Proc. of the 2nd International Conference on Electrical, Communication and Computer Engineering (ICECCE)
12-13 June 2020, Istanbul, Turkey

Reconfigurable Microstrip Antenna Optimization Through Artificial Neural Networks

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***Abstract*— Artificial neural networks are applied to reconfigurable microstrip antenna design and optimization in this paper. The change of resistor value leads to two different results, exploited as the less and the high-performance models and align them as a solution through artificial neural networks. Two phases of optimization are employed by (I) using multilayer perceptron, and (II) prior knowledge input methods. The optimization techniques are implemented through Matlab. In the proposed antenna example, the S-parameter is optimized in separate optimization processes. The proposed reconfigurable microstrip antenna resonates initially at dual-band between 1-5 GHz. The antenna is modified by adding a control circuit included separately two resistors and switches between both conductor parts. By increasing the value of resistors the decrease in the return loss at optimal operating frequencies is observed.**

Keywords—reconfigurable antenna, resistor, artificial neural networks, MLP, PKI, optimization

I. INTRODUCTION

In recent years, reconfigurable antennas have gained great research interest for many wireless communication applications, for example, cellular radio system, MIMO, radar system, mobile, and satellite communication [1]. In some applications of communication like mobile, and satellite, reconfigurable antennas are useful to support a large number of wireless applications (e.g., Wi-MAX, UMTS, Bluetooth, WiFi, DSRC) to minimize or avoid in some cases interference signal. Reconfigurable antenna technology is still necessary for multifunctional operation, especially in radar applications. The reconfigurability feature is achieved by utilizing single or array antenna systems that can be suitably qualified according to the application area as well as depending on the opearating frequency range. Therefore, controlling operating modes, directivity, gain, polarization, bandwidth, and so forth can be adapted according to the communication mission [2] [3]. Thereby improving performance can be performed as in radar cross-section (RCS). There are basically many design and optimization approaches for achieving reconfigurability which are electronic switches (e.g., MEMS, PIN diodes, varactors), tunable lumped components [1] [4], filters and conducting materials in addition to optimization methods such as artificial neural networks (ANNs), genetic algorithms, space mapping, etc [5].

ANNs have been used to a very extent in microwave engineering applications. They are reported as modeling and optimization methods shown in research interest including input/output impedance matching, microstrip patch antennas, electronic circuit design, microwave circuits, MESFET, large-scale integrated circuit interconnects (VLSI), and most recently, modeling of reconfigurable antennas and radar technology (automatic target recognition) [5]. ANNs have the ability to learn and generalize patterns from/in data sets in addition to modeling and optimization extremely nonlinear input/output relationships. Two ANN methods called multilayer perceptron (MLP) and prior knowledge input (PKI) are presented. The data has been obtained by CST-EM simulator for training the ANN models, without any additional knowledge in the MLP method while prior knowledge will be integrated as an input in the PKI method. In this case, the aim is to align the responses of the less and the high-performance models through parameter extraction in the less-performance model [6]. Then PKI performs response level adjustments to achieve a qualified match between the less and the high-performance model responses. The results obtained by activating/deactivating resistors of $R_1 = 15$ Ohms and $R_2 = 25$ Ohms called less and high-performance models respectively.

In this paper, a reconfigurable microstrip antenna is optimized and presented, the designed antenna resonates at dual-band between 1-5 GHz with improved bandwidth (BW). ANNs training and testing are performed by the Matlab environment. Mostly, MLP and PKI that is based on prior knowledge is implemented. These techniques provide generalization capability and reduce the necessity for huge training data which are shown by proposed example cases. ANNs represent the mapping between the outputs of Y_{R1} and Y_{R2} models and show the accuracy depending on error measure.

II. ANTENNA DESIGN

Fig. 1 shows the proposed antenna that collects two classes of materials: perfect electrical conductor (PEC) and dielectric. Therefore, the radiating conductors, ground plane and feeding source are PEC, while the substrate is dielectric. The antenna has a qualitative form consists of radiating conductors modeled on the first side of a thin dielectric substrate backed by a ground plane besides the feeding system is at the center of the mid conductor [7]. The radiating conductor contains two parts connected by a control circuit (two resistors and switches), a mid conductor has different side-lengths, moreover, has been wrapped on all sides by spiral conductors of $L_1(0.025\lambda_\circ)$, $L_2(0.054\lambda_\circ)$, $L_3(0.045\lambda_\circ)$, $2\text{x}L_4(0.060\lambda_\circ)$, and $L_5(0.045\lambda_\circ)$ respectively at $f_t \cong 1.4$ GHz (f_t:test frequency and $\lambda_\circ$:free-space wavelength). The dielectric substrate is Rogers RT5880 (loss free) with a thickness of 0.3175 cm, a relative permittivity ε =1.96 and μ=1. The unfilled spaces between the wrapped spiral and the mid conductors are organized carefully to avoid the effect of mutual coupling, include as well as a control circuit that consists of two resistors (R_1 *and* R_2) and switches (S_1 and S_2). The control circuit is positioned upper the side of the mid

