Optimising Design of Dual and Single Band Antenna using Deep Learning

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***Abstract*—This paper delves into the exploration of machine learning (ML) techniques, encompassing DNN (Deep Neural Networks), SVM (Support Vector Machines), decision trees, random forests, aimed at optimizing single and dual-band antenna communication. By showcasing efficient parameter selection and performance prediction capabilities, ML methods offer a data-driven approach to enhance antenna design across diverse communication applications. The study embarks on a comprehensive investigation and comparative assessment of the outcomes generated by these ML methods, juxtaposed with those derived from the high-frequency structure simulator (HFSS), with the goal of validating the precision of these techniques. Additionally, the paper integrates the examination of double T-shaped antennas with single-band functionality and slot-diff-fed vias circular antennas with dual-band capability, thereby expanding the scope of the investigation to encompass a broader range of antenna designs and applications.**

***Index Terms*—Machine learning, DNN, SVM, Decision tree, Random forest, LSTM, Single band antenna, Dual-band antenna, FOM**

I. Introduction

With the increasing adoption of IoT, the demand for antennas with unique designs such as tuned multiple buck antennas will become increasingly crucial to meet the unique demands of IoT devices. This underscores the need to advance antenna technology to develop highly efficient designs continually. Current design techniques, heavily reliant on human experts and computer-aided models, may fall short in solving complex problems, particularly those concerning three-dimensional antenna structures.

Machine learning (ML) technologies emerge as pivotal tools capable of revolutionizing antenna design processes. ML's flexibility, showcased in areas like handwriting recognition and genomic analysis, positions it as a potent force in antenna design. While ML has sporadically been used in antenna design with techniques like DNN (Deep Neural Networks), SVM (Support Vector Machines), decision trees, random forests, a comprehensive survey and evaluation of these methods is still needed.

This paper aims to fill the aforementioned gap by introducing ML-based tailored methods for automated antenna design. These techniques will be compared with electromagnetic (EM) simulations to assess their accuracy and reliability in predicting antenna performance. The study not only validates ML's capability to produce accurate and computationally efficient antenna designs but also underscores the potential of groundbreaking algorithms as computational speed and scalability improve in the future.

Furthermore, the inclusion of double T-shaped antennas with single-band functionalities and slot-diff-fed circular antennas with dual-band operation expands the investigation into antenna design optimization. Double T-shaped antennas offer simplicity and performance in single-band systems, while circular antennas with slot-diff-fed vias exhibit efficiency and multiband capabilities, making them preferable for multiband applications. Incorporating these antennas into the study broadens its scope and ensures its relevance to the evolving landscape of the IoT sector across various fields. The comprehensive examination of these antennas alongside ML techniques enriches our understanding of antenna design optimization and its applications in diverse IoT scenarios.

A. Double T-Shaped Monopole Antenna

The Double T-shaped monopole antenna is a specialized form of traditional T-shaped antenna that accomplishes the objectives of improved efficiency and versatility in antenna design. In contrast to its single T-shaped counterpart, the double T-shaped monopole antenna consists of two parallel T-shaped structures vertically arranged. The latter resembles the letter "T", with an additional crossbar, and as a result of it, the antenna configuration looks like two Ts stacked vertically.

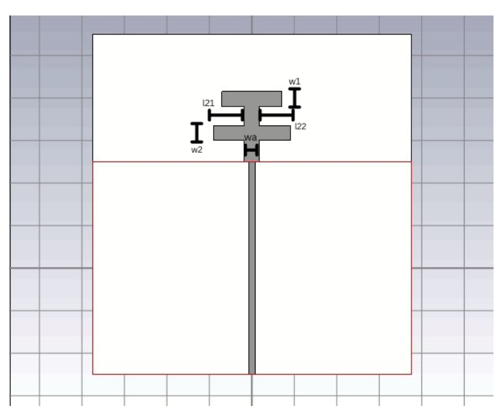


Fig. 1. Diagram of Dual T-shaped Monopole Antenna with all the relevant features

Hence, the novel appearance of the array among single T-shaped antennas has exceptional characteristics. From the first, a more prominent horizontal antenna area increases the antenna's effective radiating surface; consequently, the signal efficiency and the signal strength are better. This, to some extent, is due to the vertical nature of the T-shaped antenna, which makes the Double T-shaped monopole antenna excellent for applications demanding higher gain and longer-range communication.

