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Performance Optimisation of Modified Multiband Apollonian Gasket Fractal Antenna Using Artificial Neural Network

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Abstract – **Artificial neural networks are becoming popular for optimizing various performance parameters of fractal Antennas. in this article, an artificial neural network (ANN) model is proposed to optimize the return loss of a modified apollonian gasket antenna which works within the range of 7.4 GHz to 9.8 GHz, the model is composed of the input variables of feed line width, radius of both centred circle-slot and its surrounding little eight circles whereas optimized output variables are real and imaginary parts of return loss. Simulation studies are performed using Electromagnetic Simulation Software High Frequency Structure Simulator (HFSS®). Although the proposed model utilizes a tiny amount of training data but it shortly obtains the satisfying optimized values of the return loss.**

Keywords – **Antenna optimisation, Apollonian gasket, Artificial neural networks, Fractal antenna.**

I. INTRODUCTION

In recent decades, fractal geometries have made notable contributions across various domains of science and engineering, including their application in antennas [1]. Fractal antennas find extensive application across diverse fields ranging from communication systems to medical technology, owing to their simplicity, cost-effectiveness, flexibility, lightweight design, compact profile, reproducibility, and seamless integration with solid-state devices [2].

Several methods are reported on performance optimizations of antenna design, there has been a widespread attempt to deploy artificial intelligence-related modern technologies, particularly deep learning using neural networks (NNs), in various industrial domains, with a significant focus on wireless communications [3]. Artificial neural networks are considered essential in machine learning (ML), demonstrating the operation of vital neural networks in the real human brain [4]. These networks were initially introduced in antenna modelling and design [5], making them a valuable tool for accelerating the optimization process [6, 7] Recently, ANN models have gained remarkable importance in wireless communications, mainly due to their ability and adaptability to learn and generalize features [8, 9] They can be trained using measured, calculated, and/or simulated samples to minimize the error between the reference and actual output, predicting results quickly for variations in geometry, both for electrically thin and thick Microstrip Antennas [10].

Different ANN models [11, 12] have been proposed for optimizing various parameters of a rectangular patch antenna. Farzad Mir et al. [13] have presented an ANN model specifically designed for optimizing a multiband MIMO antenna. Linh Ho Manh et al. [14] utilized ANN for optimizing the bandwidth of a microstrip antenna. Return loss and radiation pattern have been optimized in [15] using ANN. Jinhua Huang, et al. [16] proposed a novel ANN model for optimizing a broadband patch antenna. Pedro A. B. Leao et al. [17] presented a neural network model that predicts and optimizes impedance matching. Reconfigurable Microstrip Antennas have been optimized using an ANN model in [18]. K. Kumar et al. used ANN for enhancing the bandwidth of an antenna, as mentioned in [19]. In [20], a performance comparison study using ANN for UWB (Ultra-Wideband) antenna was presented. In the literature, various ANN models applied on fractal antennas particularly optimisation, designing, computations and predictions [21] presented the application of ANN on a fractal antenna [22]. Manpreet Kaur et al [23] used three different types of geometries Minkowski, Giuseppe Peano and Koch curves to design fractal antenna, PSO and ANN were used for optimisation, the antenna operates within the Industrial, Scientific and Medical frequency bands. Another approach to designing a fractal antenna with Koch and Meander curves for its design [24], used ANN and IFS to optimize the line feed position, the maximum gain obtained 8.6 dB. Nirthika et al [25] presented a compact Hilbert curve fractal antenna of size 13.5×9 mm^2 was designed that optimized by artificial neural network (ANN) and verified by an equivalent circuit analysis using ADS software suitable for LTE, Wi-Max and WLAN.

Therefore, based on the mentioned considerations, in this research work, a unique structure of a modified apollonian gasket fractal antenna has been designed and its performance was optimized using artificial neural networks giving a genuine insight and exploration into the behaviour of its performance analysis. Section II provides a detailed exploration of the antenna's intricate geometry and design rationale, emphasizing the unique features of the modified Apollonian gasket fractal structure and its impact on antenna performance metrics. The neural-networks model architecture is discussed in Section III. Section IV illustrates the validation results and discussion. Finally, the manuscript concludes with conclusion.

