A CAD Neural Model for Quasi – Static Analysis of CPW Synthesis

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Abstract- In recent years, Computer – Aided Design (CAD) approach based on ANN has been introduced to microwave modeling, simulation & optimization. In this work, closed form synthesis formulae (quasi static analysis) for Coplanar Waveguides (CPWs) have been analyzed with the use of ANN Models. The neural models were trained with Levenberg – Marquardt (LM) learning algorithm and that was found to be the best algorithm among all. This conclusion is inferred from the error calculation of four methods. A comprehensive comparison has been made with the Quasi – Static results. This has facilitated the usage of ANN models. The notable benefits are simplicity & accurate determination of the characteristic parameters of CPW’s. The greatest advantage is lengthy formulas can be dispensed with.

Index Terms- Artificial Neural Networks, Coplanar Waveguide, Characteristic Design Parameters, Effective dielectric Permittivity, Synthesis.

I. INTRODUCTION

In Monolithic Microwave Integrated Circuits (MMIC’s), CPW has a complex Structure in contrast with the first proposal of C.P. Wen [11-14]. The full wave analysis is usually used to characterize such complex structure. Most of the earlier study efforts have been directed towards obtaining the design parameters by full wave numerical methods [2] or quasi-static conformal mapping methods [4 - 8]. Present analysis provides general characteristics suitable for CAD analysis [1], [3], [9-10] and high precision in a wide frequency band. This novel method does not restrict the frequency limit as being restricted in quasi static analysis. Once trained, the complexity of full wave computation is also dispensed with.

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. No closed form synthesis formulas for coplanar waveguide are available; in contrast, both analysis and synthesis closed – form formulas for micro strip lines have existed for a long time [12]. Such closed – form design equations obtained by conformal mapping method, which is the simplest & most often used quasi – static method, consist of complete elliptic integrals which are difficult to calculate even with computers. For this reason, the approximate Artificial Neural Networks (ANNs) recently gained attention as a fast and flexible tool to microwave modeling and design.

Neural network modeling is relatively new to the microwave community. The learning & 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.

Furthermore, accurate and efficient microwave circuit components and micro strip antennas have been designed with the use of ANNs. 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 paper, simple and accurate neural models are presented for CPW synthesis. These neural models were trained with LM algorithm to obtain better performance and faster convergence with a simpler structure. For the validation of the neural models proposed in this paper, the neural synthesis results have been compared with the results of the quasi - static analysis and the synthesis formulas proposed by other researches.

II. SYNTHESIS FORMULAS FOR CPW

A CPW with substrate thickness (H) and dielectric constant \((\varepsilon_r)\) is shown in figure 1.

Fig. 1. Coplanar waveguide configuration

Where \(S\), \(W\) & \(Z_0\) are gap width, central conductor width and the required characteristic impedance.

It is well known that the closed form quasi - static analysis formula for CPW is available [13-15]. After some trivial function approximation [6] and curve fitting of numerical quasi-static analysis results, the synthesis formulae takes the following closed form expressions.

The following synthesis formula [22], [25] is proposed in calculating the conductor width \(W\), for a given substrate \((\varepsilon_r, H)\) and required characteristics impedance \(Z_0\) by choosing appropriate gap width \(S\).

\[ A. \text{ Synthesis (1)} \]

\[ \begin{align*}
  &\text{When } \frac{S}{H} \leq \frac{10}{3(1 + \ln \varepsilon_r)} \quad \frac{W}{H} \leq \frac{80}{3(1 + \ln \varepsilon_r)} \\
  &\text{and } \varepsilon_r \geq 6, W = S \cdot G(\varepsilon_r, H, Z_0, S)
\end{align*} \]

\[ G = \left\{\begin{array}{ll}
  0.25 \exp\left(\frac{30\pi^2}{Z_0 T}\right) + \exp\left(-\frac{30\pi^2}{Z_0 T}\right) - 1 & \text{for } Z_0 < \frac{60\sqrt{2\pi}}{\sqrt{\varepsilon_r} + 1} \\
  \left[0.125 \exp\left(\frac{Z_0 T}{60}\right) - 0.5\right]^{-1} & \text{for } Z_0 \geq \frac{60\sqrt{2\pi}}{\sqrt{\varepsilon_r} + 1}
\end{array}\right. \]

\[ T = \sqrt{\left[(\varepsilon_r + 1) T_A T_B\right]} \]

