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Design and Optimization of Planar Antenna Using Machine Learning for 5G Sub-6 Ghz

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Abstract— In these days, it is inevitable to apply machine learn- ing techniques in all fields of science and engineering including electromagnetic applications. Traditional antenna optimization methods involve solving modified versions of the original antenna design for each iteration, resulting in time-consuming processes dependent on convergence criteria and iteration times. This work introduces an approach for designing a planar antenna tailored for the Sub-6 GHz band of the fifth generation (5G) wireless network. The antenna has linear polarization characteristics and is intended to cover the 3.3-3.7 Ghz frequency band. The datasets for the suggested antenna are created using parametric analysis carried out in HFSS software to aid in the optimization process. Machine learning algorithms are subsequently employed to optimize the reflection coefficient (S11) of the antenna design. The results obtained through these machine learning techniques align closely with the simulated values in HFSS software. Finally, the optimized antenna design is fabri- cated and rigorously tested, offering a promising solution for efficient 5G communication within the sub-6 GHz spectrum.

Keywords— component, formatting, style, styling, insert.

I. INTRODUCTION

In the age of the enhanced wireless communication and the internet of things, the design of antennas has become crucial for meeting communication standards and electromagnetic wave propagation requirements. Efficient signal transmission and reception, especially for multiband operations like 5G, heavily rely on antenna configuration. Consequently, there is a growing need to optimize antenna design to enhance communication efficiency and overall performance.

Traditionally, antenna design involved tuning parameters like substrate, size, shape and materials through experience-driven methods, which consumed significant computational resources and time. But creating small, multipurpose antennas has gotten harder as a result of issues like raising radiated power efficiency, controlling thermal concerns, widening the bandwidth for quicker data transfer, and meeting the need for application-specific antennas.

For antenna synthesis and design, electromagnetic simulation has been a popular technique that necessitates high-performance computing capability. Machine learning (ML) algorithms offer a promising approach to mitigate these computational challenges and achieve better optimization results. Several machine learning algorithms have been utilized to create advanced antenna technologies with automated and economical designs, surpassing conventional methods based on trial and error and mathematical formulas.

In this paper, we investigate many machine learning algorithms to evaluate the output strength for different proposed antenna dimensions. Additionally, we present a dataset generated from simulations conducted on the antenna, with detailed information provided in the Methodology section. The research offers a comparative analysis of different Machine Learning methods to evaluate antenna strength across different datasets.

II. LITERATURE REVIEW

Nayan Saker et.al [1] present a comprehensive examination of artificial intelligence, particularly focusing on machine learning and deep learning, applied within antenna engineering for wireless communications. It explores various optimization techniques like parallel optimization and multilayer ML-assisted optimization, as well as the use of electromagnetic (EM) simulators like CST, HFSS, and FEKO for ML and DL-driven antenna design.

Furthermore, the paper explores intelligent antenna applications of ML/DL across various wireless communication systems, while also addressing challenges and outlining future research directions in the field. It underscores the significance of meticulous antenna design for achieving efficient wireless communication and underscores the potential of ML/DL in enhancing antenna behavior prediction and reducing design intricacies.

Kanhaiya Sharma et.al [2] introduce an efficient Gaussian Process Regression (GPR) technique for surrogate modeling in the characterization of compact microstrip antennas.ML has positively impacted various aspects of communication, offering advantages such as improved efficiency, reduced operational costs, and quicker optimization. The paper discusses the application of ML in predicting and optimizing the parameters of different antennas, emphasizing its role in addressing challenges posed by the demand for compact and multi-functional designs. The study introduces a dataset, evaluates various regression-based ML techniques, and concludes that Gaussian Process Regression performs well in predicting parameters of Single Patch Compact Microstrip Antennas (SPCMAs). Actual versus predicted plots demonstrate the effectiveness of the models in minimizing prediction errors.

