Computational Investigation of Asymmetric Coplanar Waveguides Using Neural Networks: A Microwave Engineering Exercise

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Abstract: - In order to compute the characteristic impedance and the relative effective dielectric constant of an asymmetric coplanar waveguide with infinite or finite dielectric thickness, the use of artificial neural networks is valuable. The method of neural computing presented in this paper uses only one neural model for both parameters, for this specific waveguide type. The BFGS quasi-Newton back-propagation algorithm was used to train the developed neural network. Numerical results are given for several configurations along with comparisons with previously published data.

Keywords: - Coplanar waveguide, Microstrip, Neural networks, Quasi-Newton back-propagation algorithm.

1 Introduction

1.1 Microwave engineering education

Microwaves play an increasingly important role in wireless communications, cellular telephony, wireless local- and personal- area networks, remote sensing, radar technology, multi-sensor integrated systems' detection and identification, microwave hardware design, electromagnetic compatibility, and bio-electromagnetics, as well as in many other applications at complex natural or man-made environments. Thus microwave engineering, being the foundation of many different branches of engineering sciences and technologies, deserves a special place in modern electronic and computer engineering education.

At the Technological Educational Institute of Crete (TEI-C), the Microwave Communications and Electromagnetic Applications (MCEMA) Lab has comprehensive modern facilities for teaching and research activities in theoretical and computational electromagnetics, antenna analysis and design, microwave theory and applications, advanced communication, radar, and electronic warfare systems, and electromagnetic compatibility issues.

This work concentrates upon microwave engineering education at TEI-C's Electronic Engineering Dept, whose undergraduate curriculum includes the advanced telecommunications-specialty mandatory course: *Microwaves and Applications*. This course is fully supported by the MCEMA Lab, with exercises, simulations, measurements and lab projects, like the neural network investigation of an asymmetric coplanar waveguide presented herein.

1.2 Coplanar waveguides

The use of coplanar waveguides (CPW) provides strong advantages, i.e. low radiation and dispersion, easy-made connections between shunts and series, and absence of a fragile substrate. A CPW may be easily adapted to external element connections and monolithic circuits. This advantage, along with the radiation reduction and the effective dielectric constant increment, make CPWs very useful and promising microstrip/microslot transmission lines.

CPWs have been treated by many researchers, using a variety of methods (conformal mapping, finite difference time domain method, etc) [1]-[5]. However, these methods have difficulty in making a practical circuit design feasible within a reasonable period of time and require the use of complicated theory and complex mathematics. So, the approximation of unknown mapping related to a circuit, regarding time limitations, led to the use of curve-fitting techniques [6].

An increasing number of applications in the area of microwave engineering use neural networks (NNs). NNs provide real-time operation in short time, easy implementation, and the powerful features of learning and generalization. These characteristics made NNs a powerful tool suitable for finding solutions in many fields [7]. The accuracy and the efficiency of the yielded solution are two of the features that made NNs popular in microwave circuit component simulation and microstrip antenna design [8]-[17]. In such applications, NNs are usually better and simpler in real-time operation than the classical techniques.

In this paper, an asymmetric coplanar waveguide (ACPW) is modeled using NNs. The created model is not time-consuming, so it can easily be included in a computer-aided design system. As in most of the published studies, we deal with the characteristic impedance and the relative effective dielectric constant, which are the two most useful parameters in the microwave integrated circuit design.

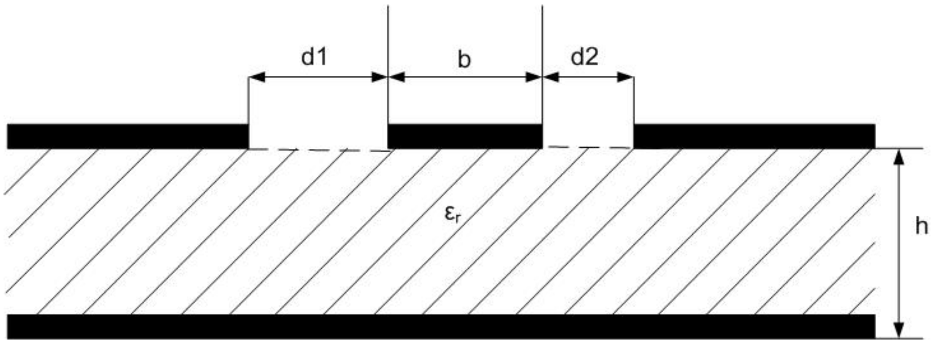

Figure 1. Geometry of an asymmetric coplanar waveguide.

