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Adaptive neuro-fuzzy inference system to compute quasi-TEM characteristic parameters of microshield lines with practical cavity sidewall profiles

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Abstract

Neural networks have recently been introduced to the microwave area as a fast and flexible vehicle to microwave modeling, simulation and optimization. In this paper, a new approach based on adaptive neuro-fuzzy inference system (ANFIS) was presented for the quasi-TEM characteristics of microshield lines with practical cavity sidewall profiles. The proposed ANFIS model combines the neural network adaptive capabilities and the fuzzy qualitative approach. The ANFIS models were presented to produce a good approximator of the nonlinear relationship between the geometrical parameters and the quasi-TEM characteristics (characteristic impedance and cavity capacitance sensitivity) of microshield lines. The results of the ANFIS models for the characteristic impedance and the cavity capacitance sensitivity of the microshield lines and the results available in the literature obtained by using conformal-mapping technique (CMT) were compared. The drawn conclusions confirmed that the proposed ANFIS models could provide an accurate computation of the characteristic impedance and the cavity capacitance sensitivity of the microshield lines.

Keywords: Adaptive neuro-fuzzy inference system (ANFIS); Microshield lines; Quasi-TEM characteristics; Conformal mapping

1. Introduction

In the recent years, the microshield line, one type of transmission line, has been the subject of growing interest as it has presented a solution to technical and technological problems encountered in the design of microstrip and coplanar lines. The microshield line, when compared with the conventional ones, has the ability to operate without the need for via-holes or the use of air-bridges for ground equalization. There are further advantages, like reduced radiation loss, reduced electromagnetic interference, and the availability of a wide range of impedance [3]. Various types of microshield structures have been reported, including rectangular, V, elliptic, and circular-shaped transmission lines [9,12]. An analytical solution for the characteristic impedance of a microshield line with imperfectly etched cavity sidewalls (Fig. 1) can be performed using conformal-mapping technique (CMT). Line parameter sensitivity analysis of a rectangular-shaped microshield line fabricated by an imperfect sidewall etching process has been performed [3]. The charactrerization of the microshield lines presented in Fig. 1 is extremely important because it could offer additional flexibility in the design of integrated circuits. Furthermore, it allows one to evaluate the actual characteristics of a microshield line normally designed to be rectangular-shaped, but the fabrication of which is imperfect. The sensitivity of the characteristics of a rectangular-shaped microshield line to an imperfect sidewall etching process, leading to nonvertical sidewall profiles has been examined [3].

Method of moments and CMT have been used for the analysis of the microshield lines [3]. Full-wave three-dimensional electromagnetic simulation and optimization

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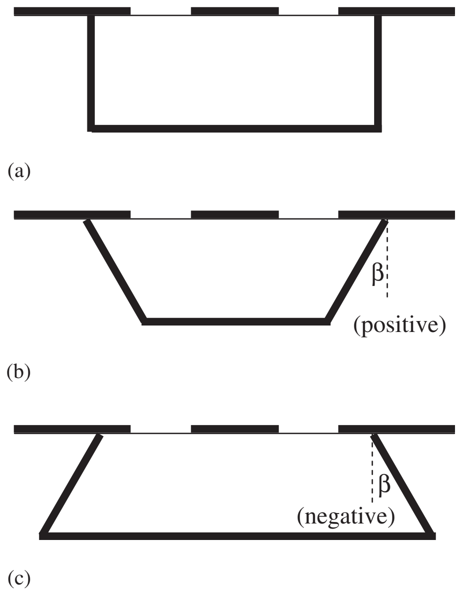

Fig. 1. Microshield line. (a) Rectangular-shaped, (b) and (c) Practical profiles, positive or negative slope depending upon the orientation and etching conditions.

of microwave and millimeter-wave components forming any high speed digital system are essential parts of design and optimization in order to ensure its proper performance. Electromagnetic characterization of microwave and millimeter-wave components requires the use of a rigorous numerical method like that based on finite elements or finite difference in time domain, which involves the numerical solution of Maxwell's equations [2,8,10,11]. These methods have different levels of complexity, require vastly different computational efforts and can generally be divided into two groups: simple analytical methods and rigorous numerical methods. Simple analytical methods can give a good intuitive explanation of microwave and millimeter-wave components properties. Exact mathematical formulations in rigorous methods involve extensive numerical procedures, resulting in round-off errors, and may also need final experimental adjustments to the theoretical results. They are also time consuming and not easily included in a computer-aided design (CAD) package.

