Optimisation of Antenna Design using Machine Learning

Project report submitted in partial fulfillment of the requirement for the degree of

Bachelor of Technology

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(December 2023)

CANDIDATE DECLARATION

We hereby declare that the thesis entitled "Optimisation of Antenna Design Using Machine Learning" submitted for the B. Tech. degree program. This thesis has been written in our own words. We have adequately cited and referenced the original sources.

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CERTIFICATE

It is certified that the work contained in the project report titled "Optimisation of Antenna Design Using Machine Learning," by "Akshat Punia" has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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CERTIFICATE

It is certified that the work contained in the project report titled "Optimisation of Antenna Design Using Machine Learning," by "Sarvesh Sankaran" has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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ABSTRACT

For electromagnetic design problems, various computation methods have been applied and have shown promising results. However, these algorithms often entail substantial computational expenses due to the demanding nature of electromagnetic simulations. As a consequence, direct application of these algorithms for optimization can result in extensive time requirements, sometimes spanning weeks. This drawback restricts their applicability within numerous real-world industrial scenarios. This project aims to address this limitation by exploring and implementing machine learning techniques. The objective is to facilitate simulation- optimized antenna design within a feasible timeframe. This will be achieved through the utilization of a simulated dataset, encompassing various samples with distinct design parameters while maintaining a consistent substrate material and thickness. The dataset will be generated via the electromagnetic simulator CST Microwave Studio.

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Chapter 1

Introduction

1.1 Background and Motivation

Electromagnetic design problems have been addressed using various computational methods, which have demonstrated promising results. However, these algorithms often come with substantial computational expenses due to the demanding nature of electromagnetic simulations. Consequently, the direct application of these algorithms for optimization can lead to extensive time requirements, sometimes spanning weeks or even longer. Such a drawback significantly limits their applicability within numerous real-world industrial scenarios, where rapid design iterations are crucial for competitiveness and efficiency.

1.2 Research Objective

This project seeks to overcome this limitation by exploring and implementing machine learning techniques in the domain of antenna design. The primary objective is to enable simulation-optimized antenna design within a feasible timeframe. To achieve this, we aim to leverage a simulated dataset comprising various samples, each with distinct design parameters. Throughout this endeavor, we will maintain a consistent substrate material and thickness to isolate the effects of design variations. The dataset will be generated through the use of the electromagnetic simulator CST Microwave Studio, a widely used tool in the field of antenna design. By harnessing machine learning's capabilities, we intend to revolutionize the antenna design process and open doors to enhanced efficiency and competitiveness.

Chapter 2

Literature Survey

The literature survey in the field of antenna design and optimization reveals a significant emphasis on leveraging machine learning and deep learning techniques to streamline and improve the design process. Researchers have increasingly explored the integration of electromagnetic simulators like CST and HFSS with machine learning and deep learning-based approaches, including reinforcement learning, to advance antenna design processes (Khan et al., 2022). Moreover, studies have demonstrated the potential of machine learning methods, such as modified linear regression, Gaussian process, and Support Vector Regression, to generate accurate antenna models even with small datasets, thereby enhancing design efficiency and reducing computational resource requirements (MLMethods, 2022).

Additionally, artificial intelligence (AI) has found applications in antenna design, particularly in the context of metamaterial-based reconfigurable antennas. Techniques such as evolutionary algorithms and knowledge representation ontologies have been reviewed, highlighting AI's role in enhancing antenna design flexibility and adaptability (AIinAntenna, 2022). Furthermore, recent progress in antenna design optimization has emphasized the use of machine learning techniques to address efficiency and optimization challenges, promising significant impacts on future antenna development across various applications (AntennaOptimization, 2022).

This literature survey underscores the transformative potential of machine learning and deep learning in antenna design, aligning with the project's aim to employ these techniques for optimizing microstrip patch antenna designs, ultimately leading to substantial time savings in the design and simulation phases.

Chapter 3

Work Done

3.1 Designing the Antenna and Preparing Dataset

The essence of the project lies in the creation of a series of designs of Rectangular Microstrip Patch Antenna each optimized for different frequency ranges simulating their performance and collecting a dataset for machine learning model training. The antennas, ranging from 1 to 10 GHz, are designed using CST Studio, considering various parameters such as length, width, and inset length. The goal is to create a dataset that can be leveraged to predict antenna parameters based on frequency and S parameter magnitude.

3.1.1 Calculating Antenna Parameters

Figure 3.1: Patch Calculator

Constant Values

- Height of the Conductor: 0.035 mm

- Height of the Substrate: 1.6 mm

- Width of the Feedline: 3.137 mm

- Height of Inset: 1mm

- Material for Ground and Patch: Copper (Annealed)

- Material for Substrate: FR-4 (Lossy)

These constant values provide a foundation for the designs, ensuring uniformity and adhering to industrial norms. The choice of materials, specifically copper for the ground and patch and FR-4 for the substrate, aligns with common industry practices for Microstrip patch antennas.
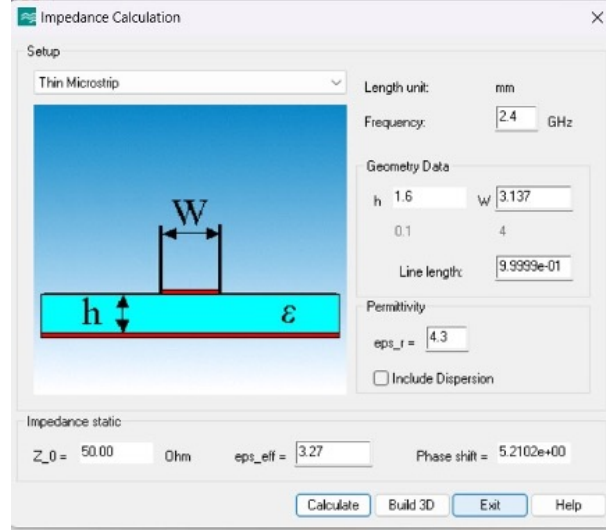
Figure 3.2: Calculation of Feedline Width

