Surrogate Model Assisted Design of CSRR Structure using Genetic Algorithm for Microstrip Antenna Application

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Abstract. *Soft-computational approaches have enabled quicker and more efficient means for antenna design. In the present work, a genetic algorithm (GA) based method is reported for the design of complementary split-ring resonator (CSRR) structures for antenna design. A multi-objective optimization problem is formulated to design the antenna. The cost function of the optimization problem is calculated from a surrogate model of the CSRR structure. The surrogate model is created first using an analytical model of the CSRR structure and then using an artificial neural network (ANN). A comparative study of the result shows that the ANN-based surrogate model is accurate as compared to the surrogate model using an analytical approach. An antenna with an integrated filter is fabricated using a CSRR structure designed applying the proposed method. The performance of the antenna is validated from the simulation and measurement results.*

Keywords

Artificial neural network, surrogate model, complementary split-ring resonator, microstrip antenna, genetic algorithm, soft-computational design

1. Introduction

Multi-objective antenna design is a complex process which involves optimization of the physical dimensions of an antenna to meet multiple desired goals. It is indispensable for a designer to identify the tradeoff between various design goals for this purpose. Soft-computational multi-objective simulations are essential for identifying and optimizing these tradeoffs [1]. In antenna design problems, the three most commonly used soft-computational algorithms are: genetic algorithm (GA) [2], [3], particle swarm optimization (PSO) [4], [5], and differential evolution (DE) [6], [7]. The complementary split-ring resonator (CSRR) structure is a metamaterial structure reported by Falcone et al. as a band-stop filtering element in a microstrip line [8]. This structure yields an effective negative value of the permittivity, ε of a material at a narrow band near its resonant frequency. Owing to the negative value of permittivity, a microstrip line loaded with a CSRR structure at its ground plane eliminates a narrow band near its resonant frequency. Later, the CSRR structure became popular in the design of microstrip antennas. CSRR structure is reported in the use of dual-band [9–11] and UWB antennas with integrated filter [12], [13]. The CSRR structure is also reported in an antenna for a superheterodyne receiver which has an inherent capability to eliminate two possible image frequencies [14].

A full-wave EM simulation involves a huge set of computations and hence such simulations are often time-consuming. This significantly limits the efficiency of evolutionary approaches for the design of antennas. A solution to this problem is the introduction of a surrogate model. In [15], a surrogate model assisted evolutionary algorithm (SAEA) is proposed. Surrogate modeling methods include Gaussian process or Kriging, response surface methods, artificial neural networks (ANN), support vector machines and radial basis function models. In [16], a surrogate model-assisted optimization technique for metamaterial devices is proposed. Surrogate models are explored in [17] for constrained, multi-objective antenna design problems.

A surrogate model is a low-fidelity model which is cheap in terms of computational time and resources. Surrogate models are of two types – physics-based surrogate model and approximation-based surrogate model [18]. In a physics-based surrogate model, an analytical expression is derived from the known operating principle of the structure. An approximation-based surrogate model is an approximation of a high fidelity full-wave model which is created by training a soft-computational tool such as an artificial neural network (ANN) with results obtained from the high-fidelity model.

In this paper, a GA-based approach is used to optimize the dimensions of a CSRR structure for the designing of a microstrip antenna with an integrated filter. The CSRR structure has two resonant frequencies where it acts as a notch filtering element owing to the negative value of its

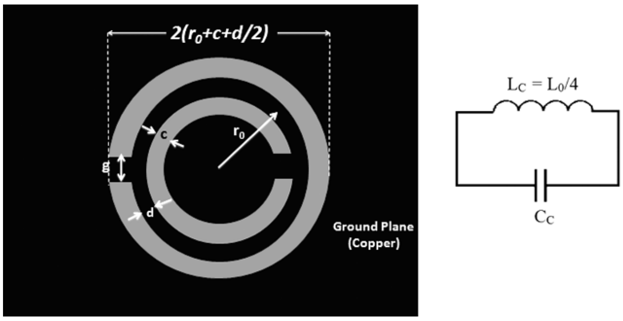


Fig. 1. (a) The topology of the CSRR structure. (b) The LC equivalent circuit of the CSRR structure.

effective permittivity (ε_r) [14]. The two resonant frequencies depend upon the dimensions of the CSRR structure. Thus, the design of a CSRR structure may be formulated as a multi-objective optimization problem where the input parameters are the physical dimensions of the CSRR structure as shown in Fig. 1 and the output parameters are the two resonant frequencies of the CSRR structure.

