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Artificial Neural Design of Microstrip Antennas

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Abstract

A general design procedure is suggested for microstrip antennas using artificial neural networks and this is demonstrated using rectangular patch geometry. In this design procedure, synthesis is defined as the forward side and then analysis as the reverse side of the problem. Worked examples are given using the most efficient materials.

Key Words: *Microstrip antennas, artificial neural networks, reverse modeling.*

1. Introduction

In high-performance spacecraft, aircraft, missile and satellite applications, where size, weight, cost, performance, ease of installation, and aerodynamic profile are constraints, low profile antennas may be required. Presently, there are many other government and commercial applications, such as mobile radio and wireless communications that have similar specifications. To meet these requirements, microstrip antennas can be used [1]. These antennas are low-profile, conformable to planar and non-planar surfaces, simple and inexpensive to manufacture using modern printed circuit technology, mechanically robust when mounted on rigid surfaces, compatible with MMIC designs, and when particular patch shape and mode are selected they are very versatile in terms of resonant frequency, polarization, pattern, and impedance. In addition, by adding loads between the patch and the ground plane, such as pins and varactor diodes, adaptive elements with variable resonant frequency, impedance, polarization, and pattern can be adjusted [2].

Often microstrip antennas are also referred to as patch antennas because of the radiating elements (patches) photoetched on the dielectric substrate. This radiating patch may be square, rectangular, circular, elliptical, triangular, and any other configuration. In this work, rectangular microstrip antennas are the ones under consideration (Figure 3). The patch dimensions of rectangular microstrip antennas are usually designed so its pattern maximum is normal to the patch. Because of their narrow bandwidths and effectively operation in the vicinity of resonant frequency, the choice of the patch dimensions giving the specified resonant frequency is very important. In the literature, artificial neural network (ANN) models have been built usually for the analysis of microstrip antennas in various forms such as rectangular, circular, and equilateral triangle patch antennas [4-7]. In these works, the analysis problem can be defined as to obtain resonant frequency for a given dielectric material and geometric structure (Figure 2). However, in the present work, the corresponding synthesis ANN model is built to obtain patch dimensions of rectangular microstrip antennas (W,L) as the function of input variables, which are the height of the dielectric substrate (h), dielectric constants of the dielectric material $(\varepsilon_r, \varepsilon_y)$, and the resonant frequency (f_r) (Figure 1). This synthesis problem is solved using the electromagnetic formulae of the microstrip antennas. In this formulation, 2 points are especially emphasized: the resonant frequency of the antenna and the condition for good radiation efficiency. Using reverse modeling, an analysis ANN is built to find out the resonant frequency immediately for a given rectangular microstrip antenna system. The models are simple, easy to apply, and very useful for antenna engineers to predict both patch dimensions and resonant frequency. Thus, in the following sections, the forward and reverse sides of this design problem are defined as black-ANN boxes; then the electromagnetic background is briefly summarized for building the synthesis ANN model. In the following section, also, this synthesis model is reversed for the analysis purpose of the given antenna system whose results are compared with those in the literature.

2. Design Problem for the Microstrip Antenna

In this work, the patch geometry of the microstrip antenna is obtained as a function of input variables, which are height of the dielectric material (h), dielectric constants of the substrate material $(\varepsilon_r, \varepsilon_y)$, and the resonant frequency (f_r), using ANN techniques (Figure 1). Similarly, in the analysis ANN, the resonant frequency of the antenna is obtained as a function of patch dimensions (W, L), height of the dielectric substrate (h), and dielectric constants of the material $(\varepsilon_r, \varepsilon_y)$ (Figure 2).

Thus, the forward and reverse sides of the problem will be defined for the rectangular patch geometry in the following subsections.

2.1. The forward side of the problem: The synthesis ann

The input quantities to the ANN black-box in synthesis (Figure 1) can be ordered as:

- h: height of the dielectric substrate;
- $\varepsilon_r, \varepsilon_y$: electrical properties of the dielectric substrate, where $\varepsilon_r, \varepsilon_y$ are the permittivities in the x and y directions of the dielectric material used in the system, respectively;
- f_r : resonant frequency of the antenna.

