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Random forest machine learning approach for efficient optimization of Sierpinski carpet fractal antenna

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Abstract

The rapid advancement in communication-based based on Artificial Intelligence (AI) applications has driven the next-generation wireless communication networks, with a notable shift from traditional systems. This evolution promises improved coverage and enhanced spectrum efficiency. Leveraging augmented computational processing capabilities and substantial data storage, Machine Learning (ML) concepts, particularly in the domain of antennas, have gained prominence. The optimization of design parameters is a key focus for achieving favourable computational outcomes, surpassing the opportunities for improvement within analytical methodologies that often result in significant computation overheads.

This paper explores the utilization of leading AI frontiers such as Machine Learning (ML), Artificial Neural Networks (ANN), and Deep Learning (DL) in wireless communication networks. With a particular emphasis on employing Random Forest machine learning algorithms for the purpose of antenna design and optimization. A comparative analysis between machine learning algorithms and conventional design approaches is presented. This paper specifically investigates the use of the Random Forest machine learning algorithm for the optimization of the Sierpinski fractal carpet antenna. The work carried out assesses the computational feasibility enhancements and the antenna's application viability in comparison to conventional methods, demonstrating that Random Forest machine learning algorithm yields satisfactory and superior results in antenna design and miniaturization

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Subject Classification: *94A78.*

Keywords: *Machine learning, Sierpinski, Random forest, HFSS, Fractal antenna, Optimization.*

1. Introduction

With rising demand in antennas for ultra wide band and wideband, significant attempt is exercised to design antenna that exhibits multiband behavior. The attributes like minimized size, multiband characteristic features etc are marking revolution in antenna design, thus making fractal antenna a better choice for the antenna designers. The fractal geometry concept applied to traditional antenna provides the best possible shapes of antenna thereby leading to reduction in the overall size of antenna at large. Among various fractal geometries, only some are adopted in microstrip antenna design, Sierpinski Carpet fractal antenna is one among them.

At present the optimization of design parameters is major consideration to acquire useful computational results. The optimization of design parameters is a key focus for achieving favorable computational outcomes, surpassing the challenges associated with analytical methods that often result in significant computation overheads. To address this, a trial-and-error approach is employed [1].AI techniques are utilized in optimization and design of antenna decades ago ever since 90s [2,3]. The main advantage of the artificial intelligence techniques in design of antenna in comparison to the conventional techniques is its ability to handle multifunctional problems to accomplish the desired outcome in addition to providing the best Solutions [4,5].

Several methods for the optimization of design are proposed in literature namely genetic, particle swarm, Biogeography optimization techniques etc [6]. Optimization technique defines the lower limit or higher limit of an operator with respect to the cost function. Various antenna parameters S_{11}, VSWR, BW, size, gain (dB) [7] can be optimized using Machine Learning algorithms. ML is a diverse technique employed in data analytics to train machines to learn and forecast new data based on training. ML is preferred over other techniques due to its ability to provide solutions to complex numerical problems involving enormous data. The algorithms demonstrate consistent performance, validated through both simulation and measured results With the increased popularity in employing fractals with multiband behavior for various applications viz Global System for Mobile Communication, Wireless LAN, DECT, ISM band hand set, machine learning is gaining huge popularity in recent days. For quick design of antenna Machine learning is considered as most reliable method. The proposed model is rather simple, time effective and does not involve complex numerical estimation. The data used for training in ML can be used to estimate accurate values of parameters with high efficiency [8-12]. Rapid advancement in artificial intelligence and machine learning techniques have judiciously proved as alternative solutions to highly priced simulators used in antenna design and optimization [13-16] thereby providing quick and robust solutions to enhance antenna in terms of its performance parameters [17-19]

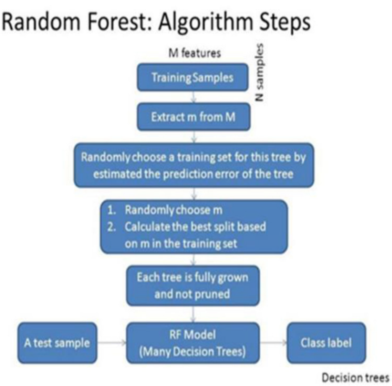


Figure 1

Flowchart of Random Forest Machine Learning Algorithm in Sierpinski carpet Fractal Antenna Design

2. Random Forest Machine learning algorithm in Sierpinski Carpet Fractal

Antenna Optimization

Random Forest represents a widely applied Supervised ML Algorithm utilized in both Regression plus Classification scenarios. Decision trees are built on a variety of samples and derives that classification has major role as compared to regression which plays minimal role.. Notably, Random Forest Algorithm excels in handling datasets with a mix of continuous variables, as observed in regression problems, and categorical variables, as seen in classification tasks.