2 Determination of the parameters of a ACPW using conformal mapping

Fig. 1 shows the geometry of an ACPW. We assume that the ground planes are infinitely wide and the strips infinitely thin and perfectly conducting. There is one central strip of width b, between the two upper ground planes with spacing d_1 from the left and d_2 from the right boundary of the central strip. We assume that these boundaries behave like perfect magnetic walls. The substrate, on which the strip elements are located, has thickness h and relative permittivity ε_r.

Using the conformal mapping technique, we can approximate the characteristic line impedance Z_0 and the total line capacitance per unit length C, as:

$$Z_0 = \frac{30\pi}{\sqrt{(1+\varepsilon_r)/2}} \cdot \frac{K'(k_1)}{K(k_1)}, \tag{1}$$

$$C = 2\varepsilon_0 \left(1+\varepsilon_r\right)\left[K(k_1)/K'(k_1)\right], \tag{2}$$

where K(k) is the complete integral of the first kind, $K'(k) = K(k')$, $k' = (1-k^2)^{1/2}$, and

$$k_1 = \frac{(b/2)\cdot\left[a\cdot\left((b/2)+d_1\right)\right]}{(b/2)+d_1+a\cdot\left(b/2\right)^2}, \tag{3}$$

$$a = \frac{d_1 d_2 + b/2\cdot\left(d_1+d_2\right) \pm \left[d_1 d_2\left(b+d_1\right)\left(b+d_2\right)\right]^{1/2}}{(b/2)^2\left(d_1-d_2\right)} \tag{4}$$

The total line capacitance for finite dielectric thickness equals to the sum of C_1 and C_2, where C_1 is the line capacitance per unit length in free space (ε_r=1) when the dielectric is replaced by air and C_2 is the line capacitance per unit length when the electric field is concentrated in a dielectric of thickness h and relative permittivity (ε_r-1).

$$C_1 = 4\varepsilon_0 \frac{K(k_1)}{K'(k_1)}, \quad C_2 = 2\varepsilon_0\left(\varepsilon_r - 1\right)\frac{K(k_2)}{K'(k_2)}, \tag{5}$$

where

$$k_2 = \frac{W_A\left(1+a_1 W_B\right)}{W_B + a_1 W_A^2}, \; W_A = \sinh\left(\frac{\pi b}{4h}\right), \tag{6.a}$$

$$W_B = \sinh\left[\frac{\pi}{2h}\left(\frac{b}{2}+d_1\right)\right], \tag{6.b}$$

$$W_E = -\sinh\left[\frac{\pi}{2h}\left(\frac{b}{2}+d_1\right)\right], \tag{6.c}$$

$$a_1 = \left(W_B + W_E\right)^{-1} \cdot$$
$$\cdot\left[-1-\frac{W_B W_E}{W_A^2} \pm \left\{\left(\frac{W_B^2}{W_A^2}-1\right)\left(\frac{W_E^2}{W_A^2}-1\right)\right\}^{1/2}\right]. \tag{6.d}$$

Finally, using the expressions for k_1 and k_2, the relative effective dielectric constant ε_{eff} and the characteristic impedance Z_0 are given by:

$$\varepsilon_{eff} = \frac{C_1+C_2}{C_1} = 1+\frac{1}{2}\left(\varepsilon_r-1\right)\frac{K(k_2)}{K'(k_2)}\cdot\frac{K'(k_1)}{K(k_1)}, \tag{7}$$

$$Z_0 = \frac{30\pi}{\left(\varepsilon_{eff}\right)^{1/2}}\cdot\frac{K'(k_1)}{K(k_1)}. \tag{8}$$

3 Artificial Neural Networks

NNs are designed in order to simulate the human brain process, been able to gain knowledge from patterns and relationships between data. The structure of a NN is organized in layers and it is formed from hundreds of single units, artificial neurons or processing elements connected with weights. The connection of weights, which are adjustable parameters, between neurons determines the power of the computations. Each neuron has a number of weighted inputs, a transfer function and one output. The NN's architecture, learning rule and transfer function determine its behavior. The network activates through the sum of the inputs. The activation signal is passed through a transfer function and produces the output of a neuron. The transfer function introduces to the network the term of non-linearity. Here is used the sigmoid function:

$$f(\mathrm{net}) = \frac{1}{1+e^{-\mathrm{net}}} \ . \qquad (9)$$

During training, the network connections are optimized until a minimum error in prediction (which determines the network's level of accuracy) is reached. When the training is over, new input data is entered to the network and a new output is calculated.

