

Machine Learning-Based Design and Optimization of a Circularly Polarized Dielectric Resonator-Based MIMO Antenna for 5G Sub-6 Ghz

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Abstract:

In this work, we develop and analyse a 5G sub-6 GHz band multiple-input multiple-output (MIMO) antenna based on a two-port dielectric resonator (DR). A ceramic cylinder is excited by an L-shaped opening that has been slanted at an angle. The circularly polarised (CP) waves and HEM₁₁ mode are produced inside the ceramic by this feeding system. The suggested antenna's left-handed circular polarisation features allow it to cover the possible 5G range between 2.8 and 3.05 GHz. Datasets are generated using the suggested antenna using parametric analysis in HFSS. Several machine learning methods are used to the datasets in order to optimise the suggested antenna design's reflection coefficient (S₁₁), isolation (S₂₁), and axial ratio (AR). The approach suggested here employs a number of different machine learning techniques, including Decision Tree (DT), Deep Neural Network (DNN), k-Nearest Neighbours (KNN), Random Forest (RF), and EXtreme Gradient Boosting (XGBoost). The algorithms produce accurate findings that agree with HFSS simulations. DNN, KNN, and RF, however, produce results that vastly outperform those of DT and XGBoost.

Keywords: Machine learning, Dielectric resonator antenna, MIMO, Circularly polarized, Sub-6 GHz band, 5G

1. Introduction

In the modern day, antenna design is crucial to the success of wireless communication. The data rate, gain, and independence from antenna orientation can all be improved with a well-designed antenna. An MIMO (multiple-input multiple-output) antenna based on a circularly polarised dielectric resonator (CPDR) can meet all these needs. MIMO antennas use spatial diversity and spatial multiplexing to give a higher data rate without increasing the power level. Dielectric resonators increase antenna gain because they incur no losses due to the absence of metal. When MIMO-based DRA is used in conjunction with circular polarisation, a transmitter/receiver antenna can be rendered orientation-independent and the duration of the fading effect can be reduced [1]. Researchers today are also compelled by the need for quicker wireless communication and sufficient signal power to propose cutting-edge antenna designs that can accommodate the emerging 5G Sub-6 GHz applications [2]. Researchers have responded to this need by developing a wide range of CPDR-based MIMO antennas for 5G Sub-6 GHz use [3].

In its current iteration, machine learning is utilized to enhancements to antenna settings. In a short amount of time, machine learning algorithms can analyse massive datasets of antenna characteristics. Y. Sharma has used an ANN (Artificial Neural Network) and KNN (k-Nearest Neighbour) to improve a T-shaped microstrip antenna [4]. Ranjan et al. [5] use Random Forest, ANN, and KNN to drastically cut down on optimization time for an Ultra-Wideband (UWB) printed monopole antenna.

J. Gao et al. [6] use Gaussian Process to simulate the resonant frequencies of microstrip antennas. C. Maeurer et al. [7] have shown how the data-driven simulation approach may significantly accelerate antenna optimisation by employing a number of machine learning algorithms to improve antenna performance.

K. Sharma et al. [8] employ ANN, GPR (Gaussian Process Regression), and SVM (Support Vector Machines) to determine the resonant frequency in the dominant mode TM₁₁ of an ARCMA (annular ring compact microstrip antenna).

K. Sharma et al. apply regression-based ML algorithms to calculate the TM₁₀ resonant frequency. In addition to measuring the slot of a square patch, we measure the patch parameters of an SPCMA (square patch compact microstrip antenna) in the range of 0.4856–7.8476 GHz [9].

In [10], Cong Hu et al. use machine learning and Particle Swarm Optimisation (PSO) to fine-tune the S₁₁ parameter of a DRA. To broaden the frequency range across which rectangular DRA can function, N. Sehwat et al. presented a material perturbation concept. Using ANN models, we can forecast the relationship between the resonant frequency of the output and the design parameters [11].

