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Design and Development of Machine Learning Assisted Cylindrical Dielectric Resonator Antenna

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Abstract: The design of a Dielectric Resonator Antenna (DRA) utilizing machine learning approaches is presented in this study. Antennas are an essential part of a wireless network. An antenna with a decent design will reduce system requirements and improve overall system performance. Full-wave electromagnetic simulation is exact and necessary in antenna design. Still, it takes more time to perform, resulting in enormous challenges in designing, optimizing, and performing sensitivity analysis. The data in this study is subjected to several Machine Learning (ML) algorithms for optimizing antenna efficiency and S-parameter value. To expedite antenna design, machine learning-assisted optimization (MLAO) has proven to be the most effective method. A wide range of regression techniques, including as Support Vector Machine (SVM), Decision Tree Regression (DTR), and Random Forest Regression (RFR), have been used in machine learning (ML) techniques to develop antenna models, enabling quick response prediction and optimum S_{11} value. Multiple MLAO algorithms have been implemented using these machine-learning techniques for various applications out of which Decision Tree Regression and Random Forest Regression outperforms among all the above-mentioned algorithms with 99.98% and 99.99% of accuracy. First, a broad overview of recent advancements in ML approaches for antenna modelling is presented.

Keywords: MLAO; Dielectric resonator antenna; Machine learning; Support vector machine; Random forest regression

1. Prerequisites for the publication

The field of wireless communications has grown at a breakneck pace over the previous decade. The antenna is the most important part of any wireless network or piece of equipment. In current age of wireless communications, low-cost and small-size antennas are greatly sought for mobile devices such as cell phones, notebook computers, personal digital assistants (PDA), and so on. Our cities will soon be engulfed in antennae of all shapes and sizes. Low-cost, multi-functional, and multi-band wireless systems, on the other hand, are greatly sought for security and portability. All of these stringent standards necessitate high-quality, low-profile production. Small antennas that can be turned into wireless devices that are embedded. In the last two decades, two classes of new antennas have been tested and widely published. The dielectric resonator antenna (DRA) and the micro-strip patch are their names. These are ideal for the manufacture of modern wireless communication[1)]. A DRA is a radio antenna that is very commonly used at millimeter wave frequencies, consisting different types of shapes made up of ceramic, a

Dielectric resonator mounted at ground level on a metal shield. The benefit of using DRA is that they do not have metallic parts that dissipate energy and at high frequencies generating more losses. These antennas have more loss reduction and are extra stable at high millimeter wave frequencies than metal antennas. In certain dense portable wireless designs and military millimeter wave radar equipment, dielectric waveguide antennas are applied[2-4)]. DRA based antennas are hopeful candidates for displacement Conventional radiating elements at long frequencies, especially in applications at and beyond millimeter waves.

Nowadays, machine learning and other approaches is widely utilized to solve a variety of difficult problems, such as making predictions and performing pattern recognition[5-15)]. In modern era, there are others optimization techniques which is used in antenna structures like heuristic optimization techniques like genetic algorithms and particle swarm optimization[16-20], but these algorithms examine for solution which is optimal by analyzing the output on individual data points and generating new and possibly improved search directions until a global maxima or minima is identified.