The arrangement of the remaining sections of the paper is as follows. The construction of the physics-based surrogate model and the approximation-based surrogate model are discussed in Sec. 2. The construction of the CSRR structure using GA and the approximation-based surrogate model is discussed in Sec. 3. In Sec. 4, the performance of the two surrogate models is analyzed from experimental results. The paper is concluded in Sec. 5.

2. Formulation of the Surrogate Model of the CSRR Structure

In this section, two surrogate models of the CSRR structure are presented. An existing LC-tank circuit analytical model of the CSRR structure is used as the physics-based surrogate model. An ANN is trained with results obtained from full-wave simulations to construct the approximation-based surrogate model.

2.1 The Physics-Based Surrogate Model of the CSRR Structure

The CSRR structure yields negative value of the permittivity (ε) at a narrow band near its resonant frequency. This behavior enables the use of CSRR structure as filtering elements at its resonant frequency. The CSRR structure is modeled as an LC tank circuit as shown in Fig. 1. The values of L_0 and C_C are computed analytically from the physical dimensions of the CSRR structure. The expression for computation of C_C and L_0 are available in [19] and [20] respectively. These expressions are shown in (1) and (2):

$$C_C = \frac{\pi^3 \varepsilon_0}{c^2}\int_0^\infty \frac{[bB(kb)-aB(ka)]^2}{k^2}\left[0.5\left(1+\frac{1+\frac{\varepsilon}{\varepsilon_0}\tanh(kh)}{1+\frac{\varepsilon_0}{\varepsilon}\tanh(kh)}\right)\right]\mathrm{d}k, \quad (1)$$

$$L_0 = \frac{\pi^3 \mu_0}{4c^2}\int_0^\infty \frac{[bB(kb)-aB(ka)]^2}{k^2}\mathrm{d}k \,. \quad (2)$$

Here, a and b are given by (3) and (4) respectively:

$$a = r_0 - \frac{c}{2}, \quad (3)$$

$$b = c + a. \quad (4)$$

$B(x)$ is given by (5)

$$B(x) = S_0(x)J_1(x) - S_1(x)J_0(x). \quad (5)$$

$S_n(x)$ is the n^{th} order Struve function of x and $J_n(x)$ is the n^{th} order Bessel function of x.

The value of L_C can be calculated from L_0 using (6)

$$L_C = \frac{L_0}{4}. \quad (6)$$

Once, L_C and C_C are calculated, the resonant frequency of the LC-tank circuit can be determined using (7)

$$f_r = \frac{1}{2\pi\sqrt{L_C C_C}}. \quad (7)$$

This set of expressions can be used as a surrogate model to compute the resonant frequency of the CSRR structure.

In practice, a physics-based surrogate model requires further fine-tuning of its parameters which is usually carried out with the help of a high-fidelity model. This increases the accuracy of the low fidelity model.

2.2 The ANN Based Surrogate Model

In order to construct the approximation-based surrogate model of the CSRR structure, the first two resonant frequencies of a CSRR structure are obtained experimentally using Ansys HFSS® for several combinations of the geometrical parameters of the CSRR structure. The experimental method used for this measurement is illustrated in [11]. The topology of the neural network used is shown in Fig. 2.

