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Neural network based characterizing parameters of coplanar waveguides

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Abstract

Artificial neural networks (ANNs) has been a promising tool for microwave modeling, simulation and optimization. In this paper we present the estimation of characteristic parameters of top shielded multilayer coplanar wave-guides(MPCWs) using ANN model. For training the model is done with Levenberg-Marquardt algorithm. Our result shows that the neural network successfully calculates characteristic parameters of top shielded Microwave coplanar waveguides with the high accuracy (error is just about 0.05%). Using these models one can calculate effective relative permitivity and the characteristic impedance of the top shielded MCPWs 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_0 after training. It should also be emphasized that both parameters can be determined from one neural model.

Keywords: Coplanar waveguides, artificial neural networks (ANNs).

Introduction

In Microwave and millimeter-wave integrated circuits (MWICs), coplanar waveguides (CPWs), coplanar lines and microstrip lines have been widely used-as transmission line. Principle of these devices is the location of the ground plan which is on the single line, which 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 conformal mapping theory were given by WEN, 1969. In the theory, assumption for infinite thickness of substrate was made. Afterwards full wave analysis of CPW was introduced by Change *et al*. (1991), which provides comparatively high precision in a wide frequency band. Although the precision level with above technique is higher for analytic calculation of characteristic parameters but 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, and time-consuming numerical calculations which need very expensive software packages. So they are not very attractive CAD models.

Artificial neural network recently gained attention as a fast and flexible tool to microwave modeling and design. Neural networks learn by example. It gathers representative data, and then invokes training algorithms to automatically learn the structure of the data.

In the following sections, artificial neural network and calculation of characteristic parameters through classical technique are dealt in details. Results obtained through ANN are also discussed.

Artificial neural network

ANN is 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 patters and relationships in data and learn through their architectures and learning algorithms. There are many types of neural networks for various applications available in literature (Fan *et al*, 2003, Levenberg, 1944; Marquardt,1963; Chen, 2003). Multilayered perceptron neural networks (MLPNNs) are simplest neural network with some universal approximations.

In this paper MLPNNs have been adapted for the computation of effective relative permittivity εeff and the characteristic impedance Z_0 of the top shilded CPM. A general neural structure used in this work is shown in the Fig.1. MLPNNs used in this work are trained with the modified Levenderg Marquardt (MLM) learning algorithm. It consists of three layers: an input layer, an output layer and an intermediate or hidden layer. Processing element (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.,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.

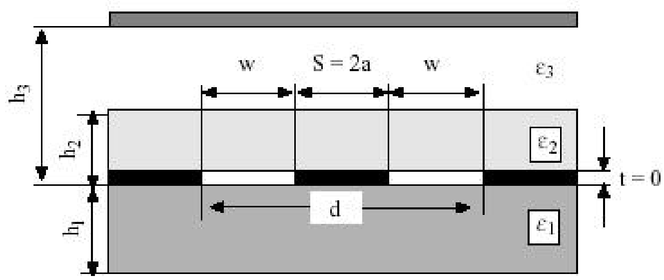
Training a MLPNN by MLM involves presenting it's sequentially with all training tuples (input, target, output). Differences between the target output and the actual output of the MLPNNs are propagated back through the network to adopt its weights. A training iteration is completed after a tuple in the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

Training network consists of adjusting its weights using 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;

$E=1/2\sum(yd_j-y_j)^2$

Where yd_j is the desired value of output neuron j and y_j is the actual output of that neuron. Each weight w_{ij} is adjusted by adding an increment Δw_{ij} is selected to reduce E as rapidly as possible. The adjustment is carried out over several training iteration until a satisfactory small value of E is obtained or a given number of iterations are reached. How Δw_{ij} is computed depends on the training algorithm. Training process ends when the maximum number of epochs is reached, the performance has been minimized to the goal, the performance gradient falls below minimum gradient or alidation performance has increased more than maximum fail times since the last time it decreased using validation. The learning algorithm used in this work is Modified Levenberg- Marquardt (Jinyan, 2006).