In the machine learning dataset used for training the data, a correlation is made between input features and intended output labels, which is used to simulate one sort of learning known as "supervised" learning. The model association is also used to quantify output labels for a succession of fresh input features (test dataset), and is often done in the sense of discrete value labels (i.e., classification) or continuous value labels (i.e., classification) (i.e., regression). Unsupervised learning, on the other hand, refers to the recovery of a dataset's underlying structure without regard for desired marks. The secret set or groups from a dataset are revealed by clustering data points together; this is a simple example of the unsupervised learning technique[21-23]. In both the common and military radio systems, the reception apparatus is a basic segment. From a German physicist named H. Hertz's first sparkle, developed in 1886 by a dipole reception system, and G's main significant distance signal transmission. In 1901, alongside the rapid improvement of remote interchanges, radar, road, radio cosmology, distant detection, and various other radio applications, the reception apparatus was advanced and developed by Marconi for more than a century. As an electromagnetic (EM) transducer, the radio wire assumes a component that transforms guided waves to free-space waves or the other way around. In many applications, the receiving wire likewise goes about as a directional gadget, which amplifies the sent or got energy in assigned ways while smothering it in different ways. The ML-assisted enhancement (MLAO) techniques for reception apparatus configuration could be used as a proxy prototype-based improvement strategy. In this computationally efficient framework, ML strategies are used to predict the assigned attributes at potential focuses in the plan space using the preparation set produced at the inspected focuses based on the first computationally expensive model. Different Machine Learning procedures, such as Gaussian cycle relapse (GPR), uphold SVM, and counterfeit neural organizations, were offered in MLAO strategies for receiving apparatus plans (ANNs). The most widely used machine learning (ML) methods in the field of radio wire showing are examined, together with their key definitions and demonstration methodology[24]. Due to their potential to learn from experimental or simulated antenna data through a training process and then aid to accelerate the entire antenna design procedure, machine learning (ML) approaches have been widely explored and implemented in antenna designs in recent years[25]. When there are multiple factors to tune or massive structures to build, ML approaches have significant advantages in terms of decreasing large computing times. Several antenna geometries, particularly those with inventive structure, complicated geometries, or non-linear loads, are still challenging to describe analytically with antenna theories, particularly because some of them have low accuracy. When optimizing geometrical parameters to satisfy some specific design requirements such as desirable radiation characteristics, ML can be the ideal approach to eliminate the time spent in trial-and-error simulations, especially if some of these parameters have to be changed in real-time[26-27]. In 2022, A. Srivastava et.al. presented the various machine learning (ML) algorithms such as Artificial neural network (ANN), Random Forest, XG boost, K nearest neighbor (KNN), and Knowledge-based neural network (KBNN) are used for efficient optimization of dielectric resonator antenna (DRA)[28].

In this work, we show a cylindrical dielectric resonator antenna's designing and performance benchmarking. Then, cylindrical-DRA optimization using ML approaches is given. Ansoft's high-frequency structure simulator (HFSS) was used to do numerical study. The key innovation of this research is the substantial reduction in time, matrix formulation, and memory requirements while constructing a cylindrical DRA utilizing ML approach as compared to existing simulation tools like HFSS. In order to validate the numerical analysis, a machine-learning approach has been incorporated which shows a good agreement between them. The organization of the work as follows: firstly, machine learning assisted optimization methods has been presented. In the second section DRA design are presented. In the third section, implementation and testing has been explained and section four result and discussion is presented. In the last section conclusion has been presented.

2. Machine Learning Assisted Optimization Methods

2.1 Artificial Neural Network (ANN)

ANNs became acquainted with the EM field and microwave design as amongst the most noteworthy ML tactics during the 1990s. ANNs have found use in radar applications such as radio wires, circuit schedules, estimate issues, distant detection, and a variety of other domains. The purpose of neural organizations is to explain how the human cerebrum performs a given task. The whole significance of a neuronal architecture is accorded equal weight. Model micro-strip receiving gadgets were initially introduced to ANNs in the late twentieth century. The plan's boundaries were changed using ANN, which included measurements of the dielectric stability and reception apparatus[23].

2.2 Support Vector Machine (SVM)

All difficulties of arrangement and relapse will be solved by the SVM. In a relapse problem, the SVM maps the info space into a high-dimensional space called the part space, where the relapse can be appropriately completed utilizing straight ability. Unlike ANNs, the

SVM was familiar with the receiving wire configuration area due to its increased speculating capacity. In common sense applications, the size of the preparation sets generated by full-wave EM recreations is often limited, which could lead to over-fitting in certain Artificial Neural Network applications. SVM, on the other hand, requires fewer explanations to train for precise effects, resulting in a faster planning technique[29]).

2.3 Gaussian Process Regression (GPR)

Recently, the GPR has received widespread attention in the field of EM design, including for receiving wire plans. Unlike the other two ML strategies, GPR can provide the vulnerability of expected outcomes at new plan focuses, which will aid architects in investigating global optima. When no preparation points were provided, the GPR was familiar with model reception apparatus reactions such as the reflection coefficient, crosstalk level, and addition execution for three different radio wire models[30]).

