A COMPARATIVE STUDY OF NEURAL NETWORKS FOR RESONANT FREQUENCY COMPUTATION OF ELECTRICALLY THIN AND THICK CIRCULAR MICROSTRIP ANTENNAS

Sinan Gültekin[1], Kerim Güney[2], Şeref Sağıroğlu[3]
e-mail:sgultekin@selcuk.edu.tr e-mail:kguney@erciyes.edu.tr e-mail:ss@erciyes.edu.tr
[1]Selçuk University, Faculty of Engineering and Architecture, Department of Electric and Electronic Engineering, 42031, Konya, Turkey,
[2]Erciyes University, Faculty of Engineering, Department of Electronic Engineering, 38039, Kayseri, Turkey,
[3]Erciyes University, Faculty of Engineering, Department of Computer Engineering, 38039, Kayseri, Turkey

Key words: Neural networks, microstrip antenna, resonant frequency

ABSTRACT

Neural models for calculating the resonant frequency of electrically thin and thick circular microstrip antennas, based on the multilayered perceptrons and the radial basis function networks, are presented. Five learning algorithms, delta-bar-delta, extended delta-bar-delta, quick-propagation, directed random search and genetic algorithms, are used to train the multilayered perceptrons. The radial basis function network is trained according to its learning strategy. The resonant frequency results obtained by using neural models are in very good agreement with the experimental results available in the literature.

I. INTRODUCTION

Accurate determination of resonant frequency is important in the design of microstrip antennas (MSAs) because they have narrow bandwidths and can only operate effectively in the vicinity of the resonant frequency. Several methods [1-14] varying in accuracy and computational effort have been presented and used to determine the resonant frequency of circular patch antenna, as this is one of the most popular and convenient shapes. However, most of the previous theoretical and experimental work has been carried out only with electrically thin MSAs, normally of the order of $h/\lambda_d \leq 0.02$, where h is the thickness of the dielectric substrate and λ_d is the wavelength in the substrate. Recent interest has developed in radiators etched on electrically thick substrates. This interest is primarily for two major reasons. First, as these antennas are used for applications with increasingly higher operating frequencies, and consequently shorter wavelength, even antennas with physically thin substrates become thick when compared to a certain wavelength. Second, the bandwidth of the circular microstrip antenna is typically very small for low profile, electrically thin configurations. One of the techniques to increase the bandwidth is to increase the thickness proportionately. The design of microstrip antenna elements having wider bandwidth is an area of major interest in microstrip antenna technology, particularly in the fields of electronic warfare, communication systems and wideband radars. Consequently, this problem, particularly the resonant frequency aspect, has received considerable attention.

In this study, models based on artificial neural networks (ANNs) are presented for the resonant frequencies of both electrically thin and thick circular microstrip antennas. Ability and adaptability to learn, generalizability, smaller information requirement, fast real-time operation, and ease of implementation features have made ANNs popular in the last few years [15-25]. Because of these fascinating features, artificial neural networks in this article are used to model the relationship between the parameters of the microstrip antenna and the measured resonant frequency results.

In previous works [13,20-24], we also successfully introduced ANNs to compute the various parameters of the triangular, rectangular and circular MSAs. In these works, only the multilayered perceptrons (MLPs) were used as the neural network architecture. However, in this paper, both the MLPs and the radial basis function networks (RBFNs) are used for calculating the resonant frequency. Furthermore, in the most of our previous works, only the backpropagation algorithm was employed to train the MLPs. However, in this study the five learning algorithms, the delta-bar-delta (DBD), the quick propagation (QP), the extended delta-bar-delta (EDBD), the directed random search (DRS), and the genetic algorithms (GA), are used to train the MLPs.

