

Neurocomputational Analysis of Square Microstrip Antenna Characteristics

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Abstract

Procedures using Artificial Neural Networks (ANN) are developed for characterizing square microstrip antennas. A Multi-Layer Perceptron (MLP) is used to find out the resonant frequency of the antennas. Same ANN is used to accomplish the task of obtaining different important antenna characteristics like gain, return loss and bandwidth of operation at once. The developed ANN is tested experimentally on laboratory prototype antennas.

Keywords

Artificial neural network, Levenberg-Marquardt backpropagation, square microstrip antenna, antenna gain, return loss, bandwidth.

I. Introduction

Planar antenna designs, such as “microstrip antennas” (known variously as “microstrip patch antennas” or simply “patch antennas”) are often preferred for mobile and satellite communication antennas due to their added advantage of small size, low manufacturing cost and conformability. In recent years square microstrip antennas have found increasing demand in communication scenario due to their polarization diversity, particularly ability to realize dual or circularly polarized (CP) radiation patterns [1–2]. Such antennas are attractive for many military and commercial applications to ensure ubiquitous and reliable communication. They have found applications in space-based radar, aircraft, unmanned aerial vehicles, communication satellites, electronic intelligence and many other communication and sensing applications.

Electromagnetic simulations which are based on full-wave analysis techniques, such as Method of Moment (used in IE3D™ [3]) give more accurate analysis of microstrip patch antenna characteristics, such as S-parameters, radiation patterns, etc. compared to the approximate models, such as transmission line model, cavity model, etc. [1]. Though such electromagnetic simulations, based on full-wave analysis techniques give very accurate results, they suffer from the drawback of time-consuming, intensive computations compared to the approximate models which are less accurate but faster. ANN can help in this situation. The relationship between square microstrip antenna parameters and its characteristics is highly nonlinear in nature, hence difficult to model. ANNs have emerged in recent years as a powerful technique for modelling general non-linear input-output relationships. ANN models can be more accurate than other nonlinear models such as, polynomial equations, and offer host of other advantages [4–6]. Characteristics of ANNs such as learning from data, to generalize patterns in data and to model nonlinear relationships, make them good candidates for applications to many different branches of engineering. A properly trained ANN can do time efficient calculations for analysis of microstrip antennas. Thus ANNs can predict microstrip antenna characteristics much

more accurately than the approximate models and at the same time much faster than the full-wave numerical techniques.

Some earlier reported works use ANN for analysis of microstrip antennas [7–14], particularly rectangular microstrip antennas to find the resonant frequency [15], [16] or resonant frequency and bandwidth [17] or resonant frequency and minimum return loss [18]. The novelty of the work presented here is that an ANN model is proposed for the analysis of square microstrip antennas for four important characteristics, namely, resonant frequency, return loss, gain and bandwidth – all at once.

The trained ANN is used to determine different important antenna characteristics for various structural input variables (physical parameters). This is treated as a mapping problem and is accomplished by an MLP trained in the backpropagation mode. The work presented here is in continuation of authors' earlier reported work in [19].

The following section describes the square microstrip antenna structure under study. In Sections III and IV the theoretical background of neurocomputational technique and its application to the present problem are presented respectively, while Section V gives validation of the model.

II. The Antenna Structure

A typical structure under investigation is shown in Fig. 1. Top surface of the antenna corresponds to a conducting square microstrip ($L = W$) and fed by a 50 Ω SMA connector. Antenna ground plane is taken at least three times that of the top layer microstrip, such that fringing effect is properly taken care of and the antenna parameters do not differ significantly from their corresponding infinite ground plane consideration values [2].