Several machine learning methods have been used in the aforementioned research efforts to fine-tune antenna design parameters. However, there is scant evidence in the literature that ML techniques are used to optimise CPDR-based MIMO antenna. A select few researchers have used machine learning methods to perfect the S₁₁ antenna design. To date, no academics have been completely honest about optimising the axial ratio of CPDR-based MIMO antennas with ML algorithms. In addition, the lack of enough data leads to subpar precision in antenna design optimisation. All of these deficiencies inspired the research and development that this paper describes. The following are some of the things that this paper adds:

- Covering the most crucial spectrum for Sub-6 GHz applications, we present the design and analysis of a CPDR-based MIMO antenna that operates in the range of 2.8 GHz to 3.05 GHz.
- Parametric analysis in HFSS software used to generate datasets;
- Comparison of the machine learning methods utilised in the proposed study based on their performance; Optimisation of the simulation results (S₁₁, S₂₁, and axial ratio) using multiple machine learning algorithms.

To optimise the antenna's far-field component, axial ratio (AR), researchers have turned to a number of machine learning algorithms for the first time. The material is further divided into sections for ease of reading. The proposed antenna's structural layout is described in Section 2. The machine learning optimisation framework is described in Section 3. Section 4 presents the analysis and findings of the suggested antenna's optimisation. Section 5 describes the experimental outcomes and diversity parameters. The final section of the report summarises the findings.

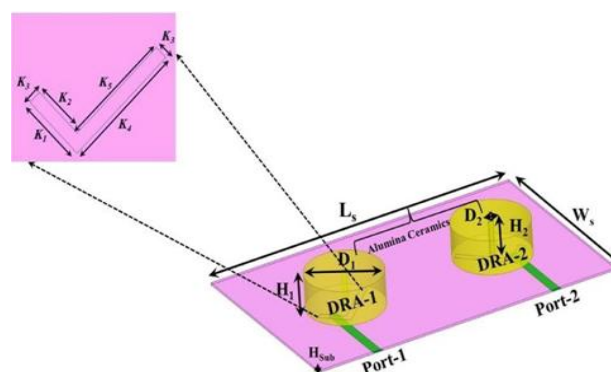


Figure 1. Proposed Antenna's Geometrical Layout

2. The planned antenna's structural layout

Circularly polarised (CP) antennas have low multipath impact and are effective in many wireless communication systems due to their orientation-independent properties. The generation of orthogonal degenerated modes and the presence of a mode pattern with a phase shift of 90° are both necessary for the generation of circular polarisation waves. A ceramic ring with an L-shaped opening at an angle can be used to generate orthogonal degenerated modes. While this is true, the second condition must also hold true. This is achieved by adjusting the length of an L-shaped aperture's inner arm to meet the necessary criteria.

Different modes and resonant frequencies are generated by exciting the circularly polarised (CP) dielectric resonator antenna (DRA) with either amicrostrip, probe, or aperture. The resonance frequency is determined by the size and dielectric constant. The resonance frequency and dielectric constant of the materials choose the size of DRA. DRA employs multiple feeding systems to deliver superior radiation efficiency and flexibility.

Fig. 1 depicts the dielectric resonator's structural arrangement with two ports. Alumina is used to create a ceramic in a cylindrical shape (Alumina = 9.8; $\tan \delta = 0.002$). The DRA has an approximate height (H_1) of 13.0 mm and an approximate diameter (D_1) of 30.0 mm. An L-shaped aperture with a little slant has been etched from the ground plane of the FR-4 substrate (FR-4 4.4; $\tan \delta = 0.02$). Each critical parameter of the proposed radiator is sized and described in the figure's caption. The ceramic is stuck to the base with the aid of fevi-quick.

The suggested two-port CPDR based MIMO antenna is gradually analysed using the electromagnetic field (EM) simulator Ansys HFSS. Figure 2 displays the difference in $|S_{11}|$ between a single-port antenna equipped with a ring DRA and one without. As can be observed in Fig. 2, the entire frequency range of 2.8 to 3.05 GHz is generated by the cylindrical ceramic. Using ring-shaped ceramic instead of cylindrical ceramic improves impedance bandwidth. E-field rotation on a cylinder of ceramic displays the mode pattern that is responsible for the 2.96 GHz resonance. Since the opening serves as a magnetic dipole, this is immediately obvious [12].

