A Comprehensive Survey to Explore Microstrip Antennas optimization using Machine Learning

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Abstract: Because of their intrinsic limitations in handling complex optimization problems involving multiple, frequently conflicting design objectives, conventional antenna design approaches occasionally struggle to meet the requirements of more effective, economical, and compact antenna systems. Because machine learning has gained a lot of attention as a means of finding antenna optimization solutions for the current generation of wireless communication networks, this paper presents a thorough literature survey on the application of ML in antenna design and optimization by using advanced optimization techniques to improve microstrip antenna designs. Training machine learning models for output optimization and antenna parameter prediction is demonstrated. Better computational feasibility features, fewer simulations, faster antenna design, and the viability of antenna applications in comparison to traditional methods are emphasized. According to the study's findings, including machine learning into the design of microstrip antennas can expedite the process while significantly enhancing performance metrics. The comparison analysis opens the door for the development of more intelligent telecommunication engineering by providing deep insights into the efficient application of each machine learning technique in antenna design scenarios. This study lays the groundwork for further research, where more complex machine learning models may be developed and even integrated into real-time design processes for telecom applications.

Keywords: Artificial Intelligence, Antenna optimization, Machine learning, Microstrip antenna, Telecommunication.

1. INTRODUCTION

Human-like skills like learning, problem-solving, and decision-making are being developed by machines. ML uses data analysis to automate the creation of analytical models. With its widespread applications in automating repetitive operations and providing revolutionary insights across all fields of science and engineering, machine learning (ML) has become a global phenomenon in recent decades. The antenna is one of the numerous applications that can benefit from the use of machine learning. Antenna system design and optimization are critical to effective signal transmission and reception in the telecommunications industry [1]. ML is used to optimize the performance of antennas as their complexity rises. Multiple trained models for antenna design applications have been produced using machine learning (ML), which has increased the speed and efficiency of these applications. Without the use of machine learning techniques, designing and maintaining antennas is challenging. It is also very difficult to accelerate simulation, reduce simulation, maintain work feasibility, and calculate antenna behavior. [2]

The optical approximation approach can be used to observe the radiation field of antennas. Partial differential equations with boundary conditions must be solved for antenna simulations. Computers and electromagnetic simulators can be used for these. ML is selected as the ideal technique to lessen these anomalies and boost optimum outcomes. Since machine learning (ML) is still a component of artificial intelligence (AI) and focuses on obtaining information from data, it is constantly utilized in the statistical data science domain.

In the areas of antenna design and antenna behavior prediction, machine learning (ML) has enormous potential for greatly speeding up the process while preserving accuracy. Antennas are characterized by their intricate shapes and usually lack closed-form solutions. Maxwell's equations are used in computational electromagnetics (CEM) [3] to describe how electromagnetic fields interact with antennas. In order to obtain a physical understanding of the antenna design, approximate solutions are typically employed. As numerical techniques improved, linear antennas were solved using integral equations. However, the quality, quantity, and availability of data—all of which might be difficult to come by in some situations are critical to the success of machine learning techniques. Since there is currently no standardized dataset for antennas, like those for computer vision, this data must be obtained, if it isn't already accessible, from the standpoint of antenna design. Later, as computers advanced, it became feasible to use integral and differential equation solvers to solve Maxwell's equations. This can be accomplished by using CEM simulation software to simulate the desired antenna on a broad range of parameters. To train an ML model and determine whether it is successful in generalizing on additional inputs, a dataset can be constructed and separated into train, cross-validation, and test sets based on the findings achieved. [4]

. The use of machine learning (ML) in antenna design and optimization is presented and examined in this work, which also offers a thorough analysis of all antenna designs that have used various ML techniques in the literature.

