Full-Wave Simulation-Based Phasing Characteristics of Microstrip Patches for Reflectarray Optimization with Neural Network

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***Abstract*—Microstrip reflectarray antennas (RAs) are able to provide equivalent performance of a traditional parabolic reflector, but with simple and light electromagnetic and mechanical structures; this can be achieved by an effective control of the phase response of each microstrip element on the reflecting surface. Thus the main problem is the fast and accurate modelling of the unit microstrip patch to be used in the array optimization. Since using simulators in the optimization procedure is computationally very ineffective, herein artificial intelligence is used as a rapid and accurate tool for characterization of the reflection angle of the microstrip unit element in terms of its geometry, substrate parameters and frequency. For this purpose, modelling of Omega shaped patch within the X-band is considered 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. Thus a continuous function is obtained for the reflection angle in the geometry, substrate and frequency domain of the microstrip patch unit element that ensures the reflectarray optimization procedure as fast as using the analytical functions and as accurate as the 3D simulators. In the paper, full-wave simulation- based MLP modelling of the omega shaped microstrip patch is given in details.**

Keywords—Artificial Neural Network, X- Band, Multi-Layer Perceptron, Omega patch

I. INTRODUCTION

Reflectarray antennas (RA) have the advantage of combining the both traditional parabolic reflector and phased array antennas without using complex and lossy transmission line feed networks [1–4]. Microstrip Reflectarray's (MRA's) have many advantages that can be categorized into both electromagnetically and mechanical aspects. Electromagnetics aspect of this antenna type is that, MRA has a high gain value, low side-lobes, ability for beam steering. As for the mechanical aspect, MRA is a light weighted design and easy to fabricate.

Forming a pencil beam in a specified (θ°, φ°) direction can be achieved by designing each RA element to reflect the incident wave independently with a phase compensation proportional to the distance from the phase center of the feed-horn as is well-known from the classical array theory. Thus, "Phasing" is very important process in designing reflectarray. In phasing method, variable size patches is preferable due to simplicity. In order to satisfy requirements as the capability to radiate a shaped beam or multibeams, or also to enhance the frequency behavior and bandwidth, it is necessary to uses advanced element configurations, showing several degrees of freedom. The management of different parameters and the need of satisfying requirements such as providing phase compensation, enhancement of bandwidth, high gain that could be also in opposite each other make necessary multi-objective design optimization a challenging problem. On the other hand, the optimization process requires a large number of cost function evaluation using the 3D simulation model that mathematically described the problem to be optimized which is usually is computationally expensive and slow.

Therefore in order to have a computationally efficient optimization process, a fast and accurate model of the unit elements reflection phase is needed, to act as a continuous function of the input variables of the unit element. Then by using this fast and accurate model, it is possible to perform a computationally efficient optimization process.

Herein artificial intelligence is used as a rapid and accurate tool for characterization of the reflection angle of the microstrip unit element in terms of its geometry, substrate parameters and frequency. For this purpose, modelling of Omega shaped patch within the X-band is considered 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 design of Artificial Neural Network Firstly, an Omega shaped unit cell is studied with its variables parameters given in Figs. 1-2. A series of simulation are done for the given parametric values in Table 1 in order to create training and test data set for ANN model using 3D simulator CST. The proposed ANN based cell model is utilized with MLP black box model using simulated reflection phase values obtained from 3D

Bu çalışma ASYU-2017 Konferansında sunulmuş ve sadece özet olarak
Bildiri Özetleri Kitabı (ISBN: 978-605-84722-8-0)'nda yayımlanmıştır.

simulator. The proposed ANN based model is resulted a sufficient accuracy for the fast designing a RA with high realized gain and low side-lobe level within the enhanced operation bandwidth.

II. DEFINITION OMEGA RA ELEMENT

Herein, the Omega symbol, which is one of the popular symbols that is used in many fields, is used as the model for designing a unit cell element for RA designs. Omega letter is the 24th and last letter of the Greek alphabet. It has a value of 800 in the Greek numeric system. As the last letter of the Greek alphabet, Omega is often used to denote the last, the end, or the ultimate limit of a set [7].

In this work, in order to design a unit cell RA, a popular symbol Omega letter from the Greek alphabet is chosen. In Fig. 1, 3D simulation- based model of the Omega unit cell is presented alongside of its variables. The variables of the design are, the Radius of the inner circle R, width of the ring K, and gap between the ends of ring's sides, that in this work is taken equal to G. In Table 1, the limits of variables to be used for generating the training and test data sets are given, the variation of the shape within the given limits is given in Fig. 2 for some cases. For simplicity, the height and dielectric constant of the microstrip material are taken 1.52mm and 6.15 (Rogers 3006 [8]) dielectric material, respectively.