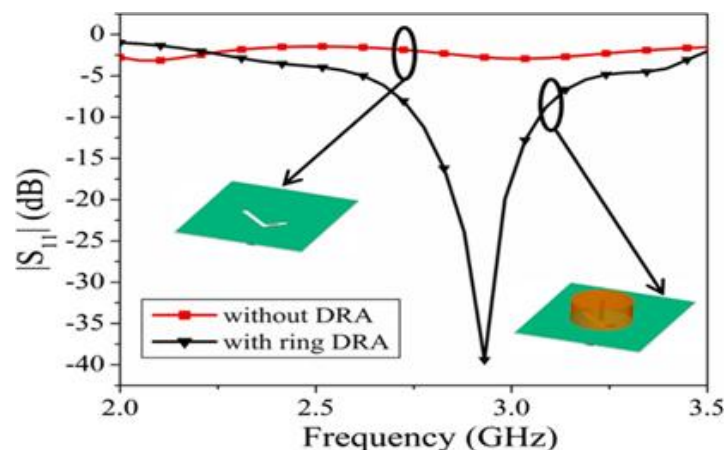


Figure 2. Reflection Coefficient Variation (both with and without a ring DRA)

3. Optimization with machine learning

The HFSS EM simulator produces four distinct datasets for the proposed antenna. Some machine learning models are trained using these datasets and then tested and assessed using prediction.

The single-port proposed antenna is used to create Dataset-1 (DS-1), while the two-port proposed antenna is used to create Dataset-2 (DS-2). Both datasets' data points are generated by cycling between 10 and 20 mm for the dielectric resonator's radius (RDRA) and 8 and 18 mm for its height (HDRA). The output responses are acquired at 100 places in the aforementioned frequency range of 2–3.5 GHz. Both DS-1 and DS-2 datasets are complete, with approximately 252,400 and 260,100 points each.

The proposed MIMO DRA is used to produce Datasets 3 (DS-3) and 4 (DS-4) by changing the feedline length

(Lfeedline) and slot parameters (K1 and K5). Slot parameters K1 and K5 are changed from 9.5 mm to 12.5 mm and 19 mm to 22 mm, respectively, while Lfeedline is changed from 31 mm to 33 mm. The output responses are acquired at 100 sites in the 2–3.5 GHz frequency range. In the end, a total of 17,600 data points were produced for dataset DS-3, and 14,200 data points were produced for dataset DS-4.

Some machine learning models are trained using the data collected. The predictive accuracy of these trained models is also evaluated. In order to accomplish its goals, the proposed study employs a number of different machine learning techniques, including Decision Tree (DT), Deep Neural Network (DNN), k-Nearest Neighbour (KNN), Random Forest (RF), and EXtreme Gradient Boosting (XGBoost).

