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MULTILAYER PERCEPTRON NEURAL ANALYSIS OF EDGE COUPLED AND CONDUCTOR-BACKED EDGE COUPLED COPLANAR WAVEGUIDES

P. Thiruvalar Selvan and S. Raghavan

Department of Electronics and Communication Engineering
National Institute of Technology
Tiruchirappalli 620015, Tamilnadu, India

Abstract—In recent years, Computer Aided Design (CAD) based on Artificial Neural Networks (ANNs) have been introduced for microwave modeling, simulation and optimization. In this paper, the characteristic parameters of edge coupled and conductor-backed edge coupled Coplanar Waveguides have been determined with the use of ANN model. Eight learning algorithms, Levenberg-Marquart (LM), Bayesian Regularization (BR), Quasi-Newton (QN), Scaled Conjugate Gradient (SCG), Conjugate Gradient of Fletcher-Powell (CGF), Resilient Propagation (RP), Conjugate Gradient back-propagation with Polak-Ribiere (CGP) and Gradient Descent (GD) are used to train the Multi-Layer Perceptron Neural Networks (MLPNNs). The results of neural models presented in this paper are compared with the results of Conformal Mapping Technique (CMT). The neural results are in very good agreement with the CMT results. When the performances of neural models are compared with each other, the best results are obtained from the neural networks trained by LM and BR algorithms.

1. INTRODUCTION

Advances in Monolithic Microwave Integrated Circuit (MMIC) technology and progress in CAD tools have led the researchers to develop CAD models for the analysis and synthesis of the generic transmission lines. The Coplanar Waveguides (CPWs) are ideally suited for modern Microwave Integrated Circuit (MIC) as well as MMIC applications and high speed integrated circuits. They have been the most studied transmission lines because of their several

Corresponding author: P. Thiruvalar Selvan (tvs742002@yahoo.co.in).

advantages over conventional micro strips for MMICs [1]. These include ease of parallel and series insertion of both active and passive components and high circuit density, drilling of holes or slots through the substrate is not needed [2], low radiation, low dispersion and avoidance of need for thin fragile substrates [3]. The field of CPWs are less confined than those of microstrip lines, thereby increasing sensitivity to environmental constraint such as conductor backing and line to line coupling [4]. Conventional edge-coupled coplanar waveguide structure was proposed in 1970 to implement a CPW directional coupler. However, the coupling effect is relatively weak due to its edge coupled configuration. The coupling coefficient of edge-coupled CPW structure can be enhanced by adding an extra floating conductor on another side of the substrate [5]. Conductor backing is often introduced in order to improve both the mechanical strength and the power handling capability of the line. Moreover it allows easy implementation of mixed coplanar micro strips circuits and lowers the impedance of the line.

In MMIC's, CPW has a complex structure in contrast with the first proposal of Wen [6, 7]. The full wave analysis is usually used to characterize such complex structure. Most of the earlier study efforts have been directed towards obtaining the design parameters by full wave numerical methods [8] or quasi-static conformal mapping methods [9]. Present analysis provides high precision in a wide frequency band and also general characteristics suitable for CAD analysis [4]. This novel method does not restrict the frequency limit as being restricted in quasi-static analysis. Once trained, the complexity of full wave computation is also dispensed with.

The fullwave methods mainly take tremendous computational efforts and cannot lead to 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. No closed form synthesis formulas for coplanar wave-guide are available; in contrast, both analysis and synthesis closed-form formulas for micro strip lines have existed for a long time [10]. Such closed-form design equations obtained by CMT method, which is the simplest & most often used quasi-static method, consists of complete elliptic integrals which are difficult to calculate even with computers. For this reason, the artificial neural networks recently gained attention as a fast and flexible tool to microwave modeling and design [11]. Neural network modeling is relatively new to the microwave community. The learning & generalization ability, fast real time operation features have made ANNs popular in the last decade. The process of neural model development is not trivial and involves many critical issues such as data generation, scaling, neural network training, etc. [13].

Furthermore, accurate and efficient microwave circuit components and micro strip antennas have been designed with the use of ANNs. 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 paper, the quasi-static parameters (effective permittivity, characteristic impedance, mode-velocity ratio and coupling coefficient) of Edge Coupled CPW (ECCPW) and Conductor-backed Edge Coupled CPW (CB-ECCPW) have been determined with the use of only one neural model. The neural model was trained with eight different learning algorithms to obtain better performance and faster convergence with simpler structures. The results obtained from ANN models have shown that the determined characteristics parameters are in very good agreement with the CMT results.