NNs represent a promising modeling technique, especially for problems that deal with non-linear relationships that are frequently encountered in engineering. In model specification problems NNs require no knowledge of the data source but, they often contain many weights that must be estimated.

Problems can be solved by combining and incorporating both literature-based and experimental data. Various NNs' applications can be summarized into prediction, modelling, classification or pattern recognition [7]. There are several types of NNs for various applications available in the literature. Multilayered perceptrons (MLPs), which are feed-forward networks and universal approximations, are among the simplest and most common architectures. In the present work, we have used an MLP for the calculation of the effective permittivity and the characteristic impedance of an ACPW.

MLPs can be trained using many different learning algorithms. The MLP used here, was trained using the BFGS quasi-Neuton back-propagation algorithm, which is used only if the networks' weight, input and transfer functions have derivative functions. The back-propagation is a common technique used for MLP training. It is a supervised method using an error correction learning rule. Two passes take place while the network is been trained: one forward pass, which fixes all weights, and one backward pass, which adjusts the weights according to an error correction rule. Fig. 2, shows the architecture of a MLP consisting of three layers: an input layer, an intermediate (hidden) layer and an output layer.

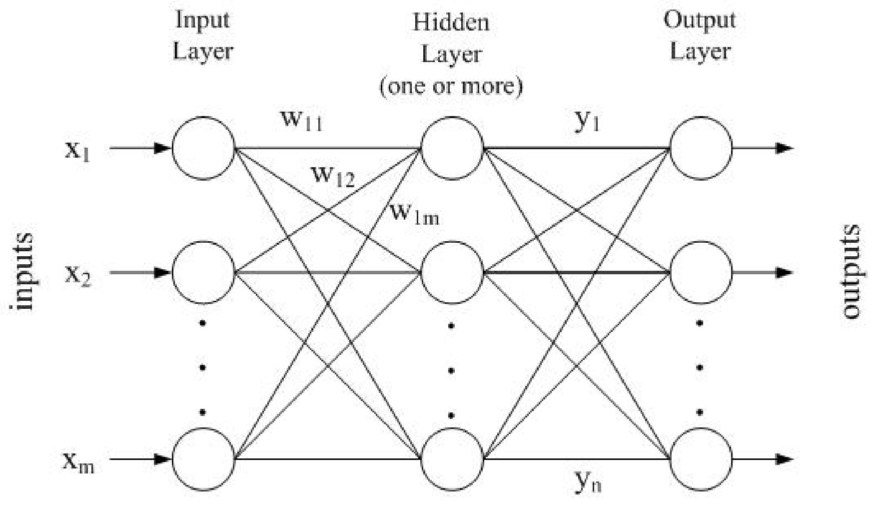

Figure 2. General form of multilayered perceptrons.

The input layer's neurons (indicated with circles in Fig. 2) act like buffers for distributing the input signals x_i to the neurons of the hidden layer. The hidden layer's neurons sum up their input signals x_i, after weighting them with the strengths of the respective connections w_{jj} from the input layer, and compute the network output y_j as a function of the sum:

$$y_j = f\left(\sum_i w_{ji} x_i\right), \qquad (10)$$

where f is a threshold (sigmoidal or hyperbolic tangent) function. The neurons' output in the output layer is computed in a similar way.

Training of a neural network means adjustment of the previously mentioned weights by a training algorithm. The training algorithms adopted in this work optimize the weights by minimizing the sum of squared differences between the desired and the actual values of the output neurons, namely:

$$E = \frac{1}{2}\sum_{j}\left(y_{dj} - y_{j}\right)^{2}, \qquad (11)$$

where y_{dj} is the desired value of output neuron j and y_j is the actual output of that neuron. Weights w_{ji} are adjusted by adding an increment Δw_{ji} to each one. This parameter, is selected to reduce E as rapidly as possible. The weight adjustments get carried out over several training loops until a decent value of E is obtained or a pre-assigned number of iterations is reached. The training algorithm used in a NN determines the Δw_{ji} computation.

