Machine Learning Assisted mm-Wave MIMO Antenna Design with High Isolation for 5G Applications

Ramasamy R., Rajavel V., and Rachit Jain

Abstract—**This study investigates the design and performance of millimeter-wave (mm-Wave) Multiple-Input Multiple-Output (MIMO) antennas for fifth-generation (5G) applications, with a particular focus on the consequences of incorporating a ring resonator within the antenna system. This study compares two design variations—one with a ring resonator and one without—to assess their impact on enhancing the antenna's performance characteristics. The research employs five machine learning algorithms, namely, Decision Tree, Random Forest, K-Nearest Neighbors (KNN), XG-Boost, and Gradient Boosting Regressor (GBR), to estimate return loss. Among these, the Random Forest algorithm demonstrates superior performance in terms of accuracy, Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and R-squared metrics. The proposed MIMO antenna system shows better performance in Envelope Correlation Coefficient (ECC), Diversity Gain (DG), Channel Capacity Loss (CCL) and Total Active Reflection Coefficient (TARC). The results indicate that including a ring resonator in the antenna design significantly improves the antenna's performance, and machine learning algorithms, particularly Random Forest, can effectively predict and optimize critical parameters for antenna design in 5G applications.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9776

Index Terms— **Decision Tree, Gradient Boosting Regressor, K-Nearest Neighbors, MAPE, MAE, MSE, Random Forest, XG-Boost**

I. Introduction

FOR 5G applications, Multiple-Input Multiple-Output (MIMO) millimeter-wave (mm-Wave) antennas are crucial because they offer high data rates, enhanced network capacity, and decreased latency. With a frequency range of 24 GHz to 100 GHz, these antennas enable higher bandwidths and simultaneous transmission and receipt of multiple data using multiple antennas. Using advanced beam-forming techniques increases the network capacity and improves the signal strength. By facilitating adaptive beam shaping, dynamic resource allocation, and predictive maintenance, the integration of Machine Learning (ML) further enhances the antenna performance. Diversity Gain (DG), which uses multiple antennas to increase signal reliability; Total Active Reflection Coefficient (TARC), which measures the overall efficiency of the multiple-antenna system; gain, which shows the antenna's capacity to direct radio waves in particular directions; Envelope Correlation Coefficient (ECC), which gauges the correlation between antenna elements; and isolation, which ensures that there is little interference between antennas, are important performance parameters. A ML-based MIMO antenna optimization approach was proposed in [1] for sub-6GHz 5G applications. A ML technique was developed to estimate the structural parameters of the MIMO antenna, effectively reducing computation time, minimizing mutual coupling between antenna elements, and enhancing overall computational efficiency. For 5G new radio applications, [2] proposed various machine learning algorithms for MIMO antenna design. Several optimization algorithms, including Artificial Neural Network (ANN), Decision Tree (DT), Random Forest (RF), and Extreme Gradient Boosting (XGB), have been developed to estimate the value of S-parameters without compromising accuracy. Several MIMO antenna parameters, such as diversity gain, TARC, and ECC, were analyzed, and the results were within acceptable limits. A deep learning algorithm for MIMO antenna design for sub-6 GHz 5G and satellite applications was proposed by [3].

A feature reduction strategy was suggested to minimize the design space during the design phase. The Deep Convolutional Neural Network (DNN) algorithm was developed to estimate the S-parameters efficiently. A deep-learning technique was proposed in [4] to determine the optimal physical parameters for MIMO antenna design in 5G applications. A dual-channel DNN approach was developed to estimate the S-parameters efficiently. The proposed method demonstrates improved results in terms of the impedance bandwidth, ECC, TARC, and isolation. For MIMO antenna dimension design characterization and optimal throughput, a machine-learning approach was suggested in [5]. MIMO antennas were developed to convert a linearly polarized wave to a circularly polarized wave. The proposed method demonstrated improved performance in isolation, TARC, ECC, and diversity gain. For 5G mm-wave applications, various machine learning algorithms for MIMO with Dielectric Resonator Antenna (DRA) were developed [6]. The Knowledge-Based Neural Networks (KBNN), ANN, and ML algorithms were created

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for S-parameter estimation and antenna optimization. The proposed approach yielded improved TARC, Channel Capacity Loss (CCL), DG, and ECC outcomes. A machine-learning algorithm for MIMO antenna design for wireless applications was proposed in [7]. The suggested MIMO antenna features a petal-shaped structure, rectangular ring, and defective ground plane to maximize the gain and radiation efficiency while enhancing the isolation and impedance bandwidth. Several machine-learning algorithms were proposed to optimize antenna characteristics effectively [8]. DT, DNN, and XGB machine learning models were developed to enhance the axial ratio, S_{11}, and isolation. A deep-learning approach for MIMO antenna design utilizing 5G smartphone applications was proposed in [9].