The foundational concept of the Random Forest Algorithm is rooted in the decision tree algorithm. The key distinction lies in the fact that, the decision tree algorithm depends on a individual (Single) tree for decision making, while the RFA incorporates multiple trees, forming a forest. The effectiveness of random forest regression is contingent on the number of trees, influencing prediction accuracy. However, it's essential to recognize that a higher number of trees doesn't necessarily translate to superior predictions. Thus, determining the optimal number of trees is critical for achieving maximal prediction results. In the construction of a training model within Random Forest, a multitude of decision trees is indispensable. For each decision tree the following steps are performed as illustrated in Figure 1.

The implementation of this algorithm is demonstrated in the following steps;

Step 1: Initially original dataset D is derived from HFFS simulator with K- Decision Trees of an assembly. A tree is built with N number of samples as long as each node has less than / equal to N (consider N=5 if task is regression) Features with F number are arbitrarily chosen for every node in the decision tree. For splitting the node a feature from set of F number of features is selected, for example Feature F= SQRT if the task is regression, F represents no. of features of dataset D

Step 2: K-subset of data are derived from the dataset D by Random Forest algorithm. If samples are not part of any subset they are termed as out of bag errors

Step 3: Further K- trees are constructed with a single subset following which each tree is created until there are equal to / lesser than N number of samples in every node. Additionally F features are arbitrarily added in each node, which involves a feature employed for splitting of the node.

Step 4: K-models appropriately trained are structured as an assembly and on averaging the predicted results of each trees, the regression task will achieve its final outcome.

Hyper-Parameters

Predictive Power:

- **n estimators** is the hyper parameter that portray the number of trees well before algorithm is built The more the number of trees ,the model exhibits higher performance but decreases the speed of the
- **max features** represents the maximal number of features that can be best fit in the given algorithm.
- **min sample leaf** is associated with predictive power modification, signifies minimal leaves taking part in splitting the node

Model Speed:

- **n jobs** is the hyper parameter dictates the engine regarding the number of processors that can be used tells the engine that how many processors it can use. If n jobs=1 one processor can be utilized, in case n jobs=-1,no limitation is imposed on using number of processor.
- **random state** duplicates the output, same results will be obtained for some definite values of random state.
- **oob score** is a parameter used to track model speed.1/3rd of data is not primarily used in training but at later stages the data is utilized for model evaluation, Therefore the samples are categorized as out of bag.

Mean Squared Error (MSE)

Mean Squared Error (MSE) quantifies error evident in the models operating on statistics It is the average of squared differences between the experimental and the estimated/predicted values. The mean square error tends to zero in case the model has zero errors. With rise in model error there is a subsequent increase in MSE value .The equation below shows Mean Squared Error (MSE) where yi represents experimental value, ŷi corresponds to estimated value and n is the number of experimental values.

$$MSE = \frac{\Sigma(y_i - \hat{y}_i)^2}{n}$$

3. Analysis between Conventional approach& Machine Learning (ML) approach for Sierpinski Carpet Fractal Antenna Optimization

The Figure 2 below illustrates differences between the Conventional and ML Computational approach

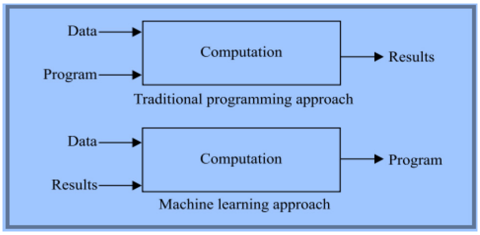
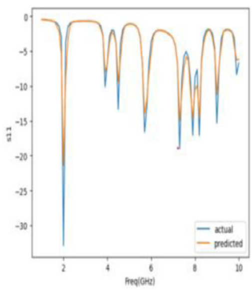
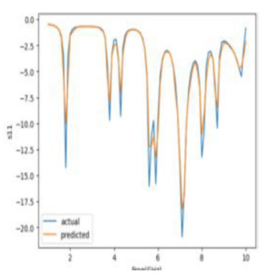