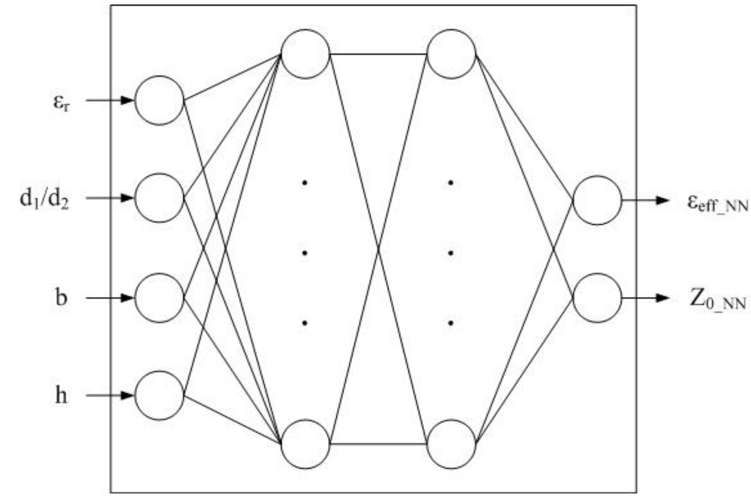

Figure 3. Calculation of the characteristic parameters of an ACPW, using MLP.

4 Application of a NN to ACPW

The technique used in this study involves an MLP, which is trained in order to calculate the effective permittivity ε_{eff} and the characteristic impedance Z_0, with given values of ε_r, d_1/d_2, and calculated values of b and h. The training data sets' ranges are $2 \le \varepsilon_r \le 12.5$ and $0.5 \le d_1/d_2 \le 0.95$, while the ranges of b and h are $2.021 \le b \le 41.053$ and $3.0913 \le h \le 12.829$.

The architecture of the used neural model is shown in Fig. 3. ε_{eff} and Z_0 are calculated by the same neural model. The MLP's training procedure involves the presentation of different data sets (ε_r, b, d_1/d_2 and h) sequentially or/and randomly and of the corresponding ε_{eff} and Z_0 calculated values. Adaptation is a network's ability to adjust its weights according to the differences between the actual outputs and the target outputs of the MLP. The adaptation is carried out after the presentation of each data set (ε_r, b, d_1/d_2, h, ε_{eff} and Z_0) until the accuracy of the network is satisfactory, according to some error criterion or to the maximum number of epochs allowable for the network.

Here, we obtain the training and test data using the conformal mapping technique. In particular, a total of 3,960 data sets is used in training and testing of the network. After several tests, we have found that a network consisting of four layers achieves the highest accuracy. This most suitable configuration is a 4x20x20x2 network, meaning that this specific network has four inputs, two hidden layers of 20 neurons in each layer and two outputs. The weights are initialized by a set of random values between -0.1 and $+0.1$, while the input and output data are scaled between 0 and 1, and the hidden and output layers use a sigmoid function.

5 Results and Conclusions

The herein presented neural network, possess some advantages due to its learning ability, generalization capability, implementation ease, and hardware availability. The alternative classical methods of CPW parameters' calculation would need great computational effort, leading to a long time delay in order to make a practical circuit design feasible.

Figs 4-9 present the ε_{eff} and Z_0 parameters as functions of the normalized central strip width $b/(b+d_1+d_2)$. Each graph presents different values of ε_r and d_1/d_2, for a standard ratio of $(b+d_1+d_2)/h$ (in our case the ratio equals to 3). It is obvious that our results are in very good agreement with the results presented in [2]. Moreover, the excellent agreement between the theoretical and the computed parameters proves the validity of the used neural model. After training, the network takes only a few microseconds to produce the values of ε_{eff} and Z_0.

