

OPTIMIZATION OF PLANAR ANTENNAS USING MACHINE LEARNING

1906810-PROJECT WORK-PHASE II

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ABSTRACT

In contemporary wireless communication systems, optimizing planar antennas remains a crucial task. Conventional design techniques can involve prolonged computer simulations and a great deal of trial and error. Through the use of machine learning approaches to the optimization process, this study seeks to overcome these issues. To improve the design of planar antennas by creating and applying cutting-edge machine learning algorithms, with an emphasis on important performance parameters including gain, bandwidth, and efficiency. The method entails gathering comprehensive data on the performance of antenna designs, training machine learning models to forecast and optimize antenna parameters, and rigorously testing these models to validate them.

Recently, to speed up the design of antennas and arrays, machine-learning-assisted optimization or MLAO, has been frequently used. Surrogate models of antennas have been created using ML techniques, including KNN, SVMs, and Random Forest regression, in order to provide quick response prediction. Various machine learning approaches are utilized to examine and optimize the performance of the antenna using the data.

The primary focuses of the endeavour is to optimize planar antennas more especially, planar or microstrip antennas by utilizing machine learning techniques. Important elements consist of Data collection: Compiling extensive information about the performance characteristics of planar antenna designs. Validation and Testing: Assessing how well machine learning models work in comparison to more conventional optimization techniques to improve antenna design. Implementation: To improve and expedite the design process. The creation and application of machine learning techniques is to improve planar antenna design parameters. The aim of this system is to minimize the amount of time and processing resources needed for the design process while simultaneously improving antenna performance.

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LIST OF ABBREVIATION

CMA	CHARACTERISTIC MODE ANALYSIS
CST	COMPUTER SIMULATION TECHNOLOGY
CST MWS	COMPUTER SIMULATION TECHNOLOGY MICROWAVE STUDIO
DG	DIVERSITY GAIN
DGS	DEFECTED GROUND STRUCTURE
ECC	ENVELOPE CORRELATION COEFFICIENT
EM	ELECTROMAGNETIC
EMC	ELECTROMAGNETIC COMPATIBILITY
FNBW	FIRST NULL BEAMWIDTH
FSS	FREQUENCY SELECTIVE SURFACES
FR4	FLAME RETARDANT 4
HF	HIGH FREQUENCY
HPBW	HALF-POWER BEAMWIDTH
LTE	LONG TERM EVOLUTION
LPF	LOW PASS FILTER
MEG	MEAN EFFECTIVE GAIN
MIMO	MULTIPLE INPUT MULTIPLE OUTPUT
MMWAVE	MILLIMETRE WAVE
PBG	PHOTONIC BAND GAP

PCB	PRINTED CIRCUIT BOARD
PCS	PERSONAL COMMUNICATION SYSTEM
RF	RADIO FREQUENCY
RFID	RADIO FREQUENCY IDENTIFICATION
R_{loss}	RETURN LOSS
R_r	RADIATION RESISTANCE
SAR	SPECIFIC ABSORPTION RATE
S11	SCATTERING PARAMETER – RETURN LOSS
SWR	STANDING WAVE RATIO
TCSRS	TRIANGULAR COMPLIMENTARY SPLIT RING SLOT
TEM	TRANSVERSE ELECTROMAGNETIC
UWB	ULTRA WIDEBAND
VHF	VERY HIGH FREQUENCY
VSWR	VOLTAGE STANDING WAVE RATIO

CHAPTER 1

INTRODUCTION

1.1 MOTIVATION

Advent of 5G technology has revolutionized the wireless communication landscape by introducing higher data rates, lower latency, and better connectivity. One of the key technologies enabling the success of 5G networks is MIMO (Multiple Input Multiple Output), which utilizes multiple antennas at both the transmitter and receiver ends to significantly increase the capacity and reliability of wireless communication systems. Designing efficient antennas for this high-frequency range presents several challenges, including minimizing signal interference, maximizing coverage, and optimizing antenna size and performance.

In recent years, ML has emerged as a powerful tool for optimizing complex systems, including antenna design. Machine learning algorithms can be used to analyze large datasets and predict the performance of antennas under various conditions. This approach enables faster, more accurate designs compared to traditional trial-and-error methods. By using data-driven models, researchers can explore a wide range of design parameters.

This paper presents a machine learning-based framework for optimizing MIMO antennas in the 25 GHz frequency band for 5G mm Wave applications. By leveraging full-wave simulations and real-world measurements, this study aims to improve the performance of MIMO antenna systems, specifically in terms of signal-to-noise ratio (SNR), bit error rate (BER), and impedance matching. The use of machine learning algorithms, including Random Forest, KNN, and SVM, allows for efficient training of models that can predict and optimize antenna designs for improved performance in real-world conditions. Through this research, we aim to demonstrate the effectiveness of machine learning in the optimization of next-generation antenna systems for 5G communication.

1.2 LITERATURE SURVEY

A. Gupta, B. Sharma “Optimization of MIMO Antennas for 5G Networks” Fifth International Conference on Image Information Processing (ICIIP) Volume-106, 2019.

Technologies and Algorithms Used: Machine Learning (ML), Genetic Algorithms, Full-Wave Simulations. This study enhances the design of MIMO antennas by reducing optimization time using ML models. It improves antenna performance for 5G applications by considering a wide range of antenna design variables. Full-wave simulations are integrated to test antenna designs, and the combination of ML and genetic algorithms helps in handling complex design spaces efficiently.

The major limitation is the computationally expensive simulations required for full-wave testing. These methods also require high-performance hardware, which may not be accessible to all research teams. Moreover, genetic algorithms may take longer to converge to an optimal solution.

J. Zhang, M. Li “Performance Optimization of 5G MIMO Antennas” International Journal of Electronic Engineering Research Volume 1, Number 1 pp. 71–77, 2021.

Technologies and Algorithms Used: Machine Learning, Impedance Matching, Frequency Response Analysis. By incorporating impedance matching and frequency response analysis, this research optimizes antenna performance in a practical manner. Machine learning techniques help predict antenna efficiency and evaluate performance under different conditions.

The reliance on impedance matching data may not always translate well to real-world conditions, as the simulation environment might differ from actual deployment scenarios.

R. Kumar, D. Verma “Design of MIMO Antennas for mmWave”, AEU - International Journal of Electronics and Communications volume-109, July 2023.

Technologies and Algorithms Used: Genetic Algorithms, Neural Networks, Antenna Array Configurations. This research successfully integrates neural networks with genetic algorithms to design antennas optimized for high-frequency mmWave communications, significantly improving performance. The system is more adaptable to variations in environmental factors.

The optimization process can be slow, requiring fine-tuning of algorithm parameters. Additionally, neural networks need large datasets to avoid model underfitting or overfitting, and the results might not generalize well to all real-world conditions.

K. Kaboutari, A. Zabihi, B. Virdee and M. Pilevari ,“Microstrip Patch Antenna Array with Cosecant-Squared Radiation Pattern Profile”, AEU - International Journal of Electronics and Communications volume-11, 2023.

The cosecant-squared radiation pattern microstrip patch antenna array proposed in this research was designed to deliver a steady signal intensity across a specified angular range. The antenna array operates in the X-band (9.97–11.90 GHz) and is made up of 16 radiating elements organized in an 8×2 arrangement. This design aims to provide a broad impedance bandwidth and high gain, making it suitable for radar applications where reliable coverage is crucial.

In order to reduce interference and guarantee the intended radiation pattern, the antenna array makes use of Rogers RO4003 substrate with optimal element spacing.

The cosecant-squared profile, which guarantees steady performance for moving targets, is attained by distributing the power asymmetrically among the patches. Simulations reveal a peak gain of 14.95 dBi and an impedance bandwidth of 1.93 GHz. Gain and bandwidth have been balanced in the design, and the structure is kept small at $106 \times 34 \times 0.813$ mm³. Simulations and anechoic chamber measurements were used to confirm the antenna's performance. The success of the design is confirmed by the near match between the measured and simulated results. Future enhancements can involve extending the antenna's capabilities to accommodate more frequencies or further refining the feed network. A useful, high-performing architecture appropriate for contemporary radar and communication applications is demonstrated in this paper.

L. Zhang, M. Iqbal “Design and Optimization of Antennas for 5G Using AI”
International Journal of Applied Engineering Research ISSN 0973-4562 Volume 6,
Number 9, pp. 1099-1104, 2024.

Technologies and Algorithms Used: AI Techniques, Antenna Array Analysis, Machine Learning Models. The study applies AI to automate antenna array analysis and optimize performance, offering a streamlined design process. Machine learning models help to reduce errors and improve the antenna's ability to handle complex 5G mm Wave communication environments.

One of the main challenges is the complexity of the AI models, which can require substantial data preprocessing and may not generalize well to untrained conditions. Also, real-time deployment and adjustments might not be as effective compared to simulations.

Bhuvidha Singh Tomar , Sumit Bharadwaj , Punit Gupta ,“Designing A Microstrip Rectangular Patch Antenna”, Fifth International Conference on Image Information Processing (ICIIP) 2024.

A study on the design and analysis of a micro strip patch antenna is included in the paper. Micro strip antennas are one of the most innovative ideas in reception equipment theory and design in recent years, and they are increasingly finding use in a wide range of contemporary microwave systems. Additionally, micro strip patch antennas have become the most popular among antenna designers due to their versatility, planar profile preferences, ease of manufacturing, resemblance to incorporated circuit innovation, and resemblance to a formed surface.

After giving a quick summary of the basic characteristics of micro strip antennas, this paper focuses on the most important virtual products that may be used to outline tiny strip antennas. The focus is on advancements in the logical display of micro strip patch antennas and arrays, as well as new antennas for improved electrical execution and manufacturing. The design and simulation of a 2.25 GHz microstrip patch antenna are presented in this study. Utilizing Ansoft or Ansys HFSS, the square patch micro strip antenna was examined.

1.3 EXISTING SYSTEM:

The existing systems for optimizing MIMO antennas largely rely on traditional methods such as simulation-based design and empirical testing. These methods typically involve running full-wave simulations of antenna designs, followed by physical prototype testing to verify performance metrics. This iterative process can be resource-intensive, time-consuming, and costly, especially when designing for high-frequency bands such as the 28 GHz mm Wave. While these methods provide detailed insight into antenna behavior, they often struggle to efficiently explore a large design space or optimize configurations based on varying environmental conditions.

Another existing approach uses basic optimization algorithms like genetic algorithms or particle swarm optimization to tune antenna parameters for better performance. However, these techniques are limited in their ability to handle complex, high-dimensional design spaces efficiently and often require a significant amount of computational power. Furthermore, these systems can be prone to overfitting when faced with diverse datasets and may not generalize well to unseen scenarios.

1.4 PROPOSED SYSTEM

The proposed system integrates ML techniques to optimize the design and performance of MIMO antennas used in 5G mm Wave applications. By leveraging large datasets generated through full-wave simulations and real-world measurements, the system can predict the optimal antenna configurations that maximize key performance metrics such as SNR, BER, and impedance matching. This approach eliminates the need for expensive physical testing and reduces the reliance on trial-and-error methods.

In the proposed system, machine learning algorithms like Random Forest, KNN, and SVM are used to identify patterns in the data, optimize antenna parameters, and make predictions for antenna performance under different conditions. This data-driven approach provides faster and more accurate optimization, improving the overall efficiency of the antenna design process. Furthermore, the system allows for the exploration of a broader range of design variables and configurations, resulting in optimized antenna systems that can adapt to the evolving demands of 5G networks.

CHAPTER 2

ANTENNA THEORY

Antennas are important components in communication systems and play a role in transmitting and receiving signals. The antenna (aerial, EM radiator) is a device, which radiates or receives electromagnetic waves. The antenna is the transition between a guiding device (transmission line, waveguide) and free space (or another usually unbounded medium). Its main purpose is to convert the energy of a guided wave into the energy of a free space wave (or vice versa) as efficiently as possible, while at the same time, the radiated power has a certain desired pattern of distribution in space.