CAD of microwave components typically requires the development of suitable codes for modeling, possibly in a full-wave manner, the electrical response of the considered structure. In recent years a novel CAD model based on artificial neural network (ANN) technology has been introduced in the microwave community, for the modeling of passive and active microwave components, and microwave circuit design. Recent works by microwave researchers demonstrated the ability of ANNs to accurately model a variety of microwave components, such as microshield lines, microstrip interconnects, via interconnects, spiral inductors, power transistors and power amplifiers, coplanar waveguide circuit components [1,2,4,8,10,11].

Fuzzy inference systems (FISs) are nonlinear systems capable of inferring complex nonlinear relationships between input and output variables. The nonlinearity property is particularly important when the underlying physical mechanism to be modeled is inherently nonlinear. In this study, a new approach based on adaptive neuro-fuzzy inference system (ANFIS) was presented for the quasi-TEM characteristics of microshield lines with practical cavity sidewall profiles. Neuro-fuzzy systems are fuzzy systems which use ANNs theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of the two paradigms: fuzzy logic and ANNs, by utilizing the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way man processes information. A specific approach in neuro-fuzzy development is the ANFIS, which has shown significant results in modeling nonlinear functions. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion [6,7]. The ANFIS models were presented to produce a good approximator of the nonlinear relationship between the geometrical parameters and the quasi-TEM characteristics (characteristic impedance and cavity capacitance sensitivity) of microshield lines. The ANFIS proposed in this study does not require any formula for the computation of the characteristic impedance and the cavity capacitance sensitivity of microshield lines. The proposed system only requires the values of angle and the geometrical ratios of the microshield line. Toward achieving this aim, the ANFIS models were developed with sets of training and testing data generated by the CMT. The outputs of the ANFIS models were the characteristic impedance and the cavity capacitance sensitivity of the microshield line.

The main objectives of this study are:

- to show the applicability of the ANFIS to the computation of the characteristic impedance and the cavity capacitance sensitivity of microshield lines;
- to determine optimally the modifiable parameters of the ANFIS by using the hybrid algorithm combining the least squares method and the gradient descent method;
- to compare the results of the ANFIS and the results available in the literature obtained by using the CMT [3].

The outline of this study is as follows. In Section 2, we briefly explain the analysis of microshield line with nonvertical cavity sidewalls. In Section 3, we describe the architecture and learning algorithm of the ANFIS. In Section 4, we present the results obtained by the proposed two ANFIS models for the characteristic impedance and the cavity capacitance sensitivity of the microshield line. Finally, in Section 5 we conclude the study.

2. Analysis of microshield line with nonvertical cavity sidewalls

The configuration to be studied is shown in Fig. 2, where the lower ground plane is bent within the dielectric to form a trapezoidal cavity. All metallic conductors are assumed to be infinitely thin and perfectly conducting, and the upper ground planes to be sufficiently wide as to be considered infinite in the model. It is assumed that the air-dielectric boundary between the center conductor and the upper ground plane behaves like a perfect magnetic wall. The center conductor, of width $2a$, is placed between the two upper ground planes, of spacing $2b$, which are located on a substrate thickness h, with relative permittivity ε_r. The overall capacitance per unit length of the line can therefore be considered as the sum of the capacitance of the upper region (air) and the lower region (dielectric). The capacitance of the lower region can be evaluated through a suitable sequence of conformal mappings. First, the interior of the lower region is mapped onto the t domain (Fig. 2) by the Schwartz–Christoffel transformation and then back onto the w domain using a second mapping function. If the total capacitances of the upper and lower regions are referred to as C_1 and C_2, respectively, then the overall capacitance per unit length of the line is defined as [3]

$$C_T(\varepsilon_r) = C_1 + C_2 = 2\varepsilon_0 \frac{K(k_1)}{K'(k_1)} + 2\varepsilon_r\varepsilon_0 \frac{K(k_2)}{K'(k_2)}. \tag{1}$$

$K(k)$ is the complete elliptic integral of the first kind, $k_1 = a/b$, and $k_2 = t_a/t_b$. Hence, the effective permittivity and the characteristic impedance of the line are, respectively,

$$\varepsilon_{\text{eff}} = \frac{C_T(\varepsilon_r)}{C_T(1)}, \tag{2}$$

$$Z_0 = v_0^{-1}[C_T(\varepsilon_r)C_T(1)]^{-1/2}, \tag{3}$$

where v_0 is the speed of light in free space. The line parameters can therefore be calculated from Eqs. (1)–(3), using the simple formulas of Hilberg [5] for the ratio $K(k)/K'(k)$.