The Transmission Line equations

- To Find Width (W)

$$W = \frac{c}{2f_r\sqrt{\frac{\varepsilon_r+1}{2}}} \tag{3.1}$$

- To find the effective dielectric constant

$$\varepsilon_{eff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\left(1 + 12\frac{h}{W}\right)^{-\frac{1}{2}} \tag{3.2}$$

- To find the effective length

$$L_{eff} = \frac{c}{2f_r\sqrt{\varepsilon_{eff}}} \tag{3.3}$$

Online calculators were used to get rough values of Length and Width of Patch for design. Calculating width of Feedline using the in-built calculator in CST Microwave Studio. Even with the given formulas, the calculated parameters don't often give us the desired result. Optimizing the antenna at desired frequencies involves iterative adjustments of the width and length, accompanied by different simulations of parameter sweeps of different

parameters. These sweeps enabled us to visualize the performance metrics across a range of parameter values, ensuring optimal performance at the desired frequency.

Insets, strategically integrated gaps within the antenna structure, serve as a critical design element. They are employed to manipulate electrical properties and tailor the antenna's behavior. The variation in inset length is systematically explored, providing insights into its influence on the dip in the magnitude of the S parameters.

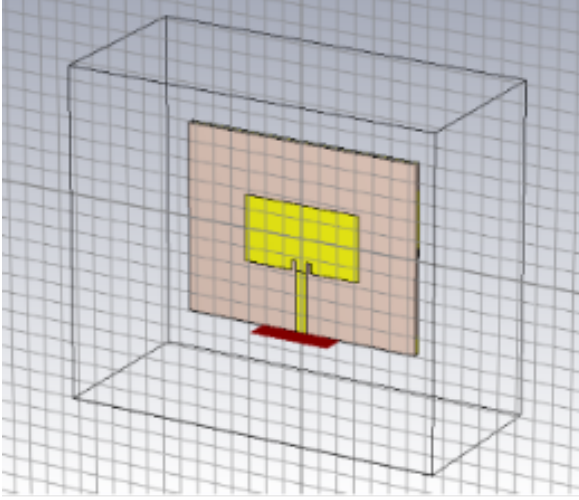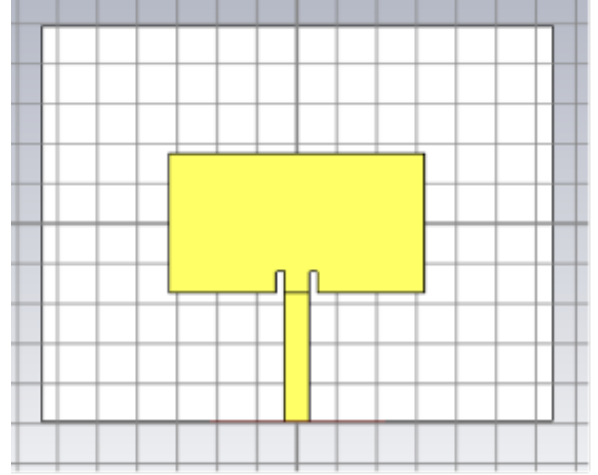Figure 3.3: Perspective View of 4 GHz Design
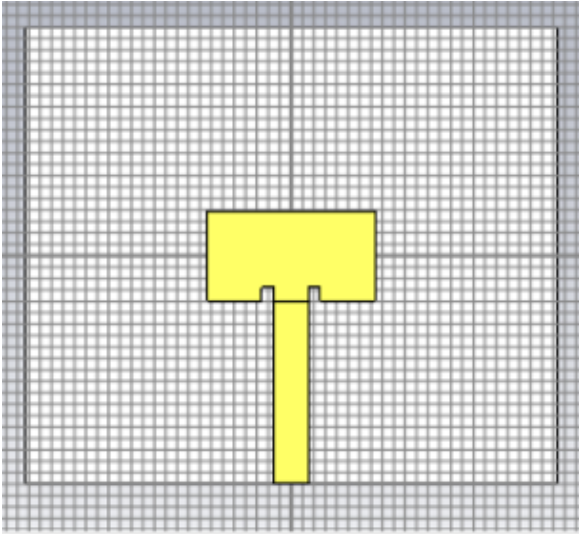

Figure 3.4: Front View of 4 GHz Design

Figure 3.5: Perspective View of 8 GHz Design
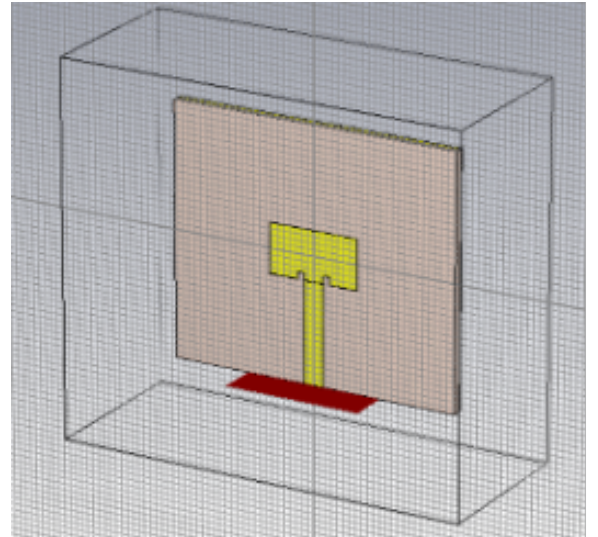
Figure 3.6: Front View of 8 GHz Design