Briefly, the Double T-shaped monopole antenna is an innovative development in antenna design, which combines the advantages of single T-shaped antennas and at the same time, extends the range of operation and offers more versatile performance. Its dual-element configuration supports highly efficient radiation multiple communication bands and supports various communication standards, which are features that make it an integral component in modern wireless gadgets and networks.

B. Slot-Diff-Fed via Circular Antenna

The slot-diff-fed vias circular antenna being an innovative and advanced design that makes use of the idea of slot antennas and vias to get the most efficient polarization circular polarization. This antenna design comprises a circular radiating structure with slots designed into the substrate; these latter function as radiating elements. Through vias, which are empty holes filled with metal, radial electromagnetic energy is fed into the slots that are distributed around the central region of the disc.It has the ability to yield high efficacy and low axial ratio in circular polarized radiation as the main benefit. The antenna has the feeding point slotted and the via mechanism that enables the antenna to be precisely controlled through the polarization characteristic parameters. This therefore makes the antenna suitable for applications where circular polarization is required such as satellite communication, radio astronomy and wireless networking.The circularly shaped antenna is ideal for applications where coverage has to be homogenous in all directions as a result of the omnidirectional radiation pattern provided. Moreover, the antenna's small size and low profile also make it easy to incorporate it into small form devices as well as systems.

The slot-diff-fed ring antenna forms a source with adjustable parameters including, slot dimensions, via intervals, and substrate materials which enables it to handle various frequency bands and application needs. In addition, the application of modern manufacturing techniques, such as printed circuit board (PCB) fabrication, paves the way towards the development of affordable and mass produced antennas.

In this project, we propose various machine learning algorithms based on the data collected from the CST design of both the mentioned antennas. We use the double T-shaped antenna for optimization of S11 based figure of merit while lot-diff-fed ring antenna is necessary to analyze the optimisation of S12 parameters of antenna.

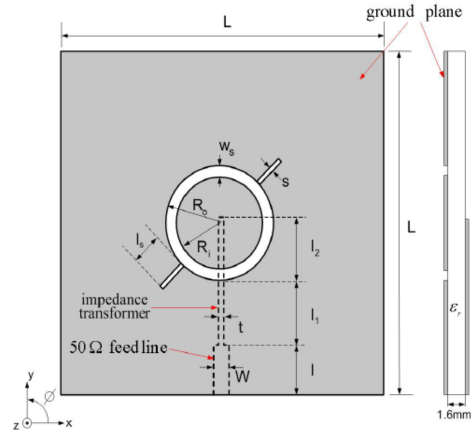


Fig. 2. Diagram of Slot-Diff-Fed vias Circular Antenna with all the relevant features

II. Related Works

[1] is about the rapid IoT advancement and the increase in demand for customized antennas, which made the conventional design techniques less effective. Humanize: It suggests utilizing ML methods such as ANNs, lasso, and kNN for the implementation of automatic antenna design optimization. Previous similar research on applying ML in antenna design is reviewed, and this becomes crucial due to a requirement of systematic comparisons. The paper starts from the new ML models developed as well as their accuracy compared to electromagnetic simulations involving the double T-shaped monopole antenna. Its main goal is filling in the void between comprehensive and in-depth considerations of various types of deep learning methods for antennas. Finally, it tries to develop scalable and efficient algorithms for dealing with complicated designs.