A. Machine Learning in Antenna Design

The DNN approach was developed to estimate the S-parameters and optimal physical parameters efficiently. The proposed method achieved better performance regarding isolation, TARC, ECC, CCL, and impedance bandwidth. In addition, the DNN technique reduces the design space and attains excellent accuracy with minimal computing time. A machine learning model for MIMO antenna design for Ultra-Wide Band (UWB) applications was proposed in [10]. For comparative analysis, Multivariate Relevance Vector Regression (MVRVR), Gaussian Process Regression (GPR), Support Vector Regression (SVR), and ANN models were developed; however, the MVRVR model demonstrated superior accuracy and effectively reduced forward and reverse issues. For 5G mm-Wave applications, various types of machine learning algorithms were presented in [11]. Several algorithms, including ANN, Radial Basis Function Neural Network (RBFNN), and Adaptive Network-Based Fuzzy Inference System (ANFIS), have been developed to estimate the dimensions of a dual-band circular patch antenna with defective ground for comparative analysis of parameters such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). A ML technique for optimizing the antenna decoupling structure was proposed [12], where the authors developed the MAE neural network algorithm in combination with the k-means clustering method to achieve effective structural decoupling. Decupling structure classification was performed using the k-means method. MAE employed an optimum design to decouple the structure. A machine-learning approach for a circularly polarized dual-port MIMO antenna was proposed. An ANN was developed to optimize MIMO antenna design using the Adaptive Moment Estimation (ADAM) optimizer. The proposed approach yielded improved results in terms of MSE, R-squared (R^2), impedance matching, ECC, and diversity gain, as reported in [13]. An Artificial Intelligence (AI) approach for 3D MIMO antenna design for 5G applications was introduced in [14]. An AI-based machine learning algorithm was developed to address spectrum efficiency, energy efficiency, and throughput.

B. Related Work: Machine Learning Techniques in Antenna Design and Analysis

ML approaches are commonly used in antenna design to improve performance characteristics such as isolation, S_{11}, ECC, DG, and radiation efficiency. These methodologies allow for the modelling of intricate interactions between antenna geometry and performance, while greatly lowering design iteration time.

Several ML-based algorithms have been developed to optimize MIMO antennas across various frequency bands and applications. For example, a linear regression model was used to improve the isolation, S_{11}, and radiation efficiency of a circular patch MIMO antenna for radar applications [15]. In the context of 5G applications, fractal monopole antenna designs were investigated in [16-17], which operate in the 2-5.2 GHz spectrum and show improvements in ECC, gain, and isolation [18]. Other research focused on multi-band MIMO antennas built for 5G New Radio (NR), with architectures that can handle a variety of communication standards [19-20]. A dual-band split-ring resonator MIMO antenna resonating at 24.5 GHz and 28.5 GHz was introduced in [21-22], demonstrating considerable increases in isolation, ECC, DG, gain, and radiation efficiency [23-24]. Complementary wideband antennas analyzed using characteristic mode analysis was also proposed for MIMO systems [25]. Similarly, tiny antennas operating at frequencies below 6 GHz were optimized for 5G NR and Wi-Fi 6 bands, resulting in consistent radiation performance, robust isolation, and acceptable ECC and DG [26–27]. In [28-30], a 10-element MIMO antenna operating at 3.5 GHz with a T-shaped feeding structure was found to improve radiation efficiency, ECC, gain, and isolation. Beyond structural designs, machine learning's capacity to recognize patterns and create data-driven predictions has transformed antenna design procedures [31-34]. Supervised, unsupervised, and reinforcement learning have all found applications in tuning geometrical parameters, modelling antenna behavior, and increasing overall design efficiency [35-37]. These features address performance optimization difficulties, particularly minimizing mutual coupling and attaining high isolation without requiring expensive trial-and-error procedures.

While these studies collectively indicate the power of ML in improving traditional MIMO antenna performance, a significant gap persists. Most previous research has focused on frequency bands less than 6 GHz or has not taken advanced resonator-integrated structures into consideration. In particular, the use of machine learning particularly deep learning to optimise mm-Wave MIMO antennas combined with ring resonators is mainly unexplored.

In order to bridge this gap, the present research suggests a machine learning-based design framework tailored for mm-Wave MIMO antennas that use circular ring resonators. The system captures intricate correlations between geometrical factors and important performance indicators, including ECC, TARC, and DG, by utilising five distinct machine learning techniques. Design iteration time is decreased, isolation is greatly enhanced, and automatic performance adjustment is made possible by this data-driven method. The creation of a novel ML-driven optimisation technique for mm-Wave MIMO antennas, the demonstration of notable gains in important performance metrics, and a comparison with traditional design strategies that establishes the scalability of the suggested approach for upcoming wireless communication systems are among the work's main contributions.

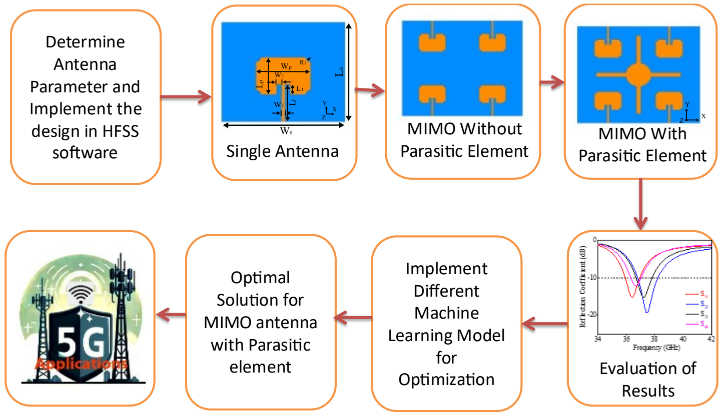

Fig. 1. Block diagram of 5G antenna design using HFSS and machine learning optimization.

