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COMPARISON OF ADAPTIVE-NETWORK-BASED FUZZY INFERENCE SYSTEM MODELS FOR ANALYSIS OF CONDUCTOR-BACKED ASYMMETRIC COPLANAR WAVEGUIDES

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Abstract—A method based on adaptive-network-based fuzzy inference system (ANFIS) is presented for the analysis of conductor-backed asymmetric coplanar waveguides (CPWs). Four optimization algorithms, hybrid learning, simulated annealing, genetic, and least-squares, are used to determine optimally the design parameters of the ANFIS. The results of ANFIS models are compared with the results of conformal mapping technique, a commercial electromagnetic simulator IE3D, and the experimental works realized in this study. There is very good agreement among the results of ANFIS models, quasi-static method, IE3D, and experimental works. The proposed ANFIS models are not only valid for conductor-backed asymmetric CPWs but also valid for conductor-backed symmetric CPWs.

1. INTRODUCTION

Conductor-backed coplanar waveguide (CPW) provides superior mechanical strength and heat sinking capabilities than conventional CPWs in designing microwave integrated circuits (MICs). They have several other advantages such as low dispersion, high flexibility in the design of characteristic impedance, and easy connection to the shunt lumped elements or devices [1–5]. CPWs backed with a conductor also allow easy implementation of mixed coplanar/microstrip circuits, reduce radiation effects, and raise effective permittivity. These

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advantages make conductor-backed CPWs ideally suited for MIC as well as monolithic MIC (MMIC) applications [1–11].

Several researchers have analyzed conductor-backed CPWs by using quasi-static approximations [1–7]. Most of them have used conformal mapping technique (CMT) to calculate the characteristic parameters of conductor-backed CPWs [1–5]. In practice, asymmetric CPWs are more useful in some particular applications. In 1999, the asymmetric CPW backed with a conductor has been analyzed by using CMT [4]. The effect of the presence of upper shielding and conductor-backing on the quasi-static parameters of asymmetric CPWs was discussed in [5]. The quasi-static spectral domain approach (SDA) was also used for the analysis of conductor-backed CPWs [6, 7]. On the other hand, dispersion characteristics of conductor-backed CPWs have been reported in [8–10] with the use of full-wave analysis methods. In these studies, full-wave SDA [8], alternative formulations of the transverse resonance technique [9] and two-dimensional finite-difference time-domain method [10] were used for the calculation of the dispersion characteristics of conductor-backed CPWs. In [11], models based on the adaptive-network-based fuzzy inference system (ANFIS) [12, 13] were proposed for the quasi-static analysis of conductor-backed symmetric CPWs. Each of methods proposed in the literature [1–11] has its specific advantages and disadvantages.

The ANFIS is a class of adaptive networks which are functionally equivalent to fuzzy inference system (FIS). The FIS is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. It is a very powerful approach for building complex and nonlinear relationship between a set of input and output data [11, 14–25]. It can be trained with no need for the expert knowledge usually required for the standard fuzzy logic design. Both numerical and linguistic knowledge can be combined into a fuzzy rule base by employing fuzzy methods. Fuzzy membership functions (MFs) can be tuned optimally by using optimization algorithms. Other advantages of the ANFIS include its nonlinear ability, its capacity for fast learning, and its adaptation capability. Because of these attractive features, in this paper ANFIS models are used for the analysis of conductor-backed asymmetric CPWs. The proposed ANFIS models are not limited to the calculation of the characteristic parameters of conductor-backed asymmetric CPWs. These models can easily be applied to other microwave problems. Accurate, fast, and reliable ANFIS models can be developed from measured/simulated microwave data. Once developed, these ANFIS models can be used in place of computationally intensive numerical models to speed up microwave devices design. The ANFIS structure can also be implemented in real time by using state-of-the art hardware devices, such as FPGAs (Field Programmable Gate Array). In this way, the computation time of the system is limited only by the response time of the FPGA, which is in the order of a few microseconds. A prominent advantage of ANFIS computation is that, after proper training, an ANFIS completely bypasses the repeated use of complex iterative processes for new cases presented to it. Thus, the ANFIS is very fast after training. Since the ANFIS models presented in this paper have high accuracy and require no complicated mathematical functions, they can be very useful for the development of fast CAD algorithms. These CAD models, capable of accurately predicting the characteristic parameters of conductor-backed asymmetric CPWs, are also very useful to microwave engineers.

