Design and Optimization of a Terahertz Antenna for 6G Applications using CSRR and Machine Learning

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Abstract: **The rapid evolution of sixth-generation (6G) wireless networks necessitates high-performance terahertz (THz) antennas with optimized design parameters. This paper presents the design and performance enhancement of a THz antenna by incorporating a Complementary Split Ring Resonator (CSRR) on the ground plane to improve return loss and impedance matching. A dataset of various design parameters is generated and used to train a machine learning model, enabling the prediction of optimal configurations. The proposed methodology reduces design iterations and enhances antenna efficiency. Simulation results show that before applying machine learning, the CSRR-based antenna achieved a return loss of -39.6 dB at 3.6–3.8 THz. After optimization, the return loss was -32.7 dB at 1.6–1.7 THz, indicating a trade-off between impedance matching and frequency tuning. These findings highlight the potential of ML-driven antenna design for next-generation wireless communication systems.**

Index Terms — **Antenna design, machine learning optimization, return loss, terahertz (THz) communication.**

INTRODUCTION

The rapid advancement of wireless communication technologies has led to the exploration of terahertz (THz) frequencies for sixth-generation (6G) networks. THz communication offers ultra-high data rates, low latency, and massive connectivity, making it a key enabler for future wireless systems. However, designing efficient antennas for the THz spectrum presents several challenges, including high propagation losses, impedance mismatching, and fabrication constraints. To address these challenges, researchers are focusing on novel antenna designs with enhanced performance parameters.

One such technique involves the incorporation of Complementary Split Ring Resonators (CSRR's) on the ground plane to improve impedance matching and enhance return loss characteristics. CSRR structures introduce additional resonance modes, leading to better electromagnetic performance while maintaining compact antenna dimensions. Despite these advantages, optimizing the antenna design manually through iterative simulations is time-consuming and computationally expensive.

To overcome this limitation, machine learning (ML) techniques have been integrated into antenna design to predict optimal configurations efficiently. By generating a dataset of different design parameters and corresponding return loss values, an ML model can learn patterns and predict the best antenna configuration without exhaustive simulations. This approach accelerates the design process and ensures optimal performance with minimal iterations.

This paper presents a THz antenna design for 6G applications, incorporating CSRR structures for enhanced performance. A machine learning-based optimization framework is implemented to predict the best return loss, reducing design complexity and improving efficiency. The proposed methodology offers a data-driven approach to next-generation antenna design, demonstrating its potential for high-frequency wireless communication systems.

RESEARCH OBJECTIVES

- Design and analyse a terahertz antenna for 6G applications.
- Incorporate CSRR in the ground plane to enhance return loss and impedance matching.
- Develop a dataset by varying design parameters and recording performance metrics.
- Implement machine learning to predict the optimal design for minimal return loss.
- Evaluate the performance of the proposed design through simulations.

SCOPE AND ORGANIZATION

This research aims to design and optimize a THz antenna for 6G applications using CSRR structures and machine learning techniques. The primary objectives include:

- Designing and analysing a terahertz antenna with improved impedance matching.
- Incorporating CSRR in the ground plane to enhance return loss.
- Developing a dataset by varying design parameters and recording performance metrics.
- Implementing machine learning models to predict the optimal design for minimal return loss.
- Evaluating the performance of the proposed design through simulations.

This paper is structured as follows:

- Section 1 introduces the research background, motivation, and significance of THz antennas in 6G networks.
- Section 2 presents the literature review, discussing related works on CSRR-based antennas and ML optimization techniques.
- Section 3 details the proposed antenna design, including its dimensions, configuration, and integration of CSRR structures.
- Section 4 describes the machine learning implementation and performance evaluation based on return loss predictions.
- Section 5 discusses the simulation results, optimized parameters, and overall improvements in antenna performance.
- Section 6 concludes the paper by recapitulating crucial findings and outlining unborn exploration directions.

LITERATURE REVIEW

Several studies have explored the design and optimization of THz antennas for 6G applications. Researchers have investigated the use of metamaterials, CSRR structures, and various optimization techniques to enhance antenna performance. Previous works have demonstrated that integrating CSRRs into the antenna ground plane can significantly improve return loss and bandwidth. Additionally, machine learning approaches, such as regression models and neural networks, have been employed for antenna parameter optimization, reducing the need for extensive simulations. This paper builds upon existing research by combining CSRR-based THz antenna design with machine learning-based optimization to achieve superior performance.

