NEURAL MODEL FOR MULTILAYERED COPLANAR WAVEGUIDES WITH FINITE-WIDTH GROUND PLANES

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ABSTRACT

The two characteristic parameters of multilayered coplanar waveguides with finite-width ground planes have been determined with the use of only one neural model. The model was trained with six different training algorithms to obtain better performance and learning speed with simpler structure. The results have shown that the estimated characteristic parameters are in very good agreement with the other theoretical and experimental results available in the literature.

I. INTRODUCTION

In microwave and millimeter-wave integrated circuits (MMICs) coplanar waveguides (CPWs) have been widely used as an alternative to microstrip lines. The principal of CPWs simplifies the fabrication process by eliminating via holes. CPWs are often used in designing power dividers, balanced mixers, couplers and filters. The first analytic formulas for calculating quasi-static parameters of CPWs have been given by Wen [1] with the use of conformal mapping theory (CMT). However, Wen's formulas were based on the assumption that the substrate thickness is infinitely large; many researchers have extended the application of conformal mapping to CPWs with finite dimensions [2, 3]. To date, CPWs have been analyzed as complex structures in contrast with that first proposed by Wen. However all these analytical formulas are useful only for the CPWs with a single dielectric layer. In practice, there are many circumstances in which the substrates are multilayer. For example, in integrated circuits, connection lines either on buried between dielectric layers. In addition most of the initial studies on CPWs with finite-width ground planes were limited to dielectric substrates of infinite thickness. However, in a practical circuit, the thickness of the substrate is always finite. Hence subsequent studies considered CPWs with finite ground planes on a dielectric substrate [3-5], and sandwiched between two dielectric substrates [6], and sandwiched between multiple dielectric substrates [7].

To date, CPWs have been analyzed with use of quasi-static methods such as CMT [1-7] or full-wave techniques [8-10] in the literature. Full-wave analysis provide high precision in a wide frequency band and CMT leads to closed form analytical solutions suitable for CAD software packages and they provide simulation accuracy comparable with full-wave techniques for frequencies up to 20 GHz [7].

These methods, used to obtain the effective dielectric permittivity and the characteristic impedance of CPWs, have some disadvantages. The full-wave methods mainly take tremendous computational efforts, can not still make a practical circuit design feasible within a reasonable period of time and require strong mathematical background knowledge and time-consuming numerical calculations which need very expensive software packages. So they are not very attractive for the interactive CAD models. On the other hand, the closed-form design equations obtained by CMT consist of complete elliptic integrals which are difficult to calculate even with computers. For this reason, the approximate formulas are proposed in calculation of elliptic integrals [11].

Learning and generalization ability, easy of implementation and fast real-time operation features have made artificial neural networks (ANNs) popular in the last decade. Neural network modeling is relatively new to the microwave community. Furthermore, accurate and efficient microwave circuit components and microstrip antennas have been designed with the use of ANNs [12-17]. In these applications, ANNs have more general functional forms and are usually better than the classical techniques, and provide simplicity in real-time operation.

In this study, the characteristic parameters of Multilayered CPWs with finite-width ground planes (MCPWs-FWGP) have been determined with the use of only one neural model. ANNs were trained with six different training algorithms to obtain better performance and learning speed with simpler structure. Levenberg-Marquardt (LM), quasi-Newton (QN), Bayesian Regulation (BR), Conjugate with Fletcher (CGF), Gradient descent with momentum and adaptive learning rate (GDX) and Resilient Backpropagation (RP) training algorithms were used to train neural model. The inputs of this model are effective relative constants of the dielectric layers ε_{r1}, ε_{r2} and ε_{r3} and six geometric dimensions of MCPWs-FWGP (h_1, h_2, h_3/h_2, b/c, a/b and c). The outputs are the effective permittivity (ε_{eff}) and characteristic impedance (Z_0) of MCPWs-FWGP. In addition, the proposed neural model can be useful for different CPW configurations by choosing the appropriate geometric dimensions. This means, one can calculate the characteristic parameters of different CPW configurations with finite ground planes such as; conventional CPWs (ε_{r1}=1 and ε_{r2}=1), sandwiched CPWs between two dielectric substrates (ε_{r2}=1), sandwiched CPWs between three dielectric substrates and supported CPWs (SCPWs) (ε_{r1}=1). This flexibility is one of the other advantages of the proposed neural model.