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II. Antenna Design

A. Antenna Design Procedures

The geometry of the proposed antenna is a modification of the well-known Apollonian gasket. The antenna, as depicted in Figure 1, is designed on a low-cost FR4 glass epoxy substrate with a thickness (*h*) of 1.6 mm and a dielectric constant (εr) of 4.4. The overall dimensions of the substrate are 30×30 mm². The area of the patch can be calculated using the following formula.

$$area = \pi r^2 - \pi rad^2 - \pi radi^2 . \qquad (1)$$

The variable "fw" serves as a critical parameter for determining the impedance matching and signal transmission efficiency of the antenna's feed line. Meanwhile, "rad" and "radi" define the dimensions and positions of the central circle and the smaller circles, influencing the antenna's radiation pattern and directivity. The variable "r", associated with the circular patch, dictates the resonant frequency and bandwidth characteristics crucial for optimal antenna performance.

In Table 1, comprehensive listings of these variables are provided alongside frequency inputs, enabling a systematic exploration of how each parameter influences the antenna's behaviour across different operational frequencies.

TABLE 1
RANGE OF THE PARAMETERS

Parameter	Min value	Max value	Count
freq	7.4 GHz	9.8 GHz	100
fw	1 mm	3 mm	8
r	12mm	12 mm	N/A
rad	3 mm	6 mm	5
radi	0.5 mm	2 mm	5
Wg	30 mm	30 mm	N/A
Lg	30 mm	30 mm	N/A