3.1.2 Dataset Preparation and Antenna Simulation

Simulations in CST Studio yield S parameter results for each antenna design. The meticulous focus is on collecting data for frequencies within the 1 to 10 GHz range, ensuring that

the dip in magnitude is consistently less than -20 dB. This stringent criterion guarantees the inclusion of simulations representing antennas meeting the specified requirements.
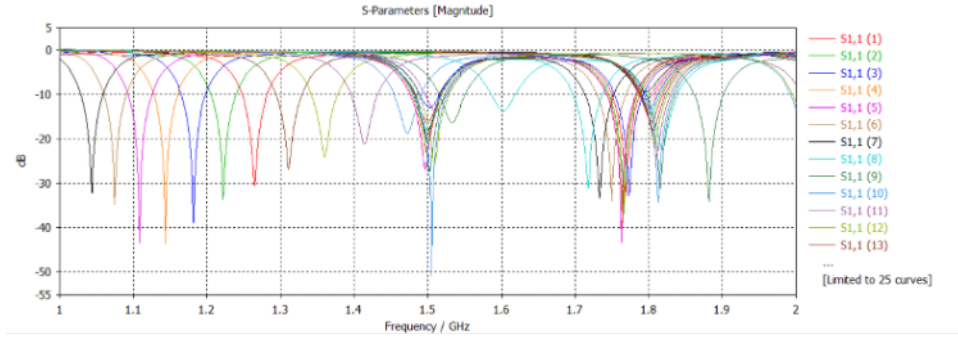
Figure 3.7: S parameters for different parameter values from a single design based on frequency range from 1 to 2 Ghz
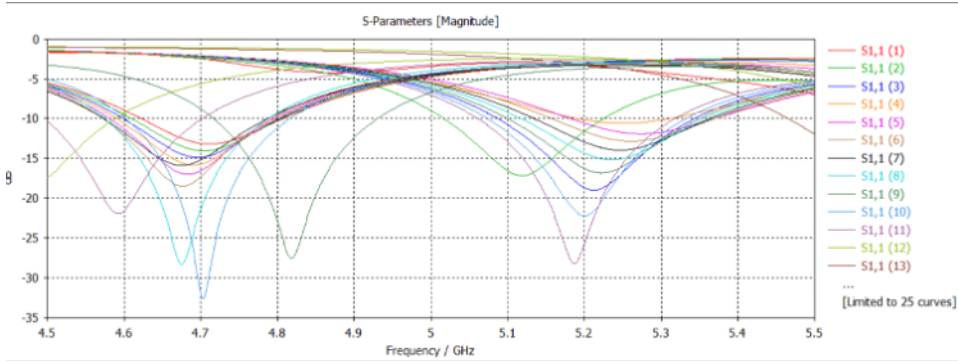
Figure 3.8: S parameters for different parameter values from a single design based on frequency range from 4.5 to 5.5 Ghz

The overarching objective is to develop a machine learning module capable of predicting antenna parameters—length, width, and inset length—based on the frequency and magnitude of the S parameters. The dataset is structured to encompass input features such as frequency and magnitude, with corresponding outputs being the antenna parameters. The utilization of consistent values across designs provides a controlled environment for the study.

Table 3.1: Detailed Antenna Parameters and Measurements

S.no	F (GHz)	L (mm)	W (mm)	b (mm)	Mag(db)
1	2.16	28.4	66.5	3	-38.86
2	2.113	28	68	3	-20.3
3	2.32	29	68	3	-25.1
4	2.165	29	66.5	6	-22.9
5	1.025	68	90	10	-32

Table 3.1 continued from previous page

S.no	F (GHz)	L (mm)	W (mm)	b (mm)	Mag(db)
6	1.1	63	90	6	-39.4
7	1.06	65	90	6	-39.62
8	1.085	64	90	6	-42.3
9	1.05	66	90	6	-35.44
10	1.024	68	86	6	-28
11	3	23	40	3	-21.6
12	1.814	46	78	8	-42.5
13	1.81	49	78	8	-23.9
14	4	16.87	30	3	-42.4
15	4.1	16.4	30	3	-21.55
16	3.94	17.2	30	3	-30.8
17	3.89	17.4	30	2.7	-21.41
18	3.88	17.4	32	2.7	-28.3
19	2.01	34	64	3	-21.78
20	1.81	38	64	3	-32.3
21	1.86	37	64	3	-42.8
22	1.9	36	64	3	-36.18
23	4.55	15	26	2.5	-26.86
24	4.56	15	25.5	2.5	-21.42
25	4.63	14.7	26	2.5	-28.79
26	4.71	14.4	26	2.5	-25.2
27	4.63	14.4	26	2.6	-47.5
28	2.12	28.4	68	7.5	-29.84
29	2.4	29	38	6	-20.8
30	1.265	55	78	8	-30.55
31	1.1	63	78	8	-43.4
32	1.22	57	78	8	-33.5
33	1.18	59	78	8	-39
34	1.14	61	78	8	-43.6
35	1.414	49	78	8	-21.2
36	1.36	51	78	8	-23.98
37	1.31	53	78	8	-26.91
38	1.5	46	80	6	-20.56
39	1.497	46	80	3	-26.81
40	1.5	46	70	8	-25.5
41	1.68	41	70	6	-22.56
42	1.6	43	70	6	-28.7
43	1.53	45	70	6	-39.05
44	1.86	37	64	5	-23.43
45	1.61	43	64	5	-26
46	5.2	13	21.5	2.5	-22.24
47	5.18	13	22	2.5	-28.25
48	4.67	14.5	24	3	-28.33