Figure 2

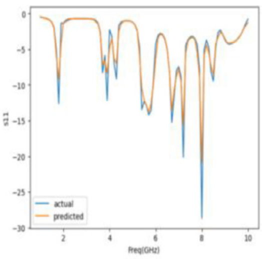
Conventional Versus Machine learning Computational Approach

Table 1

Comparison ofAnsysHFSS15.0 & RFA Results of S_{11} Parameter for Iteration 0.1 & 2

Sl. No.	Iteration-0						
	Fabricated Result		HFFS Result (Actual)		RFA Result (Predicted)		
	Freq (GHz)	S11 (dB)	Freq (GHz)	S_{11}(dB)	Freq (GHz)	S_{11}(dB)	
1)	2.0	-30.10	2.0	-10.5823	**2.0**	-10.5612	
2)	3.9	-10.07	3.9	-9.27797	**3.9**	-9.24482	
3)	4.5	-15.04	4.5	-13.3425	**4.5**	-13.2934	
4)	5.7	--12.02	5.7	-15.5095	**5.7**	-15.4339	
5)	7.3	-13.06	7.3	-13.2721	**7.3**	-13.2379	
6)	7.9	-7.50	7.9	-17.0913	**7.9**	-16.967	
Sl. No.	Iteration-1						
	Fabricated Result		HFFS Result (Actual)		RFA Result (Predicted)		
	Freq (GHz)	S11 (dB)	Freq (GHz)	S_{11}(dB)	Freq (GHz)	S_{11}(dB)	
1)	1.8	-10.12	1.8	-14.2372	1.8	-14.0698	
2)	3.8	-8.73	3.8	-9.69094	3.8	-9.6729	
3)	4.3	-8.81	4.3	-9.31359	4.3	-9.274	
4)	5.6	-20.09	5.7	-16.0323	5.6	-14.9691	
5)	7.2	-30.30	7.3	-16.2289	7.2	-16.2453	
6)	8.0	-8.50	8.0	-13.2373	8.0	-13.2013	

Contd...

Sl. No.	Iteration-2						
	Fabricated Result		HFFS Result (Actual)		RFA Result (Predicted)		
	Freq (GHz)	S11 (dB)	Freq (GHz)	S_{11}(dB)	Freq (GHz)	S_{11}(dB)	
1)	1.8	-19.61	1.8	-12.3756	1.8	-9.17	
2)	3.9	-10.17	3.7	-9.28273	3.7	-9.27216	
3)	4.3	-8.23	4.2	-8.98406	4.2	-8.97006	
4)	5.7	-20.02	5.7	-14.1977	5.7	-14.1501	
5)	7.1	-25.03	7.1	-8.88396	7.1	-8.87547	
6)	8.0	-36.01	8.0	-12.2999	8.0	-12.2693	

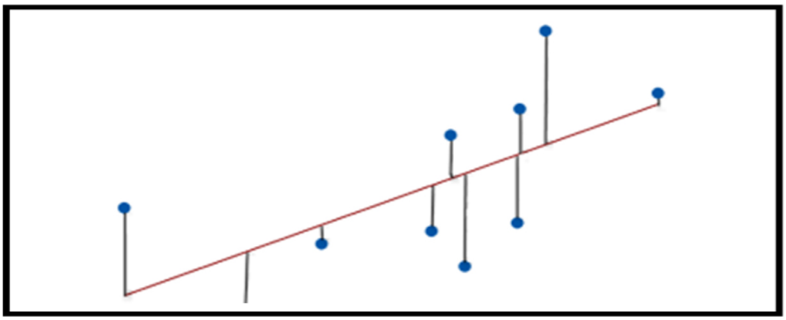
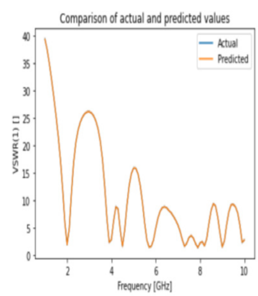