- i. One supervised learning technique that can be used for both classification and regression problems is the Decision Tree. This tree-based classifier or regressor uses internal nodes to represent attributes of the dataset, branches to indicate decision rules, and final conclusions at the nodes' leaves. A Decision Tree has two types of nodes, the Decision Node and the Leaf Node. Leaf nodes are the consequence of such decisions and have no more branches, whereas Decision nodes are used to make those decisions and have many branches. The properties of the provided dataset are utilised to make judgements or conduct experiments. It's a visual representation of the range of possible outcomes from a given set of criteria. Trees that pose questions and branch off into other trees depending on the response (Yes/No) are called decision trees [13].
- ii. Nodes are the interconnected building blocks of a deep neural network. They're the tiniest building blocks of the human brain's neuronal network, and they function just like neurons. An action potential is generated when a cell receives a signal. Based on the data, a signal is transmitted from one neuron to the next. This has led to the emergence of a sophisticated network capable of adapting to new information. The layers serve to categorise the nodes. The many layers between the input and output are processed to solve the issue. To process a deeper network requires more layers, hence the term "deep learning." The number of levels involved in resolving an issue can be seen using the CAP (Credit Assignment Path) technique. When the CAP index is greater than two, it is said that the neural network is deep. Deep Neural Network applications are highly effective and helpful in the real world.
- iii. The k-Nearest Neighbours algorithm is one of the cornerstones of Supervised Machine Learning. By assigning a new case to the group that best matches the existing groups, the KNN method infers that the present case/data is analogous to those of the past. When fresh data is received after the training phase is complete, the KNN approach employs the average of k-nearest neighbours to either classify the data into a category (in the case of classification problems) or predict new values (in the case of prediction problems).when dealing with regression issues). KNN calculates the distance between two points using the Euclidean distance formula [13].
- iv. Random Forest: Random Forest is a highly effective supervised machine learning technique that may be used for both regression and classification. To solve a difficult problem and boost model performance, this method combines multiple classifiers into a single one. To improve the projected accuracy of a dataset with n observations, "Random Forest is a classification that consists of a number of decision trees on various subsets of a given n dataset and takes the average to increase the dataset's projected accuracy," as the name suggests. The random forest takes the predictions from all of the trees and makes a final prediction based on which ones are the most popular. More data points in the forest improve accuracy and help prevent overfitting.
- v. EXtreme Gradient Boosting (XGBoost): XGBoost is a supervised machine learning technique. Gradient boosted decision trees are used and a gradient boosting architecture is employed in XGBoost. In this method, decision trees are constructed one step at a time. Weights play a crucial role in XGBoost. The decision tree is used to make predictions by factoring in the weights assigned to each independent variable. Incorrectly anticipated variables are given more weight and are passed on to the next decision tree. When these numerous classifiers and predictors are merged, a more robust and accurate model is produced. It can be used for a wide variety of tasks, including but not limited to regression, classification, ranking, and user-defined prediction [13].

Decision Tree training uses the default settings for all parameters. DNN consists of five layers: three hidden, one input, and one output. The activation function is a Rectified Linear Activation Unit (ReLU). Adam is used as an optimizer during DNN training, with an initial learning rate of 0.001 for 200 iterations. 700 examples of 3, 5,

and 7 are used to teach Random Forest. With a maximum training depth of 8, XGBoost is trained with a learning rate of 0.01.

Some measuring factors are used to evaluate and compare the efficiency of various machine learning models. R2 (R-Squared) Score, Mean-Squared Error (MSE), Root-Mean-Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) [13] are utilised as measurement parameters in the suggested study.

The MAPE measures how well a certain forecasting system performs. It is expressed as a percentage and is found by taking the average absolute percent error and subtracting the actual values from the real values for each time period. It can be expressed as follows:

Table 1. Performance Comparison of ML Algorithms using Dataset DS-1 for Prediction of S11.

Algorithm	R2 Score	MSE	MAE	RMSE	MAPE	RMSPE
DT	0.971	0.807	0.341	0.898	0.046	0.072
DNN	0.987	0.359	0.283	0.599	0.046	0.065
KNN (N = 3)	0.97	0.816	0.341	0.903	0.047	0.078
KNN (N = 5)	0.957	1.199	0.413	1.095	0.06	0.106
RF	0.987	0.353	0.206	0.594	0.029	0.048
XGBoost	0.835	4.612	1.201	2.147	0.231	0.313