Table 3.1 continued from previous page

S.no	F (GHz)	L (mm)	W (mm)	b (mm)	Mag(db)
49	4.818	14	24	3	-27.56
50	4.7	14.4	24	3	-32.65
51	4.59	14.8	24	3	-21.95
52	4.67	13.5	22	2.5	-28.33
53	5.15	13.1	22	2.5	-25.26
54	5.12	13.2	22	2.5	-23.2
55	5.05	13.4	22	2.5	-20.29
56	5.034	13.4	22	3	-44.8
57	5	13.55	22	3	-32.43
58	4.95	13.7	22	3	-26.98
59	4.9	13.85	22	3	-23.54
60	5.367	12.5	21	3	-23
61	5.485	12.2	20.6	3	-20.38
62	5.45	12.3	20.6	3	-22.55
63	5.41	12.4	20.6	3	-25.2
64	5.34	12.6	20.6	3	-34.59
65	6.05	10.5	33	1.6	-31.21
66	6.315	10	33	1.6	-21.76
67	6.26	10.1	33	1.6	-23.047
68	6.21	10.2	33	1.6	-24.5
69	6.1	10.4	33	1.6	-28.42
70	5.975	10.7	33	1.6	-40.1
71	5.88	10.9	33	1.6	-39.8
72	5.83	11	33	1.6	-33.98
73	7.82	8.4	15.4	1.2	-37.78
74	7.79	8.4	15.6	1.2	-25.85
75	7.68	8.6	15.6	1.2	-26.58
76	7.62	8.7	15.4	1.2	-20.37
77	8.16	8	14.8	1.2	-23.1
78	8.22	7.9	14.7	1.2	-21.28
79	10.44	6.5	9.2	1.8	-42.9
80	10.34	6.6	9.2	1.8	-25.94
81	9.78	7	9.7	1.9	-24.13
82	9.97	6.8	9.7	1.9	-33.68
83	9.88	6.9	9.7	1.9	-33.1
84	9.7	7.1	9.7	1.9	-20
85	9.57	7.2	9.7	2	-21.8
86	9.353	7.4	9.7	2.1	-20
87	9.23	7.5	9.7	2.2	-21.98
88	9.16	7.5	10	2.2	-28.94
89	8.95	7.7	10.2	2.2	-21.62

3.2   Machine Learning Model Tuning

3.2.1   Dataset Compilation

The dataset, crucial for the ML model, was compiled from a range of simulations. This data is instrumental in training the machine learning model to predict optimal antenna parameters.

3.2.2   Model Selection

The RandomForestRegressor was chosen due to its robustness and effectiveness in handling regression tasks with high-dimensional data, characteristic of electromagnetic design problems.

3.2.3   Data Preparation

The dataset was loaded into a pandas DataFrame, a flexible and powerful data manipulation tool for Python, allowing for easy data analysis and manipulation. The dataset consists of input features such as the frequency and magnitude of the S parameters, with the target variables being the length (L), width (W), and inset length (b) of the antenna.

Splitting the Data

A key step in machine learning model preparation is splitting the dataset into training and testing sets. This is crucial for evaluating the model's performance on unseen data. The standard practice of an 80-20 split provides a substantial amount of data for training while reserving enough for an unbiased assessment of the model's generalization capabilities.

3.2.4   Model Training

The RandomForestRegressor model, a collection of decision trees, is known for its high accuracy and ability to run in parallel. It's an ensemble method that fits multiple decision tree classifiers on various sub-samples of the dataset and averages the results to improve predictive accuracy and control over-fitting.

Performance Evaluation

Training the model involves adjusting the decision trees to best fit the training data. The Mean Squared Error (MSE) metric is used post-training on the test set to quantify the model's prediction accuracy.

3.2.5   Model Evaluation and Visualization

Visualizations of the actual versus predicted values offer an intuitive understanding of the model's performance. The proximity of the predicted points to the actual points indicates the level of precision achieved by the RandomForestRegressor model.

3.2.6   Code Implementation

The code snippets demonstrate the process using Python's machine learning library, scikit-learn.

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error

# Load the dataset
file_path = 'Dataset_inset.xlsx'
df = pd.read_excel(file_path)

# Separate data into features (X) and target variables (y)
X_rev = df[['F', 'Mag(db)']]
y_rev = df[['L', 'W', 'b']]

# Split the data into training and testing sets (80% train, 20% test)
X_rev_train, X_rev_test, y_rev_train, y_rev_test = train_test_split(X_rev, y_rev, test

# Train Random Forest models
model_rev = RandomForestRegressor(n_estimators=100, random_state=42)
model_rev.fit(X_rev_train, y_rev_train)

