NEURAL ANALYSIS OF BOTTOM SHIELDED MULTILAYERED COPLANAR WAVEGUIDES

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ABSTRACT

The two characteristic parameters of bottom shielded multilayered coplanar waveguides (CPWs) have been determined with the use of only one neural model. The model was trained with four different learning algorithms to obtain better performance and learning speed with simpler structure. This neural model is also valid for conductor-backed (CB), CB sandwiched and bottom shielded CPWs. The results have shown that the estimated characteristic parameters are in very good agreement with the results of theoretical results available in the literature.

I. INTRODUCTION

Coplanar waveguides (CPWs) have been used widely in microwave and millimeter-wave integrated circuits (MMICs) as an alternative to microstrip lines. The principal of a CPW is that the locations of ground planes are on the same substrate surface as the signal line. This 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 [2-4]. In microwave integrated circuits (MICs) CPWs have complex structures in contrast with that first proposed by Wen. In packaged MICs metal walls are introduced above and below the CPW [5].

CPWs have been analyzed with use of full-wave analysis [6-8] or quasi-static analysis such as CMT [1-4, 9-11] 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 [10, 11].

These methods, used to obtain the effective dielectric constant 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 conformal mapping method 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.

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 [12-16]. 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 bottom shielded multilayered CPWs (MCPWs) have been determined with the use of only one neural model. Artificial neural networks (ANNs) were trained with four different training algorithms to obtain better performance and learning speed with simpler structure. Levenberg-Marquardt (LM), bayesian regulation (BR), quasi-Newton (QN) and backpropagation (BP) learning algorithms were used to train neural model. The inputs of this model are relative permittivities of the dielectric layers ε_1 and ε_2 and five geometric dimensions of bottom shielded MCPW (h_2/h_1, h_3/h_1, w/S, d/h_1 and S/h_1). The outputs are the effective relative permittivity (ε_{eff}) and characteristic impedance (Z_0) of bottom shielded MCPW. In addition, the proposed neural model can be useful for a wide variety of CPW structures by choosing the appropriate geometric dimensions. This means, one can calculate the characteristic parameters of different CPW configurations such as; CPW with bottom shielding (BS), conductor-backed CPW (CBCPW), conductor-backed sandwiched CPW (CBSCPW) and bottom shielded MCPW. This flexibility is one of the other advantages of the proposed neural model.

II. THEORY

Figure 1 shows the structure of the bottom shielded MCPW. In the figure, *S* represents the width of the signal ground. *w* is the width of the slots. h_1 and h_2 are the thicknesses of the dielectric substrates. h_3 is the distance between the signal grounds and bottom shielding. ε_i's are the effective relative permittivities 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 capacitance.

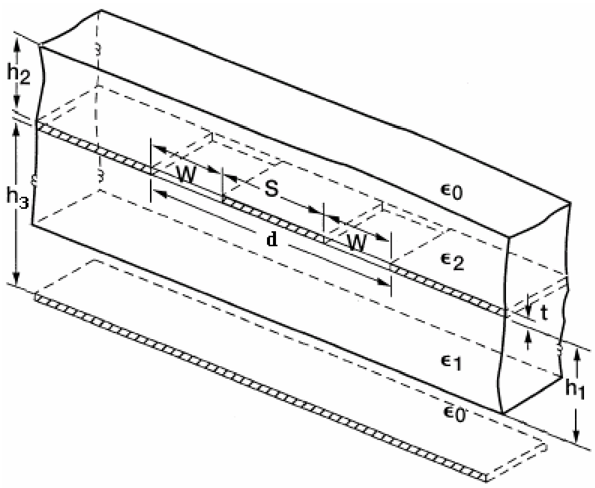


Figure 1. Bottom shielded MCPW

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

$$C = C_1 + C_2 + C_{03} + C_{04} \tag{1}$$

where C_1 is the capacitance of below dielectric material thickness h_1. C_2 is the capacitance of above dielectric material thickness is h_2. C_{03} is the capacitance of the line thickness is h_3 and effective dielectric constant ε_1=1. C_{04} is the capacitance of the line thickness is h_4 and effective dielectric constant ε_2=1. The capacitances of C_1, C_2, C_{03} and C_{04} are determined by means of the conformal mapping theory [17] and can be written as