2. ANALYSIS OF CHARACTERISTIC PARAMETERS OF PROPOSED STRUCTURES

2.1. Edge-coupled CPW (ECCPW)

When two transmission lines are placed in close proximity, there is a strong interaction between their fields and power is coupled from one line to the other. The amount of coupling is dependent on the distance of separation between the lines and the interaction length. An edge coupled coplanar waveguide with two parallel coupled strip conductors symmetrically located between two grounds planes are shown in Figure 1. This structure can support two modes of propagation, the even and odd mode. For the even excitation a magnetic wall is placed along the plane of symmetry. Through a sequence of conformal mapping steps.

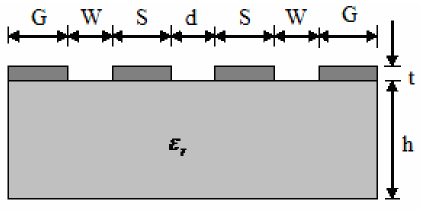


Figure 1. Cross section of edge coupled coplanar waveguides.

The even-mode effective dielectric constant can be defined as [12]

$$\varepsilon_{\mathit{eff},e} = 1 + (\varepsilon_r - 1)\frac{K(\psi k_2)}{K'(\psi k_2)}\frac{K'(\delta k_1)}{K(\delta k_1)} \tag{1}$$

where $K(\delta k_1)$ and $K'(\delta k_1)$ and $K(\psi k_2)$ and $K'(\psi k_2)$ are the complete elliptic integrals of the first kind with modules ψk_1.

The even-mode characteristics impedance $Z_{0,e}$ is

$$Z_{0,e} = \frac{60\pi}{\sqrt{\varepsilon_{\mathit{eff},e}}}\frac{K'(\delta k_1)}{K(\delta k_1)} \tag{2}$$

By using the similar procedure as that of the even mode, the odd mode effective dielectric constant $\varepsilon_{\mathit{eff},o}$ is defined as

$$\varepsilon_{\mathit{eff},o} = 1 + (\varepsilon_r - 1)\frac{K(k_3)}{K'(k_3)}\frac{K'(\delta)}{K(\delta)} \tag{3}$$

The odd-mode characteristics impedance $Z_{0,o}$ is

$$Z_{0,o} = \frac{60\pi}{\sqrt{\varepsilon_{\mathit{eff},o}}}\frac{K'(\delta)}{K(\delta)} \tag{4}$$

2.2. Conductor Backed Edge Coupled CPW (CB-ECCPW)

In the structure shown in Figure 2, a magnetic wall and an electric wall is placed along the plane of symmetry for the even and odd mode of excitation respectively and one-half of the structure is isolated.

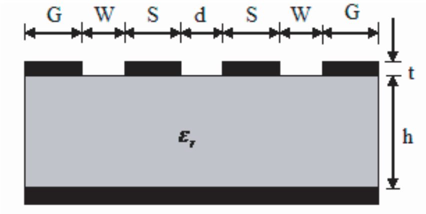


Figure 2. Cross section of conductor-backed edge-coupled CPW.

Through the sequence of conformal mapping steps the total capacitance per unit length is obtained. From the capacitance value, the effective dielectric constant, characteristics impedance, coupling coefficient and mode-velocity ratio are obtained. The odd-even mode effective dielectric constant $\varepsilon_{\mathit{eff},A}$ and the characteristics impedance $Z_{0,A}$ is given by [11, 12]

$$\varepsilon_{\mathit{eff},A} = \frac{\left[2\varepsilon_r\frac{K(x)}{K'(x)} + \frac{K(y)}{K'(y)}\right]}{\left[2\frac{K(x)}{K'(x)} + \frac{K(y)}{K'(y)}\right]} \tag{5}$$

$$Z_{0,A} = \frac{120\pi}{\sqrt{\varepsilon_{eff,A}}\left[2\frac{K(X)}{K'(X)} + \frac{K(Y)}{K'(Y)}\right]} \tag{6}$$

where $A = e$, $x = K_e$ and $y = \delta K_1$ for even mode and $A = o$, $x = Ko$ and $y = \delta$ for odd mode respectively. Further $K(K_e)$ and $K'(K_e)$ are the complete elliptic integrals of the first kind with modulus K_e.

