A CAD Oriented Model for Calculating the Characteristic Parameters of Broadside - Coupled CPW Based On Artificial Neural Networks

P. Thiruvalar Selvan[#1], S. Raghavan[*2]

1. Research Scholar, 2. Professor, Department of Electronics and Communication Engineering,
National Institute of Technology, Tiruchirappalli, TAMIL NADU, INDIA.
Email: tvs742002@yahoo.co.in

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 Broadside - Coupled Coplanar Waveguides (BSCCPWs) 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.**

Index Terms- **Artificial neural network; Broadside – coupled coplanar waveguides; characteristic impedance; Effective dielectric permittivity; Coupling coefficient; Mode velocity ratio.**

I. INTRODUCTION

For many years, coplanar microstrip lines are widely used in Microwave Integrated Circuits (MICs) due to their flexibility in the design of complex microwave circuitry requiring series and shunt connections. But at millimeter wave frequencies, it may not be the medium of choice due to disadvantages such as via holes needed to ground active devices introduction of significant inductance and degrade circuit performance. CPWs have been used widely as an alternative to micro strip lines [1] due to their several advantages on GaAs Substrates [2]; such as ease of parallel and series insertion of both active and passive components, high circuit density, Elimination of via holes in connecting circuit elements to ground.

A novel broadside – coupled structure, first proposed by Dalley using strip line technique and subsequently investigated by Allen and Estes. This structure also has several desirable features such as strong coupling, multiple stop-band and multizero pass-band responses from a single filter section. This new structure is suitable for application requiring wide bandwidths, tight coupling and large mode effective dielectric constant ratio. Further, the use of CPW in realizing the broadside – coupled transmission line produces additional desirable features for both MIC and Monolithic MICs (MMICs) application resulting from the top-surface ground plane such as very low dispersion [7], ease in realizing the compact balanced circuits [3-6], minimization of cross talk and ease and accurate on-wafer RF measurements.

In spite of several advantages offered by CPWs, their use in actual design has been less widespread than would be expected. The reasons for this are the limited variety of circuit elements available and lack of CAD facilities in coplanar circuit design. Some fast analytic formulas for calculating the parameters of some CPW structure suitable for MMIC CAD programs are already available in the literature [8]. A CPW fabricated on dielectric substrate was studied and

analytic formulas were obtained by means of CMT by C.P.Wen [9] with the assumption that the substrate thickness is infinitely large [10]. Veyres and Hanna have extended the application of CMT of CPW's with finite dimension & substrate [11]. CPWs having complex structures have been analyzed recently by many authors using quasi – static method [12] or full- wave method [13] in the literature. The full wave methods, mainly take tremendous computational efforts, cannot make a practical circuit design feasible in with a reasonable period of time, and require a strong mathematical background knowledge and time – consuming numerical calculations. Hence, they are not very attractive for interactive CAD models. On the other hand, the closed form design equation obtained by CMT, is the simplest and most often used quasi-Static methods. Due to increasing popularity of BSCCPW, it is desirable to have an efficient and reliable method in computing their TEM parameters. The first broadside – coupled CPW consists of complete elliptic integrals which are difficult to calculate even with computer aid [14]. For this reason, the approximate formulas are proposed in calculation elliptic integral.

Learning and generalization ability, fast real – time operation features have made ANNs to apply in many areas for design of accurate and efficient microwave components and micro strip antennas [15]. ANNs have more general functional forms and are usually better than the classical techniques and provide simplicity in real time operation [16].In this paper, the quasi static parameters such as effective permittivity and characteristic impedance, coupling coefficient and mode velocity ratio of BSCCPW have been determined with the use of multilayer perceptron neural model. The neural model was trained with eight different learning algorithms to obtain better performance and learning speed with simpler structure.

II. DETERMINATION OF CHARACTERISTIC PARAMETERS OF BSC-CPW BY USING CMT

A "coupled line" configuration consists of two transmission lines parallel to each other and in close proximity has strong interaction between their fields and power is coupled from one line to another. The configuration we are dealing with is shown in figure1. It consists of two coupled strips placed face to face on a dielectric layer. A pair of ground planes that acts as a shield is placed symmetrically above and below the coupled coplanar wave guides respectively as shown in figure. This structure supports two fundamental modes, namely odd and even. The approach used is based on isolating the odd and even modes by assuming an electric wall for the odd mode and a magnetic wall for the even mode.

