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Optimization of 5G Sub Band Antenna Design Using Machine Learning Techniques for WiFi & WiMAX Application

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Abstract

Objectives: This article presents the design of a 5G-n78 sub-band frequency antenna for WiMAX and WLAN applications, along with its design optimization using four supervised machine learning models: Polynomial Regression (PR), Decision Tree (DT), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). The performance of the machine learning models is evaluated using the Root Mean Square Error (RMSE) metric for both the test and train datasets. Furthermore, the dimensions obtained from the most efficient model, XGBoost, are utilized for fabrication and verification purposes. **Method:** The proposed patch antenna, designed on an FR-4 substrate with a relative dielectric constant of 4.4, a thickness of 1.6 mm, and a loss tangent of 0.002, is modeled in the High-Frequency Structural Simulator (HFSS) at a frequency of 3.3 GHz. The design dimensions are analyzed over a wide range to generate the dataset required for machine learning implementation to optimize the dimensions. Polynomial regression models of orders 2 and 7 are verified, with better accuracy in terms of RMSE obtained from all four ML models. **Findings:** The proposed metal patch antenna, with dimensions of ($0.304\lambda_0 \times 0.238\lambda_0$) mm^2, resonates at 3.3 GHz, achieving a return loss (S_{11}) of -37.4 dB, a standing wave ratio (SWR) of 1.03, and a gain of 4.06 dBi. A dataset of 2000 records was generated using a full-wave electromagnetic simulator for training and testing purposes across all four ML models. The Root Mean Square Error (RMSE) values obtained for training and testing were 4.42 and 4.44 for the Decision Tree model, 2.04 and 3.17 for the seventh-order Polynomial Regression model, 0.81 and 2.20 for the Random Forest model, and 0.72 and 1.14 for the XGBoost model. The dimensions obtained from the XGBoost model (18 mm in length and 28.5 mm in width) were used for fabrication. The proposed, ML-based simulated, and fabricated return loss values were verified, further, the computational time required for ML simulation is 0.0578s against 9.05m in HFSS simulator. **Novelty:** Present work reveals the introduction of ML techniques in conventional electromagnetic solvers for better optimization in less time with more efficiency and reachable to antenna engineers.

Keywords: High Frequency Structural Simulator; Machine Learning Algorithm; Microstrip Patch Antenna; Return loss; Root Mean square error

1 Introduction

An antenna is an electromagnetic device that converts electrical signals into electromagnetic waves. It is a mandatory element in any communication system. Antennas for emerging technologies, particularly for 5G mobile communications, offer higher data rates, greater capacity, higher bandwidth, increased security, and lower latency, creating significant opportunities in advanced societies. 5G and 6G technologies are expected to significantly improve the living standards of society. Various technologies, such as massive Multi-Input and Multiple-Output (MIMO), hybrid beamforming, mobile broadband speed, and potential applications in virtual reality (VR), the Internet of Things (IoT), and autonomous vehicles, are key features of 5G. Compact fractal designs, including MIMO structures for 3G, 4G, and 5G, have been studied for WLAN, WiMAX, ISM, and LTE bands[1,2]. However, existing conventional electromagnetic solvers need to be integrated with advanced technologies to optimize the design and performance parameters of antennas more effectively. A dual-band antenna for WiMAX applications at 3.3 GHz can be achieved by introducing a split-ring resonator, which is a negative-index metamaterial device[3]. The design of microstrip patch antenna for satellite and communication applications is explained for multiband operations but the optimization process is tedious ML introduction is essential[4,5]. Feeding techniques for any antenna design are crucial to obtain the performance and design parameters at optimum values[6]. However, enhancing bandwidth while ensuring ease of design remains a challenge. Achieving better optimization with less computational effort and improved performance parameters for antennas is crucial. Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) offer promising solutions for optimizing antenna design.

Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are not just fancy terms but are well-regarded for their ability to automate complex, non-linear problems with minimal human intervention. The potential of ML in predicting future values has attracted the scientific community to apply ML in high-computing electromagnetic applications, including antennas[7]. A comprehensive review of the design exploration and optimization of antennas using machine learning algorithms and techniques is available in literature. Authors[8,9] introduced procedural optimization of antennas using various ML and DL techniques, along with performance metrics such as Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Gini Index, and Distortion Pattern, among others. The application of decision tree supervised models to optimize the length and width of a patch antenna is discussed, but validation through fabrication measurements remains pending[10]. Fabrication of antennas based on machine learning-determined dimensions and their validation in terms of RMSE has not yet been reported. Shilpa Pavithran and others explained 5G antenna design using decision trees, random forest, higher-order polynomial regression, and extreme gradient boosting (XGBoost) techniques to overcome overfitting problems[11]; however, validation is still pending. Antenna dimensional reduction using ML techniques is also mentioned but with very limited data records[12]. A large dataset is critical for the efficiency of AI and ML techniques to avoid overfitting and underfitting issues. VV Reddy and others applied ML techniques to optimize a C-slot-loaded Minkowski fractal antenna[13], but validation through proper fabrication was not reported. Validation of proposed antenna designs from ML models through proper fabrication is a pressing need.

Considering the research gaps in the mentioned literature on various design methodologies and ML introduction this article is an alternative solution to conventional EM simulators to mitigate computational time and licensing issues by efficient AI/ML models based on reliable datasets. The first part of this article provides a detailed design approach for a rectangular microstrip patch antenna for 5G n78 sub-band applications. The work's second part focuses on the optimization and validation of the proposed antenna design's return loss as the target variable, using Polynomial Regression**,** Decision Tree**,** Random Forest, and Extreme Gradient Boost (XGBoost) ML algorithms in the open-source Python language. Performance analysis is carried out in terms of RMSE. The converging dimensions from all four models are analyzed, and the XGBoost technique is selected for fabrication. The fabricated results based on the ML approach align with simulation outcomes, which is a novel contribution to literature. The next chapters explain the design methodology using a simulator and ML application procedure and its results discussed at the end of the draft.

2 Methodology

The basic design of the antenna consists of a metallic patch over a dielectric substrate with a metallic ground plate[14]. Wp, and Lp are width and length of the patch, height and relative dielectric constant of substrate material respectively. The microstrip line feed technique is used and the feed line length is adjusted in such a way that it matches to 50Ω line impedance with the input port. Preliminary antenna proposal mathematical Antenna designs using patch models with their design equations were discussed in the literature[15,16] along with their current distribution and field analysis. A 21.66mm length, 27.66mm width metal patch upon 1.6mm thick FR-4 substrate with 4.4 relative dielectric constant such that it resonates at 3.3GHz frequency. Here in this communication HFSS which works based on finite element method full wave EM solver is used for design purposes. The proposed antenna is radiating at 3.3GHz with a return loss of -37.4dB, VSWR of 1.03 and 4.06dBi Gain. The basic proposed antenna and its return loss which is the target variable of the proposed antenna for ML approximation is mentioned in Figure 1**(a) & (b)** respectively. The performance characteristics of the MPA are measured in terms of return loss S_{11}, Voltage Standing Wave Ratio (VSWR), Gain, & Resonance Frequency. Here application of advanced techniques like AI, ML, and DL in the design of antenna would help to achieve the required antenna parameters effectively. The next chapters explain the basics of AI, ML, DL and their application in antenna design.