A sensitivity approach for investigating the effect of an imperfect sidewall etching process on the characteristics of a rectangular-shaped microshield line is given. The sensitivity of the lower region capacitance (C_2) with respect to sidewall angle β is shown here [3]

$$\left.\frac{1}{C_2}\frac{\mathrm{d}C_2}{\mathrm{d}\beta}\right|_{\beta=0} = \frac{k_2^2}{\pi\gamma(k_2)}\{\psi(a,t_a) - \psi(b,t_b)\}. \tag{4}$$

3. Adaptive neuro-fuzzy inference system

3.1. Architecture of ANFIS

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [6,7]. Such framework makes the ANFIS

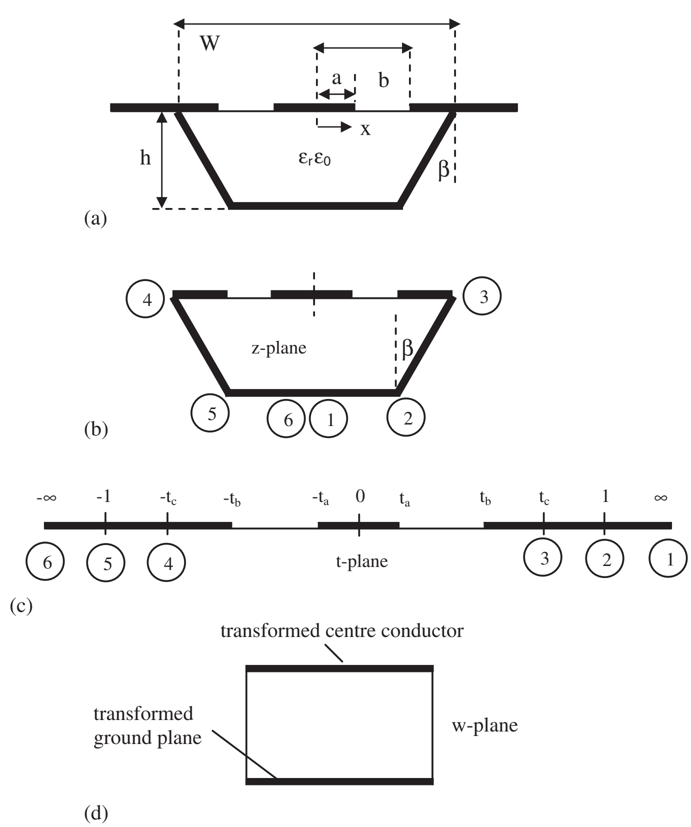

Fig. 2. Conformal mapping of microshield line with nonvertical cavity sidewalls.

modeling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy if–then rules based on a first-order Sugeno model are considered:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p_1x + q_1y + r_1$),

Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p_2x + q_2y + r_2$),where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Fig. 3, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by

$$O_i^1 = \mu_{A_i}(x), \quad i = 1, 2, \tag{5}$$

$$O_i^1 = \mu_{B_{i-2}}(y), \quad i = 3, 4, \tag{6}$$

where $\mu_{A_i}(x)$, $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function. For example, if the bell shaped membership function is employed, $\mu_{A_i}(x)$ is given by

$$\mu_{A_i}(x) = \frac{1}{1 + \{((x - c_i)/a_i)^2\}^{b_i}}, \tag{7}$$

where a_i, b_i and c_i are the parameters of the membership function, governing the bell shaped functions accordingly.

In the second layer, the nodes are fixed nodes. They are labeled with M, indicating that they perform as a simple multiplier. The outputs of this layer can be represented as

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2 \tag{8}$$

which are the so-called firing strengths of the rules.

In the third layer, the nodes are also fixed nodes. They are labeled with N, indicating that they play a normalization role to the firing strengths from the previous layer.

The outputs of this layer can be represented as

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \tag{9}$$

which are the so-called normalized firing strengths.

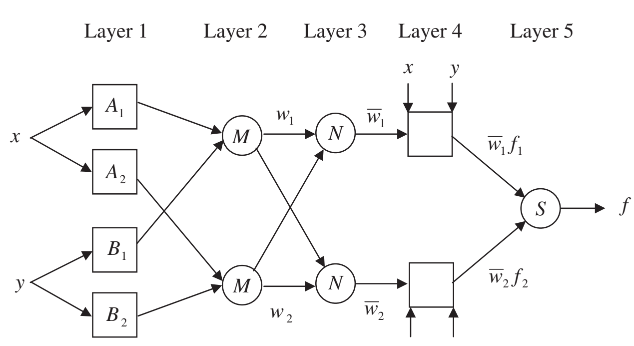

Fig. 3. ANFIS architecture.