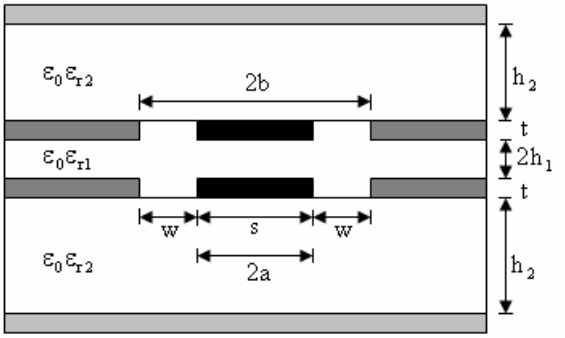

Fig. 1 Cross- sectional view of the BSCCPW

For each of these modes analytical expressions are presented to determine the effective dielectric constant, characteristics impedance, coupling co-efficient and mode velocity ratio based on conformal mapping method. We believe that the presented quasi – static TEM analytic formulas can be used in the design of coplanar MMICs up to 40GHz.

The even - mode effective dielectric permittivity $\varepsilon_{eff,e}$ is defined as [2]

$$\varepsilon_{eff,e} = \varepsilon_{r2} + q_e(\varepsilon_{r1} + \varepsilon_{r2}),$$

$$\text{Where } q_e = \frac{\frac{K(k_{e1})}{K(k'_{e1})}}{\frac{K(k_{e1})}{K(k'_{e1})} + \frac{K(k_{e2})}{K(k'_{e2})}}$$

$$k_{e1} = \frac{\sinh(\pi S/4h_1)}{\sinh(\pi(S+2W)/4h_1)}, \quad k'_{e1} = \sqrt{1-k_{e1}^2}$$

$$k_{e2} = \frac{\tanh(\pi S/4h_2)}{\tanh(\pi(S+2W)/4h_2)}$$

$k'_{e2} = \sqrt{1-k_{e2}^2}$ And $K(k_{ei})$ and $K(k'_{ei})$, $i = 1, 2$ are

the complete elliptic integral of the first kind and its complement.

The even – mode characteristic impedance $Z_{0,e}$ is defined as

$$Z_{0,e} = \frac{60\pi}{\sqrt{\varepsilon_{eff,e}}} \frac{1}{\frac{K(k_{e1})}{K(k'_{e1})} + \frac{K(k_{e2})}{K(k'_{e2})}}$$

The odd - mode effective dielectric permittivity $\varepsilon_{eff,o}$ is defined as

$$\varepsilon_{eff,o} = \varepsilon_{r2} + q_o(\varepsilon_{r1} - \varepsilon_{r2}),$$

Where $q_o = \frac{\frac{K(k_{o1})}{K(k'_{o1})}}{\frac{K(k_{o1})}{K(k'_{o1})} + \frac{K(k_{o2})}{K(k'_{o2})}}$

$$k_{oi} = \frac{\tanh(\pi S/4h_i)}{\tanh(\pi(S+2W)/4h_i)}$$

And $K(k_{oi})$ and $K(k'_{oi})$, $i = 1, 2$ are the complete elliptic integral of the first kind and its complement. The odd – mode characteristic impedance $Z_{0,o}$ is defined as

$$Z_{0,o} = \frac{60\pi}{\sqrt{\varepsilon_{eff,o}}} \frac{1}{\frac{K(k_{o1})}{K(k'_{o1})} + \frac{K(k_{o2})}{K(k'_{o2})}}$$