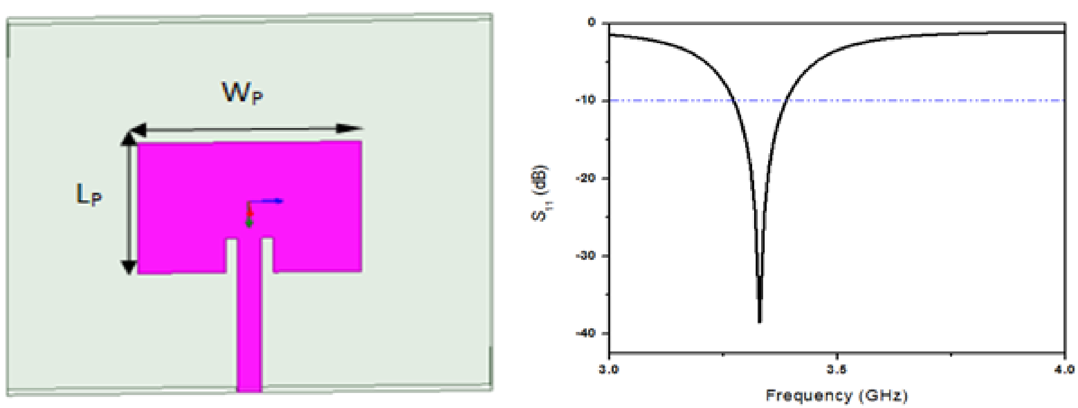


Fig 1. (a) Proposed antenna (b) Return loss characteristics of the proposed antenna

Machine Learning (ML) which is the subset of Artificial Intelligence (AI) is one of the emerging technological solutions for all domains due to its wide variety of applications. It uses mathematical statistical computation analysis in designing the mathematical model interims of input and output variables. It is mostly data driven system, where it expects huge data which may be trained or untrained. Based on the dataset and type of learning system like supervised, unsupervised, or reinforcement it provides the mathematical model that best suits the given problem in identifying the optimum solution. Deep Learning widely uses the artificial neural network which mimics the human brain functionality of multiple neurons. The main aim of this research article is to introduce antenna design optimization by using ML algorithms.

The basic flow chart of Machine learning approach in antenna design is shown in Figure 2. The Proposed antenna is designed in HFSS, and after the data preparation from the simulator, various ML techniques needed to be studied for a better performing model.

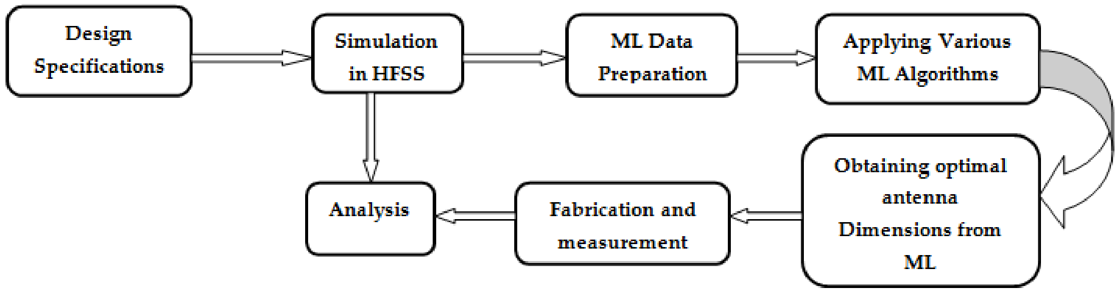
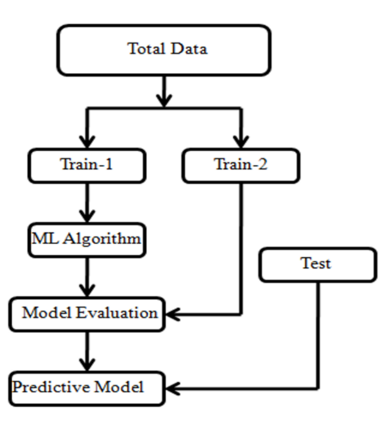


Fig 2. Flow chart of theproposed work

In this article, Polynomial Regression, Decision Tree, Random Forest and Extreme gradient Boost techniques are presented which are supervised models. The order of the polynomial decides the error rate while applying the polynomial regression model. The root node is chosen in such a way that the attribute has the lowest Gini value or entropy, where the Gini index measures the impurity of the feature. An increase in the depth of the tree leads to better accuracy in decision-making, and lesser overfitting and underfitting problems in machine learning techniques. Performance of the model is carried out by Gini index, mean square error and root mean square error and their respective equations are mentioned in equations Equations (1), (2), (3) and (4), Where N is the total number of incidence, Pi is probability of an event.Figure 3**(a) & (b)** explain the ML Basic ML procedure and RMSE comparison of various order polynomial such that train and test cases match effectively.



