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DESIGN AND OPTIMIZATION OF 5G SUB-BAND ANTENNA USING MACHINE LEARNING

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Abstract
Now a days, machine learning techniques is inevitably be used in all branches of engineering and research, including electromagnetic applications. This article presents a methodical attempt to build a 5G microstrip patch antenna for wireless WiMAX/WLAN applications using support vector machine and random forest techniques. A 5G microstrip patch antenna of (27.64 X 21.64) mm^2 is designed at 3.3GHz operating frequency on FR-4 substrate (ε_r =4.4) using insert line feed technique. The proposed antenna is radiating at 3.3GHz frequency with return loss (S_{11}) of -34.3dB, VSWR of 1.02 and gain of 5.21dBi. The designed antenna is optimized using supervised machine learning techniques support vector machine and random forest models targeting frequency and return losses. The required data set has been prepared using full wave electromagnetic solver High Frequency Structural Simulator (HFSS) choosing variable dimensional values and open ware python is used for machine learning optimization. Machine learning based train and test scores, mean square error, mean absolute error and root mean square errors were obtained for validation purpose .Support vector method and random forest has train and test score of (0.867,0.903) & (0.99, 0.96) in case of return loss target variable, and it is (0.79, 0.8) & (0.99 & 0.95) for frequency target variable respectively.

Keywords: antenna, machine learning, microstrip patch, support vector machine, random forest.

Introduction
A wide variety of antennas is available, including wire, plane, loop, and strip antennas. The Microstrip Patch Antenna (MPA) is distinct from all other antennas due to its multidimensional uses and real time adaptability. It is lightweight, easy to integrate into any electronic circuit, and operates at a wide range of frequencies with the necessary polarization. It can also be designed in a flexible manner using several feeding methods that are documented in literature. Therefore, it is imperative that antenna engineers build and optimize the MPA using machine learning techniques. Very few attempts of antenna optimization with machine learning in the literature is available [1]–[3]. Fig. 1 depicts the patch antenna's basic layout. The following chapters provide an overview of machine learning and the design of the proposed patch antenna.

Because of its mathematical optimization approaches, artificial intelligence (AI), machine learning (ML), and deep learning (DL) have become buzzwords in daily life. They are more than just fancy phrases; because they can automate complicated non-linear issues with little human intervention, they are qualified to remain in their current positions. The scientific community is considering using machine learning (ML) to high-performance computing electromagnetic applications, including antenna design, due to its ability to forecast future values of problems. Because there is a wealth of data available, there are many research articles in the literature on image processing, signal processing, and particularly large-scale integration domains. The first condition for applying machine learning techniques is the availability of data which is very challenging task for antenna engineer to apply ML techniques.

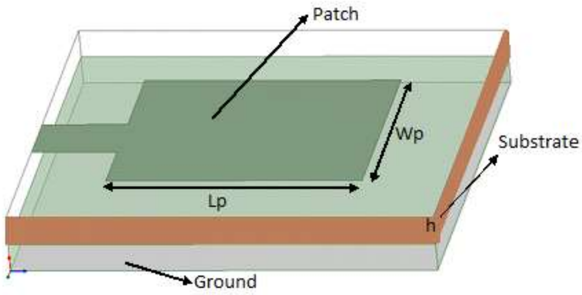

Figure 1 Basic Patch Antenna

Overview of Machine Learning

Because of its various uses, machine learning (ML), a subset of artificial intelligence (AI), is one of the growing technical solutions for many disciplines. The mathematical model interims of input and output variables are designed using mathematical statistical computing analysis. Most of the time, it is a data-driven system that requires vast amounts of trained or untrained data. It runs and provides the mathematical model that best fits the given problem in identifying the optimal solution based on the type of data provided and the type of learning system. As listed below, there are primarily three distinct learning systems.

- Supervised Learning
- Unsupervised Learning
- Reinforce Learning.

