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Design and optimisation of CPW antenna using machine learning algorithms

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Abstract: In this paper, a novel design and optimisation method of coplanar waveguide-based antenna with two radiating arms surrounded by coplanar ground has been proposed. Optimisation of lengths and widths of the CPW antenna arms produce better impedance matching, better gain and multiband radiation characteristics. The optimisation of the proposed antenna is carried out with the help of familiar machine learning algorithms namely KNN, decision tree, linear regression and ridge regression. These optimisation algorithms are implemented using python programming and applied to obtain optimised dimensions on the basis of root mean square error (RMSE). The output parameters chosen for optimisation are gain and bandwidth of the antenna. The proposed antenna is simulated, optimised and analysed using high frequency structure simulator (HFSS) software. The high gain antenna can be operated for dual resonance frequencies 2.4 GHz and 5.8 GHz with optimum bandwidth with peak gain of 10 dB.

Keywords: coplanar waveguide antenna; optimisation; machine learning algorithms; KNN; decision tree; root mean square error; RMSE.

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1 Introduction

Artificial intelligence (AI) is the skill of teaching machines to carry out functions like learning, making decisions, and problem-solving that needs human thought processes. In short, AI is the application of human reasoning skills to machines. The current developments in big data accessibility, capability of software engineering, and reasonably priced high processing power have made AI an indispensable component of modern research. It is anticipated that it will have a significant impact on the majority of our daily activities, fundamentally alter science and engineering, and have enormous social repercussions. It will enable the creation, transformation, and optimisation of numerous aspects and applications of our daily lives. The computer or machine needs to possess a number of qualities in order to implement and develop AI (Liu et al., 2018b). For instance, good communication in English requires natural language processing, and retaining information requires knowledge representation. Automated reasoning is needed to answer queries and draw conclusions from data stored, but machine learning (ML) is needed to identify patterns in data, forecast outcomes, and adjust to changing circumstances. Robotics and computer vision are required for object perception and manipulation. By using clever algorithms and large data sets, iterative processing enables AI software to automatically learn from patterns or features. ML is built on algorithms that can learn from data without the need for rules-based programming (Samek et al., 2021; Ray, 2019). One of the rapidly developing sciences is ML, which has broad applications in the disciplines of engineering, science, medicine, and economics, among others. The field is a branch of AI that looks for a mathematical model that describes input and output data using computational statistics. The ML-based algorithms are effectively applicable for numerous applications where optimisation plays a vital role. Neural networks are presented in Shaban and Shalaby (2012) as an intelligent tool to automate the recognition of various control chart patterns and to precisely optimise their parameters. To optimise the piecewise regression model while simultaneously taking factors into consideration, a new method based on mathematical programming is carried out in Laari et al. (2019). The applications of the established technique of artificial neural network (ANN) to activity networking in the supervision of quality programs are presented in Badiru (2019).

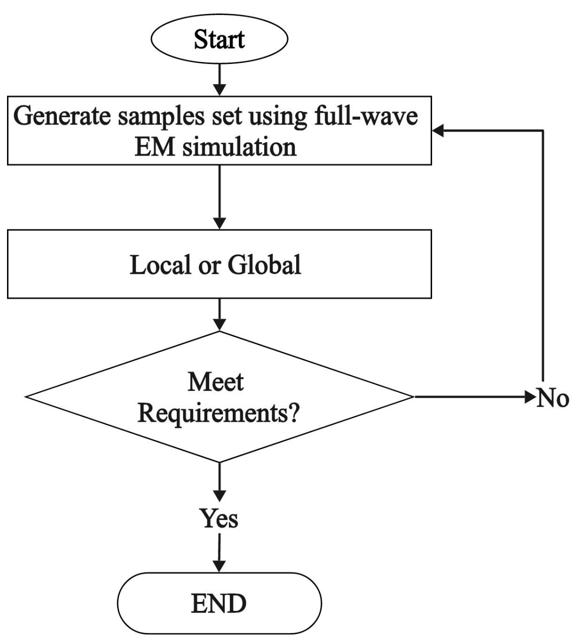
Applications of ML to engineering design and optimisation have been examined in a number of research studies. It can offer a faster design process while preserving high levels of accuracy, reducing errors and saving time, as well as the ability to predict design parameters, improve computational efficiency, and run fewer simulations (Misilmani and Naous, 2019; Akinsolu et al., 2020; Wu et al., 2020; Chu, 2022). The use of ML in electromagnetics and antenna design has recently been expanded. Rapid optimisation approaches are particularly desired since the antenna must be adjusted to maximise performance while minimising size. Future intelligent beam steering and smart beam forming applications, including as 5G, IoT, industry and healthcare, are well suited for this important demand, and CPW-based antennas are well suited for it (Kansal et al., 2022; Gautam et al., 2013; Bod and Taheri, 2012; Azim et al., 2011; Emadian et al., 2012). When compared to traditional rectangular microstrip components, CPW architectures have better propagation and dispersion characteristics. Coplanar construction provides consistent, dependable electrical shielding. The undesired surface waves can be avoided by enclosed ground attached with an arbitrary shaped patch.

A strip of thin metallic film on the surface of a dielectric slab serves as the coplanar waveguide (CPW) antenna, and two ground electrodes are positioned next to and parallel to the strip. In addition to making it simple to connect external devices in hybrid integrated circuits, the coplanar transmission system arrangement also suitable for easy fabrication of monolithic integrated systems. The optimisation of the dimensions of the proposed CPW configuration enhances the performance characteristics. Identification of optimum dimensions for CPW antenna is the major task in the antenna design. By performing multiple numbers of simulations, the data set of input dimensions and output characteristics is developed. ML is based on algorithms that can learn from data without relying on rules based programming. After training the learning algorithm on a given data set, the algorithm generalises to give accurate predictions to all possible inputs. With the help of familiar ML approaches and algorithms, the results would be better. In this paper the optimisation of CPW antenna dimensions with the help of ML-based algorithms are exercised and improvement in performance characteristics is obtained. Various ML algorithm approaches can be applied by collecting learning data to the computer by doing multiple simulations on high frequency structure simulator (HFSS) platform.