The main aims of this paper are

- to present an efficient alternative to the previous methods for calculating the effective permittivities and characteristic impedances of both symmetric and asymmetric CPWs backed with a conductor by using the ANFIS architecture;
- to train the ANFIS by hybrid learning (HL) algorithm [12, 13], simulated annealing (SA) [26] algorithm, genetic algorithm (GA) [27, 28], and least-squares (LSQ) algorithm [29, 30];
- to determine the most appropriate ANFIS model in calculating the characteristic parameters of conductor-backed CPWs; and
- to compare the results of ANFIS models with the results of CMT [5], a full-wave electromagnetic simulator IE3D [31], and experimental works realized in this study.

2. CHARACTERISTIC PARAMETERS OF CONDUCTOR-BACKED ASYMMETRIC CPWs

The cross-section of a conductor-backed asymmetric CPW is depicted in Fig. 1. In this figure, W represents the central strip width, s_1 and s_2 represent the slot widths, G shows the distance between the surface ground planes, and h indicates the thickness of the dielectric material

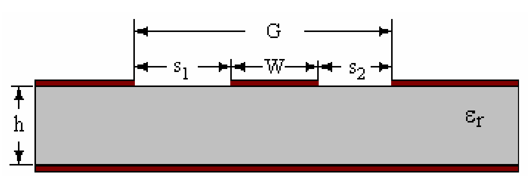


Figure 1. Cross-section of a conductor-backed asymmetric CPW.

with relative permittivity ε_r. Using the quasi-static approximations, the effective permittivities (ε_{eff}) and characteristic impedances (Z_0) of conductor-backed asymmetric CPWs can be written as [5];

$$\varepsilon_{eff} = 1 + (\varepsilon_r - 1) \cdot \frac{K(k_1)/K(k_1')}{K(k_0)/K(k_0') + K(k_1)/K(k_1')} \tag{1}$$

and

$$Z_0 = \frac{120\pi}{\sqrt{\varepsilon_{eff}}} \frac{1}{K(k_0)/K(k_0') + K(k_1)/K(k_1')} \tag{2}$$

where $K(k_i)$ and $K(k_i')$ are the complete elliptic integrals of the first kind with the modulus of k_i and k_i'. k_i' is the complementary modulus of k_i and equals to $(1 - k_i^2)^{1/2}$. The modulus k_i are defined in terms of geometrical dimensions of conductor-backed asymmetric CPWs as given in [5]:

$$k_0 = \sqrt{\frac{W \cdot (W + s_1 + s_2)}{(W + s_1) \cdot (W + s_2)}} \tag{3}$$

and

$$k_1 = \sqrt{\frac{W' \cdot (W' + s_1' + s_2')}{(W' + s_1') \cdot (W' + s_2')}} \tag{4}$$

with

$$W' = e^{-w\pi/2h}(e^{w\pi/h} - 1) \tag{5}$$

$$s_1' = e^{-(w+2s_1)\pi/2h}(e^{s_1\pi/h} - 1) \tag{6}$$

$$s_2' = -e^{-(w+2s_2)\pi/2h}(e^{-s_2\pi/h} - 1) \tag{7}$$

3. APPLICATION OF ANFIS TO THE ANALYSIS OF CONDUCTOR-BACKED ASYMMETRIC CPWs

The FIS forms a useful computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The ANFIS is a class of adaptive networks which are functionally equivalent to FISs [12, 13]. The selection of the FIS is the major concern in the design of an ANFIS. In this paper, the first-order Sugeno fuzzy model is used to generate fuzzy rules from a set of input-output data pairs. Among many FIS models, the Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency, and built-in optimal and adaptive techniques.

