Analysis the Impact of Inset Fed Design with Reference Impedance of Rectangular Microstrip Patch Antenna using Neural Network

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***Abstract* -- Research on microstrip antennas is currently growing in prevalence, as their compact design and low cost make them simple to adapt to various needs. The goal of this study is to find out how the inset-fed depth affects the impedance matching of a rectangular microstrip antenna using a simple Rectangular Microstrip Antena (RMSA) design. The main problem encountered is the duration of the simulation with CST which is quite time consuming and the optimization process is still manual, especially for various antenna parameters. To overcome this, the author offers a solution by implementing a Neural Network (NN). The author designs the antenna to operate at a frequency of 2.4 GHz with an FR-4 epoxy substrate and simulates it using CST Suite Studio 2019 software. The research shows that adding an inset fed with a depth of 5 mm results in an impedance value of 49.81 + j3.20 Ω, which is close to the desired impedance. The data from CST are used for NN dataset, the computation process using Neural Network reduces simulation time by 65% faster compared to CST simulation.**

Keywords— Rectangular Microstrip antenna, Inset-fed, CST Suite Studio, Matching Impedance, Neural Network

I. INTRODUCTION

An antenna is a crucial component that facilitates wireless signal transmission. The requirements for antennas in wireless devices include a relatively small size and low production costs. The one commonly used form of microstrip antenna in wireless communication systems is the rectangular one. Microstrip antennas can come in various shapes and dimensions, even when operating at the same frequency [1]. This antenna mounts a thin, conductive, rectangular patch on a ground plane and separates it by a dielectric substrate. The advantages of this antenna include its low profile, simple design, and ease of fabrication using modern printed-circuit technology. However, the main disadvantages of this type of microstrip antenna are low efficiency, poor polarization, and very narrow bandwidth frequency [2,3,5].

Impedance mismatches can happen in microstrip patch antennas because of bad fed positioning, mistakes in fabrication, choosing the wrong substrate, effects from the environment, and resonance that isn't working as well as it should. To address these issues, careful design and fabrication are required, along with accurate calculations of the frequency and appropriate material selection.

The primary goal of using an inset-fed is to precisely control the input impedance at the fed point. By changing the depth of the inset, it will impact on the impedance value that works with the transmission line. This also lowers the Voltage Standing Wave Ratio (VSWR) and keeps the amount of power that is reflected to a minimum. At the edge of the patch, the input impedance of the microstrip antenna is at its maximum value, which is often much greater than 50 Ω. This is because at the edge of the patch, the electric field is strongest, resulting in high impedance. On the other hand, at the center of the patch, the input impedance reaches its minimum value, which is usually close to zero ohms because this position is at the node of the electric field. Thus, the inset depth shifts the fed position from the edge (high impedance) to the center (low impedance), allowing us to match the antenna impedance with the 50 Ω to achieve optimal impedance matching. This results in better impedance matching, reduced reflection loss, and improved antenna efficiency. Properly designed inset-fed antennas can also offer broader bandwidth and enhanced performance in wireless communication applications.

Over the past few decades, a lot of research has been done on neural network engineering, which has applications in a wide range of disciplines, including energy science, psychology, economics, control engineering, automation, aerospace, and health. Developing autonomously learning and evolving computers is the aim of the machine learning field. Using neural networks in a variety of applications across numerous fields, including telecommunications, is extremely appealing because to its high level of accuracy and processing speed.

II. METHODS

The design method has been implemented to maintain minimal return loss at the frequency of 2.4 GHz. The design technique and parameter calculation formulas for the proposed rectangular inset-fed microstrip patch antenna are derived from [1] and subsequently optimized using CST Suite Studio 2019. The dielectric constant of the substrate is not an independent parameter, as it depends on the dielectric material used.