The voltage-coupling coefficient K is defined as

$$K = \frac{Z_{0,e} - Z_{0,o}}{Z_{0,e} + Z_{0,o}}$$

The even – and odd – mode velocity ratio is defined as

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

III. ARTIFICIAL NEURAL NETWORKS (ANNs)

ANNs is a very powerful approach for building complex and nonlinear relationship between a set of input and output which are the characteristics of the device under consideration. Though, the precise operation details of ANNs are quite different from human brains, they are similar in three aspects: it consists of huge number of neurons (processing elements), each neuron connects to a large number of other neurons, and the performance of network is determined by modifying the strengths of connections (weights) by training process. ANNs have many structures and architectures. The type of ANN and/or architecture selected for a particular model implementation depends on the problem to be solved. Neural network modeling is relatively new to microwave community. Furthermore, accurate and efficient microwave circuit components and micro strips antennas have been analyzed and designed with the use of ANNs[17]. After several trails using different architectures coupled with different training algorithms, in this paper, the MLPNN is used for the parametric calculations of broadside coupled CPW. The MLP is one of the most extensively used ANN structure, due to well known general approximation capabilities, despite its limited complexity. MLPs have a simpler layer structure in which successive layers of neurons are fully interconnected, with the strength of connection controlled by weights.

The MLP comprises an input layer, an output layer and a number of hidden layers. Neurons in the input layer only act as buffers for distributing the input signals x_i to the neurons in the hidden layer. The neurons in the hidden layer sum up its input signals x_i after weighting them with the strength of the respective connections and computers its output. The output is expressed as

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

where y_j can be output; f can be a simple threshold function, a sigmoid or hyperbolic tangent function and w_{ji} can be connection weights respectively. The most important and time consuming step in neural model such as development is training after generating the data sets. Training a network consists of adjusting weights of the connections using the different learning algorithms. In this article, the following eight learning algorithms described briefly were used to train the MLPs:

A. Levenberg – Marquardt [LM]

The LM algorithm is a least-squares estimation method based on the maximum neighborhood idea [18]. It does not suffer from the problem of

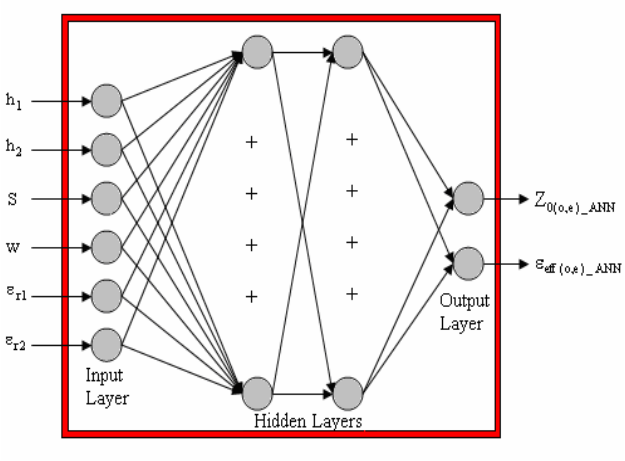

Fig. 2 MLPNN structure for determination of BSCCPW parameters.

slow convergence. The LM method combines the best features of Gauss - Newton and Steepest – descent method and avoids many of their limitations. This algorithm is very efficient when training small network [19].

B. 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 [20]. 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 [21].

C. 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. 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 $w_{k+1} = w_k - g_k / A_k$, A_k is the Hessian matrix of the performance index at the current value of the weights and biases [22].

D. Scaled conjugate gradient [SCG]

This algorithm was developed by Moller, to avoid the time consuming line search. It combines the Model-trust region approach and the conjugate gradient approach [23]. Backpropagtion is used to calculate derivation of performance with respect to the weight and bias variables.

E. Conjugate gradient of Fletcher – Powell [CGF]

This method updates weights and bias values according to the conjugate gradient with Fletcher-Reeves [24]. 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.

F. 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 is also has the nice property that it requires only a modest increase in memory requirements.

G. 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 [26]. It can train any network as long as its weight, net input, and transfer functions have derivative functions. 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 $p_k = -g_k + \beta_k p_{k-1}$