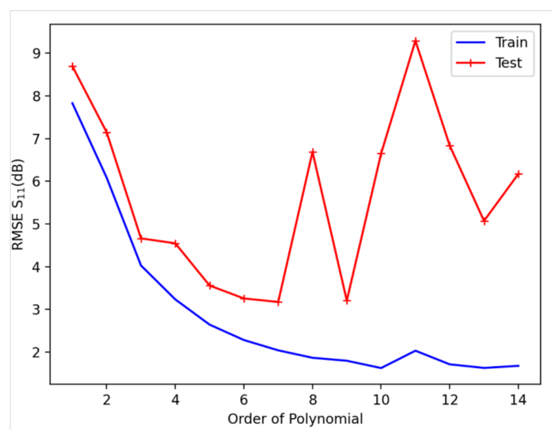


Fig 3. (a) Block Diagram for ML Approach (b) RMSE Error in various Polynomial orders

$$Gini = 1 - \sum_{i=1}^{N} (P_i)^2 \tag{1}$$

$$Out\ Error = (Desired\ output) - (Predicted\ output) \tag{2}$$

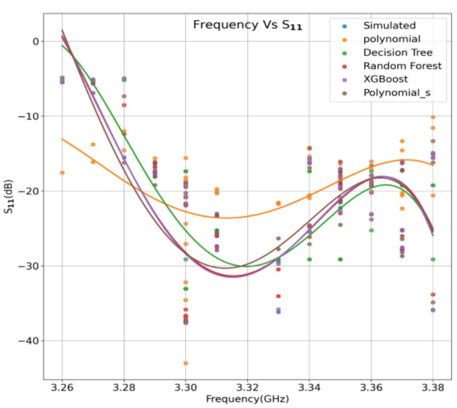
$$Mean\ Square\ Error\ (MSE) = \frac{1}{N}\sum_{i=1}^{N}(Output\ Error)^2 \tag{3}$$

$$Root\ \ Mean\ Square\ Error\ (RSME) = \sqrt{MSE} \tag{4}$$

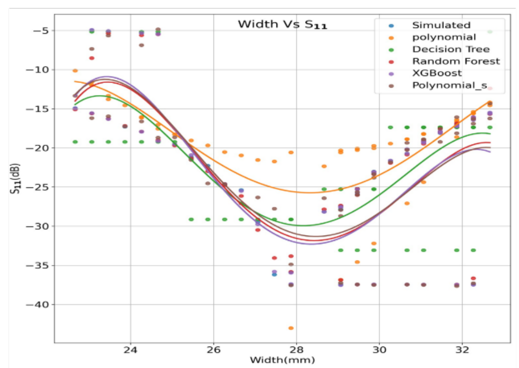
The sample data set required for ML is collected from HFSS simulator by keeping S_{11} as the target variables and frequency of operation and length, width of the patch as Independent variables and all other parameters are kept constant. The next chapter explains the ML model performance of the proposed design. RMSE is relatively better matching at order seven.

3 Results and Discussion

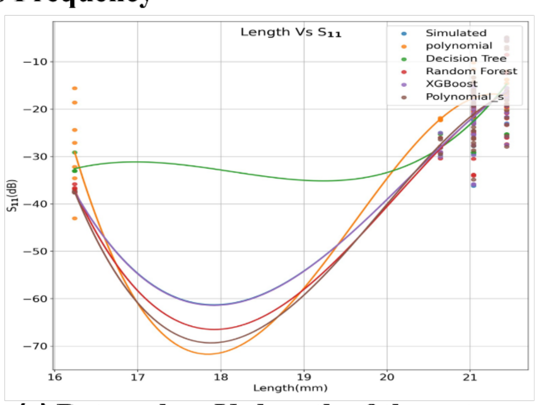
Multiple simulations were conducted to create the data set of 2000 records. Out of 2000 records, 80% of data (1600 records) is considered as training data and the remaining 20%, that is, 400 records is kept for testing purposes. Polynomial regression is studied for various orders such that test and train modes are in close agreement to avoid overfitting and underfitting issues. Operating frequency optimization of the proposed antenna for return loss is mentioned in Figure 4**(a)**, which indicates simulated and four ML models along with second order polynomial majority of data points are converging at 3.3 to 3.32 GHz frequency and polynomial of order seven and XGBoost model are overlapped in all graphs due to their common efficiency value. Dots represent target distribution and continuous lines represent the converging values of respective models. Similarly, optimization of length and width variables is represented in Figure 4**(b)& (c)** where length converges at 18mm and width converges at 28.5mm respectively. Further root mean square error values are obtained from all four models for train & test cases. The dimensions obtained from XGBoost model due to its low error rate were used for fabricating the antenna. Figure 5 **(a) & (b)** shows the fabricated antenna measurement on test bench and respective return loss comparison with simulation, ML based simulated and measured antenna. Further, the computational time required for antenna design in HFSS simulator is 9.05m whereas in ML case it is 0.0578s for 7000 tree node points when both are run in a 4GB RAM computer system. This indicates ML computation is 10^4 faster than conventional simulator.