The following quantities can be obtained from the output of the black-box as functions of the input variables:

- W: width of the patch;
- L: length of the patch.

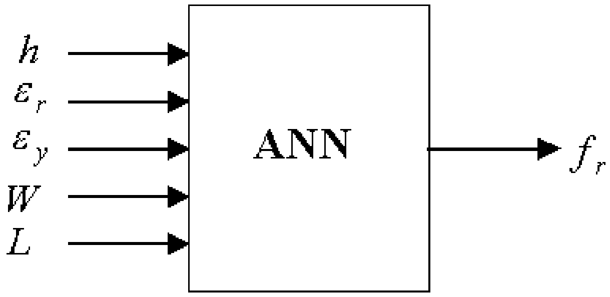

Figure 1. The synthesis ANN model.

2.2. The reverse side of the problem: The analysis ann

In the analysis side of the problem, terminology similar to that in the synthesis mechanism is used, but the resonant frequency of the antenna is obtained from the output for a chosen dielectric substrate and patch dimensions at the input side (Figure 2).

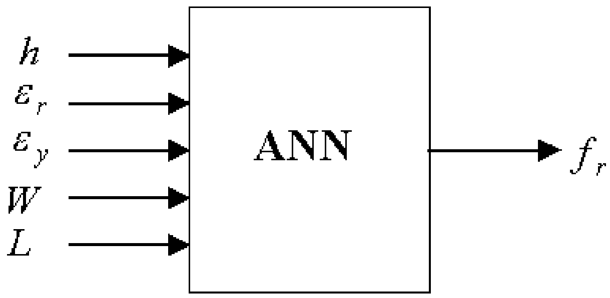

Figure 2. The analysis ANN model.

2.3. Electromagnetic Working of Microstrip Antennas

Microstrip patch antennas, which are the most common printed-board radiating elements at RF and microwave frequencies, have 2 basic models to explain electromagnetic working: (i) transmission line; (ii) cavity. Both of them give good physical insight; however, the cavity model is more accurate, and at the same time more complicated. Later a full-wave analysis has been developed including primarily the integral equations/moment methods to treat accurately single elements as well as finite and infinite arrays, stacked elements, arbitrary shaped elements, and coupling.

In recent decades, neural network models have been developed especially for the calculation of resonant frequencies for the various shapes of antennas such as equilateral triangular, circular, and rectangular microstrip antennas, respectively in [4-9]. The accurate evaluation of the resonant frequency of microstrip antennas is a key factor to determine their correct behaviors. Training and test data sets used for these ANN models were obtained either analytically or measured from previous works in the literature. ANN models developed for the evaluation of the input impedances of microstrip antennas are also available in the literature [10, 11]. There is also a fast technique to evaluate the resonant frequency of microstrip antennas using neuro-fuzzy networks [12]. In [13] and [14], a neural technique is combined with the spectral (wavenumber domain) analysis together the resulting “neurospectral” analysis to apply the square-patch antenna basically for analysis but then reversing the model for the synthesis of the antenna. Another role for ANNs in reverse modeling is as function/inverse function approximators for RF/Microwave transmission line design problems [15].

2.4. Rectangular microstrip antennas

The rectangular microstrip antennas are made of a rectangular patch with dimensions width, W, and length, L, over a ground plane with a substrate thickness h and dielectric constants $\varepsilon_r, \varepsilon_y$, as given in Figure 3. Dielectric constants are usually used in the range $2.2 \leq \varepsilon_r \leq 12$. However, the most desirable ones are the dielectric constants at the lower end of this range together with the thick substrates, because they provide better efficiency and larger bandwidth, but at the expense of larger element size [3].

