# ML-Investigations on Goblet shaped Microstrip Antenna with Defected Ground Structure

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**Abstract:** The development of compact microstrip patch antennas for extensive electromagnetic simulations is becoming complex in design and time-consuming in process. This paper describes a machine learning enabled method to predict the return loss of a goblet-shaped microstrip patch antenna having a defected ground structure. The proposed antenna has -10dB bandwidth from 4-10 GHz and the maximum resonance at 4 and 8.8 GHz. A large dataset is generated from the antenna design parameters through parametrization. The dataset is employed to train the ML model and then testing to predict return loss for new goblet-shaped patch design. Performance Evaluation is measured based on the predicted return loss with the help of $R^2$, MAE, MSE, RMSE, and MAPE. The proposed method decreases the number of full-wave simulations, and reduces the time spent on iterative antenna design. The proposed method is used to design reliable next-generation communication systems with the help of ML.

**Keywords**: Goblet-shaped microstrip patch; Defected ground structure; ML model; Return Loss; Prediction; Performance evaluation

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## Introduction

This paper presents the Machine Learning based solution to design an antenna effectively and reduce the human efforts. This approach reduces the manual optimization and to attain required performance metrics with the help of ML modelling.

## Related work

In Ref [1], an inset fed microstrip patch antenna is designed and different algorithms like ANN, SVR and RF are modelled and tested with datasets. It is found that ANN has given good matching of prediction and actual values. In Ref [2], a patch antenna is designed for an operating frequency of 2-3 GHz and RF algorithm is modelled. It is observed that error between actual and predicted is 12.46% for $S_{11}$. Ref [3] discusses on a narrow band antenna design and it finds that RF algorithm works well. Table 1 discusses the overall comparison.

*Table 1. Compares this work with previous research by other researchers*

| Ref. | Operating frequency | ML techniques | Best Technique | Error range |
|---|---|---|---|---|
| [1] | 0.5 – 10.5 GHz | ANN, SVR, RF | ANN | - |
| [2] | 2 – 3 GHz | Random Forest | - | 12.46% for S11 |
| [3] | 2.4 – 2.5 GHz | ANN, RF, DT and SVR | RF | - |
| This work | 4 – 10 GHz | RF, ET, Catboost, GB and LR | Random Forest | 1.11% to 1.69 % for S11 |

**Key Contribution**

In this work, a Goblet shaped microstrip patch antenna is designed with an operating frequency from 4-10 GHz using Full wave simulation software ANSYS HFSS. A parametric analysis is carried out for two design values i.e. $L_p$ (Length of patch) and $W_f$ (feedline width) (Refer to Table 2) and 4000 datasets are generated which is then used in ML modelling.

**Method, Experiments and Results**

The schematic of the proposed Goblet shaped radiator is depicted in Fig 1a and the ground is a Defected Ground Structure as shown in Fig 1b. There is a presence of two narrow slots in the ground for impedance matching. The overall dimension of the antenna is 20.8 x 31 x 0.8 $mm^3$. The antenna is designed using the FR4 substrate of 0.8 mm thick. Table 2 shows the design parameters.