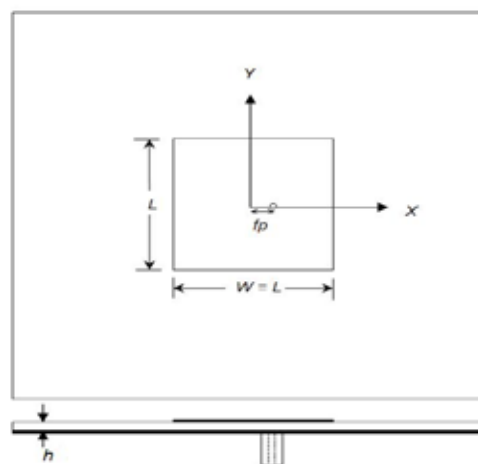


Fig. 1: Top and front view of square microstrip antenna

The dielectric constant of substrate used is ϵ_r . The thickness of the dielectric substrate is h . The probe position along the width (or the length) with respect to microstrip centre is f_p .

III. Theoretical Background of ANN

MLP neural networks are by far the most popular type of neural

networks capable of approximating generic classes of functions [7]. These networks trained in backpropagation mode have already been used in many microwave engineering applications and especially for antennas [8-9].

Various algorithms exist for adapting weights and biases for faster convergence of the network. One of such fast converging backpropagation algorithm is Lavenberg-Marquardt Backpropagation (LMBP) algorithm [20]. Advantage of LMBP algorithm for function approximation problems is that for networks that contain up to a few hundred weights, the LMBP algorithm will have the fastest convergence. This advantage is particularly useful if very accurate training is required. In many cases, LMBP algorithm is able to obtain lower mean square errors than any of the other algorithms tested.

The LMBP algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), the Hessian matrix in this case can be approximated as

$$H \approx J^T J$$

and the gradient can be computed as

$$g = J^T E$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and E is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix.

The LMBP algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$X_{k+1} = X_k - [J^T J + \mu I]^{-1} J^T E$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm.

Selection of training parameters for neural networks and the entire training process mostly depends on experience besides the type of problem at hand. The accuracy of a properly trained ANN depends on the accuracy and the effective representation of the data used for its training. Numerical data has to be generated for those parameters the user wants to use in neural network training.

IV. Applying Neurocomputational Technique for Analysis of Square Microstrip Antennas

A. Problem formulation

The purpose here is to correlate different antenna characteristics, within the operational frequency range of the antenna, with the square microstrip antenna physical parameters as closely as possible.

Different square microstrip antennas are designed and are considered for generating training and testing data sets. Inputs to the ANN to be trained are physical parameters of the microstrip, which include length, thickness or height of antenna substrate, probe-feed position and the dielectric constant of the substrate. The outputs are antenna characteristic to be obtained, which include resonant frequency, return loss, gain

and bandwidth.

B. Data generation and pre-processing

For generating data, we simulated the frequency domain response of the antenna for various frequencies, using method of moments based simulation software IE3D™.

For training and testing of the ANN, 2048 data sets are generated by simulation using IE3D™ simulation software, considering four equally spaced values of microstrip length from 21 to 30 mm, eight equally spaced values of substrate thickness from 0.5 to 4 mm and 16 different values of dielectric constant from 2.1 to 4 for commercially available substrates. The feed position is varied in very close steps varying around one sixth of the length (from microstrip center) within ± 1.5 mm along the length and halfway along the width. This is done to ensure maximum coupling of dominant mode.

These sampled points are then scaled to remain within the range [-1, 1] and used as the training data for the network. Scaling of data is desirable for efficient training of neural networks.

C. ANN implementation

In the present problem, the ANN architecture shown in the Fig. 2 uses MLP model, which consists of input layer (four nodes), output layer (four nodes) and two hidden layers (twenty nodes each). Neurons of hidden layer nodes use tan-hyperbolic transfer function; whereas neurons of output layer nodes use linear transfer function. Four inputs (the input vector) correspond to physical parameters of antenna which include, square microstrip length L (mm), substrate thickness h (mm), relative permittivity of the substrate ϵ_r and probe feed position fp (mm).

The four outputs (the output vector) correspond to antenna characteristics which include, resonant frequency f_r (GHz), return loss S_{11min} (dB), gain G (dBi) and bandwidth BW (MHz). In Fig. 2, w_{ji}^{11} represents weight of connection between input layer node (source) i and the first hidden layer node (destination) j , w_{kj}^{21} represents weight of connection between the first hidden layer node (source) j and the second hidden layer neuron (destination) k and w_{lk}^{32} represents weight of connection between the second hidden layer node (source) k and the output layer node (destination) l .

