

On the Performance of a Multi-Band High-Efficiency Fractal Antenna Systems

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Abstract- In this work an antenna design based on fractal geometry with metamaterial defects is proposed to operate at multi frequency bands including: 0.7GHz, 1.25GHz, 1.75GHz, 1.95GHz, 3.1GHz, 3.75GHz, 4.1GHz, 4.4GHz, 5.1GHz, and 5.8GHz. The antenna patch is constructed with four major parts: the radiator patch, matching step transformer, the quarter-wavelength transformer, and step aperture etched from patch centre. The proposed antenna is backed with metamaterial based on fractal geometry as defect with a partial ground plane. The antenna is loaded with two SMD capacitors for matching and suppressing surface wave effects. The key reason of using the proposed fractal approach for the proposed design is to reduce the size of the antenna ultimately. The antenna is mounted on an FR4-Epoxy substrate of $\epsilon_r=4.3$ with loss tangent of 0.00182 and 1.8mm thickness. For this work we adopted the use of Finite Integral Technique (FIT) of CSTMWS formulation with Genetic Algorithm (GA) for optimization regards. The antenna gain is achieved to 4dBi in maximum at 3.1GHz to is suitable for wireless communication systems at 5G bands. In general, the proposed antenna is found suitable for wireless communication at different frequency bands at sub-6GHz. Finally, the proposed antenna is validated numerically with HFSS software package using Finite Element Method (FEM) algorithms.

Keywords: multi-bands, fractal antenna, microstrip, FIT, GA, FEM.

I. Introduction

Because of the huge growth of current wireless communication services, our surroundings are now full of electromagnetic waves [1]. A lot of the energy that is sent out is squandered in the air, while only a little quantity is received [2]. If radio frequency (RF) energy can be collected and utilized correctly, it might be reused and added to natural sources of energy like sun and wind [1, 2]. The captured RF energy is the principal power source for many low-power devices, such as sensor networks [3], RFID [4], the Internet of Things [5], and electric clocks [6]. An omnidirectional antenna is the best choice for collecting ambient RF energy since it can pick up signals from many

different directions and the source location is not known [6]. One possible approach is to employ rectenna systems, which have a lot of promise for usage in engineering. Rectenna systems have a long life (they don't require batteries), but they are hard to work with since they are not very efficient and their gain goes down because of how they are built. This drop might happen when the signal changes from RF to DC. Also, the rectenna systems are generally made for lower ISM bands, such as 2.45 GHz. So, the antennas should be low profile, cheap, and work well. Using microstrip technology to build the antenna in the rectenna systems might make this happen. So, it is very important to carefully put a well-designed antenna with high gain, bandwidth, low profile, cheap cost, and efficiency into the rectenna system. Using fractal geometry to create the antenna may make it much more energy efficient [7]. Fractal geometries are widely used in antenna design because they can occupy space and are self-similar, which makes them good for antennas.

This work is realized to design a multi-band high-gain antenna-based fractal metamaterial defects on the ground plane to operate at ten different frequency bands at su-6GHz. Computer Simulation Technology (CST) software is designed the proposed antenna and optimize the performance with GA. The obtained results are validated using HFSS software. After then, the suggested antenna is made on a standard FR-4 substrate. The obtained results from the invoked methods are found to agree well. In this paper, section two discusses the proposed antenna design. Section three explores the optimization process and methodology. Section four discusses the obtained results. The paper is concluded in section five.

II. Antenna Design Details

There is something quite special about fractal dimension. There are many different ways to show fractal dimensions, such as the Hausdorff dimension, the topological dimension, the self-similarity dimension, and the box-counting technique dimension. The self-similarity trait is the most important thing that is utilized to study and describe the diverse fractal shapes [8–10]. The proposed antenna is inspired from [9] to be exemplified for this study and the self-similarity parameter of fractal geometry is defined as:

