Machine Learning Driven Impedance Matching for Inverted F Antennas

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***Abstract*—This project explored a deep learning technique to predict capacitive matching elements of a Inverted F Antenna. we came up with a custom Neural Network that takes the S11 values as input and accurately estimated the Cs (Series Capacitor) and Cp (Parallel Capacitor) magnitudes of the gamma matching circuit.**

***Index Terms*—Antenna design, Impedance matching, Inverted F Antenna**

I. Introduction

With wireless communication systems evolving so quickly, there's a growing need for antennas that are not just compact and efficient but also capable of working across a wide range of frequencies. One type that's been getting a lot of attention is the **Inverted F Antenna**. These antennas stand out because they can deliver wideband performance in a relatively small footprint which makes them a great fit for everything from smartphones to satellite systems.

That said, one of the key challenges when designing antennas is getting the impedance matching correct. Why does that matter? Because poor impedance matching can hurt both the efficiency and bandwidth of the antenna. Traditional methods for handling this like manual tweaking or using analytical formulas can be time consuming and computationally expensive, especially when you're dealing with complex, multi-band setups.

An Inverted-F Antenna (IFA) is a type of compact antenna commonly used in wireless communication systems. It features a simple structure with a radiating element resembling the letter ”F” rotated upside down. The antenna is typically mounted on a ground plane, with a feed point at the top of the ”F” shape and a shorting pin connecting the bottom portion to the ground. This design helps achieve a small physical size while maintaining good performance in terms of impedance matching, bandwidth, and radiation characteristics, making it suitable for portable devices like mobile phones and wireless routers. [1]

The gamma matching circuit as shown in Fig. 1. is a handy technique used in antenna design to fix impedance mismatches between an antenna and a standard 50 ohm transmission line. Basically, it uses two capacitors a series capacitor (C) and a parallel capacitor (C) to balance out the complex impedance of the antenna. These components help cancel the unwanted reactive (imaginary) part and adjust the real part to the desired level. According to Ansys HFSS simulations, the imaginary part of the impedance tends to be quite high, so adding capacitors helps bring it down. The series capacitor is connected directly in line with the antenna feed, while the parallel one connects between the feed and ground. This setup allows fine-tuning depending on the frequency. For example, at 1.4 GHz, using C = 0.9 pF and C = 3 pF works well, while at 0.9 GHz, higher values like C = 3 pF and C = 20 pF are more suitable. These values are not random they are carefully calculated based on the antenna's impedance to get the best signal performance.

Matching should be applied for the capacitor values to match at the lowest and highest resonant frequencies of 0.9 and 1.4 GHz, respectively. For resonance at 1.4 GHz, the values of the series (Cs) and parallel (Cp) capacitors should be 0.9 and 3 pF, respectively. For resonance at 0.9 GHz, the respective values should be 3 and 20 pF. These values for the matching circuit were determined by mathematical calculations based on accurate information about the real and imaginary parts of the antenna impedance.

Although it is possible to measure S11 including its real and imaginary parts by using a network analyzer, expensive equipment is required. Instead, we propose a method for determining the matching element values using the S11 magnitude in a Neural Network. As the magnitude does not include phase information, an accurate matching value cannot be determined mathematically. However, through learning, the proposed method determines the matching element values solely from the input impedance magnitude.

The Inverted-F Antenna (IFA) was chosen for its compact and efficient design, making it ideal for space-limited devices like smartphones and routers. Unlike bulkier antennas, IFAs provide good performance and impedance matching in a small footprint. Their simple structure also allows easy integration onto a ground plane. For tuning, we used a gamma matching circuit, which offers a straightforward way to adjust the antenna's frequency response using two capacitors (C_s and C_p). This method is simpler and more adaptable than alternatives like stub matching, making it well-suited for compact, modern wireless systems where size and performance are key.

Machine learning (ML) is starting to make a real impact. Instead of relying solely on trial-and-error or intense mathematical calculations, ML gives us a data-driven way to **optimize antenna parameters more efficiently**. Recent research has shown that techniques like neural networks and regression models can predict and fine-tune these parameters to improve both impedance matching and overall radiation performance [2], [3]. Even more exciting is that ML can help us understand the often complex relationships between an antenna's physical shape and how it performs something that's tough to nail down using traditional approaches.

In this project, we dive into how ML can be used to tackle impedance matching for Inverted F antenna. We introduce a framework that combines simulation data with predictive modeling to streamline the design process. By building on existing work in both antenna design and ML, our goal is to help push forward smarter, faster design strategies for future wireless technologies.