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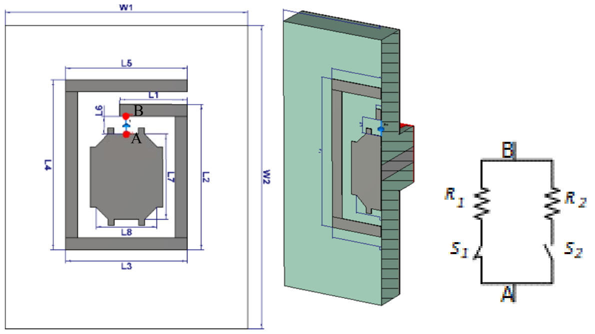
conductor interconnected to L_1 conductor. Switches are used to activate or deactivate the connection between two points (A and B), also are to control distributing current paths through the spiraled conductors as shown in Fig. 1 (a) and (c). Note that the current distributions on both patches are not symmetry, because of the configuration of the form.

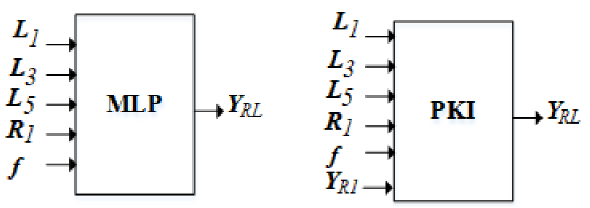


(a) (b) (c)

Fig. 1. Perspective of (a) top, (b) side and (c) control circuit views of reconfigurable microstrip antenna

III. Neural Network Modeling

Various ANNs are known as RF/microwave modeling, design and optimization methods [5] [6]. They are a learning process supervised and built on a large number of neurons. A neuron is a major unit of the layers. ANNs consist of an input layer, an output layer, and at least one hidden. Each layer contains many neurons for learning. Each neuron can accurately settle simple solutions and supply those solutions to the next neurons, in other interlinked layers. The input accepts the independent variables/vector of the model/problem and the output layer generates required predictions. On the other hand, they are limited by the number of input and required outputs, while the hidden layer has a large number of neurons depends on the nonlinearity and complexity of the problem/model. As a result, the input vector of $x = [x_1, x_2, \ldots\ldots, x_n]$ is fed through the neural network yielding the output vector of $y = [y_1, y_2, \ldots\ldots, y_n]$. Therefore, the relationship between them as $y = g(x)$, the function of "g" can be extremely nonlinear and multidimensional. In this section, two methods of feedforward neural networks are described and shown in Fig. 2.



(a) (b)

Fig. 2. Perspective of (a) MLP and (b) PKI models

A. Mutilayer Perceptron (MLP)

MLP contains an input layer, two hidden layers {7 7}, and an output layer [6]. The input vector is $x = [L_1, L_3, L_5, R_1, f]^T$ as shown in Fig. 2 (a). Variables in x are the width of the spiral conductor (L_1, L_3, and L_5), the resistor (R_1), and frequency (f). Noting that the result of EM simulation is Y_{R1} at $R_1 = 15\,Ohms$, which means S_1 and R_1 are in a connection state. The target is $Y_t = [Y_{R2}]^T$, where Y_{R2} is the result of the return loss of EM simulation at $R_2 = 25$ Ohms, which means S_2 and R_2 are in a connection state besides it represents the high-performance model.

B. Prior Knowledge Input Method (PKI)

PKI has the same learning steps as MLP, but the difference is in the number of neurons in hidden layers which are {2 2} and input variables as well [6]. The input vector of PKI contains data form two models (less and high-performance models). $x = [L_1, L_3, L_5, R_1, f, Y_{R1}]^T$ as shown in Fig. 2 (b). The data of Y_{R1} is integrated as an additional knowledge of the input and considered the result of the return loss of EM simulation, in which Y_t is the target as well.

C. Error Measure

To find the accuracy and generalization capability, the normalized mean absolute error (NMAE) measure will be computed which is the absolute difference between the output of PKI, MLP (Y_{RL}) and the target (Y_t) values as shown in (1).

$$NMAE = \frac{1}{N} \sum_{i=1}^{N} \frac{Y_{RLi} - Y_{ti}}{Y_{ti}} \quad (1)$$

where N is the number of the data samples and i is the start sample in the test data set.