II. RESONANT FREQUENCY OF A CIRCULAR MICROSTRIP ANTENNA

Consider a circular patch of radius a over a ground plane with a substrate of thickness h and a relative dielectric constant ε_r, as shown in Fig. 1. The resonant frequency of a circular disc MSA for the TM_{nm} mode is given by

$$f_{nm} = \frac{\alpha_{nm}}{2\pi a\sqrt{\mu_o \varepsilon}} = \frac{\alpha_{nm} c}{2\pi a\sqrt{\varepsilon_r}} \qquad (1)$$

where α_{nm} is the mth zero of the derivative of the Bessel function of order n and c is the velocity of electromagnetic waves in free space. The dominant mode is TM_{11} (n=m=1), for which α_{11} =1.84118. The TM_{11} mode of the circular microstrip patch is widely used in MSA applications. Equation (1) is based on the assumption of a perfect magnetic wall and neglects the fringing fields at the open-end edge of the microstrip patch. To account for these fringing fields, there were a number of suggestions in the literature [1-14]. It is clear from the studies presented in the literature [1-14] that the resonant frequency of a circular microstrip antenna for TM_{11} mode is determined by ε_r, a, and h.

III. ARTIFICIAL NEURAL NETWORKS

ANNs are biologically inspired computer programs designed to simulate the way in which the human brain processes information. Multilayered perceptrons (MLPs) [15,25] are the simplest and therefore most commonly used neural network architectures. MLPs can be trained using many different learning algorithms [15-19, 26-30]. In this work, MLPs are trained with the use of DBD, EDBD, QP, DRS and GA algorithms.

The DBD algorithm [18] is a heuristic approach to improve the speed of convergence of the connection weights in MLPs. Experimental studies suggest that each dimension of the weight space may be quite different in terms of the overall error surface. In order to account for the variation of the error surface, specially, that every connection of a network should have its own learning coefficient. The idea is that the step size suitable for one weight dimension may not be appropriate for all weight dimensions. By assigning a learning coefficient to each connection and permitting this learning coefficient to change continuously overtime, more degrees of freedom are introduced to reduce the time to convergence. By using past values of the gradient, heuristic can be applied to infer the curvature of the local error surface. With this type information, intelligent steps can be taken in the weight space using a number of straightforward algorithms.

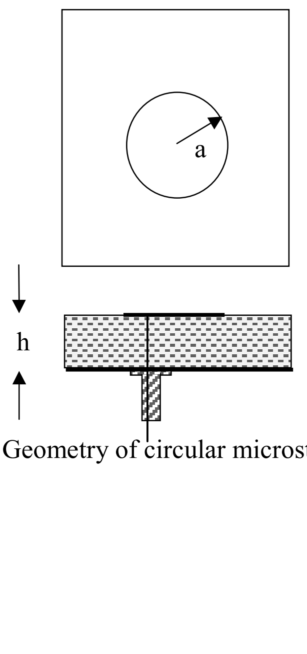

Figure 1. Geometry of circular microstrip antenna

The EDBD algorithm [19] is an extension of the DBD algorithm and based on decreasing the training time for multilayered perceptrons. The use of the momentum heuristics and avoiding the cause of the wild jumps in the weights are the features of the algorithm. The EDBD algorithm includes a little-used error recovery feature which calculates the global error of the current epoch during training. If the error measured during the current epoch is greater than the error of the previous epoch, then the network's weights revert back to the last set of the weights produced the lower error. However, a patience factor has been included into the error recovery feature, which may produce the better performance of the networks through the use of this feature.

The QP algorithm was developed by Fahlman [17] as a new method of improving the rate of convergence in multilayered perceptrons.

The GA [29] is a parallel, robust, and probabilistic search technique that is simple and easily implemented without gradient calculation, compared with the conventional gradient-based search procedure. Most important of all, the genetic algorithm also provides a mechanism for global search that is not easily trapped in local optima. The advantage of applying GA to neural network training is that there is scope for optimising the complete network (the network configuration, activation function as well as connection weights). However, the GA tends to be slower in producing a solution as it has to handle several possible solutions simultaneously.

The DRS [30] is a reinforcement learning approach and is used to calculate the weights of MLPs. This algorithm also tries to minimize the overall error. Random steps are taken in the weights and a directed component is added to the random step to enable an impetus to pursue previously search directions. The DRS is based on four procedures as random step, reversal step, directed procedure and self-tuning variance.