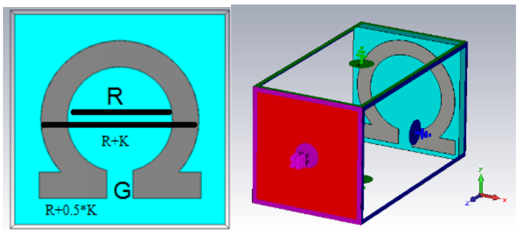


Fig. 1. (a)Schematic, (b) 3D view of the Omega unit cell

TABLE I
RANGE OF THE OMEGA UNIT CELL'S PARAMETERS

Parameter	Range	Step Size
R	0.5-1.1	0.1
K	0.1-0.9	0.1
f (GHz)	8-12	0.5
Data Size	567	

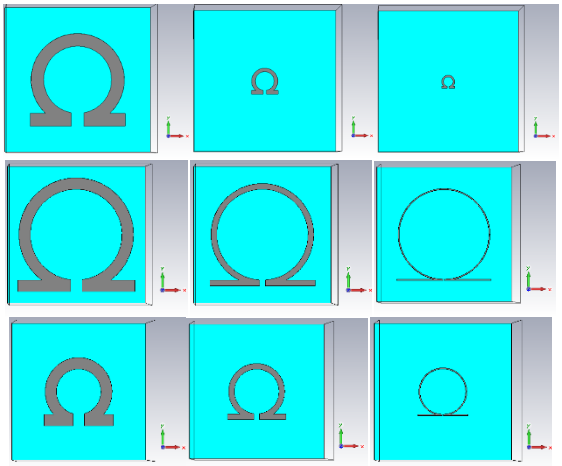


Fig. 2. View of the Sigma unit cell in different parametric values.

III. FULL-WAVE SIMULATION-BASED ANN MODELLING OF THE OMEGADEFINITION OMEGA RA ELEMENT

The obtained data from parameter sweep in CST studio in the last section is going to be separated into training and test data for creating the ANN based model of Omega RA element. The data in table I, is used to create the training and test data sets, given in table II, for 2 different cases to study the sensitivity of the model according to the parameters. All the data in Table II had been shared publicly in [9] for all who would like to make contributions in this field.

TABLE II
DATA SET FOR MODELLING OF OMEGA UNIT CELL WITH ANN

Case	Parameter	Training	Test
1	R	0.5:0.1:1.1	
	K	0.1:0.2:0.9	0.2:0.2:0.8
	f (GHz)	8:0.5:12	
Data Size		315	252
2	R	0.5:0.2:1.1	0.6:0.2:1
	K	0.1:0.1:0.9	
	f (GHz)	8:0.5:12	
Data Size		324	243
3	Randomly Shuffled	284	283

IV. VALIIDATION

In this section the training and test data given in Table II, is given to Multi-Layer Perceptron (MLP) Networks for modelling an ANN based unit element model of Omega shape RA, Fig. 3. The design parameters of the MLP network are taken as follows:

TABLE III
USER DEFINED PARAMETERS OF THE MLP NETWORK

Number of neurons in hidden layer (N)	5, 10, 15, 20
Activation Function	Tangent Sigmoid
Training Algorithm	Levenberg–Marquardt
Max epoch	2x(Train data size)

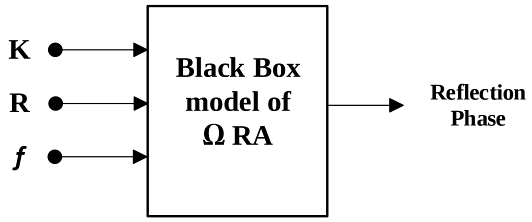


Fig. 3. Black Box model of the Omega RA element

The performance of the MLP network would be judged by the commonly used error metrics Mean Absolute Error (MAE) and Maximum Error (MXE) for 10 runs.

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

$$MXE = \max\left(\left|T_i - P_i\right|\right) \qquad (2)$$

For a better performance evaluation of the ANN model a cross fold validation with k=2 is done by using train and test data sets. The following results in Tables IV-VIII are belong to the ANN models trained with data in Table 2.