Sotirios K. Goudos et.al [3] study explores the application of artificial intelligence techniques in antenna design, focusing on evolutionary algorithms (EAs), and machine learning (ML). The paper reviews applications, discussing EAs and ML algorithms for antenna synthesis, analysis, and direction-of- arrival estimation. It emphasizes overcoming the limitations of traditional antenna design methods and presents a comprehensive overview of AI methods in antenna design, including deep learning, support vector machines, Gaussian processes, and ANFIS. The advantages and disadvantages of ML methods for antenna design are summarized, contributing to a broader understanding.

Sarbagya Ratna Shakya et.al [4] investigate the application of machine learning algorithms in maximizing the output power of three fundamental antennae: shot antenna, patch antenna, and bowtie antenna. Traditional antenna design involves multiple iterations and extensive testing, but ML offers a quicker and smarter alternative. The study analyzes different regression- based ML models to predict output strength (S11) for various antenna parameters and compares their performance. Three approaches are employed: individual ML algorithms analysis, k-fold cross-validation, and ensemble methods. The paper contributes by providing a simulated dataset, comparing ML algorithm performance, and proposing an ensemble approach for optimizing antenna design. The datasets include a publicly available slot antenna dataset and two simulated datasets for microstrip patch and bowtie antennas. The study showcases the potential of ML in efficiently designing antennae, reducing computational challenges, and improving performance over traditional methods.

John Colaco et.al [5] present the design of a microstrip patch antenna for high-quality online education and 5G applications, focusing on uninterrupted streaming in developing countries like India. The antenna operates at 26 GHz within the 5G millimeter-wave bands. The rectangular patch, designed using Rogers RT/Duroid substrate, exhibits a resonant frequency of 26 GHz, providing a good return loss of -33.4 dB The proposed design aims to support e-learning and offer high data rates, and large bandwidth for improved online education quality. This paper is used to determine the width and length of the patch microstrip patch antenna.

Sawyer D. Campbell et.al [6] explores the growing influence of artificial intelligence (AI) on society, raising concerns about its potential impact on various job sectors. It highlights the extensive applications of AI, machine learning (ML), and deep learning (DL) in Antennas and Propagation (AP-S). The discussion categorizes recent work in AP into areas such as for- ward modeling, inverse modeling, remote sensing, and inverse design. Examples include using DL to speed up computational electromagnetic solvers, predicting channel state information, and enhancing various electromagnetic applications. The text provides a comprehensive overview of the intersection of AI and AP, emphasizing its transformative potential.

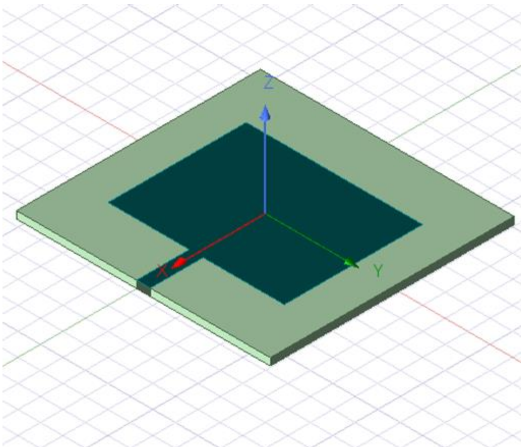
Yiming Chen et.al [7] paper explores the application of machine learning (ML), specifically linear regression using support vector regressor (SVR), in predicting the resonant frequency (RF) of a microstrip patch antenna. Two datasets with varying sample sizes are generated through accurate full- wave simulations. The SVR model achieves mean R2 scores of

0.582 and 0.647 for the small and large datasets, respectively, indicating the model's ability to predict RF accurately. The study highlights the potential of ML to streamline antenna design, emphasizing the need for larger datasets to enhance prediction accuracy.