Fig.1. Top shielded multilayered CPW



Conformal mapping technique for characterizing CPWs

Fig.1 shows the structure of the top shielded CPW. Fig.2 represents the width of the single ground, w is the width of the slots, h_1 and h_2 are the thickness of the dielectric substrates, h_3 is the distance between the signal grounds and top shielding, ε_1 is the dielectric constants of the dielectric materials. In the quasi TEM limits of the basic characteristics of CPW can be determined when the capacitance per unit length is known.

The capacitance per unit length of wave guiding structures is determined assuming zero thickness of the metal strips. The line capacitance of CPWs can be given as a sum of partial capacitance using the quasi static approximations, the effective relative permittivity and characteristic impedance of transmission line are:

$$\varepsilon_{eff} = \frac{C}{C_0} \quad (1); \qquad Z_0 = \frac{\sqrt{\varepsilon_{eff}}}{C.v_0} \quad (2)$$

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:

$$C = C_1 + C_2 + C_{03} \quad (3)$$

Where C_1 is the capacitance of the line whose thickness in h_1 and effective dielectric constant ε_1, C_2 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 (Gevorgian, 1995) and can be written as:

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

$$K_1^{'} = \sqrt{1-k_1^2}$$

and $$k_1 = \frac{\sin\left(\dfrac{\pi.S}{4.h_1}\right)}{\sinh\left(\dfrac{\pi.(a+w)}{4.h_1}\right)} \quad (5)$$

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

$$K_2^{'} = \sqrt{1-k_2^2} \text{ and } k_2 = \frac{\sin\left(\dfrac{\pi.S}{4.h_2}\right)}{\sinh\left(\dfrac{\pi.(a+w)}{4.h_2}\right)} \quad (7)$$

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

$K_3^{'} = \sqrt{1-k_3^2}$ where k_3 is equal to k_0, because $\varepsilon_3=1$.

$$k_3 = \frac{\sin\left(\dfrac{\pi.S}{4.h_3}\right)}{\sinh\left(\dfrac{\pi.(a+w)}{4.h_3}\right)} \quad (9)$$

Where $k(k_i)$ and $K(k_i^2)$ are the complete elliptical integrals of the first kind. The effective relative permittivity of the line can be determined as given in equation (10);

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

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

$$q_1 = \frac{K(k_1)}{K(k_1^{'})} . \frac{K(k_3)}{K(k_3^{'})} \quad (11)$$

$$q_2 = \frac{K(k_2)}{K(k_2^{'})} . \frac{K(k_3)}{K(k_3^{'})} \quad (12)$$

The characteristic impedance (Z_0) can be determined as given in equation (13):

$$Z_0 = \frac{60\pi}{\sqrt{\varepsilon_{eff}}} . \frac{K(k_3^{'})}{K(k_3)} \quad (13)$$

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Table 1.Training and testing rms error for characteristic impedance through MLM

Data Type	Thickness of the substrate	Value of Z_0 through CMT	Value of Z_0 through ANN	Difference between the values	%error
Training	0.2	65.756	65.7545	0.0015	0.002%
	0.3	53.456	53.451	0.005	0.009%
	0.4	47.134	47.131	0.003	0.006%
	0.5	42.546	42.5445	0.0015	0.0035%
	0.6	39.254	39.2465	0.0075	0.019%
Testing	0.15	71.675	71.6745	0.0005	0.00079%
	0.25	58.234	58.2339	0.0001	0.0007%
	0.35	50.765	50.7599	0.0051	0.01%
	0.45	44.234	44.2289	0.0051	0.011%
	0.55	41.876	41.8753	0.0007	0.0016%