2 Optimisation of antenna design using ML

As illustrated in Figure 1, the traditional optimisation approach uses simple random trial and error based global or local optimisation (Wu et al., 2020). Using traditional algorithms, predicting the optimum output for a given set of inputs is laborious and time-consuming.

Figure 1 Conventional approach of antenna optimisation



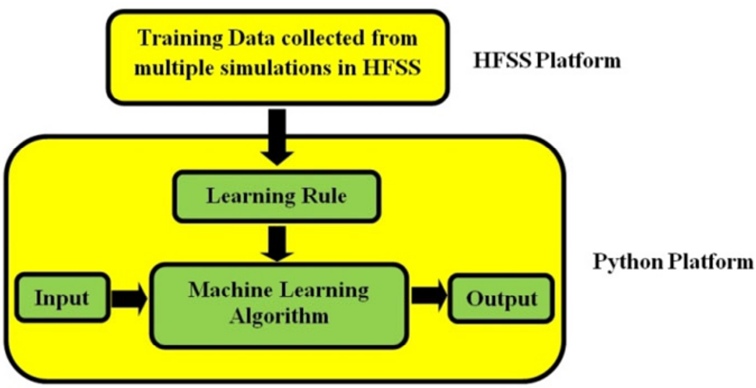
The use of ML in antenna design has been examined in several studies (Wu et al., 2019a, 2019b; Akinsolu et al., 2019; Liu et al., 2018a). ML methods are useful to speed up the design process of antenna while maintaining high precision levels, minimisation of errors, time saving, and possibly predicting antenna behaviour. It will also improve computational efficiency and decrease the number of simulations required. The following process has been executed to employ ML methods in antenna optimisation and design as shown in Figure 2.

1 The electromagnetic properties of an antenna are found by numerous simulations in HFSS platform.

2 A database containing these features is utilised as a learning data set to train a particular ML algorithm.

3 The algorithm creates the antenna that yields the closest results after generating predictions based on the designer's specifications.

Figure 2 Antenna optimisation using machine leaning algorithm (see online version for colours)



2.1 ML algorithms

Algorithms that can learn from data without using rules-based programming are the foundation of ML. The learning method generalises to make correct predictions for all conceivable inputs after being trained on a specific data set. Figure 3 illustrates the application of ML algorithms to build surrogate model, optimisation and validation of required design parameters and dimensions of the chosen output parameter.

Identification of suitable algorithm for required model is essential for effective application. ANNs, support vector machines, logistic regression, and linear regression are just a few examples of supervised learning techniques. Large interconnections of 'neurons', or essentially simple processing cells, are employed in ANN to achieve high performance. Neural networks offer an alternate approach to ML in situations when numerous features and complex functions are discovered. As shown in Figure 4, neural networks consist of several layers, including the input layer, the output layer, and hidden layers between the input and output levels. The feed-forward neural network, one of the various varieties of neural networks, uses a weighted average of connected.

Figure 3 Optimisation using ML algorithms

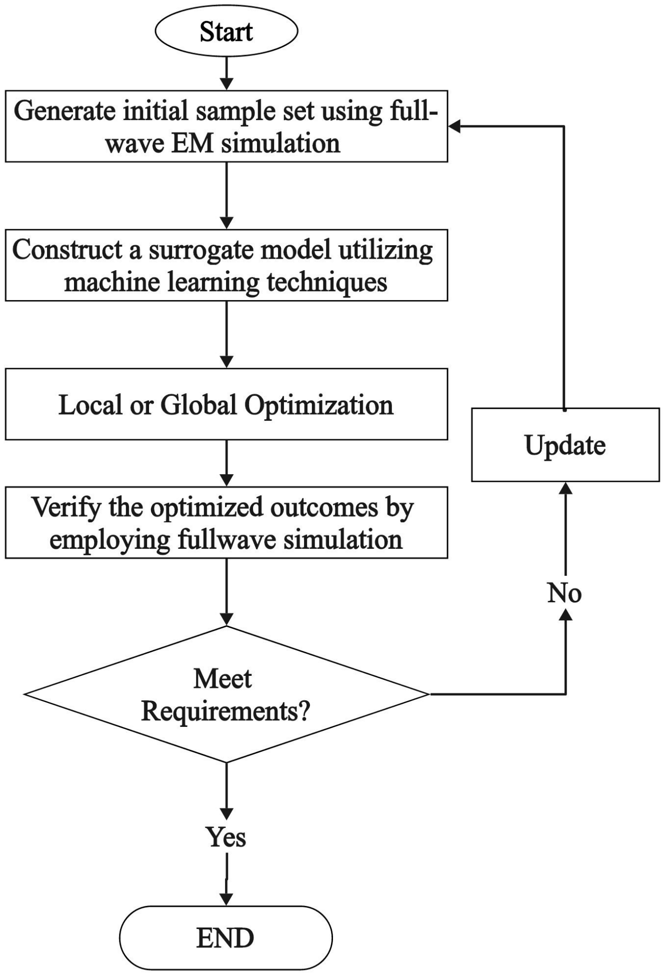
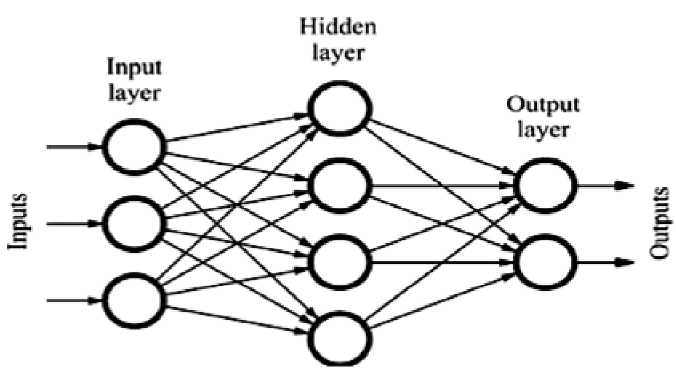


Figure 4 Schematic diagram of ANN



One of the easiest ML techniques to understand is K nearest neighbours (KNN). Once it has learned to memorise the training set, it utilises the outputs of its closest neighbours in the training set to predict the output of each new input. With the K-means clustering approach, the variables in the data are grouped together based on their correlations with each other. The selection criteria of the proper ML algorithms are based on the functionality, usability, merits and demerits as described in Table 1.