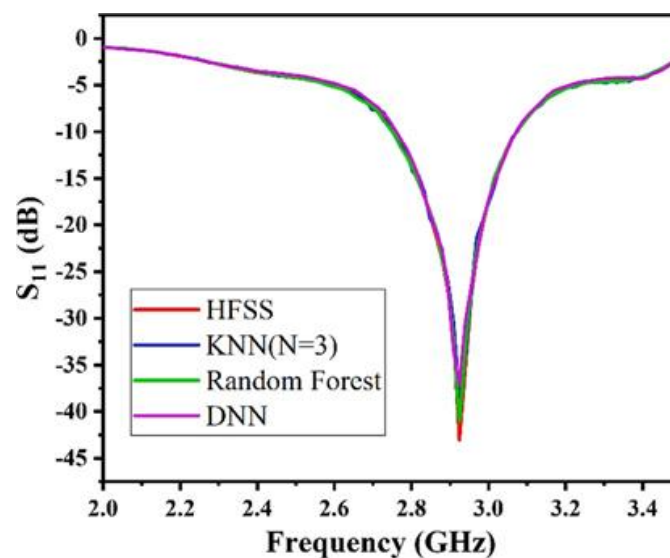


Figure 3. S11 presents a scatter plot contrasting ML algorithms (DS-1) with HFSS

4. Analysis of the Optimisation Results

Machine learning algorithms are used for training, testing, and prediction after four datasets have been generated. There are two halves to each dataset. Each dataset is divided into two sections, with the first section including 70% of the data points used for training the models and the second section containing 30% of the data points used for testing the models.

The training set consists of 70% (176680) of the overall dataset, whereas the testing set consists of 30% (75720) of the dataset. In Table 1, we see how well several algorithms estimate the reflection coefficient (S11) using various performance metrics. Table 1 shows that when compared to other algorithms, DNN and RF yield the

best outcomes.

Graph 5 compares S_{11} against frequency at 13 mm height and 15 mm radius using KNN Random Forest and DNN with HFSS results. As can be seen in Fig. 3, the values produced by these algorithms are quite close to those produced by HFSS.