IMPLEMENTATION OF PROJECT

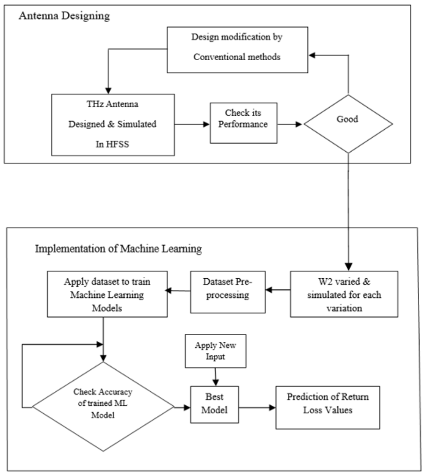


Figure 1: Block diagram of proposed system

This section describes the two main workflows of the project: antenna design and machine learning implementation.

1. Antenna Designing:

The process begins with designing and simulating a THz antenna using HFSS (High-Frequency Structure Simulator). The antenna's performance is then evaluated. If the performance is satisfactory ("Good"), the design is finalized. If not, the design is modified using conventional methods, and the performance is rechecked until it meets the required standards.

2. Implementation of Machine Learning:

The machine learning process starts by applying a dataset to train machine learning models. The dataset undergoes pre-processing, followed by applying W2 (a parameter) with varied and simulated variations. The pre-processed data is fed into the best machine learning model, which is selected based on its accuracy. Finally, the model predicts return loss values, which are used to assess performance.

ANTENNA DESIGN

The proposed antenna structure as seen in Figure2 is designed to operate in the terahertz (THz) frequency band. The dimensions of the antenna are summarized in Table 1. The substrate has a length of (100μm), a width of (100μm), and a thickness of (10μm), as illustrated in Figure 4. The radiating element consists of a concentric circular patch with a radius of (40μm) and a width of (10µm), which is divided into two halves, as shown in Figure 5.

A micro strip feed line, with a length and width of (10µm), is positioned on the substrate near the circular patch to facilitate signal excitation. Additionally, a parasitic element with a length of (10µm) and a width of (4µm) is placed above the circular patch to enhance antenna performance.

The antenna employs a partial ground plane configuration, with a ground plane length of (100µm) and a width of (50µm). To improve resonance characteristics, a Complementary Split Ring Resonator (CSRR) is implemented on the ground plane. The CSRR consists of two rectangular rings with opposing splits, as shown in Figure 3. The outer ring has dimensions of (30µm) in length and (40µm) in width, with a thickness of (5µm) and a (4µm) downward slit. The inner ring measures (10µm) in length and (20µm) in width, featuring a (4µm) upward slit, forming the CSRR structure.

The antenna design and its performance are analysed using Ansys HFSS, which provides accurate simulation results and insights into the antenna's radiation characteristics and impedance matching.

Figure 2: Antenna design

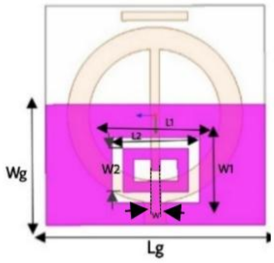


Figure 3: Ground of the Antenna

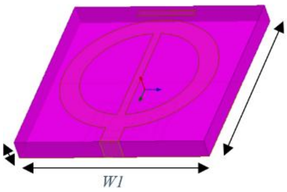


Figure 4: Substrate of the Antenna

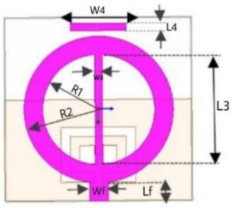


Figure 5: Patch of the Antenna

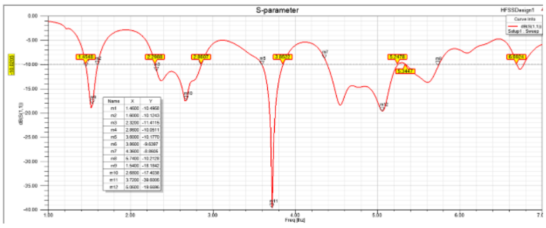
Antenna Dimensions:

