ANN Synthesis Models for Asymmetric Coplanar Waveguides with Finite Dielectric Thickness^{*}

WANG Zhongbao and FANG Shaojun

(School of Information Science and Technology, Dalian Maritime University, Dalian 116026, China)

Abstract — Novel and accurate Computer-aided design (CAD) models based on Artificial neural networks (ANNs) are proposed for the synthesis of Asymmetric coplanar waveguides (ACPWs) with finite dielectric thickness. First, the ACPWs are analyzed by using the Conformal mapping technique (CMT) to obtain the training data sets. Then, six training algorithms are used to train the ANNs for finding proper training algorithm. Highprecision models are obtained by using the Levenberg-Marquardt (LM) training algorithm. The models also can be used for symmetric coplanar waveguides. At last, the models are validated by the comparison with the CMT analysis, HFSS electromagnetic simulation, and experimental results available in the literature. The proposed CAD models are extremely useful to microwave engineers for accurately calculating the physical dimensions of ACPWs with finite dielectric thickness.

Key words — Synthesis models, Artificial neural networks, Conformal mapping, Asymmetric coplanar waveguides (ACPWs) with a finite dielectric thickness, Symmetric and Asymmetric coplanar waveguides (Asymmetric CPWs).

I. Introduction

Coplanar waveguides (CPWs) are widely adopted in many practical RF circuits and antennas^[1,2]. CPWs offer several advantages over microstrip lines in designing and manufacturing Monolithic microwave integrated circuits (MMICs). These advantages include high ?exibility in the control of characteristic impedance, easy connection to the shunt lumped elements, and low dispersion. Asymmetric coplanar waveguides (ACPWs)^[3] provide additional degrees of freedom to control the line characteristic and optimize the circuit layout.

Recently, the various ACPWs have been analyzed by using full-wave methods^[4,5] or quasi-static methods^[6-11]. The characteristic parameters of ACPWs with finite dielectric thickness have been obtained by using the full-wave analysis methods such as Finite-difference time-domain (FDTD)^[4] and Multi-resolution time-domain (MRTD)^[5]. Full-wave analysis methods are the most accurate tools for obtaining transmission-

line characteristics, but they are mathematically complex with tremendous and time-consuming computational efforts. For the quasi-static analysis, the Conformal mapping technique (CMT) is a powerful $tool^{[6-9]}$. In 1981, the ACPW with infinite substrate thickness was first analyzed by V.F. Hanna and D. Thebault^[6]. In their study, twice conformal transformations were adopted. As a result, the analysis formulas are very complicated. In 1995, using SchwartzChristoffel transformation, simple analytical formulas for quasi-static parameters of asymmetric coplanar lines had been obtained^[7]. In 1999, the effective permittivity, characteristic impedance, and electricfield strength of Conductor-backed ACPWs (CBACPWs) had been reported^[8]. In 2002, shielded multilayered ACPWs have been analyzed by using the CMT^[9]. Based on the data sets obtained from the quasi-static analysis results, the analysis models of ACPWs with finite dielectric thickness and CBACPWs had been obtained by using Artificial neural networks (ANNs)^[10] and an Adaptive-network-based fuzzy inference system (ANFIS)^[11].

It is noted that so far, most of the Computer-aided design (CAD) models are the analysis models that have been used to obtain characteristic parameters of various ACPWs. Whereas synthesis CAD models used to directly obtain the physical dimensions of ACPWs for the required design specifications are very scant. In 2011, synthesis CAD models for CBACPWs had been reported^[12], but the models can't be used for synthesis of conductor-backed symmetric CPWs. Furthermore, to best of our knowledge, there is no synthesis CAD model for ACPWs with finite dielectric thickness.

In this paper, novel and accurate CAD models based on ANNs are proposed for the synthesis of ACPWs with finite dielectric thickness. To obtain the training data sets, the CMT is first used to analyze the ACPWs with finite dielectric thickness. Based on the CMT analysis results, six training algorithms are used to train the ANNs for obtaining accurate CAD models. The validity and accuracy of the proposed synthesis models have been verified by the comparison with the CMT analysis, HFSS electromagnetic simulation^[13] and experimental results previously published in Ref.[3].