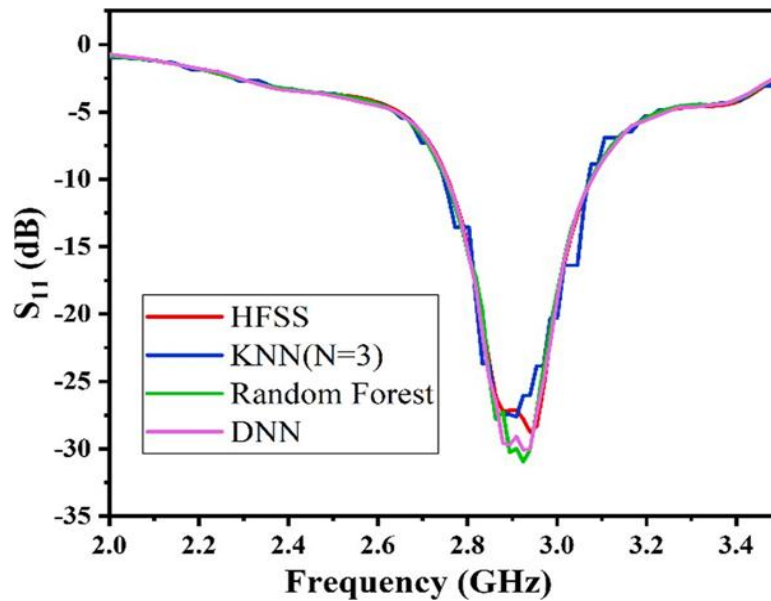


Figure 4. S_{11} comparison graph of ML algorithms (DS-2) with HFSS

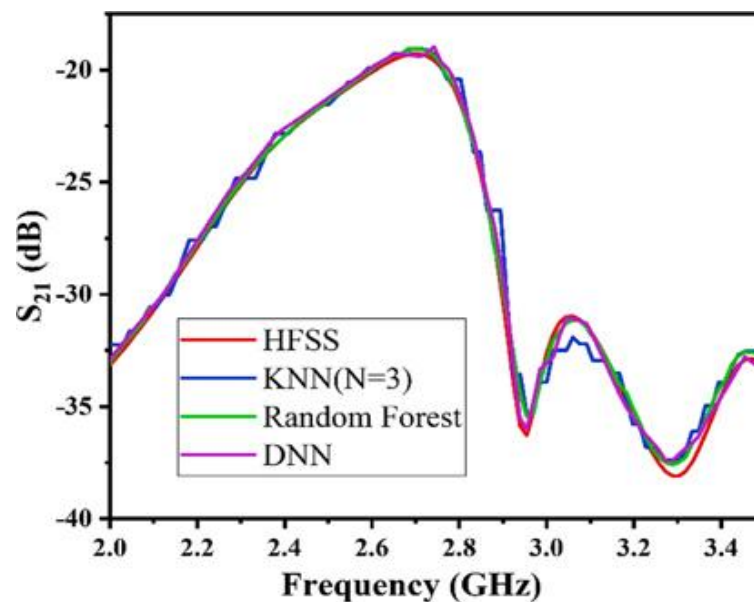


Figure 5. S_{21} comparison graph of ML algorithms (DS-2) with HFSS

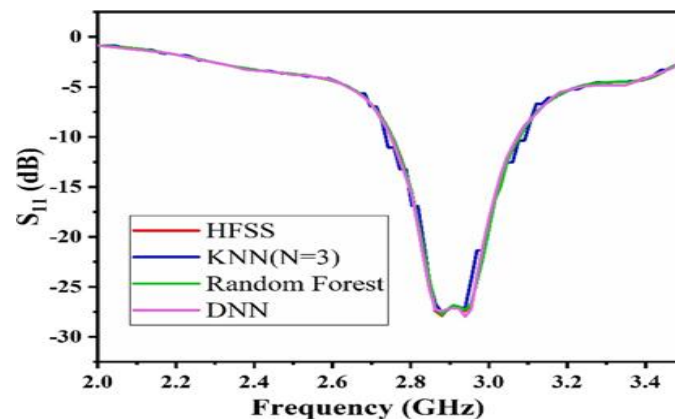


Figure 6. S11 comparison graph of ML algorithms (DS-3) with HFSS

Fig. 4 and Fig. 5 show the S11 vs. frequency and S21 vs. frequency comparison graph, respectively at height of 13 mm and radius of 15 mm for KNN, Random Forest, and DNN with the HFSS results. It can be observed from both the Fig. 4 and Fig. 5 that the values obtained from DNN and Random Forest almost matched with the HFSS results.

The proposed two-port DRA is used to generate the DS-3 dataset, which includes attributes such as feedline (Lfeedline), slot parameters (K1 and K5), and frequency. Both the isolation (S21) and reflection coefficient (S11) models have names.

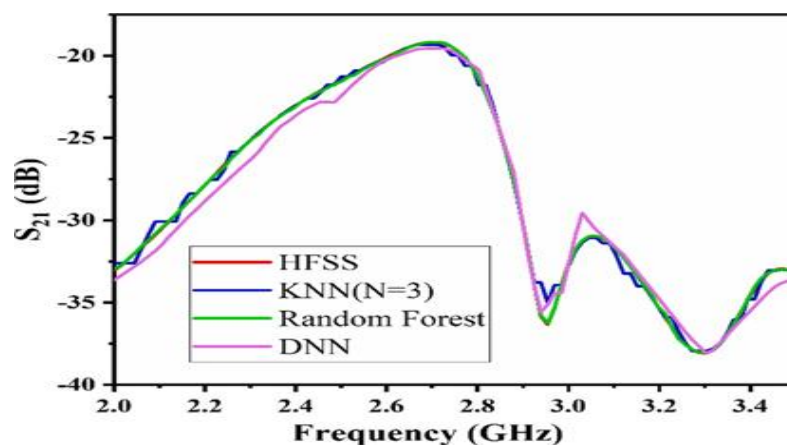


Figure 7. S21 comparison graph of ML algorithms (DS-3) with HFSS.