II. MIMO Antenna Design Configuration

The Fig. 1 illustrates the process of utilizing High Frequency Structure Simulator (HFSS) software and machine learning to create and optimize a 5G antenna system. The initial step involves defining the antenna parameters and implementing the design using HFSS software. Next, a single microstrip patch antenna is created and integrated into a parasitic element-free MIMO system. The design of the MIMO system involves the addition of parasitic components, and the S_{11} parameter is used to evaluate the results and assess the reflection coefficients. Machine-learning models play a crucial role in this process, as they are applied to improve the antenna design, resulting in an optimal resolution suitable for 5G applications. MIMO technology is a significant enabler for modern wireless communication systems, providing substantial improvements in data throughput and link reliability by utilizing multiple antennas at both the transmitter and receiver ends. Its benefits are particularly notable in mm-Wave communication systems, which function within the 30–300 GHz spectrum. mm-wave frequencies offer large bandwidths and high data rates essential for 5G and beyond communication systems. Still, they also present challenges, such as higher propagation losses and limited range. Efficiently designing MIMO antennas for mm-Wave applications is critical for overcoming these challenges and achieving the desired performance.

A. Single Antenna Design

The single antenna in our MIMO system is designed as a primary rectangular patch antenna resonating at 39.5 GHz. The antenna dimensions are 7.25 mm in length, 6.2 mm in width, and 0.3 mm in height, chosen to ensure resonance at the desired frequency while maintaining a compact form factor suitable for integration into larger systems. The substrate material selected was Rogers RT/Duroid 5880, which has a dielectric constant of 2.2 and a low loss tangent of 0.0009 as shown in Fig. 2(a). This material is preferred owing to its excellent electrical properties, ensuring minimal signal loss and high performance at mm-wave frequencies. The rectangular patch features curvature-type slots at each of the four corners. Introducing these slots helps achieve better impedance matching, wider bandwidth, and improved radiation characteristics. The curved slots create additional current paths, which help achieve better resonance characteristics and improve the antenna's radiation efficiency. The single antenna is designed to resonate precisely at 39.5 GHz as shown in Fig. 2. It is chosen for its relevance in mm-wave applications, particularly in 5G and beyond communications systems, where high data rates and large bandwidths are essential. Initial simulations indicate that the antenna achieves a return loss of better than -10 dB at 39.5 GHz, with a bandwidth of 38.57-40.72 GHz, a Voltage Standing Wave Ratio (VSWR) of less than two from 38.52-40.81 GHz, and a peak gain of approximately 5 dB. The antenna design was validated using electromagnetic simulation software, HFSS. The simulations involved analyzing the return loss, VSWR, and gain to ensure the antenna meets the design specifications. The optimized dimensions are listed in Table I.

TABLE I
ANTENNA DESIGN PARAMETER

Parameters	Value	Parameters	Value
L_s	7.25 mm	W_f	0.125 mm
W_s	6.2 mm	L_1	1.5 mm
L_p	3.2 mm	W_1	0.75 mm
W_p	2.3 mm	R_1	0.125 mm
L_f	1.75 mm	-	-

B. Design Evolution

The evolution of the antenna design is discussed in three stages. Initial simulations, a crucial part of the design process, indicated structural modifications needed to meet the desired operational frequency and performance metrics. The first design started with a conventional rectangular patch antenna

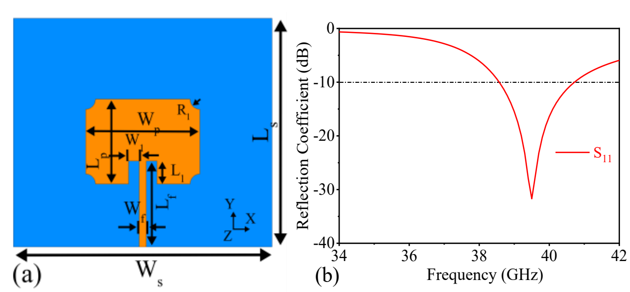

Fig. 2. (a) Proposed antenna geometry (b) Single antenna S_{11} response.

resonating at 37.5 GHz, with a bandwidth of 36.82-38.23 GHz, and was excited using a microstrip line feed. The initial design served as a baseline for evaluating the fundamental performance characteristics and identifying potential limitations. In the second step, the feed mechanism was modified to use an inset cut feed to excite the signal while maintaining the same conventional microstrip patch antenna with dimensions $W_p \times L_p$. This change resulted in the antenna resonating at 38.3 GHz, with an improved bandwidth of 37.60-39.27 GHz as shown in Fig. 3. The inset cut feed helped achieve better impedance matching and slightly improved performance over the initial design.