\[ T_d = 0.5 + \left[0.02125 - 0.345Q - 0.0005(0.25 + Q)\varepsilon_r\right] \times \frac{QS}{H} \]

\[ \left\{\begin{array}{l}
  \frac{\varepsilon_r^6}{(\varepsilon_r + 1)^7} \left(\frac{150.4}{Z_0}\right)^2 \times \exp\left[1 + 0.0008\varepsilon_r Z_0 \frac{S}{H}\right] \ln\left(0.3 + \frac{S}{H}\right) & \\
  1 + \exp\left[3.5 - 1.55\ln\left(\frac{S}{H}\right)\right]^{-1} & \text{for } Z_0 < \frac{60\sqrt{2\pi}}{\sqrt{\varepsilon_r} + 1}
\end{array}\right. \]

\[ Q = \left\{\begin{array}{l}
  1 - 0.5 + 0.25 \exp\left(\frac{30\sqrt{2\pi^2}}{Z_0 \varepsilon_r + 1}\right) - 1 & \\
  4 \exp\left(-\frac{Z_0}{120}(2\varepsilon_r + 1)\right) & \text{for } Z_0 \geq \frac{60\sqrt{2\pi}}{\sqrt{\varepsilon_r} + 1}
\end{array}\right. \]

Therefore in CPW design, the central conductor strip width \(W\) can be evaluated immediately by choosing an appropriate slot width \(S\) and \(Z_0\) for a given substrate.

\[ B. \text{ Synthesis (2)} \]

Similar to the above sets, the following synthesis formula presented by Deng et al calculates the slot width \(S\) in terms of a dielectric substrate \((\varepsilon_r, H)\), characteristics impedance \(Z_0\), and the chosen central conductor strip width \(W\).
When \( \frac{S}{H} \leq \frac{10}{3(1 + \ln \varepsilon_r)} \), \( \frac{W}{H} \leq \frac{80}{3(1 + \ln \varepsilon_r)} \)
and \( \varepsilon_r \geq 6 \), \( S = \frac{W}{G}(\varepsilon_r, H, Z_o, W) \) \( (2) \)

\[
G = \begin{cases} 
0.25 \exp \left( \frac{30\pi^2}{Z_0T} \right) + \exp \left( - \frac{30\pi^2}{Z_0T} \right) - 1 \\
\text{for } Z_0 < \frac{60\sqrt{2\pi}}{\varepsilon_r + 1}
\end{cases}
\]

\[
G = \left[ 0.125 \exp \left( \frac{Z_0T}{60} \right) - 0.5 \right]^{-1}
\]

\[
T = \sqrt{[1 + (\varepsilon_r - 1)\sqrt{\varepsilon_r + 1}Z_oT_A]}(1 + T_B)
\]

\[
T_A = \frac{1}{837.5} \ln \left( \frac{2(1 + g)}{1 - g} \right) \text{ for } 0.841 \leq g \leq 1
\]

\[
T_A = \left[ 84.85 \ln \left( \frac{2(1 + \frac{4}{\sqrt{1 - g^4}})}{1 - \frac{4}{\sqrt{1 - g^4}}} \right) \right]^{-1}
\]

\[
g = \sqrt{\frac{\sinh \left( \frac{\pi W}{4H} \right)}{\sinh \left( \frac{\pi(1 + 2/4Q)W}{4H} \right)}}
\]

\[
T_B = \tanh \left( \frac{\varepsilon_r^3}{(\varepsilon_r + 1)^3} \frac{60}{(Z_0)^2} \times \exp \left( \frac{1 + 0.0002e_r}{\ln \left( \frac{W}{QH} \right)} \right) \right)
\]

\[
Q = \begin{cases} 
0.25 \exp \left( \frac{30\sqrt{2\pi^2}}{Z_0\sqrt{\varepsilon_r} + 1} \right) + \exp \left( - \frac{30\sqrt{2\pi^2}}{Z_0\sqrt{\varepsilon_r} + 1} \right) - 1 \\
\text{for } Z_0 < \frac{60\sqrt{2\pi}}{Z_0\sqrt{\varepsilon_r} + 1}
\end{cases}
\]

\[
Q = \left[ 0.125 \exp \left( \frac{Z_0\sqrt{\varepsilon_r} + 1}{60\sqrt{2}} \right) - 0.5 \right]^{-1}
\]

\[
\text{for } Z_0 \geq \frac{60\sqrt{2\pi}}{\varepsilon_r + 1}
\]