In this review article [2], a survey on the existing progress and efficient use of AI technologies for antenna design and optimization in wireless communication is discussed. It studies the use of ML and DL algorithms towards the improvement of design task speed. Review will cover EM simulators like CST and HFSS which were used in ML and DL for antenna design involving the RL approaches in the last section. It presents optimization techniques that include parallel optimization technique, single and multi-objective optimization, and surrogate-based optimization. A further topic of the paper is the application of AI in the selection of antennas for wireless devices. In addition, the paper focuses on data generation methods utilization of computational electromagnetics software, highlighting ML/DL role as a means to catalyze antenna design process through optimizing prediction accuracy and computational efficiency.

[3] presents a comprehensive review of recent advancements in utilizing machine learning (ML) techniques for optimizing antenna designs. It surveys various ML methodologies such as support vector machines, artificial neural networks, and genetic algorithms, highlighting their applications in antenna engineering. Through an extensive examination of existing

literature, the paper identifies trends, challenges, and opportunities in the field of ML-based antenna design optimization, providing valuable insights for researchers and practitioners.

Focusing on conformal antenna arrays, [4] investigates the application of machine learning (ML) techniques for optimization purposes. It explores the effectiveness of ML algorithms, including genetic algorithms and neural networks, in improving the performance of conformal antenna arrays. By analyzing experimental results and simulation studies, the paper demonstrates the potential of ML-based approaches in enhancing the design and performance of conformal antennas for various wireless communication applications.

[5] introduces a machine learning-based approach specifically tailored for optimizing dielectric resonator antennas. It demonstrates the effectiveness of artificial neural networks in enhancing the performance of these antennas. By leveraging machine learning techniques, [6] presents a novel method for achieving optimized designs of dielectric resonator antennas. Focusing on patch antenna arrays, this paper explores multi-objective optimization using machine learning algorithms. It evaluates the performance of techniques like particle swarm optimization and genetic algorithms in optimizing these arrays. By considering multiple objectives simultaneously, the paper offers insights into achieving efficient and effective designs of patch antenna arrays.

[7] introduces a novel approach for optimizing antenna designs using deep reinforcement learning (DRL). It presents a framework that combines DRL algorithms with electromagnetic simulations to automatically discover optimal antenna configurations. Through experimental validation and comparative analyses, the paper demonstrates the effectiveness of the DRL-based optimization approach in achieving superior performance and efficiency compared to traditional optimization methods. This research opens up new avenues for leveraging advanced machine learning techniques in antenna design optimization to address the increasing complexity and demands of modern wireless communication systems.

III. Methodology

To demonstrate our proposed methodologies, we utilize the design of dual T-shaped and slot fed circular antenna for data collection in order to train our optimization algorithm.

A. *Design of antenna*

The antenna design is simulated using CST Microwave Studio, a powerful electromagnetic simulation tool. The simulation setup includes the antennas design parameters, and the frequency of 1-10 GHz for the parametric sweep. Parametric sweeps are performed to optimize the antenna's performance over the desired frequency bands. The design process begins with the selection of appropriate antenna geometry and design parameters. The T-shaped monopole antenna structure is chosen for its simplicity and effectiveness in achieving dual-band resonance. The dimensions of the antenna elements, including the length and width of the T-shaped arms, the spacing between the arms, and the length of the feedline, are carefully chosen based on desired operating frequencies and performance goals.

The choice of substrate material plays a crucial role in determining the antenna's performance characteristics. A dielectric substrate with low loss tangent and suitable dielectric constant is selected to minimize losses and achieve efficient radiation. Various substrate materials such as FR-4 are considered, and their dielectric properties are analyzed to determine the most suitable option for the desired frequency bands.