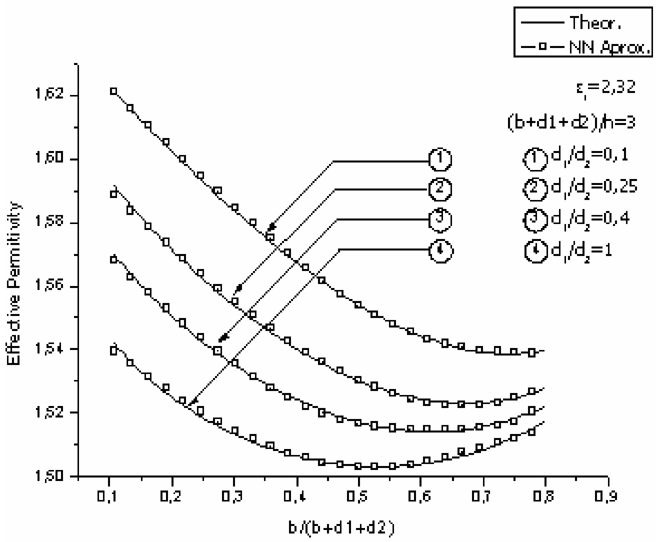

Figure 4. ε_{eff} vs b/(b+d_1+d_2), when $\varepsilon_r = 2.32$.

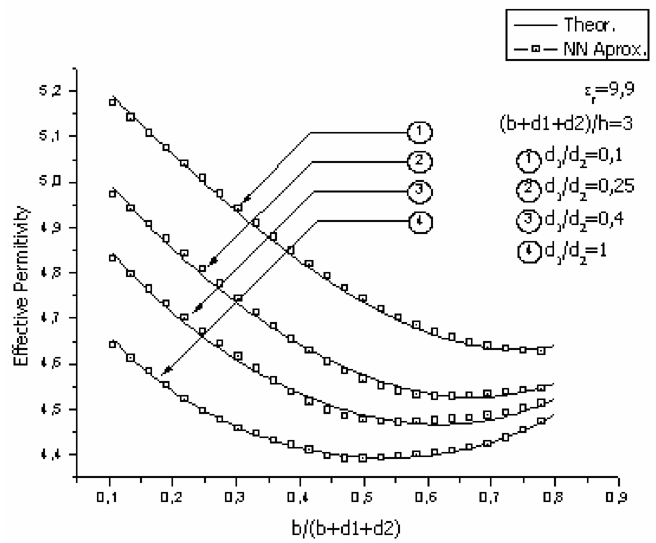

Figure 5. ε_{eff} vs b/(b+d_1+d_2), when $\varepsilon_r = 9.9$.

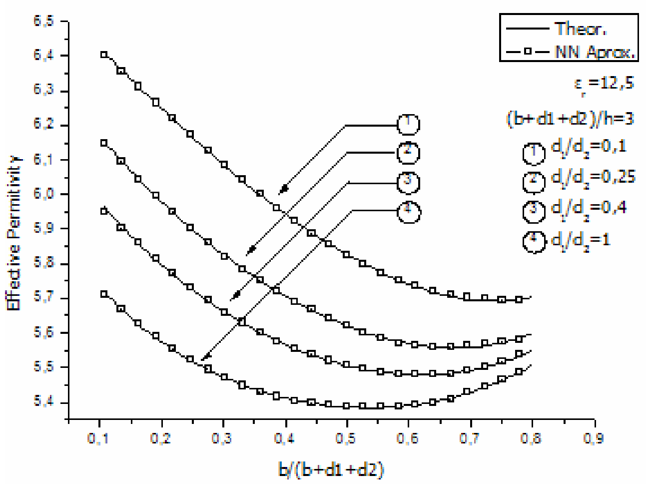

Figure 6. ε_{eff} vs b/(b+d_1+d_2), when $\varepsilon_r = 12.5$.

The achieved accuracy, the less computational effort and the waveguide's background information, make the neural model useful for the development of fast CAD algorithms, as accurate prediction of ε_{eff} and Z_0 is very useful to engineers working in this field. So, we expect that the proposed NN model will find wide applications in computer-aided design of monolithic microwave integrated circuits.