Table 1 Selection criteria for the ML algorithms

Algorithm	*Functionality*	*Used in*	*Merits*	*Demerits*
K-nearest neighbours	Data points are classified by KNN based on the training data's k-nearest neighbours' dominant class. It averages the goal values of its K-nearest neighbours for regression.	Classification, regression	Simple: easy to understand	Sensitive to noisy data
Decision trees	Decision trees iteratively divide data according to the most significant feature in order to create a structure resembling a tree. These criteria include Gini impurity and information gain. On the basis of traversing this tree, they categorise or forecast.	Classification, regression	Interpretability, easy to explain	Prone to over-fitting
Linear regression	By fitting a linear equation (a straight line) to the data, linear regression models the relationship between the independent factors and the dependent variable. It reduces the total squared errors.	Regression	Simplicity: straightforward modelling	Assumes linear relationships
Ridge regression	A regularisation term is added to the linear equation in the ridge regression variation of linear regression. It incorporates a penalty term for high coefficient values and minimises the sum of squared errors.	Regression	Handles multi-calling easily	Requires tuning of regularisation parameter

3 CPW design methodology

The proposed CPW antenna is motivated from basic CPW design in Gautam et al. (2013) and the optimisation of the required dimensions are carried out using ML algorithms for improved performance. The antenna is designed and simulated on HFSS platform according to the obtained dimensions in the layout in Figure 5.The performance of the antenna is observed in terms of return losses (S_{11}), VSWR, gain, efficiency, etc.

Because a microstrip antenna only has one resonance, its bandwidth is typically not very wide. Therefore, two or more resonant components, each operating at its resonance, are needed to construct a UWB antenna. The overlapping of these numerous resonances may result in multiband or broadband performance. In order to achieve an ultra wide bandwidth, this design creates multiple resonant bands. Furthermore, in this design, both the grounds were etched on the same plane of the monopole, as opposed to the standard UWB monopole antenna, which uses a solid ground plane on the opposite side. The aforementioned design abilities are used to achieve UWB band with strong impedance matching throughout the full working band. The rectangular patch that serves as the monopole radiator's foundation is two strips with an L-shaped inversion that extend from the patch's upper two edges. The patch has the proportions of length and breadth. The vertical and horizontal strips are both a part of each of the two strips. As for the ground plane, it is embedded from the patch's left and right sides on the same plane to give the CPW feed, in contrast to the conventional practice of using a solid rectangular plane for a microstrip-fed monopole antenna. The antenna's overall dimensions are 25 mm × 25 mm × 1.6 mm, and each of the surrounded grounds has a 25 mm vertical portion and a 10.5 mm and 10.6 mm horizontal section on the top and bottom faces, respectively.

Equations (1) to (5) provide the necessary mathematical framework and instructions for designing conventional CPW structures, which the proposed CPW antenna adheres to. Any CPW structure's initial dimensions are directly influenced by the operating frequency and the effective dielectric constant of the substrate. By incorporating a closed-shaped grounding into a coplanar structure, the CPW structure can be constructed.

Figure 5 CPW antenna layout (see online version for colours)

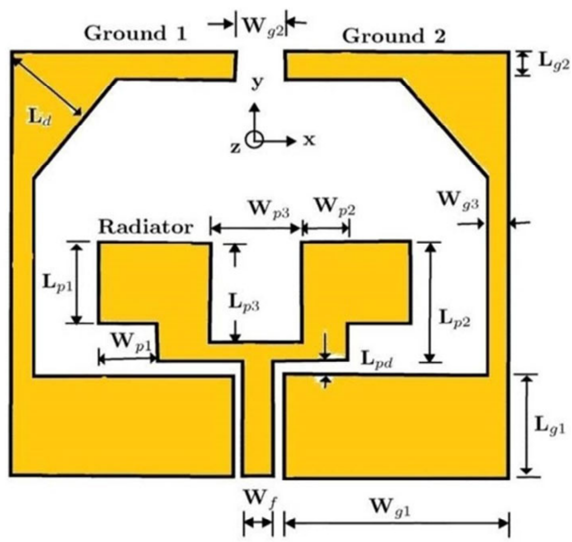
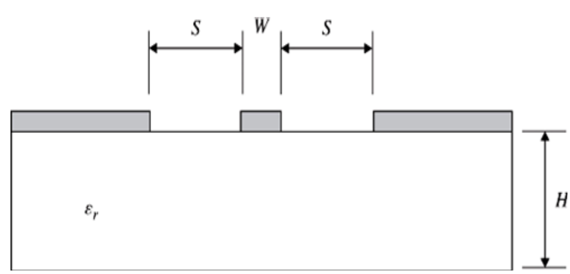


Figure 6 CPW antenna side view



To achieve the perfect impedance matching the dimensions of the feed need to be pre-calculated to set characteristic impedance (Z_0). This may be calculated as

$$Z_0 = \frac{30\pi}{\sqrt{\varepsilon_{eff}}} \frac{K(k')}{K(k)} \tag{1}$$

where

$$\varepsilon_{eff} = 1 + \frac{\varepsilon_r - 1}{2} \frac{K(k')K(k_1)}{K(k)K(k_1')} \tag{2}$$

$$k = \frac{W}{W + 2S} \tag{3}$$

$$k_1 = \frac{\sinh\left(\frac{\pi W}{4H}\right)}{\sinh\left(\frac{(W+2S)\pi}{4H}\right)} \tag{4}$$

$$\text{and } k' = \sqrt{(1-k)^2} \tag{5}$$

To ensure 50Ω characteristic impedance, the CPW feedline's width is specified at 3.0 mm. The narrow gap between the ground plane and the radiator, which is used to reduce the antenna area by surrounding the radiator with metal, greatly contributes to the excessively strong capacitive coupling. A 0.4 mm gap separates the horizontal feed segment from the ground. While building the CPW, minimising conduction, dielectric, and radiation losses for maximising the gain is a crucial factor to take into account. Maintaining a suitably high thickness can help prevent conductor losses because the attenuation constant is inversely related to the CPW structure's substrate thickness. The choice of substrate material should have a low loss tangent since dielectric losses are independent of dimensions and only depend on the dielectric material.