An alternative network architecture to the MLP is the RBF network [26-28]. In most general terms, a network with an internal representation of hidden neurons, radially symmetric, is named as a RBF network. The topology of the RBF network is obviously similar to that of the three-layered MLP, and the differences lie in the characteristics of the hidden neurons. The construction of a radial basis function network in its most basic form involves three entirely different layers. The input layer is made up of source neurons. The second layer is a hidden layer of high dimension serving a different purpose from that in a MLP. This layer consists of an array of neurons. Each neuron contains a parameter vector called a centre. The neuron calculates the Euclidean distance between the centre and the network input vector, and passes the result through a non-linear function. The output layer is essentially a set of linear combiners and supplies the response of the network. The transformation from input layer to the hidden layer is non-linear, whereas the transformation from the hidden layer to the output layer is linear. The output of an hidden layer is a function of the distance between the input vector and the stored centre. Linear regression, or a gradient descent algorithm is used to determine the weights from the hidden layer to the output layer. In this work, BP is used to train the weights of the layer.

IV. NEURAL NETWORKS FOR THE RESONANT FREQUENCY COMPUTATION

ANNs have been adapted for the calculation of the resonant frequency (RF) of electrically thin and thick circular MSAs. MLPs are trained with the use of DBD, EDBD, QP, DRS and GA algorithms. RBFN is trained according to its learning strategy [16,26-28]. For the neural models, the inputs are a, h, and ε_r, and the output is the measured resonant frequency f_{me}.

In the MLP structure, input layer has the linear transfer function and the hidden and output layers have the tangent hyperbolic function. In the RBF the gaussian function was used. Training an ANN with the use of a learning algorithm to compute RF involves presenting it sequentially with different sets (a, h, ε_r) and corresponding measured values f_{me}. Differences between the target output f_{me} and the actual output of the ANN are evaluated by a learning algorithm. The adaptation is carried out after the presentation of each set (a, h, ε_r) until the calculation accuracy of the network is deemed satisfactory according to some criterion (for example, when the error between f_{me} and the actual output for all the training set falls below a given threshold) or the maximum allowable number of epochs or generations is reached.

The training and test data sets used in this paper have been obtained from the previous experimental works [1-2,4-8], and are given in Table 1. The 17 data sets in Table 1 were used to train the networks. Only, 3 data sets that are shown in boldface type in Table 1 were used for test because of the limited experimental data available in the literature.

After several trials, it was found that three hidden layers network achieved the task in high accuracy except for RBFN. The number of neurons in the three hidden layers and the iteration numbers are given in Table 2. A set of random values distributed uniformly between -0.1 and +0.1 was used to initialize the weights of the networks. However, the tuples were scaled between -1.0 and +1.0 for inputs and –0.8 and +0.8 for outputs before training. The random and sequential training strategies are followed.

The parameters of the networks are: *for DBD,* κ=0.01, φ=0.5, θ=0.7, α=0.2; *for EDBD,* κ_α=0.095, κ_μ=0.01, γ_μ=0.0, γ_α=0.0, φ_μ=0.01, φ_α=0.1, θ=0.7, λ=50; *for QP,* δ=0.0, α=0.1, ε =1.0, μ=9.0; *for RBF*, the learning coefficient was set to 0.15, and the momentum coefficient was fixed to 0.4; *for DRS*, the weight bound is fixed to 15 and the variance is 0.0001; *for GA*, the individuals=50, the mutation factor=4.0, the mutation probability=0.01, the crossover probability increment =0.09 and the parental biases=1.6. The meanings of the learning algorithm parameters given above and detailed discussion of the learning algorithms are available in the literature [15-19,25-30].

V. RESULTS AND CONCLUSIONS

The resonant frequency results obtained by using neural models for electrically thin and thick circular MSAs are compared with the measured results in Table 1. The training and test absolute errors, and total absolute errors between the computed and experimental results in Table 1 for every neural model are also listed in Table 3.