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II. CMT Analysis

The cross-section of an ACPW with finite dielectric thickness is shown in Fig.1(*a*). In this figure, *w* represents the central strip width, g_1 and g_2 represent the slot widths, and the dielectric substrate has thickness of *h* with relative dielectric constant ε_r . If the dielectric interfaces in the slots are modeled as magnetic walls and all the conductors are assumed to be infinitely thin and perfectly conducting, the overall capacitance per unit length of ACPW with finite dielectric thickness can be written as:

$$C = C_a + C_s \tag{1}$$

where capacitance C_a is air-space capacitance after removing the dielectric substrates and capacitance C_s is introduced by the dielectric substrate of thickness h having the equivalent dielectric constant ($\varepsilon_r - 1$).



Fig. 1. Conformal mappings for calculating the capacitance of ACPW with finite dielectric thickness. (a) Original ACPW structure; (b) Intermediate mapping for the dielectric region; (c) Mapping into parallel-plate capacitor

First, in order to obtain the air capacitance C_a , assuming the ACPW without the substrate, the upper half plane in Fig.1(*a*) is transformed into the rectangular region in *r*-plane by means of the Schwartz - Christoffel transformation

$$r = \int_{i_1}^{i} \frac{di}{\sqrt{(i-i_1)(i-i_2)(i-i_3)(i-i_4)}}$$
(2)

As a result, the air capacitance per unit length of the line is

$$C_a = 2 \cdot \varepsilon_0 \frac{K(k_i)}{K(k'_i)} \tag{3}$$

where $K(k_i)$ is the complete elliptical integrals of the first kind with the module k_i and

$$k'_{i} = \sqrt{1 - (k_{i})^{2}} \tag{4}$$

$$k_i = \sqrt{\frac{(i_3 - i_2)(i_4 - i_1)}{(i_3 - i_1)(i_4 - i_2)}} \tag{5}$$

with

$$i_1 = -\left(\frac{2g_1 + w}{2}\right), i_2 = -\frac{w}{2}, i_3 = \frac{w}{2}, i_4 = \frac{2g_2 + w}{2}.$$

Second, in order to compute the dielectric capacitance, the dielectric region in Fig.1(a) is transformed into the lower half

region shown in Fig.1(b) by the hyperbolic sine transformation

$$i' = \sinh\left(\frac{\pi f}{2h}\right) \tag{6}$$

Then, using the Schwartz—Christoffel transformation, the dielectric capacitance per unit length of the line can be obtained as follow:

$$C_s = (\varepsilon_r - 1) \cdot \varepsilon_0 \frac{K(k_f)}{K(k'_f)} \tag{7}$$

where

$$k_f = \sqrt{\frac{(i'_3 - i'_2)(i'_4 - i'_1)}{(i'_3 - i'_1)(i'_4 - i'_2)}} \tag{8}$$

with

$$i_{1}' = \sinh\left(\frac{\pi f_{1}}{2h}\right) = -\sinh\left(\frac{\pi (2g_{1} + w)}{4h}\right),$$

$$i_{2}' = \sinh\left(\frac{\pi f_{2}}{2h}\right) = -\sinh\left(\frac{\pi w}{4h}\right),$$

$$i_{3}' = \sinh\left(\frac{\pi f_{3}}{2h}\right) = \sinh\left(\frac{\pi w}{4h}\right),$$

$$i_{4}' = \sinh\left(\frac{\pi f_{4}}{2h}\right) = \sinh\left(\frac{\pi (2g_{2} + w)}{4h}\right).$$

Finally, the overall capacitance per unit length of the ACPW with finite dielectric thickness is

$$C = 2 \cdot \varepsilon_0 \frac{K(k_i)}{K(k'_i)} + (\varepsilon_r - 1) \cdot \varepsilon_0 \frac{K(k_f)}{K(k'_f)}$$
(9)

