Development of Knowledge Based Response Correction for a Reconfigurable N-Shaped Microstrip Antenna Design

Ashrf Aoad, Murat Simsek, Zafer Aydin
Department of Electrical and Electronics Engineering, Bahcesehir University, Istanbul, Turkey
Department of Astronautics Engineering, Istanbul Technical University, Istanbul, Turkey
Department of Computer Engineering, Abdullah Gul University, Kayseri, Turkey

***Abstract*—This study presents the use of prior knowledge of inverse artificial neural network (ANN) to model and optimize a reconfigurable N-shaped microstrip antenna. Three accurate prior knowledge inverse ANNs with large amount training data are proposed where the frequency information is incorporated into the structure of ANN. The complexity of the input/output relationship is reduced by using prior knowledge. Three separate methods of incorporating knowledge in the second step of the training process with a multilayer perceptron (MLP) in the first step are demonstrated and their results are compared to EM simulation.**

Keywords—artificial neural networks; reconfigurable microstrip antenna; prior knowledge input

I. Introduction

With the fast development of wireless communication, especially in radar systems, MIMO techniques, and portable computers [1]. The reconfigurable antennas are gaining a great attention. Through change the structure of reconfigurable antennas different characteristics (resonant frequency bands, radiation patterns, directivity, etc.) can be obtained [2]. In addition, they are a light weight, a small dimension, easily fabricated, low price and profile compared to traditional microstrip antennas [3]. In this application, only ON-ON state of the PIN diode is studied [1], which the operating range of the frequency is between 2-6 GHz.

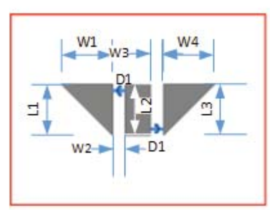
ANN models provide a general structure for modelling non-linear relationships between multiple outputs and inputs. They also much faster than EM models. Therefore, ANNs are considered as an optimization method for antenna design [1], microwave circuits, statistical design and signal integrity analysis [4].

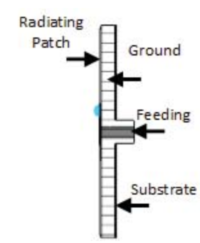
This paper reports some of the growing needs in the continuing application of ANNs in reconfigurable antenna designs. ANNs depend on sufficient training data for modelling and optimizing the results of any microwave application, which is their accuracy also depends on the data presented during the training process. In this application, training data is generated by CST-EM simulator.

In this study, EM-ANN inverse model is proposed using MLP in the first step to model and optimize the geometrical dimensions of the reconfigurable antenna. Another approach is to add prior knowledge into neural networks in the second step to optimize or correct the response that obtained from first step. Finally, the obtained from second step will be designed by EM-simulator.

II. Reconfigurable antenna design

The studied antenna reports as a novel reconfigurable N-shaped microstrip patch antenna (RNSMPA). This RNSMPA consists of three layers and feeding system at the center of the middle patch. The radiating conductors (first layer) consist of two mirrored triangles with dimensions of 0.8 cm for each parameter of L_1,L_2, L_3, W_1 and W_4. They are modeled on FR-4 substrate board (second layer) with a thickness of 0.2 cm and a relative permittivity of 4.3. The ground plane (third layer) is printed on the back side of the substrate. The unfilled space (W_2 and W_3) between the triangles and the middle microstrip is 0.2 cm includes two PIN diodes (D_1 and D_2). The PIN diodes positioned in the upper of the left and the lower of the right sides of the triangles to distribute the current paths on the microstrips depending on its bias state as shown in Figure 1. To realize the ON-ON state two resistors are used of the PIN diodes [5]. Each resistor has a resistance value of 5 Ohms. For simplicity, the series inductor and parallel capacitor of the lumped elements are neglected in the equivalent circuit model [6] [7].





(a) (b)

Figure 1 Reconfigurable antenna (a) Top view and (b) side view

III. Proposed knowledge based response correction methods

The proposed knowledge based response correction (KBRC) inverse model consists of two steps in the neural network area then followed by EM simulator to redesign the output of KBRC for obtaining the correct response or optimized results (closer or better than the fine model) of the RNSMPA. Thus, the relationship between the inputs of Y and the outputs of X is multidimensional and nonlinear [4]. Input for the EM- KBRC inverse models is only frequency sample points (f_f), while outputs are the desired geometrical dimensions of the reconfigurable antenna. The training data obtained from EM-simulator was 312500 samples. This large amount of training data reduced to be 3125 samples only. The reduction procedure depends on the selection of resonant frequency samples which are located between 1-10 GHz. The frequency sample points are 100 which are considered the input of the studied models and the outputs is 5 parameters which are considered the geometrical dimensions of the reconfigurable antenna. In the models testing stage, three testing data sets are selected. The first two testing data sets selected inside training data while the third is selected outside the training data which are used to test the accuracy of the models for interpolation [4] and extrapolation [8].