When the performances of neural models are compared with each other, the best results for training and test were obtained from DBD and EDBD, respectively. In training and testing, the worst result for was obtained from GA. The highest accuracy in the total absolute errors was achieved with the EDBD. When the two heuristic approaches were compared with each other, the DRS was found better than the GA. The standard DRS algorithm is the simplest of the algorithms evaluated. Its implementation only requires the selection of two parameters, as opposed to four for DBD and QP, five for GA, and eight for EDBD. In general, the need for choosing large numbers of parameters in the algorithms increases the possibility of incorrectly setting their values. DBD was found the most successful ANN in training but it failed in test. In conclusion, EDBD remains the algorithm of choice for training and testing MLPs although care must be paid to select the appropriate eight parameters of the network for the design of MLP structures for the given tasks.

In order to determine the most appropriate suggestion given in the literature, the total absolute errors between the experimental results and the theoretical results obtained by using the other methods proposed in the literature [2-4,7,9-12,14] for circular MSAs given in Tables 1 are also listed in Table 4. When the results of neural models are compared with the theoretical results of other scientists, the results of MLPs trained by DBD, EDBD, QP, and RBFN are better than those predicted by other scientists. The good agreement between the measured values and our computed resonant frequency values supports the validity of the neural models.

Table 1. Comparison of measured and calculated resonant frequencies obtained by using neural models for electrically thin and thick circular microstrip antennas.

a (cm)	h (cm)	ε_r	h/λ_d	Measured f_{me} (MHz)	Present Neural Models EDBD (MHz)	DBD (MHz)	QP (MHz)	DRS (MHz)	GA (MHz)	RBF (MHz)
6.800	0.08000	2.32	0.003392	835□	835	835	835	835	930	835
6.800	**0.15900**	**2.32**	**0.006692**	**829□**	**828**	**828**	**828**	**932**	**898**	**812**
6.800	0.31800	2.32	0.013159	815□	815	815	815	816	899	815
5.000	0.15900	2.32	0.009106	1128Δ	1128	1128	1126	1126	944	1129
3.800	0.15240	2.49	0.011567	1443∇	1443	1443	1446	1443	1435	1440
4.850	0.31800	2.52	0.018493	1099x	1099	1099	1100	1098	1081	1099
3.493	0.15880	2.50	0.013140	1570♦	1570	1570	1568	1572	1582	1572
1.270	0.07940	2.59	0.017336	4070♦	4070	4070	4070	4070	4028	4070
3.493	0.31750	2.50	0.025268	1510♦	1510	1510	1509	1510	1516	1510
4.950	0.23500	4.55	0.013785	825♦	825	825	826	828	885	826
3.975	0.23500	4.55	0.017210	1030	1030	1030	1029	1024	1013	1029
2.990	**0.23500**	**4.55**	**0.022724**	**1360**	**1361**	**1364**	**1357**	**1362**	**1198**	**1399**
2.000	0.23500	4.55	0.033468	2003	2003	2003	2003	2007	1996	2004
1.040	0.23500	4.55	0.062659	3750	3750	3750	3750	3747	3751	3749
0.770	0.23500	4.55	0.082626	4945	4945	4945	4945	4947	4943	4946
1.150	0.15875	2.65	0.038118	4425†	4428	4425	4426	4413	4471	4427
1.070	0.15875	2.65	0.040684	4723†	4720	4723	4721	4732	4690	4719
0.960	**0.15875**	**2.65**	**0.045006**	**5224†**	**5224**	**5232**	**5225**	**5261**	**5184**	**5230**
0.740	0.15875	2.65	0.057146	6634†	6634	6634	6633	6617	6632	6630
0.820	0.15875	2.65	0.052300	6074†	6075	6074	6075	6094	6078	6080

□These frequencies measured by Dahele and Lee [5];Δthis frequency measured by Dahele and Lee [6];∇ this frequency measured by Carver [4]; x this frequency measured by Antoszkiewicz and Shafai [8];♦these frequencies measured by Howell [2]; † these frequencies measured by Itoh and Mittra [1]; the remainder measured by Abboud et al. [7].