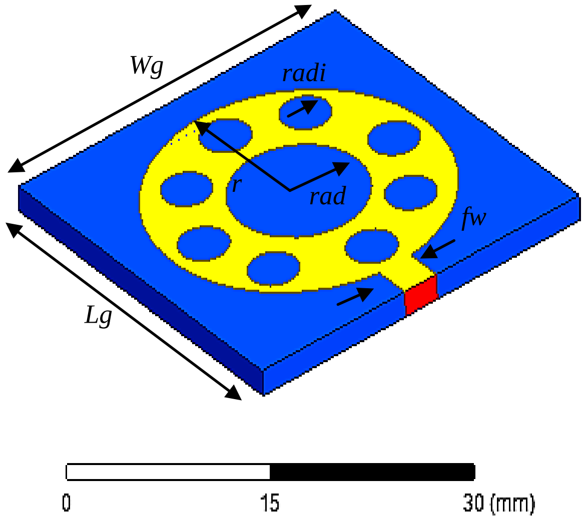

Fig. 1. Proposed antenna structure

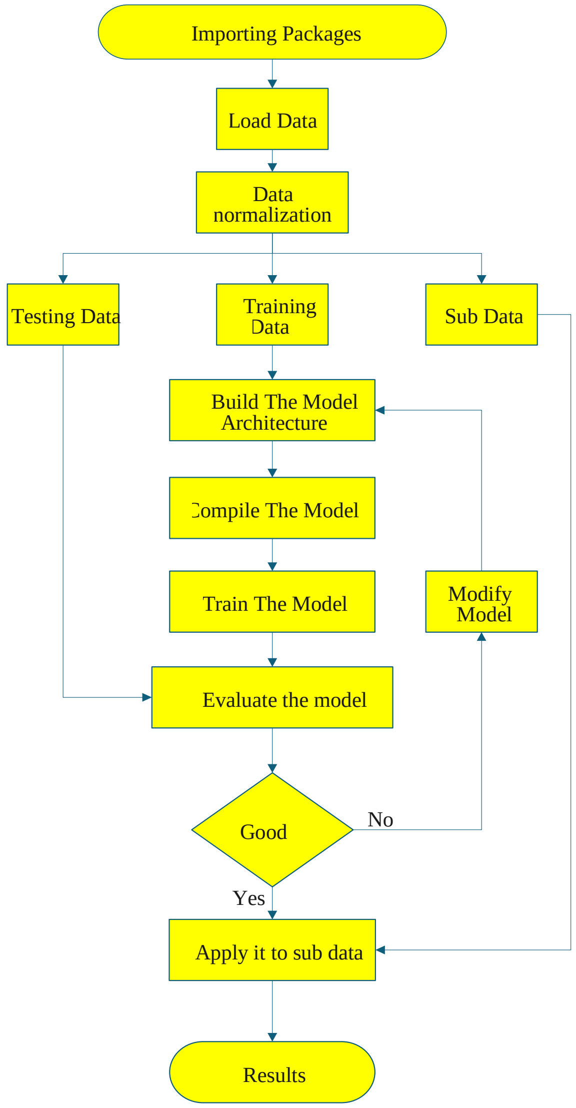

Fig. 2. Flowchart of the proposed ANN model

III. ANN Model Architecture

A. Data Collection

To train the model, a dataset of 20,000 samples spanning 7.4 GHz to 9.8 GHz was prepared, incorporating various feed line widths, central circle sizes with sub-circles, and values for each frequency spectrum portion. Derived from 200 HFSS simulation results, the real and imaginary parts of S11 (return loss in dB) were exported and organized in an Excel spreadsheet. This dataset was used to train a machine learning model to optimize antenna design parameters, with advanced data preprocessing ensuring quality and consistency.

B. ANN Model Structure

To ensure accurate results, this model has been developed by continuously adjusting the number of its hidden layers and neurons. Therefore, before determining the suitable network for this task, extensive training attempts were conducted. The proposed model consists of eight layers; in addition, ReLu and Sigmoid are chosen to be employed as activation functions.

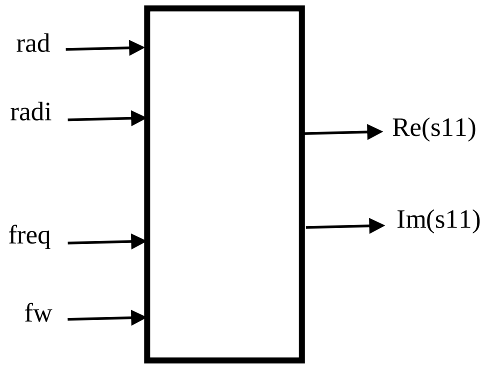

Fig. 3. Proposed ANN model network

C. Activation Function

The importance of the activation function lies in its ability to activate a neuron. ReLu, short for Rectifier Linear unit, is a type of activation function gaining popularity in research communities due to its simplicity and fast convergence. It is crucial to assign an appropriate activation function to achieve better performance. ReLu has been employed in this proposed model for some hidden layers, while Sigmoid has been utilized as an activation function for the rest layers. For the remaining hidden layers, linear activation is employed for all output layers, as it is suitable for regression problems. Most deep learning networks nowadays tend to utilize ReLu and Sigmoid. Equations (2) and (3) illustrate the mathematical functions of ReLu. Whereas (4) illustrates the mathematical function of Sigmoid. To further enhance model performance, it's essential to carefully consider the activation functions used in various layers and their impact on the network's behaviour and convergence.

$$f(x) = \max(0, x), \quad (2)$$

$$, if \;\; x < 0, \;\; f(x) = 0 \;\; and \;\; if \;\; x \geq 0, f(x) = x \quad (3)$$

$$s(x) = \frac{1}{(1 + \ell^{(-x)})}. \quad (4)$$

D. Optimize Function

In recent deep learning models, various optimization algorithms are employed for different types of problems. Therefore, selecting an appropriate optimization function is crucial to ensure network performance and the speed of learning. For the proposed model, the Adam Optimizer is utilized as the optimizing function. This choice is due to its adaptive learning rate capabilities and computational efficiency, making it well-suited for training complex neural networks in antenna design applications.