Antenna parameters	Dimensions
Lg	100 µm
Wg	50 µm
L1	40 µm
W1	30 µm
L2	30 µm
W2	20 µm
w	4 µm
Ls= Ws	100 µm
Hs	10 µm
L3	30 µm
W3	4 µm
L4	4 µm
W4	10 µm
R1	40 µm
R2	30 µm
Lf= Wf	5 µm

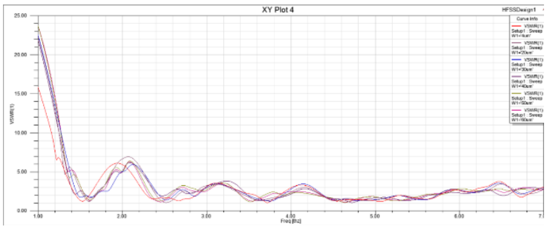
Table 1: Antenna Parameters and their dimensions.

After designing and simulating the antenna, the following results were obtained:

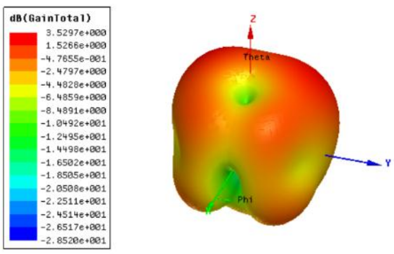
- The return loss is found to be -39.6 dB. Within the bandwidth 3.6 THz - 3.8 THz
- The gain of the antenna is 3.52 dB.



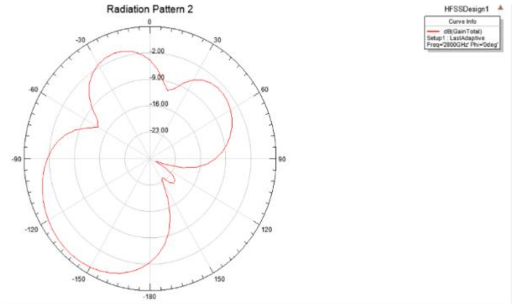
Result 1: S-parameter of the designed Antenna



Result 2: VSWR of the designed Antenna



Result 3: 3D Polar plot of the Antenna



Result 4: Radiation pattern of the Antenna

After the simulation of the Antenna design, a dataset was created by varying the width of the circular patch. Initially, the width was set to (4µm) and was incrementally varied from (10µm) to (60µm). Which is why the VSWR plot has multiple results as shown in Result 2. Along with this variation, the corresponding values of frequency, S11, and Voltage Standing Wave Ratio (VSWR) were recorded in the dataset. This dataset was used to evaluate the accuracy of a machine learning model in predicting antenna performance.

MACHINE LEARNING ALGORITHMS

Machine learning models were implemented using Python, employing the following algorithms:

- Support Vector Regressor (SVR): A Support Vector Regressor (SVR) is a machine learning algorithm based on Support Vector Machines (SVM) that predicts continuous values by finding a function that best fits the data within a defined margin (ε), focusing on key data points called support vectors to ensure robustness and generalization.
- Linear Regression: Linear Regression is a fundamental machine learning algorithm that models the relationship between independent and dependent variables by fitting a straight line that minimizes the sum of squared errors.
- Random Forest Regressor: A Random Forest Regressor is an ensemble learning algorithm that predicts continuous values by averaging the outputs of multiple decision trees, improving accuracy and reducing overfitting through random feature selection and bootstrapping.
- Gradient Boosting Regressor: A Gradient Boosting Regressor is an ensemble learning algorithm that builds sequential decision trees, where each tree corrects the errors of the previous one, leading to high accuracy and strong predictive performance.
- XGBoost Regressor: An XGBoost Regressor is an optimized gradient boosting algorithm that improves performance using advanced regularization, parallel processing, and efficient handling of missing values, making it fast and highly accurate.
- LightGBM Regressor: A LightGBM Regressor is a gradient boosting algorithm that builds trees using a leaf-wise approach, making it faster and more efficient with large datasets while maintaining high accuracy.
- CatBoost Regressor: A CatBoost Regressor is a gradient boosting algorithm optimized for categorical features, using an efficient encoding technique to reduce overfitting and improve predictive performance.
- K-Nearest Neighbors (KNN) Regressor: A K-Nearest Neighbors (KNN) Regressor predicts a continuous value by averaging the target values of the k-nearest data points, making it simple, non-parametric, and effective for local pattern recognition.