$$\beta_k = \frac{\Delta g_{k-1}^T g_k}{g_{k-1}^T g_{k-1}} \text{ and}$$

$$\Delta g_{k-1}^T = g_k^T - g_{k-1}^T .$$

H. 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.

IV. NEURAL MODELS FOR BSCCPW

In this paper, MLPNN model are proposed for calculating the quasi-static parameters of BSCCPW. The neural models for calculating the odd- and even-mode characteristic impedances and effective dielectric permittivity, voltage coupling coefficient and mode velocity ratio of BSCCPW are shown in figures 2 respectively. ANN models are a kind of black box models whose accuracy depends upon the data presented to it during training process. A well distributed, sufficient and accurately simulated data is the basic requirement to obtain an accurate model. The complete training data sets used in this work have been obtained from conformal mapping theory introduced by Bedair and Wolff. A total of 1366 data set have been used to train the neural model. For the neural model, the inputs are the relative dielectric permittivities of substrate materials ε_{r1}, ε_{r2} and four geometrical dimensions h_1, h2, S and w and the outputs are the effective dielectric permittivity (ε_{eff}) and the characteristic impedance (Z_0) of odd and even – mode. The range of training data sets are $1 \le \varepsilon_{r1} \le 13$; $1 \le \varepsilon_{r2} \le 13$; $10\,\mu m \le w \le 90\mu m$; $0 \le S \le 500\mu m$, $25\,\mu m \le 2\,h_1 \le 250\,\mu m$, and $0.5\,mm \le h_2 \le 6\,mm$.

The aim of training, the network is to minimize the training error between the target output and the actual output from MLPNN. The errors obtained are used to adapt the weights of the model. The adaptation is carried out by presenting each set of data until the calculation accuracy of the networks is satisfactory according to some criterion.

A common practice of trail and error approach to strike a balance between memorization and generalization is used to determine the number of hidden layers and the number of neurons. After several trail, it was found that two hidden layered model were achieved the task of calculating, $\varepsilon_{eff(o,e)}$, $Z_{0(o,e)}$ and coupling co-efficient(K),mode velocity ratio(M) respectively. The most suitable network configuration found was 6 X 6 X 10 X 2 for calculating ε_{eff} and Z_0 The tangent sigmoid and logarithmic sigmoid activation functions were used in the first and second hidden layers respectively. The linear activation function was used in the input & output layers of the neural model.

V. RESULTS AND DISCUSSION

The odd – and even- mode characteristic impedances and effective permittivities of BSCCPW were successfully computed by using MLP neural models. The results obtained from the neural model trained by LM training algorithm are compared with the CMT results. Figure 3&4 shows the comparison of ε_{eff} and Z_0 values from the network with the results of CMT for the different values of $2h_1$ from $50\mu m$ to $200\mu m$. It can be seen from the figures 3 & 4 that the results of MLPNN method are in very good agreement with the results of the CMT. This very good agreement shows the accuracy of the model and supports the validity of MLPNN model presented in this work. In this paper the neural model is trained by LM algorithm to calculate the coupling coefficient & mode velocity ratio by using the odd –and even- mode characteristic impedance values obtained from the MLPNN structure. The test results of MLPNN for coupling coefficient and velocity ratio are compared with the results of CMT. The comparison shown in figures 5 & 6 gives confirmation for the MLPNN method proposed here. In order to prove the validity of the neural models, the proposed structure was trained with eight different algorithms.

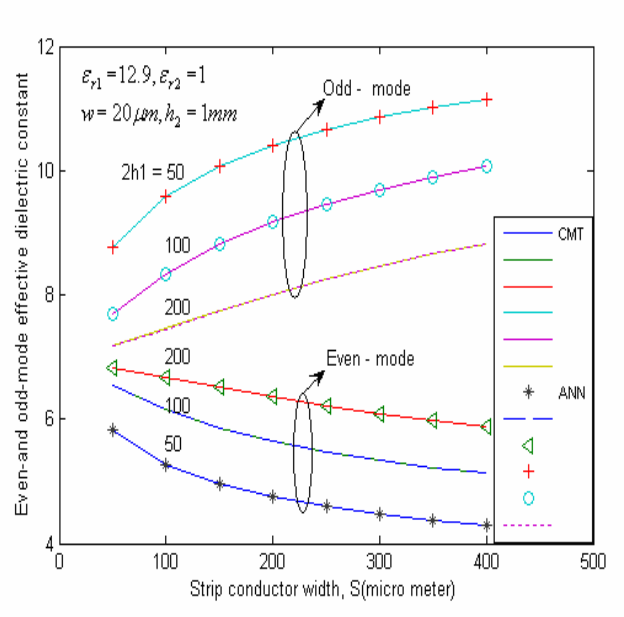

Fig. 3 Computed even – and – odd – mode effective dielectric constant using ANN model