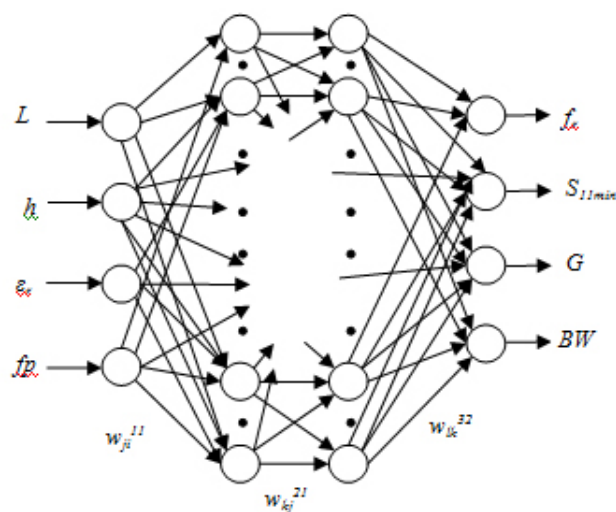


Fig. 2. Architecture of artificial neural network ANN training

The network is trained using all of 2048 input-output vector

pairs - obtained using simulations by IE3D™ simulation software. The training uses random initial biases (not shown in the Fig.) and random initial weights. LMBP algorithm is used for the training. Fig. 3 shows the graph of Mean Square Error (MSE) versus number of epochs. The performance goal (i.e. targeted MSE between desired output and calculated output at the end of training) is 0.001, which is reached at the end of 81st epoch.

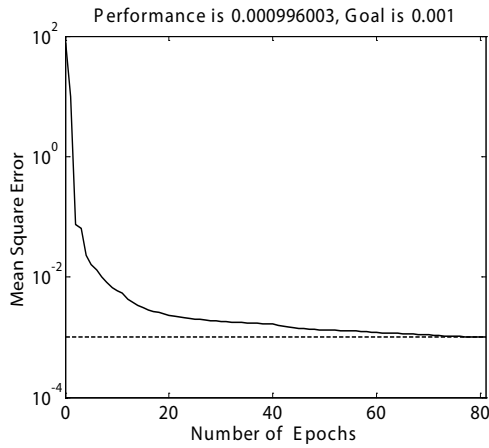


Fig. 3 : ANN training: MSE versus the number of epochs

IV. Experimental Verification

Four square microstrip antennas, hereafter called “Test Antenna 1 – 4”, of dimensions 30 mm × 30 mm, 26 mm × 26 mm, 23 mm × 23 mm and 20 mm × 20 mm respectively are fabricated on RT Durroid® (εr= 2.4) substrate of thickness 1.524 mm for validating purpose. The values of fp (feed position with respect to center of microstrip as shown in Fig. 1) are 5 mm, 4.5 mm, 4 mm and 3.5 mm respectively. These specifications are not part of the simulation data base generated for the purpose of training ANN.

A network analyser from Agilent Technologies™ (series ENA, model E5071B) is used for measurement of resonant frequency, minimum return loss and bandwidth. Before measurement, the network analyser is calibrated using Agilent® E-calkit 85092-60008 as per the recommended procedure.

Gain of each antenna is measured using standard horn antenna. Agilent® analogue signal generator (N5181AMXG) is used as source.

V. Results

The antennas fabricated for validation of ANN are simulated using IE3D™ simulation software for comparison and validation purpose of ANN, because the specifications of these antennas are not included in the training data base. The results of ANN, IE3D™ simulation and experimental measurement of resonant frequency are given in Table 1.

Other antenna characteristics obtained by using the trained ANN, IE3D™ simulation, and experimental measurement are compared by plotting as functions of corresponding antenna resonant frequency in Fig. 4 through Fig. 6.