The ANFIS architecture used in this paper for computing the effective permittivities and characteristic impedances of conductor-backed asymmetric CPWs is illustrated in Fig. 2, in which a circle

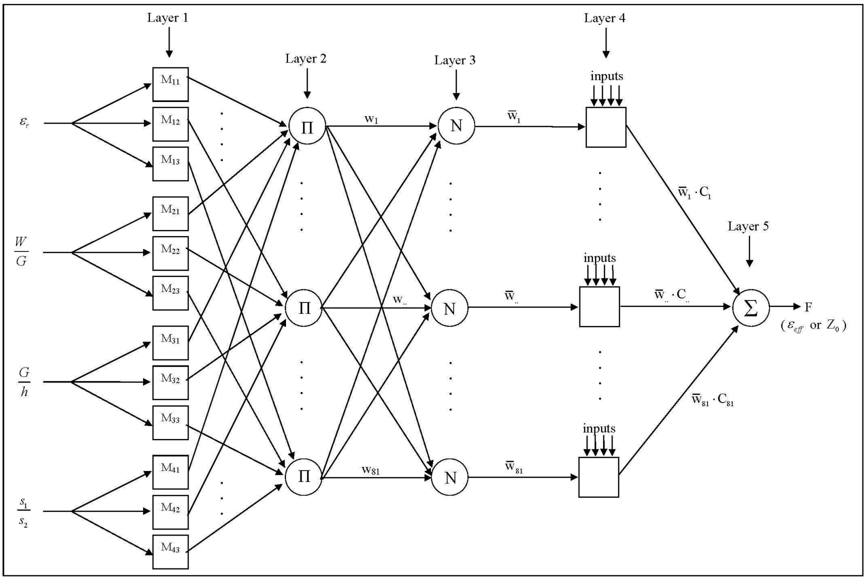


Figure 2. Structure of the ANFIS models.

indicates a fixed node, whereas a rectangular indicates an adaptive node. For the ANFIS, the inputs are ε_r, W/G , G/h, and s_1/s_2, and the output is the effective permittivity (ε_{eff}) or characteristic impedance (Z_0) of conductor-backed asymmetric CPWs.

The accuracy of a properly trained ANFIS depends on the accuracy and the effective representation of the data used for its training. The training data sets used in this work are obtained by using CMT [5]. 1128 data sets are used to train the ANFIS models. Training data sets are in the range of $2 \leq \varepsilon_r \leq 22$, $0.01 \leq W/G \leq 1.6$, $0.01 \leq G/h \leq 10$, and $0.1 \leq s_1/s_2 \leq 1.0$. 252 data sets, which are completely different from training data sets, are used to test the ANFIS models.

In the design of ANFIS, MFs that can have a strong influence on the behavior of fuzzy system for a particular problem should be optimally determined. However, no common approach is available for determining these functions. A careful determination of MFs has to be performed in each problem. In some cases, they are attained subjectively as a model for human concepts. In other cases, they are based on statistical or/and empirical distributions, heuristic determination, reliability with respect to some particular problem, or theoretical demands. In this paper, MFs are selected heuristically and verified empirically. Therefore, the optimal fuzzy MF configuration which gives the best result is chosen for the calculation of the effective permittivities and characteristic impedances of asymmetric CPWs backed with a conductor.