$$C_1 = 2\cdot(\varepsilon_1 - 1)\cdot\varepsilon_0\cdot\frac{K(k_1)}{K(k_1^{'})} \tag{2}$$

$$C_2 = 2\cdot(\varepsilon_2 - 1)\cdot\varepsilon_0\cdot\frac{K(k_2)}{K(k_2^{'})} \tag{3}$$

$$C_{03} = 2\cdot\varepsilon_0\cdot\frac{K(k_3)}{K(k_3^{'})} \tag{4}$$

$$C_{04} = 2\cdot\varepsilon_0\cdot\frac{K(k_4)}{K(k_4^{'})} \tag{5}$$

$K(k_i)$ and $K(k_i^{'})$ are the complete elliptic integrals of the first kind with the modules of k_i and $k_i^{'}$. The parameters in the equations (2)-(5) are $k_i^{'} = \sqrt{1-k_i^2}$ and

$$k_i = \frac{\sinh(\frac{\pi\cdot S}{4\cdot h_{1i}})}{\sinh\left[\frac{\pi\cdot d}{4\cdot h_i}\right]}, \qquad i = 1,2 \tag{6}$$

$$k_3 = \frac{\tanh(\frac{\pi\cdot S}{4\cdot h_3})}{\tanh\left[\frac{\pi\cdot d}{4\cdot h_3}\right]} \tag{7}$$

$$k_4 = k_0 = \frac{S}{d} \tag{8}$$

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

$$\varepsilon_{eff} = 1 + q_1\cdot(\varepsilon_1 - 1) + q_2\cdot(\varepsilon_2 - 1) \tag{9}$$

where q_i is the partial filling factors. These filling factors are given by

$$q_1 = \frac{K(k_1)}{K(k_1^{'})}\cdot\left[\frac{K(k_3)}{K(k_3^{'})} + \frac{K(k_0)}{K(k_0^{'})}\right] \tag{10}$$

$$q_2 = \frac{K(k_2)}{K(k_2^{'})}\cdot\left[\frac{K(k_3)}{K(k_3^{'})} + \frac{K(k_0)}{K(k_0^{'})}\right] \tag{11}$$

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

$$Z_0 = \frac{60\pi}{\sqrt{\varepsilon_{eff}}}\cdot\left[\frac{K(k_3)}{K(k_3^{'})} + \frac{K(k_0)}{K(k_0^{'})}\right]^{-1} \tag{12}$$

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. In this case, the characteristic impedance and effective relative permittivity of bottom shielded MCPW easily and simply determined by neural modeling approach.

III. ARTIFICIAL NEURAL NETWORKS (ANNs)

ANNs are the computer programs which are biologically inspired to simulate the way in which the human brain processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn through their architectures and learning algorithms. There are many types of neural networks for various applications available in the literature [12-16, 18].

In this paper, ANNs have been adapted for the effective relative permittivity ε_{eff} and the characteristic impedance Z_0 of bottom shielded MCPW, CPW with BS, CBCPW, and CBSCPW.

A general neural structure used in this work is shown in Figure 2. ANNs used in this work are trained with the LM, the BR, the QN, and the BP learning algorithms. An ANN consists of three layers: an input layer, an output layer and an intermediate or hidden layer. Processing elements (PEs) or neurons in the input layer only act as buffers for distributing the input signals x_i to PEs in the hidden layer. Each PE 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 f of the sum, viz.,

$$y_j = f(\sum w_{ji} x_i) \tag{13}$$

f can be a simple threshold function, a sigmoid or tangent hyperbolic function. The output of PEs in the output layer is computed similarly.

Training a network consists of adjusting its weights using a training algorithm. The training algorithms adopted in this study optimize the weights by attempting to minimize the sum of squared differences between the desired and actual values of the output neurons.