The coupling coefficient and mode velocity ratio of both structures are given by

$$C = 20 * \log \frac{Z_0^{even} - Z_0^{odd}}{Z_0^{even} + Z_0^{odd}} \tag{7}$$

$$M = \frac{v_e}{v_o} = \sqrt{\frac{\varepsilon_{eff,\,o}}{\varepsilon_{eff,\,e}}} \tag{8}$$

3. ARTIFICIAL NEURAL NETWORKS (ANNS)

Neural networks, also called Artificial Neural Networks are information processing systems with their design inspired by the studies of ability of human-brain to learn from observations and to generalize by abstraction. Neural networks are first trained to model the electrical behavior of passive and active components/circuits. These trained neural networks, often referred to as neural network models (or simply neural models), can then be used in high-level simulation and design, providing fast answers to the task they have learned. Neural networks are efficient alternatives to conventional methods such as numerical modeling methods, which could be computationally expensive; or analytical methods, which could be difficult to obtain for new devices; or empirical models whose range and accuracy could be limited. Neural network techniques have been used for a wide variety of microwave applications such as embedded passives, transmission line components, vias, bends, CPW components, spiral inductors, FETs, amplifiers etc.. Neural networks have also been used in impedance matching, inverse modeling, measurements and synthesis [13, 14].

ANN learns relationships among sets of input-output data which are characteristics of the device under consideration. It is a very powerful approach for building complex and non-linear relationship between a set of input and output data [15–17]. There are many types of neural networks for various applications available in the literature. The MultiLayered Perceptron Neural Network (MLPNN) structure used in this work is shown in Figure 3. These structures with three layers (input output and hidden) are feed-forward networks and universal approximates. They are the simplest and therefore most commonly used neural network architecture.

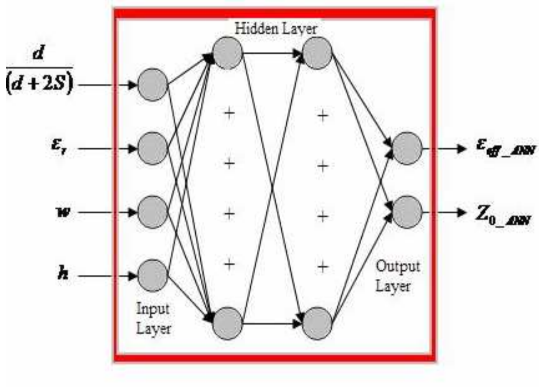


Figure 3. Configuration of proposed ANN model.

A neural network consists of many processing elements called neurons, each connected to many others. Every connection entering a neuron has a weight assigned to it. This weight is used to amplify, attenuate and change the sign in the incoming connection. An input vector containing distinct input element is entered in to the network. Each neuron operates on the output of the other neuron connected to it according to its transfer function and delivers a single output. Often the transfer function sums up the incoming signals to determine the values of the neuron's next output signals. The result is an output vector representing some characteristics associated with the input. The process of training the network is the matter of altering the connection weights systematically [18] to encode the desired input-output relationships. Most microwave applications used the supervised learning back propagation network in which the weights are adjusted on the basis of the difference between the values of output units and desired values. The eight learning algorithms used in this work are summarized below.

3.1. Levenberg-Marquardt [LM]

The LM algorithm is a least-squares estimation method based on the maximum neighborhood idea. It does not suffer from the problem of slow convergence. The LM method combines the best features of Gauss-Newton and Steepest-descent method and avoids many of their limitations [28]. This algorithm is very efficient when training small network [19, 20].

3.2. Bayesian Regularization [BR]

This algorithm takes place within the LM and requires more training and memory than the LM. This algorithm can train any network as long as its weight, inputs and transfer functions have derivative function [21]. It updates the weight according to LM optimization and minimizes a linear combination of squared errors and weights, and then determines the correct combination so as to produce a well generalized network [22]. It also modifies the linear combination so that at the end of training the resulting network has good generalization qualities.

3.3. Quasi-Newton [QN]

This is based on Newton's method but doesn't require calculation of second derivatives. At each iteration of the algorithm, the Hessian matrix (A_k) update is computed as a function of the gradient [28]. The line search function is used to locate the minimum. The first search direction is the negative of the gradient of performance. In succeeding iterations the search direction is computed according to the gradient. Newton's method often converges faster than conjugate gradient methods. The weight update for the Newton method is $w_{k+1} = w_k - g_k/A_k$, where A_k is the Hessian matrix of the performance index at the current value of the weights and biases [23].

3.4. Scaled Conjugate Gradient [SCG]

This algorithm was developed by Moller, and used to avoid the time consuming line search. It combines the Model-trust region [24] approach and the conjugate gradient approach. Backpropagation is used to calculate the derivation of performance with respect to the weight and bias variables.

3.5. Conjugate Gradient of Fletcher-Powell [CGF]

This method updates weights and bias values according to the conjugate gradient with Fletcher-Reeves [29]. This version of conjugate gradient uses the norm square of the previous gradient and the norm square of the current gradient to calculate the weights and biases.

3.6. Resilient Propagation [RP]

This algorithm provides faster convergence than other algorithm and avoids the bad influence of the size of the partial derivative on the weight update [25]. It also has the nice property that it requires only a modest increase in memory requirements.