A wearable thin substrate with a dielectric constant of 4.3 and a height of 1.6 mm has been utilized for the proposed antenna. Multiple parameters are required for the desired design; hence, the dielectric constant and substrate thickness are established as constant values to ensure optimal impedance matching the inset fed patch antenna.

After estimating the parameters of the antenna, the structure is modeled and simulated using CST Suite Studio.

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The Figure 1 presents the design of the proposed antenna configuration. Changes in the inset width result in variations in the frequency, whereas alterations in the inset length affect the return loss [4]. The inset fed thickness must exceed 50% of the fed line thickness [6].

The fed position along the rectangular patch influences the input impedance of a microstrip antenna. The impedance at the edges of the patch reaches its maximum value, often exceeding 100 Ω, due to the concentration of the electric field. In contrast, near the center of the patch, the impedance approaches zero, as this region corresponds to the node in the electric field. Characteristic Impedance equation is shown below [1].

$$Zc = \frac{120\pi}{\sqrt{\varepsilon reff\left[\frac{W0}{h}+1.393+0.667\ln\left(\frac{W0}{h}+1.444\right)\right]}}, \frac{W0}{h} > 1 \qquad (1)$$

W_0 represents the patch width, h is the thickness of the substrate and $\varepsilon reff$ is the effective permittivity of the dielectric substrate.

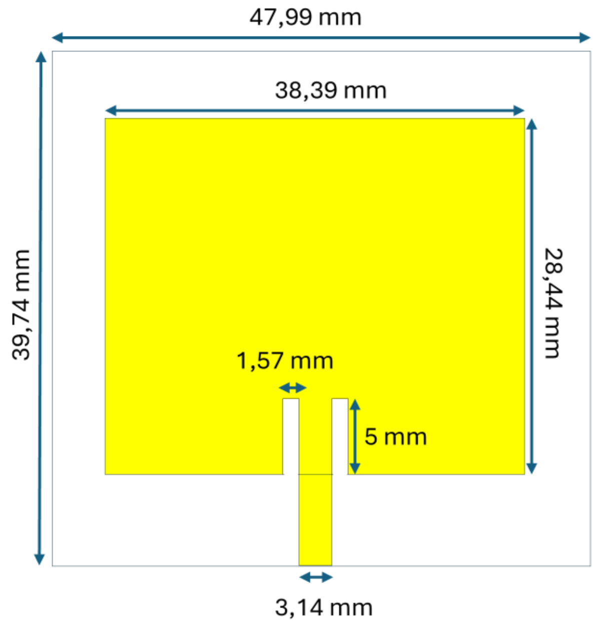

Figure 1. Design RMSA with Inset-fed

Certain parameters have been tuned in CST Suite Studio to achieve the desired frequency, and the final optimized parameters are presented in Table 1.

Table 1. Parameter RMSA

Parameter	Value
Patch Dimensions: Width of the patch (W_p) Length of the patch (L_p)	 38.39 mm 28.44 mm
Ground plane dimensions: Width of the Ground plane (W_g) Length of the ground plane (L_g)	 47.99 mm 39.74 mm
Fed line dimensions: Width of the 50Ω microstrip line (W_0)	 3.14 mm
Inset fed dimensions:	
Width of the Inset Length of the inset (y_0) Characteristic impedance of the microstrip line (Zc)	1.57 mm 5 mm 50Ω

This study employs a Neural Network to forecast the actual impedance value utilizing a dataset derived from CST application simulations, with the primary variable being the feedline size (Wf). The dataset is created with Wf variables ranging from 0.1 to 15 mm, allocated 80% for the training set and 20% for the test set[7]. The Neural Network model employs a regression methodology, utilizing inset feed depth and operating frequency as inputs, while producing the real impedance value as the output. The model architecture comprises two hidden layers containing 64 and 32 neurons, respectively. The training procedure employed the Mean Squared Error (MSE) as the loss function and utilized the Adam Optimizer for optimization, with a learning rate ranging from 0.01 to 0.1. Subsequent to the training procedure, the model undergoes evaluation using the test set to assess its predictive performance on novel data, informed by the generated loss value.

