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Research Article

Artificial Neural Network Based Microstrip Reflectarray Unit Element Design

Mehmet BEREKET[1*], Aysu BELEN[2], Mehmet Ali BELEN[3]

[1*] İskenderun Technical University, Faculty of Engineering and Natural Sciences, Electrical Electronic Engineering, Hatay, Turkey, mehmet.bereket@iste.edu.tr
[2]İskenderun Technical University, Iskenderun Vocational School of Higher Education, Turkey, aysu.belen@iste.edu.tr
[3] İskenderun Technical University, Faculty of Engineering and Natural Sciences, Electrical Electronic Engineering, Hatay, Turkey, mali.belen@iste.edu.tr

Abstract

Microstrip reflectarray antennas (RAs) are designs that can achieve equivalent performance of parabolic reflector, but with simple and light electromagnetic and mechanical structures. The challenging problem in design of RA is the fast and accurate modelling of the unit element for the array optimization. 3D EM simulators are computationally very ineffective, thus in this study artificial neural network based unit element modelling for characterization of the reflection phase of the unit element in terms of its geometry, and operation frequency is studied. For this mean, a Malta Cross shaped design for X-band applications is taken into the consideration using Multilayer Perceptron (MLP) neural network trained the 3D CST microwave Studio simulator data. Validation of the MLP model is also worked out successfully with the 3D CST data. By this mean, a continuous function is obtained for the reflection phase of the unit element with respect to the variation of geometrical design parameters and operation frequency had been achieved which can be used for a design optimization process fast as analytical approach design while being accurate as 3D EM simulator tools.

Keywords: Artificial neural network; multi-layer perceptron; reflectarray antenna; X-band.

1. Introduction

Reflective array antennas (RAs) have the advantages of both conventional parabolic reflectors and phased array antennas without using complex and lossy transmission line feed networks [1-6]. Microstrip Reflective Array antennas (MRAs) have many advantages that can be categorized both electromagnetically and mechanically. Electromagnetically, its advantages are high gain, low side lobes, and beam directing ability. When we look at the mechanical aspect, it has the advantages of being a light and planar design and easy production. Since the phase distribution of reflective array antennas is performed with a large number of unit cells, a great deal of flexibility is provided. By optimizing the unit cell geometry and their arrangement, beam forming can be achieved at a low cost. Generating a pencil beam in a specific (θ^o, φ^o) direction can be achieved by designing a phase compensation proportional to the distance from the feed horn antenna phase center so that each RAs element reflects the incoming wave independently, as is well known from classical array theory. Therefore, phase tuning is a very important process in reflector array design. In the phase tuning method, patches of variable size are preferred because simplicity is desired. To meet requirements such as the ability to reflect a shaped patch or multiple patches, or also to improve frequency behavior and bandwidth, it is necessary to use advanced element configurations with several degrees of freedom. The need to manage different parameters and provide phase compensation, increase the bandwidth, and meet the requirements such as high gain opposite to each other makes the necessary multi-objective design optimization a challenging problem.

In order to have a computationally efficient optimization process, a fast and accurate unit element model is needed to act as a continuous function of the unit element's input variables. Then, using this fast and accurate model, it is possible to perform a computationally efficient optimization process. One of the commonly used solutions for achieving computationally efficient optimization process is the usage of data driven surrogate models [7-12]. These numerical models are efficient solution to create a mapping between input and outputs of the selected design problems. Some of the recently published applications of data driven surrogate modelling technique for design optimization of microwave designs can be named as application of machine learning for optimal selection of antenna for wireless communication [7], low cost modelling of antenna designs [8-9], and novel deep learning and ensemble based surrogate models for modelling of different types of microwave stages [10-12].

Here, it is aimed to create a fast and accurate model for the characterization of the reflection angle of the microstrip unit element in terms of geometric parameters and frequency by using artificial intelligence. For this purpose, it is aimed to model the Malta Cross-shaped patch in the X-band by using a Multilayer Perceptron (MLP)

*Corresponding author e-mail address: mehmet.bereket@iste.edu.tr

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neural network trained with 3D electromagnetic modeling program data. The validation of the MLP model has also been successfully done with the 3D CST data design of the Artificial Neural Network. First, a Malta Cross shaped unit cell with variable parameters given in Figure 1-2 is investigated. In order to create the ANN model, a series of training and test sets were created using the parametric values given in Table 1. The proposed ANN-based cell model was used together with the MLP black box model using simulated reflection phase values obtained from the 3D simulator, the flow chart of the proposed design methodology had been presented in Fig. 1.