Therefore, the effective dielectric constant and characteristic impedance are, respectively,

$$\varepsilon_{\text{eff}} = C/C_0 = 1 + (\varepsilon_r - 1) \cdot q \tag{10}$$

where the filling factor q is expressed as

$$q = \frac{1}{2} \cdot \frac{K(k'_i)}{K(k_i)} \cdot \frac{K(k_f)}{K(k'_f)}$$
(11)

and

$$Z_0 = \frac{60\pi}{\sqrt{\varepsilon_{\text{eff}}}} \cdot \frac{K(k_i')}{K(k_i)} \tag{12}$$

III. ANN Synthesis Models

ANNs have been developed for many years. Recently, ANNs have gained attention as fast and flexible vehicles for microwave modeling, simulation, and optimization. Feed-forward neural networks are a basic type of neural networks suitable for modeling high-dimensional and highly nonlinear problems. An important class of feed-forward neural networks is Multilayer perceptron (MLP). An MLP consists of three types of layers: an input layer, an output layer and one or more hidden layers. The success of MLPs for a particular problem depends on the adequacy of the training algorithm regarding the necessities of the problem. To obtain high-precision synthesis models, Back-propagation with momentum (BPM), Resilient back propagation (RBP), Scaled conjugate gradient (SCG), Conjugate gradient with Fletcher- Reeves (CGF), Broydon-Fletcher-Goldfarb-Shanno (BFGS), and Levenberg-Marquardt

Table 1. Errors obtained from Arriv synthesis models trained with different learning algorithms												
Learning algorithm	First ANN synthesis model						Second ANN synthesis model					
	MRE (%)		ARE $(\%)$		MSE		MRE $(\%)$		ARE $(\%)$		MSE	
	Training	Test	Training	Test	Training	Test	Training	Test	Training	Test	Training	Test
BPM	242	203	18.0	18.3	6.80×10^{-3}	7.40×10^{-3}	492	324	20.5	20.8	2.33×10^{-2}	2.63×10^{-2}
RBP	102	101	4.24	4.56	4.88×10^{-4}	5.49×10^{-4}	194	120	4.10	4.39	1.40×10^{-3}	1.70×10^{-3}
SCG	37.5	25.9	1.27	1.39	4.66×10^{-5}	5.68×10^{-5}	43.1	27.7	1.25	1.34	1.17×10^{-4}	1.48×10^{-4}
CGF	28.7	29.1	1.33	1.41	5.34×10^{-5}	6.46×10^{-5}	60.7	86.3	1.41	1.67	1.59×10^{-4}	2.21×10^{-4}
BFGS	7.67	8.54	0.44	0.46	6.35×10^{-6}	7.77×10^{-6}	23.1	45.0	0.71	0.78	3.92×10^{-5}	4.81×10^{-5}
LM	0.69	0.77	0.02	0.03	1.73×10^{-8}	5.03×10^{-8}	0.78	2.51	0.03	0.04	6.14×10^{-8}	2.47×10^{-7}

Table 1. Errors obtained from ANN synthesis models trained with different learning algorithms

(LM) algorithms^[10,14,15], have been used to train the MLPs for finding proper training algorithm.

The aim of this paper is to develop two accurate ANN synthesis models for ACPWs with finite dielectric thickness. Fig.2 gives the ANN synthesis models. The first ANN synthesis model can be used to calculate the central strip width w for a given substrate (h, ε_r) and required characteristic impedance Z_0 by choosing appropriate g_1 and g_2 . The second ANN synthesis model can be used to compute the slot width g_2 for a given substrate (h, ε_r) and required characteristic impedance Z_0 by choosing appropriate w and g_1/g_2 .



Fig. 2. ANN synthesis models for ACPWs with finite dielectric thickness. (a) The first ANN synthesis model; (b) The second ANN synthesis model

The ANN model is a kind of black box models, whose accuracy depends on the data sets used during training. In this study, the training data sets were obtained from the CMT analysis presented in the Section II. For each ANN model, 5000 different data sets were used in this study. 3500 data sets were used in training and the rest of the data sets were used to test the ANN models. The design parameter ranges of ACPWs with finite dielectric thickness are $2 \leq \varepsilon_r \leq 22$, $0.1 \leq w/h \leq 0.9$, $0.1 \leq g_2/h \leq 2$, $0.1 \leq g_1/g_2 \leq 1$, and $25\Omega \leq Z_0 \leq 220\Omega$.