3.7. Conjugate Gradient Back Propagation with Polak-Ribiere [CGP]

This algorithm is a network training function that updates weight and bias values according to the conjugate gradient back propagation with Polak-Ribiere updates. It can train any network as long as its weight, net input, and transfer functions have derivative functions [26]. It is used to calculate derivatives of performance with respect to the weight and bias variables. The line search function is used to locate the minimum point. In succeeding iterations the search direction is computed from the new gradient. The search direction at each iteration is determined by updating the weight vector as:

$$w_{k+1} = w_k + \alpha p_k,$$

where $p_k = -g_k + \beta_k p_{k-1}$, $\beta_k = \frac{\Delta g_{k-1}^T g_k}{g_{k-1}^T g_{k-1}}$ and $\Delta g_{k-1}^T = g_k^T - g_{k-1}^T$.

3.8. Gradient Descent [GD]

This is one of the line search minimization procedures. This method smoothen the descent direction in the steepest decent method [27]. The weights and biases are updated in the direction of the negative gradient of the performance function.

4. APPLICATION TO THE PROBLEM

The proposed technique involves training an ANN to calculate the effective dielectric permittivity, characteristics impedance of odd and even mode, coupling coefficient and mode velocity-ratio of ECCPW and CB-ECCPW when the values of s, w, d, h and ε_r are given. Only one neural model is used to calculate the characteristic parameters of both structures with different geometrical dimensions and electrical properties. The CMT was used to generate data for the input ranges of $0.1 \leq d/(d+2S) \leq 0.9$, $0.2 \leq (d+2S)/(d+2S+2w) \leq 0.7$ and $[(d/2)+S]/h = 0.5$. The MLPNN used in this work is trained by eight different algorithms. Training the ANNs with the use of a learning algorithm to calculate the characteristic parameters of ECCPW and CB-ECCPW involves presenting them sequentially and/or randomly with different sets (s, w, d, h and ε_r) and corresponding characteristic parameters (ε_{eff} and Z_0). First, the input vectors (s, w, d, h and ε_r) are presented to the input neurons and output vectors (ε_{eff} and Z_0) are computed. ANN outputs are then compared to the known outputs of the training data sets and errors are computed. Error derivatives are then calculated and summed up for each weight until all the training examples have been presented to the network. These error derivatives are then used to update the weights for neurons in the model. Training proceeds until errors are lower than prescribed values.

Even if there have been a number of approaches to find suitable number of neurons and layers in the literature, most of all are application specific. The number of neuron and hidden units for the application presented in this work were selected after several trials. It was found that a network with two hidden layer achieved the task with better accuracy. The most suitable network configuration found was $4 \times 12 \times 10 \times 2$; this means that the number of neurons were 4 for the input layer, 12 & 10 for the first & second hidden layers and 2 for the output layer. The tangent hyperbolic activation function was used in the input and hidden layers. Linear activation function was employed in the output layer.

5. NUMERICAL RESULTS AND DISCUSSION

ANNs have been successfully introduced to compute the odd-and even-mode characteristic impedances and effective permittivities of ECCPW and CB-ECCPW. In order to obtain the fast convergence with better performance & simpler structure, the proposed network were trained with eight different learning algorithms as mentioned above. The performance of learning algorithms are compared with each other and obtained training and test RMS errors are represented in the Figures 4

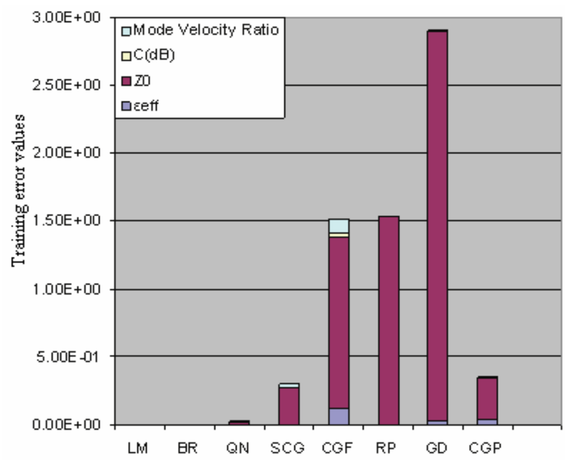


Figure 4. Bar chart comparison of training RMS error for different eight learning algorithms.

