Progress In Electromagnetics Research B, Vol. 3, 1–22, 2008

QUASI-STATIC MODELS BASED ON ARTIFICIAL NEURAL NETWORKS FOR CALCULATING THE CHARACTERISTIC PARAMETERS OF MULTILAYER CYLINDRICAL COPLANAR WAVEGUIDE AND STRIP LINE

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Abstract—In this paper, two different neural models are proposed for calculating the quasi-static parameters of multilayer cylindrical coplanar waveguides and strip lines. These models were basically developed by training the artificial neural networks with the numerical results of quasi-static analysis. Neural models were trained with four different learning algorithms to obtain better performance and faster convergence with simpler structure. When the performances of neural models are compared with each other, the best test results are obtained from the multilayered perceptrons trained by the Levenberg-Marquardt algorithm. The results obtained from the neural models are in very good agreements with the theoretical results available in the literature.

1. INTRODUCTION

Various coplanar waveguides (CPWs) and coplanar strip lines (CPSs) on planar substrates are widely used in microwave and millimeter wave integrated circuits due to their flexibility in the design of complex microwave circuitry requiring series and shunt connections. Recently, cylindrical CPW (CCPW) and cylindrical CPS (CCPS) with a single dielectric substrate or multilayer dielectric substrates have been proposed, which have the potential to be used in applications such as antennas, sensors, wireless communications, transition adapters, and baluns.

So far, the various CCPWs and CCPSs have been analyzed by many researchers. CCPW with a single dielectric substrate has been analyzed with the use of full-wave [1, 2] and quasi-static [3–5] methods. Multilayer CCPW has been analyzed by Alkan et al. [6] with the use of conformal mapping technique (CMT) which is the most often used quasi-static method. The quasi-static parameters of CCPS having a single dielectric substrate [7, 8] and multilayer dielectric substrates [9, 10] have been determined with the use of CMT.

As mentioned above, CCPW and CCPS with a single dielectric substrate or multilayer dielectric substrates have been analyzed with the use of quasi-static or full-wave methods. While full-wave methods are the most accurate tools for obtaining the characteristic parameters of transmission lines and analytically extensive, quasi-static methods are quite simple but do not threaten the dispersive nature of generic transmission lines. Consequently, the approximation of the quasi-static methods becomes worse as the transmission line becomes dispersive.

The aim of this paper is to present a new approximation based on artificial neural networks (ANNs) to determine the quasi-static parameters of multilayer CCPW and CCPS as an alternative method. As is well known, the quasi-static approximation is valid only at low frequencies. However, Bedair and Wolff [11] have shown that quasi-static approximation can be used in the design of coplanar monolithic microwave integrated circuits up to 40 GHz because of their very low dispersion. For this reason the neural models to be proposed in this work can also be used to discuss the propagation characteristics of multilayer CCPW and CCPS, at least up to millimeter-wave frequency range.

Learning and generalization ability, fast real-time operation and ease of implementation features have made ANNs popular in the last decade [12–14]. ANNs have been applied in many areas because of these features. Accurate and efficient microwave components, filters and microstrip antennas have been analyzed and designed with the use of ANNs [15–25]. 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 work, two different neural models are proposed for calculating quasi-static parameters, the effective permittivity and characteristic impedance, of multilayer CCPW and CCPS. It should also be emphasized that the presented neural models are not only valid for multilayer CCPW and CCPS but also valid for CCPW and CCPS with a single dielectric layer. These neural models were trained with quasi-Newton (QN), Conjugate gradient with Flecther (CGF), Levenberg-Marquardt (LM) and Bayesian regulation (BR) learning algorithms to obtain better performance and faster convergence with simpler structure.

The performances of the neural models trained with different learning algorithms have been compared to each other. The inputs to the neural models are the three relative permittivities of the substrate materials and the three geometrical dimensions of multilayer CCPW and CCPS. The outputs of the neural models are the effective permittivity and characteristic impedance.

2. DETERMINATION OF THE QUASI-STATIC PARAMETERS OF MULTILAYER CCPW AND CCPS

The cross-sections of multilayer CCPW and CCPS to be considered in this work are depicted in Figs. 1(a) and 1(b), respectively. In these figures, S and w represent central strip and slot width for multilayer CCPW and represent slot width and strip width for multilayer CCPS. On the other hand, h_1, h_2 and h_3 indicate the thickness of the dielectric materials with the relative permittivities ε_{r1}, ε_{r2} and ε_{r3} respectively.

In quasi-static analysis, all conductor materials are assumed to be perfectly conducting and the thickness of the conductor t is ignored. Using the quasi-static approximations, the effective permittivity $\varepsilon_{\mathit{eff}}$ and the characteristic impedance Z_0 of the transmission lines are given as;

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

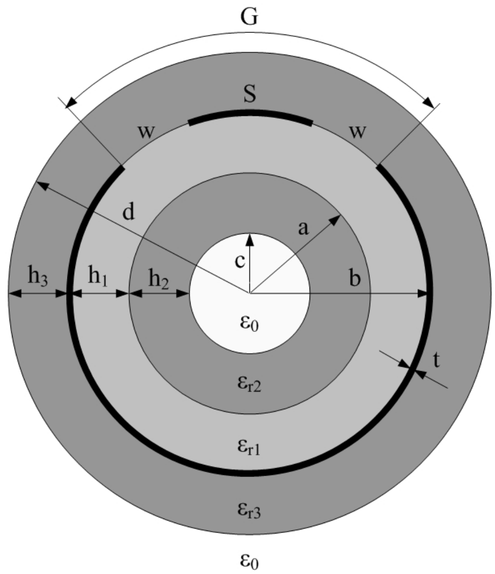
$$Z_0 = \frac{\sqrt{\varepsilon_{\mathit{eff}}}}{C \cdot v_0} \tag{2}$$