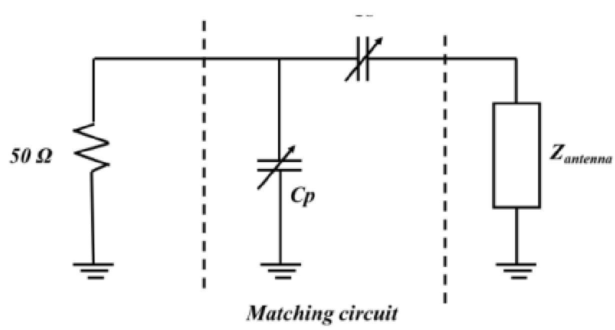

Fig. 1. Gamma Matching Circuit

II. Related Works

Various studies have explored the application of machine learning techniques to optimize impedance matching across a range of antenna and plasma systems, each offering unique methodologies and insights into performance enhancement.

D. Cao et al. focused on improving impedance matching in single-frequency capacitively coupled plasma (CCP) systems, which are critical in semiconductor processing and materials fabrication. Their approach integrates a **genetic algorithm (GA)**—known for its global optimization capabilities—with a **support vector machine (SVM)** model to form a hybrid learning framework. The GA generates optimal parameter sets for system capacitance and resistance, while the SVM predicts the outcome of those sets, allowing rapid convergence to ideal matching conditions. This fusion of heuristic and machine learning methods significantly enhances the system's efficiency and stability in real-world plasma operations, where impedance mismatches can result in energy loss and equipment damage. [4]

Choo et al. applied neural networks to improve impedance matching in a **bent monopole antenna**, which is often used in compact or embedded systems due to its small footprint. They developed a **multilayer perceptron (MLP)** neural network, training it on a dataset derived from extensive electromagnetic simulations. The model learned to map geometric features of the antenna (such as bend angles, lengths, and trace widths) to impedance characteristics, allowing rapid predictions of impedance response for any given antenna configuration. This technique streamlines antenna prototyping by replacing time-consuming simulations with fast, data-driven predictions, thereby accelerating the design cycle and enhancing impedance accuracy. [3]

Hasan et al. proposed an **adaptive impedance matching technique** using a shallow learning model grounded in **ridge regression**, a form of linear regression that includes L2 regularization. Unlike deeper architectures, this method is computationally lightweight yet effective, making it ideal for real-time or resource-constrained applications. The model predicts the optimal values of capacitive elements for tuning circuits, with hyperparameters finely adjusted through **grid search** to achieve robust performance. By addressing issues of multicollinearity and overfitting through ridge regularization, this approach achieves a reliable balance between accuracy and simplicity in antenna impedance matching tasks. [5]

L. F. Ong et al. employed machine learning for **classification tasks** related to **circular patch antennas**, focusing on sorting antennas by their resonance and impedance behaviors. Utilizing an **SVM classifier**, they trained the model on a labeled dataset of antenna responses, enabling the automatic identification of antenna types based on their impedance and resonance signatures. This automation dramatically reduces the manual labor and computational effort typically associated with antenna categorization, paving the way for intelligent antenna design platforms that can quickly adapt designs based on desired electrical characteristics. [6]

S. Jeong et al. developed a **range-adaptive impedance matching system** for **wireless power transfer (WPT)** applications, where maintaining high efficiency over varying distances is a significant challenge. Their solution employs a **feedforward neural network** that dynamically predicts optimal matching parameters based on the real-time distance between transmitting and receiving coils. By continuously adjusting the impedance network, their model maximizes power transfer efficiency and minimizes energy loss, making it especially useful for applications like electric vehicle charging or portable electronic devices where mobility and distance variability are common. [7]

Together, these studies highlight the versatility and effectiveness of machine learning in solving complex impedance matching problems, whether in the realms of antenna design, plasma systems, or wireless power transfer. Each approach tailors its learning model and optimization strategy to the specific domain, demonstrating how AI can unlock new levels of performance and design flexibility in high-frequency systems.

III. Data Acquisition

To enable machine learning based impedance matching Inverted F Antennas, we created a synthetic dataset that mimics how S11 magnitude responses change with different matching circuit configurations. Instead of relying on time-consuming electromagnetic simulations or real-world measurements, we used a mathematical model to simulate the S11 magnitude as it varies with different values of series (C_s) and parallel (C_p) capacitors over a range of frequencies.

We built a grid of possible capacitor combinations, similar to methods used in existing research [2]. We used 13 values for C_s and 29 for C_p, giving us 377 unique combinations. For each of these, we calculated the S11 magnitude at 401 frequency points ranging from 0.8 GHz to 1.5 GHz to capture the resonance behavior accurately.

