# **Estimation of Effective Dielectric Constant of a Rectangular Microstrip Antenna using ANN**

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#### **Abstract**

The present work is utilizing multilayer feed-forward back-propagation artificial neural network (MLFFBP-ANN), Cascade forward back propagation (CFBP) and Radial basis network (RBF) to approximate neural model for the estimation of effective dielectric constant of a rectangular patch Antenna. A relative performance of the different variants of back propagation training algorithms is also carried out for estimating the effective dielectric constant with particular attention paid to the speed of computation and accuracy achieved. This type of performance comparison has not been attempted so far for this particular design parameter. The network training and test data is generated using relevant electromagnetic relationships. Results of the network when compared with the theoretical and simulation findings, found quite satisfactory.

**Index terms:** Microstrip antenna, artificial neural network, Back-propagation, Simulation, Modeling.

## Introduction

Artificial neural network have been very intensively used for modeling active and passive components, design and optimization of microwave circuits, modeling microstrip antennas, reverse modeling of microwave devices, automatic impedance matching, etc. Using artificial neural networks, microwave engineers have tried to simplify a rather difficult and time consuming design of microwave systems. In the literature [1-9], artificial neural network (ANN) models have been built for the

analysis of different microwave devices including Microstrip antennas as a tool to improve the CAD designs techniques.

However, in the present work, the synthesis ANN model is built to obtain the effective dielectric constant ( $\varepsilon_{reff}$ ) of the rectangular patch antenna as the function of input variables, i.e. patch dimension W , L (length and width) of the patch, height of the dielectric substrate (h) and the resonant frequency (fr).

A method for estimating the effective dielectric constant of a rectangular microstrip patch antennas, based on the multilayered-perceptron back propagation feed forward neural network (MLPBPFF) with different variants of back propagation training algorithm , Cascade forward back propagation (CFBP) and radial basis function neural network (RBFNN) is presented .The models are simple, easy to apply, and very useful for antenna engineers to predict effective dielectric constant of the patch antenna.

# **Design and Data Generation**

The rectangular Microstrip antennas [10] are made up of a rectangular patch with dimensions width (W) and length (L) over a ground plane with a substrate thickness h having dielectric constant  $\varepsilon_r$ . There are numerous substrates that can be used for the design of Microstrip antennas, and their dielectric constants are usually in the range of  $2.2 \le \varepsilon_r \le 12$ . Thin substrates with higher dielectric constants are desirable for microwave circuitry because they require tightly bound fields to minimize undesired radiation and coupling, and lead to smaller element.

Accurate analysis of a microstrip line requires a cumbersome computational technique. The neuro computational technique can simplify the calculation of the effective dielectric constant ( $\varepsilon_r$ ) of Microstrip line. Substrate dielectric constant ( $\varepsilon_r$ ) and the width to height (W/H) ratio are the inputs to the network. The network training and test data is generated using relevant electromagnetic relationships.

As an example microstrip line feed patch is preferred. The substrate chosen is epoxy glass material with dielectric constant  $\epsilon_r$ = 4.4 and height h =1.6mm. Here the electromagnetic formula [10] used to calculate effective dielectric constant for the given value of  $\epsilon_r$ , W and h is given by equation (1)

$$\varepsilon_{reff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2} \left[ 1 + 12 \frac{h}{W} \right]^{-1/2} \tag{1}$$

## **Applying the Neuro Computational Technique**

In this paper, a multilayerfeed-forward back propagation artificial neural network[11] with one hidden layer and trained by different variants of back propagation training algorithms is used to model the design problem. Apart from MLPBPNN other networks like Cascade forward back propagation (CFBP) and radial basis function neural network (RBFNN) are also used to estimate the effective dielectric constants of

a rectangular Microstrip antenna. The above three different networks are also compared to evaluate the performance for the presented example as shown in table 1.0, The MLPFFBP network is trained with 7 different training algorithms to achieve the required degree of accuracy and hence compared for network performance as shown in table 2.0

Set of 73 input-output pairs is created out of which 60 patterns are used in training set and rest 13 input-output pairs for the validation set.. Neural network trained on data dictionary have been applied to calculate the effective dielectric constant, ( $\varepsilon_{reff}$ ) for given values of W in the specified range 28 mm $\leq$ w/h $\leq$ 40mm keeping h as constants. Table 3.0 shows the comparison of CFBP, MLPBP RBF ANN with the Target values and simulation findings from PCAD Software to evaluate network performance for 13 test patterns which are not included during the training of neural model.