2.1 ANTENNA PROPERTIES

The performance of the antenna is determined by several factors. The properties of those factors are as follows:

2.1.1 Gain

The gain of an antenna is essentially a measure of the antenna's efficiency. If an antenna is 100% efficient, it would have a gain equal to its directivity. There are many factors that affect and reduce the overall efficiency of an antenna. The relationship between dB_i and dB_d is given by

$$dB_i = dB_d + 2.15 \text{ dB} \quad (2.1)$$

Where,

dB_i - decibel referenced to an isotropic antenna

dB_d - decibel referenced to a half wavelength dipole

2.1.2 Directivity

Directivity, D is an important parameter that shows the ability of the antenna to focus radiated energy. Directivity is the ratio of maximum radiated to radiate reference antenna. A reference antenna usually is an isotropic radiator where the radiated energy is the same in all directions and has a directivity of 1. Directivity is defined as the following equation:

$$D = F_{\max} / F_0 \quad (2.2)$$

Where,

F_{\max} = Maximum radiated energy

F_0 = Isotropic radiator radiated energy

2.1.3 Resonant frequency

Signals of different frequencies reach the antenna simultaneously and for it to be of any importance, it should be able to select only one frequency of interest at a time. That frequency is called the resonant frequency and it is achieved by the use of a tuned circuit at the receiver or transmitter. Antennas are only effective for a range of frequencies over which they can operate and this is determined by their physical length. The Resonant frequency of an antenna is represented in Fig 2.1.

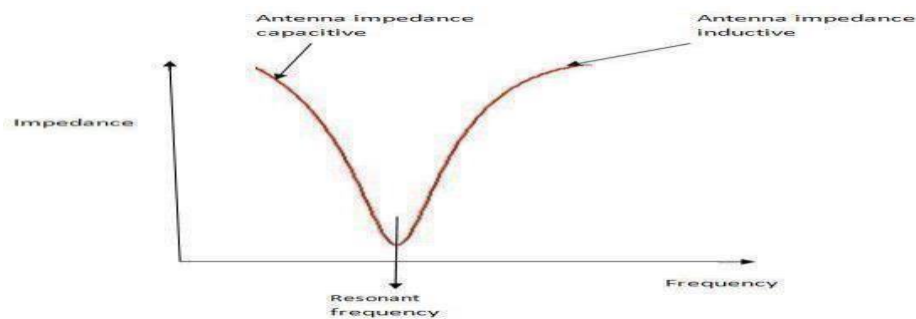


Fig 2.1 Resonant frequency

2.1.4 Radiation Pattern

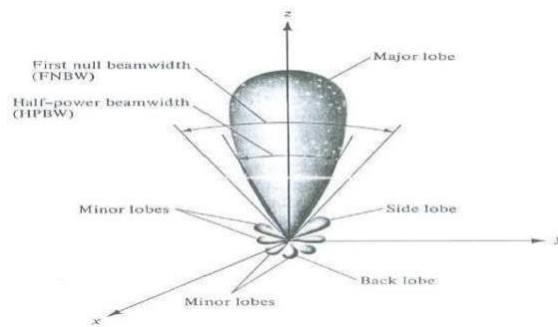


Fig 2.2 Radiation pattern

The radiation patterns of an antenna are represented in Fig 2.2 and provide information that describes how the antenna directs the energy it radiates. All antennas if 100% efficient, will radiate the same total energy for equal input power regardless of the pattern shape. Radiation patterns are generally presented on a relative power dB scale

Fig 2.2 shows the following:

- 2.1.4.1 HPBW: The half-power beamwidth (HPBW) can be defined as the angle subtended by the half-power points of the main lobe.
- 2.1.4.2 Main Lobe: This is the radiation lobe containing the direction of maximum radiation.
- 2.1.4.3 Minor Lobe: All the lobes other than the main lobes are called the minor lobes. These lobes represent the radiation in undesired directions. The level of minor lobes is usually expressed as a ratio of the power density in the lobe in question to that of the major lobe.

This ratio is called the side lobe level (expressed in decibels).

Back Lobe: This is the minor lobe diametrically opposite the main lobe.

Side Lobes: These are the minor lobes adjacent to the main lobe and are separated by various nulls. Side lobes are generally the largest among the minor lobes.

In most wireless systems, minor lobes are undesired. Hence a good antenna design should minimize the minor lobe.

2.1.5 VSWR

Standing wave ratio (SWR) is the ratio of the amplitude of a partial standing wave at an antinode (maximum) to the amplitude at an adjacent node (minimum), in an electrical transmission line. The SWR is usually defined as a voltage ratio called the VSWR, for the Voltage standing wave ratio. Voltage standing wave are,

$$\text{VSWR} = V_{\max} / V_{\min} = 1 + \rho / 1 - \rho \quad (2.3)$$

Where,

ρ - Reflection coefficient

V_{\min} – Minimum voltage

V_{\max} – Maximum voltage

2.1.6 Bandwidth

The term bandwidth simply defines the frequency range over which an antenna meets a certain set of specification performance criteria. The important issue to consider regarding bandwidth is the performance trade-offs between all of its performance properties described above. There are two methods for computing an antenna bandwidth. An antenna is considered broadband if $f_H/f_L \geq 2$.

CHAPTER 3

ANTENNA DESIGN

3.1 DESIGN METHODOLOGY

Square is chosen as the base structure by considering the formula listed below
The Width of Folded loop antenna patch is calculated using equation

$$w = \frac{c_0}{2f_r} \sqrt{\frac{2}{\epsilon_r + 1}} \quad (3.1)$$

Where,

W - Width of the patch

c_0 -Speed of light

ϵ_r -substrate dielectric

f_r - Frequency of Resonance

Length Of the Square Patch is calculated using equation

✓ Effective dielectric constant ϵ_{eff}

$$\epsilon_{eff} = \frac{\epsilon_r + 1}{2} + \frac{\epsilon_r - 1}{2} \left(1 + \frac{12h}{W}\right)^{-\frac{1}{2}} \quad (3.2)$$

✓ Effective length L_{eff}

$$L_{eff} = \frac{c}{2f\sqrt{\epsilon_{eff}}} \quad (3.3)$$

✓ Rectangular Patch length L

$$L = L_{eff} - 2\Delta L \quad (3.4)$$

Where,

ϵ_r -substrate dielectric constant

h - Thickness of substrate material

f_r - Frequency of Resonance

3.2 DESIGN PROCESS

The design of the MIMO antenna was designed using the CST Microwave Tool. The following steps make the design processes:

- STEP-1: To select the suitable antenna for this specific application.
- STEP-2: To design an antenna with operating frequency range is 20 GHz to 30 GHz.
- STEP-3: The dimension of the antenna geometry will be improved by means of full-wave simulation carried out through the commercial software CST Microwave software.
- STEP-4: Measure the antenna parameters ($|S_{11}|$, VSWR, Gain, Radiation pattern) from simulated results.
- STEP-5: The performance of the antenna parameters will be analyzed.
- STEP-6: Decide on Array Configuration and geometry and from the basic structure propose the MIMO of antenna.
- STEP-7: The Parameters of an antenna ($|S_{11}|$, VSWR, Gain, Radiation pattern) to be measured.

3.3 SIMULATION TOOL

Thomas Weiland founded CST in 1992. Maxwell's equations using the Finite Integration 2019 CST offers a collection of new features for designing, managing and simulating complex devices and systems. The 2021 version includes some new features that are especially useful for simulating planar antennas on printed circuit boards. The software can now directly calculate far fields on complex multilayer substrates, and the characteristic mode analysis Stool can consider dielectric substrates.

3.4 ANTENNA STRUCTURE

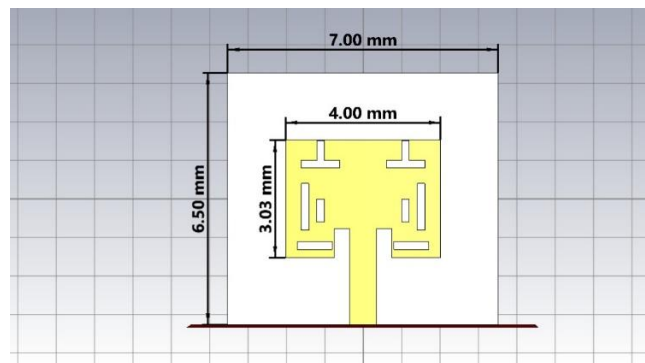


Fig.3.1 SINGLE ELEMENT STRUCTURE

3.4.2 MIMO ANTENNA

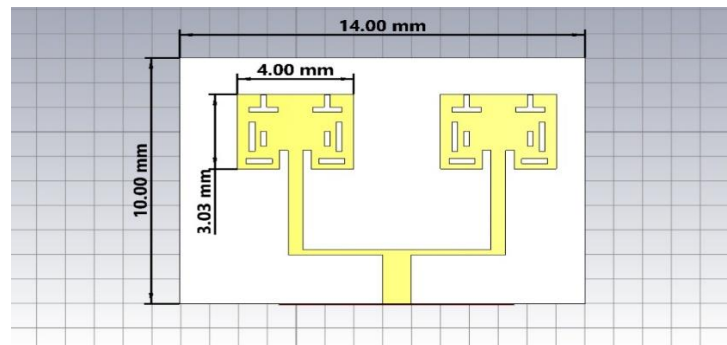


Fig. 3.2 MIMO STRUCTURE

3.4.3 FRONT VIEW

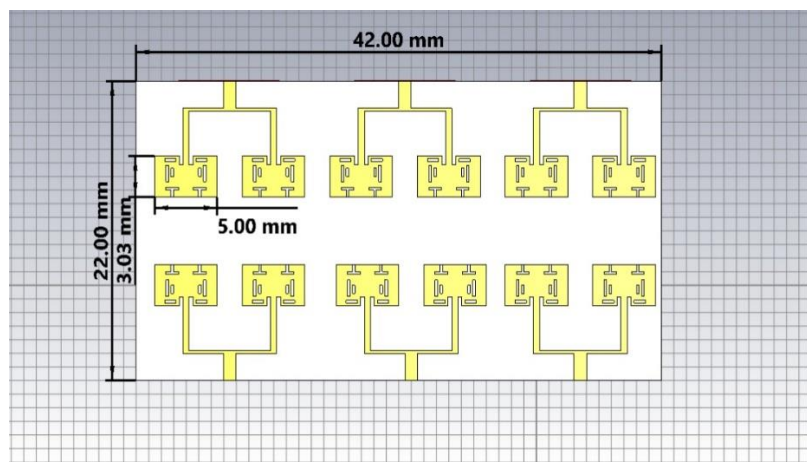


Fig.3.3 FRONT VIEW OF ANTENNA

3.4.4 BACK VIEW

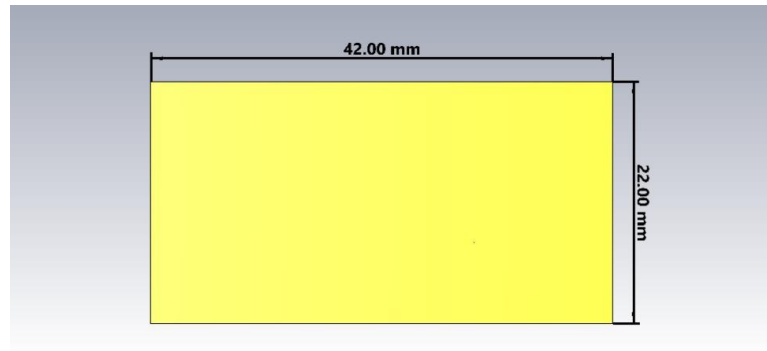


Fig.3.3 BACK VIEW OF ANTENNA

TABLE 3.1: Dimensions of the proposed antenna

SPECIFICATION	DIMENSIONS (mm)
Length of Substrate	22
Width of Substrate	42
Thickness of Ground / Patch	1.04
Thickness of Substrate	1.00
Length of Ground	22
Width of Ground	42
Patch Material	Copper
Substrate Material	FR 4 LOSSY
Ground Material	Copper

CHAPTER 4

SIMULATED RESULTS

4.1 S-PARAMETER

The s-parameter is obtained with the frequency 20 GHz to 30 GHz. Return loss is the difference between forward and reflected power in dB. The return loss is given by PR/PT . Return loss is the loss of power in the signal reflected by a discontinuity in a transmission line. The magnitude ranges from 0 to 1, where 0 means perfect matching. The bandwidth is determined from the range of frequencies for which $S_{11} < -10$ dB, Hence the value obtained for S-Parameter is 25.1 GHz, 24.8 GHz, 25.5 GHz.