The CPW antenna dimensions have been determined, and the design process has been executed on the HFSS platform by implementing the subsequent procedures, shown in Figure 7.

Step 1 Calculate all the dimensions of the CPW structure and specify the dielectric constant of the substrate.

Step 2 Obtain the dimensions of the ground and substrate according to the CPW size.

Step 3 Insert required number of ground planes to form a CPW substrate with pre-calculated dimensions.

Step 4 Insert edge feed to the patch with optimised dimensions to obtain impedance matching.

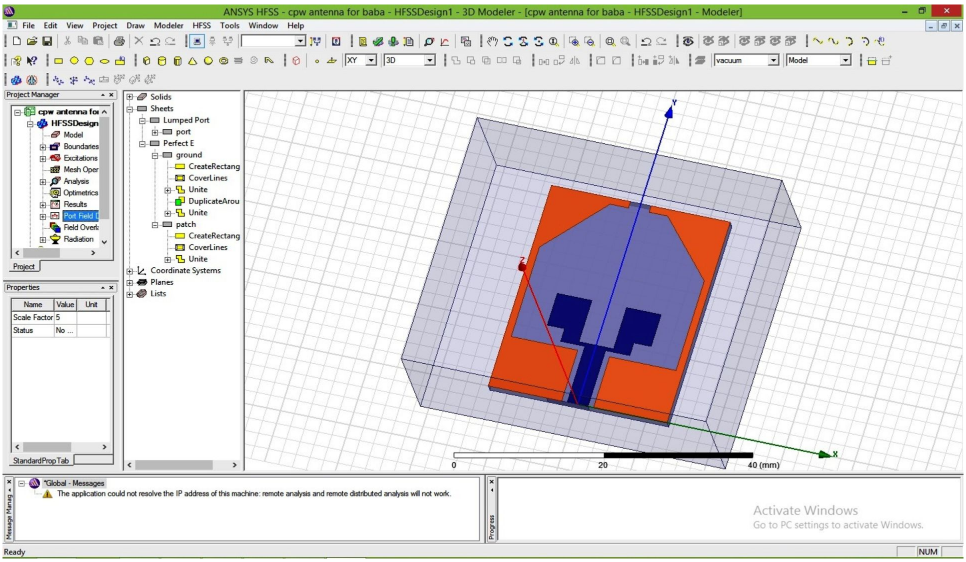
Step 5 Insert coaxial feed cable at the edge of the CPW structure at an optimised location and apply the required boundary conditions.

Step 6 Insert *analysis setup* and *frequency sweep* according to the requirements.

Step 7 Complete the *validation check* and go for *analyse all*.

Step 8 Obtain the results in terms of 2D, 3D radiation patterns, return losses, gain, efficiency, etc.

Figure 7 Design of CPW antenna on HFSS platform (see online version for colours)



4 Optimisation

The typical method for design optimisation involves modelling the antenna until the required values are achieved; this is a computationally intensive and time-consuming procedure. By predicting the relation among desired input and output parameters, ML helps quicken the design process. Generally, the following process can be used:

- Numeric values associated with the desired inputs with their relative outputs are obtained by exercising multiple simulations and are stored in a excel sheet based database as shown in Figure 8.
- This dataset is then divided into training, validation, and test datasets, with the proportion of each set depending on the number of data samples.
- This data is fed into an ML algorithm for learning. Once the model has been trained and tested, it may be utilised for predicting output values for the necessary inputs.
- The choice of algorithm is determined by the problem's complexity, the amount of data at hand, and the method's mathematical formulation.

5 Data collection for optimisation

The performance of the proposed antenna is assessed in terms of return loss, bandwidth, gain, and radiation pattern. The dimensions Lp1, Lp2, Lp3, Wp1, Wp2 and Wp3 are chosen as optimisation variables. These are considered as specific parameters used for training and evaluating the ML models to ensure reproducibility and comparability. The recommended antenna has been customised to provide the required performance parameters using ML algorithms. KNN, decision tree, linear regression, and ridge regression are some of these methods.

The complete numerical data of dimensions as well as corresponding outputs for the operating frequencies 2.4 GHz and 5.8 GHz are stored in an excel file as shown in Tables 2 to 4. For the specified dimensions Lp1, Lp2, Lp3, Wp1, Wp2 and Wp3 as optimisation variables, twelve combinations of optimisations namely OPTIMISATION 1 to OPTIMISATION 12 are developed and corresponding data is collected by doing multiple simulations in HFSS platform.

The following steps need to be executed in the Python platform to obtain the desired optimised parameters:

Step 1 Imported Pandas Library to read data from excel.

Step 2 Checked all data rows and columns/features

Step 3 Taken predicted label as dB(gain).

Step 4 Imported Scikit learn library train test split to split data in to train set and test set.

Step 5 Spitted data in to 80% for training and 20% for testing.

Step 6 Selected ML algorithms such as KNN, linear regression and decision tree.

Step 7 Labelled data like X_train, Y_train and X_test and Y_test.

Step 8 Imported plotting libraries to visualise performance of data.

Step 9 Performed hyper parameter search to select best hyper parameter on validation data and checked with root mean square error (RMSE) value whichever RMSE value is low then we select that hyper parameter as best.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2} \tag{6}$$

where y_i = actual value, $\widehat{y}_i$ = predicted value and n = size of the sample.