II. THEORY

Figure 1 shows the structure of the MCPW with finite-width ground planes. In the figure, *S* (*2a*) represents the width of the signal ground. *w* is the width of the slots. *g* is the width of the ground planes. h_1, h_2 and h_3 are the thicknesses of the dielectric substrates. ε_{ri}'s are the effective relative constants of the dielectric materials. In the quasi-TEM limit the basic characteristics of CPWs can be determined when the capacitance of per unit length is known. The capacitances per unit length of waveguiding structures are determined with the assumption of the metal strips thickness are zero. The line capacitance of CPW can be given as a sum of partial capacitances.

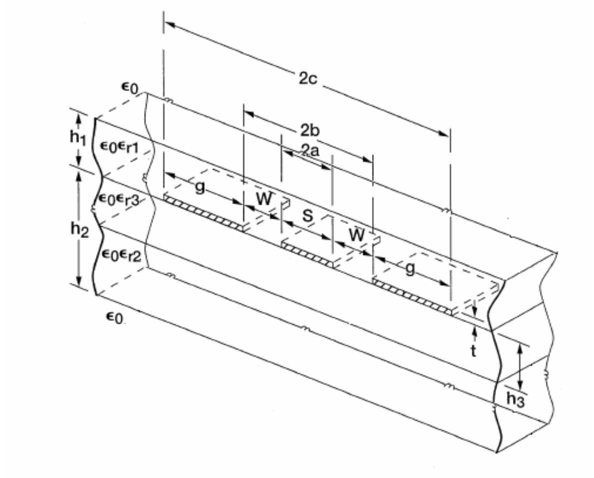


Figure 1. MCPW with finite ground planes

Therefore, in order to obtain the characteristic parameters of MCPWs-FWGP one only has to find the partial capacitances. Thus, the total capacitance of the transmission line is

$$C = C_0 + C_1 + C_2 + C_3 \tag{1}$$

where C_0 is the capacitance of the line in the absence of all dielectrics. C_1, C_2 and C_3 are the capacitance of the line assuming here is that the electric field exists only in the dielectric layers of thickness h_1, h_2 and h_3 and relative dielectric constants (ε_{r1}-1), (ε_{r2}-1) and (ε_{r3}-ε_{r2}), respectively. The capacitances of C_0, C_1, C_2, and C_3 are determined by means of the conformal mapping theory [7] and can be written as

$$C_0 = 4\varepsilon_0 \frac{K(k')}{K(k)} \tag{2}$$

$$k = \frac{c}{b}\sqrt{\frac{b^2 - a^2}{c^2 - a^2}} \tag{3}$$

$$C_1 = 2\varepsilon_0(\varepsilon_{r1} - 1)\frac{K(k_1')}{K(k_1)} \tag{4}$$

$$C_2 = 2\varepsilon_0(\varepsilon_{r2} - 1)\frac{K(k_2')}{K(k_2)} \tag{5}$$

$$C_3 = 2\varepsilon_0(\varepsilon_{r3} - \varepsilon_{r2})\frac{K(k_3')}{K(k_3)} \tag{6}$$

$K(k_i)$ and $K(k_i')$ are the complete elliptic integrals of the first kind with the modules of k_i and k_i'.

$$k_i = \frac{\sinh(\pi c/2h_i)}{\sinh(\pi b/2h_i)}\sqrt{\frac{\sinh^2(\pi b/2h_i) - \sinh^2(\pi a/2h_i)}{\sinh^2(\pi c/2h_i) - \sinh^2(\pi a/2h_i)}} \tag{7}$$

$$k_i' = \sqrt{1 - k_i^2} \tag{8}$$

The effective permittivity (ε_{eff}) of the line can be determined as;

$$\varepsilon_{eff} = \frac{C}{C_0} \tag{9}$$

The characteristic impedance (Z_0) can be then determined as;

$$Z_0 = \frac{30\pi}{\sqrt{\varepsilon_{eff}}}\frac{K(k)}{K(k')} \tag{10}$$

These closed-form expressions obtained by CMT consist of complete elliptic integrals of first kind which are difficult to calculate even with computers. Because of this, the approximate formulas were proposed calculation of elliptic integrals [11]. In this case, the characteristic impedance and effective permittivity of MCPWs-FWGP easily and simply determined by neural modeling approach.