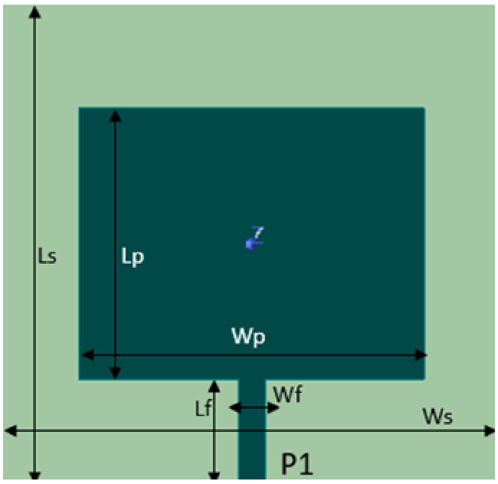
III. METHODOLOGY

A. Traditional Optimization Method

The traditional optimization method entails the utilization of ANSYS software for the design and optimization of antennas through frequency sweeping. Initially, the dimensions of the antenna are determined using appropriate equations for the desired frequency. Following the initial design phase, a frequency sweep is conducted across various frequency-feed position combinations. A total of 201 distinct designs are created, and their corresponding reflection coefficient plots are generated to analyze frequency dips. Through iterative processes, Base design of the structure is rectangular shape with dimensions 29.44mm X 38.3mm. The 3D view and top view of the proposed antenna with dimension is shown in Figure 1. The final optimized design achieves a reflection coefficient of -32 dB at a frequency of 3.54 GHz. S Parameter (Reflection coefficient) plot is shown in figure 2.



(a)



(b)

Fig. 1. Proposed antenna Design (a) 3D View (b) Top View

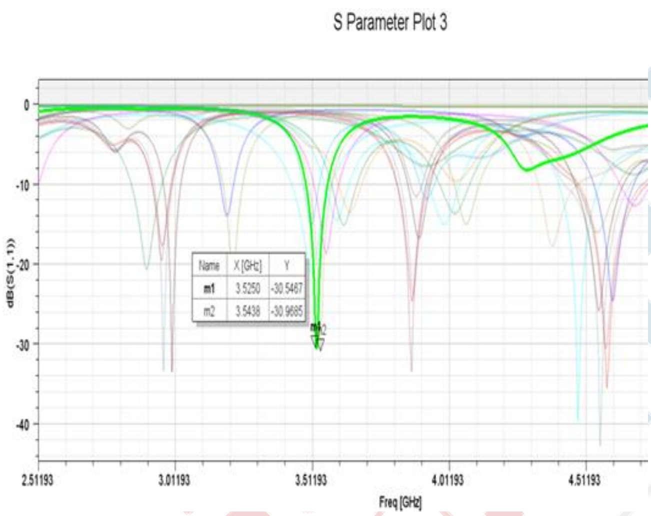


Fig. 2. S Parameter plot of Base design

B. Dataset Creation

The dataset comprises 8020 data points, with each data point corresponding to an S11 measurement. All designs were simulated across the frequency range from 2.5 GHz to 5 GHz, with each frequency corresponding to a single entry in the dataset. The dataset includes the physical parameters of the antennas as input, such as lengths in millimetres, and the S11 parameter as the output, represented in dB. The data generation process involved sweeping the length parameters one by one with different values. Due to computational constraints, it was not feasible to simulate every possible variation, leading to a non-uniform distribution among the data points. The generation of the 8020 data points took approximately 10 hours to complete and utilized more computational resource.

C. Machine Learning Algorithm

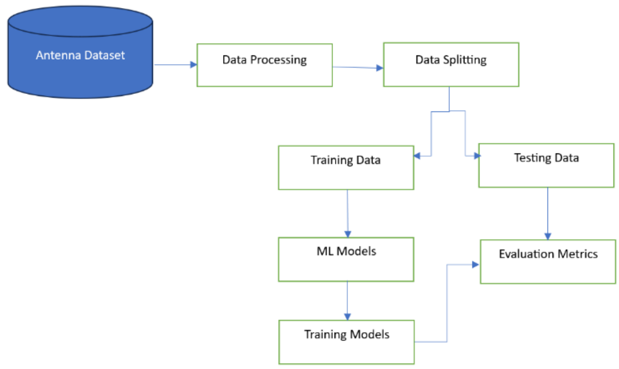


Fig. 3. Machine learning workflow

Machine learning (ML) algorithms, known for their ability to learn from data, have found utility in solving various antenna design challenges. These problems are typically approached as supervised regression tasks, where the goal is to model the relationship between input parameters (such as antenna dimensions) and output parameters (like the reflection coefficient). In this study, five different regression models were employed: Linear regression, Logistic regression, Lasso regression, Decision Tree regressor, and Random Forest Regressor. These ML algorithms were trained using the provided dataset to predict the reflection coefficient values. Performance was evaluated using the R2-Score and Root Mean Squared Error (RMSE) metrics.