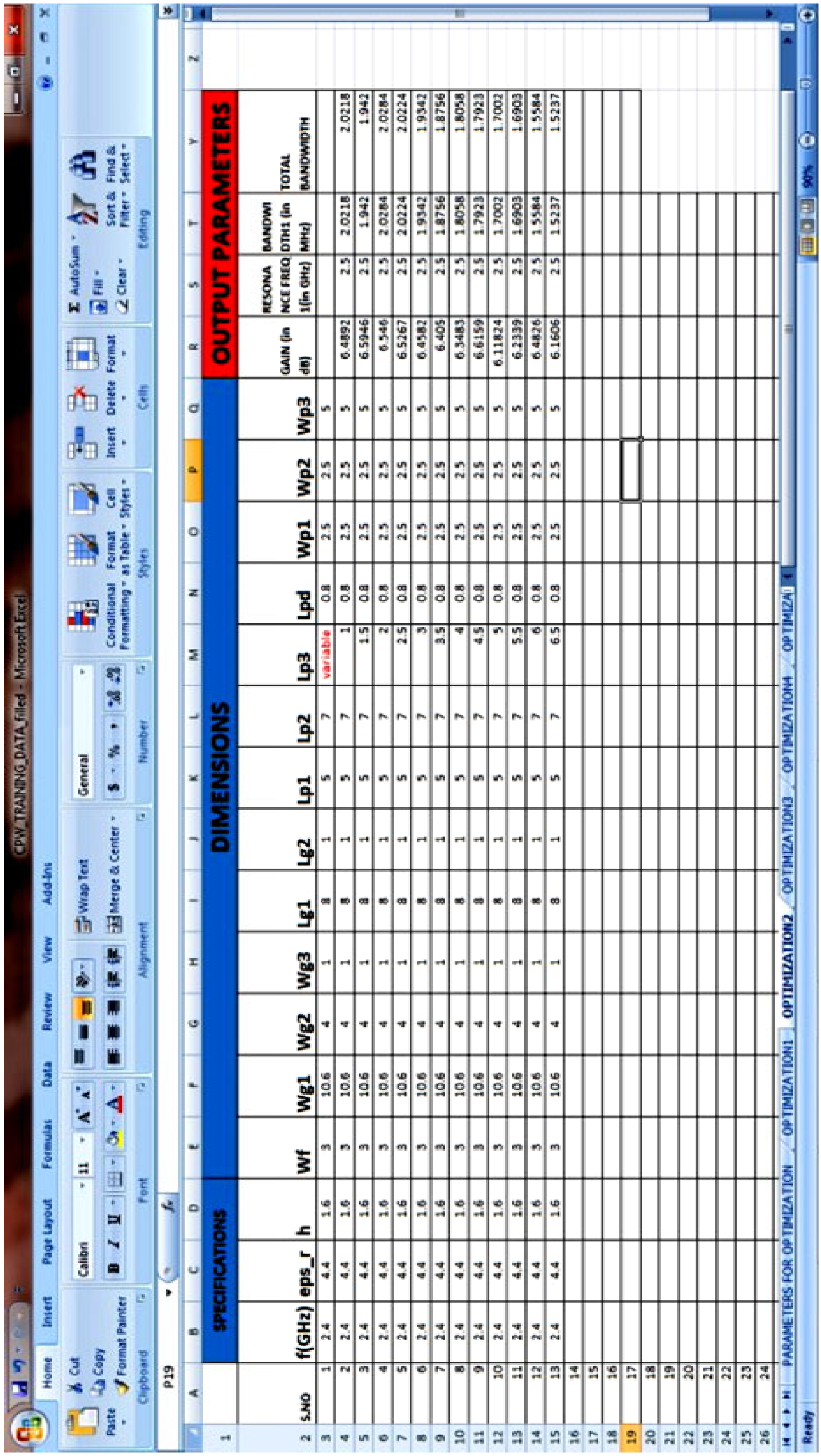
Step 10 After getting best hyper parameter we need to apply ML algorithm on training data.

Step 11 After getting best ML algorithm we need to predict dB(gain) on testing data.

Step 12 We performed same operation for all three optimisers such as LP1, LP3 and WP1.

Step 13 Plotted with different ML algorithm with respective error rate whichever algorithm gives low error rate we need to select that ML algorithm as best for simulations.

Figure 8 Training data for from multiple simulations in HFSS (see online version for colours)



	SPECIFICATIONS			DIMENSIONS													OUTPUT PARAMETERS			
S.NO	f(GHz)	eps_r	h	Wf	Wg1	Wg2	Wg3	Lg1	Lg2	Lp1	Lp2	Lp3	Lpd	Wp1	Wp2	Wp3	GAIN (in dB)	RESONANCE FREQ 1(in GHz)	BANDWIDTH1 (in MHz)	TOTAL BANDWIDTH
1	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	variable	0.8	2.5	2.5	5				
2	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	1	0.8	2.5	2.5	5	6.4892	2.5	2.0218	2.0218
3	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	1.5	0.8	2.5	2.5	5	6.5946	2.5	1.942	1.942
4	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	2	0.8	2.5	2.5	5	6.546	2.5	2.0284	2.0284
5	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	2.5	0.8	2.5	2.5	5	6.5267	2.5	2.0224	2.0224
6	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	3	0.8	2.5	2.5	5	6.4582	2.5	1.9342	1.9342
7	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	3.5	0.8	2.5	2.5	5	6.405	2.5	1.8756	1.8756
8	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	4	0.8	2.5	2.5	5	6.3483	2.5	1.8058	1.8058
9	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	4.5	0.8	2.5	2.5	5	6.6159	2.5	1.7923	1.7923
10	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	5	0.8	2.5	2.5	5	6.11824	2.5	1.7002	1.7002
11	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	5.5	0.8	2.5	2.5	5	6.2339	2.5	1.6903	1.6903
12	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6	0.8	2.5	2.5	5	6.4826	2.5	1.5584	1.5584
13	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	2.5	2.5	5	6.1606	2.5	1.5237	1.5237