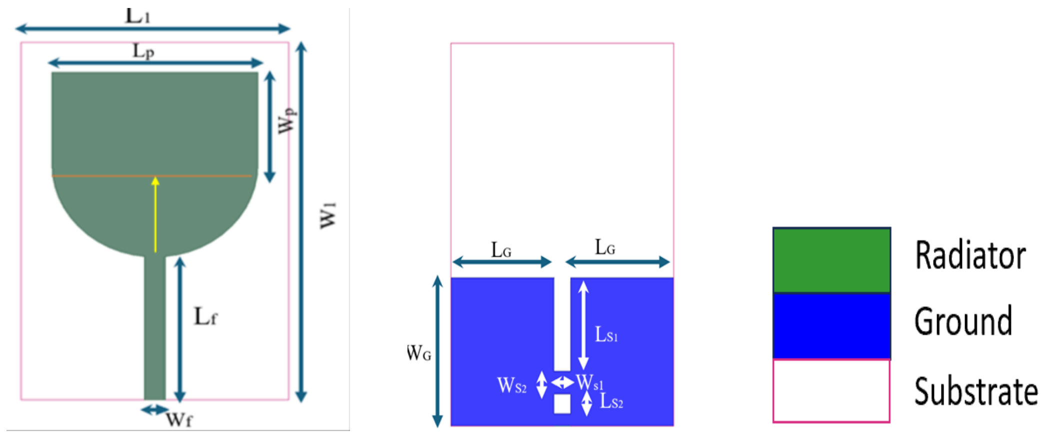


*Figure 1. (a) Top Radiator* *(b) Ground* *(c) Legend*

Fig 3a displays the simulated Reflection coefficient which shows that operating frequency is from 4 to 10 GHz. There is two maximum resonances observed at 4 GHz and 8.8 GHz having reflection coefficient values -37 dB and -42 dB respectively. Fig 3b displays simulated VSWR between the acceptable range of 1 and 2. Fig 3c displays the simulated radiation pattern in which E field is "figure of eight" and H field is omnidirectional.

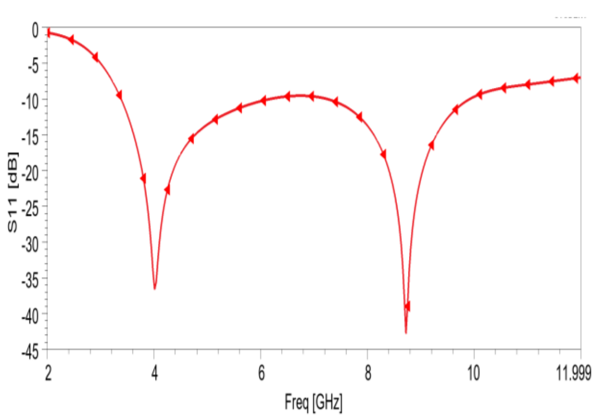


Fig 3a Simulated Reflection Coefficient

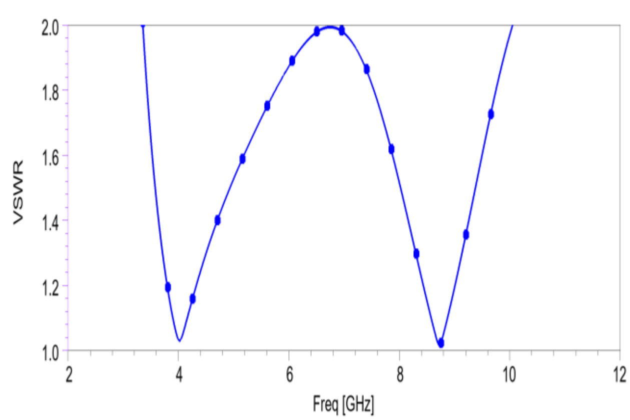


Fig 3b Simulated VSWR

Table 2: Design Values

| Parameter | Values (mm) |
|---|---|
| $L_1$ | 20.8 |
| $W_1$ | 31 |
| $L_P$ | 16 |
| $W_P$ | 8.4 |
| $L_F$ | 12.4 |
| $W_F$ | 1.5 |
| $L_G$ | 9.6 |
| $W_G$ | 1.5 |
| $L_{S1}$ | 8 |
| $L_{S2}$ | 1.6 |
| $W_{s1}$ | 1.5 |
| $W_{s2}$ | 1.8 |
| r | 8.5 |

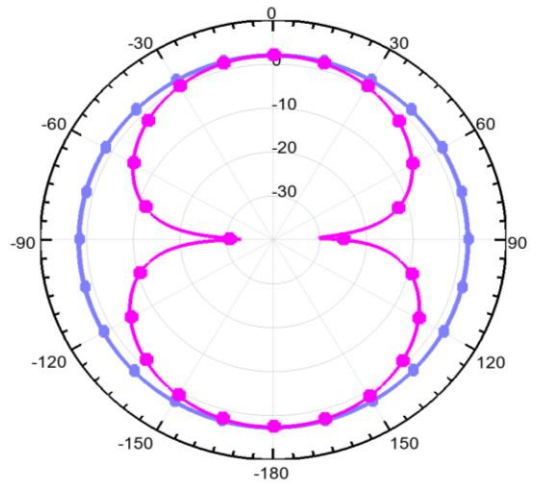


Fig 3c Radiation Pattern of Proposed Antenna

Fig 4a displays the simulated parametric analysis of the antenna design in which $L_p$ and $W_f$ are assigned different values at the step size of 0.1 mm (actual $L_p$ = 16 mm and $W_F$ = 1.5 mm) to get the plot. From the plot, 4000 datasets are generated and these datasets are employed to model the ML.