III. MULTILAYER PERCEPTRON NEURAL NETWORK (MLPNN)

Neuro computing technologies have emerged as powerful modeling [17] techniques. The class of neural network and/or architecture selected for a particular model implementation is dependent on the problem to be solved. The neural network architecture used in this modeling effect is the MLPNN. In theory, these networks can, perform any complex nonlinear mapping [18-19]. MLPNN are feed-forward networks and universal approximators. They are the simplest and therefore most commonly used neural network architecture. The relationships are mapped between input and output data through an adaptive weight connection matrix [20].

In the MLPNN neural network, the neurons are grouped into layers. The first and last layers are called input and output layers respectively and the remaining layers are called hidden layers. In this network, each neuron processes the stimuli (inputs) received from other neurons. The process is done through a function called the activation function and the processed information becomes the output of the neuron. For example, every neuron in the \( i \)th layer receives stimuli from the neurons of the [21] (1-1)th layer, i.e., \( z_{i-1}^{1}, z_{i-1}^{2}, \ldots, z_{i-1}^{N_{i-1}} \). A typical \( i \)th neuron in the \( i \)th layer processes this information in two steps. Firstly, each of the input is multiplied by the corresponding weight parameter and the product is added to produce a weighted sum \( \gamma_i^1 \), i.e.,

\[
\gamma_i^1 = \sum_{j=0}^{N_{i-1}} w_{ij}^1 z_{j-1}^{i-1}
\]

Secondly, the weighted sum in (3) is used to activate the neuron’s activation function \( \sigma() \) to produce the final output of the neuron \( z_i^1 = \sigma(\gamma_i^1) \). This output can in turn become the stimulus to
neuron in the $({l+1})^{th}$ layer. The most commonly used hidden layer activation function is the sigmoid function given by

$$\sigma(\gamma) = \frac{1}{1 + e^{-\gamma}}$$

(4)

Other functions that can also be used are the arc tangent, hyperbolic tangent function, etc. All these are smooth switch functions that are bounded, continuous, monotonic, and continuously differentiable. Input neurons use a relay activation function and simply relay the external stimuli to the hidden layer neurons, i.e., $z_i^l = x_i, i = 1, 2, ..., n$. An output neuron computation is given by

$$\sigma(\gamma_i^l) = \gamma_i^l = \sum_{j=0}^{N_{-1}} w_{ji}^l z_j^{l-1}$$

(5)

IV. ANN APPLICATION TO SYNTHESIS OF CPW

The proposed technique involves training an ANN to calculate the strip width $W$ and the central conductor width $S$, for a given substrate and required characteristics impedance $Z_0$ of CPW. The range of training data sets were $2.2 \leq \varepsilon_r \leq 50, 0.1 \leq S/H \leq 0.9$ and $0.01 \leq W/H \leq 7$ and the characteristics impedance ranges from $30 \Omega \leq Z_0 \leq 130 \Omega$. The training data sets used in this paper were obtained from the synthesis formulas proposed by T.Q. Deng [22]. In these formulas the constraints for getting the training data are

$$\frac{S}{H} \leq \frac{10}{3(1 + \ln \varepsilon_r)}, \frac{W}{H} \leq \frac{80}{3(1 + \ln \varepsilon_r)};$$

Differences between the target and the actual output of the neural 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 criterions, which are obtained from ANN for all the training set fall below a given threshold, or the maximum allowable number of epochs is reached.

In literature, number of approaches was available to find suitable number of neurons and layers in neural model. But most of all are applications specific. The numbers of neurons and hidden units for the application presented in this work were selected after several trials as stated in. As shown in figure 2, it was found that a network with one hidden layer achieved the task with high accuracy. The most suitable network configuration found was $4 \times 12 \times 1$; this means that the number of neurons were 4 for input layer, 12 for the hidden layer and 1 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.

Fig.2. Proposed neural models for CPWs Synthesis

The neural models used in this work were trained with LM, BR, QN and CGF learning algorithms. These learning algorithms are summarized below.

A. Levenberg – Marquardt (LM) algorithms

This is a least-squares estimation method based on the maximum neighborhood idea [26]. The LM method 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.