Table 2. The neuron numbers in the hidden layers and the iteration numbers.

ANNs	The number of neurons in: First hidden layer	Second hidden layer	Third hidden layer	Iteration number for training (x1000)
EDBD	8	8	5	6 100
DBD	6	6	6	30 000
QP	6	6	6	25 000
DRS	5	5	5	1 000
GA	5	5	5	250
RBF	10	5	-	7 000

Table 3. Train, test and total absolute errors between the measured and calculated resonant frequencies for various neural networks.

ANNs	Train absolute errors (MHz)	Test absolute errors (MHz)	Total absolute errors (MHz)
EDBD	7	2	9
DBD	0	13	13
QP	16	5	21
DRS	82	142	224
GA	621	271	892
RBF	27	62	89

Table 4. Total absolute errors between the measured and calculated resonant frequencies for the methods available in the literature.

Methods	[4]	[2]	[3]	[7]	[9]	[10]	[11]	[12]	[14]
Errors (MHz)	965	3341	342	253	383	352	353	1047	207

A distinct advantage of neural computation is that, after proper training, a neural network completely bypasses the repeated use of complex iterative processes for new cases presented to it. For engineering applications, the simple models are very usable. Thus the neural models given in this work can also be used for many engineering applications and purposes.

REFERENCES

1. T. Itoh and R. Mittra, Analysis of a Microstrip Disk Resonator, AEU, Vol. 27, No. 11, pp. 456-458, 1973.
2. J. Q. Howell, Microstrip Antennas, IEEE Trans. Ant. Propagat., Vol. AP-23, pp. 90-93, Jan. 1975.