A. *Multilayer Perceptron (MLP) at the first step*

MLP (without any knowledge based) consists of three perceptron layers lined as an input layer, one or more hidden layers and finally an output layer [1] and is located in the first step of EM- KBRC inverse model, corresponding to model Y and X variables respectively. The function of the input and the output vectors can be presented as $X = f(Y)$. In this study, the input parameter is $Y_f = [f]^T$ (f presents 100 frequency samples of S-parameters) and the predicted output is $X_c = [L_1, L_2, L_3, W_1, W_4]^T$.

B. *Source Difference Method (SD) at the Second Step*

The idea of SD [8] is in combining two training data sets to be the target of the network. These data sets are the EM simulation outputs of $X_f = [L_1, L_2, L_3, W_1, W_4]^T$ which represents the fine data and the output response of MLP (X_c) obtained from the first step. Thus, the input parameter of the SD (hatched MLP box) is only the frequency points $Y_f = [f]^T$, the predicted output $X_{SD} = X_C + X_{MLP}$, while the target is $\Delta X_{SD} = X_f - X_C$ as shown in Figure 2.

The function of the input and the output of the redesign case of EM-simulation is presented as

$$Y_{f-SD} = f_{EM}(X_{SD}) \tag{1}$$

where Y_{f-SD} is the optimum resonant frequency (f_{opt}) that is obtained by the redesign of the predicted output of the second step (X_{SD}). e_{SD} is the error measure computes the absolute difference between f_{opt} and Y_f which can be calculated by

$$e_{SD} = \left| f_{opt} - Y_f \right| \tag{2}$$

Equations (1) and (2) are same as a general principle in the next methods.

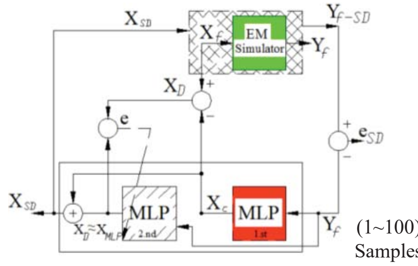


Figure 2 Two steps of EM- KBRC inverse model for SD

C. *Prior Knowledge Input Method (PKI) at the Second Step*

In this method [8], the output response of MLP (X_C) is used as input to PKI (hatched MLP box), in addition to the original input of Y_f. The target output is the fine output (X_f). Therefore, the input/output mapping is between the output response of MLP (X_c) and (Y_f). Thus, the input parameter for PKI is $Y_{PKI} = [\,Y_f, X_C\,]^T$ as shown in Figure 3.

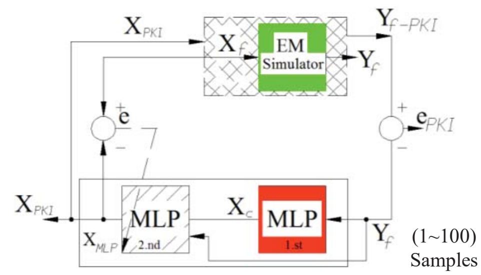


Figure 3 Two steps of EM- KBRC inverse model for PKI

D. *Prior knowledge input with difference*

PKID was proposed in [1] [8]. It exploits the advantages of two knowledge based methods explained above (PKI and SD). The prior knowledge obtained from the output response of MLP (X_C) is utilized with the input of the fine model (Y_f) to be the input of PKID (hatched MLP box). Therefore, the input parameter is $Y_{PKID} = [Y_f, X_C]^T$, while the target is $\Delta X_{PKID} = X_f - X_C$.

IV. TRAINING AND TESTING OF INVERSE ANN MODEL

At first, there are two data sets simulated: 1) Training data set, 2) interpolation and extrapolation testing data sets. The number of hidden layers is two for all models. However, the number of neurons is (60-40) for MLP and knowledge based neural networks (KBNNs). ANN inverse models are trained by using Levenberg-Marguardt algorithm, with tangent-sigmoid transfer functions (TFs) in the hidden layers and a purely linear function in the output layer [9]. The training of the model is achieved by setting the learning rate (η) to 0.1 for MLP and 0.05 for KBNNs, the performance goal to 0.000001 for MLP and KBNNs and momentum coefficient (μ) to 0.02 for MLP and 0.1 for others. The regularization coefficient of the network is chosen as 0.2.