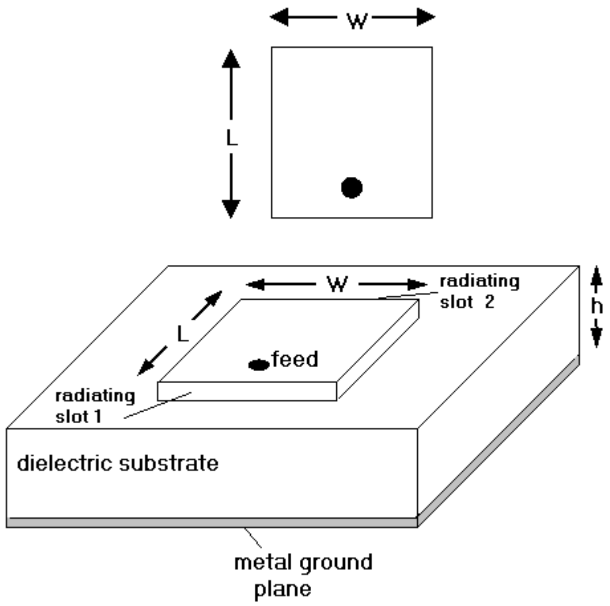

Figure 3. Rectangular microstrip antenna.

In the literature, almost all works have been done by choosing the dielectric substrate to be in an isotropic structure. In this work, the ANN model is capable of giving results for both isotropic and anisotropic structures of the dielectric substrate. For an anisotropic substrate, the spacing parameter h is replaced by the effective spacing h_e, and the geometric mean ε_g is used for the dielectric constant ε_r:

$$h_e = \sqrt{\frac{\varepsilon_r}{\varepsilon_y}}h \tag{1}$$

$$\varepsilon_g = \sqrt{\varepsilon_r \varepsilon_y} \tag{2}$$

The effective dielectric constant of the dielectric material is given in (2):

$$\varepsilon_{eff} = \frac{\varepsilon_g + 1}{2} + \frac{\varepsilon_g - 1}{2}[1 + 12\frac{h_e}{W}]^{-1/2} \tag{3}$$

For an efficient radiator, a practical width that leads to good radiation efficiencies is [2]:

$$W = \frac{v_o}{2f_r}\sqrt{\frac{2}{\varepsilon_g + 1}} \tag{4}$$

where v_o is the free-space velocity of light.

The actual length of the patch:

$$L = \frac{1}{2f_r\sqrt{\varepsilon_{eff}}\sqrt{\mu_o\varepsilon_o}} - 2\Delta L \tag{5}$$

where ΔL is the extension of the length due to the fringing effects and is given by:

$$\frac{\Delta L}{h} = 0.412\frac{(\varepsilon_{eff}+0.3)\left(\frac{W}{h}+0.264\right)}{(\varepsilon_{eff}-0.258)\left(\frac{W}{h}+0.8\right)} \tag{6}$$

3. Building Neural Networks for Rectangular Microstrip Antenna and Results

In this work, both Multilayer Perceptron (MLP) and Radial Basis Function (RBF) networks were used in ANN models. In the following 2 sections, the structures of these ANNs are described briefly.

3.1. RBF Networks

Feedforward neural networks with a single hidden layer that use radial basis activation functions for hidden neurons are called radial basis function networks. RBF networks are applied for various microwave modeling purposes. A typical RBF network structure is given in Figure 4. The parameters c_{ij} and λ_{ij} are centers and standard deviations of radial basis activation functions. Commonly used radial basis activation functions are gaussian and multiquadratic.

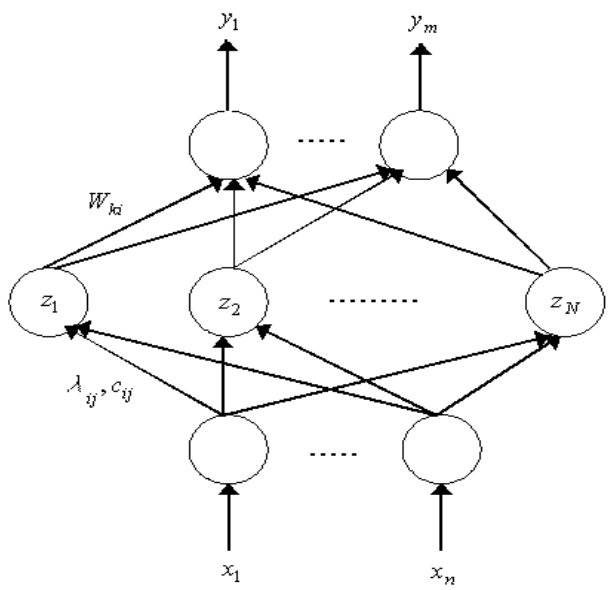

Figure 4. RBF neural network structure.