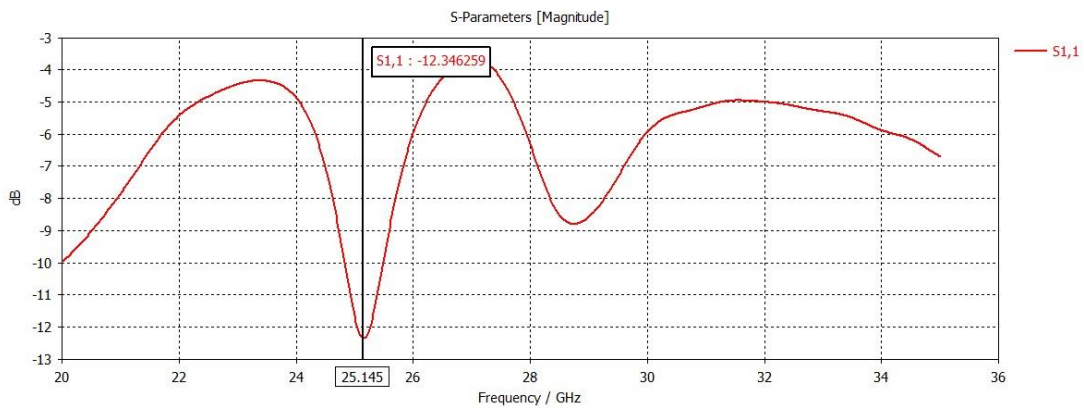


Fig.4.1 RETURN LOSS OF S11 IN dB AT 25.1 GHZ

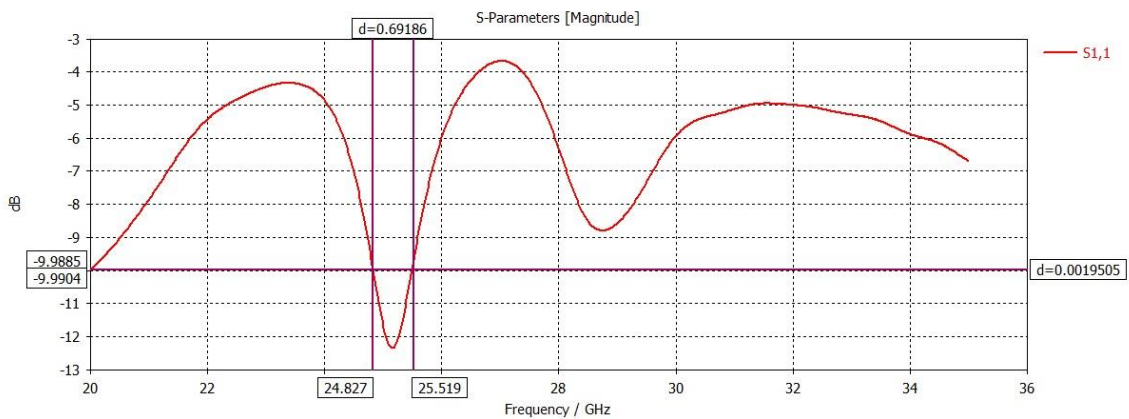


Fig.4.2 BANDWIDTH IN dB

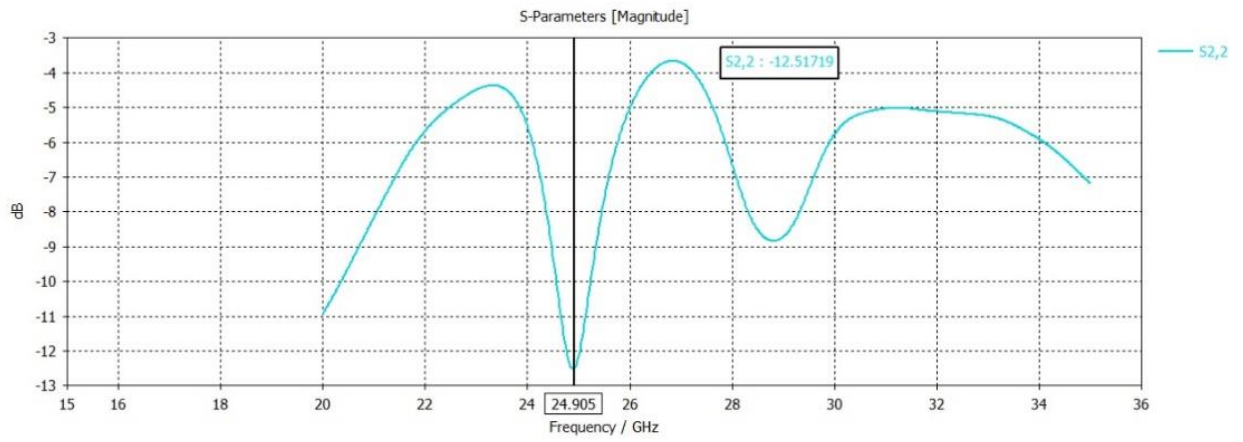


Fig.4.3 RETURN LOSS OF S22 IN dB

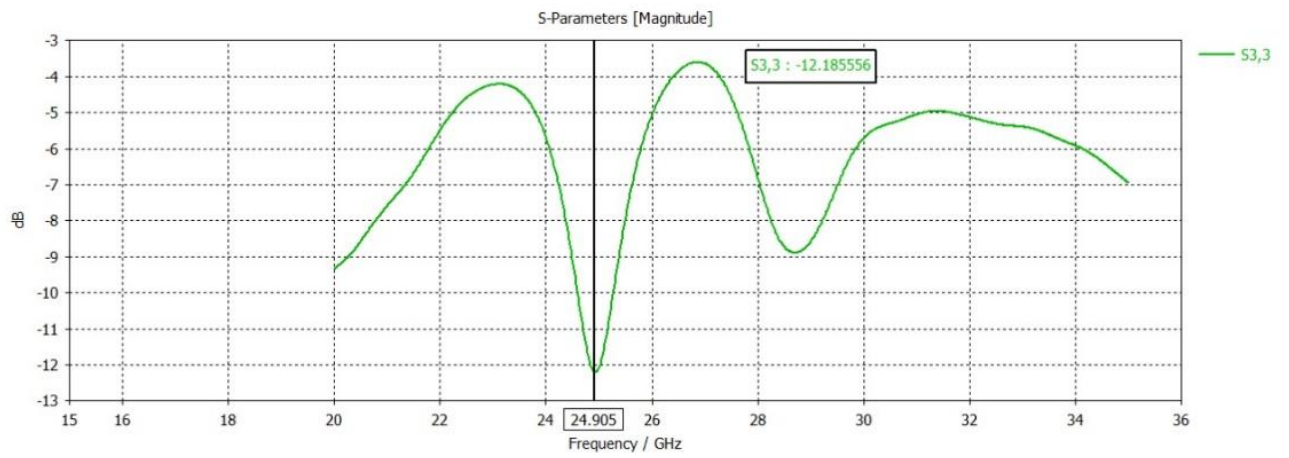


Fig.4.4 RETURN LOSS OF S33 IN dB

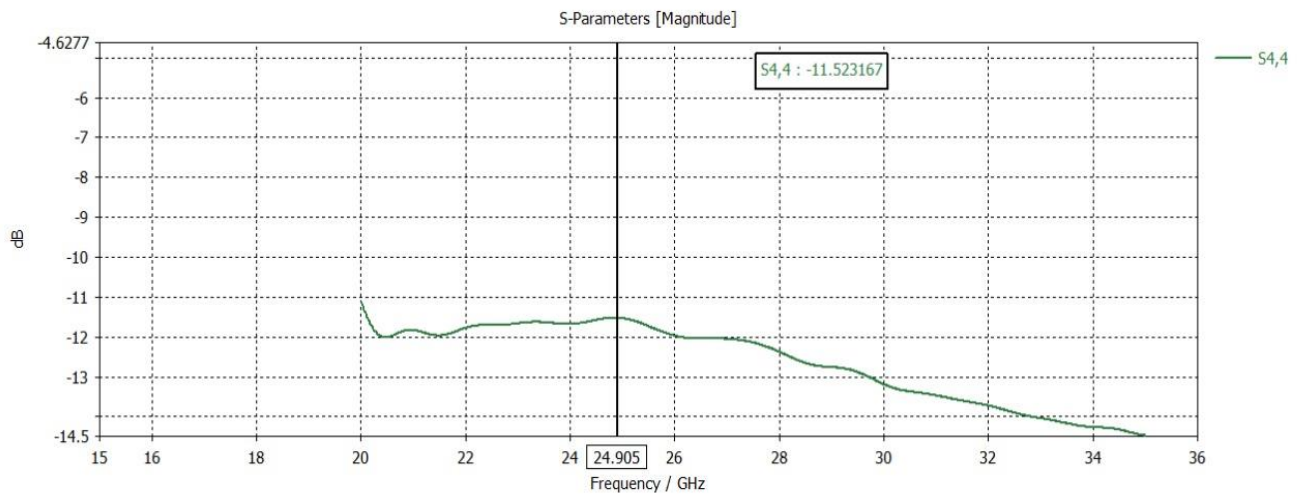


Fig.4.5 RETURN LOSS OF S44 IN dB

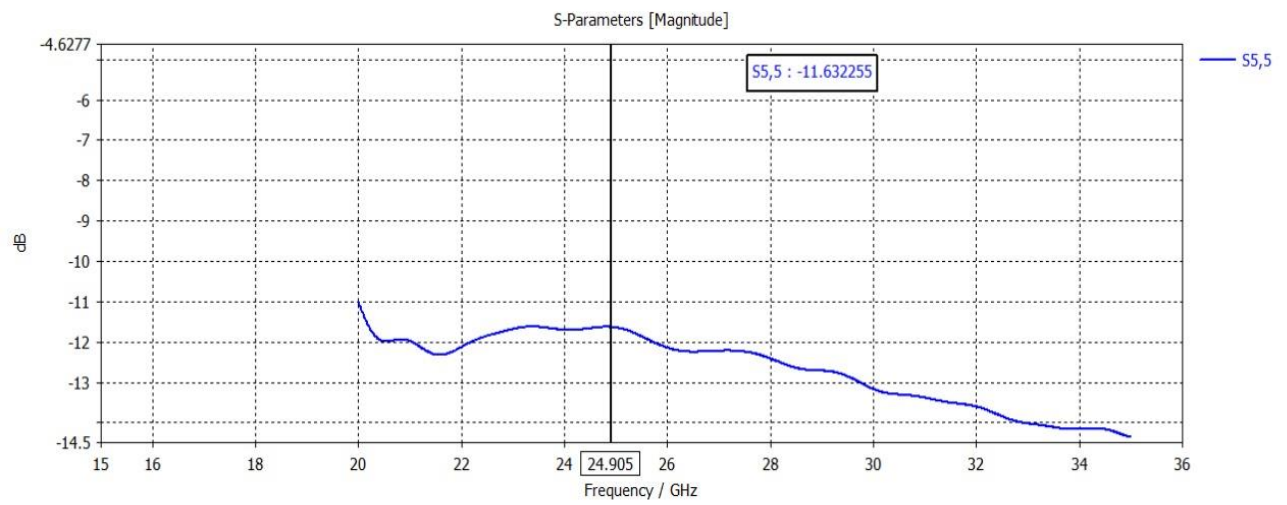


Fig.4.6 RETURN LOSS OF S55 IN dB

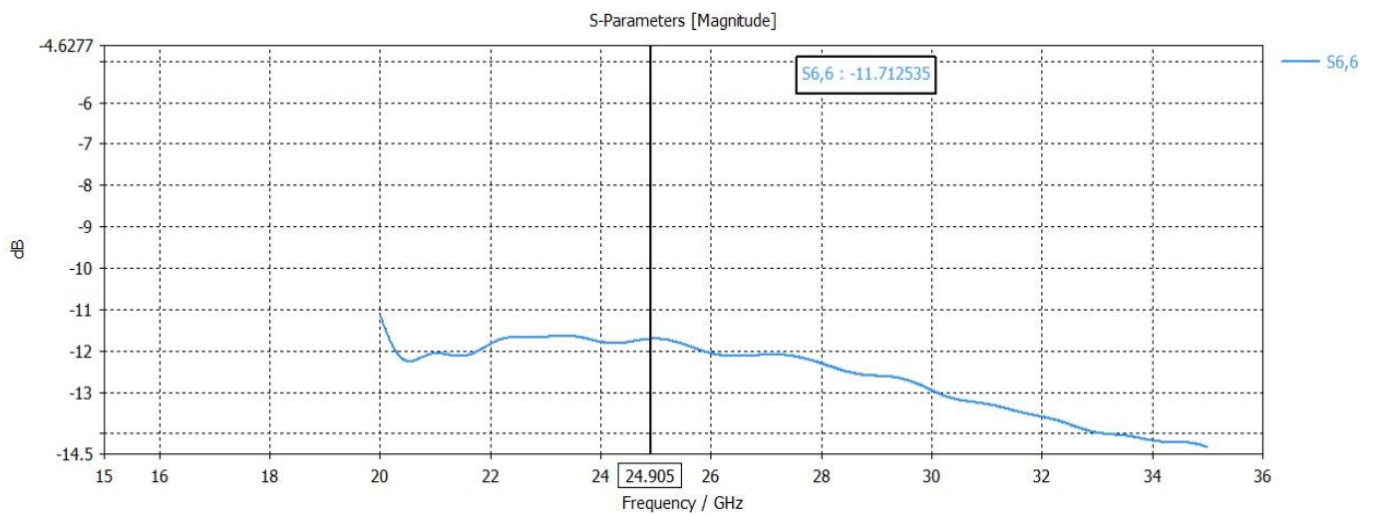


Fig.4.7 RETURN LOSS OF S66 IN dB

4.2 VOLTAGE STANDING WAVE RATIO

Voltage Standing Wave Ratio is an indication of amount of mismatch between antenna and the feed line connecting to it. VSWR (Voltage Standing Wave Ratio) is a measure of transmitted radio frequency power from the source to load. If there is no reflected power from the antenna, then $VSWR = 1$ whereas a large value of VSWR indicates greater mismatching. VSWR value under 2 is considered suitable for most antenna application. Hence the value obtained for VSWR is 25.1GHz, 24.8GHz, 25.5GHz.