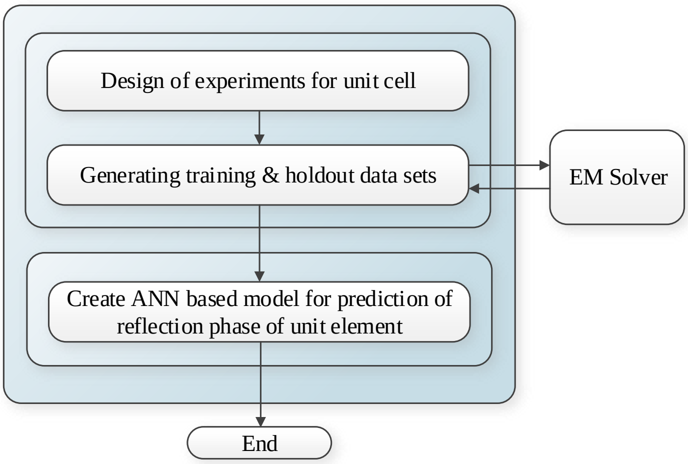


Figure 1. *Flow chart of the proposed design methodology.*

2. Unit Cell Design

In this study, a 3D simulation-based model of the Malta Cross unit cell [13] in Figure 2 is presented with its variables to design the unit cell RAs. In Table 1, the limits of the design variables to be used in the creation of the training and test data sets are given, and the variation of the shape within the given limits is given in Figure 3. For the sake of simplicity, the height values of the microstrip dielectric material are taken as 1.52 mm and 6.15 mm, respectively (compatible with Rogers 3006 material).

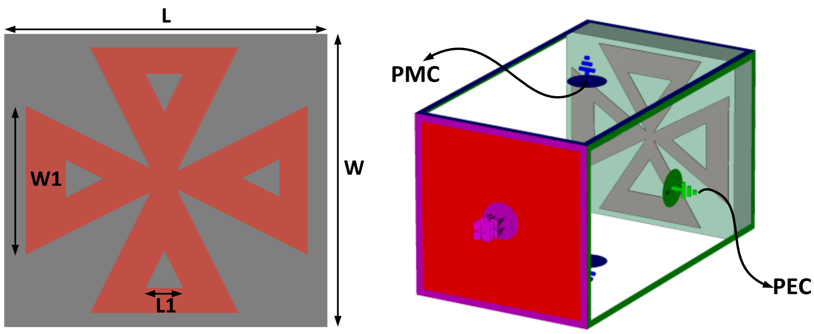


Figure 2. *3D view of the Malta Cross unit cell.*

Table 1. *Range of Unit Cell Parameters (Here W=L=15 mm).*

Parameters	Range	Step Range
W1	2-7	0.1
L1	0.2-2	0.1
f (GHz)	8-12	0.5
Data Set	8721	

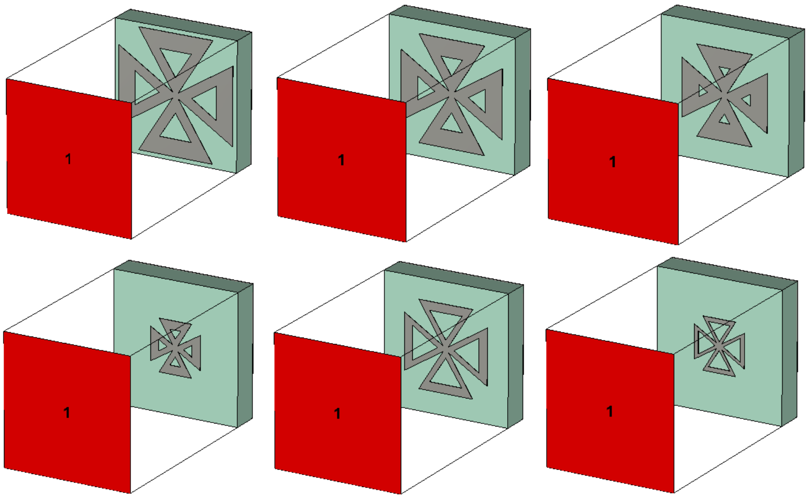


Figure 3. *The view of the unit cell in different parametric values.*

3. Unit Cell Modeling with ANN

Data from the parametric scan of the unit cell will be split into training and test data for the construction of the ANN-based model of the Malta Cross RAs element. For this process, the data generated using the k-fold validation method were divided into 2 equal parts (K=2). At this stage, a Multilayer Perceptron Network (MLP) was used to generate the ANN-based unit element model of the Malta Cross-shaped RAs using the training and test data. The network design parameters of the MLP given in Figure 4 are discussed as in Table 2.