2. METHODOLOGY

2.1 Overview of Traditional Optimisation Methods

However, the increasing demands on telecommunications networks, driven by the rise in data traffic and the introduction of technologies like 5G and IoT, are posing significant challenges to the conventional methods of building microstrip antennas. These problems include the need for antennas that are more compact and economical while still having a wider frequency range, more amplification, and improved focus. Traditional design techniques are sometimes slow and may not fully explore the complex design possibilities associated with modern antenna designs because they mainly rely on manual adjustment and simplified models. Antenna design has made extensive use of traditional optimization techniques, which mostly rely on gradient-based algorithms and human adjustment [5]. Despite the fact that these approaches have yielded useful designs, they usually fall short in meeting the complex, multifaceted demands of modern antenna standards. In order to automate and enhance the design process, academics have begun looking into machine learning-based computational optimization techniques.

2.2 Genetic Algorithms in Antenna Design

Because of its ability to mimic natural evolutionary processes and efficiently explore large solution spaces, Genetic Algorithms (GAs) have gained popularity. It will assess how well the antennas optimize with a number of complex features. To determine the advantages and potential drawbacks of this approach in reaching the desired antenna performance, a thorough analysis will be carried out [1]. A fitness function, which is frequently employed to maximize or minimize antenna parameters, defines the GA optimization process. For example, eq. 1 might be used to build the fitness function for optimizing the gain and bandwidth.

$$f(x) = w1.Gain(x) + w2.Bandwidth(x) \tag{1}$$

Where w1 and w2 are weights that reflect the relative importance of each parameter in the overall design.

2.3 Implementation of Particle Swarm optimization in Electromagnetic Applications

Inspired by the collective behavior of animals, especially flocks of birds, Particle Swarm Optimization (PSO) is a powerful algorithm. The theoretical underpinnings of particle swarm optimization (PSO) and its application to various electromagnetic design issues will be examined in this. Research demonstrating PSO's superior performance over other methods will be highlighted.

Its convergence behavior depends on the update rules that control particle position and velocity in Particle Swarm Optimisation (PSO), which are expressed mathematically in eq. 2.

$$vi + 1 = w.vi + c1.r1.(pbest - xi) + c2.r2.(gbest - xi)xi + 1 \ = xi + vi + 1 \quad (2)$$

Where v is the particle velocity, x is the current position, pbest is the best known position of the particle, gbest is the best known position among all particles, r1,r2 are random numbers, and c1,c2 are learning factors.

2.4 Incorporating Machine Learning into Antenna Design

Antenna design is one of the many technical fields where machine learning is having a revolutionary impact. Machine learning techniques have improved performance forecasts and significantly shortened design times. The development of ideal antenna designs may result from its capacity to learn from data and generate predictions [6].In machine learning, eq. 3 represents the loss function used in the training phase to minimize the difference in predicted antenna characteristics.

$$Loss = N_1 \sum_{i=1} N(yi - yi^\wedge)2 \quad (3)$$

Where N is the number of training examples, yi is the actual value, and yi^ is the model's prediction.

3. OPTIMIZATION ALGORITHMS AND ML MODELS

Since optimization techniques are employed to determine the model's ideal weight and parameters, they are regarded as a crucial component of machine learning. The best values at the lowest cost function are produced by training algorithms. The outcome of training is ML's performance. The designer, the type of data, and the data accessible all influence how optimizers are implemented. These are all predicated on the application of optimization algorithms. The constantly popular antenna optimizers include

3.1 Gradient Descent

The gradient descent algorithm, also known as GD, changes the values once the entire data set has been executed. It slows down the optimizer. Additionally, because it enters stuck mode in local minima, the optimizer is susceptible. This optimizer's latency causes it to perform poorly when the number of data samples reaches millions. The Levenberg-Marquardt (LM) algorithm is used to optimize this. It works well with datasets that are medium or small in size. [7]

3.2 Bayesian Regularized Artificial Neural Network (BRANN)

Artificial Neural Networks are trained using Bayesian regularization (BR) with the goal of avoiding the cross-validation step [8]. The purpose of BRANNs is to avoid overtraining or underfitting data sets.

3.3 Algorithms Based on Evolution

One type of algorithm derived from the evolutionary patterns of living things is the evolutionary algorithm. It includes particle swarm optimization (PSO), a genetic technique that is frequently employed in optimization [9]. It can also be applied to antenna design.