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

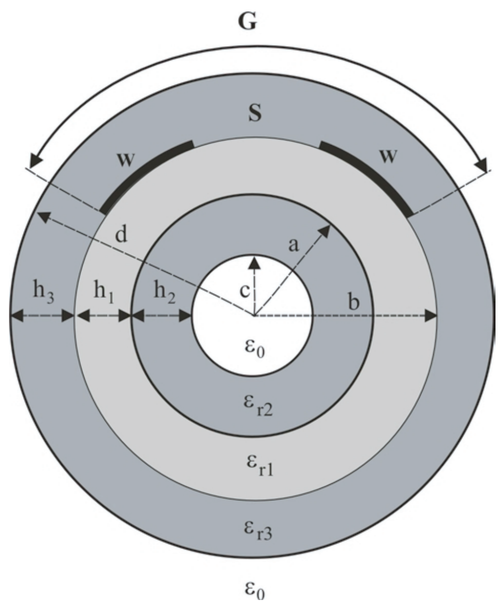
The total capacitance of multilayer CCPW and CCPS can be expressed as the sum of the air and partial capacitances as follow;

$$C = C_0 + C_1 + C_2 + C_3 \tag{3}$$

Here C_1, C_2, and C_3 are the partial capacitances of dielectric layer with thickness h_1 with relative permittivity ε_{r1}, the capacitance of dielectric layer with thickness h_2 with relative permittivity ε_{r2}, and the capacitance of dielectric layer with thickness h_3 with relative permittivity ε_{r3}, respectively.



(a)



(b)

Figure 1. Cross sections of multilayer CCPW and CCPS: (a) multilayer CCPW; (b) multilayer CCPS.

After a sequence of conformal mapping transformations, the air and partial capacitances for multilayer CCPW can be determined as described in [6]. Than the effective permittivity and characteristic impedance of multilayer CCPW can be obtained by using the air and total capacitances in Eqs. (1) and (2), respectively as;

$$\varepsilon_{eff} = 1 + q_1 \cdot \frac{\varepsilon_{r1} - \varepsilon_{r2}}{2} + q_2 \cdot \frac{\varepsilon_{r2} - 1}{2} + q_3 \cdot \frac{\varepsilon_{r3} - 1}{2} \tag{4}$$

$$Z_0 = \frac{30\,\pi}{\sqrt{\varepsilon_{eff}}} \cdot \frac{K(k_0')}{K(k_0)} \tag{5}$$

where the terms q_1, q_2 and q_3 are called the partial filling factors and they are given as

$$q_i = \frac{K(k_i)}{K(k_i')} \cdot \frac{K(k_0')}{K(k_0)} \quad i = 1,\ 2,\ 3. \tag{6}$$

where $K(k)$ and $K(k')$ are the complete elliptic integrals of the first kind with the modulus of k and complementary modulus k'. These modules have been determined in terms of geometrical dimensions of multilayer CCPW in [6] as;

$$k_0 = \frac{S}{G}\sqrt{\frac{(2\pi b)^2 - G^2}{(2\pi b)^2 - S^2}}, \qquad k_0' = \sqrt{1 - k_0^2} \tag{7}$$

and

$$k_i = \frac{\sinh\left(\dfrac{\pi \cdot S}{4 \cdot b \cdot H_i}\right)}{\sinh\left[\dfrac{\pi \cdot G}{4 \cdot b \cdot H_i}\right]}\sqrt{\frac{\sinh^2\left(\dfrac{\pi^2}{2H_i}\right) - \sinh^2\left(\dfrac{G\pi}{4bH_i}\right)}{\sinh^2\left(\dfrac{\pi^2}{2H_i}\right) - \sinh^2\left(\dfrac{S\pi}{4bH_i}\right)}},$$

$$k_i' = \sqrt{1 - k_i^2}, \quad i = 1,\ 2,\ 3 \tag{8}$$

with

$$H_1 = \ln(b/a) \tag{9}$$

$$H_2 = \ln(b/c) \tag{10}$$

$$H_3 = \ln(d/b) \tag{11}$$

The air capacitance C_0 and partial capacitances, C_1, C_2, and C_3 for multilayer CCPS can be determined with the use of CMT as described in [9], than the effective permittivity and characteristic impedance of multilayer CCPS are obtained by using the air and total capacitances in Eqs. (1) and (2), respectively as

$$\varepsilon_{eff} = 1 + \frac{\varepsilon_{r1} - \varepsilon_{r2}}{2} \cdot p_1 + \frac{\varepsilon_{r2} - 1}{2} \cdot p_2 + \frac{\varepsilon_{r3} - 1}{2} \cdot p_3 \tag{12}$$

$$Z_0 = \frac{120\,\pi}{\sqrt{\varepsilon_{eff}}} \cdot \frac{K(k_0')}{K(k_0)} \tag{13}$$

where the filling factors p_i are given by

$$p_i = \frac{K(k_i')}{K(k_i)} \cdot \frac{K(k_0)}{K(k_0')} \qquad i = 1,\, 2,\, 3 \tag{14}$$

where $K(k)$ and $K(k')$ are the complete elliptic integrals of the first kind with the modulus of k and complementary modulus k'. These modules have been determined in terms of geometrical dimensions of multilayer CCPS in [9] as;

$$k_0 = \frac{S}{S + 2w} \qquad k_0' = \sqrt{1 - k_0^2} \tag{15}$$

and

$$k_i = \frac{\sinh\left(\dfrac{\pi \cdot S}{4 \cdot b \cdot H_i}\right)}{\sinh\left[\dfrac{\pi \cdot (S + 2 \cdot w)}{4 \cdot b \cdot H_i}\right]}, \quad k_i' = \sqrt{1 - k_i^2}, \quad i = 1,\, 2,\, 3 \tag{16}$$

where H_i $(i = 1,\, 2,\, 3)$ were described in Eqs. (9)-(11).