(a) Return loss Vs Frequency



(b) Return loss Vs width of the antenna



(c) Return loss Vs length of the antenna

Fig 4. (a) Optimization of operating frequency for return loss (b) Width optimization for targeted return loss (c) Length optimization for return loss

The Field distribution over the designed antenna is presented in Figure 6**(a) & (b)** for electric and magnetic fields respectively. Electric field concentration is more at the edges of the antenna and the magnetic field is more at the centre near to feed junction of the antenna. The 2D radiation patterns are mentioned in Figure 7 **(a) & (b)** for E & H-fields which are Phi=0 and phi=90 degrees planes respectively and they are observed to be directional antenna.

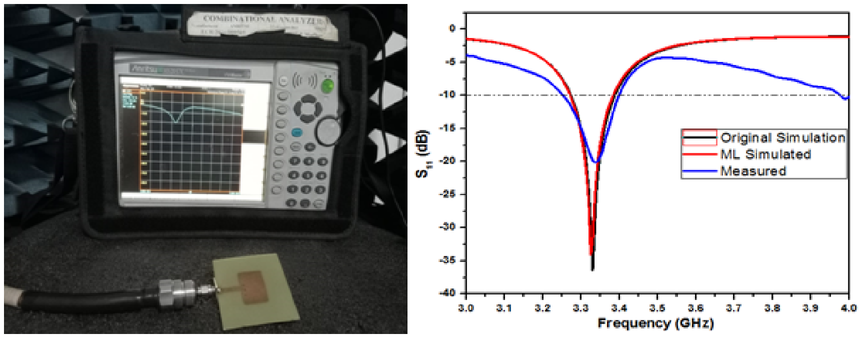


Fig 5. (a)Fabricated antenna on test bench. (b) Return loss comparison of proposed, ML simulated and fabricated antenna