Table 2. Training and testing rms error for relative permittivity through MLM

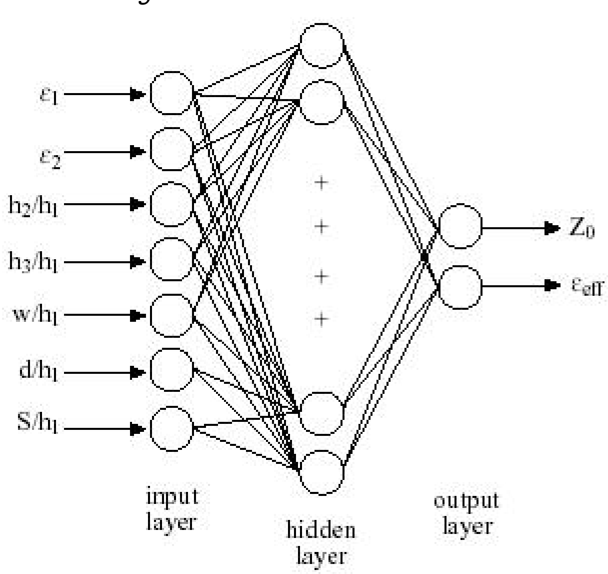
Data Type	Thickness of the substrate	Value of ε_{eff} through CMT	Value of ε_{eff} through ANN	Difference between the values	%error
Training	0.2	7.5	7.498	0.002	0.027%
	0.3	7.35	7.3482	0.0018	0.024%
	0.4	7.3	7.2997	0.0003	0.029%
	0.5	6.9	6.8992	0.0002	0.029%
Testing	0.15	7.8	7.789	0.01	0.128%
	0.25	7.43	7.4295	0.005	0.067%
	0.35	7.3448	7.3439	0.009	0.122%
	0.45	7.279	7.276	0.003	0.04%
	0.55	6.867	6.86345	0.003	0.04%

These Closed form expressions obtained by CMT consists of complete elliptical integrals of first kind, which are difficult to calculate even with computers. Because of this, the approximate formulas were proposed for the calculation of elliptical integrals. If that is the case, then the characteristic impedance and effective relative permittivity of top shielded CPW can easily and simply be determined by neural model.

Results and discussions

The proposed MLM involves training an ANN to calculate the effective relative permittivity and the characteristic impedance 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. Fig.2 shows the neural structure. Training MLPNNs using MLM algorithms involves presenting those sets (ε_1, ε_2, h_2/h_1, h_3/h_1, w/h_1, d/h_1 and S/h_1) sequentially and /or randomly and the corresponding calculated values of the effective relative permittivity and the characteristic impedance.

Fig.2. The structure of ANN model



Differences between the target and the actual outputs of the MLPNNs are calculated through the network to adapt its weight. 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 calculated accuracy of the network is deemed satisfactory according to some criterion. This criterion can be erroneous between ε_{eff} (CMT)and ε_{eff} (ANN) and Z_0 (CMT)and Z_0 (ANN), which are obtained from MLPNNs for all the training set fall below a given threshold or maximum allowed number of epochs reached. The 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 obtained earlier (Goanoet *et al.*1995) and 1500 data sets were used in training and testing processed, 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 unites for the application presented in this work were selected after several trials as stated earlier (More, 1978). It was found that a network with one hidden layer achieved the task with high accuracy. The most suitable network configuration found was 7×12×2; 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. Table 1 & 2 present a sample of the results of training and testing obtained by the ANN. Distribution of deviations of the ANN calculated relative permittivity and characteristic impedance from the corresponding desired value of relative permittivity and characteristic impedance are shown in Fig.3 and Fig.4 respectively. The distribution of deviations is almost symmetrical around zero. Most of the deviations are around zero. Fig.5 shows the comparison of relative permittivity and characteristic impedance as function of substrate width. Curve obtained from CMT calculated data and ANN data are quite identical. So we can conclude that one can calculate accurately the effective relative permittivity and the

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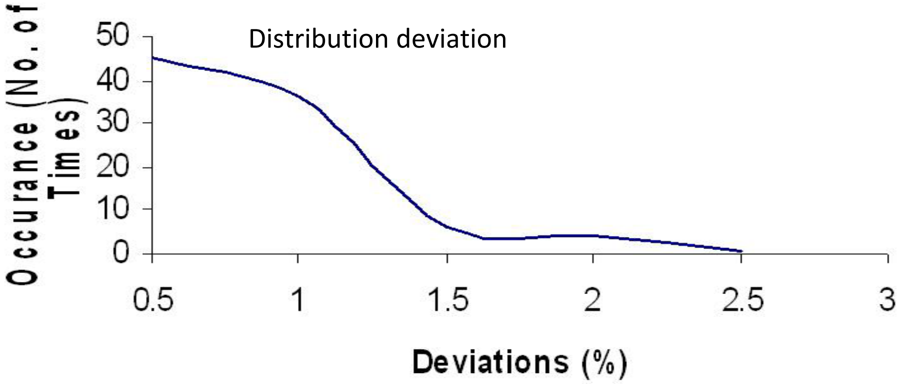
Fig.3. Distribution of deviations of the ANN calculated relative permittivity and characteristic impedance from the corresponding desired value