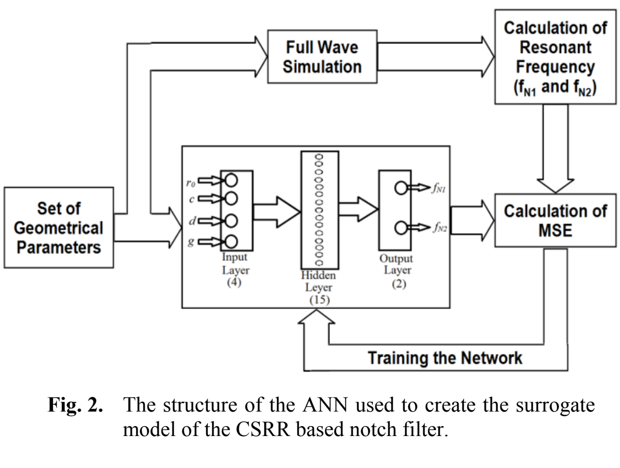
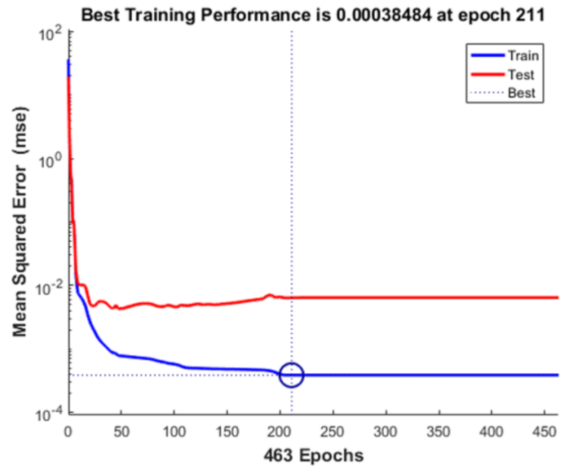
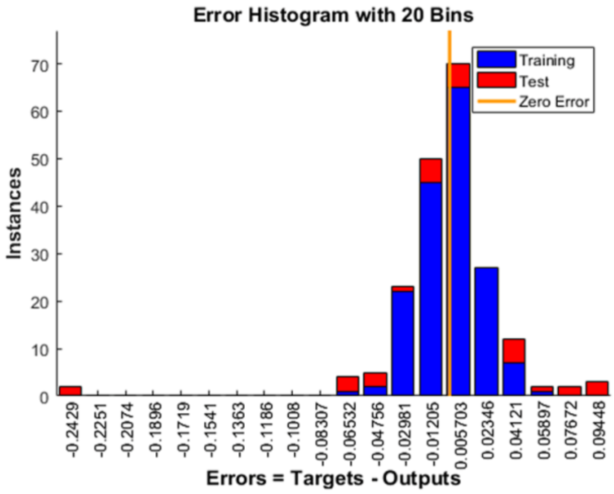


Fig. 2. The structure of the ANN used to create the surrogate model of the CSRR based notch filter.



(a)



(b)

Fig. 3. (a) Training performance curve. (b) Error histogram of the trained network for the design of CSRR based notch filter.

Bayesian regularization method is used for training the ANN. Bayesian regularized networks require less data for cross-validation and they are robust against overfitting and overtraining [21]. From experimental observations also it is verified that Bayesian regularization as a training function yields better performance of the surrogate model. The number of hidden layers is tuned by repetitive training to maximize the accuracy of the network.

The four nodes at the input layer of the ANN correspond to the four geometrical parameters of the CSRR structure, namely, r_0, c, d, and g. The two output neurons at the output layer correspond to the fundamental resonant frequency of the CSRR structure, f_0, and its first harmonic, f_1. The network is trained with a large set of experimental results which comprises of 150 simulation results. 50 more simulation results are used for testing the trained network. The training performance plot and the error histogram of the network are shown in Fig. 3(a) and (b), respectively. The training is performed many times by adjusting the size of the hidden layer. The training time was observed to be in a range of 40–100 seconds. Finally, the number of neurons at the hidden layer is set to 15, as it provided the minimum error.