**Table 1:** Performance evaluation of three different networks.

Network structure	Number of	Mean square	Estimation of
	epochs	error	$arepsilon_{reff}$
			average error Test data
Multilayer Feed forward back propagation with train LM	12	6.80801e-008	0.0103
Cascade forward back propagation	15	7.16304e-008	0.0271
Radial basis network	24	5.34334e-005	0.0089

**Table 2:** Performance evaluation of seven different variants of back propagation Training algorithm.

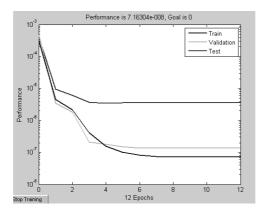
Different training algorithm	No. of	Mean square	Estimation of $\varepsilon_{reff}$
	epochs	error Average error Test	
			data
Scaled conjugate gradient	10	1.23917e-006	0.0379
Fletcher-Reeves	35	1.96182e-006	0.0365
Polka-Ribiere update	9	3.59924e-006	0.0361
Powell-beale restarts	11	1.25461e-006	0.0321
Levenberg-Marquardt	12	9.51117e-007	0.0103
Quasi-Newton Algorithms			
a) One step secant	25	6.331e-006	0.0481
b) BFGS	16	4.377e-006	0.0547
c) Resilient Back	30	1.645e-006	0.0580
propagation			

W/h	$\mathcal{E}_{r}$ eff CFBP	$\mathcal{E}_{r}$ eff MLPBP	$\mathcal{E}_{r}$ eff RBF	$\mathcal{E}_{r}$ eff THEORITICAL	$\mathcal{E}_{r}$ eff PCAD
39.000	4.187	4.186	4.187	4.187	4.217
38.125	4.182	4.182	4.183	4.183	4.213
37.250	4.179	4.178	4.178	4.178	4.209
36.375	4.174	4.175	4.174	4.174	4.206
35.500	4.169	4.168	4.169	4.173	4.202
34.625	4.164	4.164	4.165	4.165	4.197
33.750	4.160	4.161	4.162	4.167	4.193
32.875	4.155	4.155	4.155	4.155	4.19
32.000	4.150	4.151	4.150	4.152	4.189
31.125	4.144	4.144	4.144	4.144	4.184
30.250	4.138	4.138	4.138	4.138	4.179
29.375	4.1325	4.1326	4.132	4.132	4.174
28.750	4.1285	4.1282	4.128	4.128	4.168

**Table 3:** Comparison of CFBP, MLPBP and RBF ANN results with the Target values and simulation findings from PCAD software to evaluate network performance.

## **Results**

The training and test graphs for the proposed network structures are shown in fig 1.0-fig 6.0. Results shown in table 1.0, the graph depicted in figure 6.0 and comparison of CFBP, MLPBP and RBF ANN results for test patterns with the Target values and simulation findings as notified in table 3.0 concludes that Radial Basis neural network among three proposed neural networks is giving the best results with average error value of 0.0089 with the accuracy of 99.98%. A graph shown in figure 4 and 5 depicts the network performance for feed forward network with Levenberg-Marquardt (trainlm) as a training algorithm with average error 0.0132 and Cascade forward back propagation with error value equal to 0.027 for the mentioned test patterns in the specified range and found very satisfactory.