Each weight w_{ji} is adjusted by adding an increment Δw_{ji} to it. Δw_{ji} is selected to reduce the differences as rapidly as possible. The adjustment is carried out over several training epochs until a satisfactorily small value of the differences is obtained or a given number of epochs is reached. How Δw_{ji} is computed depends on the training algorithm adopted.

Training process is ended when the maximum number of epochs is reached, the performance gradient falls below minimum gradient or validation performance has increased more than maximum fail times since the last time it decreased using validation. The learning algorithms used in this work are summarized briefly.

Quasi-Newton: This is based on Newton's method but don't require calculation of second derivatives. They update an approximate Hessian matrix at each iteration of the algorithm. The 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 epochs the search direction is computed according to the gradient [19].

Levenberg-Marquardt (LM): This is a least-squares estimation method based on the maximum neighborhood idea [20, 21]. The LM combines the best features of the Gauss-Newton technique and the steepest-descent method, but avoids many of their limitations. In particular, it generally does not suffer from the problem of slow convergence.

Backpropagation (BP): It is a gradient descent method and the most commonly adopted MLP training algorithm [22]. Backpropagation has a local minima problem. The method is based on random order incremental training functions. It trains a network with weight and bias learning rules with incremental updates after each presentation of an input. Inputs are presented in random order.

Bayesian regularisation (BR): This algorithm updates the weight and bias values according to the LM optimization and minimizes a linear combination of squared errors and weights, and then determines the correct combination so as to produce a well generalised network. BR takes place within the LM. This algorithm requires more training and memory than the LM [23, 24].

IV. APPLICATION TO THE PROBLEM

The proposed technique involves training an ANN to calculate the effective relative permittivity ε_{eff} and the characteristic impedance Z_0 of bottom shielded MCPW when the values of relative permittivities ε_1 and ε_2, and the other geometric dimensions are given. Training ANNs using different algorithms involve presenting those different sets (ε_1, ε_2, h_2/h_1, h_3/h_1, w/S, d/h_1, S/h_1, ε_{eff} and Z_0) sequentially and/or randomly and corresponding calculated values the effective relative 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 criterion. This criterion can be the errors between ε_{eff} and $\varepsilon_{eff-ANN}$ and Z_0 and Z_{0-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 used in this work have been obtained from the CMT introduced in [17]. 4860 and 2160 data sets were used in training and test processes, respectively. The ranges of training and test data sets were $2 \le \varepsilon_1 \le 24$ at 6 points, $1 \le \varepsilon_2 \le 17$ at 5 points, $0.1 \le S/d \le 0.9$ at 9 points, $400\mu m \le h_1 = h_2 = h_3 \le 1000\mu m$ at 4 points, 10µm≤*w*≤110µm at 6 points. After several trials, it was found that one hidden layered network achieved the task in high accuracy. The most suitable network configuration found was 7x12x2, this means that the number of neurons were 7 for the input layer and 12 for hidden layer and 2 for output layers as shown in Figure 2. The tangent hyperbolic activation function was used in the hidden layer. Linear activation function was employed in the output layer. Root mean square (RMS) errors are considered throughout this neural model.

