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Neural Analysis of Top Shielded Multilayered Coplanar Waveguides

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Abstract

Artificial neural networks (ANNs) have been promising tools for many applications. In recent years, a computer-aided design approach based on (ANNs) has been introduced to microwave modelling, simulation and optimization. In this work, the characteristic parameters of top shielded multilayered coplanar waveguides (CPWs) have been determined with the use of ANN models. These neural models were trained with Levenberg-Marquardt, resilient propagation, Bayesian regulation, quasi-Newton, and backpropagation learning algorithms. Better performance and learning speed with a simpler structure were achieved from these models. The results have shown that the estimated characteristic parameters are in very good agreement with the computed results by using conformal mapping theory. The Levenberg-Marquardt learning algorithm was found to be the best algorithm among all. As a result, ANN models presented in this work can be used easily, simply and accurately to determine the characteristic parameters of the top shielded multilayered CPWs.

Key Words: *Coplanar Waveguides, Effective Relative Permittivity, Characteristic Impedance, Artificial Neural Networks.*

1. Introduction

In microwave and millimeter-wave integrated circuits (MMICs), coplanar waveguides (CPWs) have been used widely as an alternative to microstrip lines. The principle of a CPW is that the location of ground planes is 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 using of conformal mapping theory (CMT) were given by Wen [1]. However, Wen's formulas were based on the assumption that the substrate thickness is infinitely large [2, 3]. Veyres and Hanna have extended the application of conformal mapping to CPWs with finite dimensions and substrate thicknesses [4]. In microwave integrated circuits (MICs), CPWs have a complex structure [5, 6], in contrast with that first proposed by Wen. In packaged MIC's, metal walls are introduced above and below the CPW. Full-wave analysis is usually used to characterize such complex structures [7-9]. These analyses provide high precision in a wide frequency band. On the other hand 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].

Obtaining characteristic parameters, effective dielectric constant and characteristic impedance, of CPWs with these methods has some disadvantages. The full-wave 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. On the other hand, the closed-form design equations obtained by conformal mapping method, which is the simplest and most often used quasi-static method, consist of complete elliptic integrals which are difficult to calculate even with computers. For this reason, the approximate formulas are proposed for the calculation of elliptic integrals.

Artificial neural networks (ANNs) recently gained attention as a fast and flexible tool to microwave modeling and design. Learning and 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. [12]. 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 [13-16]. 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 top shielded multilayered CPW (MCPW) have been determined with the use of one ANN model. Multilayered perceptron neural networks (MLPNNs) are used to determine the characteristic parameters. MLPNNs were trained with five different training algorithms to obtain better performance and learning speed with simpler structures. Levenberg-Marquardt (LM), resilient propagation (RP), Bayesian regulation (BR), quasi-Newton (QN), and backpropagation (BP) learning algorithms were used to train MLPNN models. The inputs of the neural models are effective dielectric constant of the layers ε_1 and ε_2 and five geometric dimensions of top shielded MCPW (h_2/h_1, h_3/h_1, w/h_1, d/h_1 and S/h_1). The outputs of the neural models are the effective relative permittivity (ε_{eff}) and characteristic impedance (Z_0) of top shielded MCPW.

2. Theory

Figure 1 shows the structure of the top shielded MCPW. In the figure, 2a 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 top shielding, ε_i is the dielectric constants of the dielectric materials. In the quasi-TEM limits of the basic characteristics of CPWs can be determined when the capacitance per unit length is known. The capacitances per unit length of waveguiding structures are determined assuming zero thickness of metal strips. The line capacitance of CPWs can be given as a sum of partial capacitances. Using the quasi-static approximations, the effective relative permittivity (ε_{eff}) and characteristic impedance (Z_0), of transmission line are:

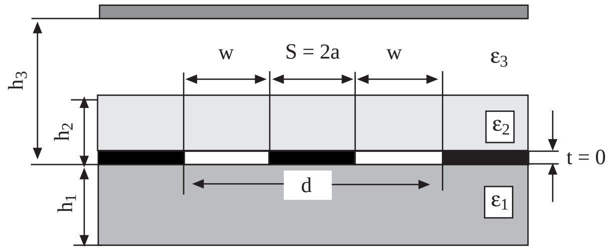

Figure 1. A top shielded multilayered CPW.

$$\varepsilon_{eff} = \frac{C}{C_0} \tag{1}$$

$$Z_0 = \frac{\sqrt{\varepsilon_{eff}}}{C \cdot v_0} \tag{2}$$

where v_0 is the speed of light in free space, C is the total capacitance of the transmission line, C_0 is the capacitance of corresponding line with all dielectrics replaced by air. Therefore, in order to obtain the characteristic parameters of CPW one only has to find the capacitances of C and C_0. Thus, the total capacitance of the transmission line is

$$C = C_1 + C_2 + C_{03} \tag{3}$$

where C_1 is the capacitance of the line whose thickness is h_1 and effective dielectric constant ε_1,C_2 is the capacitance of the line whose thickness is h_2 and effective dielectric constant ε_2. C_{03} is the capacitance of the line whose thickness is h_3 and effective dielectric constant ε_3. The capacitances of C_1, C_2 and C_{03} are determined by means of the conformal mapping theory [17] and can be written as

$$C_1 = 2 \cdot (\varepsilon_1 - 1) \cdot \varepsilon_0 \cdot \frac{K(k_1)}{K(k_1')} \tag{4}$$

$$k_1' = \sqrt{1 - k_1^2} \quad \text{and} \quad k_1 = \frac{\sinh(\frac{\pi \cdot S}{4 \cdot h_1})}{\sinh\left[\frac{\pi \cdot (a+w)}{2 \cdot h_1}\right]} \tag{5}$$

$$C_2 = 2 \cdot (\varepsilon_2 - 1) \cdot \varepsilon_0 \cdot \frac{K(k_2)}{K(k_2')} \tag{6}$$

$$k_2' = \sqrt{1 - k_2^2} \quad \text{and} \quad k_2 = \frac{\sinh(\frac{\pi \cdot S}{4 \cdot h_2})}{\sinh\left[\frac{\pi \cdot (a+w)}{2 \cdot h_2}\right]} \tag{7}$$

$$C_{03} = 2 \cdot \varepsilon_0 \cdot \frac{K(k_3)}{K(k_3')} \tag{8}$$

$$k_3' = \sqrt{1 - k_3^2}$$

where k_3 is equal to k_0, because $\varepsilon_3 = 1$;

$$k_3 = \frac{\sinh(\frac{\pi \cdot S}{4 \cdot h_3})}{\sinh\left[\frac{\pi \cdot (a+w)}{2 \cdot h_3}\right]} \tag{9}$$

where $K(k_i)$ and $K(k_i')$ are the complete elliptic integrals of the first kind. The effective relative permittivity of the line can be determined as given in eqn.(10);

$$\varepsilon_{eff} = 1 + q_1 \cdot (\varepsilon_1 - 1) + q_2 \cdot (\varepsilon_2 - 1) \tag{10}$$

where q_i is the partial filling factors, these filling factors are given by

$$q_1 = \frac{K(k_1)}{K(k_1')} \cdot \frac{K(k_3)}{K(k_3')} \tag{11}$$

$$q_2 = \frac{K(k_2)}{K(k_2')} \cdot \frac{K(k_3)}{K(k_3')} \tag{12}$$

The characteristic impedance (Z_0) can be determined as given in eqn.(13);

$$Z_0 = \frac{60\pi}{\sqrt{\varepsilon_{eff}}} \cdot \frac{K(k_3')}{K(k_3)} \tag{13}$$

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 for the calculation of elliptic integrals. If that is the case, the characteristic impedance and effective relative permittivity of top shielded MCPW easily and simply determined by neural models.

3. Artifical Neural Networks (ANNs)

ANNs are the computer programs that 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 [18]. Multilayered perceptron neural networks (MLPNNs) are feed-forward networks and universal approximators. They are the simplest and therefore most commonly used neural network architectures [18].