In this paper, the number of MFs for the inputs is determined as 3. So, the number of fuzzy if-then rules for ANFIS is 81 ($3\times3\times3\times3 = 81$) as in the following equation:

$$\begin{aligned}
&\text{Rule 1}: \text{if } \varepsilon_\mathrm{r} \text{ is } M_{11} \text{ and } \tfrac{W}{G} \text{ is } M_{21} \text{ and } \tfrac{G}{h}\\
&\ \text{is } M_{31} \text{ and } \tfrac{s_1}{s_2} \text{ is } M_{41} \text{ then } B_1 = C_1\left(\varepsilon_r, \tfrac{W}{G}, \tfrac{G}{h}, \tfrac{s_1}{s_2}\right)\\
&\text{Rule 2}: \text{if } \varepsilon_\mathrm{r} \text{ is } M_{11} \text{ and } \tfrac{W}{G} \text{ is } M_{21} \text{ and } \tfrac{G}{h}\\
&\ \text{is } M_{31} \text{ and } \tfrac{s_1}{s_2} \text{ is } M_{42} \text{ then } B_2 = C_2\left(\varepsilon_r, \tfrac{W}{G}, \tfrac{G}{h}, \tfrac{s_1}{s_2}\right)\\
&\text{Rule 3}: \text{if } \varepsilon_\mathrm{r} \text{ is } M_{11} \text{ and } \tfrac{W}{G} \text{ is } M_{21} \text{ and } \tfrac{G}{h}\\
&\ \text{is } M_{31} \text{ and } \tfrac{s_1}{s_2} \text{ is } M_{43} \text{ then } B_3 = C_3\left(\varepsilon_r, \tfrac{W}{G}, \tfrac{G}{h}, \tfrac{s_1}{s_2}\right)\\
&\text{Rule 4}: \text{if } \varepsilon_\mathrm{r} \text{ is } M_{11} \text{ and } \tfrac{W}{G} \text{ is } M_{21} \text{ and } \tfrac{G}{h}\\
&\ \text{is } M_{32} \text{ and } \tfrac{s_1}{s_2} \text{ is } M_{41} \text{ then } B_4 = C_4\left(\varepsilon_r, \tfrac{W}{G}, \tfrac{G}{h}, \tfrac{s_1}{s_2}\right)\\
&\quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots\\
&\text{Rule 81}: \text{if } \varepsilon_\mathrm{r} \text{ is } M_{13} \text{ and } \tfrac{W}{G} \text{ is } M_{23} \text{ and } \tfrac{G}{h}\\
&\ \text{is } M_{33} \text{ and } \tfrac{s_1}{s_2} \text{ is } M_{43} \text{ then } B_{81} = C_{81}\left(\varepsilon_r, \tfrac{W}{G}, \tfrac{G}{h}, \tfrac{s_1}{s_2}\right)
\end{aligned} \tag{8}$$

where M_{ij} denotes the jth MF of the input i, B_k denotes the output of the kth rule, and C_k is the kth output MF with $i = 1, 2, 3, 4$; $j = 1, 2, 3$; and $k = 1, 2, 3, \ldots, 81$. In this paper, the input MFs are all generalized bell type;

$$M_{ij}(u_i) = \frac{1}{1 + \left|\frac{u_i - b_{ij}}{a_{ij}}\right|^{2c_{ij}}} \tag{9}$$

where $\{a_{ij}$, b_{ij}, and $c_{ij}\}$ is the parameter set that changes the shapes of the input MFs, and u_i is the input variables. The output MFs are all linear type

$$\begin{aligned}
B_k &= C_k\left(\varepsilon_r, \frac{W}{G}, \frac{G}{h}, \frac{s_1}{s_2}\right)\\
&= d_{k1}(\varepsilon_r) + d_{k2}\left(\frac{W}{G}\right) + d_{k3}\left(\frac{G}{h}\right) + d_{k4}\left(\frac{s_1}{s_2}\right) + d_{k5}
\end{aligned} \tag{10}$$

where d_k is the fitting parameters that characterize the shapes of the output MFs. The parameters $\{a_{ij}$, b_{ij}, and $c_{ij}\}$ and d_k are referred to as the premise and consequent parameters, respectively. It is clear from Eq. (9) that the generalized bell MF is specified by three parameters. Therefore, ANFIS models used here contain a total of 441 fitting parameters, of which 36 ($3 \times 3 + 3 \times 3 + 3 \times 3 + 3 \times 3 = 36$) are the premise parameters and 405 ($5 \times 81 = 405$) are the consequent parameters.