A significant number of works have been done in ML for antenna design and optimization. The majority of studies have demonstrated that ANN was used to determine the relationships between antenna parameters and their properties. However, as the complexity of the antenna structure increases, so do the parameters, making it harder to establish a connection and retrieve the data. The general optimization procedure involves simulating an antenna, obtaining output, and then applying machine learning techniques to expedite the process and bring the desired values closer. Generally speaking, the following procedures are taken:

1) Simulation-derived inputs and their corresponding outputs are saved.
2) Training, validation, and test sets are slitted into the generated database.
3) This data is utilized to train a machine learning system. The choice depends on the quantity of data and the intricacy of the approach to problem-solving.
4) Forecasting the values that were taken out of training.
5) Even processes need to be executed in order to create training data blocks. The model has been created. Accurate forecasts may be made more quickly, effectively, and precisely.

3.4 Circular Patch Micro Strip Antenna

Circular patch antennas are a common type of micro-strip antenna. Resonance frequency is generated utilizing machine learning programming and radial basis function (RBF) networks derived from artificial neural networks (ANNs), which use permittivity and the patch's height and radius as feed inputs. The effectiveness of several algorithms—including extended delta-bar-delta (EDBD), directed random search (DRS), genetic algorithms, delta-bar-delta (DBD), and rapid propagation (QP)—in training machine learning programming is being monitored and recorded. Neural networks were used to build and calculate a circular antenna's feed.

The first network

A two-layered neural network (NN) was used to forecast the patch antenna's radius, directivity, and effective radius. Antenna thickness, resonance frequency, dielectric constant, and the LM optimization process were the input parameters. 45 training samples were used, and the Mean Square Error for each input was determined to be $9.70 \times 10{-}4$, $9.80 \times 10{-}4$, and $7.76 \times 10{-}4$.

The second network

To estimate input impedance, a radial basis function neural model with a single hidden layer was used [10]. After testing, the trained samples, which were pairs of 200 input-output, yielded a Mean Square Error of $2.69 \times 10{-}4$. Neural model and test generation is based on resonance frequency on circular patch radius, height, and permittivity. Resonance frequency, antenna efficiency, gain, bandwidth, and return loss (RL) were all estimated using a Feed Forward Back Propagation neural network (NN). The generated results have an MSE of $9.96 \times 10{-}7$.

3.5 Fractal Patch

Artificial neural networks were used in the construction of fractal patch antennas, which are micro strip antennas. To calculate the resonance frequency, RL, and gain, an Artificial Neural Networks with BP algorithm was used. The dataset for different antenna shape iterations was generated using IE3D software. The resulting values are used to train a model that determines the feed point's location in order to produce the best value impedance matching. In another study, artificial neural networks were used to determine the ideal value for a square-shaped antenna. The neural network iteration was run in high frequency software to get efficient qualities for the antenna size reduction. It was discussed how to use artificial neural networks to design quasi-fractal patch antennas [11]. Antenna parameters that function on a certain frequency were noted. The model, which forecasts the precise matching of a parameter to the corresponding frequency of operation, is then trained using the data.

3.6 Elliptical Patch

Elliptical antenna design was done using artificial neural networks. The elliptical micro-strip patch antenna was designed utilizing artificial neural networks with radial basis functions [12]. Permittivity, eccentricity, resonance frequency for even mode, semi-major axis, and resonance frequency for specific mode are input parameters. The error percentages in the comparative results were modest, at 0.006% and 0.043%. In an alternative design approach, a Feed Forward Back Propagation neural network was trained using the primary axes as input parameters to calculate the antenna's gain and return loss. A set or block of data was gathered during the simulation process. Once more, the comparing findings demonstrated a very good low inaccuracy of 0.2014 dB for the RL and 0.0202 dB for the Gain.