V. RESULTS AND DISCUSSION

The neural network models are repeatedly trained 50 times and the geometrical dimensions of the RNSMPA are computed on the test sets. The accuracy of the models are presented by the optimum resonant frequency and return loss of the S-parameter curves which are the results of the re-simulating the geometrical parameters that obtained by KBRC inverse models for interpolation and extrapolation.

TABLE 1 A COMPARISON BETWEEN THE RESULTS OBTAINED BY ANN INVERSE MODELS AND FINE MODEL FOR INTERPOLATION AND EXRAPOLATION TESTING DATA SETS (1.ST AND 2.ND ARE INTERPOLATION. 3.D IS EXTRAPOLATION)

Frequency (GHz)	Return loss (dB)				
	Fine	***MLP***	***SD***	***PKI***	***PKID***
f_{opt_1}=2.54	-34.67	-15.25	-19.45	-25.61	-17.06
f_{opt_2}=4.45	-26.47	-23.15	-23.98	-25.82	-24.03
f_{opt_3}=5.36	-50.23	-31.31	-34.24	-25.41	-62.77

Table 1 shows the optimum frequencies and their return losses that obtained by redesigning the physical parameters obtained by ANN inverse models, by EM simulator to be compared to the fine results as shown in Figure 4, Figure 5 and Figure 6. Each method has various values for each input variable, where every method operates successfully at a same resonant frequency band. It is important to notice that MLP response is obtained by first step of the EM- KBRC inverse models is not corrected yet. However, SD, PKID and PKI models in the second step correct the response outputted by MLP in the first step. Either exact or closer to the fine curves with different values for return loss for SD, PKID and PKI are noticed. Moreover, Figure 4, 5 and 6 show that the bandwidth is around 0.36 GHz, 0.77 GHz and 1.22 GHz respectively, for all models at a target of return loss of $\boldsymbol{S_{11} \leq -10}$ dB.

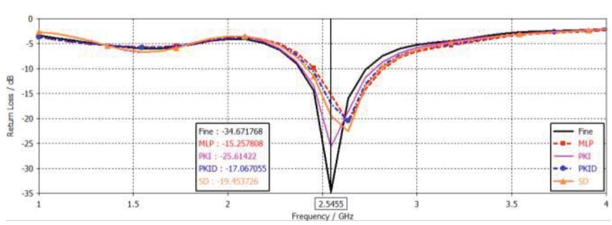


Figure 4 Model accuracy comparison of S-parameters for the designed ANN inverse models with the fine model at the first interpolation testing data set

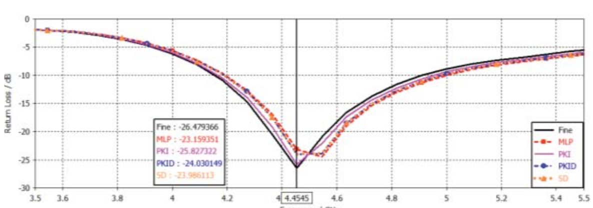


Figure 5 Model accuracy comparison of S-parameters for the designed ANN inverse models with the fine model at the second interpolation testing data set

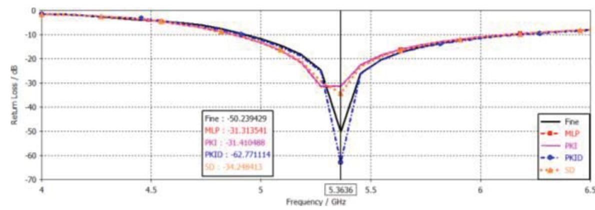


Figure 6 Model accuracy comparison of S-parameters for the designed ANN inverse models with the fine model at the third extrapolation testing data set

From the results presented above, it is noticed that KBNN models are more reliable and accurate than MLP model**.** The antenna can be reconfigured to obtain new results as well.

VI. CONCLUSION

Three methods have been explained for incorporating of prior knowledge into ANNs. SD, PKID and PKI are located in the second step of EM- KBRC inverse model to correct the response comes from MLP that is located in the first step, then the results obtained by the second step redesigned by EM simulator. All methods is applicable to 2 hidden layers. Using prior knowledge into SD, PKID and PKI show increased accuracy over MLP that does not use prior knowledge.

VII. REFERENCES

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