3. Design Details

The DRA's layout is built with Ansoft HFSS software. This tool already has the skills to aid in the design of a suitable dielectric resonator antenna with probe feed. After designing the proper excitation needed according to the demand, it is very easy to get the radiation pattern from the far-field report and the frequency vs. dB circular plot from the terminal solution data report, by which it is very easy to get the radiation pattern from the far-field report and the frequency vs. dB circular plot from the terminal solution data report after simulation. Fig. 1 depicts the building of a circular dielectric resonator antenna using Ansoft HFSS software and a pattern for the suitable size of the configured dielectric resonator antenna.

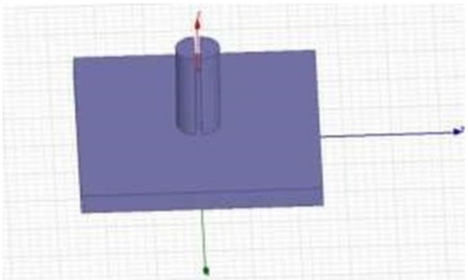
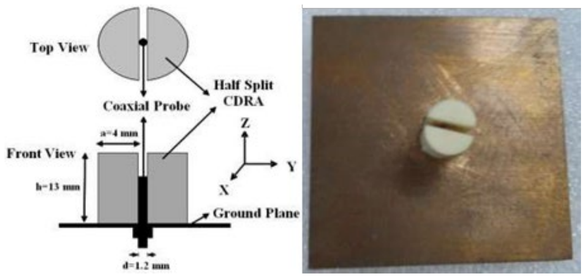


Fig. 1: Constructed Dielectric Resonator Antenna using Ansoft HFSS.

The geometry of CDRA is depicted in Fig. 2, which is divided into two uniform parts, one of which is referred to as half split CDRA. The CDRA is a two-element half-split device that has been invented and manufactured. Fig. 2(a) depicts the antenna shape and fabricated construction of the proposed two-element half-split CDRA. The suggested DRA structure has dimensions of radius a = 4 mm and height h = 13 mm for each piece. The material's relative permittivity (r) is 9.8. (Al203). Both elements are compactly packed in the proposed CDRA on a metallic ground plane with dimensions of 50 mm X 50 mm X 3 mm, as illustrated in Fig. 2, and fed through a 50-impedance coaxial probe. In the same way, a single element half split CDRA with the same dimensions as the proposed antenna has been constructed. The suggested CDRA's coaxial probe height above the ground plane is 9.1 mm and 9.0 mm, respectively, as determined by rigorous simulation for minimum return loss.



(a) (b)

Fig. 2: (a) Geometry and (b) fabricated proposed two element half split CDRA.

For the given design of the Dielectric Resonator Antenna, the required data has been collected by HFSS software. The data contain a collection of S_{11} values with varying frequency and height of Dielectric Resonator Antenna. These antenna parameters are now briefly described. The input-output correlation between ports in an electrical part is represented by S-parameters. In actuality, the coefficient of reflection, often known as S_{11}, is the most widely valued metric in antennas. The coefficient of reflection is defined as S_{11}, which represents how much power from the antenna is returned (Sometimes written as return loss). The remaining power was "accepted by" or "passed to the antenna". This resulting power may have been radiated or absorbed as a loss in the antenna. Antennas are usually designed for low loss, so much of the power transmitted to the antenna is preferentially radiated. Resonance frequency is another very important parameter defined by shifting the direction of the slit to the left or right of the patch. The antenna resonates at multiple frequencies as an output. Computer algorithms for artificial neural networks are typically used to find the perfect resonant frequency. The data collected from the HFSS software has values for these parameters. We need to apply machine learning techniques to the given data to find the reflection coefficient, which is the optimized optimal value for S_{11} (return loss)[31]). Well experiment with several MLAO strategies with the goal of optimizing the DRA antenna. We may optimize our DRA antenna using these strategies and their applications to it. Simple Linear Regression, SVM, Decision Tree Regression, and more approaches are among them. Fast response prediction can be achieved by applying these techniques to antennas[32]).