In this paper, MLPNNs have been adapted for the computation of effective relative permittivity ε_{eff} and the characteristic impedance Z_0 of top shielded MCPW. A general neural structure used in this work is shown in Figure 2. MLPNNs used in this work are trained with the LM, the RP, the BR, the QN, and the BP learning algorithms. A MLPNN 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.,

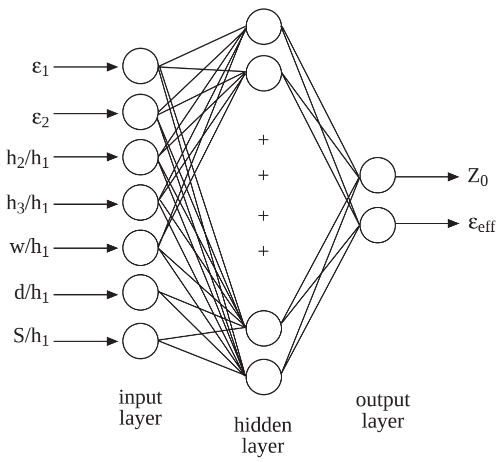

Figure 2. The structure of presented ANN model.

$$y_j = f(\sum w_{ji} x_i) \tag{14}$$

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

Training a MLPNN by BP involves presenting it sequentially with all training tuples (input, target output). Differences between the target output and the actual output of the MLPNN are propagated back through the network to adapt its weights. A training iteration is completed after a tuple in the training set has been presented to the network and the weights updated.

4. MLPNN Training Algorithms

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, namely:

$$E = \frac{1}{2} \sum_j (y_{dj} - y_j)^2 \tag{15}$$

where y_{dj} is the desired value of output neuron j and y_j is the actual output of that neuron. Each weight w_{ji} is adjusted by adding an increment Δw_{ji} to it. Δw_{ji} is selected to reduce E as rapidly as possible. The adjustment is carried out over several training iterations until a satisfactorily small value of E is obtained or a given number of iterations are 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 has been minimized to the goal, 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.

4.1. Backpropagation (BP)

It is a gradient descent method and the most commonly adopted MLPNN training algorithm [19]. This algorithm gives the change $\Delta w_{ji}(k)$ in the weight of the connection between neurons i and j at iteration k. A network training function updates weight and bias values according to gradient descent. 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. It has a local minima problem. The method is based on random order incremental training functions.

4.2. Quasi-Newton (QN)

This is based on Newton's method but does not require calculation of second derivatives. They are updated by an approximate Hessian matrix of the algorithm at each iteration. 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 iterations the search directions are computed according to the gradient [20].

4.3. Resilient propagation (RP)

This algorithm [21] generally provides faster convergence than most other algorithms and the role of the RP is to avoid the bad influence of the size of the partial derivatives on the weight update.

4.4. Levenberg-Marquardt (LM)

This is a least-squares estimation method based on the maximum neighbourhood idea [22, 23]. 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.

4.5. 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 [24, 25].

5. 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 top shielded MCPW when the values of relative permittivity ε_1, ε_2, h_2/h_1, h_3/h_1, w/h_1, d/h_1 and S/h_1 are given. Figure 2 shows the neural structure. Training MLPNNs using different algorithms involves presenting those different sets (ε_1, ε_2, h_2/h_1, h_3/h_1, w/h_1, d/h_1, S/h_1, ε_{eff} and Z_0) sequentially and/or randomly and the corresponding calculated values of the effective relative permittivity ε_{eff} and the characteristic impedance Z_0. Differences between the target and the actual outputs (ε_{eff} and Z_0) of the MLPNNs are calculated through the network to adapt its weights. The adaptation is carried out after the presentation of each set (ε_1, ε_2, h_2/h_1, h_3/h_1, w/h_1, d/h_1, S/h_1, ε_{eff} and Z_0) 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 MLPNNs, for all the training set fall below a given threshold or the maximum allowable number of epochs reached. Training times of the algorithms were at most a few minutes.