Table 2 Sample training/test data for the variable Lp3 at 2.4 GHz

	Specifications			*Dimensions*													*Output parameters*			
S. no.	*f(GHz)*	*eps_r*	*h*	*Wf*	*Wg1*	*Wg2*	*Wg3*	*Lg1*	*Lg2*	*Lp1*	*Lp2*	*Lp3*	*Lpd*	*Wp1*	*Wp2*	*Wp3*	*Gain (in dB)*	*Resonance freq. 1(in GHz)*	*Bandwidth1 (in MHz)*	*Total bandwidth*
1	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	Variable	0.8	2.5	2.5	5				
2	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	1	0.8	2.5	2.5	5	6.4892	2.5	2.0218	2.0218
3	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	1.5	0.8	2.5	2.5	5	6.5946	2.5	1.942	1.942
4	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	2	0.8	2.5	2.5	5	6.546	2.5	2.0284	2.0284
5	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	2.5	0.8	2.5	2.5	5	6.5267	2.5	2.0224	2.0224
6	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	3	0.8	2.5	2.5	5	6.4582	2.5	1.9342	1.9342
7	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	3.5	0.8	2.5	2.5	5	6.405	2.5	1.8756	1.8756
8	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	4	0.8	2.5	2.5	5	6.3483	2.5	1.8058	1.8058
9	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	4.5	0.8	2.5	2.5	5	6.6159	2.5	1.7923	1.7923
10	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	5	0.8	2.5	2.5	5	6.11824	2.5	1.7002	1.7002
11	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	5.5	0.8	2.5	2.5	5	6.2339	2.5	1.6903	1.6903
12	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6	0.8	2.5	2.5	5	6.4826	2.5	1.5584	1.5584
13	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	2.5	2.5	5	6.1606	2.5	1.5237	1.5237

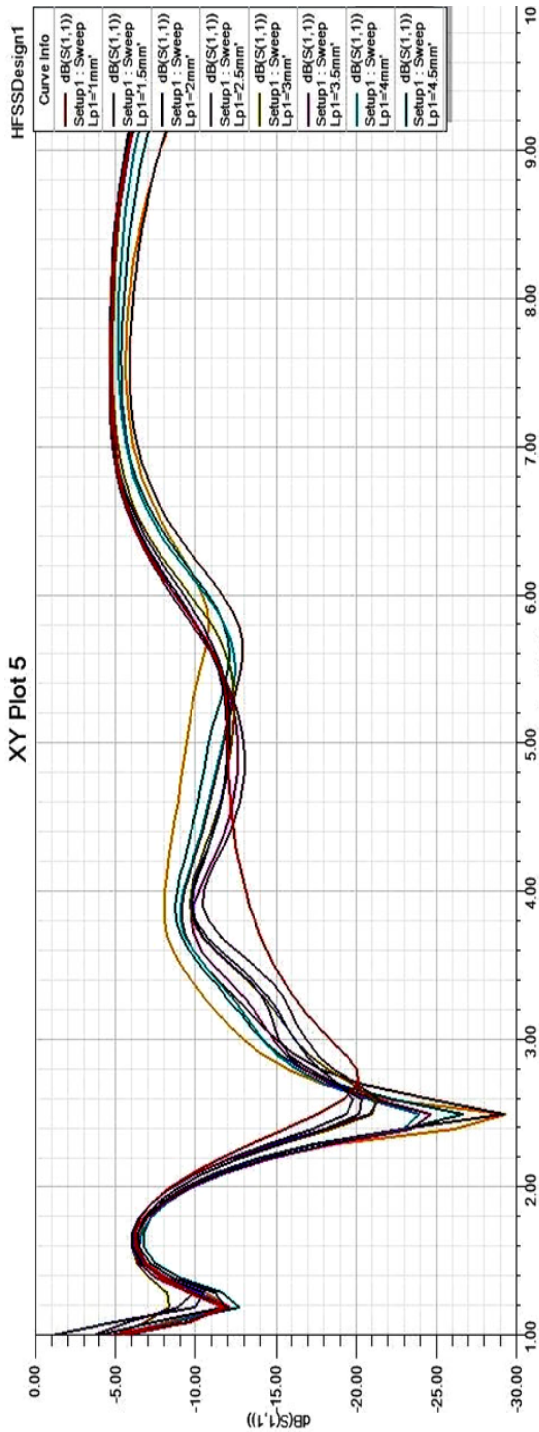
Table 3 Sample training/test data for the variable Wp1 at 2.4 GHz

	Specifications			*Dimensions*													*Output parameters*							
S. no.	*f(GHz)*	*eps_r*	*h*	*Wf*	*Wg1*	*Wg2*	*Wg3*	*Lg1*	*Lg2*	*Lp1*	*Lp2*	*Lp3*	*Lpd*	*Wp1*	*Wp2*	*Wp3*	*Gain (in dB)*	*Resonance freq 1(in GHz)*	*Bandwidth1 (in MHz)*	*Resonance freq2 (in GHz)*	*Bandwidth2 (in MHz)*	*Resonance freq3(in GHz)*	*Bandwidth3 (in MHZ)*	*Total bandwidth*
1	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	Variable	2.5	5								
2	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	1	2.5	5	6.9002	2.7	3.5196	-	-	-	-	3.5196
3	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	1.5	2.5	5	6.466	2.7	1.6244	-	-	-	-	1.6244
4	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	2	2.5	5	6.34	2.6	1.509	-	-	-	-	1.509
5	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	2.5	2.5	5	6.1606	2.5	1.5217	-	-	-	-	1.5217
6	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	3	2.5	5	6.2443	2.4	1.3109	5.7	1.3633	-	-	2.6742
7	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	3.5	2.5	5	6.5979	2.3	1.208	5.7	1.8233	-	-	3.0313
8	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	4	2.5	5	6.0459	2.3	1.0576	5.6	1.834	-	-	2.8916
9	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	4.5	2.5	5	6.4667	2.2	1.2572	5.6	1.4879	-	-	2.7451
10	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	5	2.5	5	6.2692	1.2	0.3299	2.1	0.7866	5.5	1.399	2.4388
11	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	5.5	2.5	5	5.9356	1.2	0.3631	2.1	0.7099	5.4	1.3558	2.4288
12	2.4	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	6	2.5	5	6.157	1.2	0.437	2	0.689	5.3	1.2288	2.3548