III. ARTIFICIAL NEURAL NETWORKS (ANNs)

Artificial neural networks (ANNs) are the computer programs that are biologically inspired to simulate the way in which the human brain processes information. There are many types of neural networks for various applications in the literature. ANNs are feed-forward networks and universal approximators. They are the simplest and therefore most commonly used neural network architectures [18]. ANNs gather their knowledge by detecting the patterns and relationships in data and learn through their architectures and learning algorithms. An ANN consists of three layers: an input layer, an output layer and hidden layer. Neurons in the input layer act only as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer, and computes its output y_j as a function of the sum

$$y_j = f\left(\sum w_{ji} x_i \right) \tag{11}$$

f can be a simple threshold function, a sigmoid or a hyperbolic tangent function. The outputs of neurons in the output layer are similarly computed. Following this calculation, a learning algorithm is used to adjust the strengths of the connections in order to allow a network to achieve a desired overall behavior. In this work, many learning algorithms were used to train the neural models but better performance and learning speed with simple structure were achieved from the LM, The QN, the BR, the CGF, the RP and the GDX training algorithms, among all. These algorithms were summarized in the previous works [12, 13] of authors.

IV. APPLICATION TO THE PROBLEM

The proposed technique involves training an ANN to calculate the effective permittivity ε_{eff} and the characteristic impedance Z_0 of MCPWs-FWGP when the values of relative constants ε_{r1}, ε_{r2} and ε_{r3} and the other geometric dimensions are given. Training ANNs using different algorithms involve presenting those different sets ε_{r1}, ε_{r2}, ε_{r3} , h_1, h_2, h_3/h_2, b/c, a/b *and* c , ε_{eff} and Z_0) sequentially and/or randomly and corresponding calculated values the effective permittivity ε_{eff} and the characteristic impedance Z_0. Differences between the target and the actual outputs of the model are calculated through the network to adapt its weights. The adaptation is carried out after the presentation of each set until the calculation accuracy of the network is deemed satisfactory according to some criterions. These criterions can be the errors between ε_{eff} and $\varepsilon_{eff\text{-}ANN}$ and Z_0 and $Z_{0\text{-}ANN}$, which are obtained from ANN, for all the training set fall below a given threshold or the maximum allowable number of epochs reached.

The training and test data sets have been obtained from the CMT introduced in [3, 7] and experimental study proposed in [19] used in this work. 44800 and 5302 data sets were used in training and test processes, respectively. The ranges of training and test data sets were $1 \leq \varepsilon_{r1} \leq 9.85$, $1 \leq \varepsilon_{r2} \leq 13$, $1 \leq \varepsilon_{r3} \leq 13$, $5\text{mm} \leq h_1 \leq 10\text{mm}$, $1\text{mm} \leq h_2 \leq 10\text{mm}$, $0.1 \leq h_3/h_2 \leq 0.9$, $0.1 \leq b/c \leq 0.9$, $0.1 \leq a/b \leq 0.9$ and $5.75\text{mm} \leq c \leq 24\text{mm}$. After several trials; it was found that one hidden layered network achieved the task in high accuracy. The most suitable network configuration found was 10x20x10x2, this means that the numbers of neurons were 10 for the input and second hidden layers and 20 for the first hidden layers and 2 for output layers as shown in Figure 2. The tangent hyperbolic activation functions were used in the hidden layers. Linear activation function was employed in the output layer. Root mean square (RMS) and the average absolute percentage errors are considered throughout this neural model.