Figure 3

Graph representing Mean Squared Error for S_{11} & VSWR

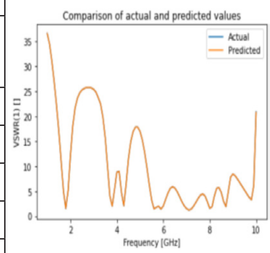
Table 2

Comparison of AnsysHFSS15.0& RFA Results of VSWR for Iteration 0.1 & 2

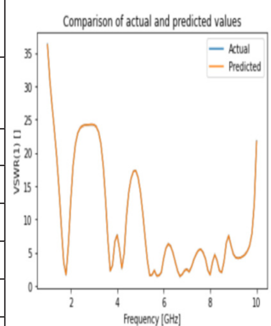
Sl. No.	Iteration-0						
	Fabricated Result		HFFS Result (Actual)		RFA Result (Predicted)		
	Freq (GHz)	VSWR	Freq (GHz)	VSWR	Freq (GHz)	VSWR	
1)	2.0	1.06	2.0	1.83	**2.0**	1.85	
2)	3.9	1.91	3.9	2.25	**3.9**	2.27	
3)	4.5	1.43	4.5	1.54	**4.5**	1.56	
4)	5.7	1.66	5.7	1.40	**5.7**	1.41	
5)	7.3	1.57	7.3	1.55	**7.3**	1.55	
6)	7.9	2.45	7.9	1.32	**7.9**	1.33	

Contd...

Sl. No.	Iteration-1					
	Fabricated Result		HFFS Result (Actual)		RFA Result (Predicted)	
	Freq (GHz)	VSWR	Freq (GHz)	VSWR	Freq (GHz)	VSWR
1)	1.8	1.90	1.8	1.48	1.8	1.53
2)	3.8	2.15	3.8	1.97	3.8	1.98
3)	4.3	2.13	4.3	2.04	4.3	2.06
4)	5.6	1.21	5.7	1.43	5.6	1.44
5)	7.2	1.02	7.3	1.36	7.2	1.36
6)	8.0	2.20	8.0	1.55	8.0	1.56



Sl. No.	Iteration-2					
	Fabricated Result		HFFS Result (Actual)		RFA Result (Predicted)	
	Freq (GHz)	VSWR	Freq (GHz)	VSWR	Freq (GHz)	VSWR
1)	1.8	1.06	1.8	1.63	1.8	1.67
2)	3.9	1.91	3.7	2.23	3.7	2.25
3)	4.3	1.43	4.2	2.61	4.2	2.63
4)	5.7	1.66	5.7	1.48	5.7	1.49
5)	7.1	1.57	7.1	2.12	7.1	2.12
6)	8.0	2.45	8.0	1.6	8.0	1.64



As depicted in Figure 3 below, in this model as the data points with respect to S_{11} & VSWR fall closer to the regression line , the model exhibits relatively a low Mean Squared Error thus providing desired results with good precision & accuracy.

4. Future Research Directions

Machine learning in antenna design prove to be an optimal choice when compared to the conventional design and other computational techniques there by exhibiting good accuracy and efficiency, minimized error, time efficient behavior. The antenna proposed is designed and optimized for 3 iterations to reduce antenna size and operated at frequency between 2 GHz to 8 GHz. As a future perspective the antenna can be designed for more number of iterations to further reduce the antenna size and frequency range for which it operates can also be extended to cover high frequency up to 20 GHz so as to provide multiband frequencies to accommodate more number of wireless applications .Random forest algorithm is used in proposed model for efficient optimization of antenna ,other machine learning algorithms like Support Vector machine, Kriging, Gaussian, and other regression algorithms can also be adopted as an alternative for achieving optimal result in antenna design and optimization process.

5. Discussion and Conclusion

Without the application of machine learning algorithms series of problems exist in antenna design namely; poor acceleration in antenna design, preserving work probability and difficulty in obtaining antenna behavior calculation.

From the above experiments and graphical outputs as illustrated in Table 1 & 2 it is evident that Random forest algorithm in Machine Learning performs well for important parameters like Return Loss S_{11} & VSWR. The S_{11} Parameter or Return losses for Sierpinski carpet fractal antenna are lowest at all iteration well below or closer to -10db, also a low VSWR at all iterations indicates a better impedance match and therefore efficient transmission of Power from source through transmission line to load thus exhibiting the multiband properties for each iteration .To conclude ML based predictions provide accurate and fast results as compared to HFSS15.0 simulated results. Further it is proved that employing machine learning algorithms in the design of Sierpinski fractal carpet antenna also provides accurate & better characterization of result as compared to conventional computational methods, thereby exhibiting multiband behaviour for frequencies between 2 GHz to 8 GHz making it suitable for multiband applications for the specified frequency ranges.

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