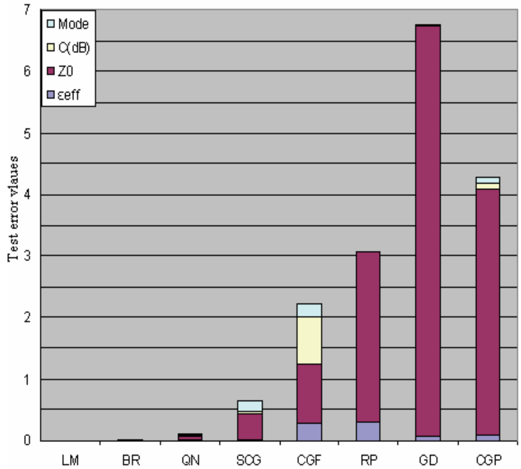
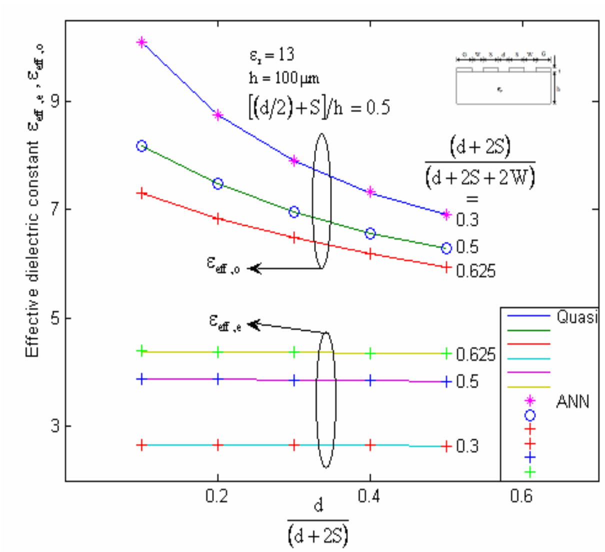


Figure 5. Bar chart comparison of test RMS error for different eight learning algorithms.

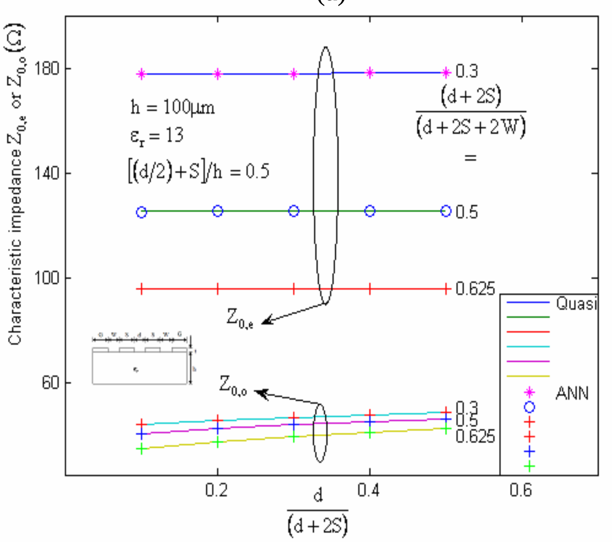
& 5 using bar chart for easy understanding. As it can be seen from all figures and bar chart that, the best network results were achieved from the models trained with LM and BR algorithms for both ECCPW and CB-ECCPW. In order to prove the validation of the proposed neural networks for the determination of characteristic parameters of ECCPW and CB-ECCPW, a comprehensive comparison has been made between the CMT results and the obtained network results. With the values of $h = 100\mu\text{m}$, $[(d/2) + S]/h = 0.5 \quad \varepsilon_r = 13$, $(d + 2S)/(d + 2S + 2w) = 0.3$, 0.5 and 0.625 the variation of characteristic parameters with respect to $d/(d + 2S)$ for ECCPW and CBECCPW are illustrated in Figures 6 & 7 respectively. As it was proved, among the eight algorithms the best LM training algorithm was used to obtain the characteristic parameters of both structures.

A distinct advantage of neural computation is that, after proper training, ANN completely bypasses the repeated use of complex iterative processes for new cases presented to it. The proposed method having the main advantage is that only one neural model is used to calculate the characteristic parameters of both ECCPW and CB-ECCPW.

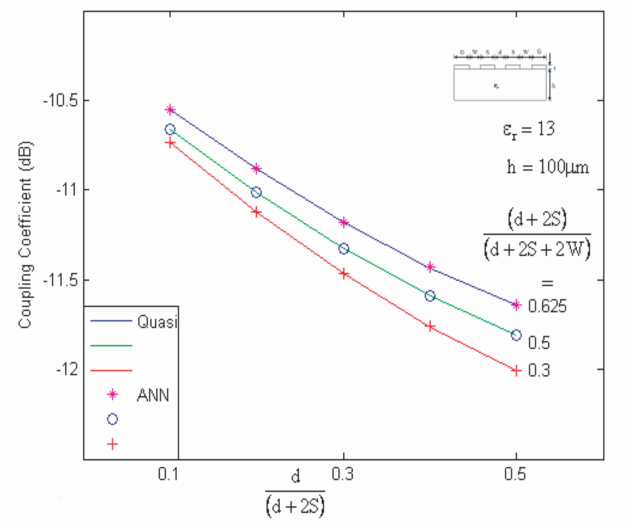
Without possessing strong background knowledge, the MLPNN models presented in this work can be used easily, simply and accurately to determine the characteristics parameters of both structures. Since the proposed models presented in this paper have good accuracy, require no tremendous computational effort and less background knowledge about CPW, they can be very useful for development of fast CAD algorithms. 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.