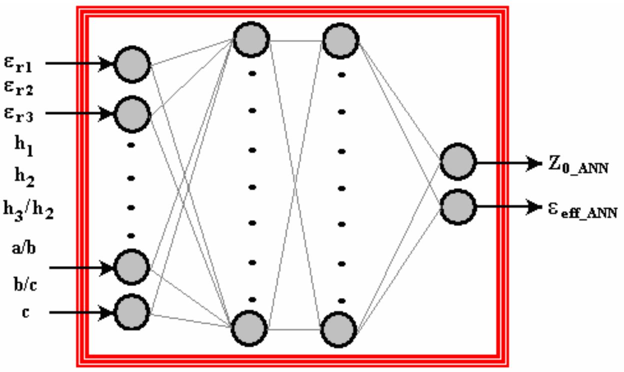


Figure 2. Neural model for MCPWs-FWGP

V. RESULTS

The training and test RMS errors obtained from neural models are given in Table 1. When the performances of neural models are compared with each other, the best results for training and test were obtained from the models trained with the LM and the QN algorithms. The results of the CMT [7] and the neural model trained with the LM for the effective dielectric permittivity and the characteristic impedance of SCPWs-FWGP and MCPWs-FWGP is given in Figure 3 (a) to (f). Figure 3.(a), (b) (c) and (d) depicted for different c values for the characteristic parameters of SCPWs-FWGP when $\varepsilon_{r1}=1$, $\varepsilon_{r2}=10.5$, $\varepsilon_{r3}=2.2$, $h_1=10$mm, $h_2=10$mm, $b/c=0.4$. Figure 3 (e) and (f) depicted for the characteristic parameters of MCPWs-FWGP when $\varepsilon_{r1}=9.85$, $\varepsilon_{r2}=10.5$, $\varepsilon_{r3}=2.2$, $h_1=10$mm, $h_2=10$mm, $b/c=0.4$, $c=9$mm. The good agreement shown in the Figure 3 supports the validity of our neural model for SCPWs-FWGP and MCPWs-FWGP. In Table 2, comparisons between the ANN model results, measured results [19] and other theoretical results [3] for the conventional CPW-FWGP available in the literature are given. The average absolute percentage errors between the measured [19] results and our neural model results is 1.331 %, the error between the measured [19] results and Veyres and Hanna's [3] formulas results is 1.609 % and the error between the measured [19] results and Chen and Chou's [7] formulas results is 1.753 %. These results obviously show that our neural models are valid for the calculation of the effective permittivity of conventional

CPWs-FWGP. As can be clearly seen from the table there is very good agreement between the results of the proposed ANN model and the other theoretical and experimental results.

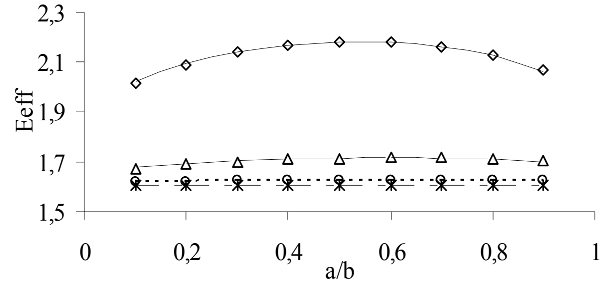
VI. CONCLUSION

The characteristic parameters of MCPWs-FWGP have been successfully determined with the use of only one neural model. Using proposed neural model, one can calculate accurately the effective permittivity and the characteristic impedance of MCPWs-FWGP without possessing strong background knowledge. In addition proposed neural model can also be used to determine the characteristic parameters of conventional CPWs-FWGP, sandwiched CPWs-FWGP between two dielectric substrates, supported CPWs-FWGP and sandwiched CPWs-FWGP between three dielectric substrates.

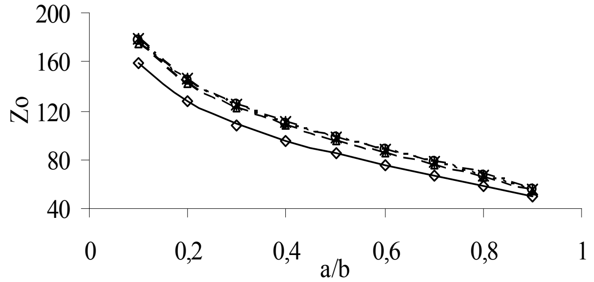
Finally, neural model presented in this work can be used easily, simply and accurately to determine the characteristic parameters of MCPWs-FWGP.

Table 1. Training and test RMS errors for the characteristic parameters of MCPWs-FWGP.

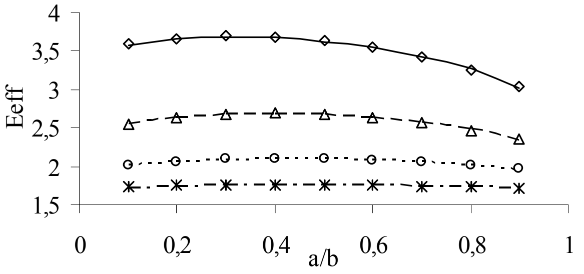
Learning Algorithms	**Training RMS Errors**		**Test RMS Errors**	
	ε_{eff}	**Z_0 (Ω)**	**ε_{eff}**	**Z_0 (Ω)**
LM	0.0310	0.0585	0.0773	0.1011
QN	2.5507	2.614	1.8722	2.1558
BR	1.1015	1.0648	1.155	2.5546
CGF	0.5962	5.6319	23.8775	21.8276
RP	8.8542	6.1968	13.6457	18.9706
GDX	22.6585	27.8889	84.1748	69.2312