TABLE IV
PERFORMANCE RESULT OF ANN MODEL WITH 5 NEURONS (N=5) FOR CASE 1 DATA

Performance		MAE	MXE
Cross-Fold 1	Best	0.11	1.67
	Worst	55.25	141.49
	Mean	32.54	85.99
Cross-Fold 2	Best	0.24	12.05
	Worst	57.87	176.2
	Mean	33.18	113.46

TABLE V
PERFORMANCE RESULT OF ANN MODEL WITH 10 NEURONS (N=10) FOR CASE 1 DATA

Performance		MAE	MXE
Cross-Fold 1	Best	0.04	1.00
	Worst	54.48	141.63
	Mean	11.21	30.98
Cross-Fold 2	Best	0.09	2.80
	Worst	42.54	156.36
	Mean	12.31	60.63

TABLE VI
PERFORMANCE RESULT OF ANN MODEL WITH 15 NEURONS (N=15) FOR CASE 1 DATA

Performance		MAE	MXE
Cross-Fold 1	Best	0.04	1.26
	Worst	0.30	2.17
	Mean	0.17	2.13
Cross-Fold 2	Best	0.06	3.80
	Worst	0.38	13.78
	Mean	0.21	10.17

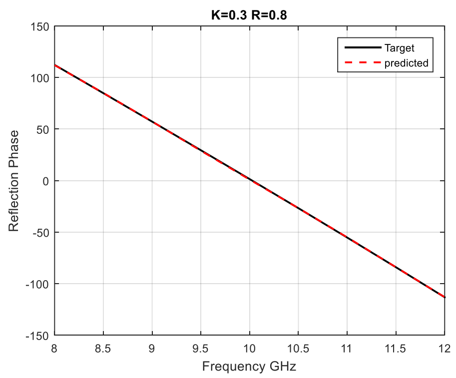
TABLE VII
PERFORMANCE RESULT OF ANN MODEL WITH 20 NEURONS (N=20) FOR CASE 2 DATA

Performance		MAE	MXE
Cross-Fold 1	Best	0.04	1.06
	Worst	0.27	1.85
	Mean	0.15	2.08
Cross-Fold 2	Best	0.05	3.65
	Worst	0.25	12.06
	Mean	0.17	9.31

TABLE V III
PERFORMANCE RESULT OF ANN MODEL WITH 15 NEURONS (N=15) FOR CASE 3 DATA

Performance		MAE	MXE
Cross-Fold 1	Best	0.12	13.74
	Worst	0.25	23.10
	Mean	0.19	20.21
Cross-Fold 2	Best	0.04	0.81
	Worst	0.32	3.122
	Mean	0.15	2.910

As it seen from tables IV-VIII, number of neurons in hidden layer is the most important design parameter in ANN model. The optimal neuron number found to be N=15, since the performance of the network with 20 neurons is almost same. The performance of the Case 3 with best results are given in the next figures for some test cases.



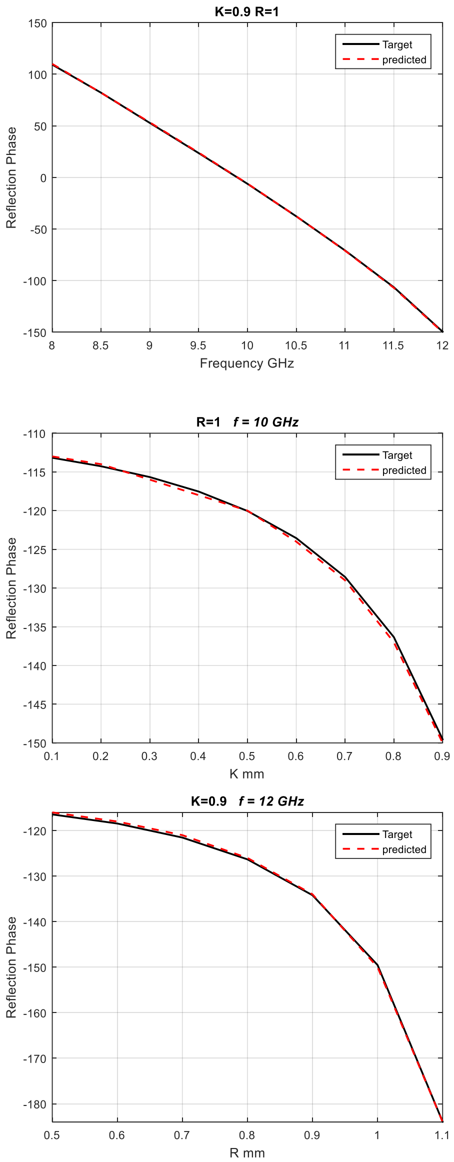


Fig 4. The performance of the Case 3 for some test cases

V. Conclusion

As it seen from simulation results, the proposed ANN based model of the Omega shaped microstrip patch RA unit cell has a high accuracy rate with 3D simulation results and is sufficient to be used as an unit element in design optimization process of a large scale RA design. In future works, it is aimed to use this ANN based model and optimization algorithms for designing an X band large scaled reflect array antenna designs.

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