4. Implementation and Testing

Implementation is the most crucial part of a project, in order to achieve critical destinations and targets, the cycle turns processes and strategies into activities. First, we need to generate the data with the help of Ansoft HFSS based on whatever design of DRA we designed in HFSS. Here, our DRA is cylindrical in shape, with the help of HFSS software, we generated the data which consist of Frequency, S-parameter with variation in height of antenna. Now, we will use this data to perform machine learning techniques and get desirable results. Here is the complete detailed implementation is as follows:

1. Data Collection: The first step in using machine learning to solve any problem is to collect the required data, which the Ansoft HFSS application generates. The data consists of frequency, S-parameter value, and variations in antenna height. So, this is the primary data set that we train and test our machine learning algorithms on. There are 10,000 data samples in this data collection.
2. Data preparation:
    - 2.1: Importing the libraries: Here, we import the required python libraries like pandas, NumPy, Matplotlib in Jupyter Notebook to perform different machine learning tasks on data to get better results.
    - 2.2: Importing the dataset: After importing the required python libraries, we import the data generated using Ansoft HFSS in Jupyter Notebook. So that we can apply different, machine learning methods to the data and get results.
    - 2.3: Missing data: If your data have any missing data, we need to use this step to get rid of this problem before applying any model on it. So that our desired result does not get affected.
    - 2.4: Manage categorical Data: This is required when the dataset has some categorical data. We need dummy variables to get rid of this problem if your data has any kind of categorical data. As our dataset has no categorical data, we need no dummy variables here.
    - 2.5: Splitting dataset in 2 parts i.e., training and testing: After, we need to split the data for training and testing, to apply the model on the training set to get predicted output for the test set. Independent data divided in two sets "X" train and "X" test set and dependent variable set divided in two set "y" train and y test set.
    - 2.6: Feature scaling: This is required when your dataset has different scales of data and this will help to put all variables into the same scale. In this project, we have variables in same scale, so we do not need this step here.
3. Choosing Learning Algorithm: This is the most crucial step in machine learning, and it is determined by our goal, data, and accuracy. There are several algorithms for various sorts of objectives and data, as well as the level of precision desired. I first attempted using regression techniques, but the accuracy was not satisfactory, so we moved on to classification algorithms and other options.
4. Training the Model: SVM/SVR/GPR model fitting to the training set. The next step is to fit the right model to the training set and then apply it to the test data to gain more insight into our model.
5. Evaluating the Model: Predicting test set outcomes. After establishing a model with a training set, we now look for expected results based on this model to see how accurate it is; if it is not, we will look for another model and check for accuracy.
6. Parameter Tuning: This is done to improve the model's accuracy when it is fitted to the training set. As was said in the preceding paragraph, the main dataset is broken up into subsets. This is carried out to improve model performance and secure it against data leakage issues. A subset of the data is kept back for the final evaluation at the end of our model creation, allowing us to test the model on data that is different from the data it was trained on and choose the optimum model design. Here, we employ a grid search hyperparameter tuning technique to improve the performance of random forest regression.
7. Predictions: Plotting the training and test sets' graphs: We use Matplot to create a graph between the observed and predicted values for both the training and testing sets.

4.1 Testing the models

One of the most critical aspects of a machine learning project is testing. This provides more information on the model we fit to the training and test sets, such as how accurate the model is at fitting the data and whether it is over-fitting, under-fitting, or best fit. If your intended result does not match your goal, you should attempt a different model to see if it may help you achieve your goal. To acquire the desired results in our model, we initially used basic linear regression on our dataset.

4.1.1 Simple Linear Regression model:

First, the SLR model applied to the data, but it was not fitting the training set properly, to check the accuracy, a mean squared error value was needed, so after writing particular code for mean squared error, given value is a proof for that it is not an accurate model so we need to try another model. Equation (1) shows the mathematical implementation of this model.

$$y = a_0 + a_1 x + \in \tag{1}$$

Where,

a_0 = It is the intercept of the Regression line (can be obtained putting x=0).

a_1 = It is the slope of the regression line, which tells whether the line is increasing or decreasing.

$\in$ = The error term.

Fig.3 shows the difference between actual and predicted values of S_{11} at different frequency values when simple linear regression model is applied. Here, it is visible the accuracy of this model is too low as the predicted(green) and the actual(red) are not coinciding. The accuracy of this model is 54.33%.

Mean Squared Error (MSE) = 45.6606. Let us assume value of frequency= 20.04 GHz, We get S_{11} = 22.02 dB.