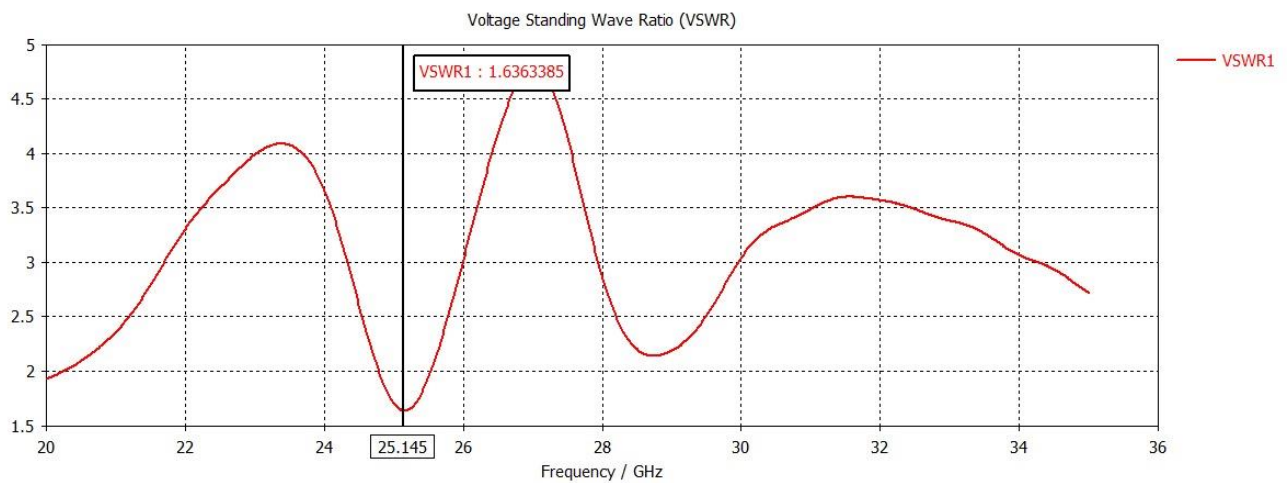


Fig.4.8 VOLTAGE STANDING WAVE RATIO AT 25.1 GHz

4.3 RADIATION PATTERN

A radiation pattern defines the variation of the power radiated by an antenna as a function of the direction away from the antenna. This power variation as a function of the arrival angle is observed in the antenna's farfield.

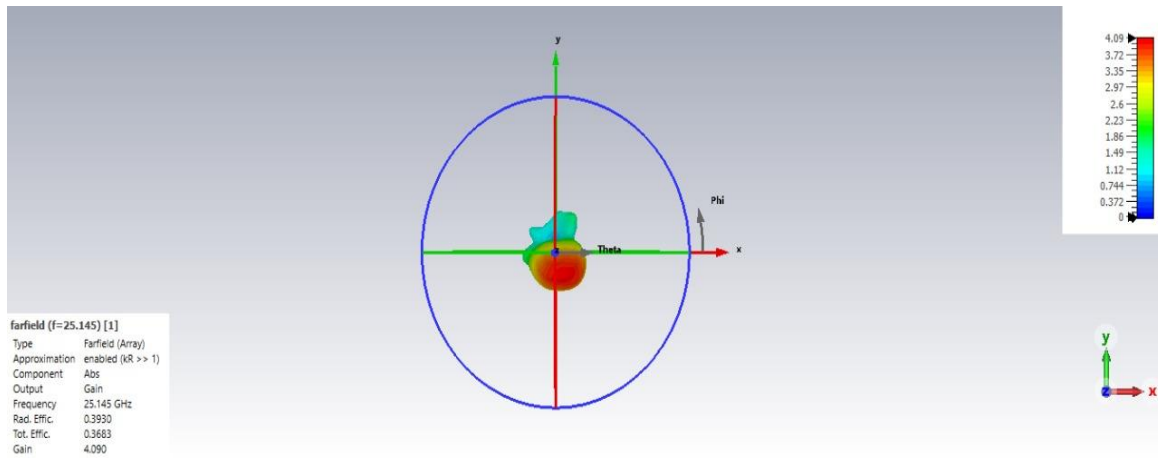


Fig.4.9 RADIATION PATTERN AT 25.1 GHz IN 3-D FORM FOR GAIN

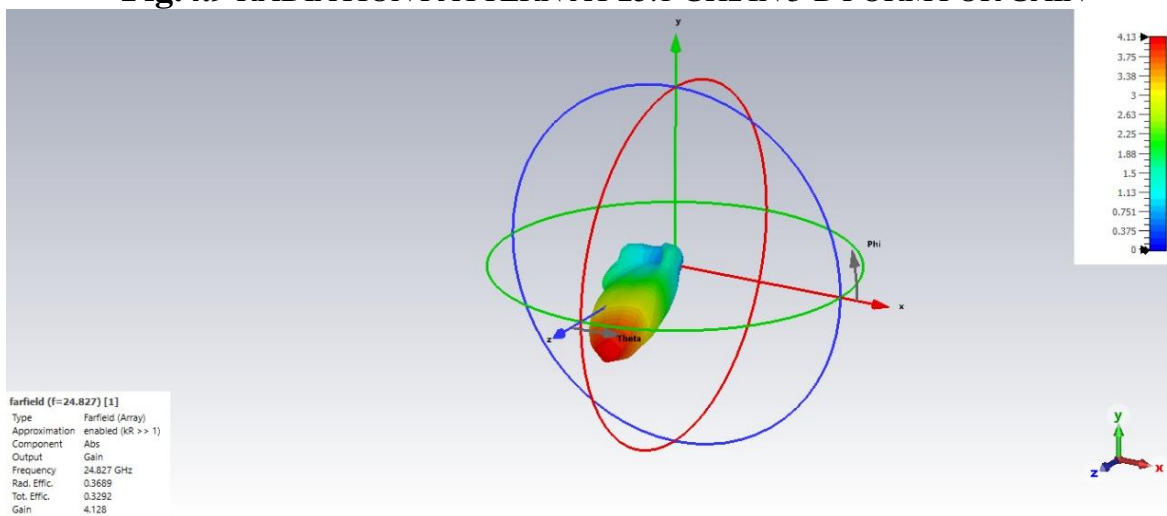


Fig.4.10 RADIATION PATTERN AT 24.8 GHz IN 3-D FORM FOR GAIN

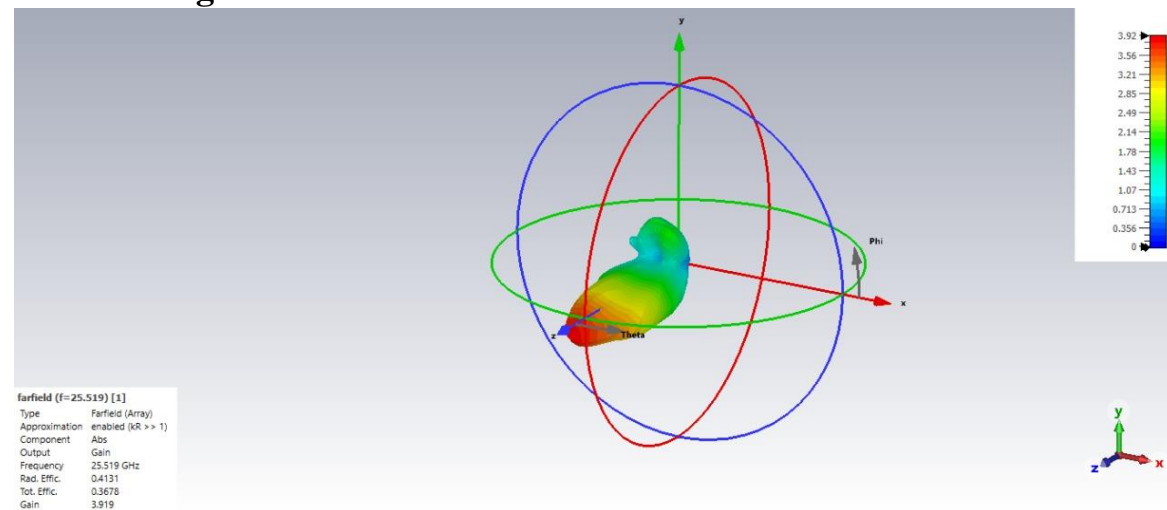


Fig.4.11 RADIATION PATTERN AT 25.5 GHz IN 3-D FORM FOR GAIN

The antenna patterns (azimuth and elevation plane patterns) are frequently shown as plots in polar coordinates. This gives the viewer the ability to easily visualize how the antenna radiates in all directions. Depending on the radiation pattern the antenna is classified into two types: Omni directional antennas and Directional antennas.