III. Results and Discussion

This section discusses the CST simulation's results, including return loss, impedance, and neural network prediction results.

A. *Return Loss*

The Figure 2 illustrates the simulation's return loss of the antenna at a frequency point of 2.4324 GHz, with an inset fed depth of 5 mm. The return loss value stands at -28,261 dB, while the good standard return loss is smaller than -10 dB. A lower return loss (larger negative value) signifies that the antenna effectively absorbs most of the sent power, with only a small portion reflecting back.

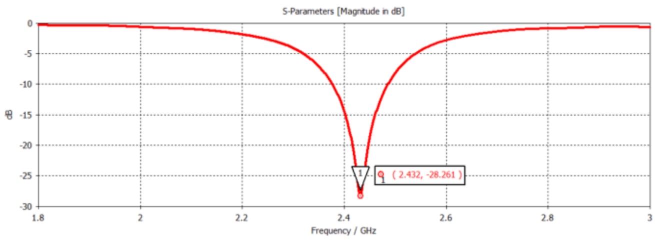

Figure 2. Return Loss of single microstrip antenna

B. *Impedance*

At a frequency of 2.4324 GHz, the antenna impedance is approximately **49.81 + j3.20 Ω** Ω, as illustrated in Figure 3. The real component of the impedance measures 50.28 Ω, which is in close proximity to the standard characteristic impedance value of 50 Ω. This suggests that the antenna exhibits effective impedance matching, with a minimal and negligible inductive reaction present. This enhances the efficiency of signal transmission at the specified frequency.

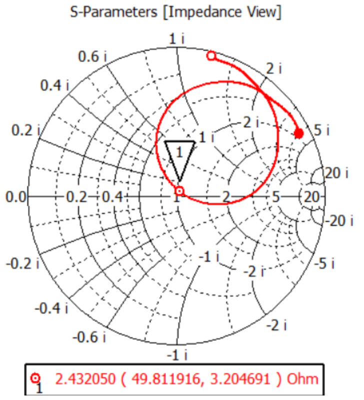

Figure 3. Impedance View of single microstrip antenna

C. Dataset Split Ratio

The optimal results are achieved with an 80% training and 20% testing split, resulting in a training loss of 4.9076 and a test loss of 4.0092, as illustrated in Table 2. This signifies that the model effectively identifies patterns while maintaining its generalization capability. As the proportion of the training dataset increases, the test loss typically decreases to a specific threshold; however, if the training component becomes excessively large (e.g., 90% training, 10% testing), performance during re-testing declines due to an insufficient number of samples for evaluation.

Table 2 Data train/test split ratio

Training Set	Test Set	Training Loss	Test Loss
10	90	3.9614	200.049
20	80	5.1538	14.0574
30	70	3.3659	16.9827
40	60	5.1166	14.3651
50	50	17.4356	22.8164
60	40	3.2685	19.3632
70	30	3.3212	23.5121
80	**20**	**4.9076**	**4.0092**
90	10	7.424	11.9243

D. Neural Network Performance

This research used a neural network to predict impedance from given frequency and inset fed depth. The training outcomes showed that a learning rate of 0.1 with 5000 epochs yielded the lowest mean squared error (MSE) value. Table 3 presents a comparison of learning rate values with respect to MSE, demonstrating a substantial drop in MSE, which signifies excellent model learning. Figure 4 shows a graph that compares the predicted results to the test data from a depth of 0 to 14 mm and a learning rate of 0.1. The graph shows that the predicted results and the original data are very closely related.