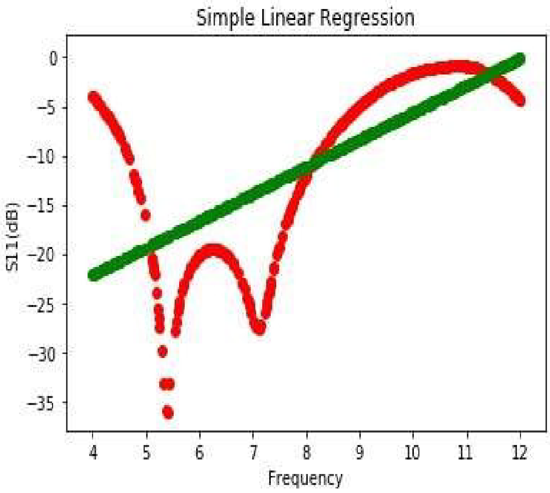


Fig. 3: Frequency Vs S_{11} for Simple Linear Regression.

4.1.2 Support Vector Regression model:

After the SLR, SVR is applied to the dataset, and here, mean squared value is lesser than what it was in the case of SLR, but more accurate model is required for this dataset, so another algorithm is also tried. The SVR model's main goal is to essentially take into account the points that are inside the decision boundary line. The hyperplane with the most points serves as our best fit line.

The equation (2) shows the hyperplane definition:

$$Y = wx + b \tag{2}$$

Any hyperplane that satisfies SVR should satisfy equation (3):

$$-a < Y = wx + b < +a \tag{3}$$

The main goal in this case is to choose a decision boundary that is located at “a” distance from the initial hyperplane such that the data points that are closest to the hyperplane or the support vectors fall within that boundary. We will therefore only consider the decision boundary-adjacent points with the least error rate, otherwise known as the Margin of Tolerance. As a result, we have a model that fits better.

When the support vector regression model is used, the difference between the actual and predicted values of S_{11} at various frequency values is shown in Fig.4. Mean Squared Error (MSE) = 3.0419. Let us assume the value of frequency= 20.04 GHz, and we get S_{11} = -9.7502 dB. The accuracy of this model is 96.95%.

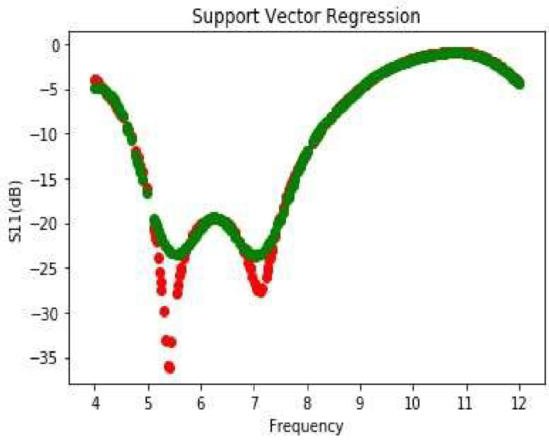


Fig. 4: Frequency Vs S_{11} for Support Vector Regression.

4.1.3 Decision Tree Regression model:

After SVR, DTR is applied to the dataset, and here, mean squared value is lesser than what it was in the case of SVR, but to get the more accurate results, another algorithm is also checked. Mean Squared Error (MSE) = 0.0173. Let us assume value of frequency= 20.04 GHz, We get S_{11} = -4.2371 dB. Fig. 5 illustrates the accuracy of this model, which is 99.98%.

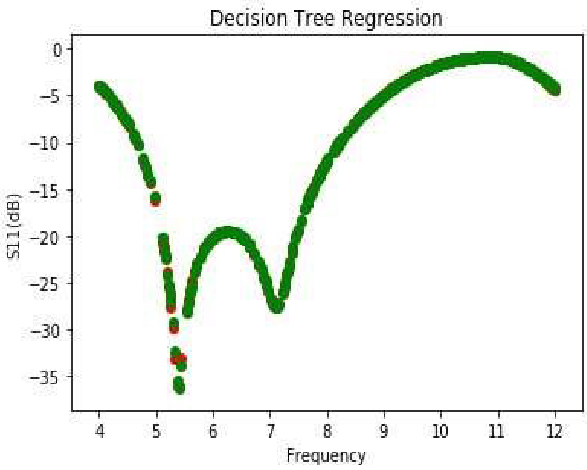


Fig.5: Frequency Vs S_{11} for Decision Tree Regression.