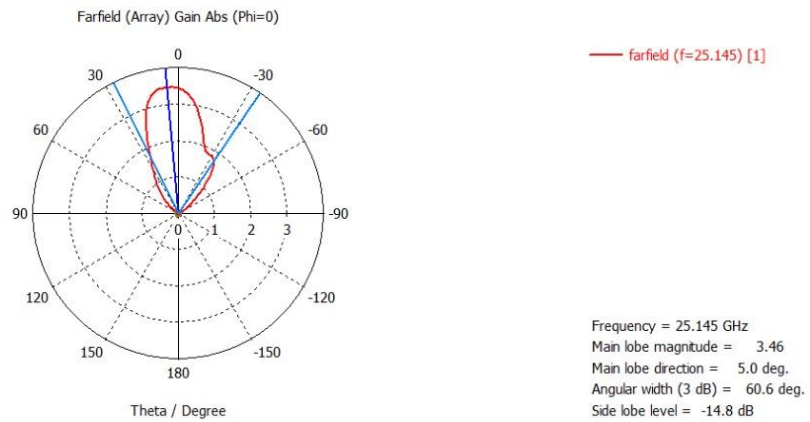


Fig.4.12 RADIATION PATTERN (GAIN) 2-D FORM AT 25.1 GHz AT 0°

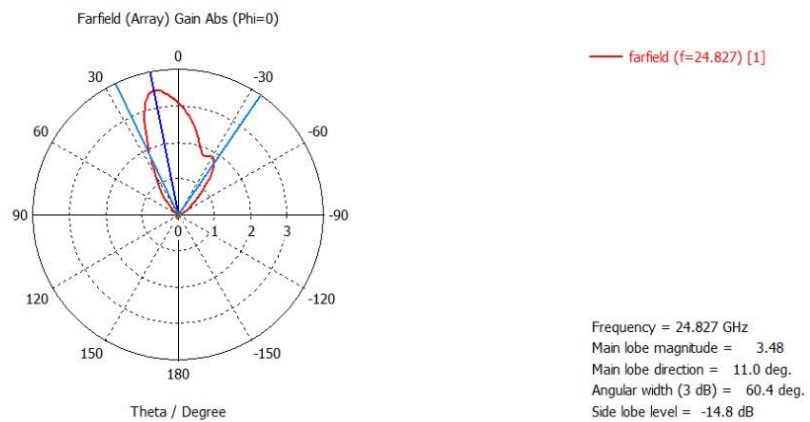


Fig.4.13 RADIATION PATTERN (GAIN) 2-D FORM AT 24.8 GHz AT 0°

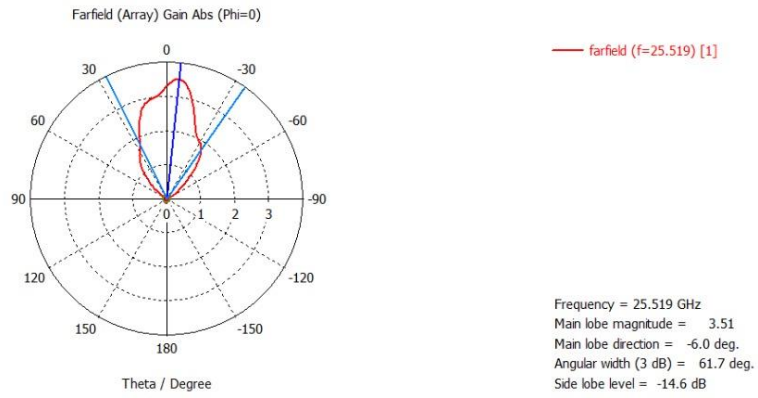


Fig.4.14 RADIATION PATTERN (GAIN) 2-D FORM AT 25.5 GHz AT 0°

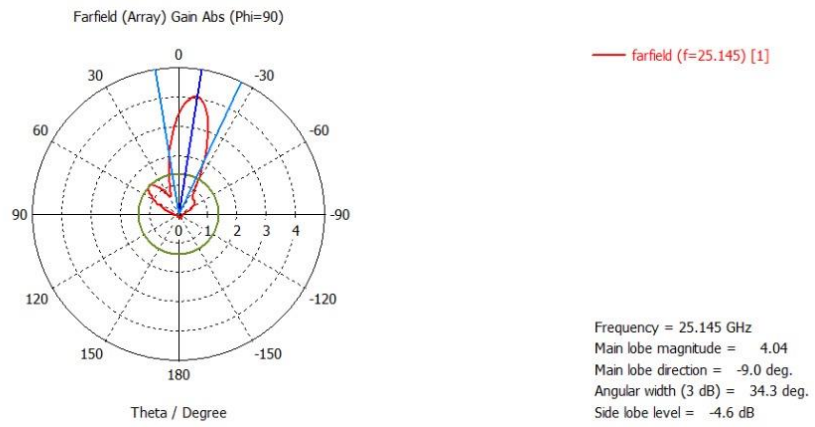


Fig.4.15 RADIATION PATTERN (GAIN) 2-D FORM AT 25.1 GHz AT 90°

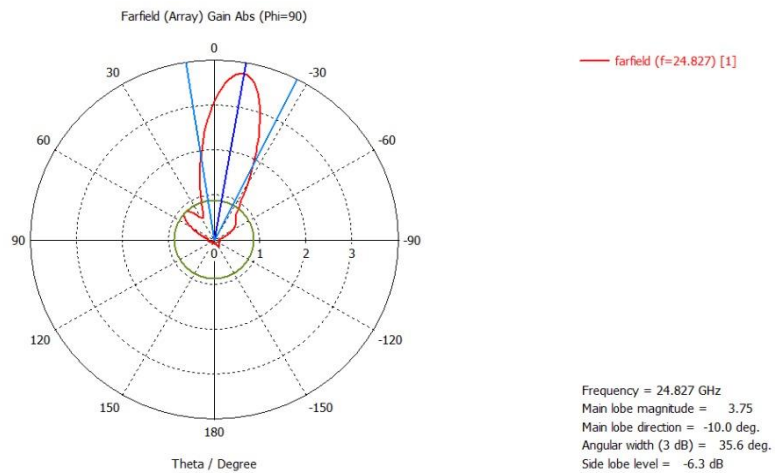


Fig.4.16 RADIATION PATTERN (GAIN) 2-D FORM AT 24.8 GHz AT 90°

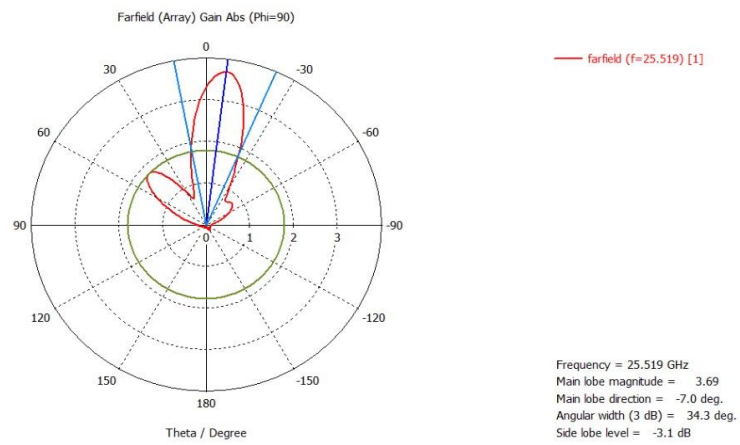


Fig.4.17 RADIATION PATTERN (GAIN) 2-D FORM AT 25.5 GHz AT 90°

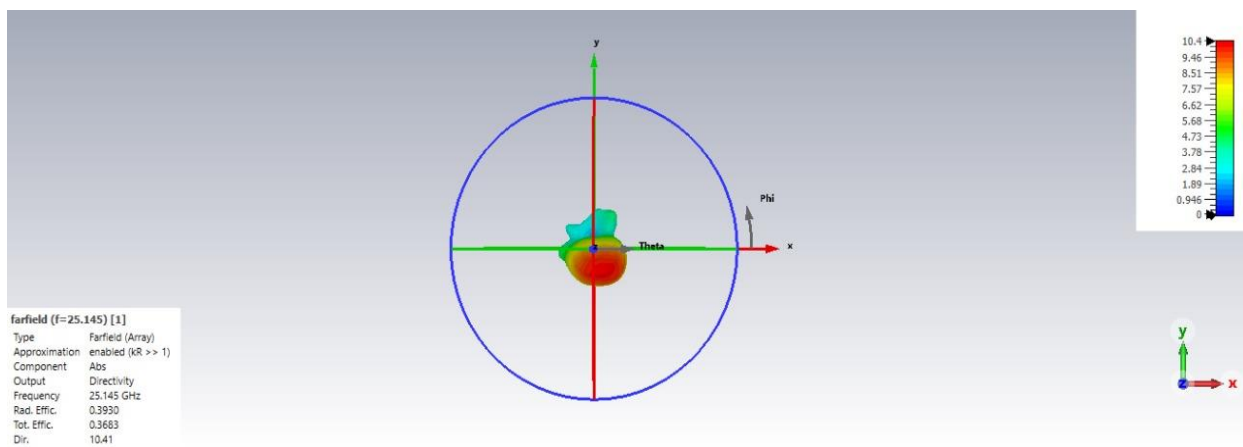


Fig.4.18 RADIATION PATTERN AT 25.1 GHz IN 3-D FORM FOR DIRECTIVITY

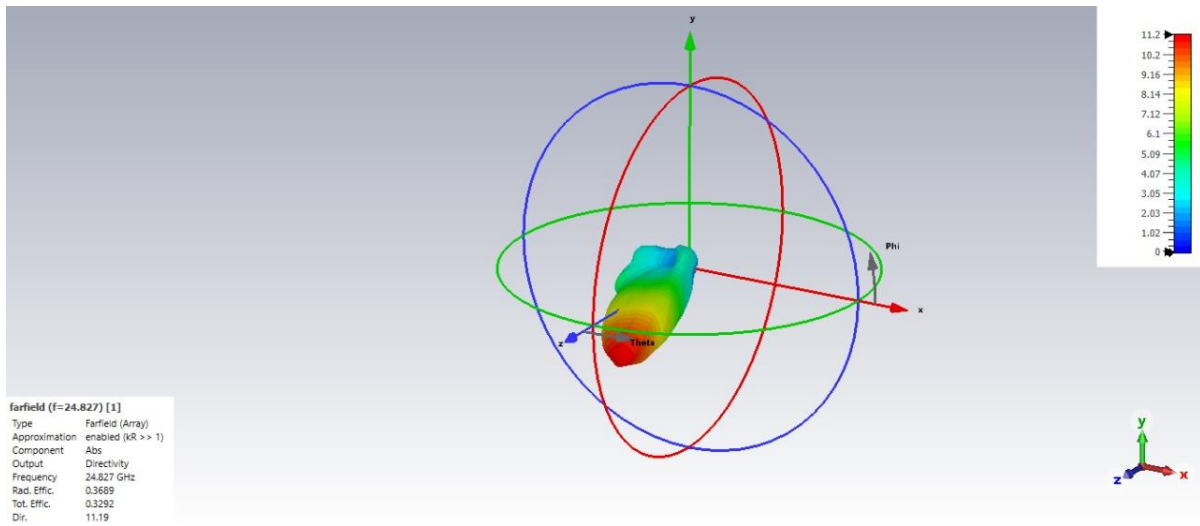


Fig.4.19 RADIATION PATTERN AT 24.8 GHz IN 3-D FORM FOR DIRECTIVITY

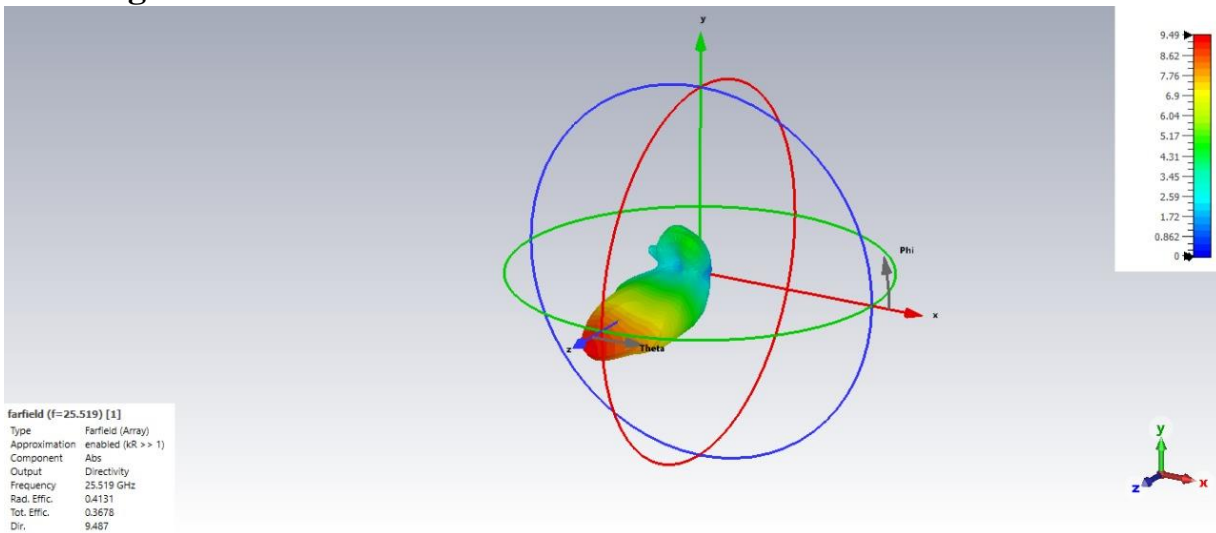


Fig.4.20 RADIATION PATTERN AT 25.5 GHz IN 3-D FORM FOR DIRECTIVITY

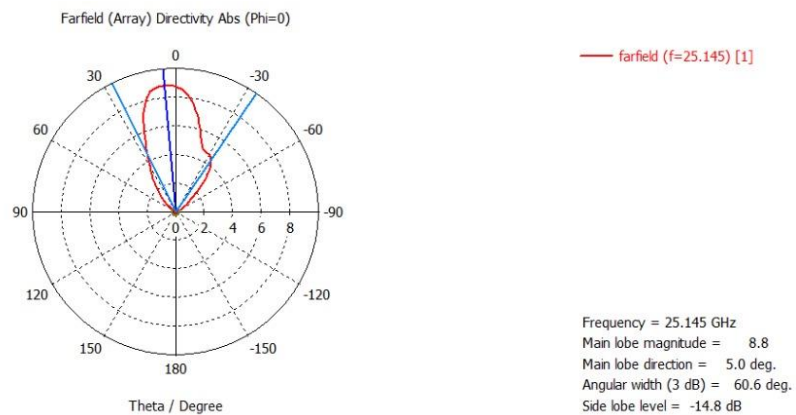
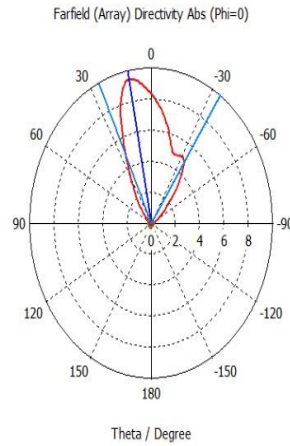


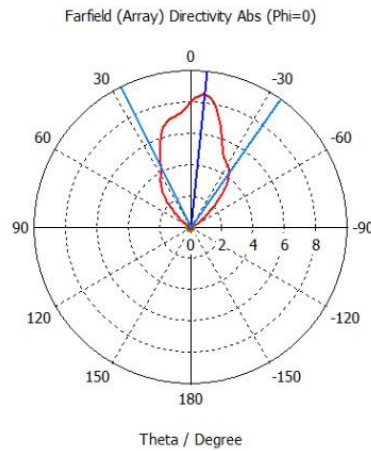
Fig.4.21 RADIATION PATTERN (DIRECTIVITY) 2-D FORM AT 25.1 GHz AT 0°



— farfield (f=24.827) [1]

Frequency = 24.827 GHz
Main lobe magnitude = 9.43
Main lobe direction = 11.0 deg.
Angular width (3 dB) = 60.4 deg.
Side lobe level = -14.8 dB

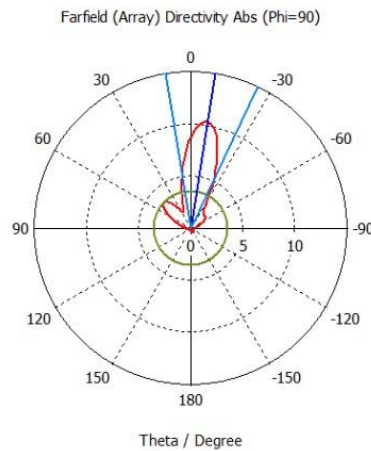
Fig.4.22 RADIATION PATTERN (DIRECTIVITY) 2-D FORM AT 24.8 GHz AT 0°



— farfield (f=25.519) [1]

Frequency = 25.519 GHz
Main lobe magnitude = 8.49
Main lobe direction = -6.0 deg.
Angular width (3 dB) = 61.7 deg.
Side lobe level = -14.6 dB

Fig.4.23 RADIATION PATTERN (DIRECTIVITY) 2-D FORM AT 25.5 GHz AT 0°



— farfield (f=25.145) [1]

Frequency = 25.145 GHz
Main lobe magnitude = 10.3
Main lobe direction = -9.0 deg.
Angular width (3 dB) = 34.3 deg.