# Make predictions on the test set
y_rev_pred = model_rev.predict(X_rev_test)

# Evaluate the model
mse_rev = mean_squared_error(y_rev_test, y_rev_pred)
print(f'Mean Squared Error for L, W, b: {mse_rev}')
```

3.3   Simulating Antennas on Predicted Values

Insets play a pivotal role in influencing impedance matching, bandwidth, and radiation patterns, offering additional degrees of freedom for design optimization...

Table 3.2: Predicted Antenna Dimensions v/s Actual Values

| F	Mag(db)	Actual_L	Predicted_L	Actual_W	Predicted_W	Actual_b	Predicted_b
1.5	-20.56	46	45.66	80	72.86	6	6.95
1.81	-32.3	38	45.71	64	74.52	3	6.6
5.15	-25.26	13.1	13.30	22	21.91	2.5	2.67
5.975	-40.1	10.7	10.83	33	32.88	1.6	1.61
2.16	-38.86	28.4	28.97	66.5	67.54	3	6.3
4.56	-21.42	15	15.00	25.5	25.3	2.5	2.76
1.31	-26.91	53	53.11	78	78.18	8	7.43
6.05	-31.21	10.5	10.60	33	32.75	1.6	1.63
1.085	-42.3	64	63.15	90	82.08	6	7.32
1.6	-28.7	43	43.98	70	67.64	6	5.3
9.78	-24.13	7	7.08	9.7	9.68	1.9	1.93
1.18	-39	59	61.05	78	81.24	8	7.46
9.23	-21.98	7.5	7.50	9.7	9.95	2.2	2.15
5.367	-23	12.5	12.48	21	20.68	3	2.97
1.024	-28	68	66.53	86	89.28	6	8.68
2.113	-20.3	28	29.07	68	67.16	3	4.46
3.94	-30.8	17.2	17.21	30	30.53	3	2.77
4.71	-25.2	14.4	14.13	26	23.58	2.5	2.88
5.18	-28.25	13	13.24	22	21.80	2.5	2.68
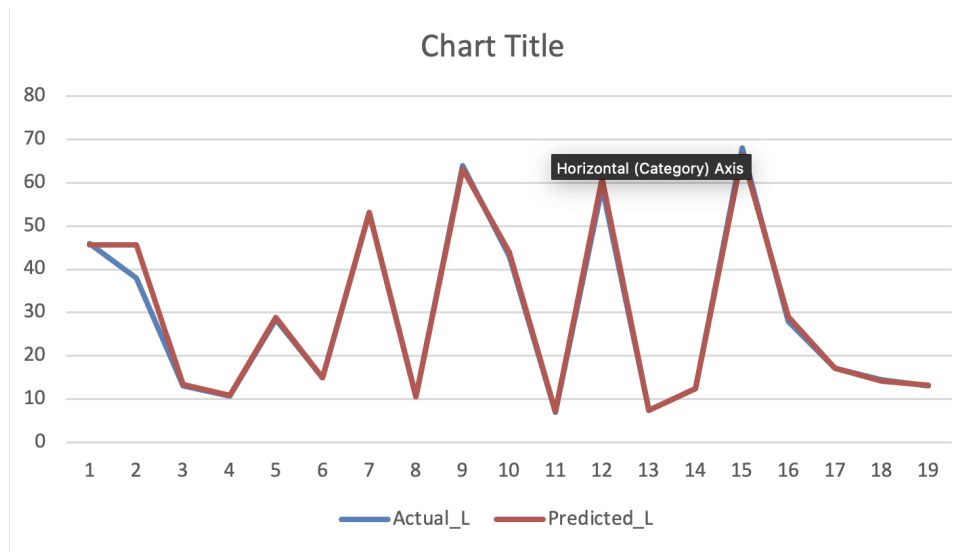
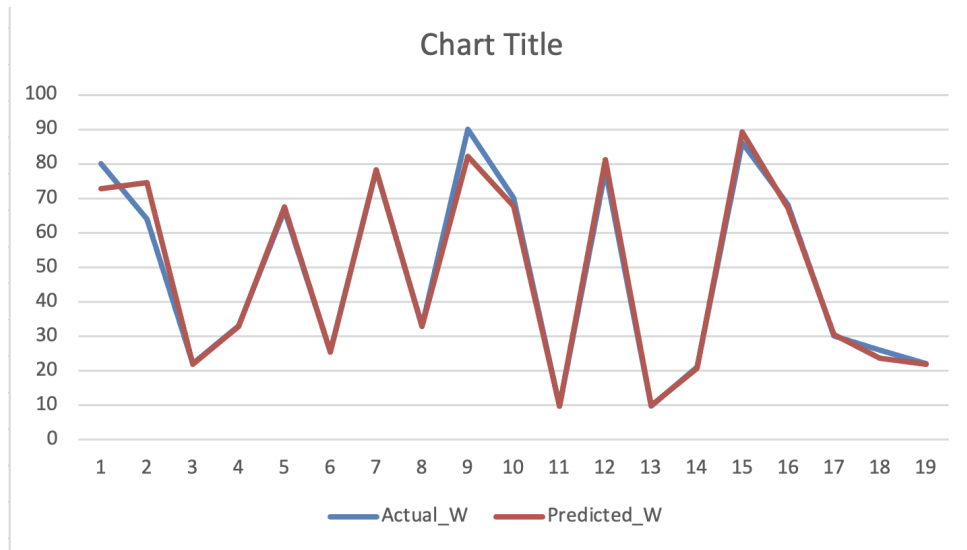Figure 3.9: Predicted Length v/s Actual Length

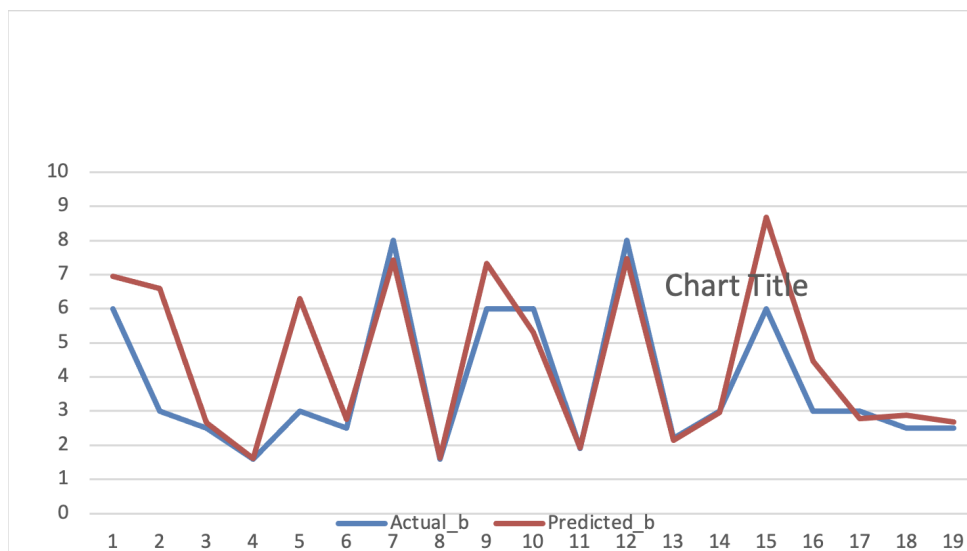Figure 3.10: Predicted Width v/s Actual Width

Figure 3.11: Predicted Inset Height v/s Actual Height