**Fig 1.** Performance pattern of training data for feed forward back propagation neural network with Levenberg Marquardt training algorithm

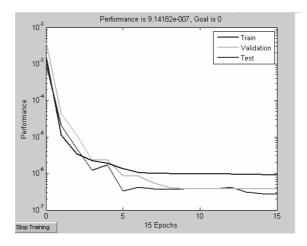


Fig 2. performance pattern of training data for Cascade forward back propagation neural network

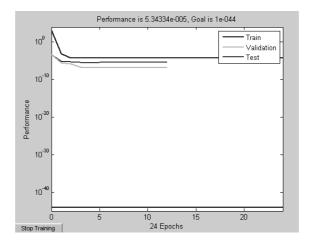


Fig 3. Performance pattern of training data for RBF neural network

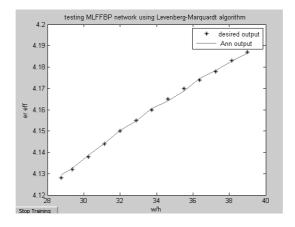
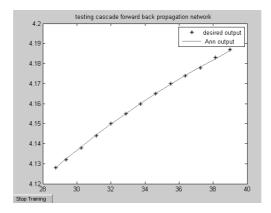
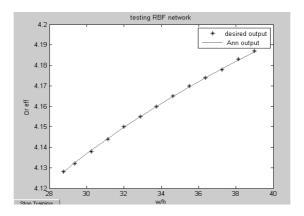


Fig 4.0 Plot between target  $\varepsilon_{\text{reff}}$  and computed  $\varepsilon_{\text{reff for}}$  feed forward back propagation neural network with Levenberg-Marquardt training algorithm



**Fig 5.** Plot between target  $\varepsilon_{\text{reff}}$  and computed  $\varepsilon_{\text{reff}}$  for Cascade forward back propagation neural network



**Fig 6.** Plot between target  $\varepsilon_{\text{reff}}$  and computed  $\varepsilon_{\text{reff}}$  for RBF neural network.

## **Conclusion**

The paper investigates a new approach utilizing an Artificial Neural Network for solving Microstrip antenna design problems. Neural Network offers the advantage of superior computational ability due to high degree of interconnectivity. This ability makes a Neural Network attractive in many applications in engineering and sciences. Conventional methods and softwares available for antenna design are time consuming or give approximate solutions while artificial intelligence based methods are fast as well as accurate. During the data generation phase effort and time are required but once the network is trained the results for any given samples are achieved almost instantaneously.

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#### References

- [1] Watson P.M., Gupta K.C., 1997," Design and Optimization of CPW Circuits Using EM ANN Models for CPW Components, IEEE Transactions on Microwave Theory and Techniques, 45(12), pp. 2515 2523,
- [2] Zaabab A. H., Zhang Q.J., Nakhla M., 1994," Analysis and Optimization of Microwave Circuits & Devices Using Neural Network Models, IEEE MTT-S Digest, pp. 393-396,
- [3] Zhang Q. J., Gupta K. C, 2000," Neural Networks for RF and Microwave Design", Artech House Publishers,
- [4] Nurhan Turker, Filiz Gunes, Tulay Yildirim, 2006," Artificial Neural Design of Microstrip Antennas", Turk J Elect. Engin, 14(3) pp. 445-453.
- [5] Devi S., Panda D.C., Pattnaik S.S., 2002, A Novel Method of Using Artificial Neural Networks to Calculate Input Impedance of Circular Microstrip Antenna, Antennas and propagation Society International Symposium, Vol. 3, pp. 462 465, .
- [6] Mishra R.K., Patnaik A., 1998," Neural network-based CAD model for the design of square-patch antennas", Antennas and Propagation, IEEE Transactions, 46(12), pp 1890 1891.
- [7] Peik F., Coutts G., and Mansour R.R., 1998, "Application of neural networks in microwave circuit modeling", Proceedings of IEEE Canadian Conference on Electrical and Computer Engineering, 2, pp 928–931.
- [8] Mishra R.K. and Patnaik A. 2000, "ANN Techniques in microwave engineering, IEEE Microwave Mag, 1, pp55–60.
- [9] Patnaik A., Mishra R.K., Patra G.K., Dash S.K., 1997,"An artificial neural network model for effective dielectric constant of microstrip line",IEEE Trans. on Antennas Propagat., 45 (11), pp.1697.
- [10] Balanis C.A., 1997,"Antenna Theory, John Wiley & Sons, Inc.
- [11] Simon Haykin, , 2003," Neural Networks "second edition pHI.