Finally, the characteristic parameters of multilayer CCPW and CCPS are achieved in terms of the closed form expressions. These closed-form expressions obtained by CMT consist of complete elliptic integrals, which are difficult to calculate even by computers. For this reason, the approximate formulas were proposed for calculation of elliptic integrals [26].

The effective permittivities and characteristic impedances of multilayer CCPW and CCPS are easily and simply determined by using the presented neural models. The inputs to ANN models are the relative permittivities of three dielectric materials, and three geometrical dimensions of multilayer CCPW and CCPS. The outputs are the effective permittivity and characteristic impedance.

3. ARTIFICIAL NEURAL NETWORKS (ANNS)

ANN learns relationships among sets of input-output data which are characteristic of the device under consideration. It is a very powerful approach for building complex and nonlinear relationship between a set of input and output data. ANNs are developed from neurophysiology by morphologically and computationally mimicking human brains [12–14]. Although the precise operation details of ANNs are quite different from those of human brains, they are similar in three aspects: they consist of a very large number of processing elements (the neurons), each neuron connects to a large number of other neurons, and the functionality of networks is determined by modifying the strengths of connections during a learning phase.

The power of neural computations comes from weight connection in a network. Each neuron has weighted inputs, summation function, transfer function, and output. The behavior of a neural network is determined by the transfer functions of its neurons, by the learning rule, and model architecture. The weights are adjustable parameters and, in that sense, a neural network is a parameterized system. The weighted sum of the inputs constitutes the activation of the neurons. The activation signal is passed through a transfer function to produce the output of a neuron. Transfer function introduces non-linearity to the network. During training process, the inter-unit connections are optimized until the error in predictions is minimized and the network reaches the specified level of accuracy. Once the network is trained, new unseen input information is entered to the network to calculate the output for test.

In the course of developing an ANN model, the architecture of the neural network and the learning algorithm are the most important factors. ANNs have many structures and architectures [12–14]. The class of ANN and/or architecture selected for a particular model implementation depends on the problem to be solved. After several experiments using different architectures coupled with different training algorithms, in this paper, the MLP neural network architecture [12] was used to compute the quasi-TEM parameters of multilayer CCPW and CCPS.

3.1. Multilayered Perceptrons (MLPs)

The MLP is one of the most extensively used ANN architecture, due to well-known general approximation capabilities, despite its limited complexity. 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 neurons in the hidden layer. Each neuron 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, namely;

$$y_j = f\left(\sum w_{ji} x_i\right) \tag{17}$$

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

Training a network consists of adjusting weights of the network by a learning algorithm. The learning algorithm gives the change $\Delta w_{ji}(k)$ in the weight of a connection between neurons i and j at time k. The weights are then updated according to the following formula;

$$w_{ji}(k+1) = w_{ji}(k) + \Delta w_{ji}(k+1) \tag{18}$$

MLPs can be trained using many different learning algorithms [12]. In this article, the following four learning algorithms used to train the MLPs were described briefly.

Levenberg-Marquardt (LM): This is a least-squares estimation method based on the maximum neighborhood idea [27, 28]. It 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.

Bayesian Regulation (BR): The BR 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 generalized network [29]. It takes place within the LM and requires more training and memory than the LM.

Conjugate Gradient of Fletcher-Powell (CGF): This method updates weights and bias values according to the conjugate gradient with Fletcher-Reeves [30, 31]. Each variable is adjusted to minimize the performance along the search direction. The line search is used to locate the minimum point. The first search direction is the negative of the gradient. In succeeding iterations the search direction is computed from the new gradient and the previous search direction. Fletcher-Reeves version of conjugate gradient uses the norm square of previous gradient and the norm square of the current gradient to calculate the weights and biases.

Quasi-Newton (QN): This is based on Newton's method but don't require the calculation of second derivatives [32]. They update an approximate Hessian matrix at an 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. In succeeding iterations the search direction is computed according to the gradient.

4. NEURAL MODELS FOR MULTILAYER CCPW AND CCPS

In this paper, two neural models are proposed for calculating the quasi-static parameters of multilayer CCPW and CCPS. For the neural models, the inputs are the relative permittivities of substrate materials ε_{r1}, ε_{r2}, ε_{r3} and three geometrical dimensions h_2/h_3, G/h_1, S/G, and the outputs are the effective permittivity (ε_{eff}) and characteristic impedance (Z_0). Neural models used in calculating the effective permittivities and characteristic impedances of multilayer CCPW and CCPS are shown in Figs. 2(a) and 2(b), respectively.

ANN models are a kind of black box models, whose accuracy depends on the data presented to it during training process. A good collection of the training data, i.e., data which is well-distributed, sufficient, and accurately simulated, is the basic requirement to obtain an accurate model. For microwave applications, there are two types of data generators, namely measurement and simulation. The selection of a data generator depends on the application and the availability of the data generator.

The training data sets were obtained from CMT introduced by Alkan et al. [6], and 1296 data sets were used to train the neural model for multilayer CCPW. 576 data sets obtained from [3, 4, 6] were used to test the neural model for multilayer CCPW. The training and test data sets were obtained from CMT proposed by Gorur et al. [9] and 1008 data sets were used to train the neural model for multilayer CCPS. 448 data sets, which are completely different from training data sets, were used to test the neural model for multilayer CCPS. The ranges of the training data sets for both multilayer CCPW and CCPS are among $2 \leq \varepsilon_{r1} \leq 14$, $1 \leq \varepsilon_{r2} = \varepsilon_{r3} \leq 10$, $0.1 \leq S/G \leq 0.9$, $1 \leq G/h_1 \leq 4$, $100\,\mu\text{m} \leq h_1 \leq 1500\,\mu\text{m}$, $200\,\mu\text{m} \leq h_2 \leq 1400\,\mu\text{m}$, $100\,\mu\text{m} \leq h_3 \leq 1400\,\mu\text{m}$. The curvature ratio $R = b/a$ was chosen for all structures as 0.8.