The acquired dataset was pre-processed and divided into two parts: 80% of the data was allocated for training the models, while 20% was used for testing. Once processed, the dataset was fed into each machine learning model to predict the optimal width value for achieving the best return loss.

Each machine learning model was evaluated based on performance metrics to determine accuracy. The performance criteria used in this study include:

- Mean Squared Error (MSE): Mean Squared Error (MSE) is a common loss function that measures the average squared difference between actual and predicted values, penalizing larger errors more heavily to indicate model accuracy. A lower MSE signifies better model performance.
- R-Squared (R^2) Error: R-Squared (R^2) Error is a statistical metric that measures how well a regression model explains the variance in the target variable, ranging from 0 to 1. A higher R^2 value indicates a better fit, with 1 meaning perfect prediction and 0 indicating no explanatory power.

PERFORMANCE EVALUATION

The performance of each ML model was assessed using MSE and R^2 error, as shown in the table below:

ML Models	Mean Square Error	R Square error
SVR model	323.8380	0.0723
Linear regression model	348.0659	0.0029
Random forest Regressor	291.1160	0.1661
Gradient boosting Regressor	298.5847	0.1447
XGB Regressor	319.2454	0.0855
LGBM Regressor	271.5277	0.2222
CatBoost Regressor	248.8217	0.2872
KNEighbour Regressor	338.9308	0.0291

Table 2: performance evaluation of the Machine learning algorithms Implemented in the proposed system.

Based on this evaluation, the width value predicted by the model with the least error was selected. The optimized width was determined to be (36μm), an increase from the initial (4μm). This modification significantly improved the antenna's performance, achieving an optimal return loss value. The revised antenna design was simulated again to validate the improvement in performance.

FINAL PARAMETERS

Following the machine learning evaluation, the antenna was redesigned by modifying the width of the circular patch from (4μm) to (36μm). This revised design was simulated in Ansys HFSS to assess its impact on the antenna's overall performance. The updated design led to a significant improvement in return loss, indicating better impedance matching and enhanced radiation characteristics. The optimized parameters have been finalized for the proposed THz antenna, ensuring improved efficiency and robustness in high-frequency applications.

Hence the antenna design of the new width of 36 μm is as depicted in Figure 6 and Figure 7.

Figure 6: Front view of the Finalized Antenna

Figure 7: Back view of the Finalized Antenna

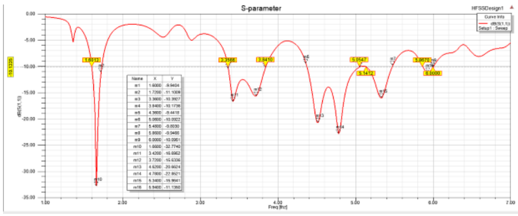
SIMULATION AND RESULTS

The optimized antenna design was simulated in Ansys HFSS to validate the improvements achieved through machine learning-based optimization. The key results observed include:

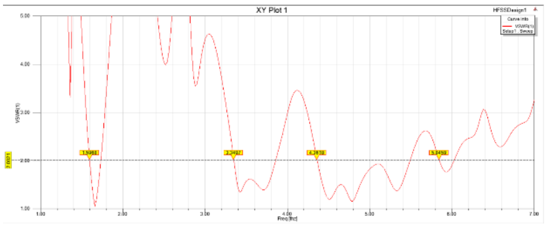
- A significant reduction in return loss, indicating better impedance matching.
- An enhanced Voltage Standing Wave Ratio (VSWR), improving signal efficiency.
- A well-defined radiation pattern, ensuring efficient THz wave propagation.

The final optimized antenna demonstrates superior performance compared to the initial design, confirming the effectiveness of the proposed machine learning-assisted optimization approach. Thus the results are as follows:

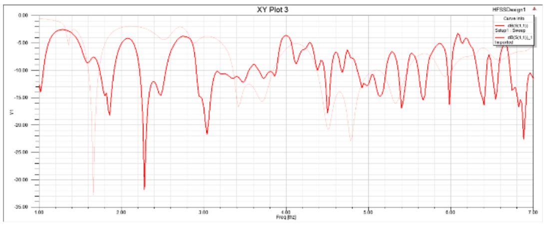
- The return loss is found to be -32.7 dB. Within the bandwidth 1.6 THz – 1.7 THz
- The gain of the antenna is 6.42 dB.