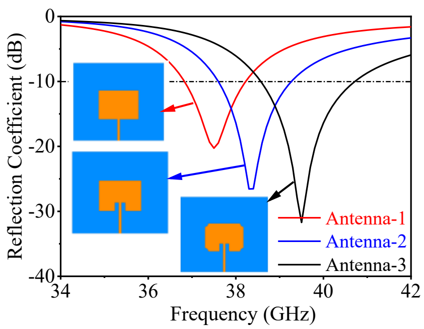

Fig. 3. S-parameter analysis of Antenna-1, Antenna-2, and Antenna-3 during the antenna evolution process.

Through a series of iterative design processes in the third step and simulation refinements, curvature-type slots were introduced at the four corners of the patch. As a result of this modification, the antenna exhibited enhanced impedance bandwidth and improved radiation efficiency. The curvature slots created additional current paths, which helped achieve better resonance characteristics. Further refinements involved optimizing the slot dimensions and their precise placement, ensuring minimal interference and maximum resonance at 39.5 GHz. The final design was validated through comprehensive simulations, confirming the anticipated performance improvements. Through continuous iterations and refinements, this stage of the design evolution significantly enhanced bandwidth and radiation efficiency, aligning the antenna with the requirements of mm-Wave applications. The performance of all the design evolution stages is compared and summarized in Table II.

TABLE II
ANTENNA DESIGN EVOLUTION: PERFORMANCE COMPARISON

Design Evolution	S_{11} (< -10 dB) in GHz	Bandwidth	Gain (dB)
Antenna – 1	36.82 - 38.23	3.76 %	4.3
Antenna – 2	37.60 - 39.27	4.35 %	4.7
Antenna – 3	38.57 - 40.72	5.42 %	5

C. *Proposed MIMO Antenna*

The proposed MIMO antenna using with resonator and without resonator is shown Fig. 4(a) and Fig. 4(b). In the MIMO configuration, a 2 × 2 array of single-patch antennas was implemented. Each antenna element in the array was optimally spaced to minimize mutual coupling and enhance the overall system performance. The inter-element spacing was carefully selected to be less than half the wavelength at 39.5 GHz, ensuring compactness while maintaining effective isolation between the elements. A MIMO array configuration without additional resonators was tested to evaluate its baseline performance. The results indicated satisfactory gain and directivity with acceptable levels of mutual coupling. Serving as a baseline, this configuration enables further performance enhancement through the addition of resonators. The MIMO antenna size is 14.5 mm × 12.4 mm × 0.3 mm. Resonators were integrated into the design to further optimize the MIMO antenna system's performance. The resonator, a circular structure with a radius of R_1, was placed at the center of the MIMO system. The resonators were strategically positioned within the MIMO array to fine-tune the impedance matching and enhance the overall gain and efficiency of the system. The inclusion of resonators resulted in significant performance improvements, particularly in terms of gain and directivity, highlighting the structural advantages of the resonator-integrated design. The optimized MIMO antenna with resonators exhibited better isolation between the antenna elements, reduced mutual coupling, and improved radiation patterns. The final design was validated through extensive simulations and experimental measurements, confirming its suitability for millimeter-wave applications. The performance of the MIMO antenna was compared in configurations with and without circular ring resonators. Table III summarizes each configuration's resonating frequencies, S_{11} values, and mutual coupling values.

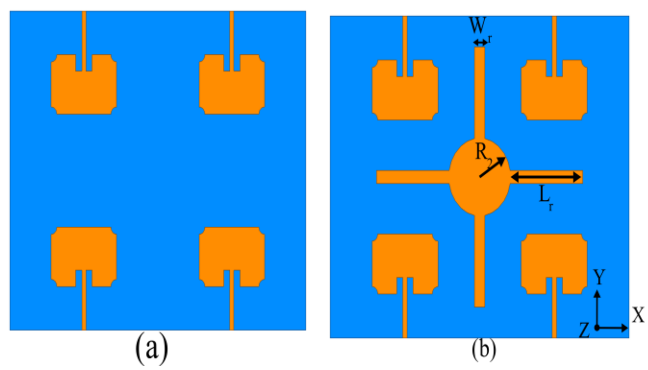

Fig. 4. (a) MIMO antenna Without Ring Resonator and (b) MIMO antenna With Ring Resonator.

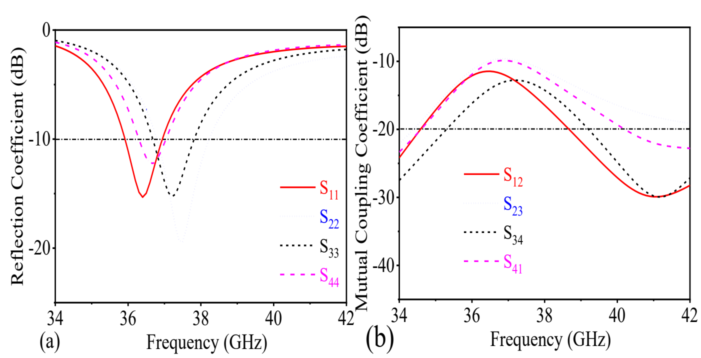

Fig. 5. (a) S-Parameters and (b) Mutual Coupling Coefficient for MIMO antenna without Ring Resonator.