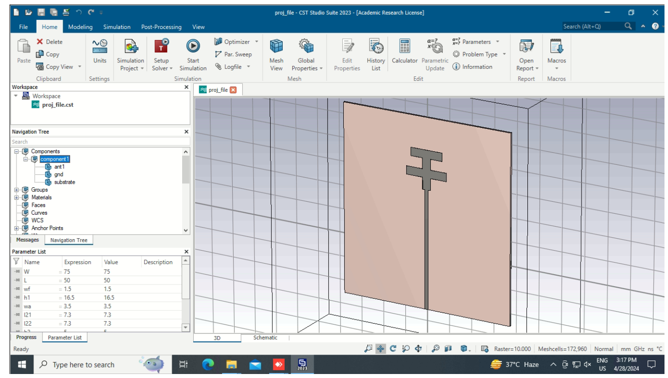


Fig. 3. CST design of dual T-shped monopole antenna

The feeding mechanism is an essential aspect of the antenna design, as it determines the antenna's impedance matching and overall performance. Different feeding techniques, such as microstrip line feed, coaxial probe feed, or aperture coupling, are evaluated to determine the most suitable approach for achieving dual-band resonance and impedance matching. Impedance matching networks, such as matching stubs or tuning capacitors, may be incorporated to ensure optimal impedance matching across the desired frequency bands.

The antenna design is simulated using CST Microwave Studio, a comprehensive electromagnetic simulation tool. The simulation setup includes defining the geometry of the antenna structure, specifying material properties for the substrate and conductive elements, and configuring the feeding mechanism. Parameters such as frequency range, mesh settings, and boundary conditions are defined to accurately capture the antenna's electromagnetic behavior.

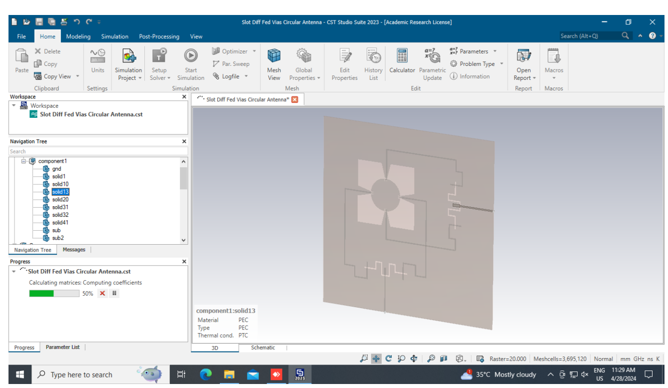


Fig. 4. CST design of Slot-Diff-Fed vias Circular Antenna

Parametric sweeps are performed to systematically analyze the effects of varying antenna dimensions, substrate properties, and feeding parameters on the antenna's performance. Optimization algorithms within CST Microwave Studio are utilized to fine-tune the antenna design and achieve desired performance metrics such as impedance matching, radiation pattern, and gain characteristics. The optimization process may involve adjusting parameters such as antenna dimensions, substrate thickness, or feedline length to optimize performance over the desired frequency bands.

Simulation results are carefully analyzed to evaluate the antenna's performance characteristics, including impedance matching, radiation pattern, bandwidth, and gain. Comparisons are made between simulated results and theoretical expectations to validate the accuracy of the simulation model. Sensitivity analysis may be conducted to assess the robustness of the design with respect to variations in environmental conditions or manufacturing tolerances.

In this communication, FOM is defined as the sum of absolute values of reflection coefficient (S11) in dB for frequency points in the range of 2.4–3.0 and 5.15–5.6 GHz. Basically, we add the absolute value of S11 at each of the frequency point falling in the band of interest in order to calculate the FOM for a given design and the same is represented mathematically as follows:

$$FOM = \sum_{f=2.4}^{3.0} |S_{11}(f)| + \sum_{f=5.15}^{5.6} |S_{11}(f)| \tag{1}$$

where f represents the frequency and $S_{11}(f)$ is the reflection coefficient value at that frequency. While collecting the sample points, these parameters take values within the following range of sample space, χ defined as: $l_{21} \in [6.3, 7.3]$, $l_{22} \in [6.3, 7.3]$, $w_1 \in [1, 3.5]$, $w_2 \in [1, 3.5]$, $w \in [1, 3.5]$, with each parameter taking a step size of 0.5 (all units are in millimeters). In the antenna design process, these five design parameters are input variables and FOM is the output or response variable.