The aim of the training process is to minimize the training error between the target outputs and the actual outputs of the ANNs. Training the ANNs with the use of a learning algorithm to calculate the effective permittivities and characteristic impedances of multilayer CCPW and CCPS involves presenting them sequentially and/or randomly with different sets (ε_{r1}, ε_{r2}, ε_{r3}, h_2/h_3, G/h_1, S/G)

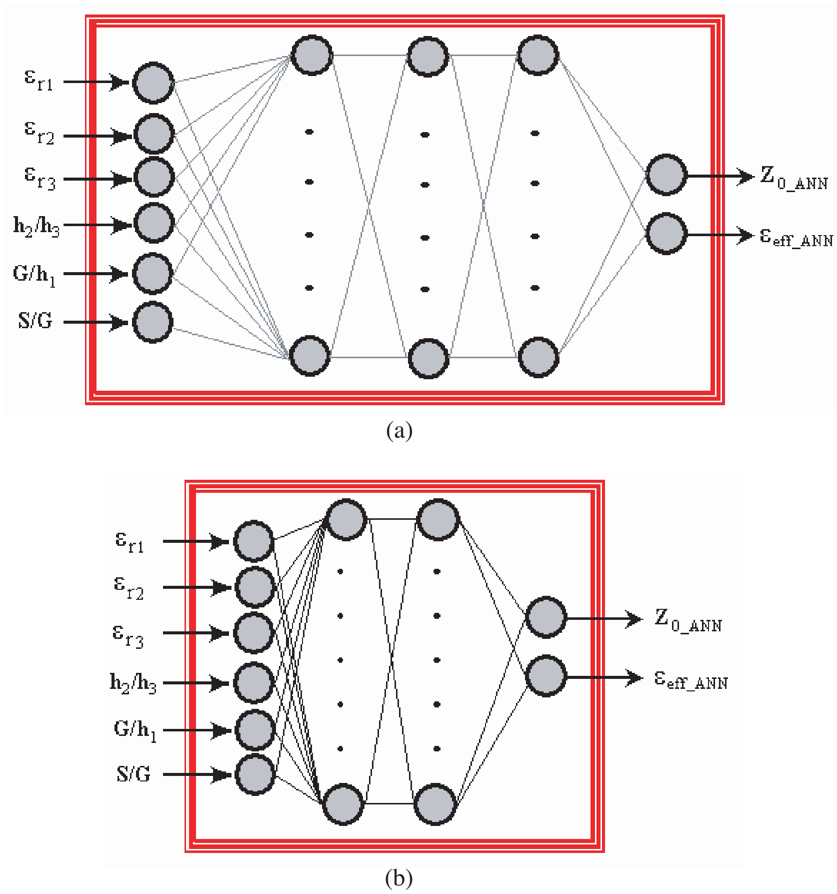


Figure 2. Neural network architectures for multilayer CCPW and CCPS: (a) neural model for multilayer CCPW; (b) neural model for multilayer CCPS.

and corresponding effective permittivities (ε_{eff}) and characteristic impedances (Z_0). First, the input vectors (ε_{r1}, ε_{r2}, ε_{r3}, h_2/h_3, G/h_1, S/G) 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 of neurons in the models. Training proceeds until errors are lower than prescribed values.

Currently, there is no deterministic approach that can optimally determine the number of hidden layers and the number of neurons. A common practice is to take a trial and error approach which adjusts the hidden layers to strike a balance between memorization and generalization. After several trials, it was found in this paper that three hidden layered and two hidden layered networks were achieved the task in high accuracy for multilayer CCPW and CCPS, respectively.

The structures of the presented neural models in this work are given in Figs. 2(a) and 2(b). The most suitable network configuration found was $6 \times 6 \times 10 \times 6 \times 2$ for multilayer CCPW. It means that the number of neurons were 6 for the input layer, 6, 10 and 6 for the first, the second and third hidden layers and 2 for the output layer. The tangent sigmoid activation functions were used in the first hidden layer, the sigmoid activation functions were used in the other two hidden layers. The network configuration found was $6 \times 6 \times 18 \times 2$ for multilayer CCPS, and 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 and output layers in the neural models for both multilayer CCPW and CCPS.

5. RESULTS AND CONCLUSIONS

ANNs have been successfully introduced to calculate the quasi-static parameters of multilayer CCPW and CCPS. ANNs were trained with four different — the LM, the BR, the CGF and the QN — learning algorithms to obtain better performances and faster convergence with simpler structure. The performances of learning algorithms are compared with each other and obtained training and test RMS errors are given in Table 1 and Table 2 for both the effective permittivities and characteristic impedances of multilayer CCPW and CCPS, respectively. As it can be seen from these tables the best ANN results were achieved from the models trained with the LM learning algorithms for both multilayer CCPW and CCPS.

In order to show the validation of the presented neural models trained with the LM learning algorithm for the determination of the quasi-static parameters of multilayer CCPW and CCPS, comprehensive comparisons have been made and obtained results are explained briefly in the following paragraphs.

Three comparisons have been made for the determination of the quasi-static parameters of CCPWs having different electrical properties and geometrical dimensions. In the first comparison, the results for the effective permittivity and characteristic impedance of CCPW having a

Table 1. Training and test RMS errors of the neural models for multilayer CCPW.