4.1.4 Random Forest Regression model:

Then after I applied RFR to the dataset, and here, mean squared value is lesser than what it was in the case of DTR. But this model is giving maximum accuracy among all these models. This is our desirable model which has very good accuracy. We will use this model to predict the most optimized value of S_{11}. Mean Squared Error (MSE) = 0.0088. let us assume value of frequency= 20.04 GHz, we get S_{11} = -4.1393 dB. Fig. 6 illustrates how the predicted and actual values in random forest regression broadly match. Because of this, this model's accuracy, which is 99.99%, is exceptionally high.

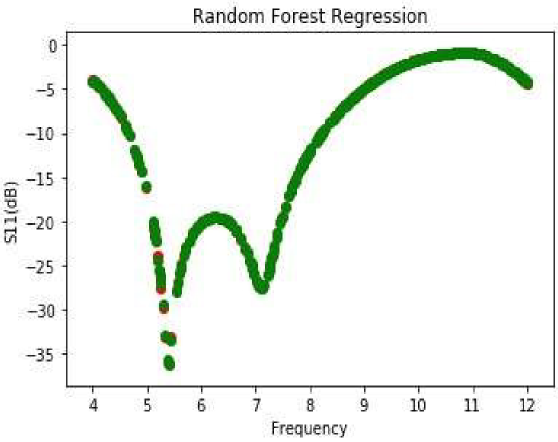
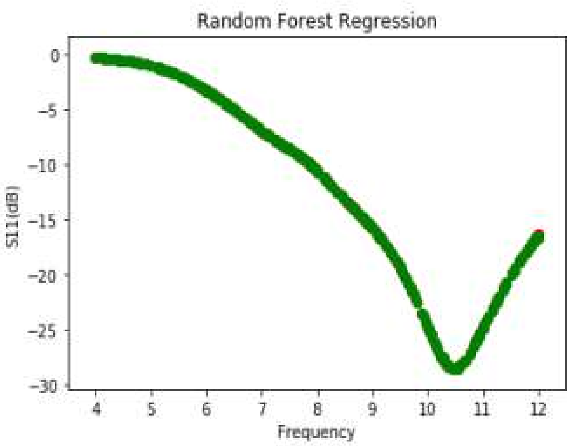


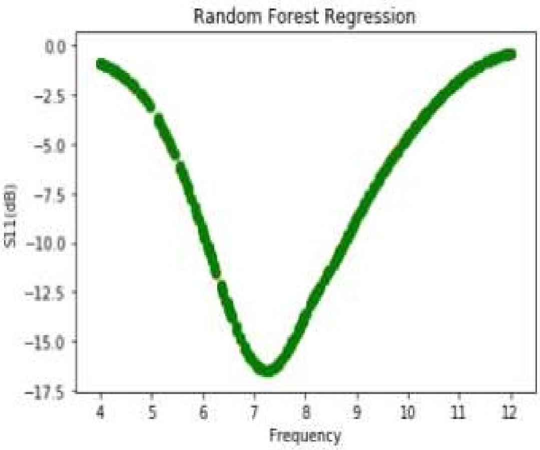
Fig. 6: Frequency Vs S_{11} for Random Forest Regression.

5. Result and Discussion

As noted in the previous section, the project's implementation and testing phases have been completed, and the most essential element of the project now is to have a better understanding of the outcome. The goal of this study is to get a more desirable, more accurate S-parameter value on variable frequency at a given height. The greater the negative value of the S-parameter, the greater the return loss, and it must be less than -10 dB. Linear Regression, SVM, Random Forest Regression, Decision Tree Regression, Logistic Regression, and many other models were applied to the data. The Random Forest Regression model and the Decision Tree Regression model have the highest accuracy and correctly match the data. Now, varied dielectric heights of the antenna are postulated to explain further insights into the results. To have a better understanding of the outcome, graphs of models have been attached below. Several types of algorithms have been used to the data. In comparison to other approaches, the Random Forest Regression method offers a higher accuracy.