Given the inputs **x**, the total input to the ith hidden neuron γ_i is given by

$$\gamma_i = \sqrt{\sum_{j=1}^{n}\left(\frac{x_j - c_{ij}}{\lambda_{ij}}\right)^2}, i = 1, 2, ..., N \tag{7}$$

where N is the number of hidden neurons. The output value of the ith hidden neuron iszij $= \sigma(\gamma_i)$, where $\sigma(\gamma)$is a radial basis function. Finally, the outputs of the RBF network are computed from hidden neurons as

$$y_k = \sum_{i=0}^{N} w_{ki} z_{ki} \tag{8}$$

where w_{ki} is the weight of the link between the ith neuron of the hidden layer and the kth neuron of the output layer. Training parameters w of the RBF network include w_{k0}, w_{ki}, c_{ij}, λ_{ij}, k = 1,2, . . . , m, I = 1,2, ...,N, j = 1,2, . . . n [17].

3.2. Multilayer perceptron networks

MLP are feedforward neural networks trained with the standard backpropagation algorithm. They are supervised networks and so they require a desired response to be trained. They learn how to transform input data into a desired response, and so they are widely used for pattern classification. With 1 or 2 hidden layers, they can approximate virtually any input-output map. They have been shown to approximate the performance of optimal statistical classifiers in difficult problems. Most neural network applications involve MLP. The basic MLP building unit is a simple model of artificial neurons. This unit computes the weighted sum of the inputs plus the threshold weight and passes this sum through the activation function (usually sigmoid). In a multilayer perceptron, the outputs of the units in one layer form the inputs to the next layer. The weights of the network are usually computed by training the network using the back propagation algorithm [16].

4. Structures of the neural networks

The MLP network, which has a configuration of 4 input neurons, 10 and 5 neurons in 2 hidden layers, and 2 output neurons with learning rate = 0.1, goal = 0.001, was trained for 400 epochs. Hyperbolic tangent sigmoid and linear transfer functions were used in MLP training. MLP models were trained with almost all network learning algorithms. Among these, those giving the best results for the MLP network are shown in Table 1. In the RBF network, the spread value was chosen as 0.01, which gives the best accuracy. Both MLP and RBF were trained with 45 samples and tested with 15 samples determined according to the definition of the problem; 5 inputs and 1 output were used for the analysis ANN and 4 inputs and 2 outputs for the synthesis ANN. The training and test data of the synthesis and analysis ANN were obtained from both experimental results given in previous works [6] and a computer program using formulae given in Section 3. The data are in matrix form consisting of inputs and target values and arranged according to the definitions of the problems.

5. Results

In Table 1, the accuracy values of analysis ANN for 4 networks giving the best results are given. As can be seen from Tables 1 and 4, in synthesis and analysis, RBF network were the one giving the best approximation to the target values whose structure is defined in the following subsection. The results of the synthesis and analysis ANN for an isotropic material ($\varepsilon_r = \varepsilon_y$) and comparison with the targets are given in Table 2 and 3, respectively.

Table 1. Accuracies of the synthesis ANN for 4 networks giving the best results.

	Accuracy%
RBF	99.09
MLP 1	96.53
MLP 2	95.05
MLP 3	94.88

RBF: Radial basis function network.
MLP 1: Multilayer perceptron network using scaled conjugate gradient backpropagation as learning algorithm.
MLP 2: Multilayer perceptron network using resilient backpropagation algorithm as learning algorithm.
MLP 3: Multilayer perceptron network using Levenberg-Marquardt optimization algorithm as learning algorithm.