In supervised learning systems, the provided data is correctly labeled; in unsupervised learning systems, the input is typically raw or unlabeled, whereas in reinforced learning systems, the system learns from its surroundings or past experiences. A subset of machine learning called deep learning (DL) is developed in order to find the best feasible solution for the given problem. Deep Learning, the more sophisticated kind of machine learning, is a very useful abstraction of the input data for improved optimization. Artificial neural networks, which simulate the multi-neuron functioning of the human brain, are commonly used in deep learning. Fig. 2 mentions the fundamental block diagram of AI, ML, and DL. This research article's primary goal is to optimize the proposed antenna using Support Vector Machine (SVM) and Random Forest techniques. The block diagram of any Machine learning system is as shown in Fig. 3[4].

Support Vector Machine: A supervised machine learning algorithm called Support Vector Machines (SVM) is useful to solve regression and classification problems. To find a decision boundary, or hyper plane, that maximizes the margin between data points of different classes is how it operates. SVM can handle both linear and non-linear data and performs well in high-dimensional spaces.

Finding the data points that are closest to the decision boundary, or support vectors, and using them to define the margin is the fundamental principle of support vector machines (SVM). The goal of SVM is to identify the hyper plane that minimizes classification errors and maximizes this margin. Additionally, SVM can handle non-linear data by converting it into a higher-dimensional space using kernel functions. SVM is widely used because of its robust, accurate results and ability to handle complex data in a variety of applications, such as bioinformatics, image recognition, and text classification.

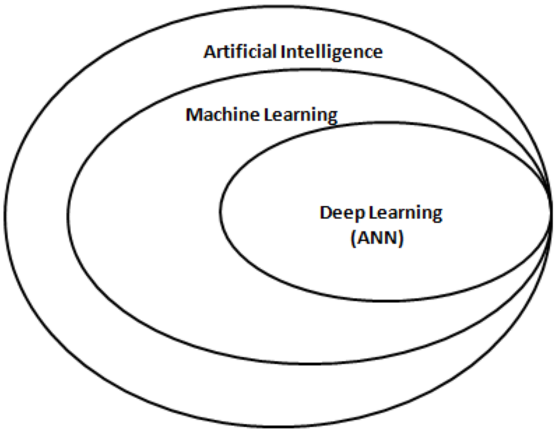

Figure 2 Block diagram AI, ML &DL

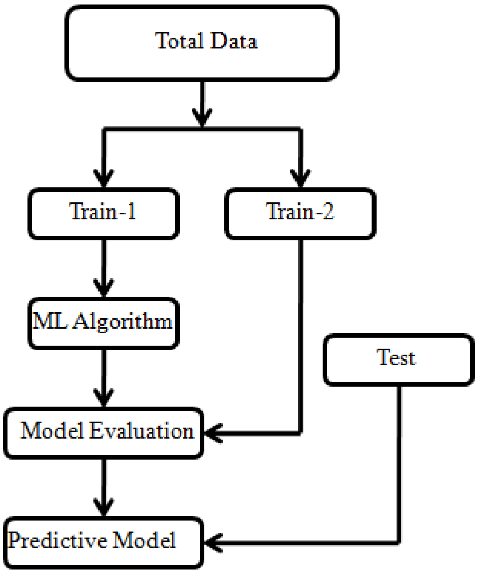

Figure 3 Basic ML model

Random Forest: Several decision trees are combined in Random Forest, an ensemble machine learning technique, to produce reliable and accurate predictions for tasks involving regression and classification. To produce more dependable results, it builds numerous decision trees during training and then aggregates their outputs.

A random subset of features may be used, and each decision tree in a Random Forest is trained using a distinct subset of the data. This variety improves the model's capacity for generalization and reduces over fitting. For classification or regression, the final prediction is typically chosen by majority vote or average. Because they can handle categorical and numerical data and are less susceptible to outliers and noise, Random Forests are renowned for their flexibility. They have a wide range of applications, including financial analysis, image classification, and recommendation systems, because they can make reliable predictions that are both accurate and robust while lowering the chance of over fitting.