The output of the network is the weighted average of the individual rule outputs. The weighting factor w_k of each rule is computed by evaluating the membership expressions in the antecedent of the rule. This is accomplished by first converting the input values to fuzzy membership values by utilizing the input MFs and then applying *"and"* operator to these membership values. The *"and"* operator corresponds to the multiplication of input membership values. Hence, the weighting factors of the rules are calculated as follows:

$$\begin{aligned}
w_1 &= M_{11}(\varepsilon_r)\ M_{21}\left(\tfrac{W}{G}\right)\ M_{31}\left(\tfrac{G}{h}\right)\ M_{41}\left(\tfrac{s_1}{s_2}\right) \\
w_2 &= M_{11}(\varepsilon_r)\ M_{21}\left(\tfrac{W}{G}\right)\ M_{31}\left(\tfrac{G}{h}\right)\ M_{42}\left(\tfrac{s_1}{s_2}\right) \\
w_3 &= M_{11}(\varepsilon_r)\ M_{21}\left(\tfrac{W}{G}\right)\ M_{31}\left(\tfrac{G}{h}\right)\ M_{43}\left(\tfrac{s_1}{s_2}\right) \\
w_4 &= M_{11}(\varepsilon_r)\ M_{21}\left(\tfrac{W}{G}\right)\ M_{32}\left(\tfrac{G}{h}\right)\ M_{41}\left(\tfrac{s_1}{s_2}\right) \\
\vdots\ \ & \vdots\qquad \vdots \qquad\quad \vdots \qquad\quad \vdots\ \ \vdots \\
w_{81} &= M_{13}(\varepsilon_r)\ M_{23}\left(\tfrac{W}{G}\right)\ M_{33}\left(\tfrac{G}{h}\right)\ M_{43}\left(\tfrac{s_1}{s_2}\right)
\end{aligned} \tag{11}$$

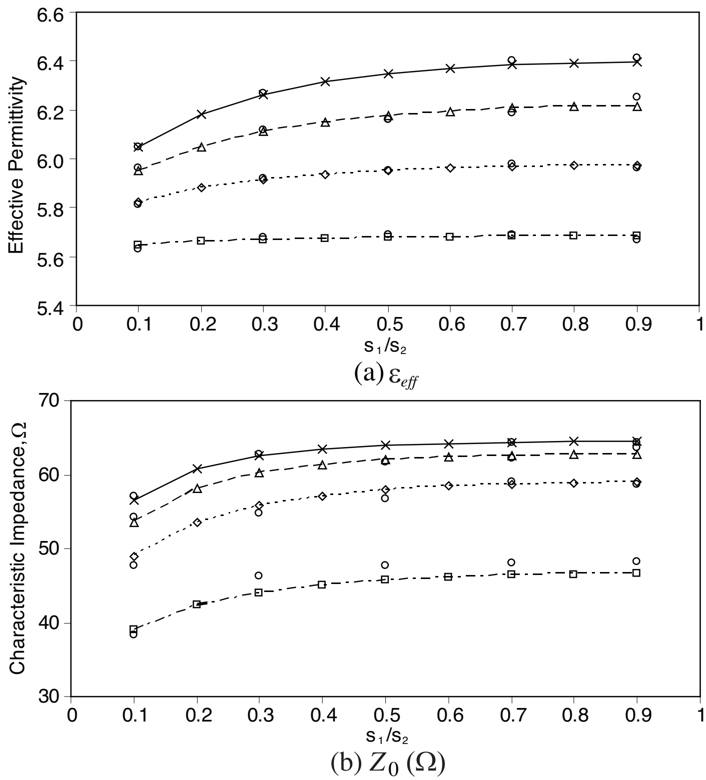
Once the weighting factors are obtained, the output of the network can be found by calculating the weighted average of the individual rule outputs. So the single node in the fifth layer calculates the overall output as the summation of all incoming signals, which is written as:

$$F = \frac{\sum_{k=1}^{81} w_k B_k}{\sum_{k=1}^{81} w_k} = \sum_{k=1}^{81} \bar{w}_k C_k \tag{12}$$

where $\bar{w}_k$ is the normalized weighting factor of each rule.