III. Results and Discussion

A. MIMO Antenna Performance Analysis

Fig. 5 shows S parameters for MIMO antenna using without resonator. The outcomes unambiguously demonstrate that incorporating circular ring resonators considerably bolsters the performance of the MIMO antenna system. The resonating frequencies are consistently centered around 39.5 GHz, the target frequency for mm-wave applications. Moreover, the S_{11} values exhibit considerable improvement, indicating superior impedance matching and lower reflection losses. The mutual coupling values are also significantly reduced, revealing enhanced isolation between the antenna elements, which is vital for the effective operation of MIMO systems. Without the resonator, the gain is 7 dB; however, the gain increases to 9 dB with the resonator. The incorporation of circular ring resonators leads to notable improvements in both gain and directivity of the MIMO antenna system. These enhancements make the resonator-integrated design more suitable for mm-wave applications, meeting key performance demands of advanced communication systems like 5G.

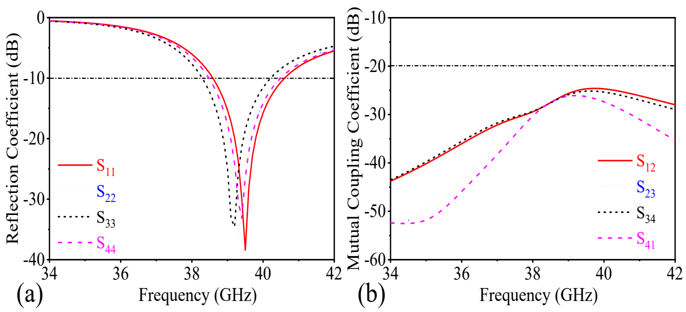

Fig. 6. (a) S-Parameters and (b) Mutual Coupling Coefficient for MIMO antenna with Ring Resonator.

The design without the resonator exhibits resonating frequencies of 36.4 GHz, 37.5 GHz, 37.2 GHz, and 36.7 GHz, accompanied by corresponding S_{11} values of -15.32 dB, -19.39 dB, -15.28 dB, and -12.21 dB, and mutual coupling values of -11.46 dB, -10.24 dB, -12.77 dB, and -9.99 dB. On the other hand, the design with the circular ring resonator achieves higher resonating frequencies of 39.5 GHz, 39.33 GHz, 39.15 GHz, and 39.37 GHz, along with significantly better S_{11} values of -38.83 dB, -39.23 dB, -38.79 dB, and -34.24 dB. Moreover, the mutual coupling values are substantially reduced to -26.41 dB, -24.85 dB, -25.69 dB, and -25.21 dB. Fig. 6 shows the S parameters of MIMO using with ring resonator.

A MIMO antenna design, with and without a circular ring resonator, exhibits various resonating frequencies and corresponding S_{11} values, as listed in Table 3. These S_{11} values, which represent the reflection coefficient and efficiency of the ante nna, range from -12.21 dB to -19.39 dB, demonstrating varying degrees of signal reflection. The mutual coupling values, which assess the interference between antenna elements, also range from -9.99 dB to -12.77 dB. In contrast, the MIMO antenna design that incorporates a circular ring resonator displays enhanced performance, with resonating frequencies in the range of 39.15 GHz to 39.5 GHz, significantly lower S_{11} values ranging from -34.24 dB to -39.23 dB, and reduced mutual coupling values between -24.85 dB and -26.41 dB. The circular ring resonator improves impedance matching and isolation, enhancing the overall performance of the MIMO system.

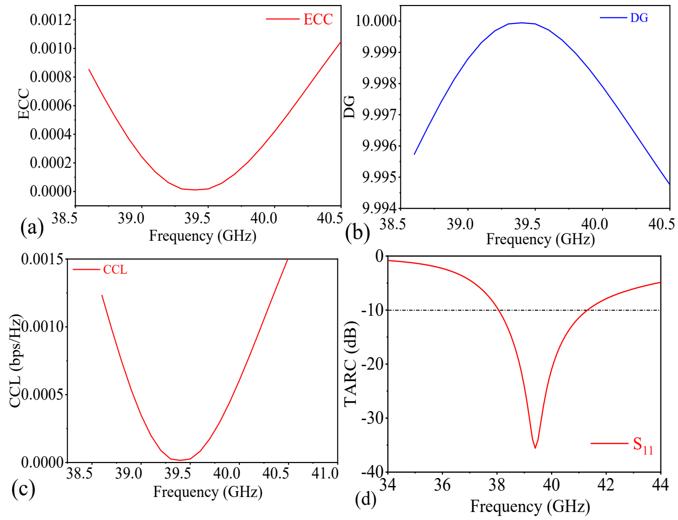

Fig. 7 Performance analysis of the MIMO antenna system (a) ECC, (b) DG, (c) CCL (d) TARC.

The MIMO antenna parameters are evaluated using the following expressions, as outlined in [23].