ANTENNA DESIGN

Basic microstrip Patch antenna's fundamental layout is mentioned in figure 1.. It is comprised of a metallic patch situated on a metallic ground plate covering a dielectric substrate. The patch's width and length are denoted by Wp and Lp, respectively, and its height and relative dielectric constant are represented by h of 1.6mm and εr. The feed length is adjusted to match the 50Ω line impedance with the port using the basic microstrip line feed techniques. The existing literature [5-7] discussed a few basic antenna designs using patch models and their design equations. The general design equations 1to 5 of the regular patch antenna are used to obtain the length and width at 3.3GHz operating frequency, where f_{res} is the operating frequency and c is the light's velocity in meters per second. The return loss characteristics obtained from the proposed design is shown in Figure 4.

$$w = \frac{C}{2 f_0 \sqrt{\varepsilon_r}} \tag{1}$$

$$l_{eff} = \frac{c}{2 f_0 \sqrt{\varepsilon_{reff}}} \tag{2}$$

$$\varepsilon_{reff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\left[1 + 12\frac{h}{w}\right]^{-1/2} \tag{3}$$

$$\Delta l = \frac{\varepsilon_{reff} + 0.300}{\varepsilon_{reff} - 0.258}\left[\frac{l/h + 0.262}{l/h + 0.813}\right] \tag{4}$$