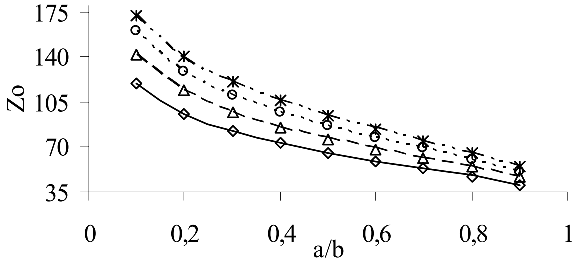
a) SCPW-FWGP (ε_{r1}=1, ε_{r2}=10.5, ε_{r3}=2.2 c=5.9 mm)



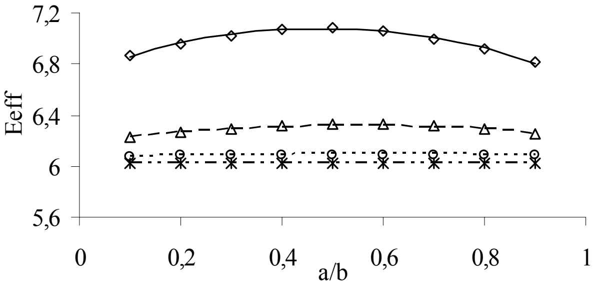
b) SCPW-FWGP (ε_{r1}=1, ε_{r2}=10.5, ε_{r3}=2.2 c=5.9 mm)



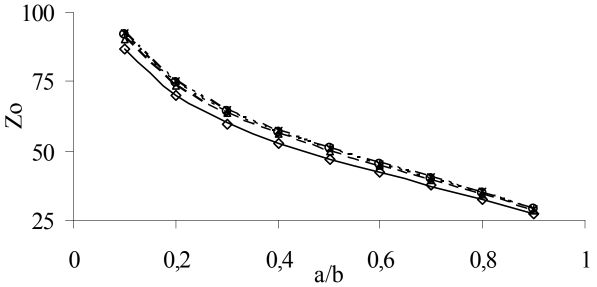
c) SCPW-FWGP (ε_{r1}=1, ε_{r2}=10.5, ε_{r3}=2.2 c= 24 mm)



d) SCPW-FWGP (ε_{r1}=1, ε_{r2}=10.5, ε_{r3}=2.2 c= 24 mm)



e) MCPW-FWGP (ε_{r1}=9.85, ε_{r2}=10.5, ε_{r3}=2.2, c=9 mm)



f) MCPW-FWGP (ε_{r1}=9.85, ε_{r2}=10.5, ε_{r3}=2.2, c=9 mm)

—— CMT and ◊ ANN for h_3/h_2=0.2
– – – CMT and Δ ANN for h_3/h_2=0.4
- - - - CMT and o ANN for h_3/h_2=0.6
– – - - CMT and x ANN for h_3/h_2=0.8

Figure 3. The neural and CMT results for different configurations of SCPWs-FWGP and MCPWs-FWGP (h_1=h_2=10mm, b/c=0.4)

Table 2. Comparison results for measured, theoretical [3, 7] and presented ANN model for conventional CPWs-FWGP h_3=0.65mm ε_{r3}=9.85 ε_{r1}=ε_{r2}=1 f=4GHz

S/h	**w/h**	**g/h**	$\varepsilon_{\mathrm{eff\_measured}}$ **[19]**	$\varepsilon_{\mathrm{eff\_calculated}}$ **[7]**	**Error %**	$\varepsilon_{\mathrm{eff\_calculated}}$ **[3]**	**Error %**	$\varepsilon_{\mathrm{eff}}$ **(ANN)**	**Error %**
2.04	0.15	11.64	4.737	4.756	0.401	4.753	0.338	4.76	0.486
1.95	0.66	11.61	4.237	4.263	0.613	4.261	0.566	4.24	0.071
1.85	1.8	10.93	3.627	3.531	2.647	3.531	2.647	3.557	1.93
1.89	3.59	11.38	3	2.856	4.8	2.856	4.8	2.92	2.667
1	1.09	35	4.41	4.338	1.633	4.338	1.633	4.363	1.066
0.37	1.03	7.75	4.75	4.789	0.821	4.789	0.821	4.816	1.389
0.76	1.03	7.75	4.5	4.535	0.788	4.535	0.778	4.569	1.533
1.55	1.03	7.8	4.17	4.136	0.815	4.136	0.815	4.13	0.959
3.1	1.04	7.75	3.7	3.655	1.216	3.655	1.216	3.633	1.811
7.7	1.01	7.7	3.23	3.107	3.808	3.15	2.477	3.185	1.393
					1.753%		**1.609%**		**1.331%**