B. Algorithms Used

1) Linear Regression: Linear regression models the relationship between a dependent variable and one or more independent variables using a linear equation of the form:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \epsilon$$

where:

- y is the dependent variable.
- β_0 is the y-intercept.
- $\beta_1, \beta_2, ..., \beta_n$ are the coefficients of the independent variables.
- $x_1, x_2, ..., x_n$ are the independent variables.
- ϵ is the error term.

In antenna design, y could be a performance metric (like return loss or gain), and $x_1, x_2, ..., x_n$ could be the antenna parameters (like length, width, etc.).

2) Ridge Regression: Ridge regression is a modification of ordinary least squares (OLS) regression, designed to handle multicollinearity, a common issue in multiple regression where predictor variables are highly correlated. This is achieved by introducing a regularization term, often called the penalty term, into the residual sum of squares (RSS) function.

The ridge regression model is given by:

$$\hat{\beta}^{ridge} = \arg\min_{\beta} \left\{ \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right\}$$

where:

- $\hat{\beta}^{ridge}$ are the estimated coefficients.
- y_i is the dependent variable.
- β_0 is the y-intercept.
- β_j are the coefficients of the independent variables.
- x_{ij} are the independent variables.
- λ is the tuning parameter that controls the strength of the penalty term.

In antenna design, ridge regression can be used to construct a theoretical model of the relationship between the strain and structural deformation. The dependent variable y_i could be a performance metric (like return loss or gain), and the independent variables x_{ij} could be the antenna parameters (like length, width, etc.). The tuning parameter λ can be adjusted to find the best balance between model complexity and model accuracy.

Ridge regression can be particularly useful in antenna optimization as it can handle multicollinearity among the antenna parameters, which is a common issue in antenna design. By introducing the penalty term, ridge regression can prevent overfitting and improve the generalization ability of the model.

3) Support Vector Machines: SVM finds the hyperplane that maximizes the margin between two classes. The equation of a hyperplane is given by:

$$w \cdot x - b = 0$$

where:

- w is the normal vector to the hyperplane.
- x is the input vector.
- b is the bias.

In antenna design, the classes could represent different antenna configurations, and the input vector could represent the antenna parameters.

4) Decision Trees: Decision Trees (DTs) are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. A tree can be seen as a piecewise constant approximation.

Decision trees make decisions based on certain conditions. Each internal node of the tree corresponds to a condition, each branch corresponds to a decision, and each leaf node corresponds to an outcome. In antenna design, the conditions could be based on the antenna parameters, and the outcomes could represent different antenna configurations.

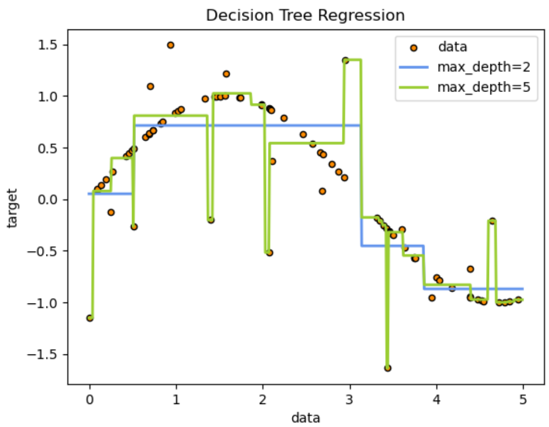


Fig. 5. Decision Tree Regression Example

5) Random Forest Regressor: A random forest is a meta estimator that fits a number of decision tree regressors on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. Trees in the forest use the best split strategy, i.e. equivalent to passing splitter="best" to the underlying DecisionTreeRegressor. The sub-sample size is controlled with the max_samples parameter if bootstrap=True (default), otherwise the whole dataset is used to build each tree.

6) Deep Neural Networks: A DNN is composed of multiple layers of neurons, where each neuron computes a weighted sum of its inputs, adds a bias, and applies an activation function. The output of the DNN is given by the neurons in the output layer. In antenna design, the inputs could be the antenna parameters, and the output could be a performance metric.