$$l = l_{eff} - 2\Delta l \tag{5}$$

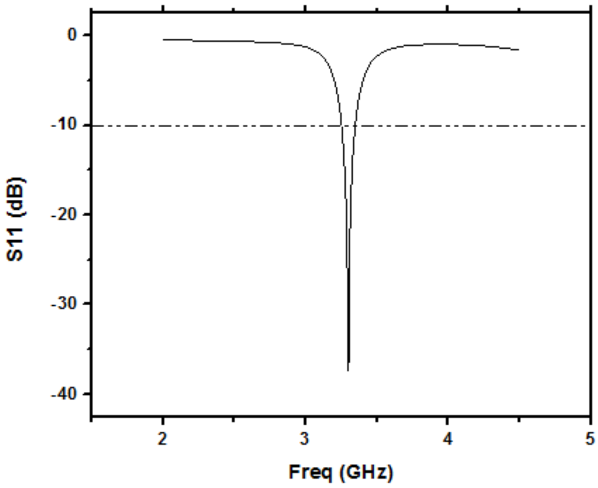

Figure 4 Return loss of the Proposed Design

```
svr=SVR(kernel="rbf")
svr.fit(X_train,y_train)
print("Train Score:",svr.score(X_train,y_train))
print("Test Score:",svr.score(X_test,y_test))
print("Mean Square Error:",MSE(y_test,y_pred))
print("Mean Absolute Error:",MAE(y_test,y_pred))
print("Root Mean Square Error:",np.sqrt(MSE(y_test,y_pred)))
```

```
Train Score: 0.8672250570480057
Test Score: 0.9032192450260221
Mean Square Error: 0.03573510324093388
Mean Absolute Error: 0.10416026696069319
Root Mean Square Error: 0.18903730647926054
```

```
rfg=RandomForestRegressor(n_estimators=100,random_state=0)
rfg.fit(X_train,y_train)
y_pred=rfg.predict(X_test)
print("Train Score:",rfg.score(X_train,y_train))
print("Test Score:",rfg.score(X_test,y_test))
print("Mean Square Error:",MSE(y_test,y_pred))
print("Mean Absolute Error:",MAE(y_test,y_pred))
print("Root Mean Square Error:",np.sqrt(MSE(y_test,y_pred)))
```

```
Train Score: 0.9912260940236247
Test Score: 0.9619596273754037
Mean Square Error: 0.03573510324093388
Mean Absolute Error: 0.10416026696069319
Root Mean Square Error: 0.18903730647926054
```

```
svr=SVR(kernel="rbf")
svr.fit(X_train,y_train)
print("Train Score:",svr.score(X_train,y_train))
print("Test Score:",svr.score(X_test,y_test))
print("Mean Square Error:",MSE(y_test,y_pred))
print("Mean Absolute Error:",MAE(y_test,y_pred))
print("Root Mean Square Error:",np.sqrt(MSE(y_test,y_pred)))
```

```
Train Score: 0.7983059188565294
Test Score: 0.8021286304647707
Mean Square Error: 0.04594513706049499
Mean Absolute Error: 0.0376439369875734
Root Mean Square Error: 0.21434816784963429
```

```
rfg=RandomForestRegressor(n_estimators=100,random_state=100)
rfg.fit(X_train,y_train)
y_pred=rfg.predict(X_test)
print("Train Score:",rfg.score(X_train,y_train))
print("Test Score:",rfg.score(X_test,y_test))
print("Mean Square Error:",MSE(y_test,y_pred))
print("Mean Absolute Error:",MAE(y_test,y_pred))
print("Root Mean Square Error:",np.sqrt(MSE(y_test,y_pred)))
```

```
Train Score: 0.9902548267002407
Test Score: 0.9582563164353676
Mean Square Error: 0.04594513706049499
Mean Absolute Error: 0.0376439369875734
Root Mean Square Error: 0.21434816784963429
```

Discussion of results

Designed antenna performance parameters from the full wave electromagnetic solver HFSS has S_{11} 0f -34.3dB, 1.02 VSWR and gain of 5.21dBi at 3.3 GHz operating frequency. Support vector machine and random forest techniques are applied on the data set, where the data set is obtained from HFSS. Total of 800 data records collected from HFSS and out of total records 600 records were used for training and 200 records kept for testing purpose. SVM and Random forest models were applied by treating return loss and frequency as target variables. Both ML models performed well in terms of train and test scores, mean square error, mean absolute error and root mean square error. The respective values are 0.867, 0.903, 0.035, 0.104 &0.189 and 0.991, 0.961, 0.035, 0.104 & 0.189 respectively in SVM and Random Forest for return loss target variable. In case of frequency target variable the performance parameters of ML models are 0.798, 0.802, 0.045, 0.037 &0.214 for SVM model and in random forest 0.990, 0.958, 0.045, 0.037 & 0.214 respectively mentioned in table.1 as ML Model Performance Comparison shown below. The table shows that Random forest is resulting better model performance than SVM in terms of train and test scores; however error values are common in both cases.

Table.1 ML Model Performance Comparison

S.No	Parameter	Return Loss Target variable		Frequency Target variable	
		SVM	Random Forest	SVM	Random Forest
1	Train Score	0.867	0.991	0/798	0.990
2	Test Score	0.903	0.961	0.802	0.958
3	Mean square error	0.035	0.035	0.045	0.045
4	Mea Absolute Error	0.104	0.104	0.037	0.037
5	Root Mean square Error	0.189	0.189	0.214	0.214

Conclusions

Application of supervised machine learning techniques support vector machine and random forest clearly indicates that, predicted values are in clear agreement with the design simulation values with reasonable performance parameters in terms of train, test score and error values. The ML models were applied on the data set with variable length and width of the patch targeting return loss and operating frequency. The proposed antenna with -34.3 dB return loss, 1.02 VSWR and 5.21dBi of gain is well suited for Indian 5G n78 free sub band applications and also it has potential use for wireless WiMAX/WLAN at 4G & 5G applications. Random forest technique is performing better with higher train and test scores and it is fit for the over fitting problems. Reasonable performance parameters of ML models suggest that conventional electromagnetic solvers with powerful ML techniques give better optimization and lesser computational time for the antenna engineers. The use of robust high end algorithms in electromagnetic solvers with large amount of dataset is suggested for the future scope of study.

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