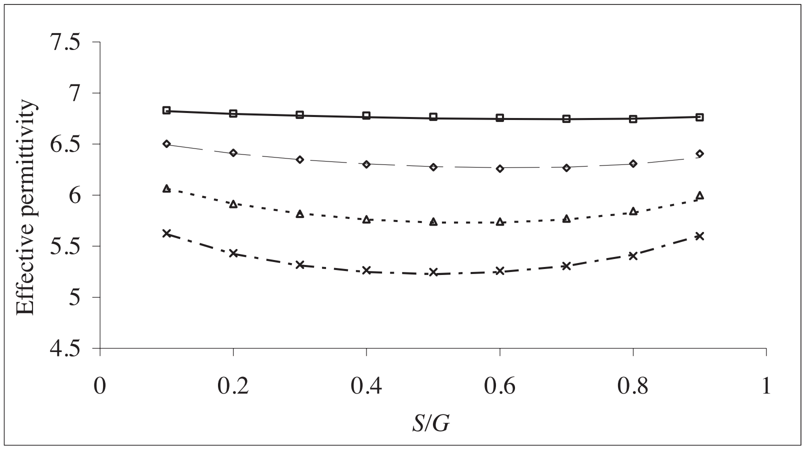
Learning Algorithms	RMS Errors for training		RMS Errors for test	
	ε_{eff}	Z_0 (Ω)	ε_{eff}	Z_0 (Ω)
LM	0.1409	0.6283	0.0512	0.1103
BR	2.5326	0.5983	0.5763	0.2428
CGF	14.4429	4.2829	1.1506	7.5709
QN	20.2353	117.4026	1.1086	8.1041

Table 2. Training and test RMS errors of the neural models for multilayer CCPS.

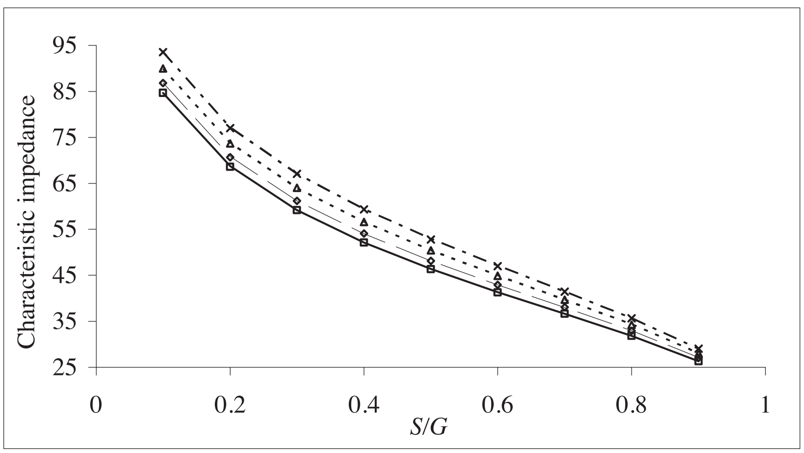
Learning Algorithms	RMS Errors for training		RMS Errors for test	
	ε_{eff}	Z_0 (Ω)	ε_{eff}	Z_0 (Ω)
LM	0.5414	0.4176	0.9829	0.2044
BR	1.9970	0.8685	3.8211	0.1822
CGF	1.6806	2.2890	18.4865	25.9225
QN	1.1837	1.5074	64.9284	78.2641

single dielectric layer are given in Figs. 3(a) and 3(b) for four different G/h_1 values with respect to the shape ratio S/G, respectively. There is a perfectly good agreement between the results of the CMT [3, 4] and the presented neural model. In order to show the validation of our neural model for multilayer CCPWs having two and three dielectric layers, the obtained ANN results are compared with the quasi-static analysis results [6] for the effective permittivity and characteristic impedance in second and third comparisons. The comparison results for the quasi-static parameters of multilayer CCPW are given in Figs. 4 and 5 for four different G/h_1 values with respect to the shape ratio S/G, respectively. These comparison results show that there are very good agreements among the results of the model trained by the LM learning algorithm and the quasi-static analysis [6].

Three comparisons have also been made for the validation of the neural model for CCPSs having different electrical properties and geometrical dimensions. The first comparison is made for the effective permittivities and characteristic impedances of multilayer CCPS. The obtained results for the characteristic parameters of multilayer CCPS are shown graphically in Figs. 6(a) and 6(b), respectively. This



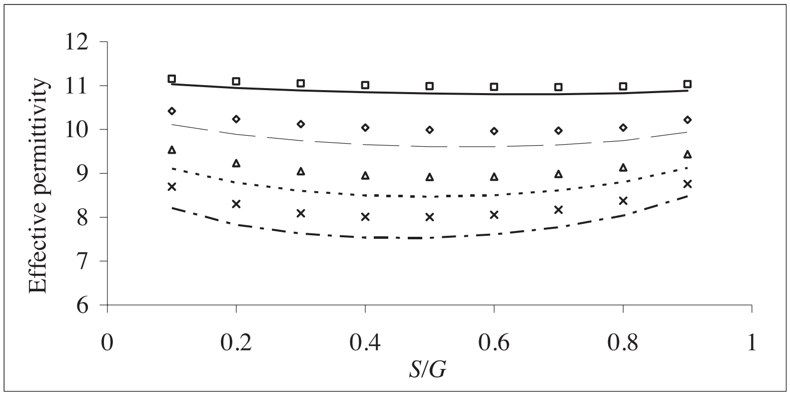
(a) ε_{eff}



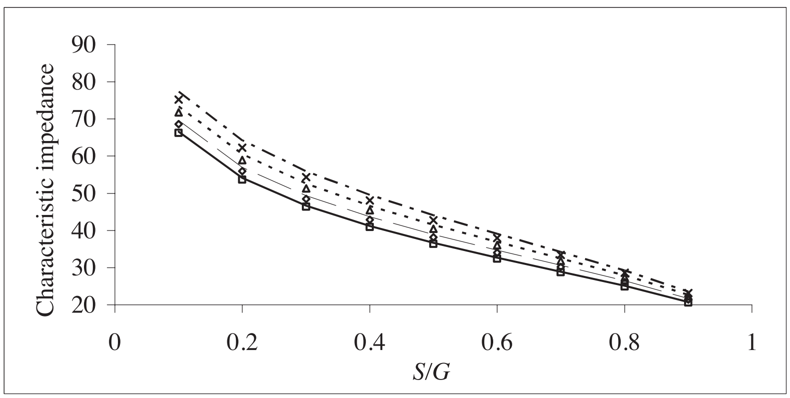
(b) Z_0 (Ω)