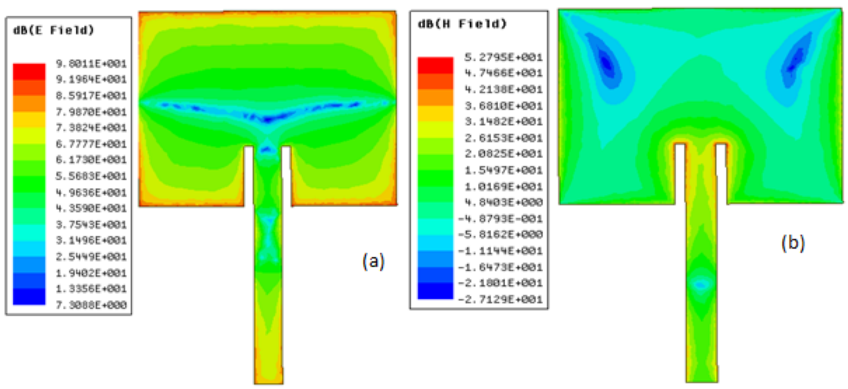


Fig 6. (a) E-filed Distribution (b) H-field distribution

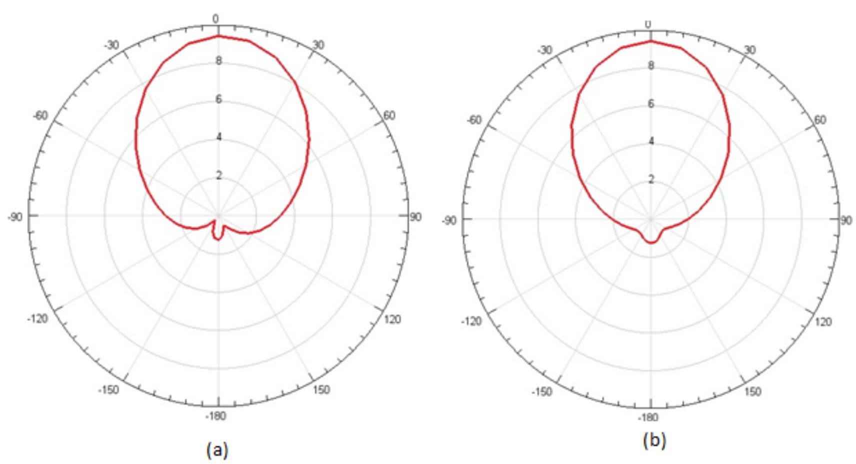


Fig 7. (a) E-field Radiation Pattern, (b) H-Field radiation Pattern of the proposed antenna

Dimensions obtained from XGBoost ML model were used for fabricating the antenna that are 18mm length, 28.5mm width & 3.3GHz frequency and is measured through vector network analyzer. From Figure 5**(b)** it is clear that the proposed design simulation, ML modeled antenna simulation and measured performance ML model are clearly matching. The Root Mean Square Error values obtained in four ML techniques are mentioned below in Table 1. The RMSE in XGBoost techniques are in close agreement in both train and test cases. The values of RMSE are very useful for future studies regarding the efficiency of the model. Table 2 gives the ML based comparison of the proposed antenna with the literature mentioned.

Table 1. Comparison of Root Mean Square Error

S.No	Decision Tree	Polynomial regression	Random Forest	XGBoost
Train	4.42	2.04	0.81	0.72
Test	4.44	3.17	2.2	1.14

Table 2. ML based Comparison with the existing literature

S.No	Ref No	Applied ML Model	Random Forest
1	10	Decision Tree	ML Optimization noted on single dimension and its validation pending
2	11	Decision Tree and Random Forest	ML based validation not reported
3	12	Polynomial Regression	ML based validation and fabrication pending
4	13	Decision Tree, Random Forest, XGBoost	ML validation & measurements not reported
5	Proposed work	Polynomial Regression, Decision Tree, Random Forest & XGBoost	ML based validation with proper fabrication measurement completed

4 Conclusion

A 5G n78 sub-band microstrip directional patch antenna operating at a 3.3 GHz frequency is designed on an FR-4 substrate using the full-wave electromagnetic solver HFSS**.** A return loss of -37.4 dB, a VSWR of 1.03, and a gain of 4.02 dBi are achieved. The proposed antenna is optimized using decision tree**,** polynomial regression**,** random forest, and XGBoost machine learning techniques, with return loss selected as the target variable. The ML model results are validated through proper fabrication. The decision tree model achieves root mean square error (RMSE) values of 4.42 and 4.44 for the training and test datasets**,** respectively. The root mean square errors (RMSE) of 2.02 and 3.17 are observed for the training and test data in seventh-order polynomial regression, while values of 0.81 and 2.20 are observed in random forest, and 0.72 and 1.14 for training and test data are observed in XGBoost techniques. The XGBoost model is used for fabrication as it is highly accurate in terms of RMSE further its computational time is 10^4 times faster than the conventional electromagnetic (EM) simulator HFSS in the proposed design when both cases are verified in a conventional 4GB RAM computer system because the computational time required in HFSS is 9.05 minutes and it is 0.0578 seconds in ML model. The fabricated antenna derived from the ML model is in full agreement with the simulated one in its return loss, as shown in Figure 5 **(b)**. Across all four ML techniques, the error rates are within acceptable levels. Powerful machine learning techniques with reliable high end datasets are essential for better microwave device design and optimization in the near future in terms of computational time and efficiency. The proposed antenna, operating at a 3.3 GHz frequency, is suitable for 5G WiFi and WiMAX applications.

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