3. The GA Based Design of the CSRR Structure

GA is used for optimizing the geometrical parameters of a structure to obtain desired performance. The first step of the process is to initialize the population of geometrical parameters of the structure. The performance parameters of the structure (f_0, and f_1) corresponding to a given set of geometrical parameters (r_0, c, d, and g) are estimated from the surrogate model. The cost function taken here is the mean square error (MSE) between the obtained performance parameters of the structure and the desired performance parameters of the structure.

From the discussion in Sec. 2, it is evident that the physics-based surrogate model of the CSRR structure derived from the analytical expressions can estimate only the fundamental resonant frequency of the CSRR structure. The ANN-based surrogate model, on the other hand, is trained for two resonant frequencies of the structure. Thus, for the multi-objective design problem of the CSRR structure, the ANN-based surrogate model is more suitable. Therefore, the ANN-based surrogate model is used with the genetic algorithm to find the performance parameters of the structure from its geometrical parameters.

Genetic algorithm is a direct search algorithm which converges to a minimum value of the cost function. Until any

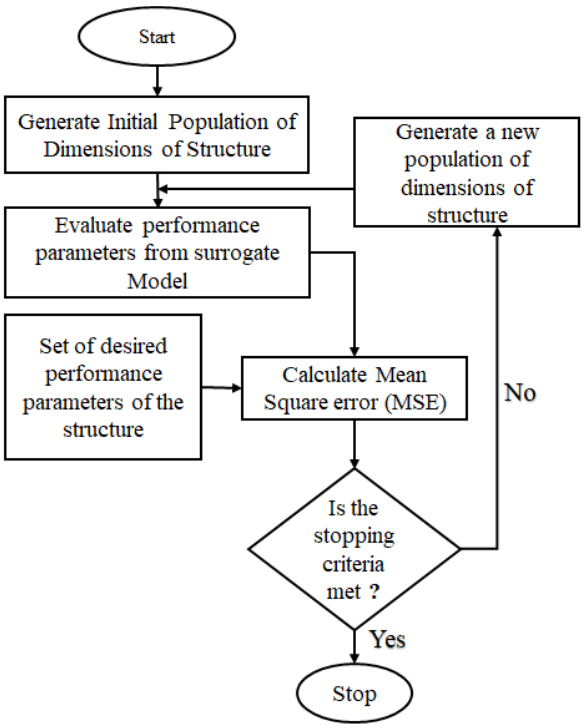


Fig. 4. Optimization algorithm of CSRR structure using Genetic Algorithm.

of the stopping criteria is met, it iteratively generates a population of the geometrical parameters. Figure 4 shows the flow diagram of the process using a genetic algorithm. Here, the rules of crossover and mutation of the genetic algorithm are used for creating a new population. The use of the surrogate model significantly reduces the computation time as it does not involve actual full-wave simulation of the structure.

4. Experimental Results and Discussions

In this section, the two surrogate models are compared based on speed and accuracy. The resonant frequency of the CSRR structure for a set of dimensions is calculated using the analytical model and the ANN model. The accuracy is validated from full-wave analysis using Ansys HFSS®. Finally, a CSRR structure is designed for a specific antenna application. The designed antenna is tested with a rectangular patch antenna with integrated notch filters. The performance of the antenna is evaluated from simulation and measurement results.

4.1 Analysis of Computation Time

The comparative analysis of the time is shown in Tab. 1. The two surrogate models are implemented using Matlab® on a Windows 8.1 operating system on a computer with Intel® i3 processor and 8 GB RAM. From the table, it is observed that both the analytical model and the ANN-based model are faster than the full-wave analysis performed using Ansys HFSS®. However, the ANN model is much faster as compared to the analytical model. The involvement of the computationally intensive Struve function and Bessel function makes the analytical surrogate model slow. It is relevant to mention here that almost 2 days were required to simulate 200 randomly picked sets of dimensions of the CSRR structure to train the network. The whole process was performed by writing a python script which tuned the HFSS project variables corresponding to the physical dimensions of the CSRR structure, performed simulations, and stored the results in CSV files. This time is not considered in Tab. 1 as training is a one-time process and once the network is trained, no more simulation is needed.