(a)



(b)



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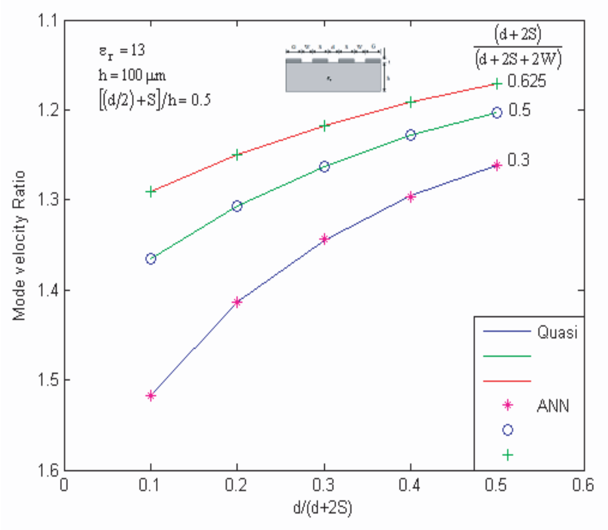
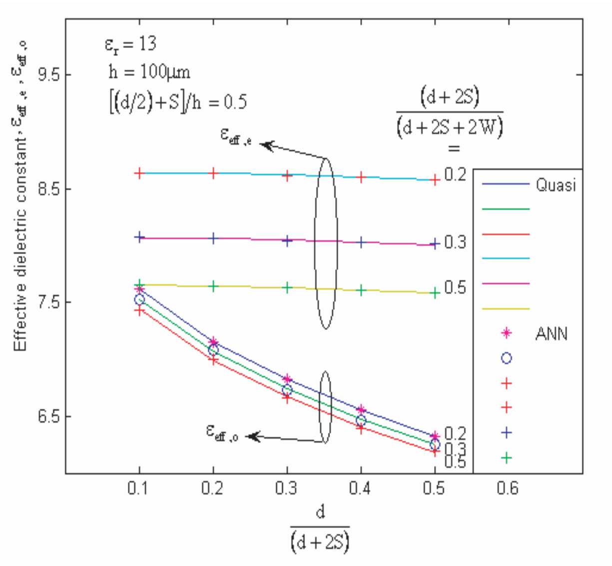
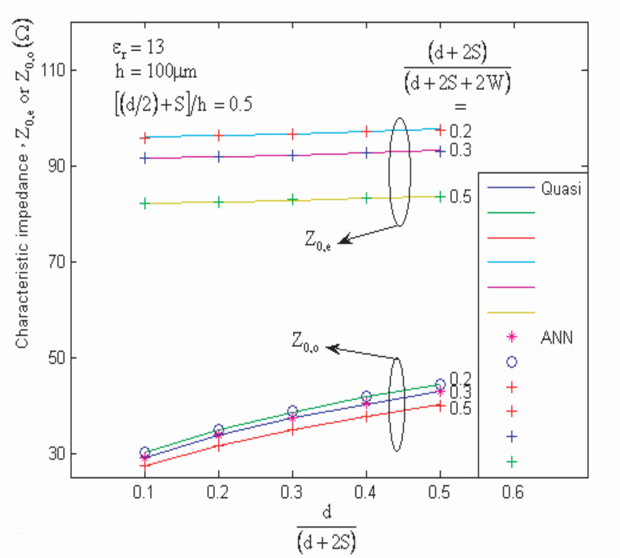


(d)