To simulate realistic S11 responses, we used a Gaussian-like function centered at the resonance frequency, which depends on the selected capacitor values. This approach ensures the data reflects how a real antenna would behave, helping the model learn the relationship between S11 curves and capacitor settings. Finally, we organized the data in a CSV format, with each row representing one configuration and its corresponding S11 values, making it easy to use for training and validating our model.

We went with synthetic data so we could keep things controlled and consistent. It let us tweak capacitor values and S11 responses exactly how we wanted, without having to worry about the messiness and random noise that comes with real-world measurements.

IV. Methodology

The model presented here is a deep neural network designed to predict the two critical components for antenna impedance matching: Cs (series capacitor) and Cp (parallel capacitor), based on input S11 impedance values. The network is structured to consist of several key components, each playing an essential role in the prediction process.

A. Input Block

The Input Block is responsible for taking the raw S11 values as input and processing them through an initial fully connected (dense) layer. This layer helps in transforming the input data into a more useful form for the network to process further. After this, a Layer Normalization step is applied to standardize the data, ensuring it has a mean of zero and a variance of one, which helps in stabilizing the training process. Next, a ReLU activation function is used to introduce non-linearity, allowing the model to learn more complex relationships between the input and the desired output. Finally, a dropout layer is incorporated to reduce the risk of overfitting by randomly setting a fraction of the input units to zero during training, ensuring that the model generalizes better.

B. Residual Blocks

The next part of the network consists of Residual Blocks, a series of layers that help the model to efficiently learn complex patterns within the data. Residual connections (also known as skip connections) allow the model to skip certain layers during training, enabling it to better handle gradient flow and avoid issues like vanishing gradients. These residual connections help the network learn more effectively and stabilize the training process, especially in deeper models where learning can otherwise become unstable.

After the residual blocks, the network is split into two distinct branches. One branch focuses on predicting Cs (the series capacitor), while the other branch focuses on predicting Cp (the parallel capacitor). The Cs branch processes the data further using a few more residual blocks and outputs a refined prediction for the series capacitor. On the other hand, the Cp branch includes additional layers to model the more complex relationships needed for predicting the parallel capacitor. This approach allows both outputs to be handled separately, with their own specific layers dedicated to refining the predictions.

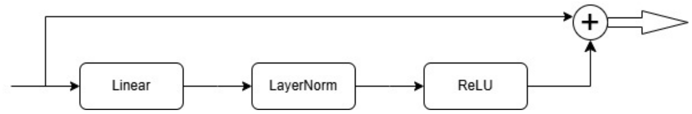

Fig. 2. Residual Block

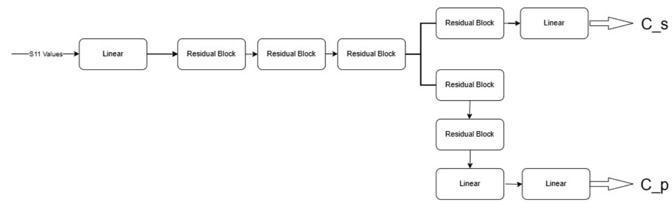

Fig. 3. Model Architecture

Finally, the model uses the Mean Squared Error (MSE) loss function to evaluate how close the predicted values are to the actual values of Cs and Cp. This loss function computes the average squared difference between the predicted values and the actual values, helping the model understand how to adjust during training. The Adam optimizer is then used to update the model's weights during training, ensuring the model learns efficiently and converges to the best possible solution.

This deep learning-based approach allows the model to automatically learn how to adjust the impedance matching circuit based on the input S11 values, optimizing the design of the antenna. By removing the need for manual tuning or complex mathematical calculations, this method significantly streamlines the design process, making it faster and more efficient.

Residual connections were introduced in our architecture to address challenges typically encountered in training deep neural networks, such as vanishing gradients and performance degradation as depth increases. By allowing gradients to flow directly through skip connections, these residual links ensure more stable and efficient learning, particularly when the network becomes deeper. This design choice helps the model retain important features from earlier layers while enabling the deeper layers to learn refinements rather than starting from scratch. Given the non-linear and high-dimensional nature of the mapping between S11 magnitude responses and capacitor values, residual connections enable the network to model complex relationships more effectively without overfitting or encountering convergence issues.

Due to time and tool constraints, we used synthetically generated data with realistic trends to validate our DNN model architecture and training process, following the structure of the original MATLAB-HFSS automation approach as in [2]. The magnitude of input impedance S11 is a scalar value ranging from 0 to 1 over 401 datapoints, corresponding to a frequency range from 0.8 to 1.5 GHz. For the training data, as 13 series capacitors and 29 parallel capacitors were used, 13 × 29 = 377 samples were obtained.