E. Data Processing

The dataset consists of multiple values. 80% of the data was used for training, while the remaining 20% was utilized for testing the network. A well-known technique called "Min-Max Scaling" has been employed, with Equation (5) depicting the mathematical form of this function.

$$x' = \frac{[x - \min(x)]}{[\max(x) - \min(x)]}. \quad (5)$$

F. Network Training

In the proposed model, four input layers were utilized, and a unique performance metric has been achieved, Mean Squared Error (MSE), and has been selected. ReLu and Sigmoid serve as the activation functions. The dataset is divided into several batch sizes, with the number of epochs constantly adjusted to optimize training. Additionally, the model undergoes rigorous fine-tuning, where parameters such as learning rate and regularization techniques are meticulously adjusted to enhance overall performance and generalization ability.

G. Network Tuning

In order to enhance the performance of the proposed models, a tuning operation has been conducted. This involved iteratively adjusting the number of epochs and the configuration of hidden layers to evaluate the network's performance. ReLu and Sigmoid serve as the activation functions in the proposed Artificial Neural Network (ANN) model.

IV. Results and Discussion

Figure 4 provides a comprehensive view of the model's training and validation journey, highlighting the convergence of loss metrics to optimal values that indicate successful training and validation outcomes. The minimal test loss of 0.012% underscores the model's robust generalization capability beyond the training data, while the blue line representing training loss demonstrates the model's precise adaptation to the complexities of the training dataset. This graphical representation not only validates the efficacy of the training process but also suggests potential avenues for further enhancing model performance and generalization across diverse datasets Figure 5 displays the real part of the actual data versus the real part of the optimized tested data diagonally in blue colour, with both sets aligned together and only a few samples appearing outside the alignment. This alignment indicates that the model is well-trained and capable of accurately predicting the real part of the data. Moreover, the consistent alignment of the majority of samples further underscores the robustness and reliability of the model's predictions, demonstrating its proficiency in capturing the underlying patterns of the data with high fidelity.

Figure 6 presents the imaginary part of the actual data plotted against the imaginary part of the optimized tested data, depicted diagonally in green colour. Both datasets are closely aligned, with only a few samples appearing outside this alignment. This alignment signifies the model's proficient training, as it effectively captures the underlying patterns of the data. Additionally, the consistent alignment of the majority of samples underscores the model's robustness and reliability in predicting the imaginary part of the data.