$$D_s = \frac{\log(N)}{\log(\frac{1}{S})} \quad (1)$$

where s is the scaling factor and N is the number of copies of the self-similar structure. Fractal design usually contains two dimensions and two parts: the initiator (0th stage), which is the fundamental structure of the fractal geometry, and the generator, which is the structure that is repeated in a sequential pattern on the initiator in the next stages with the various dimensions. The use of the fractal generator may to add or remove the initial area of the initiator n from each iteration stage in a regular sequence to create the desired fractal structure. The CST electromagnetic program was used to create the basic shape (iteration 0), which is a circular ring with an outside radius of 21 mm and an interior radius of 12.85 mm. The ring width is 1.5 mm. To get the radius, use the following formula [11]. In this context, f_r represents the resonant frequency, ϵ_r denotes the relative permittivity of the dielectric substrate, h indicates the height of the substrate, and w refers to the width of the feed line. The microstrip line feed has a typical impedance of around 50 ohms. We figure out the effective dielectric constant ϵ_{eff} from ϵ_r :

$$radius = \frac{F}{f_r} + \left[\frac{2h}{\pi \epsilon_r F} \right] \left[\ln \left(\frac{\pi F}{2h} \right) + 1.7726 \right] g^{0.5} \quad (2)$$

where,

$$F = \frac{[8.791 \times 10^9]}{f_r \epsilon_r^{0.5}} \quad (3)$$

$$\epsilon_{eff} = \frac{\epsilon_r + 1}{2} + \frac{\epsilon_r - 1}{2} \frac{1}{\sqrt{1 + 12 \frac{h}{w}}} \quad (4)$$

The initial portion of the antenna construction is a dielectric substrate made of FR4-Epoxy with ϵ_r and $\tan \delta$ values of 4.4 and 0.02, respectively. The substrate is the same size as the last antenna, which was $87.5 \times 55 \text{ mm}^2$ and 2 mm thick. The partial ground plane is the next step in building the antenna. The dimensions of this portion are $12.5 \times 55 \text{ mm}^2$, and it is printed on the bottom face of the substrate as a conductive substance. The third one is the quarter-wavelength transformer, which is shown in Table 1. The radiator patch based on the fractal approach is the final phase of the antenna assembly. The fundamental reason for adopting the fractal approach in the suggested antenna, together with the elliptical-shaped conductors within the antenna radiator, is to get the second working mode by making the current route longer, which makes the antenna more omnidirectional than it would be without this technique.

III. Methodology of Optimization

A. Problem Formulation and Design Variables

A multi-objective constrained optimization problem is set up to optimize the design of reconfigurable fractal antennas. Table 2 provides the design variables, their physical meanings and their ranges of values. The optimization is done to minimize S_{11} , maximize the operational bandwidth, maximize the antenna gain, and maximize the radiation efficiency, with physical and reconfigurability constraints.

B. Surrogate-Assisted Optimization Framework

Direct electromagnetic simulation using full-wave solvers (e.g. CST Microwave Studio, HFSS) is computationally prohibitive for population-based optimization, taking minutes per evaluation. We solve this problem using a surrogate-assisted optimization framework as depicted in Fig. 2. The framework includes three steps: (1) generation of synthetic training data, (2) neural network surrogate modeling, and (3) genetic algorithm optimization.

1) Synthetic Training Data Generation

The synthetic dataset ($N_{samples}$) design is generated using numerical based approximate models from CSTMWS. For each model i , the input vector ($x_i \in \mathbb{R}^4$) includes the normalized design variable quantity and reconfigurable state:

$$x_i = [L_{f,norm}^{(i)}, W_{p,norm}^{(i)}, f_{p,norm}^{(i)}, s^{(i)}]^T \quad (1)$$

where $s^{(i)} \in [0,1]$ characterizes the normalized reconfigurable switching state. The consistent output vector $y_i \in \mathbb{R}^4$ covers the performance metrics:

$$y_i = [S_{11}^{(i)}, BW^{(i)}, G^{(i)}, \eta^{(i)}]^T \quad (2)$$

The synthetic performance is also calculated using approximate transmission line theory and cavity models. The effective permittivity ϵ_{eff} is intended as:

$$\epsilon_{eff} = \frac{\epsilon_r + 1}{2} + \frac{\epsilon_r - 1}{2} \left(1 + \frac{12h_s}{W_p} \right)^{-0.5} \quad (3)$$