IV. Results And Discussion

The s-parameter of an antenna is the most important characteristic representing power reflection, radiation, and loss [2]. The bandwidth and operating frequency of an antenna refer to which the antenna is used in particular communication applications. Other antenna characteristics (directivity, VSWR, radiation patterns, etc.) can be calculated depending on the s-parameter result. The results of the antenna modeling and optimization are presented according to EM simulation and ANNs.

A. EM simulation results

The reconfiguration is achieved by integrating a control circuit (two resistors and switches) into the form of the proposed antenna as shown in Fig. 1 (c). Activating resistors (R_1 and R_2) by switches (S_1 and S_2) sequentially is realized for obtaining less (Y_{R1}) and high (Y_{R2})-performance models as shown in Fig. 3 (a) and (b).

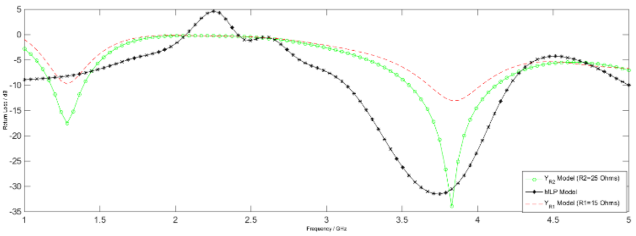
B. Training of neural networks

There are two types of data sets proposed: Training and extrapolation testing data sets. The data sets of training and testing are 800 and 100 samples, respectively. The test data is to control independently the quality of the ANNs model in terms of accuracy and generalization capability [6]. Levenberg-Marquardt algorithm (LMA) has been developed for adapting weights and tangent-sigmoid transfer functions (TFs) for mapping the input to the output vectors within limited boundary [5]. Both are situated within the neurons in the hidden layers.

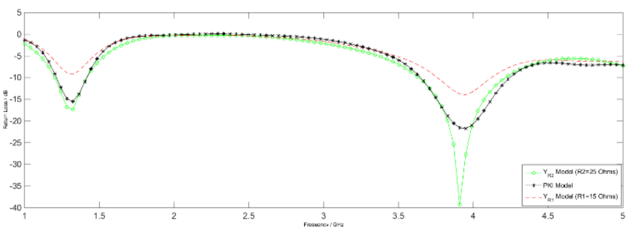
TABLE I. ANNS TRAINING PARAMETERS

	ANNs	
	MLP	***PKI***
Epoches	500	300
Learning rate	0.02	0.01
Performance goal	$0.1 * 10^{-6}$	$0.1 * 10^{-5}$
Momentum	0.8	0.9
Regularization	0.1	0.4
Training repeated	25	25

After developing the models using training parameters shown in Table I, the final model of MLP and PKI is achieved as shown in Fig. 3 (a) and (b). With a note that, MLP and PKI as optimization methods rely on finding the high-performance model of Y_{R2}, while the less-performance model of Y_{R1} is a part of the input variables in the process of PKI learning. MLP model has not given the required accuracy like the PKI model as shown in Table II. On the other hand, using fewer data samples for training PKI performs better than training MLP.



(a)



(b)

Fig. 3. Comparison of s-parameters between EM simulation, (a) MLP, and (b) PKI models

The operation frequencies at less and high-performance models are similar but the difference is in the value of return loss and bandwidths. By activating/deactivating switches (S_1 and S_2), the value of the resistor changes from 15 Ohms to 25 Ohms, the value of the return loss has decreased, while the bandwidth is slightly increased in PKI at 3.8 GHz. For PKI model, the resonant frequencies are observed at 1.28 GHz and 3.8 GHz with return losses of -17.67 dB and -23 dB respectively. The bandwidths also have changed partially to be 0.23 GHz, and 0.60 GHz respectively at a reference of -10 dB as shown in Fig. 3 (a) and (b). For MLP model, the bandwidth is 1.2 GHz at 3.8 GHz.

TABLE II. COMPARISON OF MODEL ACCURACY

NMAE Statistics	ANNs	
	MLP	***PKI***
Average NMAE	6.415	0.5316
Standard deviation	4.798	0.3960
Minimum NMAE	1.0561	0.1835

V. CONCLUSION

A double-band reconfigurable microstrip antenna is achieved, which is modeled and optimized by EM simulation and ANNs. Comparison between less and high-performance models show that additional knowledge affects the predicted output positively. In all tested processes, PKI outperformed MLP in all accuracy measures. The proposed antenna operates at 1.28 GHz and 3.8 GHz with different values of the return loss and bandwidth. This antenna can be used in various communication applications within its operating range.

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