The main objective of the ANFIS is to optimize the parameters of the fuzzy system parameters by applying an optimization algorithm using input-output data sets. The parameter optimization is done in a way such that the error measure between the target and the actual output is minimized. During the optimization process of the ANFIS, the premise parameters in the layer 1 and the consequent parameters in the layer 4 are tuned until the desired response of the FIS is achieved. In this paper, four different optimization algorithms, HL, SA, GA, and LSQ, are used to identify the parameters of ANFIS.

It is well known that the ANFIS has one output. For this reason, two separate ANFIS models with identical structure are used for computing the effective permittivities and characteristic impedances of conductor-backed asymmetric CPWs. Although the number of inputs, input values, the number of MFs, and the types of MFs are the same



- · - · -	CMT	□	ANFIS	○	IE3D	G/h = 1
- - - - - -	CMT	◇	ANFIS	○	IE3D	G/h = 2
— — —	CMT	Δ	ANFIS	○	IE3D	G/h = 3
———	CMT	×	ANFIS	○	IE3D	G/h = 4

Figure 3. Comparison results of ANFIS model, CMT [5] and IE3D [31] for the characteristic parameters of conductor-backed asymmetric CPWs with $\varepsilon_r = 10$, $W = 400\,\mu\text{m}$, and $h = 750\,\mu\text{m}$ (a) Effective permittivity and (b) Characteristic impedance.

Table 1. Training and test RMS errors of ANFIS models.

Optimization Algorithms	RMS Errors in Training		RMS Errors in Test	
	ε_{eff}	Z_0 (Ω)	ε_{eff}	Z_0 (Ω)
HL	0.019	0.193	0.029	0.244
SA	0.077	5.460	0.101	4.767
GA	0.413	6.756	0.454	7.436
LSQ	3.409	4.646	3.443	6.304

Table 2. Comparison results of ANFIS model, experimental works, CMT [5], and IE3D [31] for characteristic impedances of conductor-backed symmetric CPWs with $\varepsilon_r = 10.2$ and $h = 1270\,\mu$m.

Geometrical dimensions (μm)		Characteristic impedances (Ω)			
Strip width (W)	Slot width (s_1)	Measured	CMT [5]	IE3D [31]	ANFIS
800	950	49.73	49.87	49.87	49.59
1000	1000	50.01	50.40	50.40	50.23
900	1000	50.03	49.67	49.67	50.59
1100	1050	49.73	49.93	49.92	49.45

for each ANFIS, the values of premise and consequent parameters for each ANFIS are different. Hence, the shape of each MF of the ANFIS used for computing the effective permittivities is different from the corresponding MF of the ANFIS used for computing the characteristic impedances.

4. RESULTS AND CONCLUSIONS

In this paper, the characteristic parameters, effective permittivities and characteristic impedances, of conductor-backed asymmetric CPWs are computed by using ANFIS models. Four different optimization algorithms, HL, SA, GA, and LSQ, are used to determine the optimum values of the fuzzy system parameters and adapt the FISs. The training and test RMS errors of ANFIS models are given in Table 1. When the performances of ANFIS models are compared with each other, the best results are obtained from the models trained with the HL algorithm.

The effective permittivity and characteristic impedance test results of ANFIS models trained by the HL algorithm for conductor-backed asymmetric CPWs with $\varepsilon_r = 10$, $W = 400\,\mu$m, and $h = 750\,\mu$m are compared with the results of CMT [5] and IE3D [31] in Figs. 3(a) and 3(b), respectively. Comparison is made for a wide range of s_1/s_2

and G/h ratio. It is clear from Figs. 3(a) and 3(b) that the results of ANFIS models are in very good agreement with the results of CMT and IE3D. This very good agreement confirms the validity of ANFIS method for the quasi-static analysis of conductor-backed asymmetric CPWs.