The operation frequency resonance f_0 is given by:

$$f_0 = \frac{c}{2W_p \sqrt{\epsilon_{eff}}} (1 + 0.05(f_p - 0.5)) \quad (4)$$

The input impedance Z_{in} and reflection coefficient Γ are approximated as:

$$Z_{in} = 90 \frac{\lambda_0^2}{L_{eff}^2}, \Gamma = \left| \frac{Z_{in} - Z_0}{Z_{in} + Z_0} \right| \quad (5)$$

where $Z_0 = 50 \Omega$ is the characteristic impedance. The evaluated S_{11} spectra is given by:

$$S_{11} \text{ (dB)} = 20\log_{10}(\Gamma) - 6L_f + 2s \quad (6)$$

This synthetic model allows for the rapid generation of thousands of training samples while retaining the fundamental physical relations between geometry and electromagnetic behavior.

2) Neural Network Surrogate Modeling

The neural network, see Fig. 2, is trained on the approximate mapping $\mathcal{F}: \mathbb{R}^4 \rightarrow \mathbb{R}^4$; that consists of:

- Input layer: 4 neurons (normalized design variables + reconfigurable state)
- Hidden layer 1: 8 neurons with hyperbolic tangent activation
- Hidden layer 2: 8 neurons with hyperbolic tangent activation
- Output layer: 4 neurons with linear activation (performance metrics)

The network is trained using Levenberg-Marquardt backpropagation algorithm which provides better convergence speed for medium-sized networks. The dataset is partitioned as follows:

- Training set: 70% (model fitting)
- Validation set: 15% (early stopping)
- Test set: 15% (generalization assessment)

Training continues for up to 50 epochs, with early stopping based on no improvement in validation performance for 6 consecutive epochs. The loss function MSE (mean squared error) is defined as:

$$L_{MSE} = \frac{1}{N} \sum_{j=1}^N \sum_{k=1}^4 (y_{jk} - \hat{y}_{jk})^2 \quad (7)$$

where y_{jk} and $\hat{y}_{jk}$ are the actual and predicted performance metrics, respectively. After convergence the trained network becomes a computationally efficient surrogate that reduces the evaluation time from minutes to microseconds.

3) Genetic Algorithm Optimization

The genetic algorithm optimizes the design variables using the neural network surrogate for fitness evaluation. The optimization is performed on normalized variables $z \in [0,1]^4$, which are mapped to physical values via:

$$z_{phys} = z_{norm}(u_j - l_j) + l_j \quad (8)$$

where l_j and u_j are the lower and upper bounds of variable j , respectively.

✓ Population Initialization

An initial population $\mathcal{P}^{(0)}$ of size N_{pop} is generated using Latin hypercube sampling to ensure uniform coverage of the design space:

$$\mathcal{P}^{(0)} = \{z_1, z_2, \dots, z_{N_{pop}}\}, z_i \sim \mathcal{U}[0,1]^4 \quad (9)$$

The fractal iteration level is discretized by rounding the normalized value to the nearest valid integer level.

✓ Multi-Objective Fitness Function

A weighted-sum approach is employed to aggregate multiple performance objectives.

The fitness function $f(z)$ to be minimized is:

$$f(z) = w_{S_{11}}c_{S_{11}} + w_{BW}c_{BW} + w_Gc_G + w_{rec}c_{rec} + w_{size}c_{size} + w_{\eta}c_{\eta} \quad (10)$$

where the weights are empirically set to $w_{S_{11}} = 0.4$, $w_{BW} = 0.3$, $w_G = 0.1$, $w_{rec} = 0.1$, $w_{size} = 0.05$, $w_{\eta} = 0.05$. The individual cost components are defined as:

$$c_{S_{11}} = \max(0, \hat{S}_{11} - S_{11}^{target})^2 \quad (10.a)$$

$$c_{BW} = \max\left(0, \frac{BW^{target} - \widehat{BW}}{BW^{target}}\right) \quad (10.b)$$