7) Recurrent Neural Networks(LSTMs): An LSTM network is a type of recurrent neural network that has a special kind of neuron (LSTM cell) capable of learning long-term dependencies. The output of an LSTM cell at time t is given by:

$$h_t = o_t \odot \tanh(c_t)$$

where:

- h_t is the output at time t.
- o_t is the output gate's value at time t.
- c_t is the cell state at time t.
- $\odot$ denotes element-wise multiplication.

In antenna design, the inputs could be the antenna parameters at different times, and the output could be a performance metric.

IV. Results

After designing the antennas, we do a parametric sweep of both the antenna for a range of values for the selected design parameters for both the antennas. After that we preprocess the data for some missing values, and convert it to a form where it can be inputted to a machine learning model.

	FOM	l21	l22	w1	w2	wa
count	72628.000000	72628.000000	72628.000000	72628.000000	72628.000000	72628.000000
mean	863.773347	6.290221	6.686900	2.250923	2.104244	2.250923
std	187.991743	0.273823	0.471628	0.854638	0.843759	0.854638
min	490.522979	0.000000	0.000000	1.000000	1.000000	1.000000
25%	741.647104	6.300000	6.300000	1.500000	1.500000	1.500000
50%	830.297434	6.300000	6.800000	2.250000	2.000000	2.250000
75%	937.428699	6.300000	6.800000	3.000000	3.000000	3.000000
max	1972.646995	7.300000	7.300000	3.500000	3.500000	3.500000

Fig. 6. Description of dataset for Double T-shaped Antenna

	FOM	el1	h1	l1	m2	px	py
count	50554.000000	50554.000000	50554.000000	50554.000000	50554.000000	50554.000000	50554.000000
mean	5595.144182	6.808917	1.040127	6.808917	2.025478	27.458599	27.525478
std	383.792650	2.273194	0.247373	2.273194	0.224293	1.715404	1.723124
min	4860.961767	4.000000	0.600000	4.000000	2.000000	25.000000	25.000000
25%	5353.314409	4.000000	0.800000	4.000000	2.000000	26.000000	26.000000
50%	5493.397313	6.000000	1.200000	6.000000	2.000000	27.000000	28.000000
75%	5793.389310	8.000000	1.200000	8.000000	2.000000	29.000000	29.000000
max	7274.265755	10.000000	1.600000	10.000000	4.000000	30.000000	30.000000

Fig. 7. Description of dataset for Slot-Diff-Fed vias Circular Antenna

Here, is the description of both the created datasets:

After this we apply the various conventional approaches, and observe the result. Among them, we get the best R2 score of 0.64 for Random Forest Regressor for Slot-Diff-Fed vias Circular Antenna, and the best R2 score of 0.76 for Decision Tree Regressor.

For improving our results, we apply DNN and LSTM based approaches and observe the results for various design parameters. DNN R2 score 0.749 for double T-shaped antenna, LSTM R2 score 0.769 for double T shaped antenna, DNN R2 score 0.584 for Slot-Diff-Fed vias Circular Antenna, and LSTM R2 score 0.679 for Slot-Diff-Fed vias Circular Antenna.

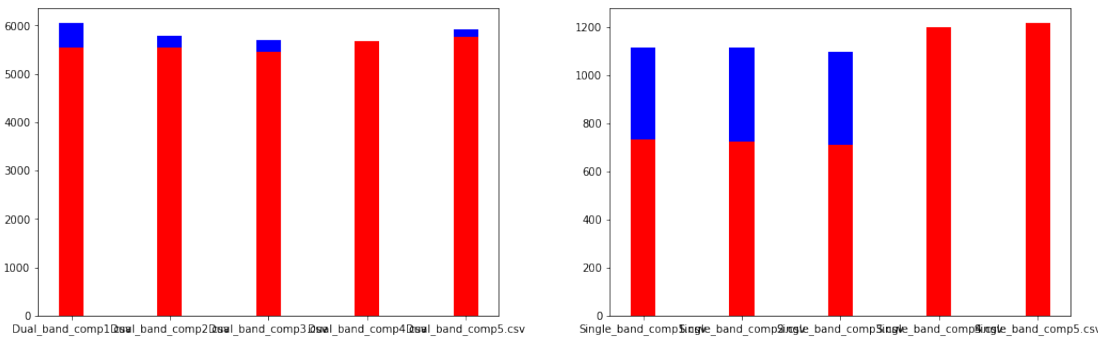
TABLE I
COMPARISON OF ACTUAL AND PREDICTED FOMS FOR DIFFERENT DESIGN PARAMETERS FOR DOUBLE T SHAPED ANTENNA