3.7 Substrate Integrated Waveguide

The SIW patch antenna was predicted using artificial neural networks. Resonance frequency and the intended return loss are being taken as inputs. The data block taken from HFSS compilers was trained using the back propagation technique and feed-forward machine learning programming. There was discussion on utilizing machine learning to design a broadband millimeter wave Substrate integrated waveguide cavity-backed slot antenna [13, 14]. A well-designed machine learning aided method with extra features (MLOMAF) was used as a reference comparison to the machine learning assisted optimization method (MLOM). The population-based meta-heuristic optimization technique is employed. After setting up a sample database, Latin-Hypercube-Sampling (LHS) is used to train the database, and the output is used to build a model. It was observed that the method stopped after 12 rounds, reducing the latency and making the antenna design and settings simpler.

4. EVALUATION METRICS AND EXPERIMENTAL DESIGN

It is a fact that higher frequency antennas are expected to be smaller in size, due to the inversely proportionate connection that exists among the resonant frequency and patch size. The formulas that follow are able to use to get the typical antenna's size. [15]:

Rectangular patch diemnsions:

Width of patch $W_p = \frac{c}{2f}\sqrt{\frac{2}{\varepsilon_r+1}}$, (4)

Length of patch $L_p = L_{eff} - 2\Delta L$, (5)

Where,

Effective-length $L_{eff} = \frac{c}{2f\sqrt{\varepsilon_{reff}}}$, (6)

Effective-relative-permittivity,

$$\varepsilon_{reff} = \frac{\varepsilon_r+1}{2} + \frac{\varepsilon_r-1}{2}\left[1+12\frac{H_{sub}}{W_p}\right]^{-\frac{1}{2}} , \quad (7)$$

Normalized extension in length,

$$\Delta L = 0.412\, H_{sub}\frac{(\varepsilon_{reff}+0.3)\left(\frac{W_p}{H_{sub}}+0.264\right)}{(\varepsilon_{reff}-0.258)\left(\frac{W_p}{H_{sub}}+0.8\right)} . \quad (8)$$

Transmission line dimensions:

Wave length $\lambda = \frac{c}{f}$, (9)

Guided wave length $\lambda_g = \frac{\lambda}{\sqrt{\varepsilon_{reff}}}$, (10)

Transmission line length $L_{tl} = \frac{\lambda_g}{4}$ (11)

Transmission line width $W_{tl} = \frac{L_f}{2}$ (12)

Ground dimensions:

Ground length $L_g = L_p + 6H_{sub}$ (13)

Ground width $W_g = W_p + 6H_{sub}$ (14)

In fore mentioned relations, Hsub is substrate's height, ε_r is relative-dielectric-permittivity & f is resonant frequency. From the research study of [16-19], the dimensions of the conventional rectangular microstrip patch antenna were calculated using the eq.4 to eq.14.
The quantitative expressions eq. 15- eq.18 used to evaluate antenna performance parameters, are given by:
The percentage of bandwidth was calculated using the eq. (15) .

$$Bandwidth\ (\%) = \frac{Upper\ frequency - lower\ frequency}{central\ frequency} \times 100 \quad (15)$$

$$Gain\ (G) = \eta \times D \quad (16)$$

$$Efficiency\ (\eta) = \frac{Power\ Radiated}{Input\ Power} \quad (17)$$

$$Directivity\ (D) = 2(\frac{n \times d}{\lambda}) \quad (18)$$

Where 'η' is efficiency, 'D' is Directivity, 'n' is number of elements in array, 'd' is inter-element spacing, 'c' is the free space velocity, 'f' is the resonant frequency and 'λ' is wavelength.
In the context of antenna theory two perpendicular linearly-polarized fields $(\hat{x}E_x + \hat{y}E_y)$ superposed with their phase difference $\delta_L = \pm\left(\frac{\pi}{2} + n\pi\right), n = 0,1,2,3, \ldots\ldots$, can be used to depict the circular polarization of antenna electromagnetic waves.