Side lobe level = -4.6 dB

Fig.4.24 RADIATION PATTERN (DIRECTIVITY) 2-D FORM AT 25.1 GHz AT 90°

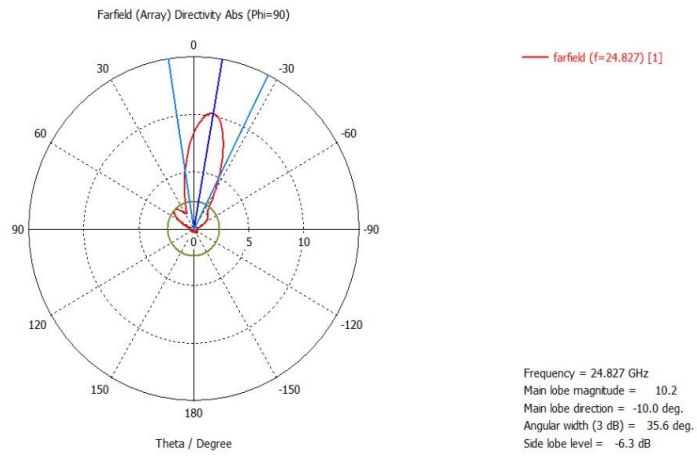


Fig.4.25 RADIATION PATTERN (DIRECTIVITY) 2-D FORM AT 24.8 GHz AT 90°

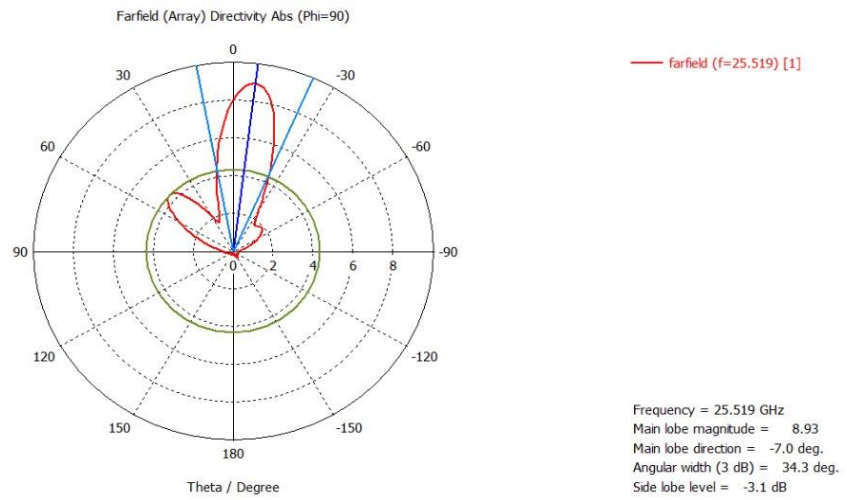


Fig.4.26 RADIATION PATTERN (DIRECTIVITY) 2-D FORM AT 25.5 GHz AT 90°

4.4 ANTENNA EFFICIENCY:

The efficiency of an antenna is a ratio of the power delivered to the antenna relative to the power radiated from the antenna. A high efficiency antenna has most of the power present at the antenna's input radiated away. A low efficiency antenna has most of the power absorbed as losses within the antenna, or reflected away due to impedance mismatch. It is a measure of the electrical efficiency with which an antenna converts the frequency power at its terminals into radiated power. Hence the value obtained for Radiation Efficiency is 0.3932 at 25.1 GHz and the value obtained for Total Efficiency is 0.3684 at 25.1 GHz.

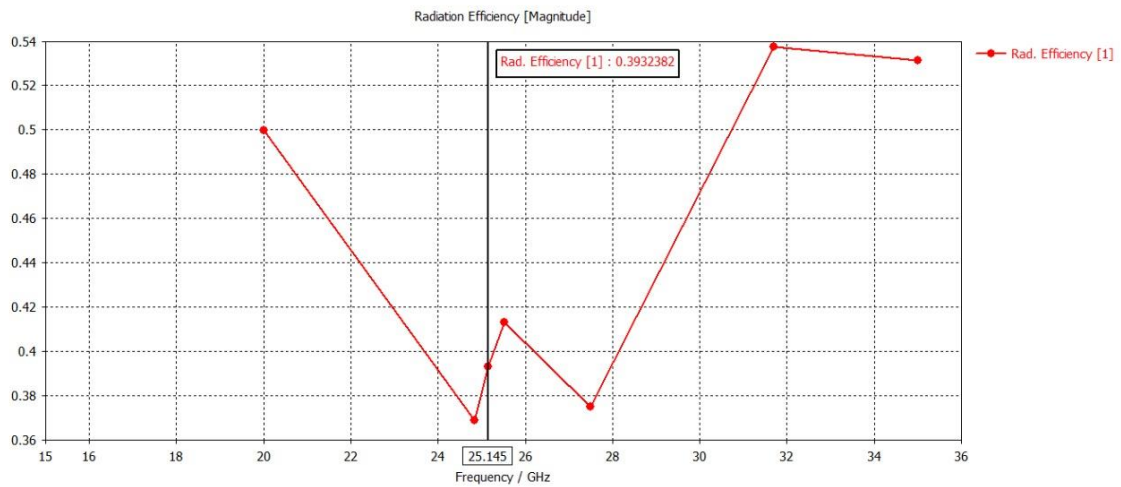


Fig.4.27 RADIATION EFFICIENCY AT 25.1 GHz

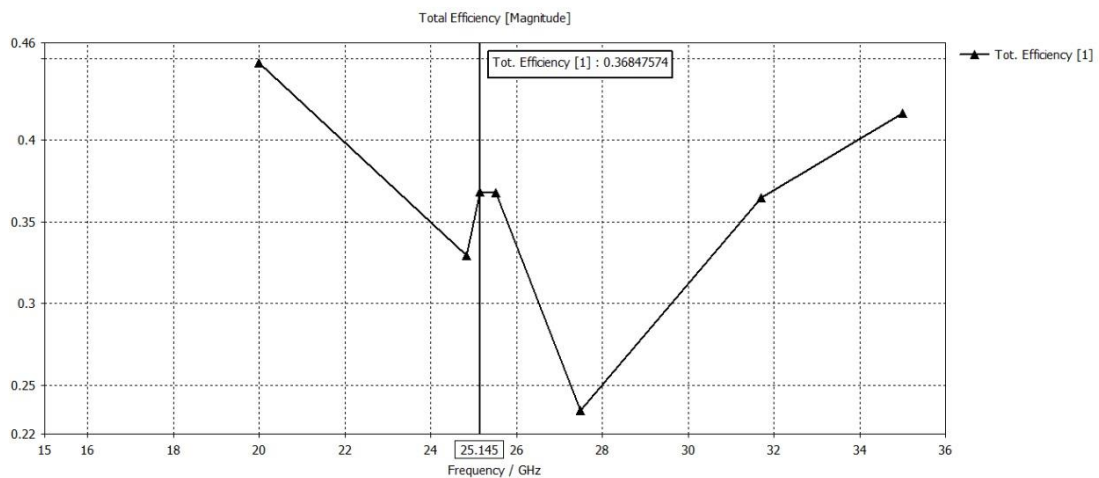


Fig.4.28 TOTAL EFFICIENCY AT 25.1 GHz

4.5 CURRENT DISTRIBUTION:

The method by which electrical currents are dispersed throughout the antenna elements is referred to as the current distribution. Understanding the antenna's radiation pattern, gain, efficiency, and any interference consequences requires knowledge of this distribution. The overall performance of the antenna array may be impacted by these hotspots, which can result in undesired sidelobes, mutual coupling between components, and a less concentrated radiation pattern. Engineers can fine-tune the radiation characteristics of the array by adjusting the excitation, phasing, and spacing of individual elements by examining the current distribution.