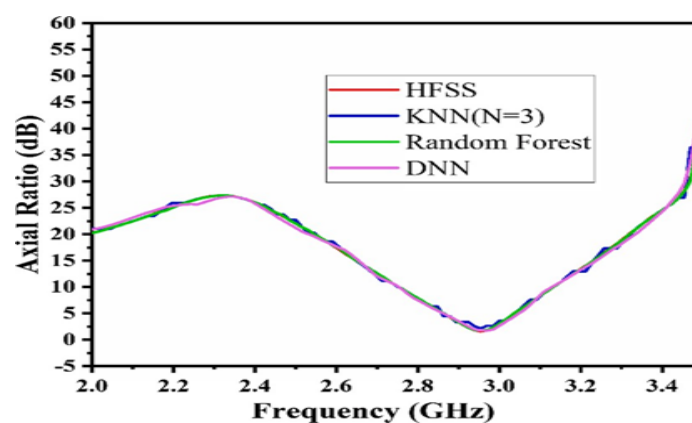


Figure 8. AR comparison graph of ML algorithms (DS-4) with HFSS.

Figure 6 shows that the values predicted by DNN and Random Forest are consistent with the HFSS findings. The values from DNN and Random Forest are very close to the HFSS results, as can be shown in Fig. 7.

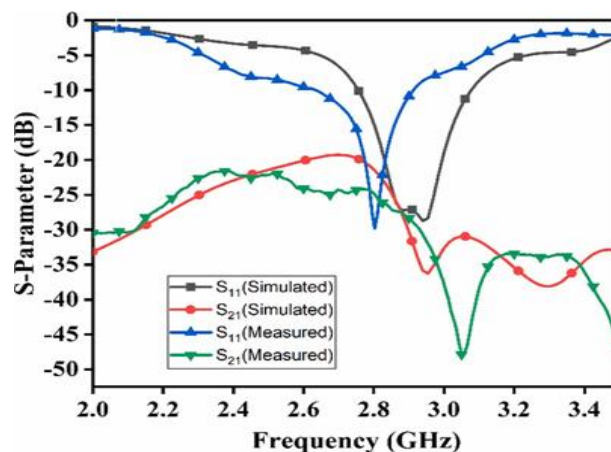


Figure 9. S-parameter of proposed antenna (Measured and simulated).

At Lfeedline = 33 mm, K1 = 12.5 mm, and K5 = 22 mm, Fig. 8 displays the axial ratio vs frequency comparison graph for KNN, Random Forest, and DNN with the HFSS results. As can be seen in Fig. 8, the values produced by these algorithms were quite close to those produced by HFSS.

In this part, measured data is used to confirm the optimal results from the simulations. An E5071C Keysight vector network analyzer is used to calculate the S-parameter of the proposed antenna. Fig. 9 shows the changes in S-parameter over time for the proposed antenna. It displays both the simulated and measured values side by side for easy comparison. As can be seen in Fig. 9, the suggested antenna has a frequency range of 2.8 GHz to 3.05 GHz and an isolation of 30 dB. As can be seen in Fig. 9, there are some small discrepancies between the measured and simulated values of Sparameter. The adhesive agent used to fasten the ceramic to the substrate is the primary source of these variations. Broadband, resonance, and radiation features of a dielectric resonator antenna were discussed by Faiz et al. [14].

5. Conclusion

In this paper, a two-port ceramic antenna with a circular polarization feature for sub-6 GHz 5G applications has been investigated. For producing the CP waves in the operating band of 2.8 to 3.05 GHz, a tilted L-shaped feeding structure has been utilized. To optimize the parameters of proposed antenna, various ML algorithms are utilized. For this purpose, four different datasets have been generated by HFSS software.

The optimization of axial ratio for CPDR based MIMO antenna using ML algorithms is performed first time. Five different ML models are used for the optimization purpose. Predicted results are quite close to the actual results. DNN and RF have outperformed the other algorithms for the prediction of axial ratios using dataset DS-4. The R2 values of DNN and RF are 0.910 and 0.924 with MSE value of 6.692 and 5.657, respectively. The experimental results, simulated results and predicted results have a match with each other. These results also validate the working of operating frequency band i.e.; 2.8–3.05 GHz. The values calculated using Far-field parameters are also matching with the standard limit. Therefore, the proposed antenna can be efficiently used for 5G Sub-6 GHz applications.

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