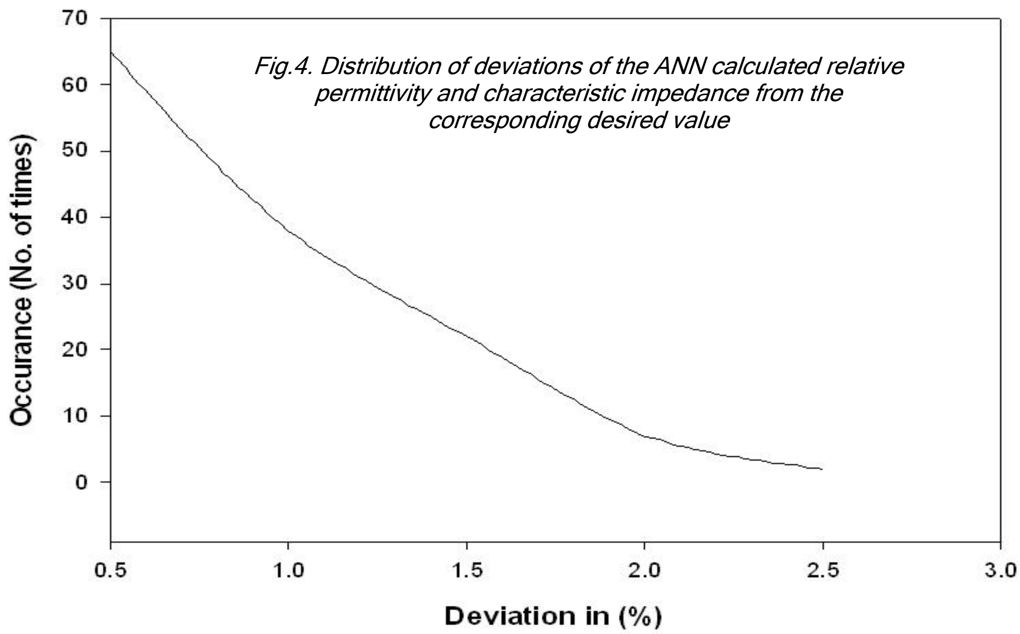
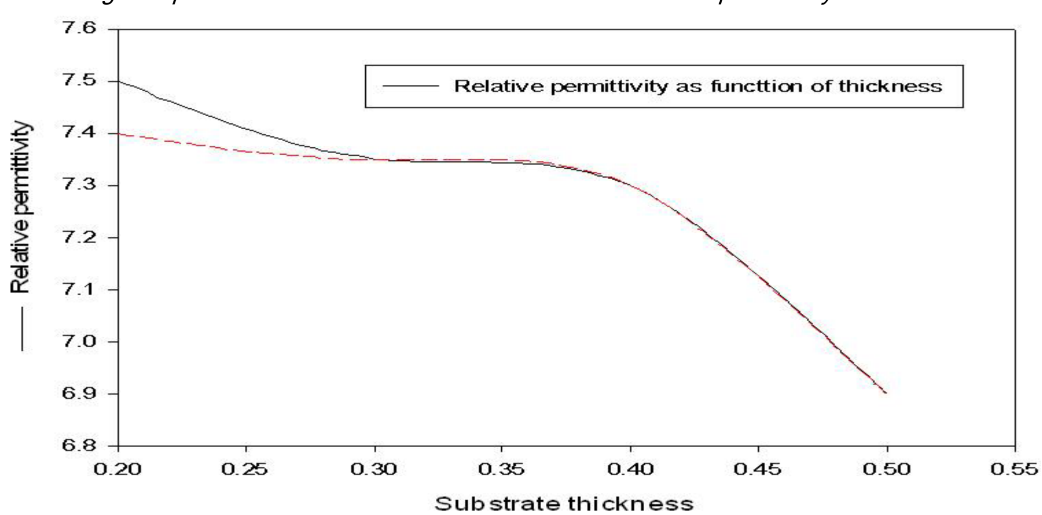