The training and test data sets used in this work have been obtained from the conformal mapping based study introduced by Gevorgian et al. [17]. 2,000 and 1,344 data sets were used in training and test processes, respectively.

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 numbers of neurons and hidden units for the application presented in this work were selected after several trials as stated in [15,16]. It was found that a network with one hidden layer achieved the task with high accuracy. The most suitable network configuration found was 7 x 12 x 2; this means that the number of neurons were 7 for the first hidden layer and 12 for second hidden layer and 2 for output layer.

The tangent hyperbolic activation function was used in the input and hidden layers. Linear activation function was employed in the output layer.

6. Results

The training and test rms errors obtained from neural models are given in Table. 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.

Table. Training and test rms errors.

Training Algorithm	Errors in training for $\varepsilon_{eff-ANN}$	Errors in training for $Z_{0-ANN}(\Omega)$	Errors in test for $\varepsilon_{eff-ANN}$	Errors in test for $Z_{0-ANN}(\Omega)$
LM	0.1511	0.0154	0.0129	0.0809
BR	0.2589	0.0431	0.1125	0.0022
BP	0.1076	2.1611	2.6369	2.6167
RP	0.4344	0.6479	5.9598	5.6341
QN	3.6104	0.2816	2.2231	1.9884

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 top shielded MCPW are shown in Figures 3 and 4, respectively.

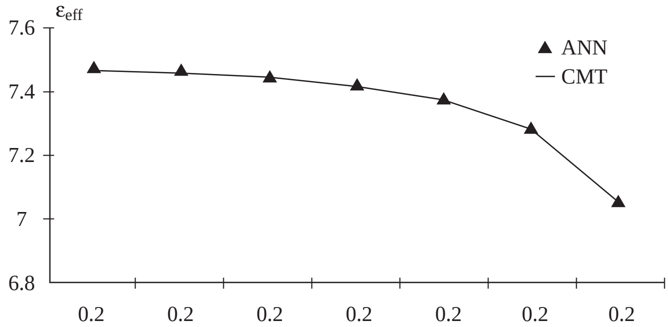

Figure 3. The effective relative permittivity of top shielded MCPW (ε_1 = 11, ε_2 = 4, h_1 = h_2 = 600 μm, h_3 = 750 μm, w = 60 μm).

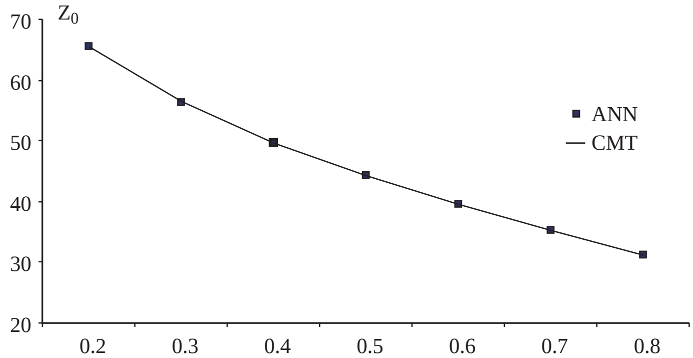

Figure 4. The characteristic impedance of top shielded MCPW (ε_1 = 11, ε_2 = 4, h_1 = h_2 = 600 μm, h_3 = 750 μm, w = 60 μm).

7. Conclusion

The characteristic parameters of top shielded MCPWs have been successfully determined with the use of neural networks.

The good agreement shown in the figures supports the validity of the neural models. Using these models, one can calculate accurately the effective relative permittivity and the characteristic impedance of top shielded MCPW without possessing strong background knowledge. Even if training takes a few minutes, the test process only takes a few microseconds to produce ε_{eff} and Z_o after training. It should also be emphasized that both parameters can be determined from one neural model.

Finally, MLPNN models presented in this work can be used easily, simply and accurately to determine the characteristic parameters of top shielded MCPWs.

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