Table 4 Sample training/test data for the variable Wp1 at 5.8 GHz

	Specifications			*Dimensions*													*Output parameters*							
S. no.	*f(GHz)*	*eps_r*	*h*	*Wf*	*Wg1*	*Wg2*	*Wg3*	*Lg1*	*Lg2*	*Lp1*	*Lp2*	*Lp3*	*Lpd*	*Wp1*	*Wp2*	*Wp3*	*Gain (in dB)*	*Resonance freq 1(in GHz)*	*Bandwidth1 (in MHz)*	*Resonance freq2(in GHz)*	*Bandwidth2(in MHz)*	*Resonance freq3(in GHz)*	*Bandwidth3(in MHz)*	*Total bandwidth*
1	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	Variable	2.5	5								
2	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	1	2.5	5	6.4797	2.8	1.7251	-	-	-	-	1.7251
3	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	1.5	2.5	5	6.0369	2.7	2.5545	-	-	-	-	2.5545
4	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	2	2.5	5	6.5611	2.6	1.4254	-	-	-	-	1.4254
5	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	2.5	2.5	5	3.3359	2.5	1.4044	-	-	-	-	1.4044
6	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	3	2.5	5	4.1776	2.4	1.2872	-	-	-	-	1.2872
7	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	3.5	2.5	5	2.8222	2.3	1.1243	5.7	1.2284	-	-	2.3527
8	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	4	2.5	5	2.7276	2.2	1.0179	5.6	1.6478	-	-	2.6657
9	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	4.5	2.5	5	1.5043	2.2	0.9091	5.6	1.5641	-	-	2.4732
10	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	5	2.5	5	2.9075	2.1	1.2045	5.6	1.3872	-	-	2.5917
11	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	5.5	2.5	5	5.6217	2	0.716	5.5	1.3005	-	-	2.0165
12	5.8	4.4	1.6	3	10.6	4	1	8	1	5	7	6.5	0.8	6	2.5	5	9.6669	5.4			1.1824	-	-	1.1824

Figure 9 Return loss of CPW antenna (see online version for colours)



6 Implementation and results

As the outcome for the steps 6 to 10, the RMSEs are calculated for the given data and tabulated in Table 5.

As per above observations form Table 5, tree based ML algorithms like decision tree working well in this case as we see that RMSE error getting low compared to other machine algorithms. And decision tree algorithm is identified as best suited in this use case. Using the outcomes of the above conclusions, the proposed antenna's performance is examined in terms of return loss, bandwidth, gain, and radiation pattern using HFSS software, which is used for simulation, optimisation, and analysis.

Table 5 Comparison table of optimising parameters

Machine learning algorithm	*RMS error of optimising parameters*		
	RMSE error for LP_1	*RMSE error for LP_3*	*RMSE error for WP_1*
KNN	0.5	1.04	0.28
Decision tree	0.29	0.31	0.31
Linear regression	1.77	2.23	1.26
Ridge regression	1.69	2.09	1.26

Figure 10 2D radiation pattern of CPW antenna (see online version for colours)

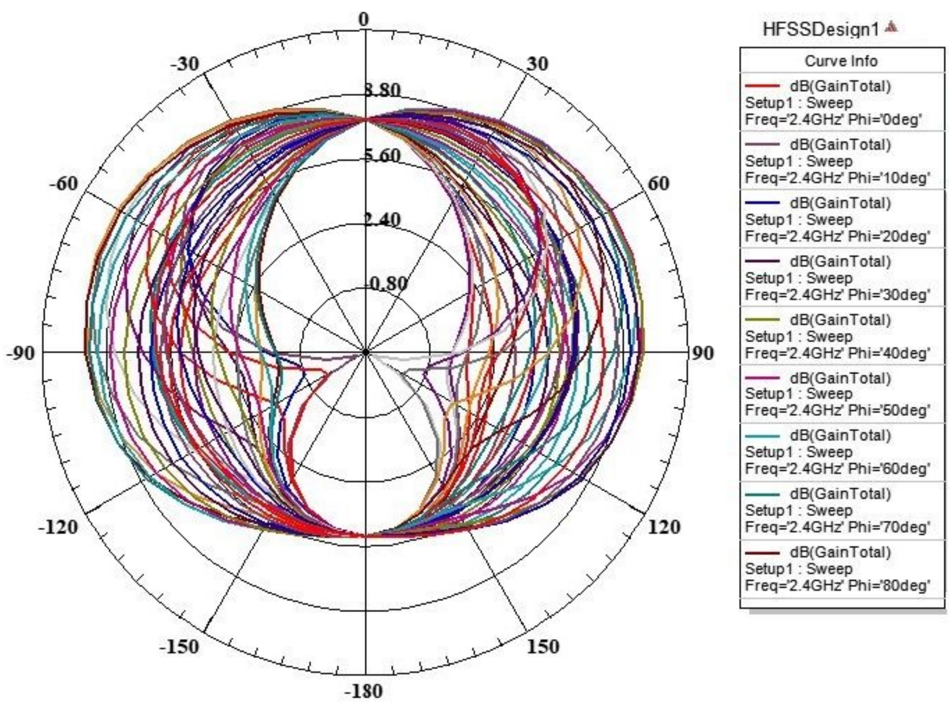
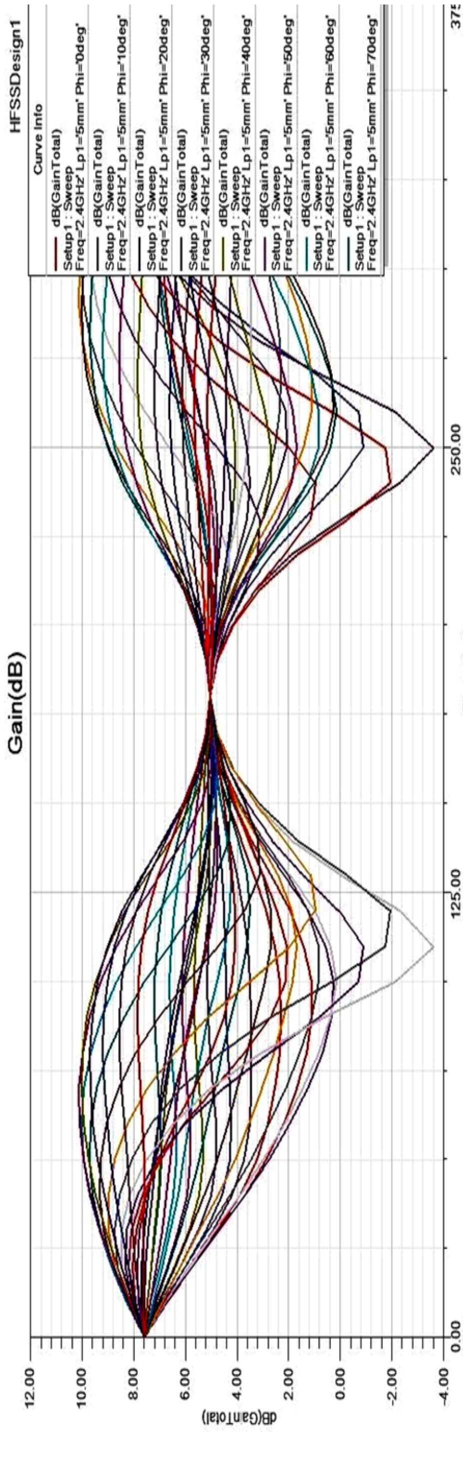