The ANFIS models proposed in this work can also be used for the analysis of conductor-backed symmetric CPWs when the slot width s_1 equals to s_2. In this paper, four different symmetric conductor-backed CPWs are fabricated on RT/duroid laminates by using the printed circuit board (PCB) excavation technique. The characteristic impedances of these CPWs are calculated from the measured S-parameters. These characteristic impedances are compared with the results of ANFIS model trained by the HL algorithm, CMT [5], and IE3D [31] in Table 2. It is clear that ANFIS results agree quite well with the results of CMT, IE3D, and measured work.

As a consequence, ANFIS models are presented to accurately calculate the effective permittivities and characteristic impedances of both symmetric and asymmetric conductor-backed CPWs. Different optimization algorithms, HL, SA, GA, and LSQ, are used to identify the parameters of ANFIS. The best results are obtained from the ANFIS trained by HL algorithm. The close agreement is satisfied between the theoretical and experimental results. The ANFIS offers an accurate and efficient alternative to previous methods for the calculation of the effective permittivities and characteristic impedances of conductor-backed CPWs.

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REFERENCES

1. Simons, R. N., *Coplanar Waveguide Circuits, Components and Systems*, John Wiley and Sons, 2001.
2. Ghione, G. and C. U. Naldi, "Coplanar waveguides for MMIC applications: Effect of upper shielding, conductor backing, finite-extent ground planes, and line-to-line coupling," *IEEE Transactions on Microwave Theory and Techniques*, Vol. 35, No. 3, 260–267, 1987.
3. Shih, Y. C., "Broadband characterization of conductor-backed

coplanar waveguide using accurate on-wafer measurement techniques," *Microwave Journal*, Vol. 34, No. 4, 95–105, 1991.

4. Fang, S. J. and B. S. Wang, "Analysis of asymmetric coplanar waveguide with conductor backing," *IEEE Transactions on Microwave Theory and Techniques*, Vol. 47, No. 2, 238–240, 1999.
5. Karpuz, C. and A. Gorur, "Effect of upper shielding and conductor backing on quasi static parameters of asymmetric coplanar waveguides," *Int. J. RF and Microwave CAE*, Vol. 9, 394–402, 1999.
6. Ghione, G. and C. U. Naldi, "Parameters of coplanar waveguides with lower ground plane," *Electronic Letters*, Vol. 19, No. 18, 734–735, 1983.
7. Cheng, K. K. M. and J. K. A. Everard, "A new technique for the quasi-TEM analysis of conductor-backed coplanar waveguide structures," *IEEE Transactions on Microwave Theory and Techniques*, Vol. 41, No. 9, 1589–1592, 1993.
8. Shih, Y. C. and T. Itoh, "Analysis of conductor-backed coplanar waveguide," *Electronic Letters*, Vol. 18, No. 12, 538–540, 1982.
9. Neto, A. G., C. S. D. Rocha, D. Bajon, and H. Baudrand, "Analysis of the conductor-backed coplanar waveguide by an alternative formulation of the transverse resonance technique," *SBMO/IEEE MTT-S Int.*, 851–855, 1995.
10. Hotta, M., Y. Qian, and T. Itoh, "Efficient FDTD analysis of conductor-backed CPW's with reduced leakage loss," *IEEE Transactions on Microwave Theory and Techniques*, Vol. 47, No. 8, 1585–1587, 1999.
11. Yildiz, C., K. Guney, M. Turkmen, and S. Kaya, "Analysis of conductor-backed coplanar waveguides using adaptive-network-based fuzzy inference system models," *Microwave and Optical Technology Letters*, Vol. 51, No. 2, 439–455, 2009.
12. Jang, J.-S. R., "ANFIS: Adaptive-network-based fuzzy inference system," *IEEE Transactions on Systems Man and Cybernetics*, Vol. 23, No. 3, 665–685, 1993.
13. Jang, J.-S. R., C. T. Sun, and E. Mizutani, *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, Prentice-Hall, Upper Saddle River, NJ, 1997.
14. Ozer, S., K. Guney, and A. Kaplan, "Calculation of the characteristic impedance and effective dielectric constant of coplanar waveguide with the use of fuzzy inference systems," *Proc. of 8th TAINN'99, Istanbul, Turkey*, 187–196, 1999.
15. Tayarani, M. and Y. Kami, "Qualitative analysis in engineering