$$c_G = \max(0, G^{target} - \hat{G}) \times 0.2 \quad (10.c)$$

$$c_{rec} = \max_{s \in \mathcal{S}} (\hat{S}_{11}(s) - S_{11}^{target})^2 + 0.1 \cdot \text{Var}_{s \in \mathcal{S}}(\hat{S}_{11}(s)) \quad (10.d)$$

$$c_{size} = \frac{\widehat{W}_p}{W_{max}} \quad (10.e)$$

$$c_{\eta} = \max(0, 0.7 - \hat{\eta}) \times 2 \quad (10.f)$$

The reconfigurability cost c_{rec} evaluates the worst-case S_{11} across all N_{states} switching configurations, penalizing both deviation from the target and inconsistency between states.

✓ Selection Operator

Tournament selection with tournament size $k = 3$ is employed. For each parent selection, three individuals are randomly drawn from the population, and the one with lowest fitness value survives:

$$\text{Parent} = \arg \min_{z \in \mathcal{T}} f(z), \mathcal{T} \subset \mathcal{P}, |\mathcal{T}| = 3 \quad (11)$$

This selective pressure balances the exploration of the design space and the exploitation of promising areas.

✓ Crossover Operator

Single-point crossover is applied with probability $p_c = 0.8$. For parent vectors $z^{(a)}$ and $z^{(b)}$, a crossover point $k \in \{1,2,3\}$ is uniformly selected, producing offspring:

$$z^{(child)} = [z_1^{(a)}, \dots, z_k^{(a)}, z_{k+1}^{(b)}, \dots, z_4^{(b)}]^T \quad (12)$$

✓ Mutation Operator

Gaussian mutation is applied to each gene with probability $p_m = 0.1$. Mutated gene values are computed as:

$$z'_j = \min(1, \max(0, z_j + \mathcal{N}(0, \sigma_m^2))) \quad (13)$$

where $\sigma_m = 0.1$ controls the mutation intensity. The clipping operation ensures mutated values remain within the normalized domain $[0, 1]$.

✓ Elitism Strategy

Elitism preserves the $N_{elite} = 2$ best individuals from the current generation to the next, guaranteeing monotonic improvement of the best fitness:

$$\mathcal{P}_{1:N_{elite}}^{(t+1)} = \{z \in \mathcal{P}^{(t)} : f(z) \text{ is minimal}\} \quad (14)$$

✓ Convergence Criteria

The optimization terminates when either:

1. The maximum number of generations T_{max} is reached, or
2. The standard deviation of the best fitness over the last 10 generations falls below $\epsilon_{conv} = 10^{-6}$:

$$\sigma_{best}^{(t)} = \text{Std}(\{f_{best}^{(t-9)}, f_{best}^{(t-8)}, \dots, f_{best}^{(t)}\}) < \epsilon_{conv} \quad (15)$$

✓ Reconfigurability Evaluation

The reconfigurable behavior is modeled by varying the switching state s across N_{states} discrete configurations. For each state, the neural network prediction is:

$$\hat{S}_{11}^{(s)} = \mathcal{F}(z, s), s = 0, 1, \dots, N_{states} - 1 \quad (16)$$

The reconfigurability-aware fitness evaluation computes the performance for all the states, so that the optimized design exhibits an acceptable S_{11} over the whole switching range. Such approach implicitly optimizes the tuning range and the uniformity of the reconfigurable antenna.

✓ Complexity Analysis

The computational complexity of the proposed framework is analyzed as follows:

- Training data generation: $O(N_{samples} \cdot K_{physics})$, where $K_{physics}$ is constant

- Neural network training: $O(N_{epochs} \cdot N_{train} \cdot H^2)$, where $H = 8$ is hidden layer size
- GA per generation: $O(N_{pop} \cdot H)$ for NN evaluation, plus $O(N_{pop} \cdot N_{states})$ for reconfigurability check
- Total complexity: $O(N_{samples} + T \cdot N_{pop} \cdot (H + N_{states}))$

For typical parameters ($N_{samples} = 1000$, $T = 50$, $N_{pop} = 30$, $N_{states} = 4$), total evaluation time is on the order of seconds, representing a speedup of approximately 10^4 compared to full-wave electromagnetic simulation.