```
Enter the frequency: 1.4

Parameters for Frequency 1.4 GHz:
Predicted Length (L): 49.62
Predicted Width (W): 77.6
Predicted Inset Length (b): 7.98
```
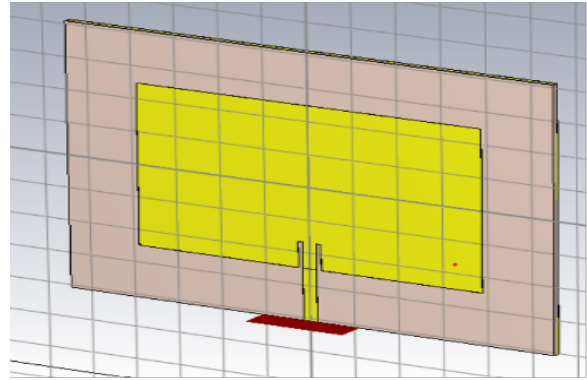
Figure 3.12: Parameters predicted for 1.4 GHz

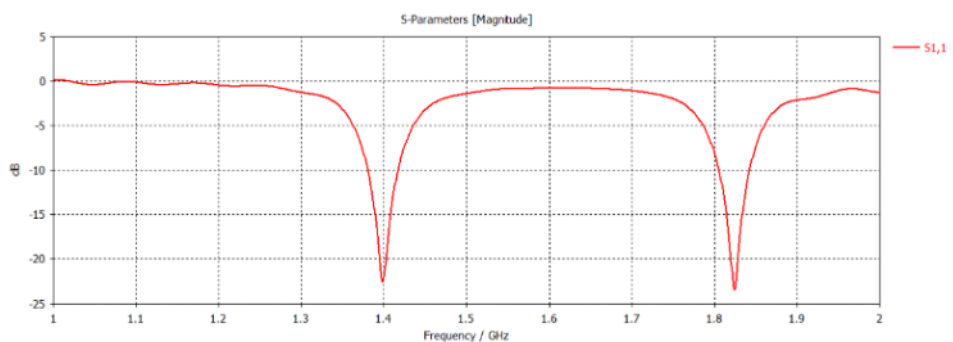Figure 3.13: Design from Predicted Parameters (1.4 GHz)

Figure 3.14: S Parameters dipping at 1.4GHz