electromagnetics: An application to general transmission lines," *IEICE Trans. on Electronics*, Vol. E84C, No. 3, 364–375, 2001.
16. Miraftab, V. and R. R. Mansour, "Computer-aided tuning of microwave filters using fuzzy logic," *IEEE MTT-S Digest*, 1117–1120, 2002.
17. Ubeyli, E. D. and I. Guler, "Adaptive neuro-fuzzy inference system to compute quasi-TEM characteristic parameters of microshield lines with practical cavity sidewall profiles," *Neurocomputing*, Vol. 70, No. 1–3, 196–204, 2006.
18. Rahouyi, E. B., J. Hinojosa, and J. Garrigos, "Neuro-fuzzy modeling techniques for microwave components," *IEEE Microwave and Wireless Components Letters*, Vol. 16, No. 2, 72–74, 2006.
19. Miraftab, V. and R. R. Mansour, "EM-based microwave circuit design using fuzzy logic techniques," *IEE Proc. Microwave Antennas Propag*, Vol. 153, No. 6, 495–501, 2006.
20. Hinojosa, J. and G. Dome'nech-Asensi, "Space-mapped neuro-fuzzy optimization for microwave device modeling," *Microwave and Optical Technology Letters*, Vol. 49, No. 6, 1328–1334, 2007.
21. Hinojosa, J., G. Dome'nech-Asensi, and J. Martı'nez-Alajarı'n, "Development of VHDL-AMS neuro-fuzzy behavioral models for RF/microwave passive components," *Int. J. RF and Microwave CAE*, Vol. 17, No. 3, 335–344, 2007.
22. Koziel, S. and J. W. Bandler, "A space-mapping approach to microwave device modeling exploiting fuzzy systems," *IEEE Transactions on Microwave Theory and Techniques*, Vol. 55, No. 12, 2539–2547, 2007.
23. Yildiz, C., K. Guney, M. Turkmen, and S. Kaya, "Adaptive neuro-fuzzy models for the quasi-static analysis of microstrip line," *Microwave and Optical Technology Letters*, Vol. 50, No. 5, 1191–1196, 2008.
24. Turkmen, M., S. Kaya, C. Yildiz, and K. Guney, "Adaptive neuro-fuzzy models for conventional coplanar waveguides," *Progress In Electromagnetics Research B*, Vol. 6, 93–107, 2008.
25. Gaoua, S., L. Ji, Z. Cheng, F. A. Mohammadi, and M. C. E. Yagoub, "Fuzzy neural-based approaches for efficient RF/microwave transistor modeling," *Int. J. RF and Microwave CAE*, Vol. 19, No. 1, 128–139, 2009.
26. Kirkpatrick, S., C. D. Gelatt, Jr., and M. P. Vecchi, "Optimization by simulated annealing," *Science*, Vol. 220, No. 4598, 671–680, 1983.

27. Goldberg, D., *Genetic Algorithms in Search, Optimization, and Machine Learning*, Reading, Addison-Wesley, MA, 1989.
28. Holland, J., *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Michigan, 1975.
29. Dennis, J. E., *Nonlinear Least-Squares, State of the Art in Numerical Analysis*, 269–312, Academic Press, 1977.
30. Marquardt, D. W., "An algorithm for least-squares estimation of nonlinear parameters," *J. Soc. Ind. Appl. Math.*, Vol. 11, 431–441, 1963.
31. Zeland Software Inc., IE3D, Version 12.12, www.zeland.com., 2007.