E. Summary of Methodology

The proposed optimization methodology employs three key innovations:

1. Surrogate modeling replaces expensive EM simulations with a neural network, enabling population-based optimization
2. Synthetic data generation based on approximate physics provides training data without requiring commercial solvers
3. Reconfigurability-aware fitness ensures robust performance across all switching states

This approach transforms the challenging multi-objective antenna optimization problem into a tractable data-driven optimization task, producing physically realizable fractal antenna designs with verified reconfigurable performance.

IV. Results and Discussions

Now, we used numerical analysis and AI to optimize the proposed to test the fractal antenna's performance in terms of S_{11} and gain. For this, we applied at first the basic antenna design performance, then, the effects of the metamaterial introduction, and later, the SMD capacitor introduction is discussed. The antenna design process is breakdown to the flowing section:

A- Basic antenna design

In this section, the basic antenna design performance without metamaterial and capacitors is evaluated using CST software in terms of S_{11} and gain spectra as seen in Fig. 4. The basic antenna general features are optimized at first using the proposed GA in the previous section. We found that the proposed antenna when realized in the CSTMWS environment with the dismissions that are generated from the proposed GA shows excellent performances as shown in Fig. 4. The antenna shows four frequencies

with S_{11} magnitude below -10dB and it is found that the proposed antenna shows maximum gain about 4.6dBi at 4.4GHz.

B- Metamaterial effects

The proposed antenna performances after introducing the proposed metamaterial that optimized and structured with the proposed GA in section III are discussed. The realized metamaterial is structured in CSTMWS environment underneath the basic antenna structure. The antenna after introducing the proposed metamaterial, the antenna performances are enhanced as seen in Fig. 5 in terms of S_{11} and gain spectra. The antenna shows several frequencies but with a degradation of matching with maximum gain of 4dBi around 5.1GHz.

C- Capacitor effects

The effects of introducing the SMD capacitor to the proposed antenna is discussed here. The proposed antenna is found to show excellent matching after introducing the capacitor elements with S_{11} below -10dB overall the frequencies. As seen in Fig. 6, the antenna performances are shown in terms of S_{11} and gain spectra. It is found that the proposed antenna shows gain of 4dBi in maximum at 3.1GHz.

V. Results Validations

Fig. 7 displays the evaluated performance of the proposed antenna from both CSTMWS and HFSS results for the proposed fractal antenna, both software packages. The proposed antenna works at 0.7GHz, 1.25GHz, 1.75GHz, 1.95GHz, 3.1GHz, 3.75GHz, 4.1GHz, 4.4GHz, 5.1GHz, and 5.8GHz with S_{11} below -10dB as seen in Fig. 7(a) to suite 5G networks. The antenna gain spectrum is shown in Fig. 7(b) to show excellent gain in the range of 4dBi that is suitable for short and medium wireless communication ranges.

Now, the predicted antenna power generated is evaluated for the suggested triangular-shaped fractal antenna are shown in Fig. 7. The proposed antenna shows a fluctuation according to the gain change and S_{11} variation.

The evaluated radiation patterns at the considered frequencies are presented in Figure 8. It is found that the proposed antenna shows gain variation from 3dBi up to 4.5dBi as seen in Figure 8. In Table 3, The obtained results are summarized and compared to the other published results in the literature.

VI. Conclusion

This paper shows how to develop a microstrip printed circuit antenna based on a third-order fractal structure for use at 0.7GHz, 1.25GHz, 1.75GHz, 1.95GHz, 3.1GHz, 3.75GHz, 4.1GHz, 4.4GHz, 5.1GHz, and 5.8GHz frequency ranges. The antenna patch is attached to a cheap FR-4 substrate. On the opposite side of the substrate, there is a partial ground plane and metamaterial defects, and the antenna patch is connected to a microstrip quarter-wavelength transformer. The suggested antenna has a return loss of below -10 dB at the mentioned frequencies. At 3.1 GHz, the antenna gain is around 4dBi, while at 5.8GHz, it is about 3.3dBi. The simulated findings are in excellent accord. This antenna might be used in the future for RF harvesting energy applications as a rectenna system.

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