Design Parameters	FOM actual	FOM predicted
l21=6.4,l22=6.3,w1=1.3,w2=1.4,wa=1.5	1112.36	732.64
l21=6.5,l22=6.5,w1=1.5,w2=1.6,wa=1.7	1113.35	725.60
l21=6.7,l22=6.9,w1=1.8,w2=1.9,wa=2	1097.32	709.86
l21=7,l22=7.2,w1=2,w2=2.3,wa=2.4	1087.77	1196.93
l21=7.3,l22=7.3,w1=3.5,w2=3.5,wa=3.5	1081.67	1218.38

TABLE II
COMPARISON OF ACTUAL AND PREDICTED FOMS FOR DIFFERENT DESIGN PARAMETERS FOR SLOT-DIFF-FED VIAS CIRCULAR ANTENNA

Design Parameters	FOM actual	FOM predicted
el1=5,h1=0.7,l1=5,m2=3,px=26,py=26	6060.13	5549.87
el1=5,h1=0.9,l1=7,m2=4,px=27,py=27	5786.88	5587.45
el1=7,h1=0.9,l1=7,m2=4,px=28,py=28	5695.29	5459.23
el1=9,h1=1.1,l1=9,m2=4,px=28,py=28	5599.53	5678.08
el1=9,h1=1.3,l1=9,m2=4,px=29,py=29	5909.11	5754.08

The above two tables use LSTM as a regression model as it gives the best R2 score for both the antennas. The differences



(a) (b)

Fig. 8. Bar graph plot of actual and predicted FOMs for a)Slot-Diff-Fed vias Circular Antenna and b) Double T-Shaped Monopole Antenna

of actual and predicted FOMs as a bar graph is shown in Figure 8.

Finally, we run the model for all possible parameter values of Slot-Diff-Fed vias Circular Antenna and get the values which give the maximum FOM and then we compare its simulated result with that of initial best results.

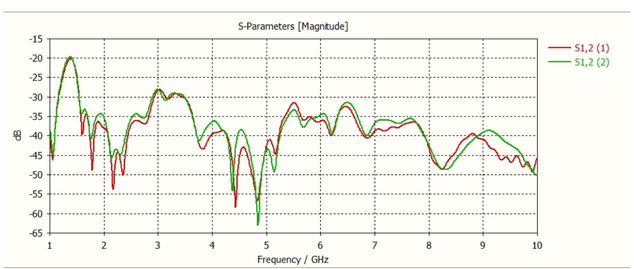


Fig. 9. Plot of S12 parameter for Slot-Diff-Fed vias Circular Antenna. S12(2) represnt the plot for the parameters derived from our LSTM model while S12(1) is the best inital result

V. Conclusion

In conclusion, our project "Optimising Design of Dual and Single Band Antenna using Deep Learning" presents a significant advancement in antenna engineering. By leveraging deep learning algorithms, the study demonstrates the potential for improved optimization techniques in antenna design. The application of machine learning not only streamlines the design process but also enhances the performance of antennas in both dual and single-band configurations. This research opens up new avenues for the development of more efficient and sophisticated antennas, catering to the growing demands of modern communication systems. Future work may focus on expanding the dataset, refining the algorithms, and exploring the integration of these optimized antennas in real-world applications.

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