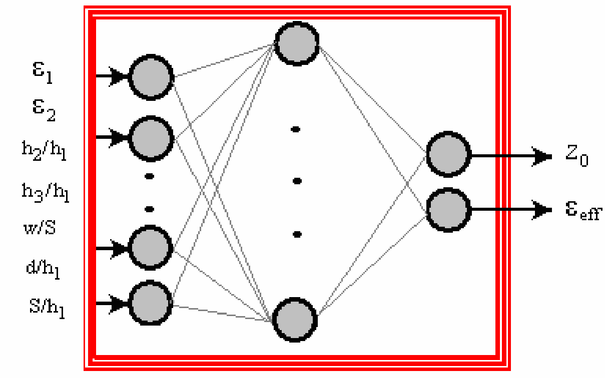


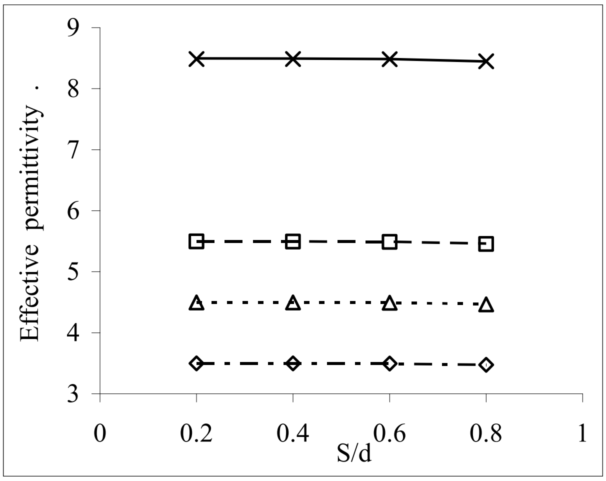
Figure 2. Neural model for bottom shielded MCPWs

V. RESULTS

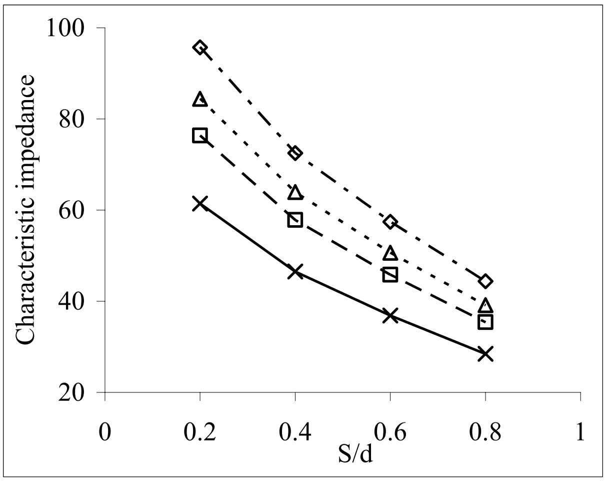
The training and test RMS errors obtained from neural models are given in Table 1. When the performances of neural models are compared with each other, the best results for training and test were obtained from the models trained with the LM and the BR algorithms. The results of the CMT [17] and the neural model trained with the LM learning algorithm for the effective relative permittivity and the characteristic impedance of bottom shielded MCPW and the other structures are shown in Figures 3.a and b, respectively. In these figures, the characteristic parameters depicted for shielded MCPW when ε_1=10, ε_2=7, h_1=600µm, h_2=650µm and h_3=900µm, CBSCPW when ε_1=2, ε_2=7, h_1=h_3=600µm and h_2=750µm, CBCPW when ε_1=6, ε_2=1 and h_1=h_3=600µm and CPW with BS when ε_1=10, ε_2=1, h_1=600µm and h_3=650µm. The good agreement shown in the figures supports the validity of the neural model presented in this work.

Table 1. Training and test RMS errors for the characteristic parameters of shielded MCPW.

Training Algorithm	Errors in training		Errors in test	
	$\varepsilon_{eff\text{-}ANN}$	$Z_{0\text{-}ANN}(\Omega)$	$\varepsilon_{eff\text{-}ANN}$	$Z_{0\text{-}ANN}(\Omega)$
LM	0.0558	0.0170	0.0097	0.0452
BR	0.0207	0.0264	0.0490	0.0013
QN	1.4920	4.0687	2.6206	2.0715
BP	91.5040	38.1405	37.2913	19.2845



a) ε_{eff}



b) Z_0 (Ω)

—— CMT and x ANN for Bottom Shielded MCPW
– – CMT and □ ANN for CPW with BS
- - - CMT and Δ ANN for CBCPW
– - – CMT and ◊ ANN for CBSCPW

Figure 3. The neural and CMT results for different configurations of CPWs

VI. CONCLUSION

The characteristic parameters of bottom shielded MCPWs have been successfully determined with the use of only one neural model. Using proposed neural model, one can calculate accurately the effective relative permittivity and the characteristic impedance of bottom shielded MCPW without possessing strong background knowledge. In addition proposed neural model can also be used to determine the characteristic parameters of CPW with bottom shielding, CBCPW and CBSCPW.

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

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