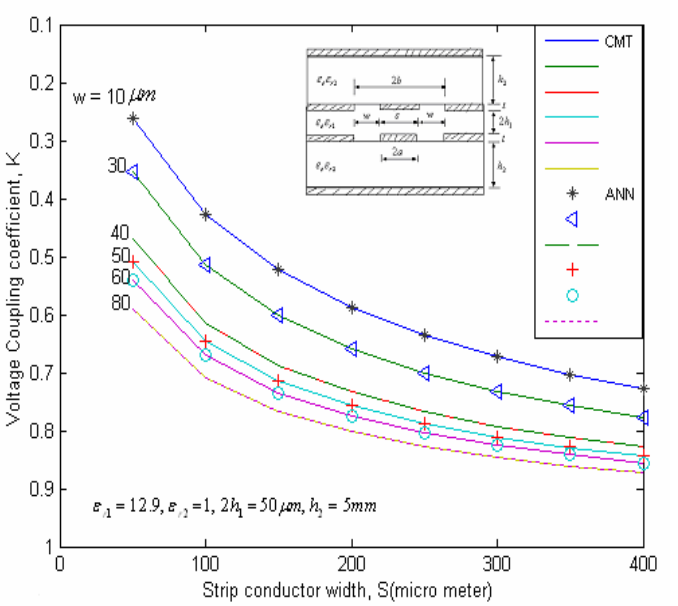

Fig.5 Computed Voltage coupling coefficient as a function of the strip conductor width using ANN model

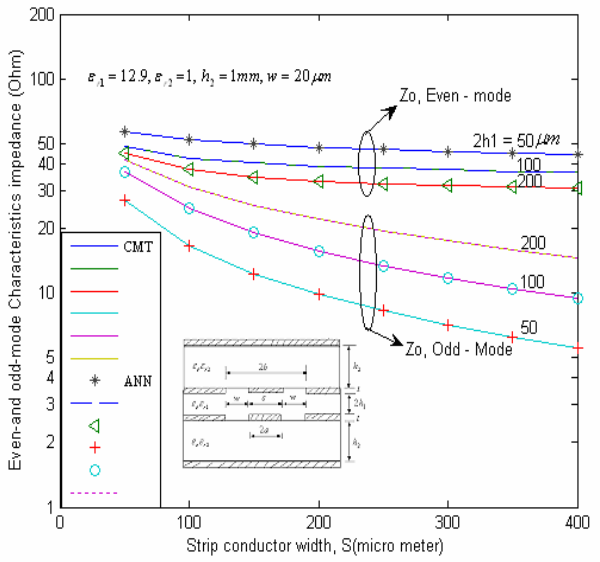

Fig.4 Computed even – and – odd – mode Characteristics impedance using ANN model

When the performance is compared with each other, the best results for training were obtained from LM and BR algorithms.

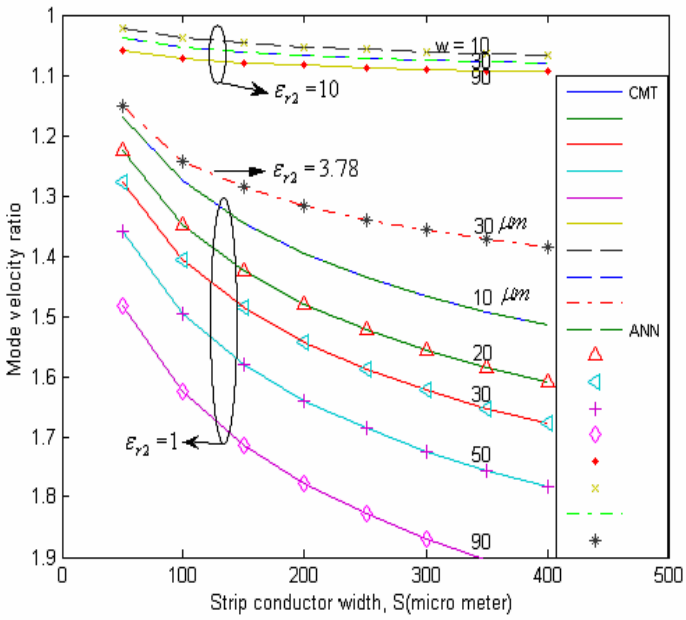

Fig. 6 Computed even – and – odd – mode velocity ratio using ANN model $\varepsilon_{r1}=12.9, \varepsilon_{r2}=1,$ $2h_1=50\mu m, h_2=5mm.$

The training and test RMS error for the comparison of different learning algorithms are given in table 1.