B. Bayesian Regularization (BR) Algorithms

This algorithm updates the weight and bias values according to their 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. This algorithm can train any network as long as its weight, inputs and transfer functions have derivative functions [27].
C. Quasi-Newton (QN) Algorithms

This is based on Newton’s method but doesn’t require calculation of second derivatives. An approximate Hessian matrix is updated. 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 [28]. The first search direction is the negative of the gradient of performance. In succeeding iterations the search direction is computed according to the gradient.

D. Conjugate Gradient of Fletcher-Reeves (CGF)

This method updates weights and bias values according to the conjugate gradient with Fletcher-Reeves [29]. Each variable is adjusted to minimize the performance along the search direction. The line search is used to locate the minimum point. 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.

V. RESULTS AND DISCUSSION

ANNs have been successfully used to compute the central conductor width and the strip width of CPW. In order to obtain better performance, faster convergence and simpler structure, ANN models were trained with the LM, BR, QN and CGF learning algorithms.

The training and test RMS error obtained from the neural models are given in Table1. When the performance of neural models are compared with each other, the best results for training and testing were obtained from the model trained by LM algorithm.

The synthesis results of the neural network trained by LM algorithm are compared with the synthesis formula proposed by Deng et al, [22].

<table>
<thead>
<tr>
<th>Learning Algorithms</th>
<th>RMS errors in training</th>
<th>RMS errors in test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S (μm)</td>
<td>W (μm)</td>
</tr>
<tr>
<td>LM</td>
<td>.0007</td>
<td>.0031</td>
</tr>
<tr>
<td>BR</td>
<td>.0014</td>
<td>.0056</td>
</tr>
<tr>
<td>QN</td>
<td>.0934</td>
<td>.0282</td>
</tr>
<tr>
<td>CGF</td>
<td>.0844</td>
<td>.0066</td>
</tr>
</tbody>
</table>
The above figures 3 and 4 show the contours of normalized gap width S/H and the normalized conductor width W/H for various values of the characteristics impedance $Z_0$ ranges from 300Ω to 1000Ω with $H = 200 \mu m$ and $\varepsilon_r = 12.9$.

Further comparisons are presented, which include another feature of the presented formula to calculate the effective dielectric constant $\varepsilon_{eff}$ by $\varepsilon_r$, $Z_0$, S, and W rather than by conventional form. The results obtained from the neural models and the quasi-static analysis for four different values of S/H is shown in figure 5.

In order to illustrate the accuracy of the neural models and quasi-static analysis, further comparisons are presented, which include the experimental results for characteristics impedance with S/H = 0.3 by Dupuis et al. at a frequency 2GHz and the curve fitting result by Gupta et al with synthesis and ANN results. A good agreement among all the results is observed in figure 6. It shows excellent agreement between the results of neural models and the quasi-static analysis.

Another group of numerical results are presented in order to assess for the validity of the presented neural models. Comprehensive comparisons with the results, which are obtained by quasi-static analysis method, used for the design of GaAs monolithic MICs up to a frequency range 20 GHz and even 40 GHz and by ANN are made and the good agreement is shown in figure 7. For different values of $\varepsilon_r$, the self-consistent agreement between the ANN and conformal mapping technique results has been clearly seen throughout the comparisons. This comparison gives rise to the validation of proposed neural model for the design in the given frequency range.

Fig. 6. Comparison of characteristic impedance calculated by neural model and the synthesis result by Deng et al with $\varepsilon_r = 9.2$. [23-24]
IV. CONCLUSION

The coplanar waveguide synthesis analysis has been successfully completed with the use of neural networks. The result of trained neural models shows better accuracy with respect to the previous conventional methods. The neural models presented in this work have good accuracy, require no tremendous knowledge about CPWs, they can be very useful for the development of fast CAD algorithms. The distinct advantages of bypassing the repeated use of complex iterative processes for new case, this neural model can also be used for microwave and antenna engineering applications. The proposed model can support for automatic development of accurate models from component and circuit data with minimum human interaction which avoids the tedious trail and error modeling process and dramatically reduces model development time. It makes easy and feasible to change the traces of CPW structures to match components lead widths while keeping the characteristics impedance constant. The neural model presented may also provide a promising approach for CAD models of CPW taper, stub and transition and other CPW components. The presented neural models have application in CPW discontinuity circuits and filters for wireless communication.

REFERENCES


