes more apparent. Therefore, we presented in this study a thorough examination of the design and analysis of antennas using machine learning. We studied in this paper the recent approaches used in optimizing the design parameters of microstrip antennas. It is clear from this study that the artificial neural networks (ANNs) approach is dominating this research field with many software packages and frameworks available for this purpose and because they offer resilience in providing accurate results when compared with traditional techniques. In addition, we presented a variety of published research articles in the literature that employ machine learning techniques in their designs. Overall, recent machine learning approaches have been introduced in this paper to supply readers with the essential understanding required for applying these approaches in the field of microstrip antenna parameters optimization.

6 Availability of Data and Material

Data can be made available by contacting the corresponding author.

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