Table 2. *User Defined Parameters of MLP Network.*

Number of Neurons in the Hidden Layer (N)	5, 10, 15
Activation Function	Tangent Sigmoid
Training Algorithm	Levenberg–Marquardt
Maximum epoch	2x(number of samples)

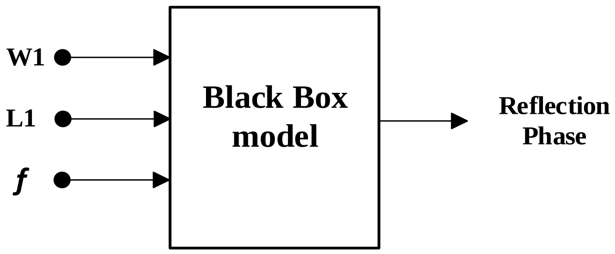


Figure 4. *Black Box model of the RAs element.*

The performance of the MLP network will be evaluated by the commonly used Mean Absolute Error (MAE) for 10 independent runs.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|T_i - P_i| \quad (1)$$

For better performance evaluation of the ANN model, the training and test datasets were made using cross-fold validation with k=2. The results obtained are presented in Table 3-5.

Table 3. *Performance Result of a Single Layer ANN Model with 5 Neurons.*

Performance		MAE
K-Fold 1	Best	26.3
	Worst	115.6
	Average	75.8
K-Fold 2	Best	36.3
	Worst	94.2
	Average	55.1
Average Performance MAE [degree]	65.5	

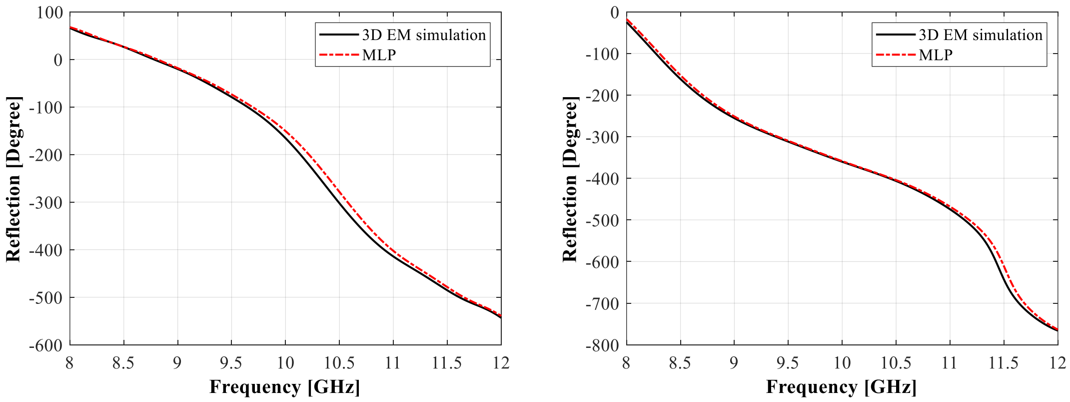
Table 4. *Performance Results of 5-10 Neuron ANN Model.*

Performance		MAE
K-Fold 1	Best	14.7
	Worst	60.3
	Average	33.7
K-Fold 2	Best	18.4
	Worst	55.2
	Average	29.7
Average Performance MAE [degree]	31.7	

Table 5. *Performance Results of ANN Model with 5-10-15 Neurons.*

Performance		MAE
K-Fold 1	Best	4.1
	Worst	9.8
	Average	5.4
K-Fold 2	Best	4.8
	Worst	10.7
	Average	6.1
Average Performance MAE [degree]	5.8	

As seen in Table 3-5, the number of neurons in the hidden layer and the number of layers are the most important design parameters in the ANN model. The optimal number of neurons was determined as N=5-10-15 and the number of hidden layers was determined as 3. In Fig. 5, the simulated results of the ANN model for selected cases are presented. As it can be seen over the required operation range the ANN model achieves a very good agreement with the targeted data. Furthermore, a performance comparison of the proposed unit element with counterpart designs in literature is presented in Table 6. As it can be seen form the table, the proposed design has a very good performance with in means of size, operation band range and range of reflection manipulation compared to the state of the art designs in literature.



(a) (b)

Figure 5. *Performance results for randomly selected designs (a) W1= 0.5 [mm], L1= 0.2 [mm], (b) W1= 0.7 [mm], L1= 2.0 [mm].*

Table 6. *Table of comparison of unit element with counterpart designs in literature*.

	Frequency [GHz]	Phase Range [Degree]	Size [mm]	Material
This study	8-12	360	15x15	FR4
[14]	8-12	203	---	
[15]	9.1-12	420	17x17	Arlon AD300
[16]	8-12	400	15x15	PLA

4. Conclusion

In future studies, it is aimed to use these ANN-based models and optimization algorithms in X-band large-scale reflective array antenna design. As can be seen from the simulation results, the proposed ANN-based model of Malta Cross-shaped microstrip patch RA unit cell has high accuracy with 3D simulation results. Thus, the proposed methodology can be used for design and optimization of a large scale RA design for X band applications.

Declaration of Interest

The authors declare that there is no conflict of interest.

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