```
Enter the frequency: 4.5

Parameters for Frequency 4.5 GHz:
Predicted Length (L): 15.646
Predicted Width (W): 26.14
Predicted Inset Length (b): 2.735
```
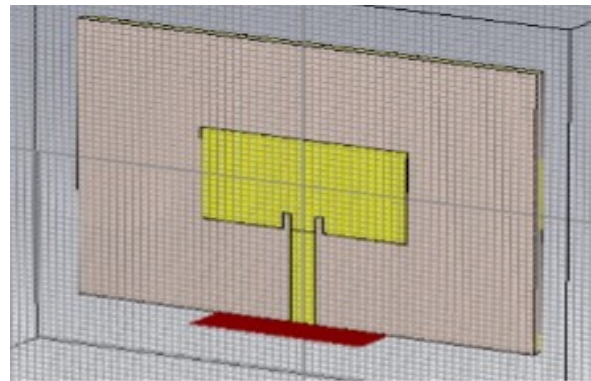
Figure 3.15: Parameters predicted for 4.5 GHz

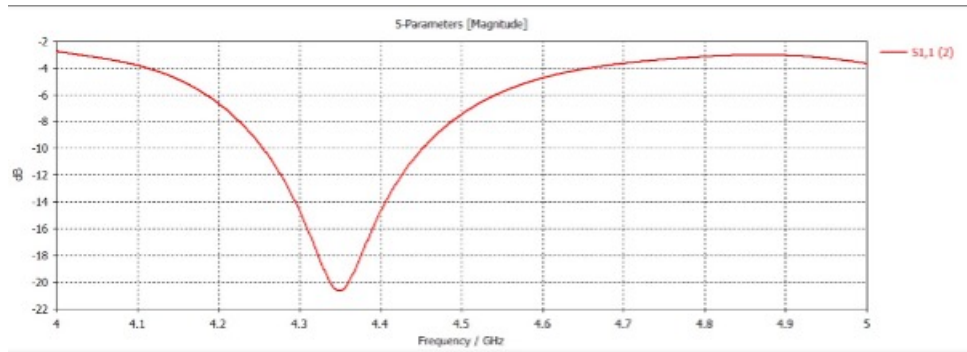Figure 3.16: Design from Predicted Parameters (4.5 GHz)

Figure 3.17: S Parameters dipping at 4.35GHz (Error of -0.15GHz)

Figure 3.18: Parameters predicted for 7.6 GHz
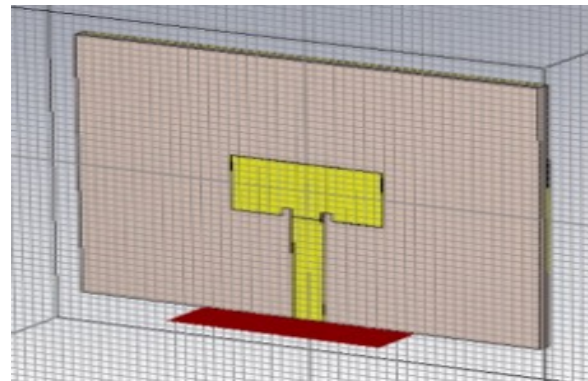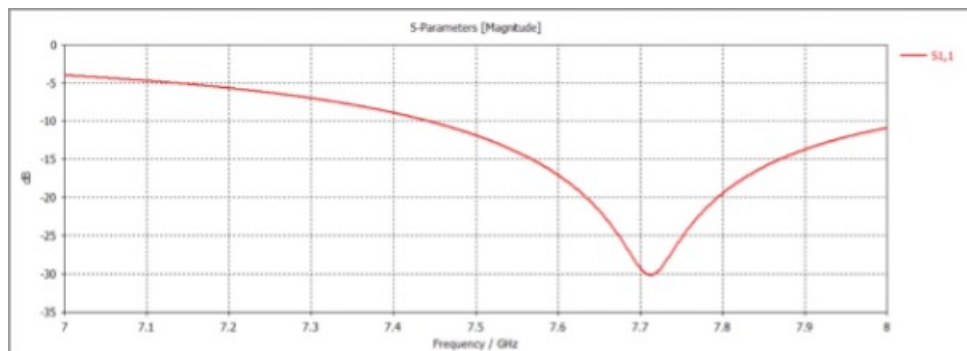

Figure 3.19: Design from Predicted Parameters (7.6 GHz)

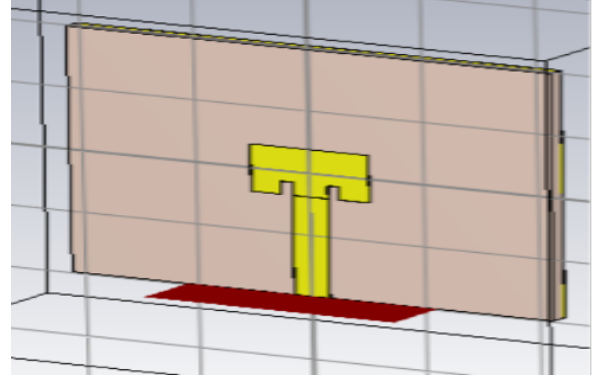Figure 3.20: S Parameters dipping at 7.71GHz (Error of 0.11GHz)

Figure 3.21: Parameters predicted for 8.8 GHz

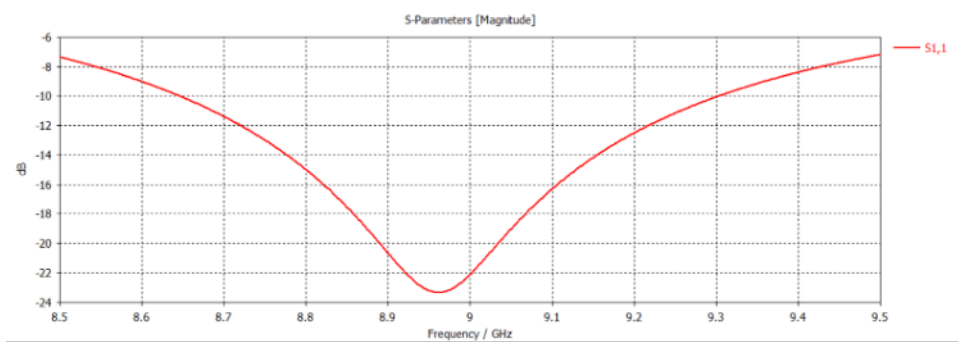Figure 3.22: Design from Predicted Parameters (8.8 GHz)

Figure 3.23: S Parameters dipping at 8.96GHz (Error of 0.16GHz)

3.3.1 Limitations

In our study, we have identified several limitations that are important to consider when using the machine learning model for design optimization:

1. **Limited Dataset Size:** The performance of the current model is contingent on the size and diversity of the dataset. A larger and more diverse dataset would likely enhance the model's ability to generalize. The long simulation time in CST Studio slows down the process for data collection, making it a very redundant and time-consuming process.

2. **Assumption of Linearity:** Random Forest models assume a certain level of linearity in relationships. If the relationships between antenna parameters are highly non-linear, the model may not capture them effectively. Consequently, this contributes to the observation that the length of the patch tends to be predicted more accurately, on average, in comparison to the height of the inset gap. The latter parameter exhibits a less linear relationship with antenna frequencies, especially at close frequency levels.

3. **Interpretability:** Random Forest models, while effective, can be challenging to interpret. Understanding the exact decision-making process of the model may be complex.

4. **Extrapolation Challenges:** The model may struggle with accurate predictions for frequencies or magnitudes outside the range of the training data. Care must be taken when extrapolating predictions. Hence, our model mostly works well only for frequencies ranging between 1 to 10 GHz.

3.4 Online Dashboard and Public Repository

To promote collaboration and accessibility, we have established an online dashboard for our research and dataset. You can explore our work and interact with the dataset at https://ml-antenna-design.streamlit.app/.

This dashboard offers a user-friendly interface for researchers and enthusiasts to delve into our findings, experiment with the dataset, and contribute to further improvements. Furthermore, we have made our dataset and machine learning model openly available on GitHub at https://github.com/akshatpunia26/optimal-antenna-design/. Our repository is designed to encourage contributions from the community, allowing researchers to access, analyze, and build upon our work. We welcome collaborative efforts to enhance the capabilities of our antenna design model.

The focus of our dataset collection has been on frequencies within the 1 to 10 GHz range, ensuring a consistent magnitude dip of less than -20 dB.
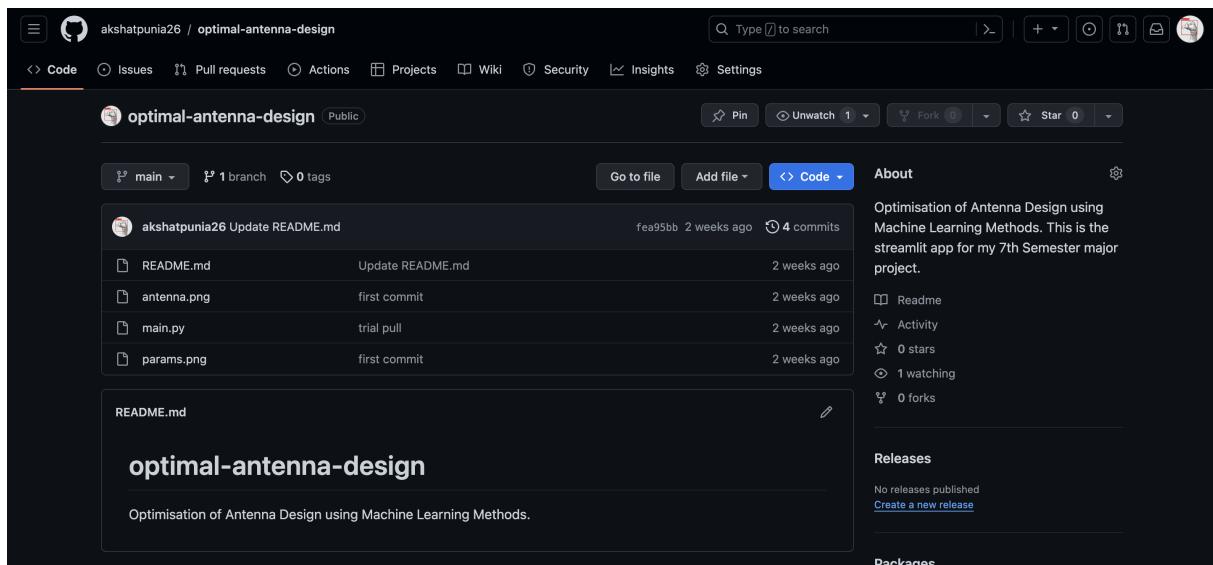
Chapter 4