CMT [3, 4] and □ ANN for $G/h_1 = 1$,
CMT [3, 4] and ◊ ANN for $G/h_1 = 2$,
CMT [3, 4] and D ANN for $G/h_1 = 3$,
CMT [3, 4] and x ANN for $G/h_1 = 4$.

Figure 3. The comparison of the quasi-static analysis results and ANN results for CCPW with a single dielectric layer as a function of the shape factor S/G and the ratio of G/h_1 ($\varepsilon_{r1} = 12.9$, $\varepsilon_{r2} = \varepsilon_{r3} = 1$ and $h_1 = 762\,\mu$m): (a) effective permittivity; (b) characteristic impedance.



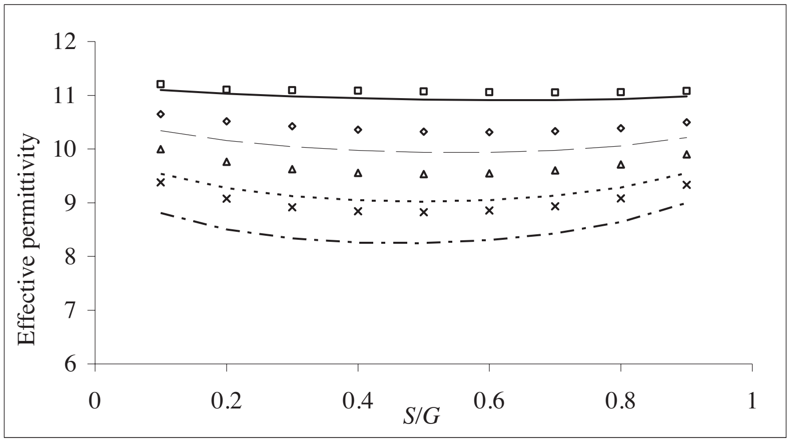
(a) ε_{eff}



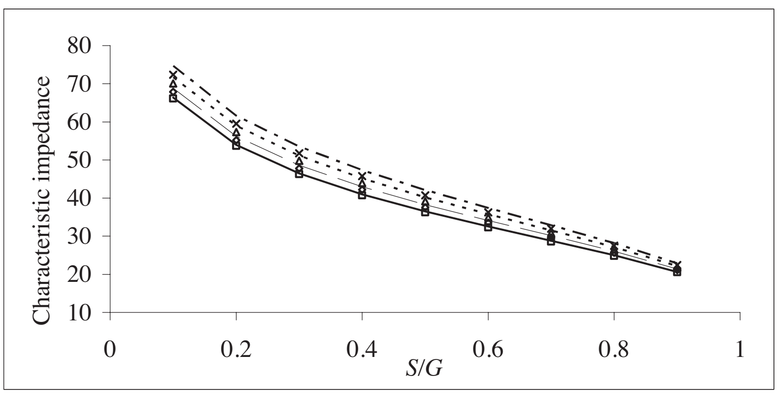
(b) Z_0 (Ω)

CMT [6] and □ ANN for $G/h_1 = 1$,
CMT [6] and ◊ ANN for $G/h_1 = 2$,
CMT [6] and D ANN for $G/h_1 = 3$,
CMT [6] and x ANN for $G/h_1 = 4$.

Figure 4. The comparison of the quasi-static analysis results and ANN results for CCPW with two dielectric layers as a function of the shape factor S/G and the ratio of G/h_1 ($\varepsilon_{r1} = 12.9$, $\varepsilon_{r2} = 1$, $\varepsilon_{r3} = 10$, $h_1 = 762\,\mu$m and $h_3 = 635\,\mu$m): (a) effective permittivity; (b) characteristic impedance.



(a) ε_{eff}



(b) Z_0 (Ω)

—— CMT [6] and	□ ANN for $G/h_1 = 1$,
– – – CMT [6] and	◊ ANN for $G/h_1 = 2$,
- - - CMT [6] and	D ANN for $G/h_1 = 3$,
– - – CMT [6] and	x ANN for $G/h_1 = 4$.

Figure 5. The comparison of the quasi-static analysis results and ANN results for CCPW with three dielectric layers as a function of the shape factor S/G and the ratio of G/h_1 ($\varepsilon_{r1} = 12.9$, $\varepsilon_{r2} = \varepsilon_{r3} = 10$, $h_1 = 762\,\mu$m, and $h_2 = h_3 = 500\,\mu$m): (a) effective permittivity; (b) characteristic impedance.