Table.1 Training and test errors of the neural network models for Broadside - coupled coplanar - waveguides

Learning Algorithms	RMS Errors for training				RMS Errors for test			
	$\varepsilon_{eff(o,e)}$	$Z_{0(o,e)}$ in ohm	C(dB)	Mode velocity-Ratio	$\varepsilon_{eff(o,e)}$	$Z_{0(o,e)}$ in ohm	C(dB)	Mode velocity-Ratio
LM	1.4278e-008	3.4250e-004	3.7115e-011	1.4816e-010	2.5930e-005	0.0076	2.5466e-004	1.0023e-006
BR	1.0657e-008	2.2631e-004	9.9556e-006	9.7387e-006	2.2631e-004	0.0230	7.3535e-005	0.0024
RP	0.0048	2.0209	0.0015	0.0042	0.1010	5.4228	0.0074	0.0054
CGF	0.0852	0.9645	0.0086	0.0050	0.1169	6.5971	0.0162	0.0185
QN	0.0018	0.5428	0.0039	0.0039	0.9645	1.9286	0.0088	0.0128
GD	0.0855	1.8649	0.0037	0.0063	0.5772	6.2461	0.0059	0.0074
CGP	0.0163	2.0011	0.0034	0.0097	0.1550	3.0084	0.0933	0.1062
SCG	0.0252	0.0870	0.0018	0.1055	0.2315	2.4440	0.0421	0.2011

VI. CONCULSIONS

Artificial Neural Models based on the MLPs are presented for computing the characteristic parameters of BSC-CPW. The proposed BSC-CPW structure can avoid leakage of energy and propagation of higher – order modes up to high frequencies and thus increase the operating frequency. It eliminates the parallel-plate mode propagation; reduce loss due to the use of wider conductor and conductor edge loss as compared with other CPW structure. The additional desirable feature of BSC-CPW includes more design flexibility and large impedance range. The presented neural models for the design of BSCCPW are trained by using different learning algorithms. The comparison among the neural model and CMT results obviously shows that our neural model is valid to determine the quasi – static parameters of BSCCPW. Since the neural models presented in this work have good accuracy, require no tremendous computational efforts & less background information about waveguide, they can be very useful for the development of fast CAD algorithms. A distinct advantage of neural computation is that, after proper training a neural network completely bypasses the repeated iterative processes new cases presented to it. Since the calculation time is less than a few microseconds, the proposed neural model can be very useful for predicting the parameters of BSCCPW and hence in many engineering applications.

REFERENCES

1. Houdart, M.: "coplanar lines: Application to Broadband Micro-wave Circuits", *In Proceedings 6th Europe Microwave Conference*, 1976, pp.49-53.
2. Simons, R.N.: *Coplanar waveguide circuits, components and systems*, John Wiley & Sons. Inc., 2001.
3. Dalley, J.E.: "A strip line directional coupler utilizing a non-homogeneous dielectric medium", *IEEE Trans. Microwave Theory Tech.*, 1969, 17, pp.706-712.
4. Allen, J.L and Estes, M.F.: "Broadside-coupled strips in layered dielectric medium", *IEEE Trans. Microwave Theory Tech.*, oct1972, Vol. 20, pp.662-669.
5. Hatsuda, T.: "Computation of coplanar-type strip-line characteristics by relaxation method and application to microwave circuits", *IEEE Trans. Microwave Theory Tech.*, 1975, Vol. 23, pp.795-802.
6. Nguyen, C.: "Dispersion Characteristics of the Broad side-Coupled Coplanar Waveguide", *IEEE Trans. Microwave Theory Tech.*, 1993, Vol.41, pp.1630-1633.
7. Kawano, K.: "Hybrid – mode analysis of a broadside-coupled microstrip line", *IEEE Proc.*, 1984, 131, pp. 21-24.
8. Bedair, S.S., Wolff, I.: "Fast and accurate analytic formulas for calculating the parameters of a General Broadside-Coupled Coplanar waveguides for (M) MIC's", *IEEE Trans. Microwave Theory Tech.*, 1989, Vol.37, pp.843-850.
9. Wen, C.P.: "Coplanar waveguide: A surface transmission line suitable for nonreciprocal gyromagnetic device applications', *IEEE Trans. Microwave Theory Tech., 1*969, Vol.17, pp.1087-1090.
10. Davis, M.E., Williams, E.W., Celestini, A.C.: "Finite boundary corrections to the coplanar