Conclusion

In conclusion, the integration of machine learning (ML) techniques into the field of antenna design has proven to be a feasible and promising endeavor. The predictive models generated through ML have demonstrated a notable closeness to the desired design parameters, significantly reducing the time and effort required for iterative design processes.

The dataset produced by the electromagnetic simulator CST Microwave Studio serves as a valuable foundation for future studies and paves the way for the integration of more advanced ML techniques and models. This innovative approach holds great potential for revolutionizing antenna design processes, making them more efficient and adaptable to various real-world applications. As we move forward, further research and development in this direction will undoubtedly yield even more remarkable results, pushing the boundaries of what is achievable in the field of electromagnetic design.

Chapter 5

Future Prospects

In the future we plan to implement the following changes. :

1. **More Diverse Dataset:**

   - *Expand Antenna Types:* The dataset can be expanded to include data from a variety of antenna types beyond Rectangular Microstrip Patch Antennas. This could encompass designs such as circular patches, triangular patches, and other non-rectangular geometries, each with unique parameter dependencies.

   - *Frequency Bands:* We aim to cover a broader spectrum of frequency bands. Different frequency bands may exhibit distinct behaviors, and the model could benefit from exposure to this extensive range.

   - *Real World Constraints:* Introducing real-world constraints into the dataset, such as manufacturing tolerances, material imperfections, or environmental factors, will make the model more robust and applicable to practical scenarios.

2. **Deep Learning Models:** There is a plan to implement deep learning models, specifically neural networks, to capture the complex non-linear relationships in the data. Neural networks have the ability to automatically learn hierarchical representations from the input features, which could prove beneficial for the model's predictive capability.

3. **Continuous Model Updating:** A system for continuous model updating will be put in place as more data becomes available. This will ensure that the model remains up-to-date and adapts to new antenna design patterns and technological advancements.

4. **Real-World Development and Integration with Design Tools:**

   - The integration of the trained model into a real-world antenna design workflow is being explored. A user-friendly interface for engineers to input parameters and receive predicted antenna dimensions could significantly streamline the design process.

- Efforts are underway to explore integration with popular antenna design tools. This could facilitate the automated extraction of design parameters and contribute to the dataset during the design process, creating a feedback loop that continuously improves the model's accuracy and reliability.

These advancements are envisioned to not only improve the precision of antenna design predictions but also to bridge the gap between theoretical models and practical, real-world applications. The future looks promising for the field of antenna design optimization, with machine learning at the forefront of this innovative journey.

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