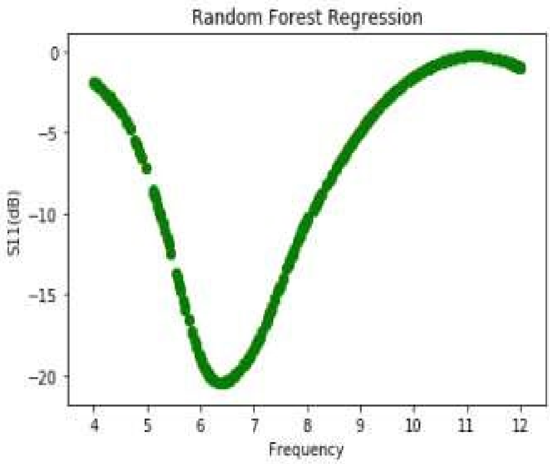


(a)

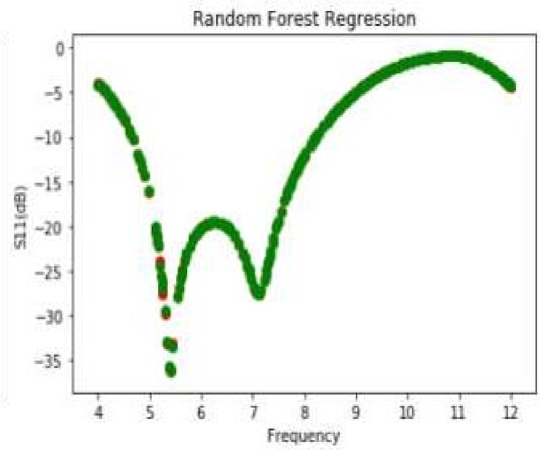


(b)

Fig. 7: Random Forest Regression at (a) height = 5 mm and (b) height = 8 mm.



(a)



(b)

Fig. 8: Random Forest Regression at (a) height = 10 mm and (b) height = 13 mm respectively.

Various graphs and assessment reports have been provided to discuss the results we obtained after completing the machine learning-based project. First, a certain height is measured, and then Random Forest regression is applied to the S-parameter and frequency data. The supplied table clearly demonstrates that the Random Forest regression model has excellent accuracy for the given data, with a precision of more than 95%, which is excellent for this data. And this also explains that if we are given a value of frequency on a specific height, we can get the most optimized value of s-parameter using this project, and it also tells us if it is okay to go with these values or not. This project explains that if we are given a value of frequency, we can evaluate the value of S-parameter for that value of frequency on a specific height. Fig.7 and 8 show the frequency vs. S_{11} values at different heights of the proposed antenna when the random forest regression model is applied. Table 1 depicts the different S11 values at different antenna heights at a particular frequency, i.e., 20.04 GHz.

Table 1. Showing predicted S_{11} value for different heights.

Heights	Frequency (GHz)	S_{11} (dB)
5 mm	20.04	-16.5702
8 mm	20.04	-0.4148
10 mm	20.04	-0.9468
13 mm	20.04	-4.1393

The most accurate model that appropriately fits the data and produces the desired outcome is chosen after various machine learning models have been applied and numerous tests have been run on the dataset of the designed DRA structure. After executing multiple machine learning models, it took a while to identify the best model that fit the data. Table 2 shows that random tree regression is the best model out of the bunch because its MSE value is close to zero (0.0088). Following that, decision tree regression performed well with an MSE score of 0.0173.

Table 2. Showing MSE values and their predicted S_{11} for different models.

Model	Mean Square Error	Predicted S_{11} (dB)
Simple Linear Regression	45.6606	22.02
Support Vector Regression	3.0419	-9.7502
Decision Tree Regression	0.0173	-4.2371
Random Tree Regression	0.0088	-4.1393

6. Conclusion

The results of an integrated study on MLAO algorithms in antenna design are given. The four main Machine Learning approaches used in antenna modelling, along with their essential frameworks and antenna modelling implementation, are introduced in the first stage. Then, a variety of ways were looked at, concentrating on a few applications that made use of various strategies to solve antenna problems utilizing machine learning methods. Any plans for MLAO's antenna design development were finally made public. While there have been significant breakthroughs in antenna optimization since the introduction of MLAO methods, many questions still need to be answered in the future. When we are provided a frequency value at a specific height, this project assists us in determining the best efficient S-parameter value. With the aid of the mean square error value, several types of algorithms are used to the supplied data to obtain the best correct model for the given data. This machine-learning model will assist us in designing antennas with the parameters we require.

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