TABLE III
Performance Comparison MIMO Antenna using with and without Ring Resonator

Antenna	Resonating Frequency	S_{11} value	Mutual coupling value
Without circular ring resonator			
1	36.4	-15.32	-11.46
2	37.5	-19.39	-10.24
3	37.2	-15.28	-12.77
4	36.7	-12.21	-9.99
With circular ring resonator			
1	39.5	-38.83	-26.41
2	39.33	-39.23	-24.85
3	39.15	-38.79	-25.69
4	39.37	-34.24	-25.21

$$\mathrm{ECC} = \frac{|S_{11}S_{12}^{*} + S_{21}S_{22}^{*}|^2}{(1-|S_{11}|^2-|S_{21}|^2)(1-|S_{22}|^2-|S_{12}|^2)} \quad (1)$$

Fig. 7 (a) shows ECC using (1), the computed ECC is about 0.00000138. The exceptionally low ECC value indicates excellent diversity performance with minimal correlation between antenna elements.

$$\mathrm{DG}=10\times\sqrt{1\text{-}\mathrm{ECC}} \quad (2)$$

Fig. 7 (b) shows DG using (2), the DG is closer to 10. Such a high value demonstrates effective use of multiple antennas to combat fading and boost signal quality, resulting in strong diversity performance. Fig. 7(c) shows our suggested MIMO antenna's CCL. CCL is essential for optimizing performance in MIMO antenna design through the use of Characteristic Mode Analysis (CMA). It facilitates the identification of current distributions and natural electromagnetic phenomena that affect mutual coupling, efficiency, and radiation patterns. Through examination of these modes, engineers can identify those that maximize impedance matching and reduce mutual coupling across antennas, hence enhancing MIMO systems' spatial diversity and isolation. Furthermore, by determining the most efficient current routes, CCL helps to improve antenna efficiency, which eventually improves MIMO network performance and capacity.

$$\mathrm{TARC}=\sqrt{\frac{(S_{11}+S_{12})^2+(S_{21}+S_{22})^2}{2}} \tag{3}$$

Fig. 7(d) shows our suggested MIMO antenna's TARC using (3). For the specified 2 × 2 MIMO antenna system, the TARC is roughly 0.0639. With a low TARC value, the system is efficiently sending the signals through the antennas with less reflection

B. Machine Learning-Based Optimization

Fig. 8 shows the implementation proposed MIMO antenna system. The procedure begins with defining antenna characteristics and then implementing the design using HFSS software to examine important performance indicators including as gain, return loss, and efficiency. A dataset containing antenna parameters and performance metrics is then loaded, followed by the extraction of features and labels. Prior to training, the dataset was preprocessed to ensure consistency and improve model performance. Feature scaling was applied using standardization (Z-score normalization), where each feature was transformed to have a mean of zero and a standard deviation of one. This step is critical for algorithms like KNN and gradient-based methods, which are sensitive to feature magnitudes. The training dataset was constructed by systematically varying key antenna parameters within defined operational bounds. Controlled random perturbations were introduced to represent practical uncertainties, thereby improving the robustness and predictive capability of the machine learning model. To prevent over fitting, the data is divided into two sets: training (80%) and testing (20%). Furthermore, 5-fold cross-validation was employed during the training phase to evaluate model generalization and mitigate bias in performance estimation. Hyperparameter tuning was conducted for each model using grid search or randomized search methods to optimize predictive accuracy. For instance, in Random Forest, the number of trees (n_estimators), maximum depth, and minimum samples per leaf were tuned, while for XGBoost, learning rate, max depth, and subsample ratios were optimized [38-39]. Several ML models, including Decision Tree Regressor, Random Forest, K-Nearest Neighbors (KNN),

XGB, and Gradient Boost Regression (GBR), are used [31]. These models are trained on the training set to predict antenna performance based on input characteristics. After training, the models are tested against the test set to predict target values, and their performance is measured using metrics such as MSE and R-squared. Finally, the actual versus anticipated values are presented to indicate how well the models' function, with the optimal alignment of expected and real antenna characteristics.

Decision Trees, fundamental machine learning algorithms, are used for classification and regression tasks. They are simple yet powerful tools for data analysis, decision-making, and predictive modelling. Random Forest is an ensemble learning method that constructs multiple decision trees and combines their results to enhance predictive performance and control over fitting. KNN is one of the simplest machine learning algorithms, where it memorizes the training set and predicts the output for any new input based on the outputs of its closest neighbors in the training set. And then there's XGB, a gradient-boosting framework that stands out for its speed and performance. It sequentially builds trees, where each tree corrects the errors of the previous trees. GBR is a technique that creates a predictive model by sequentially training a series of decision trees, each designed to correct the errors made by its predecessors [2]. To evaluate the performance of these machine learning models, several metrics [35-38] were employed. The Mean Squared Error (MSE) which represents mean of the squared differences between predicted and actual values was calculated as shown in (4):