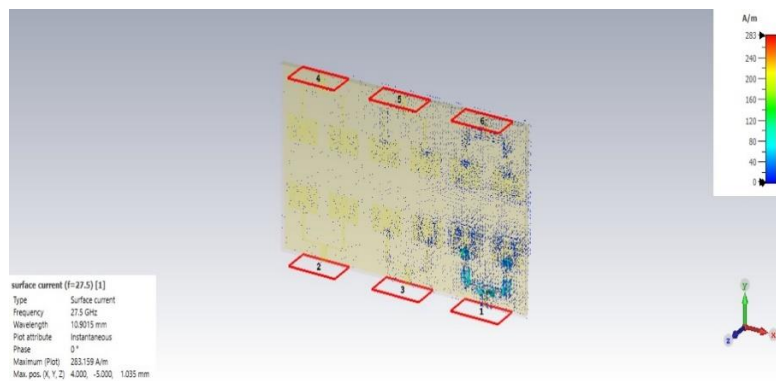


Fig.4.29 MIMO CURRENT DISTRIBUTION AT 25.1 GHz

CHAPTER 5

ML IMPLEMENTATION

5.1 Data Collection and Preprocessing

The Data Collection and Preprocessing module is responsible for gathering all the necessary input data for the antenna design optimization process. In this module, datasets are generated using full-wave simulation and measurement tools, which include parameters such as S-parameters, impedance frequency responses, and antenna feed locations. The simulation data represents the various characteristics of antenna systems and their behavior in different conditions, especially for high-frequency bands like 28 GHz used in 5G mm Wave applications. This data is crucial for training the machine learning models and ensuring they are capable of learning from diverse antenna configurations.

Once the data is collected, the preprocessing phase ensures that it is cleaned and ready for analysis. This includes handling missing data, normalizing values, and transforming categorical data into numerical format via techniques like label encoding. Irrelevant or redundant columns are also dropped, ensuring the dataset is compact and efficient. This preprocessing step helps improve the accuracy of the machine learning models, as unprocessed or noisy data can negatively impact model performance. Ensuring that the dataset is well-prepared is key to the success of the entire antenna optimization process.

5.2 Feature Engineering and Variable Definition

The Feature Engineering and Variable Definition module focuses on selecting and defining the key parameters for antenna design. This module is essential as the performance of the antenna relies heavily on the correct configuration of design variables. These include parameters like antenna feed locations, excitation voltage, element spacing, and antenna geometry.

In this stage, the module processes and transforms the data to create new features that could provide valuable insights into antenna behavior and performance. Feature engineering aims to find the most influential variables that affect performance metrics such as gain, efficiency, and SNR.

Once the important features are identified, they are structured into a format that the machine learning algorithms can effectively use. This could involve scaling, normalization, or dimensionality reduction methods like Principal Component Analysis (PCA) to reduce the number of features without losing essential information. The proper definition of features ensures that the machine learning model does not face overfitting or underfitting. This module plays a critical role in improving model performance by focusing on features that directly influence the outcome, leading to more accurate predictions for antenna optimization.

5.3 Data Splitting and Model Training

The Data Splitting and Model Training module is responsible for dividing the pre-processed dataset into training and testing sets. The training set is typically around 80% of the entire dataset, which is used to train the machine learning models, while the test set is the remaining 20%, which is used to evaluate the model's performance. Splitting the dataset into these two subsets ensures that the model can be trained on one part of the data and validated on unseen data, providing a better indication of how it will perform in a real-world scenario. This step also helps identify any issues like overfitting or underfitting.

In this module, several machine learning algorithms are implemented, including Random Forest, KNN, and SVM. These algorithms are trained on the data to learn how to predict optimal antenna configurations based on input variables.

The training process involves using algorithms to find the relationships between the input design parameters and the output performance metrics. The performance of each model is evaluated using cross-validation and accuracy metrics such as mean squared error (MSE) or accuracy scores to ensure the model can generalize well to unseen data.

5.4 Model Evaluation and Performance Metrics

The Model Evaluation and Performance Metrics module is critical for assessing the effectiveness of the trained machine learning models. After training the models on the data, this module focuses on validating how well the model performs using the test set. Key performance metrics like accuracy, precision, recall, confusion matrix, and classification reports are computed to evaluate the success of the model. Additionally, SNR, BER are measured to assess the practical performance of the antenna system predicted by the model.

This module also analyzes how well each machine learning algorithm handles the data and how it contributes to optimizing antenna performance. It may involve comparing the results of different algorithms to determine which one offers the best trade-off between computational efficiency and prediction accuracy. For example, Random Forest may perform well in handling non-linear relationships between antenna design variables, while SVM might be effective for high-dimensional spaces. The goal is to ensure the machine learning model is not only accurate but also reliable and robust when deployed for real-world antenna optimization.

5.5 Antenna Design Optimization

The Antenna Design Optimization module utilizes the trained machine learning models to predict the best configurations for MIMO antennas. Once the models are trained and evaluated, they are used to recommend optimal antenna design parameters that maximize performance.

This could include adjustments to antenna feed locations, excitation voltages, spacing, and geometry to achieve the desired gain, impedance matching, radiation patterns, and other important performance metrics for 5G mm Wave applications. The objective is to optimize these parameters based on the predictions of the machine learning model, resulting in more efficient antenna designs.

The optimization process involves fine-tuning these antenna parameters based on the objective functions defined in the project, such as maximizing efficiency, SNR, and BER. Advanced optimization algorithms, such as Genetic Algorithms or Particle Swarm Optimization (PSO), may also be employed within this module to explore various antenna configurations and identify the optimal solutions. The results from this module will ultimately guide the antenna design process, leading to an efficient and performance-optimized MIMO antenna for 5G networks.

5.6 Performance Testing and Simulation Validation

The Performance Testing and Simulation Validation module is the final stage in the antenna optimization process. After optimizing the design parameters, the performance of the predicted MIMO antenna configuration is tested through full-wave simulations. This module evaluates how well the optimized antenna design performs under real-world conditions, such as varying signal strength, interference, and environmental factors. The performance metrics gathered from these simulations, such as gain, impedance matching, and radiation patterns, are compared with the machine learning model's predictions to ensure the model's accuracy.

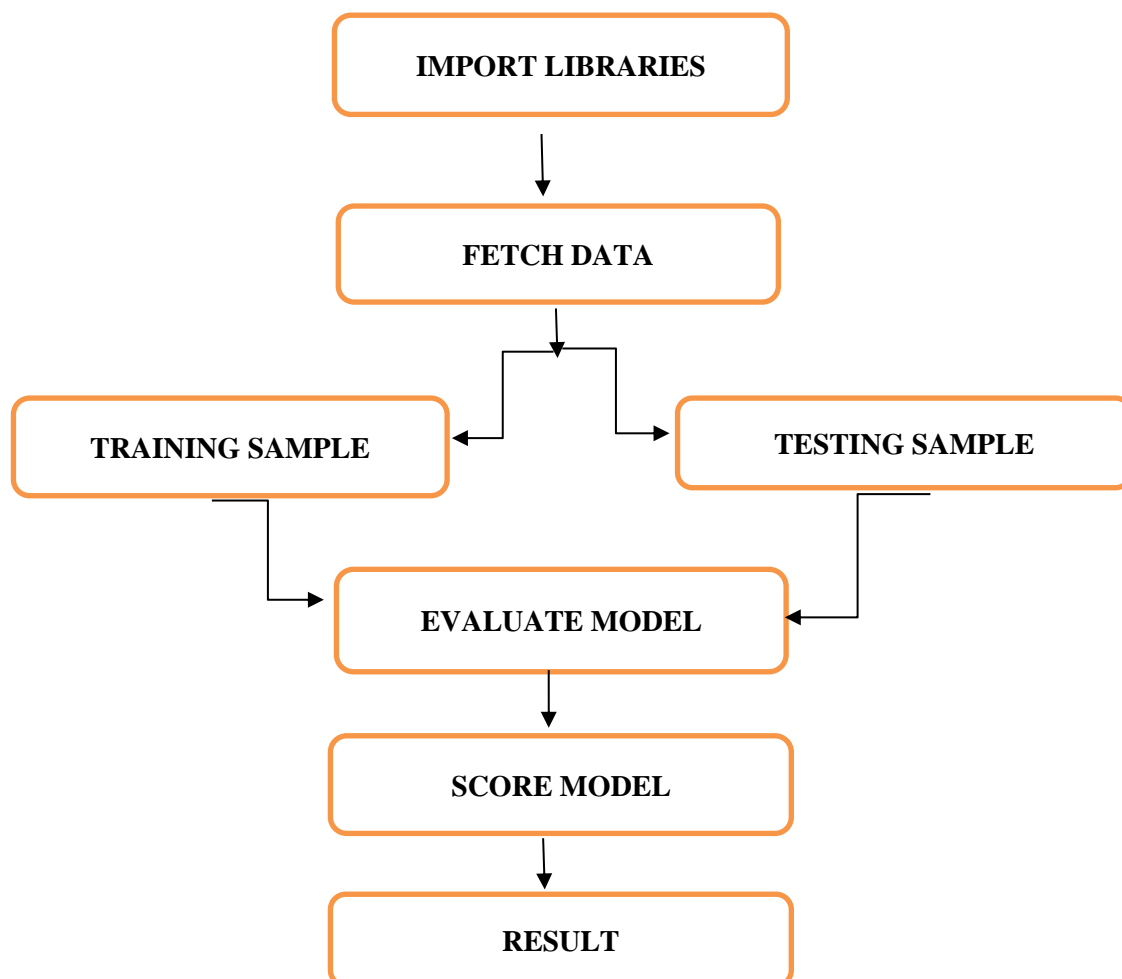
Simulation tools, such as CST Studio Suite or other antenna simulation software, are utilized in this module to validate the performance of the antenna designs. These simulations help confirm that the optimized antenna design meets the desired criteria for 5G mm Wave applications. By validating the machine learning model's predictions with simulations, this module ensures that the proposed antenna designs will function effectively in real-world environments, helping bridge the gap between theoretical optimization and practical deployment.

```
Random Forest Regression Performance:
MAE (Mean Absolute Error): 0.0615
RMSE (Root Mean Squared Error): 0.0787
R2 (R-squared): 0.8971
Train Accuracy (R2 on training data): 0.9834
Test Accuracy (R2 on test data): 0.8971

KNN Regression Performance:
MAE (Mean Absolute Error): 0.0754
RMSE (Root Mean Squared Error): 0.0961
R2 (R-squared): 0.8464
Train Accuracy (R2 on training data): 0.9834
Test Accuracy (R2 on test data): 0.8464

SVM Regression Performance:
MAE (Mean Absolute Error): 0.0462
RMSE (Root Mean Squared Error): 0.0574
R2 (R-squared): 0.9453
Train Accuracy (R2 on training data): 0.9834
Test Accuracy (R2 on test data): 0.9453
```

Fig. 5.1 Accuracy Result



CHAPTER 6

FABRICATION AND TESTING

6.1 FABRICATION:

The fabrication of the designed planar antenna involves translating the simulated model into a physical prototype. The process includes substrate selection, material deposition, etching, and assembly to ensure optimal performance. Precise fabrication is essential to maintain the expected electrical properties, minimizing losses and deviations from the simulated results.