waveguide analysis", *IEEE Trans. Microwave Theory Tech.*, 1973, Vol.21, pp.594-596.
11. Veyres, C., Hanna,V.F.: "Extension of the application of conformal mapping techniques to coplanar lines with finite dimensions", *Int. Journal Electronics*, 1980,Vol. 48, pp.47-56.
12. Bedair, S.S., Wolff, I.: "Fast, accurate and simple approximate analysis formulas for calculating the parameters of supported coplanar waveguides for (M) MIC's", *IEEE Trans. Microwave Theory Tech.*, 1992, Vol. 40, pp.41-48.
13. Liu, Y., Itoh, T.: "Leakage phenomena in multilayered conductor backed coplanar waveguide", *IEEE Trans. Microwave Theory Tech.*, 1993, 3, pp.426-427.
14. Chen, E., and Chou, S.Y.: "Characteristics of coplanar transmission lines on multilayer substrates: modeling and experiments", *IEEE Trans. Microwave Theory Tech.*, 1997, Vol.45, pp.939-945.
15. Sagiroglu, S., and Yildiz, C.: "A multilayered perceptron neural network for a micro-coplanar strip line", *International Journal Electro - magnetics*, 2002, Vol.22, pp. 553-563.
16. Yildiz, C., Sagiroglu, S., and Turkmen, M.: "Neural model for coplanar waveguide sandwiched between two dielectric substrates", *IEE Proc. - Microwave Antennas Propagation*, 2004, Vol.151, pp.7-12.
17. Zhang, Q.J., and Gupta, K. C.: *Neural networks for RF and microwave design*,(Boston MA.: Artech House, 2000).
18. Levenberg, K: "A method for the solution of certain nonlinear problems in least squares", Quarterly of Applied Mathematics, 1963, Vol.11, pp.431-441.
19. Meng- Hock Fun and Martin Hagan, T..: "Levenberg – Marquardt Training for Modular Networks", *Proceedings of the 1997 International Joint Conference on Neural Networks*, pp. 468 – 473, 1996.
20. Mackay, D.J.C.: 'Bayesian interpolation', *Neural Computation*, 1992, Vol.3,(4),pp.415-447.
21. Foresee, F.D. and Hagan, M.T. : "Gauss-Newton approximation to Bayesian regularization", *Proceedings of the 1997 International Joint Conference on Neural Networks*, 1997, pp. 1930-1935.
22. Gill,P.E.: '*Practical Optimization*' (Academic Press, New York, 1981).
23. Moller, M.F.: "A scaled conjugate gradient algorithm for fast supervised learning", *Neural Networks*, 1993, 6, pp.525-533.
24. Fletcher, R. and Reeves, C.M.: "Function minimization by conjugate gradients", *The Computer Journal*, vol.7, 149-154, 1964.
25. Reidmiller, M., and Braun, H.: "A direct adaptive method for faster backpropagation learning: the RPROP algorithm", *Proceedings of the IEEE International Conference on Neural Networks*, San Francisco, CA, 1993, pp.586-591.
26. E. Dennis, R. Schnabel, *Numerical Methods for Unconstrained Optimization and nonlinear Equations*, Englewood Cliffs, Prentice Hall, 1983.
27. Simon Haykin, *Neural Networks: A Comprehensive Foundation*, (Prentice Hall International, Inc., 1999).