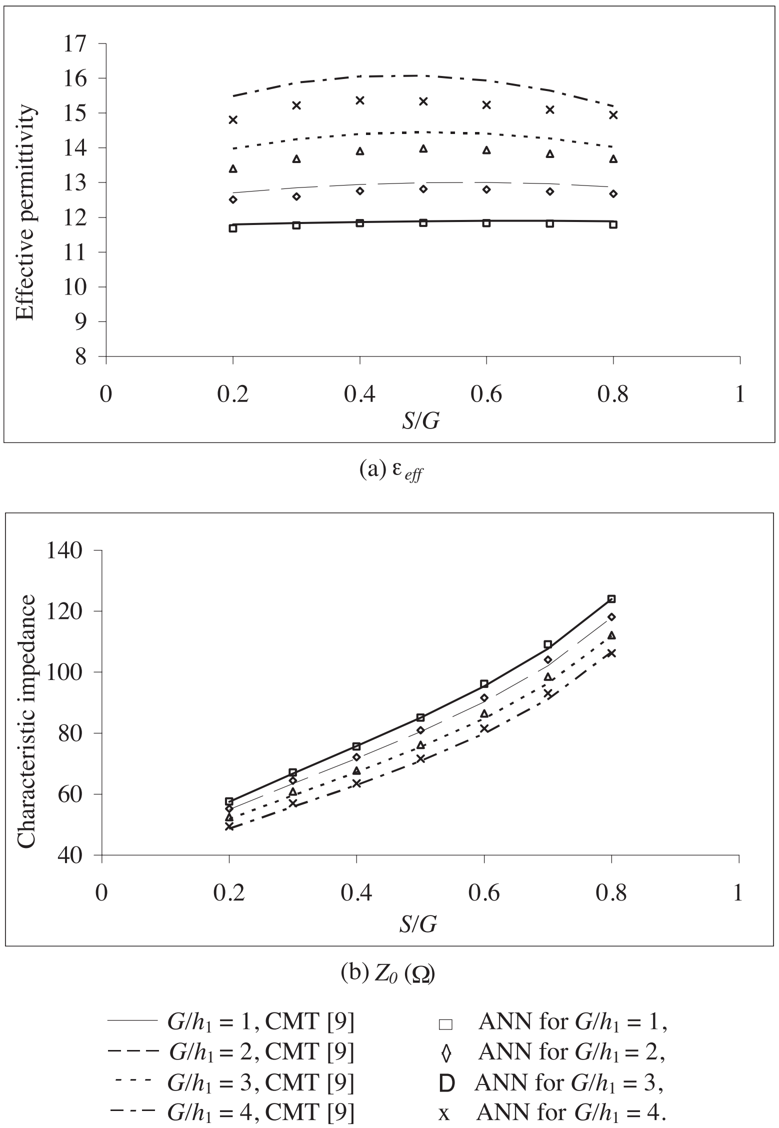
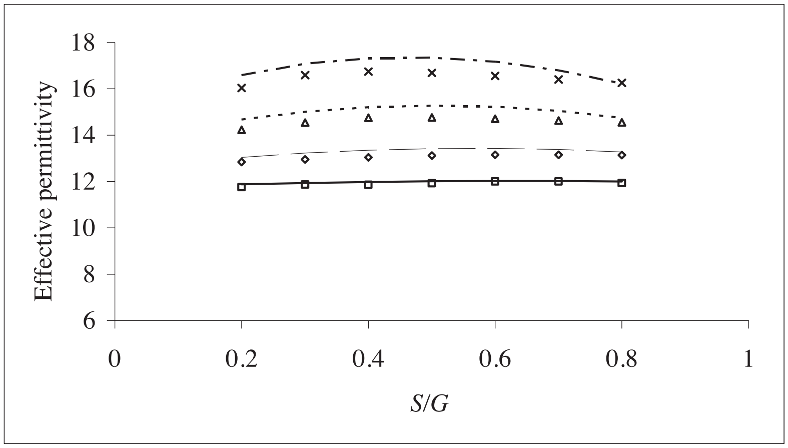


Figure 6. The comparison of the quasi-static analysis results and ANN results for CCPS with three dielectric layers as a function of the shape ratio S/G for different values of G/h_1 ($\varepsilon_{r1} = 12.9$, $\varepsilon_{r2} = \varepsilon_{r3} = 10$, $h_1 = 762\,\mu$m, and $h_2 = h_3 = 500\,\mu$m): (a) effective permittivity; (b) characteristic impedance.

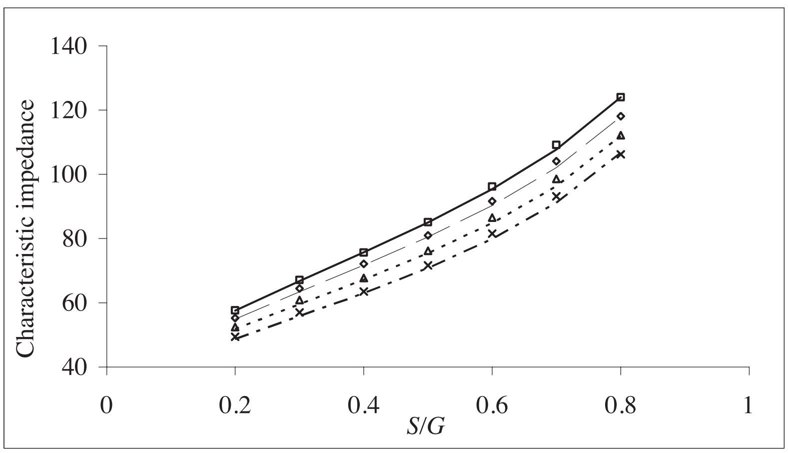
figure illustrates how the effective permittivity and characteristic impedance of multilayer CCPS varies with the shape ratio S/G for different values of G/h_1. It is apparent from Fig. 6 that the results of ANN are in very good agreement with the results of CMT [9] for both effective permittivities and characteristic impedances. The second comparison is made for the quasi-static parameters of CCPS with two dielectric layers. The obtained results for the effective permittivities and characteristic impedances of multilayer CCPS are shown in Figs. 7(a) and 7(b), respectively. It can be seen from this figure there is again very good agreement between neural model results trained with LM and CMT [9] results for the quasi-static parameters of CCPS with two dielectric layers. The last comparison is made for the characteristic parameters of CCPS with a single dielectric substrate ($\varepsilon_{r2} = \varepsilon_{r3} = 1$). The comparisons for the effective permittivity and characteristic impedance of this structure are shown in Figs. 8(a) and 8(b), respectively. This figure also show that there is very good agreement between the neural results and CMT [7] results for both effective permittivity and characteristic impedances.