From Tab. 1, it is observed that the computation time of the analytical model is many times more compared to that of the analytical model. It is because of the fact that the analytical model requires numerical computation of integrals in infinite limit. Standard library routines available in Matlab® are used for this computation.

4.2 Comparison of the Performance

The two models are compared in terms of their accuracy. The analytical model of the CSRR structure can estimate only the fundamental resonant frequency of the CSRR structure. The ANN model, on the other hand, is trained to estimate two separate resonant frequencies. Table 2 shows the comparison of the fundamental resonant frequency of the CSRR structure obtained from the analytical model and that by the full-wave simulation using Ansys HFSS®. The comparison of the first and the second resonant frequencies of the CSRR structure as obtained from the ANN model with the simulation result are shown in Tab. 3. In Tab. 2 and Tab. 3, only the serial number experiments are given. The physical dimensions (r_0, c, d, and g) are the same as Tab. 1.

Serial No.	CSRR dimensions (mm)				Computation time (in seconds)		
	r_0	c	d	g	HFSS	Analytical Model	ANN Model
1	3.50	0.50	2.00	1.00	665	4.78	0.144
2	3.25	0.25	1.00	2.00	692	8.86	0.095
3	4.00	0.50	1.00	1.50	458	8.79	0.281
4	3.75	0.25	1.00	1.00	694	6.43	0.023
5	3.75	0.75	1.00	1.00	610	8.00	0.011
6	3.50	1.25	1.00	1.50	449	4.71	0.011
7	3.50	2.00	1.00	2.00	503	6.11	0.010
8	3.00	2.00	1.00	1.5	584	8.58	0.011
9	4.00	2.00	0.50	1.50	708	7.96	0.010
10	5.00	0.50	1.00	1.00	710	8.80	0.010

Tab. 1. Comparative analysis of the computation time of the analytical model and the ANN-based model of the CSRR structure.

Serial No.	Fundamental resonant frequency (GHz)		Percentage Error (%)
	Analytical Model	HFSS	
1	3.13	3.10	0.93
2	3.54	3.50	1.10
3	2.72	2.70	0.73
4	3.10	3.10	0.05
5	2.76	2.90	4.84
6	2.66	2.90	8.42
7	2.42	2.90	16.60
8	2.74	3.30	17.06
9	2.18	2.50	12.79
10	2.04	2.10	2.89

Tab. 2. Comparison of the fundamental resonant frequencies obtained from the analytical model and full-wave simulation using HFSS.

Serial No.	Fundamental resonant frequency			Second resonant frequency		
	ANN Model (GHz)	HFSS(GHz)	Percentage Error (%)	ANN Model (GHz)	HFSS(GHz)	Percentage Error (%)
1	3.07	3.10	1.12	7.82	7.00	11.77
2	3.47	3.50	0.92	6.92	6.30	9.84
3	2.86	2.70	5.87	5.82	5.20	11.97
4	3.12	3.10	0.51	5.78	5.40	7.04
5	2.99	2.90	3.00	6.47	5.80	11.61
6	3.05	2.90	5.01	7.44	6.80	9.41
7	2.86	2.90	1.27	7.78	7.30	6.61
8	3.21	3.30	2.76	9.49	9.20	3.10
9	2.58	2.50	3.40	5.75	5.90	2.47
10	2.15	2.10	2.57	4.17	4.00	4.21

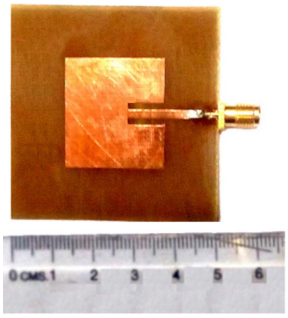
Tab. 3. Comparison of the first and the second resonant frequencies obtained from ANN model and full-wave simulation using HFSS.