To find proper ANN synthesis models for ACPWs with finite dielectric thickness, many experiments were carried out in this study. After many trials, it was found that the target in high accuracy was achieved by using two hidden layered network. The numbers of neurons in the first and second hidden layers were 12 and 24 for both ANN synthesis models. For each ANN model, the tangent sigmoid activation function was used in the hidden layers, and the linear activation function was used in the output layers. The training and testing data sets were scaled between -1.0 and +1.0 for inputs and outputs before training in order to facilitate an easier learning process.

As mentioned foregoing, the six learning algorithms are used to train the neural models. In order to compute the ratio of geometrical dimensions $(w/h)_{\rm ANN}$ or $(g_2/h)_{\rm ANN}$, training the ANN models using these learning algorithms involves presenting them sequentially and/or randomly with different data sets $(\varepsilon_r, g_2/h \text{ or } w/h, g_1/g_2, \text{ and } Z_0)$, corresponding to the ratio of geometrical dimensions w/h or g_2/h . The Mean square error (MSE) between target and the actual outputs of the networks is used to adapt the weights of the ANNs. The adaptation is carried out, after the presentation of each data set $(\varepsilon_r, g_2/h, w/h, g_1/g_2, \text{ and } Z_0)$, until the calculation accuracy of the models is deemed satisfactory according to one criterion: either the MSE for all the training data sets that fall below a given threshold or the maximum allowable number of epochs reached.

IV. Numerical Results and Discussion

ANNs have been successfully introduced for the synthesis of ACPWs with finite dielectric thickness. To obtain high-precision synthesis models, ANNs were trained by using the BPM, RBP, SCG, CGF, BFGS, and LM learning algorithms^[10,14,15]. It is noted that, for each learning algorithm, the maximum allowable number of epochs was 1000, and the Maximal relative error (MRE), Average relative error (ARE) and MSE of the ANN synthesis models were calculated.



Fig. 3. Comparison of the results obtained from the first ANN synthesis model and the CMT analysis contours for ACPWs with finite dielectric thickness ($\varepsilon_r = 12.9$, $g_2/h = 0.7$, $h = 200 \mu$ m)

The training and test errors obtained from the ANN models trained with different learning algorithms are summarized in Table 1. When the training and test performances for the six learning algorithms are compared with each other, the best results were obtained from the ANNs trained with the LM algorithm for both the first and second synthesis models. The worst results were obtained from the ANNs trained with the BPM algorithm. As it can be seen from Table 1, for each ANN synthesis models trained with the LM algorithm, the MRE is less than 2.6% and the ARE is less than 0.05%. These error values obviously show that the ANN synthesis models trained with the LM algorithm can be used for accurately computing physical dimensions of ACPWs with finite dielectric thickness for the required design specifications.



Fig. 4. Comparison of the results obtained from the second ANN synthesis model and the CMT analysis contours for ACPWs with finite dielectric thickness ($\varepsilon_r = 12.9$, w/h = 0.5, $h = 200 \mu$ m)

In order to validate the ANN synthesis models trained with the LM algorithm, the results obtained from the ANN synthesis models trained with the LM algorithm are compared with the results of the CMT analysis. Figs.3 and 4, respectively, show the CMT analysis contours of the ratios of geometrical dimensions w/h and g_2/h versus the ratio of slot widths g_1/g_2 for various characteristic impedance values with a given substrate material ($\varepsilon_r = 12.9$, and $h = 200\mu$ m). It is clear observed that there is a very good agreement between the results of CMT analysis and the ANN synthesis models trained with the LM algorithm. This good agreement supports the validity of the synthesis models proposed here. Similar results are obtained for the different dielectric substrate materials ($2 \le \varepsilon_r \le 22$), but they are not given here to avoid repetition.