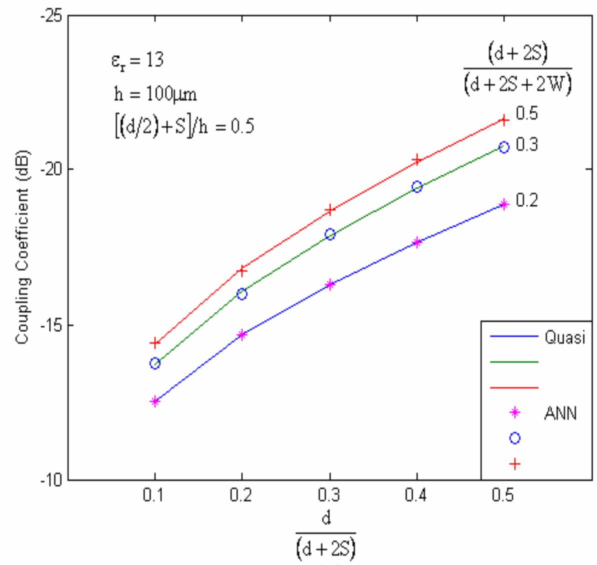
Figure 6. Comparision of CMT and neural network results of edge coupled CPW characteristics parameters, (a) effective dielectric permittivity, (b) odd & even-mode characteristics impedance, (c) coupling coefficient and (d) mode-velocity ratio.


$\varepsilon_r = 13$
h = 100μm
[(d/2)+S]/h = 0.5
(d+2S)/(d+2S+2W) =
$\varepsilon_{eff,e}$
$\varepsilon_{eff,o}$
0.2
0.3
0.5
Quasi
ANN
Effective dielectric constant, $\varepsilon_{eff,e}$, $\varepsilon_{eff,o}$
d/(d+2S)

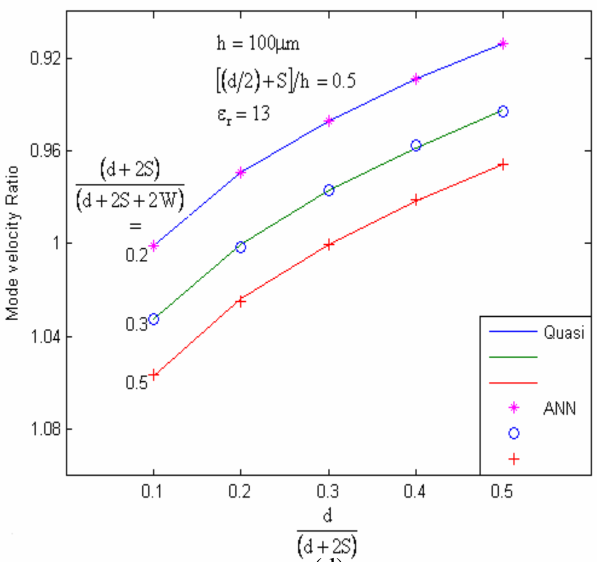
(a)


$\varepsilon_r = 13$
h = 100μm
[(d/2)+S]/h = 0.5
(d+2S)/(d+2S+2W) =
$Z_{0,e}$
$Z_{0,o}$
0.2
0.3
0.5
Quasi
ANN
Characteristic impedance, $Z_{0,e}$ or $Z_{0,o}$ (Ω)
d/(d+2S)

(b)



(c)



(d)

Figure 7. Comparision of CMT and neural network results of edge coupled conductor-backed CPW characteristics parameters, (a) effective dielectric permittivity, (b) odd & even-mode characteristics impedance, (c) coupling-coefficient and (d) mode-velocity ratio.

6. CONCLUSION

Models and formulas are proposed allowing the presence of ECCPW and CB-ECCPW for MMIC applications has been discussed. Compared with the ECCPW, the CB-ECCPW has provides better coupling co-efficient. Even though the CB-ECCPW lower the impedance level the usual trend is to improve the mechanical properties of the circuit and power capabilities without affecting the electrical behavior in comparisons with the free standing ECCPW. The ANN method proposed allow designers to obtain the physical dimensions of ECCPW and CB-ECCPW in very simple and convenient way rather than iteration approach of applying conventional design equation. Even if training takes a few minutes, the test process only takes a few microseconds to produce the results. The real time and high speed computation feature of proposed neural model strongly recommends their use in MMIC & other microwave application.

REFERENCES

1. Houdart, M., "Coplanar lines: Application to broadband microwave circuits," *Proceedings of 6th Europe Microwave Conference*, 49–53, 1976.
2. Gupta, K. C., G. R. Bahl, and I. J. Bhartia, *Microstrip Lines and Slotlines,* Artech House, Norwood, MA, 1996.
3. Salivahanan, S. and R. Ramesh, "CAD models for coplanar waveguide synthesis using artificial neural network," *IETE Technical Review,* 123–129, Vol. 8, Jun. 2001.
4. Ghione, G. and C. Naldi, "Coplanar waveguides for MMIC applications: Effects of upper shielding, conductor backing, finite-extent ground planes, and line-to-line coupling," *IEEE Trans. Microwave Theory Tech.,* Vol. 35, No. 3, 260–267, 1987.
5. Liao, C.-L. and C. H. Chen, "Quasi-static and full wave analyses of conductor-backed edge-coupled coplanar waveguide," *IEEE Proceedings of APMC 2001 Conference*, 181–183, Taipei, Taiwan, 2001.
6. Wheeler, H. A., "Transmission-line properties of parallel strips separated by a dielectric sheet," *IEEE Trans. Microwave Theory Tech.,* Vol. 13, 172–185, 1965.
7. Veyres, C. and V. F. Hanna, "Extension of the application of conformal mapping techniques to coplanar lines with finite dimensions," *International Journal Electronics,* Vol. 48, 47–56, 1980.