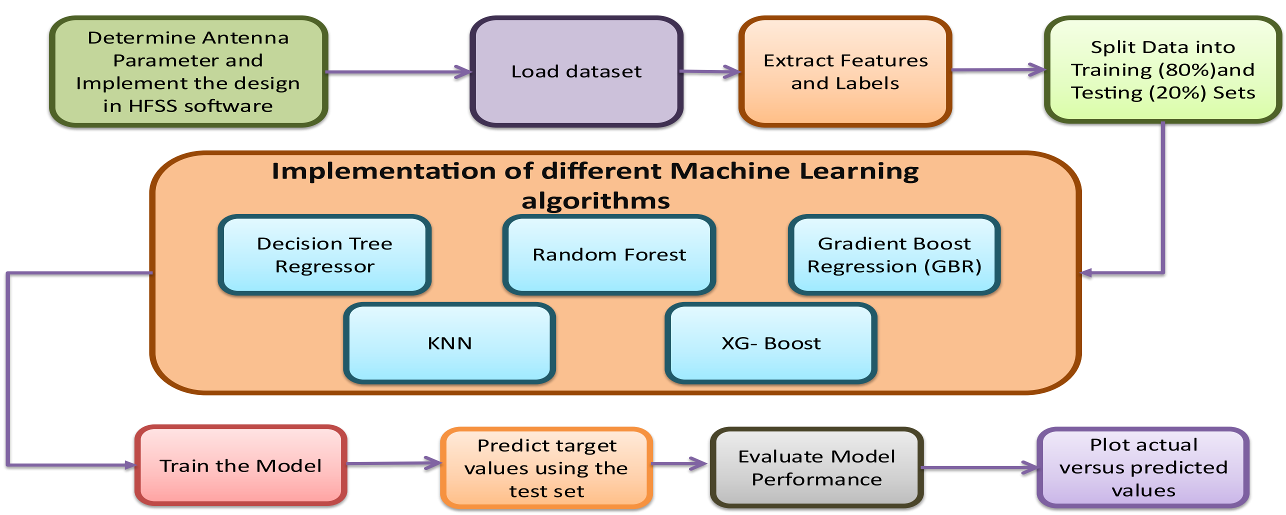

Fig. 8. Implementation of the proposed MIMO antenna system incorporating various machine learning algorithms for design optimization.

$$\text{MSE}= \frac{1}{n}\sum_{i=1}^{n} (y_i\text{-}\hat{y}_i)^2 \tag{4}$$

R-square (R^2), as shown in (5) represents the proportion of the variance in the dependent variable i.e predictable from the independent variables.

$$R^2 = 1\text{-}\ \frac{\sum_{i=1}^{n} (y_i\text{-}\hat{y}_i)^2}{\sum_{i=1}^{n} (y_i\text{-}\bar{y}_i)^2} \tag{5}$$

Mean Absolute Error (MAE), measures the average magnitude of the errors in a set of predictions, was determined by (6):

$$\text{MAE}= \frac{1}{n}\sum_{i=1}^{n} |(y_i\text{-}\hat{y}_i)| \tag{6}$$

Mean Absolute Percentage Error (MAPE), indicating the average absolute percentage difference between predicted and actual values, was calculated using (7):

$$\text{MAPE}= \frac{1}{n}\sum_{i=1}^{n} \left|\frac{(y_i\text{-}\hat{y}_i)}{y_i}\right| \times 100 \tag{7}$$

Fit Time (in seconds), as shown in (8), is the time required for the model to learn patterns from the training data.

$$T_{train} = t_{end}^{train} - t_{start}^{train} \tag{8}$$

and Prediction Time (in seconds), as shown in (9) time required to generate predictions for new, unseen data using the trained model.

$$T_{pred} = t_{end}^{pred} - t_{start}^{pred} \tag{9}$$

where n is the number of data points, y_i is the true value, $\hat{y}_i$ is the predicted value, and $\bar{y}_i$ is the mean of true values.

In the context of ML for predicting return loss, the initial step involves training a model. The process begins with the creation of a dataset comprising variations in antenna length (L) and width (W) as input features, along with frequency (F) as an additional parameter. The output is the return loss. The selected ranges for L span from 1.72 mm to 2.93 mm and for W from 2.24 mm to 3.64 mm, encompassing the entire design parameter spectrum. Using HFSS, all possible combinations within these ranges were generated, and S_{11} measurements were taken across the frequency range of 32.5 GHz to 45 GHz. A total of 15,012 data points were generated, forming a comprehensive dataset for training the ML models. To ensure accuracy and reliability, the dataset was divided into 80% for training and 20% for testing. The model training process involves determining the time required to train the ML model on a given dataset, known as fit time. Additionally, the time it takes for a trained ML model to make predictions, referred to as the prediction time, is also considered. The prediction time is influenced by factors such as the complexity of the model, dataset size, and available computational resources. Ultimately, the goal is to minimize the prediction time while maintaining high accuracy.