REFERENCES

1. C. P. Wen, Coplanar waveguide: A surface strip transmission line suitable for nonreciprocal gyromagnetic device applications, IEEE Transaction Microwave Theory Tech., Vol.17, No. 12, 1969.
2. M. E. Davis, E. W. Williams and A. C. Celestini, Finite-boundary corrections to the coplanar waveguide analysis, IEEE Trans. Microwave Theory Tech., Vol.21, 1973.
3. C. Veyres and V. F. Hanna, Extension of the application of conformal mapping techniques to coplanar lines with finite dimensions, Int. Journal of Electronics, Vol.48, 1980.
4. R. E. DeBrecht, Coplanar balun circuits for GaAs FET high-power push-pull amplifiers, in 1973 IEEE G-MTT Int. Microwave Symp. Dig., Boulder, CO, pp. 309-311, June 4-6, 1973.
5. G. Ghione, C. U. Naldi, Coplanar waveguides for MMIC applications: effect of upper shielding, conductor backing, finite-extent ground planes, and line-to-line coupling, IEEE Transactions on Microwave Theory and Techniques, MTT-35(3), 260-267, 1987.
6. M. Cai, P. S. Kooi, M. S. Leong, and T. S. Yeo, Symmetrical coplanar waveguide with finite ground plane, Microwave Optical Tech. Lett., Vol. 6, No. 3, pp. 218-220, March 1993.
7. E. Chen and S. Y. Chou, Characteristics of coplanar transmission lines on multilayer substrates: modeling and experiments, IEEE Trans. Microwave Theory Tech., Vol. 45, No. 6, pp. 939-945, June 1997.
8. M. S. Soghomonian and I. D. Robertson, Finite difference modeling of novel waveguiding structures of MMIC applications, Int. Journal of Millimeter-wave Comp. Aided Eng., Vol.3, 1993.
9. C. N. Chang, W. C. Chang and C. H. Chen, Full-wave analysis of multilayer coplanar lines, IEEE Trans. Microwave Theory Tech., Vol. 39, 1991.
10. M. R. Lyons, J. P. K. Gilb and C. A. Balanis, Enhanced domain mode operation of a shielded multilayer coplanar waveguide via substrate compression, IEEE Trans. Microwave Theory Tech., Vol. 41, 1993.
11. W. Hilberg, From approximations to exact relations for characteristic impedances, IEEE Transactions on Microwave Theory and Techniques, MTT-17, 259-265, 1969.
12. C. Yildiz, S. Sagiroglu, M. Turkmen, neural model for coplanar waveguide sandwiched between two dielectric substrates, IEE-Proceedings-Microwaves, Antennas and Propagation, Vol. 151 No. 1, pp. 7-12, 2004.
13. C. Yildiz, M. Turkmen, A CAD approach based on artificial neural networks for shielded multilayered coplanar waveguides, AEÜ International Journal of Electronics and Communications, Vol. 58 No. 1, pp. 7-12, 2004.
14. C. Yildiz, and O. Saracoglu, Simple models based on neural networks for suspended and inverted microstrip lines, Microwave Optical Technology Letters, 39(5), pp. 383-389, 2003.
15. S. Sagiroglu and C. Yildiz; A multilayered perceptron Neural Network for a Micro-Coplanar Strip Line, Int. Journal of Electromagnetics, Vol. 22, No.7, 2002.
16. C. Yildiz, Sagiroglu, S., O. Saracoglu, and M. Turkmen, Neural models for an asymmetric coplanar stripline with an infinitely wide strip, International Journal of Electronics, 90(8), pp. 509-516, 2003.
17. Q. J. Zhang and K. C. Gupta; Neural Networks for RF and microwave design, Artech House, 2000.
18. S. Haykin; Neural Networks: A comprehensive Foundation, Macmillan College Publishing Comp., 1994.
19. E. Mueller, Measurement of the effective relative permittivity of unshielded coplanar waveguides, Electronic Letters, Vol. 13, No. 24, pp.729-730, 1977.