8. Knorr, J. B. and K. D. Kuchler, "Analysis of coupled slots and coplanar strips on dielectric substrate," *IEEE Trans. Microwave Theory Tech.,* Vol. 23, No. 7, 541–548, 1975.
9. Ghione, G. and C. Naldi, "Analytical formula for coplanar lines in hybrid and (monolithic) MICs," *Electron. Letters,* Vol. 20, 179–181, 1984.
10. Hammerstad, E. O., "Equations for microstrip circuit design," *Proceedings 5th European Microwave Conference,* 268–272, Germany, 1975.
11. Thiruvalar Selvan, P., S. Raghavan, and S. Suganthi, "A CAD approach based on artificial neural networks for conductor-backed edge coupled coplanar waveguides," *IEEE Proceedings of APMC 2008 International Conference,* 1–4, Hong Kong, China, 2008.
12. Simons, R. N., *Coplanar Waveguide Circuits, Components and Systems,* Wiley Inter Science, 2001.
13. Zhang, Q. J., K. C. Gupta, and V. K. Devabhaktuni, "Artificial neural networks for RF and microwave design — From theory to practice," *IEEE Trans.*, Vol. MTT-51, 1339–1349, 2003.
14. Zhang, Q. J. and K. C. Gupta, *Neural Networks for RF and Microwave Design,* Artech House, Boston, MA, 2000.
15. Yildiz, C. and M. Turkmen, "Quasi-static models based on artificial neural networks for calculating the characteristic parameters of multilayer cylindrical coplanar waveguide and strip line," *Progress In Electromagnetics Research B*, Vol. 3, 1–22, 2008.
16. Kaya, S., M. Turkmen, K. Guney, and C. Yildiz, "Neural models for the elliptic- and circular-shaped microshield lines," *Progress In Electromagnetics Research B,* Vol. 6, 169–181, 2008.
17. Yildiz, C., K. Guney, M. Turkmen, and S. Kaya, "Neural models for coplanar strip line synthesis," *Progress In Electromagnetics Research*, PIER 69, 127–144, 2007.
18. Patnaik, A. and R. K. Mishra, "ANN techniques in microwave engineering," *IEEE International Conference on Microwave,* 55–60, Mar. 2000.
19. Fun, M.-H. and M. T. Hagan, "Levenberg-marquardt training for modular networks," *Proceedings of the 1996 International Joint Conference on Neural Networks,* 468–473, 1996.
20. Levenberg, K., "A method for the solution of certain nonlinear problems in least squares," *Quarterly of Applied Mathematics*, Vol. 11, 431–441, 1963.
21. Mackay, D. J. C., "Bayesian interpolation," *Neural Computation,* Vol. 3, No. 4, 415–447, 1992.

22. Foresee, F. D. and M. T. Hagan, "Gauss-newton approximation to Bayesian regularization," *Proceedings of the 1997 International Joint Conference on Neural Networks*, 1930–1935, 1997.
23. Gill, P. E., *Practical Optimization*, Academic Press, New York, 1981.
24. Moller, M. F., "A scaled conjugate gradient algorithm for fast supervised learning," *Neural Networks,* Vol. 6, 525–533, 1993.
25. Reidmiller, M. and H. Braun, "A direct adaptive method for faster backpropagation learning: The RPROP algorithm," *Proceedings of the IEEE International Conference on Neural Networks*, 586–591, San Francisco, CA, 1993.
26. Dennis, E. and R. Schnabel, *Numerical Methods for Unconstrained Optimization and Nonlinear Equations*, Prentice Hall, Englewood Cliffs, 1983.
27. Haykin, S., *Neural Networks: A Comprehensive Foundation,* Prentice Hall International, Inc., 1999.
28. Thiruvalar Selvan, P., S. Raghavan, and S. Suganthi, "A CAD neural model for shielded and conductor backed CPW," *IEEE Proceedings of AEMC 2007 International Conference,* 1–4, Kolkata, India, 2007.
29. Fletcher, R. and C. M. Reeves, "Function minimization by conjugate gradients," *The Computer Journal*, Vol. 7, 149–154, 1964.