Table 2. Results of the synthesis ANN and comparison with the targets.

h(cm)	ε_r	f_r(GHz)	W-target(cm)	W-RBF(cm)	L-target(cm)	L-RBF(cm)
0.3175	2.33	2.310	5.7000000e+000	5.6974505e+000	3.8000000e+000	3.7994597e+000
0.3175	2.33	2.890	4.5500000e+000	4.5474521e+000	3.0500000e+000	3.0499109e+000
0.3175	2.33	4.240	2.9500000e+000	2.9511621e+000	1.9500000e+000	1.9486281e+000
0.3175	2.33	5.840	1.9500000e+000	1.9475063e+000	1.3000000e+000	1.2971094e+000
0.3175	2.33	6.800	1.7000000e+000	1.6944723e+000	1.1000000e+000	1.1033160e+000
0.3175	2.33	7.700	1.4000000e+000	1.3929305e+000	9.0000000e-001	9.0775583e-001
0.3175	2.33	8.270	1.2000000e+000	1.1977494e+000	8.0000000e-001	7.9030186e-001
0.3175	2.33	9.140	1.0500000e+000	1.0426235e+000	7.0000000e-001	7.0188779e-001
0.9525	2.33	4.730	1.7000000e+000	1.7005360e+000	1.1000000e+000	1.1001805e+000
0.4000	2.55	7.134	7.9000000e-001	7.9083561e-001	1.2550000e+000	1.2579399e+000
0.4500	2.55	6.070	9.8700000e-001	9.8108696e-001	1.4500000e+000	1.4564505e+000
0.4760	2.55	5.820	1.0000000e+000	1.0135424e+000	1.5200000e+000	1.5142246e+000
0.4760	2.55	6.380	8.1400000e-001	8.1739191e-001	1.4400000e+000	1.4414665e+000
0.5500	2.55	5.990	7.9000000e-001	7.8253575e-001	1.6200000e+000	1.6187765e+000
0.1570	2.33	5.060	1.7200000e+000	1.7173371e+000	1.8600000e+000	1.8634147e+000

Table 3. Results of the analysis ANN and comparison with the targets.

h(cm)	ε_r	W (cm)	L (cm)	f_r -target(GHz)	f_r -RBF(GHz)
0.3175	2.33	5.7	3.80	2.3100000e+000	2.3108710e+000
0.3175	2.33	4.55	3.05	2.8900000e+000	2.8880900e+000
0.3175	2.33	2.95	1.95	4.2400000e+000	4.2060612e+000
0.3175	2.33	1.95	1.30	5.8400000e+000	5.8893107e+000
0.3175	2.33	1.70	1.10	6.8000000e+000	6.6958903e+000
0.3175	2.33	1.40	0.90	7.7000000e+000	7.7905070e+000
0.3175	2.33	1.20	0.80	8.2700000e+000	8.3661174e+000
0.3175	2.33	1.05	0.70	9.1400000e+000	9.0719890e+000
0.9525	2.33	1.70	1.10	4.7300000e+000	4.6866520e+000
0.4000	2.55	0.79	1.255	7.1340000e+000	7.0603068e+000
0.4500	2.55	0.987	1.45	6.0000000e+000	6.0940227e+000
0.4760	2.55	1.00	1.52	5.8200000e+000	5.8599528e+000
0.4760	2.55	0.814	1.44	6.3800000e+000	6.4233684e+000
0.5500	2.55	0.79	1.62	5.9900000e+000	5.9439372e+000
0.1570	2.33	1.72	1.86	5.0600000e+000	5.0258464e+000

Table 4. Accuracies of the analysis ANN for four networks giving the best results.

	Accuracy%
RBF	97.76
MLP 3	97.75
MLP 2	96.68
MLP 1	95.85

6. Conclusion

In this work, the neural network is employed as a tool in design of the microstrip antennas. In this design procedure, synthesis is defined as the forward side and then analysis as the reverse side of the problem. Therefore, one can obtain the geometric dimensions with high accuracy, which are the length and the width of the patch in our geometry, at the output of the synthesis network by inputting resonant frequency, height and dielectric constants of the chosen substrate. Furthermore, in our work, the synthesis can also be applied into anisotropic dielectric substrate. In this work, the analysis is considered as a final stage of the design procedure, therefore the parameters of the analysis ANN network are determined by the data obtained reversing the input-output data of the synthesis network. Thus, resonant frequency resulted from the synthesized antenna geometry is examined against the target in the analysis ANN network. Finally, in this work, a general design procedure for the microstrip antennas is suggested using artificial neural networks and this is demonstrated using the rectangular patch geometry.

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