From Tab. 2 and Tab. 3 it is observed that the minimum error generated is less in case of the analytical model. However, the ANN model is more consistent. The maximum error is higher in case of the analytical model. Moreover, the ANN model can be trained to estimate two resonant frequencies of the CSRR structure which is not possible in the analytical model.

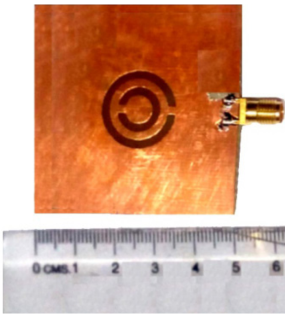
The performance of the analytical model can be improved further by fine-tuning some of its parameters with the help of data obtained from the HFSS simulation. However, since the model does not predict the second resonant frequency of the CSRR structure, the model will require some major changes.

4.3 Design of a CSRR Based Antenna using Genetic Algorithm

Due to the negative value of permittivity, the CSRR structures help in designing antennas with integrated filters. An antenna with a CSRR structure to suppress two possible image frequencies in a superheterodyne receiver was proposed in [14]. A GA based optimization technique is validated by designing an antenna with CSRR at its ground plane. Here, the physical dimensions of the CSRR structure are optimized such that the two resonance frequencies are obtained at 1.4 GHz and 3.6 GHz. From the above discussion, it is observed that the analytical model of the CSRR structure cannot predict the second resonant frequency of the CSRR structure. Further, the ANN-based model is faster and less prone to errors. Therefore, the ANN-based surrogate model is used in this problem to create the antenna with an integrated filter. The dimensions of the CSRR structure to obtain notch at 1.4 GHz and 3.6 GHz is obtained from the genetic algorithm as shown in Tab. 4. The patch antenna is designed to obtain resonance at 2.4 GHz. The length of the patch (L) is 24.2 mm, the width of the patch (W) is 26 mm and the dielectric substrate used is FR4 epoxy which has a relative permittivity (ε_r) of 4.4.



(a)



(b)

Fig. 5. (a) Top view of the fabricated antenna and (b) CSRR at its ground plane.

Geometrical Parameter of the Antenna	Values in (mm)
Average radius of the CSRR structure, r_0	6.8064
Width of the rings, c	1.6126
Gap between the rings, d	2.5157
Split of the rings, g	1.5781
Length of the patch, L	24.2
Width of the patch, W	26
Width of the feed line	2
Length of the insets	11.7
Width of the insets	1

Tab. 4. Geometrical parameters of the antenna obtained using GA.

The fabricated antenna is shown in Fig. 5. The S_{11} parameter of the antenna is measured using a Rohde and Schwarz® ZNB20 VNA. The far-field radiation pattern is measured using the VNA along with a standard horn antenna and with software-controlled automatic turn-table. The simulated and the measured frequency response of the S_{11} parameter are shown in Fig. 6. It is observed that the resonant frequency obtained from simulation is 2.4 GHz whereas the measured resonant frequency is 2.36 GHz. The two notched frequencies are obtained at 1.35 GHz and 3.65 GHz for the fabricated antenna due to possible imperfections in the fabrication process. It is observed from Fig. 6 that the return loss parameters indicate resonance at 2.4 GHz and near the two-notch frequencies. The actual notch filtering behavior of the antenna is understood from the frequency response of the far-field gain of the antenna along the direction of the major lobe.