Python programming through Google Colab [40] was utilized to execute the models due to its adaptability, extensive libraries, ease of use, and user-friendly interface. The scikit-learn library [41] was employed for data preprocessing

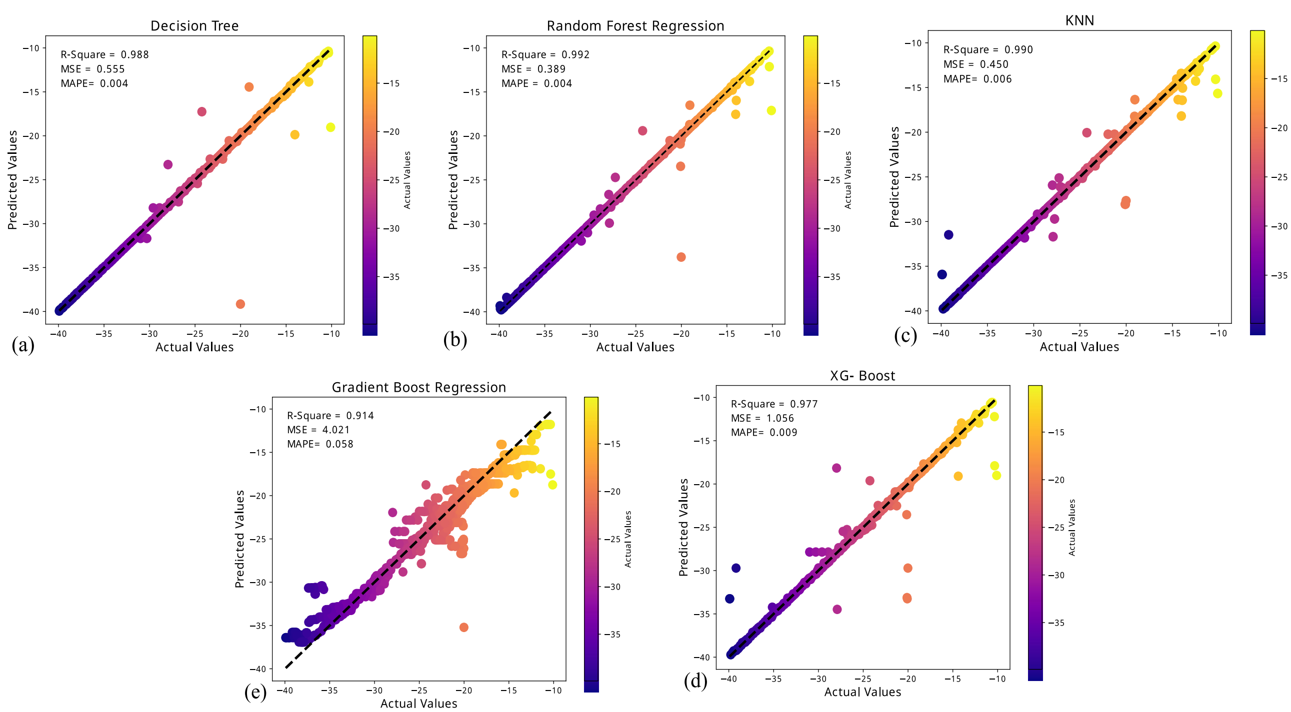

Fig.9. Actual values versus predicted values of Return Loss (a) Decision Tree, (b) Random Forest, (c) KNN, (d) XGB, (e) GBR.

TABLE IV
PERFORMANCE COMPARISON MIMO ANTENNA USING WITH AND WITHOUT RING RESONATOR

Model	R^2	MSE	MAPE	MAE	Fit Time	Predict Time
Decision Tree	0.988	0.555	0.004	0.085	0.015	0.003
Random Forest	**0.992**	**0.389**	**0.004**	**0.072**	**0.808**	**0.032**
KNN	0.990	0.450	0.006	0.116	0.004	0.008
XGB	0.977	1.056	0.009	0.195	0.094	0.006
GBR	0.914	4.021	0.058	1.287	0.373	0.004

(StandardScaler), cross-validation (KFold), and hyperparameter tuning (GridSearchCV). Table IV displays the comparison of performance metrics for various machine learning models, and Fig. 9 (a), (b), (c), (d), and (e) contrasts the predicted and actual return loss values for Decision Tree, Random Forest, XGB, KNN, and GBR models across the 32.5 to 45 GHz range. The strong correlation between the predicted and actual values indicates the models' ability to effectively learn data patterns and relationships, resulting in dependable return loss predictions. Graphs were generated using the Matplotlib library in Python on Google Colab.

Random Forest proved to be the most accurate model for predicting antenna return loss, due to its built-in randomness that prevents overfitting and improves generalization. It is pertinent to clarify that the present study is exclusively based on numerical simulations, and no physical prototype fabrication or experimental measurements have been conducted to date due to the unavailability of measurement facilities. Future work will involve fabrication and experimental validation of the proposed antenna design.

IV. Conclusion

The research demonstrates that integrating a ring resonator into the design of mm-Wave MIMO antennas for 5G applications significantly enhances antenna performance. Unlike previous designs, this work uniquely combines the ring resonator structure with machine learning techniques for rapid and accurate estimation of return loss, representing a novel approach in antenna optimization. Among the evaluated machine learning models, the Random Forest algorithm proved to be the most precise and efficient, with a fitting time of 0.808 s and a prediction time of 0.032 s, enabling faster design iterations. The measured performance (ECC = 0.00000138, DG = 10, TARC = 0.0639) demonstrates how combining ring resonator with Random Forest optimization creates a paradigm shift in antenna design. This establishes a new framework for data-driven RF development achieving both computational efficiency and electromagnetic precision which are critical for 5G technologies.

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