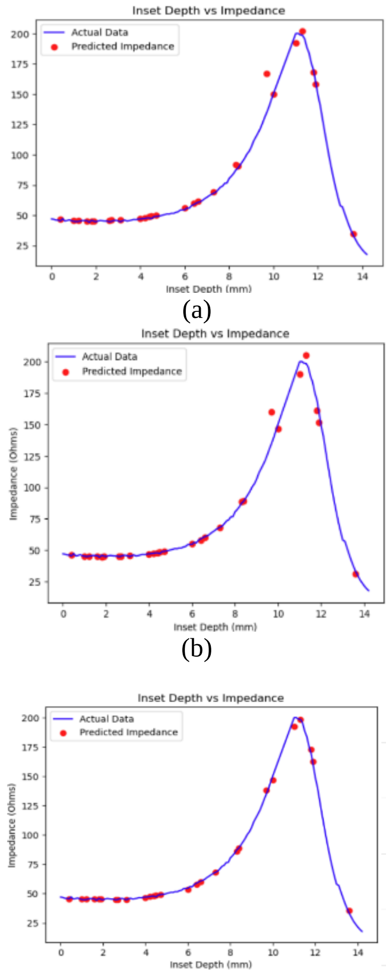

Figure 4. Inset Depth vs. Impedance
(a)Learning rate:0,01 (b)Learning rate:0,05 (c)Learning rate:0,1

Table 3 Learning Rate and Losses of Neural Network

Learning Rate	Epoch	MSE (Loss)
0.01	5000	42.8198
0.05	5000	33.8205
0.1	**5000**	**4.0092**

Higher learning rates result in faster training of the model; however, they may lead to sub-optimal solutions [8]. Lower learning rates require an extended duration for model training; however, they can lead to improved optimal solutions. The author adjusted the learning rate from a lower value to a higher value and determined that the optimal learning rate for the dataset is 0.1.

E. Computational Performance Comparison

Table 3 presents a comparative analysis of the simulation results obtained from CST and the predictions generated by the Neural Network, both evaluated at identical frequency and inset fed depth parameters. The CST results produced a Z_0 value of 50.279 Ω, whereas the Neural Network prediction resulted in a Z_0 value of 50.0812 Ω. The error deviation between the CST results and the NN results is quantified as 0.1978, representing a percentage difference of 0.39%. The low deviation value signifies that the neural network prediction results closely align with the simulation results.

Table 4 Result Comparison CST & Neural Network

Parameter	Result at 5mm inset-fed	
	Simulation	Neural Network
Frequency (GHz)	2,432	2,432
Z_0 (Ω)	50,279	50,0812

Table 4 presents a comparative analysis of the computational performance achieved through the utilization of CST versus Neural Network. The computation time for the simulation conducted with CST was 32 seconds. The computation time for the Neural Network (NN) under cold start conditions is 11.19 seconds. In contrast, when the NN is retrained, or in a hot start scenario, the computation time reduces to 6.49 seconds. During computation with the pre-trained model, the time required is 0.0020 seconds. The implementation of Neural Networks has the potential to decrease computation time by a range of 65% (cold start) to 99.99% (trained model).

Table 5. CST vs. NN Performance Comparison

Device: Notebook i5-1135G7 2.4GHz 8GB RAM	
Software	**Duration (second)**
CST Simulation	32
Calculate + Training NN cold start	11,19
Calculate + Training NN hot start	6,49
Calculate with NN Trained model	0.0020

IV. Conclusion

This research concludes that the antenna design, optimized through CST calculations, successfully produced an antenna with a working frequency of 2.4 GHz and an impedance of 50 ohms. There was an error rate of 0.39% when using a neural network to get an inset-fed value that met the working frequency and impedance requirements. Using a pre-trained neural network model cut the computation time by 99.99%. Computational using Neural networks can cut quite a lot of time compared to carrying out simulations manually using CST, but CST is still needed as a medium for collecting datasets.

This computational process is quite simple because it only has 2 inputs and 1 output so the number of layers used is also adjusted to needs. In the future, it can be developed using more layers and databases to produce more accurate predictions, especially for antennas that have more complex parameters.

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