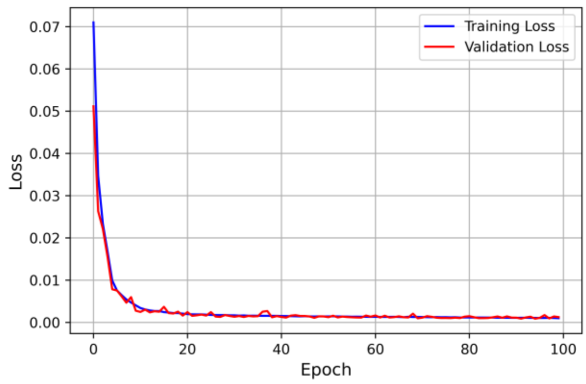

Fig. 4. Training and validation loss over epochs

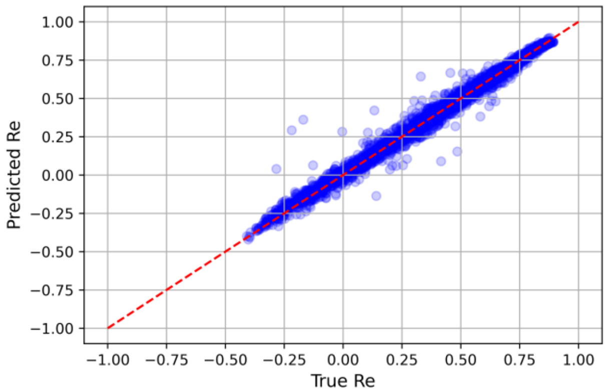

Fig. 5. Predicted Re of ANN model VS Actual Re of HFSS

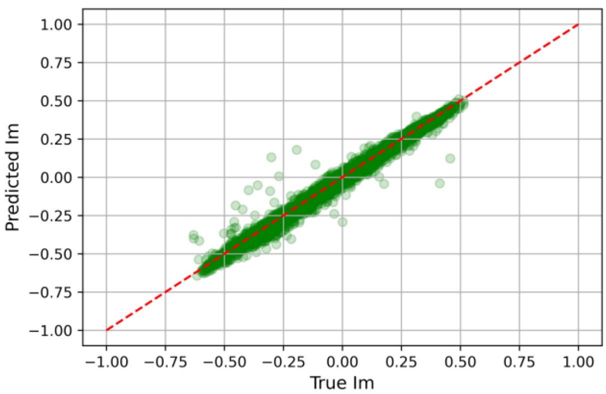

Fig. 6. Predicted Im of ANN model VS Actual Im of HFSS

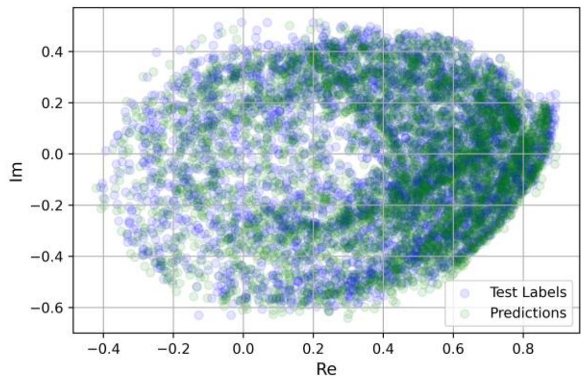

Fig. 7. Predicted ReIm of ANN model VS Real ReIm of HFSS

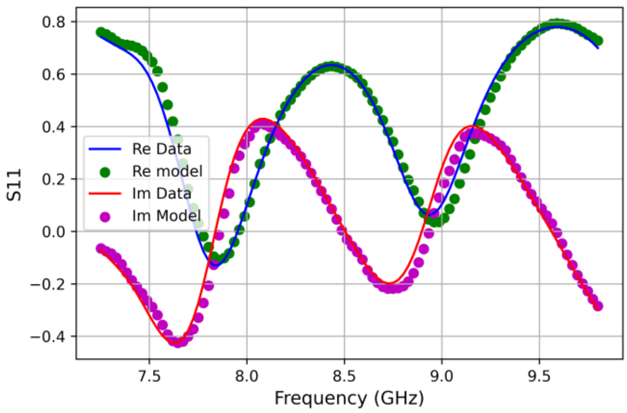

Fig. 8. Predicted VS True of both HFSS and ANN model as a function of frequency

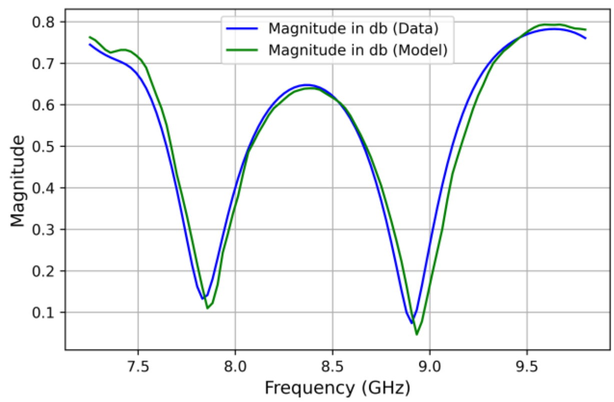

Fig. 9. Magnitudes of ANN model vs. HFSS simulation data as a function of frequency

In Figure 7, the samples of both the real and imaginary parts of the training data, as well as the optimized data, are depicted in green and blue respectively. Each sample of the real and imaginary parts from the training data closely resembles the corresponding sample from the optimized data. This closeness suggests that the model is highly accurate and well-trained each other. This alignment suggests that the model's training was excellent. The magnitude of the S11 parameter is plotted in figure 9, which represents the strength of the reflected signal, can vary between 0 and 1. When the magnitude is 0, it means that there is no reflection and all the signal is transmitted through the antenna without any loss. Conversely, when the magnitude is 1, it implies that the entire incident signal is reflected back, with no transmission through the device or component. In practical applications, the magnitude of the S11 parameter is often expressed in decibels (dB) as shown in figure.11, with values closer to 0 dB indicating less reflection and better transmission characteristics. The green curve represents the optimized magnitude of the model, which is below 0.1, indicating successful impedance matching achievement. In figure 10 the blue curve represents the phase of the training data, while the green curve represents the phase of the optimized model, both plotted as functions of frequency. This visualization allows us to observe how the phase of the model, after optimization, compares to that of the original training data across different frequencies.