Figure 11 Gain characteristics of CPW antenna (see online version for colours)



6.1 Return losses

The return loss curve helps to estimate the resonant frequencies and their corresponding bandwidths with respect to the reflection coefficient S11 (dB) in dB. Generally, –10 dB line is considered as reference for finding bandwidth of the given curve. Figure 9 illustrates the return loss curve of proposed antenna for suggested LP1 values. Maximum bandwidth of 1.49 GHz is observed for the resonant frequency 2.4 GHz.

6.2 Radiation pattern

Plotting the variation of the absolute value of field strength or power as a function of θ allows one to visualise the two-dimensional radiation patterns. One can observe parameters such as half power beam width (HPBW), first null beam width (FNBW), front-to-back ratio (FBR) and so on to determine the directional characteristics of the proposed antenna. Figure 10 shows the radiation pattern of proposed CPW antenna for φ = 0 and 900. As a result of the proposed optimisation methods maximum gain is achieved to be 10.03 dB for 2.4 GHz as shown in Figure 11.

6.3 Testing and result validation

The hardware implementation or fabricated prototype of the proposed CPW antenna is shown in Figure 12. The impedance and return loss characteristics are tested using vector network analyser and the radiation pattern and gain characteristics are measured in anechoic chamber as shown in Figure 13.

Figure 12 Fabricated prototype of CPW antenna (see online version for colours)

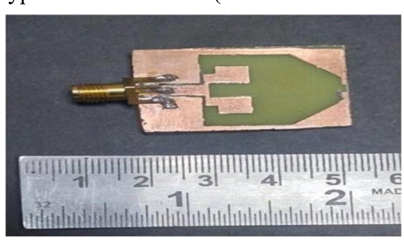
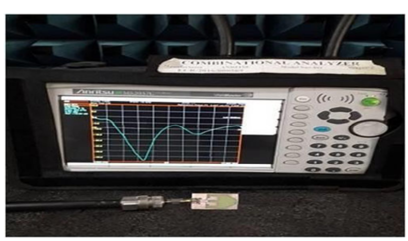


Figure 13 Testing of fabricated antenna on vector network analyser (see online version for colours)



7 Comparison

The comparison of the output parameters of the proposed antenna with and without ML based optimisation is tabulated in Table 6. Significant improvements in bandwidth from

0.47 GHz to1.49 GHz and gain from 6.47 dB to 10.03 dB are observed at 2.4 GHz. At 5.8 GHz resonant frequency, the bandwidth is increased from1.02 GHz to 1.59 GHz and gain from 6.03 dB to 9.66 dB.

Table 6 Comparison table

S. no.	*Parameter of the antenna*	*Value without optimisation*		*Value after ML optimisation*	
		2.4GHz	*5.8GHz*	*2.4GHz*	*5.8GHz*
1	Return loss (dB)	–20	–14.5	–29	–16
2	Bandwidth (GHz)	0.47	1.02	1.49	1.59
3	Gain (dB)	6.47	6.03	10.03	9.66

8 Conclusions

ML-based optimisation methods have the ability to speed up the optimisation process for obtaining practical antenna designs. A duel band CPW antenna with a FR4 epoxy substrate has been designed in the current work. HFSS software is used to simulate, optimise, and analyse the suggested antenna. The return loss, bandwidth, gain, and radiation pattern of the planned antenna are all examined for performance. To achieve the best outcomes, the design was optimised. Utilising ML algorithms, the suggested antenna is optimised to attain the necessary performance characteristics. These algorithms include KNN, decision tree, linear regression, and ridge regression.

The impedance and return loss characteristics of the proposed CPW fabricated prototype is tested using vector network analyser and the radiation pattern and gain characteristics are measured in anechoic chamber. The results show that the high gain antenna can be operated for two resonance frequencies namely 2.4 GHz and 5.8 GHz with increased bandwidth with peak gain of 10.03 dB. The proposed duel band antenna is promising to be implanted in various devices employing in IoT, WiFi and vehicular multiband applications.

In order to further speed up the ML based optimisation process for antenna design in future, it may be possible to develop hybrid surrogate models that combine data driven and physical based approaches (Indharapu et al., 2023; Durga and Godavarthy, 2022).

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