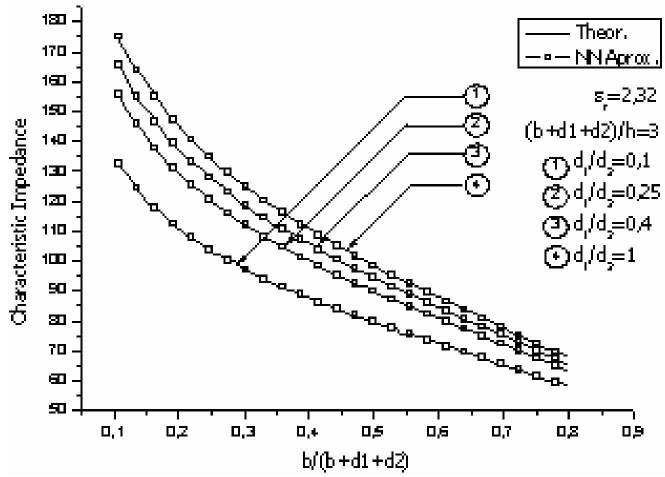

Figure 7. Z_0 vs b/(b+d_1+d_2), when $\varepsilon_r = 2.32$.

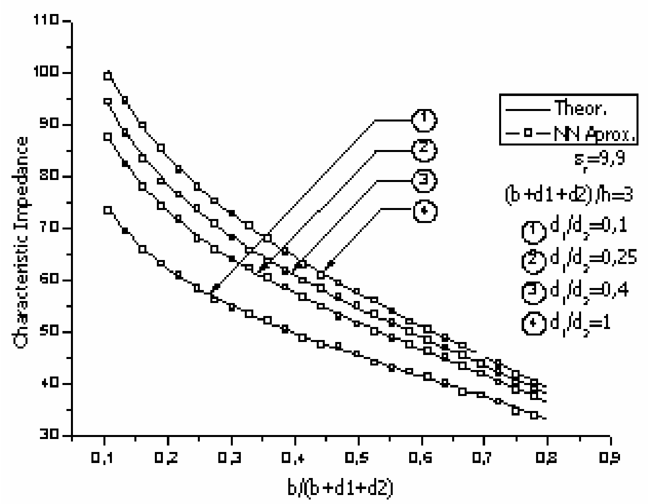

Figure 8. Z_0 vs b/(b+d_1+d_2), when $\varepsilon_r = 9.9$.

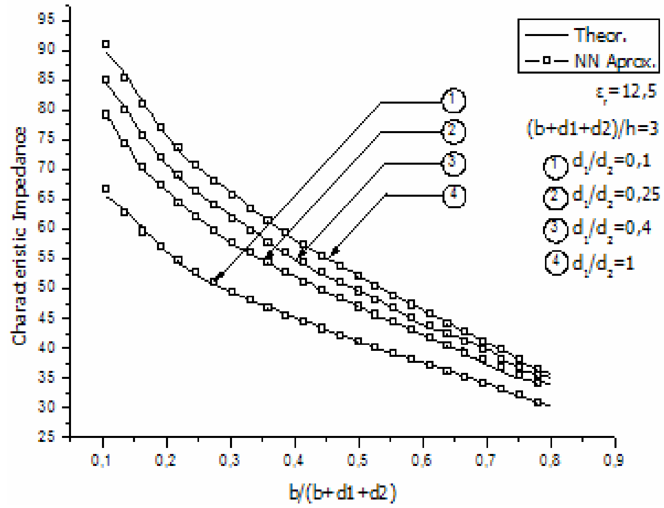

Figure 9. Z_0 vs b/(b+d_1+d_2), when $\varepsilon_r = 12.5$.

A laboratory project on the neural network investigation of an asymmetric coplanar waveguide was presented. It was designed, implemented, and simulated at the MCEMA Lab of TEI-C, aiming to develop our students' knowledge and abilities to advanced waveguiding structures. This project demands the activation, concentration and study of all participating students, cultivating the full skills and advanced qualifications of the future engineers. Therefore, by introducing novel teaching tools in electromagnetic courses and computerized solutions in microwave problems, students of TEI recovered their interest in microwave engineering courses.

Acknowledgment

This work was supported by the Greek Ministry of National Education and Religious Affairs and the European Union under the **ΕΠΕΑΕΚ ΙΙ** project "**Archimedes** – Support of Research Groups in TEI of Crete – Smart antenna study & design using techniques of computational electromagnetics and pilot development & operation of a digital audio broadcasting station at Chania (**SMART-DAB**)".

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