Element	Values (pF)
C_s	0.9, 1.1, 1.3, 1.5, 1.7, 1.9, 2.1, 2.3, 2.5, 2.7, 2.9, 3.1, 3.3
C_p	1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6, 6.5, 7, 7.5, 8, 8.5, 9, 9.5, 10, 10.5, 11, 11.5, 12, 12.5, 13, 13.5, 14, 14.5, 15

Range of Series (C_s) and Parallel (C_p) Capacitor

V. Results

To train and evaluate our model, we began by splitting our dataset of 377 samples into training and testing sets, with a 70:30 ratio. This means that 264 samples were allocated for training the model, while 113 samples were set aside for testing and validation. The training process involved running the model for 100 epochs, with a learning rate of 0.001 to fine-tune the weights during each iteration.

After training, the model achieved an impressive Mean Squared Error (MSE) loss of 0.1331, which indicates a decent fit between the predicted and actual values. To assess the model's performance, we compared the predicted values with the ground truth values for the antenna impedance matching task. This comparison, shown below, highlights the model's ability to accurately predict the required values for impedance

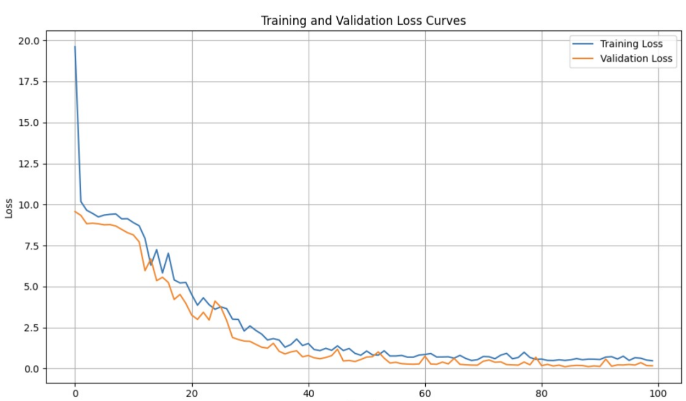

Fig. 4. Loss Curves

The predicted and ground truth values for the antenna impedance matching model are presented below.

S.No	Ground Truth (pF)		Predicted Output (pF)	
	C_s	C_p	C_s	C_p
1	2.30	10	2.31	9.24
2	0.9	7.5	1.24	6.68

VI. Conclusion

In this research, we have demonstrated the application of deep learning techniques for optimizing impedance matching in Inverted F Antennas (IFA). By leveraging a custom-designed neural network, we predicted the key capacitive matching elements, namely the series capacitor (Cs) and parallel capacitor (Cp), based on the S11 impedance values. The model was trained using synthetically generated data that followed realistic trends observed in practical antenna design.

Our approach highlights the potential of machine learning to replace traditional, time-consuming methods for impedance matching, such as manual tuning or using analytical formulas. The deep neural network architecture, particularly with the use of residual blocks and separate branches for Cs and Cp predictions, proved effective in accurately estimating the required capacitive values for optimal impedance matching.

The model achieved a strong performance with a Mean Squared Error (MSE) of 0.1331, indicating a high degree of accuracy in its predictions. The results suggest that this deep learning-based methodology offers a promising direction for streamlining the antenna design process and improving efficiency in both academic research and practical applications.

Future work can extend this approach by incorporating more diverse datasets, including real-world measurements, and exploring the potential for integrating this technique into automated antenna design tools. Additionally, optimizing the model for real-time performance could make it suitable for dynamic adjustments in practical antenna systems, particularly in applications like mobile communication and wireless networks.

Unlike earlier studies that focused on impedance matching using machine learning at lower, megahertz level frequencies and often depended on complex impedance values, our approach stands out by working effectively in the gigahertz range. Instead of needing the full complex impedance, we only use the magnitude of the S parameter as input. This not only makes the process simpler but also ensures that the capacitor values we get for gamma matching are realistic and easy to implement in actual designs.

One of the key limitations of this study is that the model was trained using synthetically generated data. While this data was designed to closely mimic real world conditions, it may not fully capture all the complexities and variations found in actual antenna designs. The synthetic data was intentionally created to resemble real world values, enabling us to explore and understand the model's behavior and performance within a controlled environment. However, since synthetic data doesn't always perfectly match real world scenarios, there is a possibility that the model's performance could be affected by this difference. To enhance the model's robustness and ensure it works effectively in real-world applications, further validation using actual, real-world data would be necessary.

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