The simulated frequency versus gain plot is shown in Fig. 7. It is observed that the gain is the maximum at the resonant frequency of the antenna which is found to be 2.4 GHz. At the notch frequencies1.4 GHz and 3.6 GHz, on the other hand, the gain shows significant attenuation. This is due to the negative permittivity of the material as a result of resonance of the CSRR. The normalized radiation pattern of the simulated and fabricated antenna at three different frequencies is shown in Fig. 8. From the radiation pattern plot, it can be further validated that with the optimized dimension of CSRR structure the designed antenna shows significant attenuation at its notched frequencies. Table 5 shows a comparative analysis of the simulated and meas-

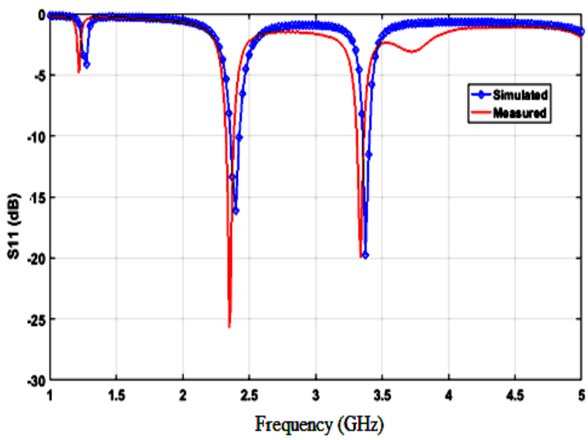


Fig. 6. The simulated and measured frequency response of far-filed radiation pattern of the antenna.

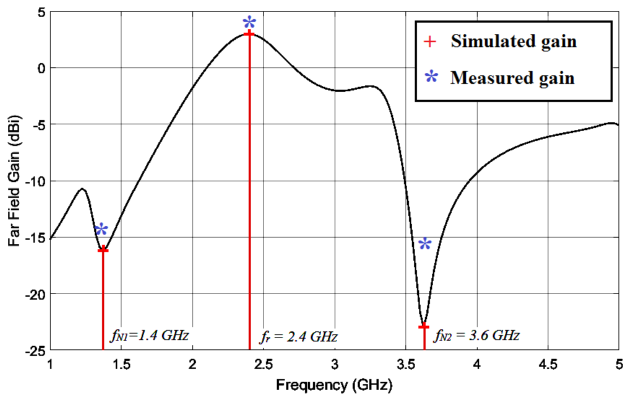


Fig. 7. Simulated frequency vs gain plot of the proposed antenna along the direction of the main lobe indicating two notched frequency.

Frequency (GHz)	Peak gain of the main lobe (dB)	
	Simulated	Measured
1.4	–16.3	–13.9
2.4	2.1	3.2
3.6	–23.5	–15.8

Tab. 5. Comparison of measured and simulated gains of the antenna at the operating frequency and the notch frequencies.

ured gains of the antenna at the operating frequency and at the notch frequencies.

4.4 Analysis of the Fabrication Tolerance

The GA based design of the CSRR structure provides a dimension of the CSRR structure with a precision of 0.0001 mm. However, it is practically not feasible to build an antenna with such a high precision. Therefore, it is necessary to provide an analysis of the fabrication tolerance of the antenna. Figure 9 and Figure 10 compares the simulated frequency responses of the S_{11} parameter and the far field gain for a precision of 0.0001 mm and a precision of 0.1 mm. From these results, it is evident that the proposed antenna has a high fabrication tolerance.

From Fig. 9 and Fig. 10 it can be seen that for the resonant frequency of the antenna at 2.4 GHz, there is no