Table 1: Evaluation metrics

ML Algorithms	R2 Score	RMSE Score
Linear Regression	0.124	4.156
Elastic Net Regression	0.0627	4.3
Lasso Regression	0.034	4.366
Decision Tree	0.9692	0.779
Random Forest	0.983	0.587

Upon analysis, it was observed that Linear regression and Logistic regression exhibited poor performance, as evidenced by their low R2 scores. In contrast, the Decision Tree and Random Forest models showed superior performance on the dataset with a R2 score of 0.96 and 0.98. These models achieved higher R2 scores and demonstrated better predictive capabilities for the reflection coefficient values. The traditional method establishes the initial design dimensions for the patch. Once a suitable ML algorithm is chosen, the goal shifts to determining the optimal lengths of the input physical parameters.

In this process, the output parameter (S11) is substituted with one of the input parameters, such as the patch length, while the input parameter is replaced with specific S11 value (e.g., -30 dB), aligning with our requirements. Instead of predicting performance values directly, the focus is on predicting length values since our objective is to optimize patch dimensions. The updated design, designated as P1, is derived from the predicted patch length values integrated into the initial design. This procedure is then repeated, replacing the patch width with S11 = -30 dB. The iterative nature of this process continues for two cycles, resulting in refined and optimized patch dimensions. Through this method, the final optimized patch dimensions are obtained.

D. Final Optimized Design:

The optimized patch dimensions obtained through machine learning are utilized to design the final patch antenna and it achieved the reflection co-efficient of -22dB at a frequency of 3.55 Ghz. The Performance of the final Design is shown as S parameter plot in figure 4.

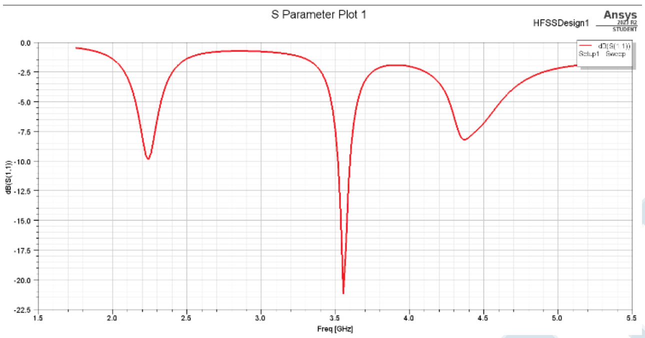


Fig. 4. S Parameter Plot of Final Antenna design

IV. RESULT

The performance of the model is based on the calculation time taken by the model to optimize a single data point. For the traditional optimization method using ANSYS, it took a total of 10 hours for 8020 datapoints. So, on a average it took 4.48 seconds for each calculation and also utilized more computational resource The machine learning iteration process for antenna design took approximately 34.2 minutes to complete, averaging 0.25 seconds for each calculation. This efficiency stands in stark contrast to the traditional method, where machine learning algorithms required significantly less time and resources for optimization, ultimately leading to a more optimized design.

Table 2: Performance comparison

	Patch Dimension	Reflection Coefficient	Freq.	Calculation Time
Traditional Method	29.44mm x 38.3mm	-30.2dB	3.54GHz	4.48s
Machine Learning	30.72mm x 39.18mm	-22.4dB	3.53GHz	0.25s

In conclusion, the utilization of machine learning algorithms for antenna design optimization has proven to be highly advantageous. The iterative process, which took approximately 34.2 minutes with an average calculation time of 0.25 seconds per iteration, demonstrates the efficiency of machine learning in rapidly exploring and refining design parameters. This efficiency is notably superior to the traditional method, which typically requires significantly more time and computational resources.

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