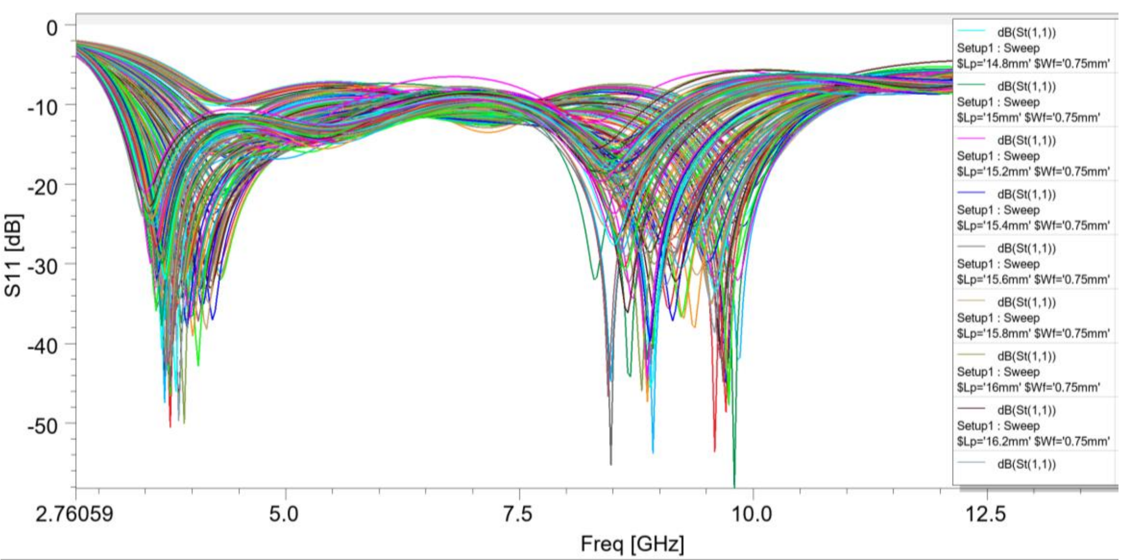


Fig 4a Simulated parametric analysis on $L_p$ and $W_f$

**Discussions**

Here, Machine learning techniques are used to predict antenna return loss ($S_{11}$). A dataset is generated by varying antenna parameters and operating frequency in HFSS simulations. The dataset is classified into 80% training data and 20% testing datasets. Five different ML algorithms are trained to learn the relationship between antenna parameters and return loss. The trained models are evaluated using performance metrics such as $R^2$, MAE, RMSE, and MSE.

**Model Evaluation**

Performance of ML models is evaluated using the below-mentioned metrics:

1. **$R^2$ Score**: It calculates prediction accuracy
2. **MSE - Mean Squared Error**: It finds the average square difference between predicted and actual values
3. **MAE - Mean Absolute Error**: It calculates the average absolute prediction error
4. **RMSE - Root Mean Squared Error**: It measures the standard deviation of prediction errors
5. **MAPE - Mean Absolute Percentage Error**: It finds the percentage error between predicted and actual values

Table 3 shows the ML model performance in aspect of $R^2$, MAE, MSE and RMSE. It is observed that Random Forest is Selected as Best Model as the $R^2$ is high and errors are comparatively less.