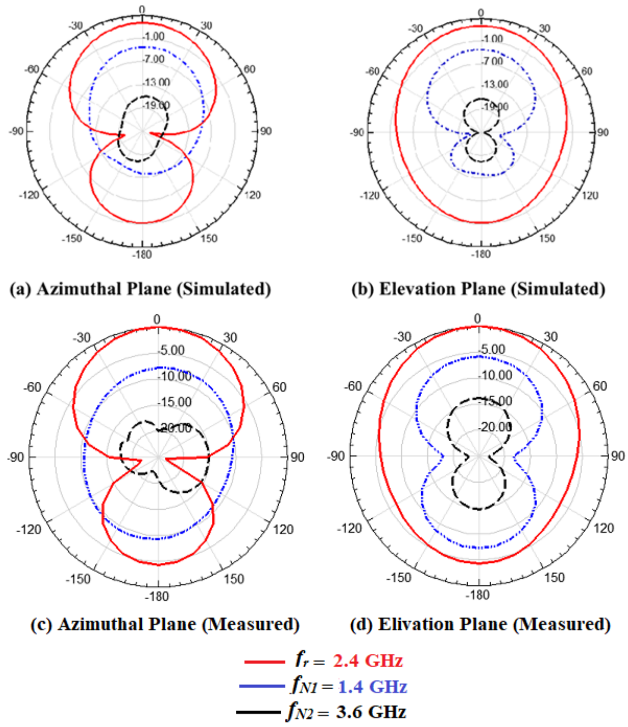


Fig. 8. Simulated and measured far field radiation pattern of the proposed antenna at the three frequencies in azimuthal plane and elevation plane.

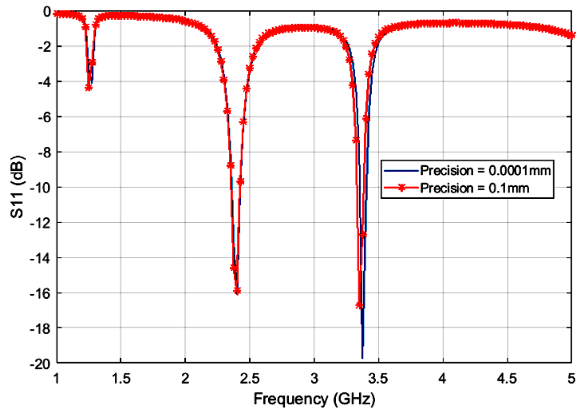


Fig. 9. Comparison of the S11 parameter plots of the designed antenna for a fabrication precision of 0.0001 mm and 0.1 mm.

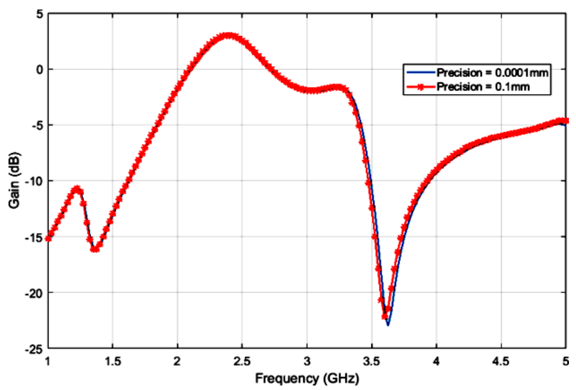


Fig. 10. Comparison of the far-field gain plots of the designed antenna for a fabrication precision of 0.0001 mm and 0.1 mm.

change in the performance of the antenna when precision is reduced to 0.1 mm. There is a negligibly small shift in the upper notch band of the antenna.

4.5 Discussion

It can be inferred that the ANN-based surrogate model is more accurate and faster compared to the traditional analytical model of the CSRR structure. The ANN-based model can be trained with two resonant frequencies of the structure. The only limitation of the ANN-based model is the requirement of a large dataset for training the network. The performance of the network must be maximized by selecting the proper training function and the size of the hidden layer. The suitability of the proposed method is validated by designing a CSRR structure for an antenna with an integrated dual-band notch filter.

5. Conclusion

A surrogate model-assisted soft-computational design method for the CSRR structure is proposed in this paper. The surrogate model is created using a conventional analytical model and an ANN-based model. It is found that the ANN-based model is more persistent and less prone to errors. Further, the ANN-based model required lesser computation time and it can be trained to estimate more than one resonant frequency. The proposed method is validated by comparing with results obtained from full-wave simulation using Ansys HFSS®.

The proposed method is further validated by designing a CSRR structure for a microstrip antenna for a superheterodyne receiver which resonates at 2.4 GHz and has the inherent capacity to notch two possible image frequencies at 1.4 GHz and 3.6 GHz. The performance of the CSRR loaded antenna is evaluated from simulation and measurement results.

Acknowledgments

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