The comparisons among the results of the ANN synthesis models trained with the LM algorithm, the symmetric CPW synthesis formula^[16], and the CMT analysis for symmetric and asymmetric CPWs with finite dielectric thickness ($\varepsilon_r = 10.2$, $h = 200\mu$ m, and $g_2/h = 0.5$) are given in Fig.5. The characteristic impedance results are plotted with respect to the ratio of geometrical dimensions w/h for three different g_1/g_2 values. It is observed that the results of the ANN synthesis models trained with the LM algorithm are in good agreement with the results of the synthesis formula^[16] and the CMT analysis. It is also seen that there is a good self-consistent agreement between the first and second synthesis models.



Fig. 5. Comparisons among the results of the ANN synthesis models trained with the LM algorithm, the symmetric CPW synthesis formula^[16], and the CMT analysis for symmetric and asymmetric CPWs with finite dielectric thickness ($\varepsilon_r = 10.2, h = 200\mu$ m, and $g_2/h = 0.5$)

In Table 2, the results obtained from the ANN synthesis models trained with the LM algorithm are compared with the results of the CMT analysis, HFSS^[13] electromagnetic simulation, and experimental work^[3]. Z_{0m} is the measured characteristic impedance value, and w, g_1 , and g_2 represent the measured geometrical dimensions of ACPWs with finite dielectric thickness. Also, Z_{0h} and Z_{0c} represent the characteristic impedance values obtained from the HFSS and CMT analysis by using w, q_1 , and q_2 , respectively. The w' represents the strip width obtained from the first ANN synthesis model by using g_1 and g_2 . The g'_2 represents the slot width obtained from the second ANN synthesis model by using w and g_1/g_2 . Finally, the CMT analysis results $(Z_{0w} \text{ and } Z_{0g})$ are calculated by using w' and g'_2 for checking. As it can be seen from Table 2, a good agreement is obtained between the theoretical and experimental results.

V. Conclusion

In this paper, novel and accurate ANN models are presented for the synthesis of ACPWs with finite dielectric thickness. For each ANN model trained with the LM algorithm, the MRE is less than 2.6% and the ARE is less than 0.05%. These error values obviously show that the proposed ANN models can be used for accurately computing the physical dimensions of ACPWs with finite dielectric thickness by a very simple way,

Table 2. Comparisons of the results of the proposed ANN synthesis models, CMT, HFSS, and experimental results

				,	1					
Measured				HFSS	CMT	First ANI	N synthesis model	Second ANN synthesis model		
$w~(\mu m)$	$g_1 \ (\mu m)$	$g_2 \ (\mu m)$	$Z_{0m}(\Omega)$	$Z_{0h}(\Omega)$	$Z_{0c}(\Omega)$	$w'~(\mu m)$	$Z_{0w}(\Omega)$	$g_2'~(\mu {\rm m})$	$Z_{0g}(\Omega)$	
747	123	1060	51.5	51.33	51.77	747.03	51.76	1056.58	51.75	
737	257	991	57.5	58.77	59.88	736.00	59.89	989.43	59.86	
1248	406	1548	62.4	62.87	62.37	1240.10	62.44	1492.36	62.16	
1244	575	1386	66.3	66.81	67.16	1242.38	67.18	1325.59	66.81	

rather than by the iteration technique of applying the analysis method. The ANN models have been validated by comparing their results with the results of the CMT analysis, HFSS electromagnetic simulation, and experimental works. Also, the proposed ANN models can be used for symmetric CPWs with finite dielectric thickness.

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WANG Zhongbao was born in Sichuan Province, China, in 1983. He received the B.E. and M.E. degrees in communication engineering from Dalian Maritime University (DLMU), Dalian, China, in 2007 and 2009, respectively, and is currently working toward the Ph.D. degree at DLMU. His current research interests include patch antennas, passive RF components and microwave technology using arueilt waverb@dlmu.edu.en)

tificial intelligence. (Email: wangzb@dlmu.edu.cn)



FANG Shaojun (corresponding author) was born in Shandong Province, China, in 1957. He received the Ph.D. degree in communication and information systems from Dalian Maritime University, Dalian, China, in 2001. He is currently a professor and doctoral supervisor in the School of Information Science and Technology, DLMU. His recent research interests include patch antennas, ACPW com-

ponents and computational electromagnetics. (Email: fangshj@ dlmu.edu.cn)