Fig.4. Distribution of deviations of the ANN calculated relative permittivity and characteristic impedance from the corresponding desired value

Fig.5.Coparison of ANN results and CMT results for relative permittivity of CPW



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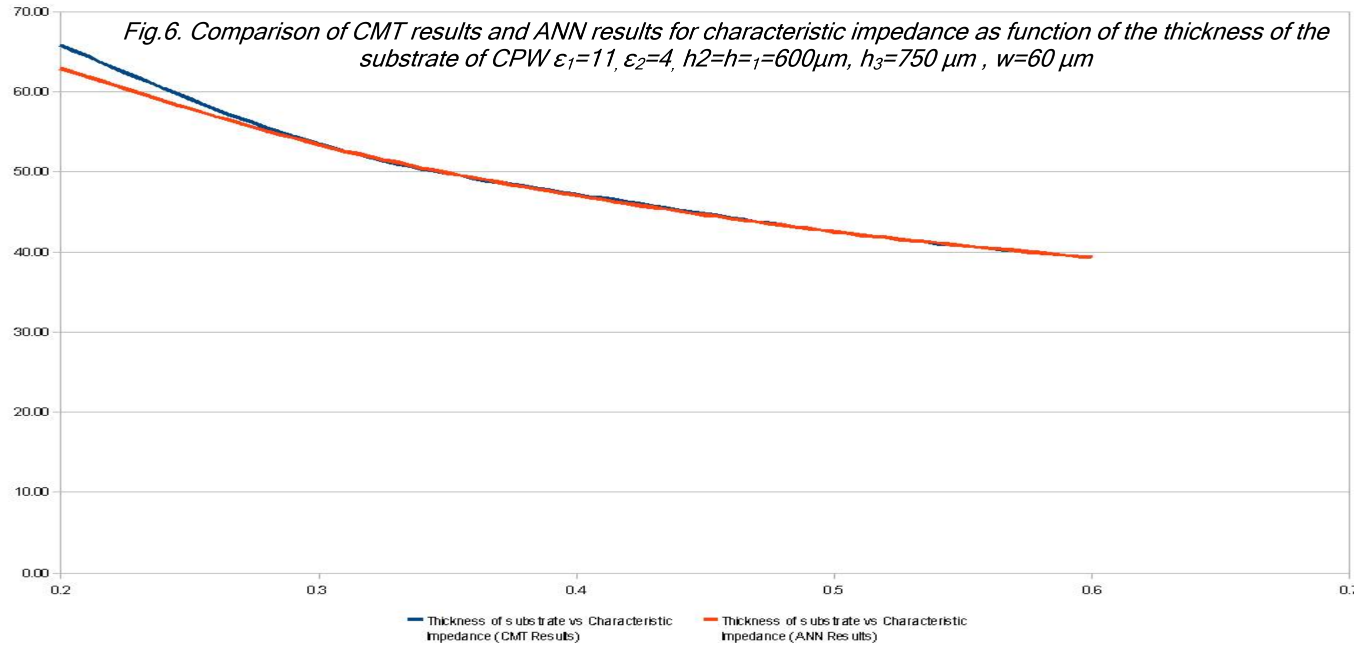

Fig.6. Comparison of CMT results and ANN results for characteristic impedance as function of the thickness of the substrate of CPW $\varepsilon_1=11$, $\varepsilon_2=4$, $h2=h=_1=600\mu m$, $h_3=750\ \mu m$, $w=60\ \mu m$

characteristic impedance of top shielded MCPW without possessing background knowledge. Even if training takes a few minutes, the test process only takes a few microseconds to produce relative permittivity and characteristic impedance 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 CPWs. When the experiment of re-training and testing of the ANN was repeated, the deviations were of similar nature and magnitude. It shows the ruggedness and reliability of the ANN.

Conclusion

So we can conclude that one can calculate accurately the effective relative permittivity and the characteristic impedance of top shielded MCPW without possessing background knowledge. Even if training takes a few minutes, the test process only takes a few microseconds to produce relative permittivity and characteristic impedance 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 CPWs.

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