Table 3: Comparison of ML Model Performance

| S. No. | Model | $R^2$ | MAE | MSE | RMSE |
|---|---|---|---|---|---|
| 1. | Random Forest | 0.98698464 | 0.226507233 | 0.36325168679 | 0.602703647 |
| 2. | Extra Trees | 0.97806929 | 0.308653229 | 1.53794748153 | 1.240140105 |
| 3. | CatBoost | 0.94489515 | 0.604575541 | 1.53794748153 | 1.240140105 |
| 4. | Gradient Boosting | 0.82315717 | 1.255009050 | 4.93559105483 | 2.221619016 |
| 5. | Linear Regression | 0.00338096 | 3.759869479 | 27.8151170699 | 5.274003893 |

Table 4: Comparison of Predicted, Actual and Difference S11

| $L_p$ [mm] | $W_f$ [mm] | Freq [GHz] | Predicted $S_{11}$ Value (dB) | Actual $S_{11}$ Value (dB) | Difference in $S_{11}$ (dB) | Error ( %) |
|---|---|---|---|---|---|---|
| 15.8 | 0.95 | 9.14 | -13.3543 | -13.7261 | 0.3717 | 2.708439 |
| 15.8 | 0.95 | 9.17 | -13.8957 | -14.0607 | 0.1649 | 1.173242 |
| 15.8 | 0.95 | 9.2 | -14.2974 | -14.4206 | 0.1231 | 0.854167 |
| 15.8 | 0.95 | 9.23 | -14.4727 | -14.8082 | 0.3354 | 2.265353 |
| 15.8 | 0.95 | 9.26 | -15.0309 | -15.2264 | 0.1954 | 1.283508 |
| 15.8 | 0.95 | 9.29 | -15.5089 | -15.6781 | 0.1691 | 1.07883 |
| 15.8 | 0.95 | 9.32 | -15.7621 | -16.1672 | 0.4050 | 2.505233 |
| 15.8 | 0.95 | 9.35 | -16.1383 | -16.698 | 0.5596 | 3.351845 |
| 15.8 | 0.95 | 9.38 | -16.5731 | -17.2755 | 0.7023 | 4.0657 |
| 15.8 | 0.95 | 9.41 | -16.4676 | -17.9059 | 1.4382 | 8.032442 |
| 15.8 | 0.95 | 9.44 | -17.7224 | -18.5962 | 0.8737 | 4.698584 |
| 15.8 | 0.95 | 9.47 | -17.9898 | -19.3549 | 1.3650 | 7.052772 |
| 15.8 | 0.95 | 9.5 | -19.4640 | -20.1915 | 0.7274 | 3.602853 |

Table 4 depicts the training data which shows the predicted $S_{11}$ values, actual $S_{11}$ values and the error percentage having minimum error % of 0.8541 and maximum error % of 8.0324. Then the model is tested using a new value of $L_p$ and $W_f$ and the $S_{11}$ values are predicted as indicated in Table 5. The same $L_p$ and $W_f$ values are incorporated in the antenna simulation environment to find the actual $S_{11}$. The error difference is calculated which is between 1.115% to 1.693%

Table 5: Testing data and Confirming with HFSS Simulation

| $L_p$ [mm] | $W_f$ [mm] | Freq [GHz] | $S_{11}$ Value from ML model | Actual $S_{11}$ Value | Difference in $S_{11}$ | Error % |
|---|---|---|---|---|---|---|
| 15.5 | 0.8 | 9.142 | -12.282 | -12.454 | 0.172 | 1.381082 |
| 15.6 | 0.85 | 9.173 | -12.673 | -12.816 | 0.143 | 1.115793 |
| 15.7 | 0.9 | 9.24 | -13.254 | -13.408 | 0.154 | 1.148568 |
| 15.9 | 1 | 9.231 | -13.523 | -13.756 | 0.233 | 1.693806 |
| 16 | 1.05 | 9.263 | -13.623 | -13.808 | 0.185 | 1.339803 |
| 16.1 | 1.1 | 9.294 | -13.503 | -13.665 | 0.162 | 1.18551 |

## Conclusions

A goblet-shaped microstrip patch antenna with a defected ground structure was successfully designed, and its performance was evaluated through parametric analysis. A machine learning model was developed and trained using antenna design parameters and corresponding datasets to effectively learn the relationship between design variables and return loss. The trained model predicted the return loss for new datasets with an error percentage ranging between 1.115% and 1.693 %, demonstrating strong generalization capability and reliable predictive performance. Performance evaluation using MAE, MSE, RMSE, and $R^2$ score confirmed the effectiveness of the proposed approach, highlighting the potential of machine learning to accelerate antenna design while reducing computational time and simulation effort.

## References


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