All these comparison results obviously show that there are very good agreements among the results of the neural models and the quasi-static analysis available in the literature for multilayer CCPW and CCPS. So the neural models presented in this work are very successful for the determination of the quasi-static parameters of CCPWs and CCPSs with a single dielectric and multilayer dielectrics. This very good agreement also shows that neural models presented in this work are not only valid for multilayer CCPW and CCPS but also a single layered CCPW and CCPS. Moreover, it should be emphasized that the proposed neural model is much simpler and more useful for the designers than the other analyzing methods with a good accuracy.

Using the proposed neural model with a personal computer, one can accurately calculate the characteristic parameters of multilayer CCPW and CCPS without processing any background knowledge. Even if training takes less than a few minutes, after training the calculation time is less than a few microseconds in real-time calculation. Thus, the neural models are very fast after training. Finally, the neural models presented in this study, achieves the determination of the quasi-static parameters of the multilayer cylindrical transmission lines with simpler structure and high accuracy. It does not require complicated mathematics and strong background knowledge so it can be very useful for the development of fast computer-aided design algorithms which are capable of accurately predicting the characteristic parameters of multilayer CCPW and CCPS.



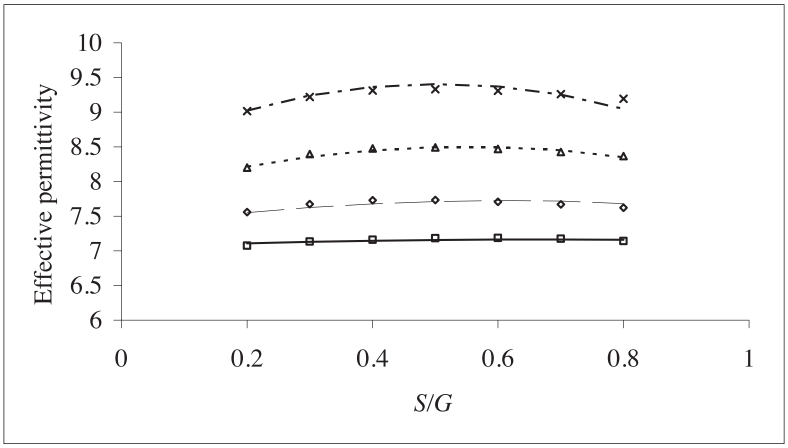
(a) ε_{eff}



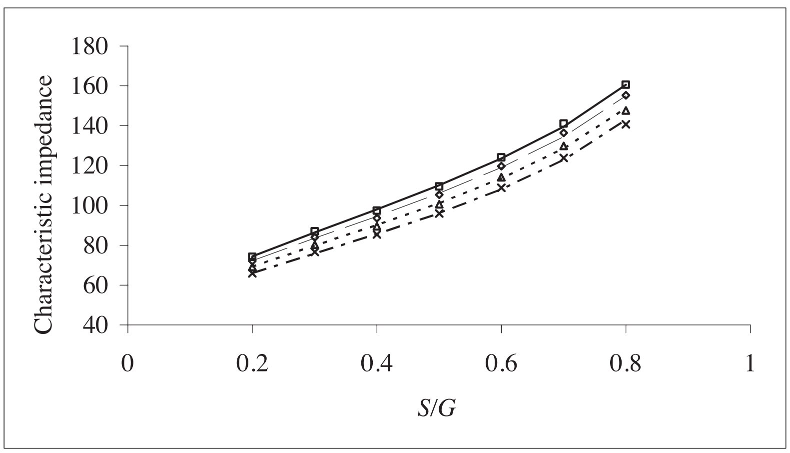
(b) Z_0 (Ω)

$G/h_1 = 1$, CMT [9] ANN for $G/h_1 = 1$,
$G/h_1 = 2$, CMT [9] ANN for $G/h_1 = 2$,
$G/h_1 = 3$, CMT [9] D ANN for $G/h_1 = 3$,
$G/h_1 = 4$, CMT [9] x ANN for $G/h_1 = 4$.

Figure 7. The comparison of the quasi-static analysis results and ANN results for CCPS with two dielectric layers as a function of the shape ratio S/G for different values of G/h_1 ($\varepsilon_{r1} = 12.9$, $\varepsilon_{r2} = 1$, $\varepsilon_{r3} = 10$, $h_1 = 762\,\mu$m and $h_3 = 500\,\mu$m): (a) effective permittivity; (b) characteristic impedance.



(a) ε_{eff}



(b) Z_0 (Ω)

—— $G/h_1 = 1$, CMT [7]	□ ANN for $G/h_1 = 1$,
– – – $G/h_1 = 2$, CMT [7]	◊ ANN for $G/h_1 = 2$,
- - - $G/h_1 = 3$, CMT [7]	D ANN for $G/h_1 = 3$,
– - – $G/h_1 = 4$, CMT [7]	x ANN for $G/h_1 = 4$.

Figure 8. The comparison of the quasi-static analysis results and ANN results for CCPS with a single dielectric layer as a function of the shape ratio S/G for different values of G/h_1 ($\varepsilon_{r1} = 12.9$, $\varepsilon_{r2} = \varepsilon_{r3} = 1$ and $h_1 = 762\,\mu$m): (a) effective permittivity; (b) characteristic impedance.

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