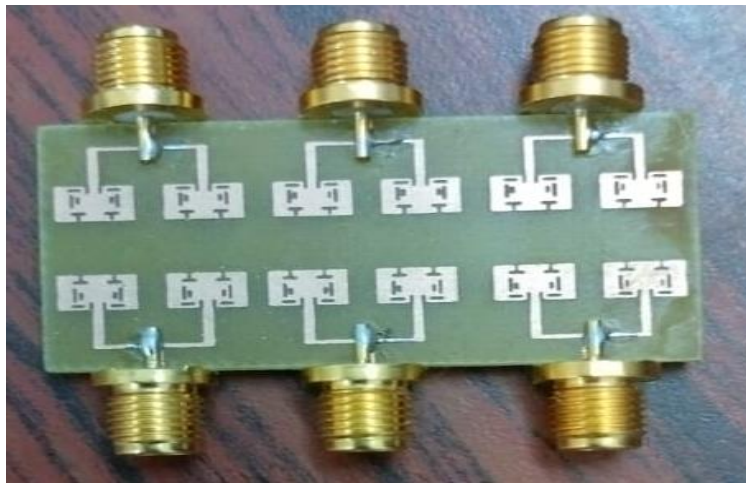


Fig.6.1 FRONT VIEW OF FABRICATED ANTENNA

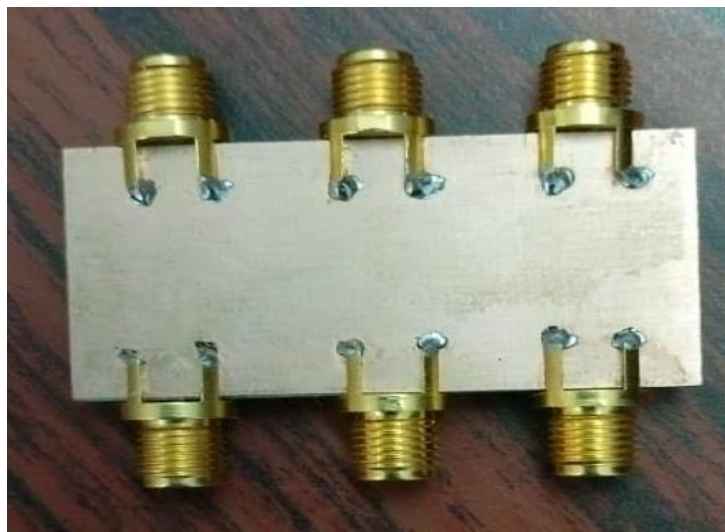


Fig.6.2 BACK VIEW OF FABRICATED ANTENNA

6.2 TESTING:

Once fabricated, the antenna undergoes testing to validate its performance against simulation data. Key parameters such as return loss (S_{11}), gain, bandwidth are measured using Vector Network Analyzers (VNA). Any discrepancies between the simulated and measured results are analyzed to identify factors such as fabrication tolerances, material imperfections, and environmental influences.

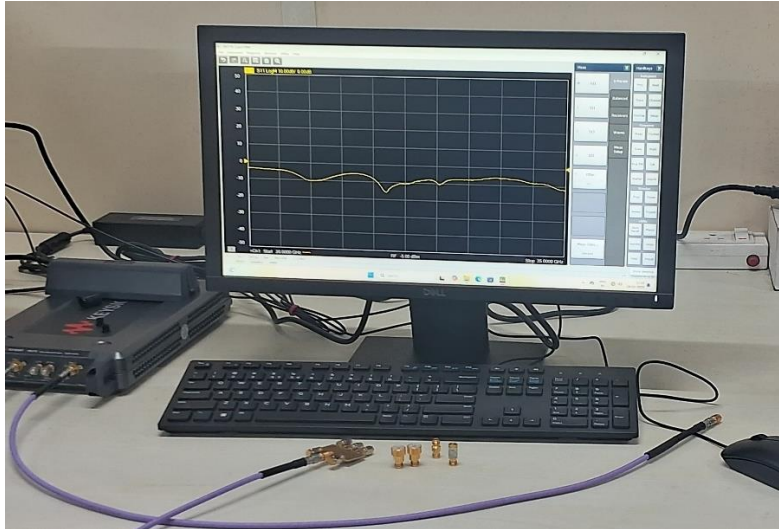


Fig 6.3 VNA SETUP FOR ANTENNA TESTING

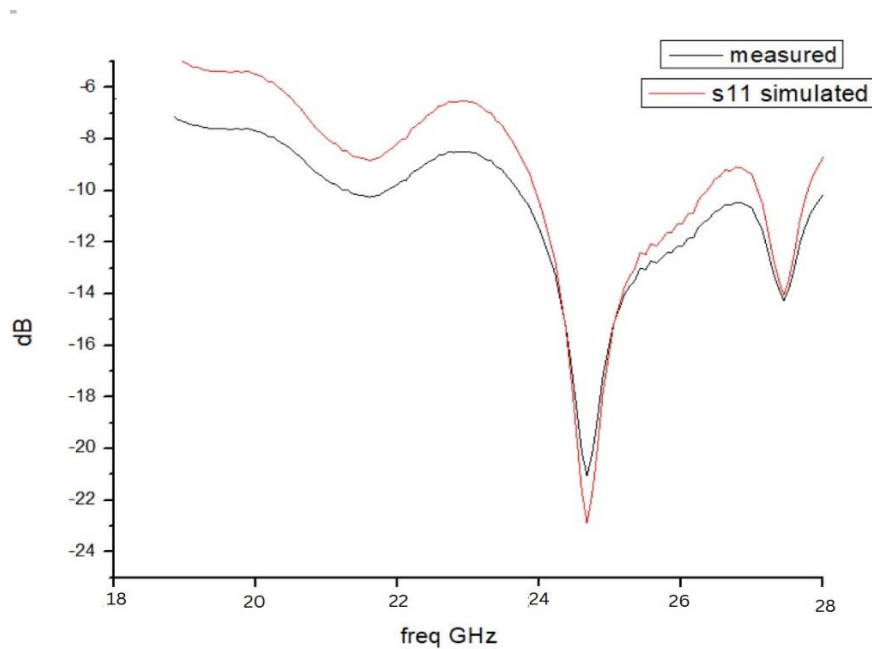


Fig 6.4 COMPARISON OF SIMULATED AND MEASURED S_{11} OF FABRICATED ANTENNA

6.3 COMPARISON

S.no	Parameters	MIMO PAPER 1	MIMO PAPER 2	MIMO antenna
1	Bandwidth(GHz)	0.499	0.573	0.693
2	Frequency range(GHz)	20-30	20-35	20-30
3	Resonant Frequency (GHz)	25	25	25.14
4	Shape	Rectangle	Rectangle	Rectangle
5	Dimensions of Substrate(mm)	3x3.45	3x4.22	3.025x5
6	Substrate material	FR4	Rogers RO4003	FR4
7	Gain(dBi)	7.55	7.05	8.25
8	Length x width of Ground(mm)	5x5.5	4.95x5	5.5x6
9	Thickness of Substrate(mm)	0.033	0.03	0.035
10	Number of Datasets	500	500	500
11	Accuracy	98	97	98
12	Algorithms	Decision tree regression XGB regression SVM regression	KNN regression XGB regression SVM regression	Random forest regression KNN regression SVM regression

Table 6.3 compares two existing MIMO antenna designs with a proposed antenna. The proposed antenna achieves the highest gain (8.25 dBi) and widest bandwidth (0.693 GHz) while maintaining high accuracy (98%) using machine learning models like Random Forest, KNN, and SVM. It operates around 25.14 GHz, uses FR4 substrate, and has slightly larger dimensions. Overall, it shows better performance and algorithm diversity than the other designs.

7. APPLICATIONS

5G Base Stations:

Enables narrow-beam, high-gain communication, which is perfect for sending data quickly and with minimal latency. Benefits: Supports the high-capacity requirements of metropolitan locations and allows for huge connectivity and high data speeds.

Massive MIMO Systems in 5G Networks:

Uses dual polarization and beamforming to enable several connections at once. Benefits: Improves network capacity and enhances signal quality in congested locations, which is crucial in user situations with a high user density.

IoT Networks and Smart City Infrastructure:

Enables dependable, long-distance communication for Internet of Things devices placed in smart cities (such as environmental sensors and traffic monitoring). Benefits: Offers reliable coverage in metropolitan areas, lowering interference and increasing the effectiveness of data collecting.

Fixed Wireless Access (FWA):

Provides high-speed internet to underserved and isolated locations at a lower cost than traditional wired connections. Advantages: Provides broadband internet with quick deployment and low infrastructure needs, enhancing rural connectivity.

Radar and Sensing Applications:

Makes use of narrow-beam and high-gain properties to detect and track objects precisely. Benefits include improved target recognition and spatial resolution, which can be used in security systems, drone sensing, and vehicle radar.

8. CONCLUSION AND FUTURE SCOPE

CONCLUSION

In conclusion, Integration of machine learning and optimization algorithms in MIMO antenna design could revolutionize technology, particularly for 5G communication systems. This system automates the design process, optimizes parameters, and improves performance metrics like SNR, BER, and efficiency. This approach contributes to more efficient antenna design and reliability in next-generation networks like 5G. The comparison of results before and after ML optimization highlights the effectiveness of the approach:

S Parameter (dB)	25.1
VSWR	1.63
Bandwidth (GHz)	0.693
Gain without ML Optimization (dB)	4.7
Gain with ML Optimization (dB)	6.1
ML Accuracy (%)	98

These results confirm the enhancement in antenna performance through ML-based optimization. The system can be seamlessly adapted for future communication standards such as 6G, ensuring its relevance in evolving network demands.

FUTURE SCOPE

The fabrication of the antenna array using machine learning-powered adaptive design enhancements is another aspect of this project's future scope. By automating the modification of crucial parameters like patch dimensions, array spacing, and substrate material selection, ML may greatly improve both the design process and the performance results. Iterative simulations and real-time modifications can be optimized through the use of machine learning techniques, providing a more effective means of reaching high-performance designs. This method saves design time while optimizing performance measures including gain, bandwidth, and return loss, which is especially useful for building arrays for numerous frequency bands or fine-tuning for particular applications.

Apart from refining design parameters, ML can enhance the array's flexibility by enabling the manufactured antenna to adjust itself to changing environmental conditions or communication requirements. For example, the constructed antenna could dynamically modify element phasing or configuration through reinforcement learning to sustain high performance and efficiency under a variety of circumstances. In 5G and IoT applications, where conditions are frequently unpredictable, this flexibility would be extremely beneficial. The research can lead the way for intelligent, self-adjusting antenna arrays that satisfy the intricate and changing needs of next-generation wireless communication networks by using ML from the design stage to post-fabrication.

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SDG CERTIFICATE

This is to certify that the project work titled “OPTIMIZATION OF PLANAR ANTENNAS USING MACHINE LEARNING” has been successfully completed by RANJINI D (142221106113) RETHINA PRADHAMESH R (142221106115) RITHIKA R (142221106116) ROGINI E (142221106117), of B.E. – Electronics and Communication Engineering, during the academic year 2024-25. This project aligns with the United Nations Sustainable Development Goals and mapped to the following Sustainable Development Goal(s) (SDGs):

SDG Number	Name	Brief Justification
SDG 9	Industry Innovation and Infrastructure	Enhances wireless communication efficiency, supporting advancements in 5G, IoT, and satellite systems. This fosters innovation, strengthens digital infrastructure, and Accelerates industrial growth.
SDG 11	Sustainable Cities and Communities	It rely on efficient networks for intelligent transport, energy management, and public services. This contributes to sustainable urban development while promoting technological progress.

**9 INDUSTRY, INNOVATION
AND INFRASTRUCTURE**



**11 SUSTAINABLE CITIES
AND COMMUNITIES**



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