3. G. Derneryd, Microstrip Disc Antenna Covers Multiple Frequencies, Microwave J., Vol. 21, pp. 77-79, 1978.
4. K. R. Carver, Practical Analytical Techniques for the Microstrip Antenna, Proc. Workshop on Printed Circuit Antennas, New Mexico State University, pp. 7.1-7.20, 1979.
5. J. S. Dahele and K. F. Lee, Effect of Substrate Thickness on the Performance of a Circular-Disk Microstrip Antenna, IEEE Trans. Ant. Propagat., Vol. AP-31, No.2, pp. 358-364, March 1983.
6. J. S. Dahele and K. F. Lee, Theory and Experiment on Microstrip Antennas with Airgaps, IEE Proc., Vol. 132, Pt.H, No. 7, pp. 455-460, December 1985.
7. F. Abboud, J. P. Damiano, and A. Papiernik, New Determination of Resonant Frequency of Circular Disc Microstrip Antenna: Application to Thick Substrate, Electron. Lett., Vol. 24, No. 17, pp. 1104-1106, 18th Aug. 1988.
8. K. Antoszkiewicz and L. Shafai, Impedance Characteristics of Circular Microstrip Patches, IEEE Trans. Ant. Propagat., Vol. AP-38, No. 6, pp.942-946, June 1990.
9. Q. Liu and W. C. Chew, Curve-Fitting Formulas for Fast Determination of Accurate Resonant Frequency of Circular Microstrip Patches, IEE. Proc., Vol. 135, Pt.H, No. 5, pp. 289-292, Oct. 1988.
10. J. S. Roy and B. Jecko, A Formula for the Resonance Frequencies of Circular Microstrip Patch Antennas Satisfying CAD Requirements, International Journal of Microwave and Millimeter-Wave Computer-Aided Engineering, Vol. 3, No. 1, pp. 67-70, 1993.
11. K. Güney, Resonant Frequency of Electrically-Thick Circular Microstrip Antennas, International Journal of Electronics (IJE), Vol. 77, No. 3, pp. 377-386, 1994.
12. K. F. Lee and Z. Fan, CAD Formulas for Resonant Frequencies of TM_{11} Mode of Circular Patch Antenna with or without Superstrate, Microwave and Optical Technology Letters, Vol. 7, No. 12, pp. 570-573, August 20, 1994.
13. S. Sagiroglu, K. Güney and M. Erler, Resonant Frequency Calculation for Circular Microstrip Antennas Using Artificial Neural Networks, Int. J. of RF Microwave and Millimeter-Wave Computer-Aided Engineering. Vol. 8, pp. 270-277, 1998.
14. A. Akdağlı and K. Güney, Effective Patch Radius Expression Obtained Using a Genetic Algorithm for the Resonant Frequency of Electrically Thin and Thick Circular Microstrip Antennas, IEE Proceedings-Microwaves, Antennas and Propagation, Pt.H., Vol. 147, no. 2, pp. 156-159, 2000.
15. S. Haykin, Neural Networks: A Comprehensive Foundation, Macmillan College Publishing Company, New York, 1994.
16. Neural Computing, A Technology Handbook for Professional II/PLUS and NeuralWorks Explorer, NeuralWare, Inc., Technical Publications Group, Pittsburgh, 1996.
17. S.E. Fahlman, Fast Learning Variations On Back Propagation: An Empirical Study, In D.S.Touretzky, G.E.Hinton and T.J. Sejnowski (Eds.), Proc. of the 1988 Connectionist Models Summer School, San Mateo, CA, Morgan Kaufmann, pp. 38-51, 1988.
18. R.A. Jacobs, Increased Rate of Convergence Through Learning Rate Adaptation, Neural Networks, Vol. 1, pp. 295-307, 1988.
19. A. A. Minai and R. D. Williams, Acceleration of Backpropagation Through Learning Rate and Momentum Adaptation, Int. Joint Conf. on Neural Networks, Vol. 1, pp. 676-679, January 1990.
20. S. Sagiroglu and K. Güney, Calculation of Resonant Frequency for An Equilateral Triangular Microstrip Antenna Using Artificial Neural Networks, Microwave and Optical Technology Letters, Vol. 14, No. 2, pp. 89-93, 1997.
21. K. Güney, M. Erler and S. Sagiroglu, Neural Computation of Mutual Coupling Coefficient Between Two Rectangular Microstrip Antennas With Various Substrate Thicknesses, Proc. of PIERS'98, Nantes, France, pp. 57, July 13-17, 1998.
22. S. Sagiroglu, K. Güney and M. Erler, Calculation of Bandwidth for Electrically Thin and Thick Rectangular Microstrip Antennas With The Use of Multilayered Perceptrons, Int. J. of RF and Microwave Computer-Aided Engineering, Vol.9, pp. 277-286, 1999.
23. D. Karaboga, K. Güney, S. Sagiroglu and M. Erler, Neural Computation of Resonant Frequency of Electrically Thin and Thick Rectangular Microstrip Antennas, IEE Proc. Microw. Antennas Propag., Vol.146, No.2, pp. 155-159, April 1999.
24. K. Güney, M. Erler and S. Sagiroglu, Artificial Neural Networks for The Resonant Resistance Calculation of Electrically Thin and Thick Rectangular Microstrip Antennas, Electromagnetics, Vol. 20, No. 5, pp. 387-400, 2000.
25. D.E. Rumelhart and J. L. McClelland, Parallel Distributed Processing. Vol.1, The MIT Press, Cambridge, 1986.
26. D.S. Broomhead and D. Lowe 1988, Multivariable Functional Interpolation and Adaptive Networks, Complex systems, Vol. 2, pp. 321-355, 1988.
27. J. Moody and C. Darken, Fast-learning In Networks of Locally-Tuned Processing Units, Neural Computation, Vol. 1, pp. 281-294, 1989.
28. S. Chen, C. F. N. Cowan and P. M. Grant, Orthogonal Least Squares Learning Algorithm for Radial Basis Function Networks, IEEE Transactions on Neural Networks, Vol. 4, pp. 302-309, 1991.
29. L. Davis, Handbook of Genetic Algorithms, (Eds), Van Nostrand Reinhold, NY, 1991.
30. J. Matyas, Random Optimization, Automation and Remote Control, Vol. 26, pp. 246-253, 1965.