Table I. Comparison of Resonant Frequency of Test Antennas

Performance parameter	Resonant Frequency (GHz)			
	Test Antenna 1	Test Antenna 2	Test Antenna 3	Test Antenna 4
Using trained ANN	3.08	3.55	3.99	4.52
Measured	3.07	3.54	3.97	4.55
Simulated using IE3D	3.09	3.56	3.98	4.56

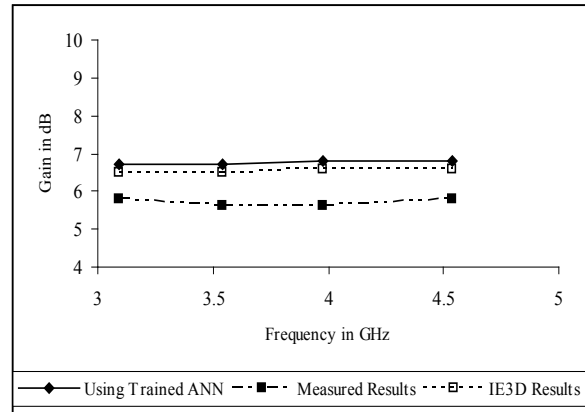


Fig. 4: Comparison of gain of test antennas obtained using different methods plotted as function of corresponding antenna resonant frequency

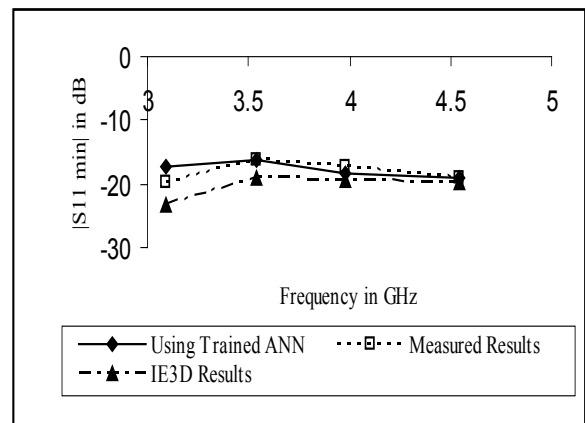


Fig. 5: Comparison of minimum return loss of test antennas obtained using different methods plotted as function of corresponding antenna resonant frequency

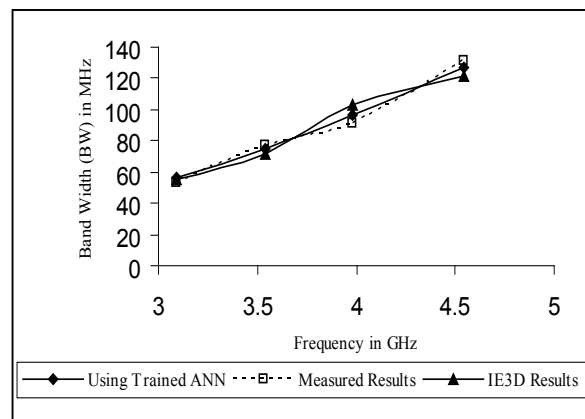


Fig. 6: Comparison of bandwidth of test antennas obtained using different methods plotted as function of corresponding antenna resonant frequency

VI. Discussion

All the Figs from Fig. 4 through Fig. 6 show clearly the efficiency of using a trained ANN. The results predicted by ANN and IE3D™ both closely match with corresponding experimentally measured values, except for the case of gain of antennas. The ANN provides antenna characteristics much faster than the numerical simulations but with same degree of accuracy. The reason of larger deviation of measured values of gain from the simulated or predicted values (using ANN) is probably due to the non-ideal measurement environment in absence of anechoic chamber and hence is not of much significance.

VII. Conclusion

Artificial neural network structure is used for analysis of square microstrip antenna characteristics. Multi-Layer Perceptron trained in the backpropagation mode (using Levenberg-Marquardt Backpropagation Algorithm) is developed, for the first time, to find four important square microstrip antenna characteristics namely, resonant frequency, return loss, gain and bandwidth, simultaneously. This neurocomputational technique significantly reduces the mathematical complexity involved in analysis using different numerical methods to model the square microstrip antenna. The developed neurocomputational methodology can be extended for characterizing other different shapes of microstrip antenna.

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