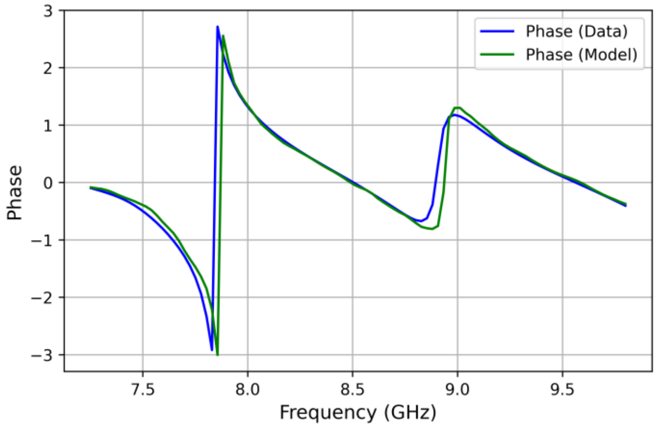

Fig. 10. Phase of the ANN model and HFSS simulation data as function of frequency

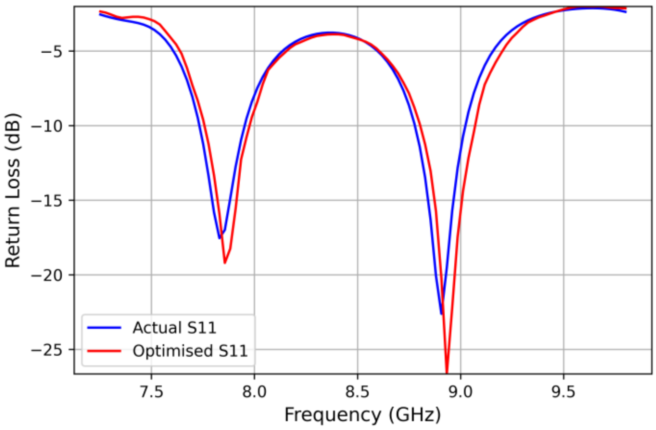

Fig. 11. Optimized return loss of the proposed ANN model vs. actual return loss of HFSS simulation

The proposed artificial neural network, which is based on two types of activation functions, ReLu and Sigmoid, alternately, utilizes the Adam optimizer for the proposed antenna. It demonstrates superior performance, achieving a test error rate of just 0.012%. Such remarkable performance underscores the efficacy of the model in accurately predicting antenna behaviour. Moreover, when comparing its performance with recent works in the literature, as shown in Table 2, it outperforms existing approaches.

TABLE 2
COMPARISON WITH REPORTED WORK IN LITERATURE

Ref	Hidden layers	Test errors
[21]	GRNN	0.41%
[22]	RBF-ANN	25%
[26]	8 Sigmoid	2.40 %
This work	5ReLu+3Sigmoid	0.012 %

V. CONCLUSION

In this article, an accurate ANN model consists of two distinct types of activation functions has been proposed to optimize the return loss values of a novel modified apollonian gasket antenna. The feed line width, the radius of the of main slot and the eight sub circles plus the frequency are considered as variables for the input layer whereas the output layer has two variables the real part and the imaginary part of the return loss, of the dataset contains 20000 samples obtained from simulation results using HFSS software, these samples are splitted in to 80% for training the model and 20% for testing operations, the proposed model utilizes a tiny amount of data to get a satisfying desired result furthermore, the proposed model has good capabilities in ANN techniques for antenna optimization purposes in the future.

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