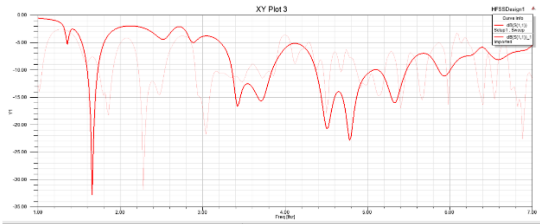
Result 5: S-parameter of the Finalized THz Antenna.



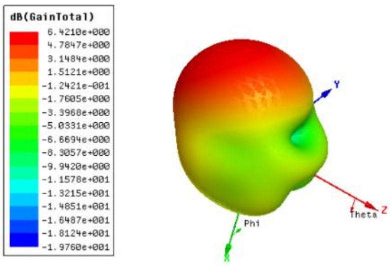
Result 6: VSWR plot of the Finalized Antenna.



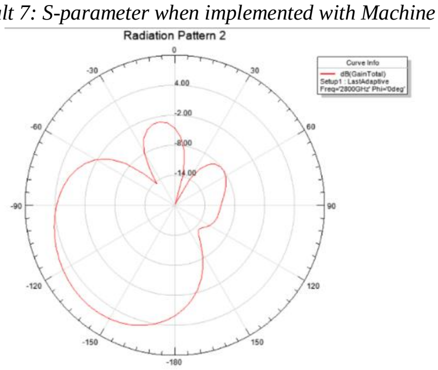
Result 6: S-parameter when implemented without Machine learning



Result 7: S-parameter when implemented with Machine learning



Result 7: 3D polar plot of the Finalized Antenna



Result 8: Radiation pattern of the Finalized Antenna

CONCLUSION

This paper presents a machine learning-assisted optimization approach for THz antenna design in 6G applications. By incorporating CSRR structures and leveraging ML models, the proposed method enhances return loss and impedance matching while reducing design iterations. Simulation results confirm the effectiveness of this approach, making it a promising solution for future high-frequency wireless communication systems.

FUTURE SCOPE

The proposed THz antenna design optimized with machine learning presents numerous opportunities for future research and development. The following areas can be explored for further enhancement:

- Experimental Validation: Fabricating the optimized antenna and validating its performance through real-world measurements.
- Advanced Machine Learning Models: Implementing deep learning techniques such as neural networks to further refine the prediction accuracy of antenna parameters.
- Multi-objective Optimization: Expanding the optimization framework to simultaneously enhance multiple antenna characteristics such as gain, bandwidth, and directivity.
- Integration with 6G Systems: Evaluating the antenna's performance in real 6G network

environments, including beamforming and massive MIMO applications.

- Material Innovations: Exploring novel substrate materials with lower losses to improve overall antenna efficiency in the THz range.
- Miniaturization Techniques: Investigating design modifications to further reduce the antenna size while maintaining high performance for compact and portable 6G devices.

These advancements will contribute to the evolution of highly efficient, compact, and intelligent THz antennas, ensuring their seamless integration into next-generation wireless communication systems.

REFERENCES

[1] H. M. E. Misilmani, T. Naous, and S. K. Al Khatib "A review on the design and optimization of antennas using machine learning algorithms and techniques," International Journal of RF and Microwave Computer-Aided Engineering, vol. 30, no. 10, Jul. 2020.

[2] Z. R. M. Hajiyat, A. Ismail, A. Sali, and Mohd. N. Hamidon "Antenna in 6G wireless communication system: Specifications, challenges, and research directions," Optik, vol. 166415, 2021.

[3] Sadiq, M., bin Sulaiman, N., Isa, M.M., and Hamidon, M.N. "A Review on Machine Learning in Smart Antenna: Methods and Techniques," TEM Journal, 11(2), p.695, 2022.

[4] V. Petrov, A. Pyattaev, D. Moltchanov, and Y. Koucheryavy "Terahertz band communications: Applications, research challenges, and standardization activities," IEEE Xplore, Oct. 01, 2016.

[5] B. Zhang, Y.-X. Guo, H. Zirath, and Y. P. Zhang "Investigation on 3-D-Printing Technologies for Millimeter-Wave and Terahertz Applications," Proceedings of the IEEE, vol. 105, no. 4, pp. 723-736, Apr. 2017

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