The electric field can be decomposed in to two normalized components,

$$E = E_x + E_y \tag{19}$$

Where $E_x = E_x e^{-j\beta z}\hat{x}$ and $E_x = E_y e^{-j\beta z} e^{j\delta_L}\hat{y}$

The eq. (19) can be expressed as follows in the far field if the antenna is assumed to be propagating waves along the Z-axis and Z=0 at a fixed position.

$$E = \hat{x}E_x + \hat{y}E_y e^{j\delta_L} \tag{20}$$

When the two orthogonal electric field component vectors have equal magnitudes and are precisely 90° out of phase, circular polarization results. This means that for circular polarization, $E_x = E_y = E_m$ should exist. Consequently, the eq. (20) for circular polarization becomes

$$E = E_x(\hat{x} \pm j\hat{y}) \tag{21}$$

An essential factor in figuring out the polarization (as eq. 21) of a circularly polarized antenna is the axial ratio. Perfect circular polarization is ensured by an axial ratio of 0 dB, although in real-world situations, an AR of 3 dB is deemed enough [20].

The procedures for implementing these eq.s, quantifying results, and verifying the effectiveness of ML-optimized designs are described [21]. The design incorporates control experiments and predefined parameters to rigorously examine the efficacy of various ML techniques.

5. DISCUSSION

5.1 Analysis of machine learning techniques in Addressing Design Complexities

The optimization function (eq. 22) can be used to assess GA's effectiveness.

$$Minimize\ f(x) = -(Gain(x) + \lambda \times Bandwidth(x)) \tag{22}$$

The relevance of bandwidth in relation to gain is weighted by λ, a balancing factor. This formula aids in assessing GA's capacity to concurrently optimize several competing criteria.

5.2 Practical Implications of the Findings

The practical results of integrating artificial intelligence into antenna design processes are the main topic of this discussion, with a focus on the benefits of increased efficiency and cost-effectiveness [22]. Variables like reduced design time and better resource use may be included in a cost savings equation.

$$Cost\ Savings = Old\ Cost\text{-New Cost= Old Time} \times Rate - New\ Time \times Rate \tag{23}$$

The clear financial benefits of using more efficient artificial intelligence methods are seen in equation 23.

5.3 Recommendations for Future Research and Applications

Equations that clarify each method's working principles might be used to improve the discussion of its advantages and disadvantages. For instance, the PSO update process can be mathematically expressed as follows:

$$vi + 1 = \omega vi + \phi p(pbesti - xi) + \phi g(gbesti - xi)xi + 1 = xi + vi + 1 \tag{24}$$

The inertia weight and the cognitive and social coefficients are denoted by ω, ϕp, and ϕg, respectively. The balance between exploration (global search) and exploitation (local search) in PSO is better understood in light of this.

One can suggest modifications to current equations or suggest new formulations in order to measure the potential for further research. For example, a combined optimization function might be used in a hybrid artificial intelligence model:

$$fhybrid(x) = \alpha fGA(x) + \beta fPSO(x) + \gamma fDL(x) \tag{25}$$

where each technique's influence is determined by the coefficients α, β, and γ. More complex, integrated optimization techniques can be developed theoretically using this equation.

6. Conclusion

In the field of antenna design, where precision and efficiency are crucial, this survey is extremely significant. The work offers a method for developing more efficient and effective antenna systems by utilizing the benefits of these advanced computational tools. Particle Swarm Optimization (PSO) and genetic algorithms are useful methods for effectively investigating the wide range of design options in the early stages of design. However, in order to meet exact performance requirements, machine learning models can improve antenna attributes. This all-encompassing method not only streamlines the design process but also cuts down on the time and cost associated with creating sophisticated antenna systems. With possible innovations that could completely alter the architecture and optimization of antenna systems, machine learning has great promise in the field of telecommunications. ML's ability to process large volumes of data and extract insights from patterns could lead to more adaptive and self-governing antenna systems. Considering environmental conditions and communication needs, these systems are able to dynamically adapt and optimize their performance in real-time. Furthermore, integrating machine learning with upcoming technologies such as 5G networks and the Internet of Things (IoT) could result in more intelligent, effective, and flexible telecommunications infrastructures that can adjust to the needs of contemporary communication.

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