In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial (for a first-order Sugeno model). Thus, the outputs of this layer are given by

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \quad i = 1, 2. \tag{10}$$

In the fifth layer, there is only one single fixed node labeled with S. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\left(\sum_{i=1}^{2} w_i f_i\right)}{w_1 + w_2}. \tag{11}$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters $\{a_i, b_i, c_i\}$, which are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first-order polynomial. These parameters are so-called consequent parameters [6,7].

3.2. Learning algorithm of ANFIS

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely $\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$, to make the ANFIS output match the training data. When the premise parameters a_i, b_i and c_i of the membership function are fixed, the output of the ANFIS model can be written as

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2. \tag{12}$$

Substituting Eq. (9) into Eq. (12) yields

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2. \tag{13}$$

Substituting the fuzzy if–then rules into Eq. (13), it becomes

$$f = \bar{w}_1(p_1 x + q_1 y + r_1) + \bar{w}_2(p_2 x + q_2 y + r_2). \tag{14}$$

After rearrangement, the output can be expressed as

$$f = (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2)r_2 \tag{15}$$

which is a linear combination of the modifiable consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard backpropagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [6,7].

4. Results and discussion

The proposed technique involved training two ANFIS models to compute the characteristic impedance and the cavity capacitance sensitivity of microshield lines. The trained ANFIS models establish the relationship between the presented inputs and the output. The collection of well-distributed, sufficient, and accurately measured—simulated input data is the basic requirement to obtain an accurate model. Fuzzy inference engine is a decision-making logic which performs the inference operations on the rules and a given condition to derive a reasonable output or conclusion. Three types of FISs, the Mamdani fuzzy model, the Sugeno fuzzy model, and the Tsukamoto fuzzy model, have been widely used in various applications. The differences between these three FISs lie in the consequents of their fuzzy rules, and thus their aggregation and defuzzification procedures differ accordingly. In this study, two first-ordered Sugeno-type ANFIS models with two inputs and one output were implemented. The first-ordered Sugeno fuzzy models have rules of the following:

$$R_i: \begin{array}{l} \text{IF } (x_i \text{ is } A_{i1} \text{ and } \ldots \text{and } x_m \text{ is } A_{im}) \\ \text{THEN } y \text{ is } g_i(x_i, \ldots, x_m) = b_0 + b_1x_1 + \cdots + b_mx_m \end{array}, \tag{16}$$

where R_i is the ith rule of the fuzzy system, $x_i(i = 1, 2, \ldots, m)$ are the inputs to the fuzzy system and y is the output of the fuzzy system. The linguistic terms A_{ij} are fuzzy sets, b_j denote crisp constants.

In comparison with the other FISs types, the Sugeno-style is computationally more effective; as the defuzzification process is simply finding the weighted average of a few data points, the implication method is multiplication and the aggregation operator models includes all the singletones. The effectiveness of computations is important, as time is a vital factor for real-time applications. Since we are more interested in obtaining precise solutions, a Sugeno-type fuzzy system is suitable for this purpose to obtain better performance.

In the proposed ANFIS models, the defuzzified value y is

$$y = \frac{\sum_i g_i(a_1, a_2, \ldots, a_m)\Pi_j \mu A_{ij}(a_j)}{\sum_i \Pi_j \mu A_{ij}(a_j)}, \tag{17}$$

where $\mu A_{ij}(a_j)$ is the degree of membership of a_j ($j = 1, 2, \ldots, m$) to the antecedent linguistic term A_{ij} for the ith rule of the fuzzy system.

The input vectors of the first ANFIS constructed as follows:

$$v_1 = \sum_{j=1}^{4000} (\beta_j, 2b_j/W_j), \tag{18}$$

where β is the values of angle and $2b/W$ is the geometrical ratio of the microshield line.

The input vectors of the second ANFIS constructed as follows:

$$v_2 = \sum_{j=1}^{4000} (a_j/h_j, 2b_j/W_j), \tag{19}$$

where a/h and $2b/W$ are the geometrical ratios of the microshield line.

Fig. 4 shows the fuzzy rule architecture of the two ANFIS models using a generalized bell shaped membership function defined in Eq. (7). Generalized bell shaped membership functions are popular for specifying fuzzy sets because of their smoothness and concise notation. The ANFIS models shown in Fig. 4 were implemented by using the MATLAB software package (MATLAB version 6.5 with fuzzy logic toolbox).

In designing ANFIS models, the number of membership functions, the number of fuzzy rules, and the number of training epochs are important factors to be considered. If they were not chosen carefully, the system might either over-fit the data (memorize) or not be able to fully tune the membership functions. The tuning is accomplished using a hybrid algorithm combining the least squares method and the gradient descent method with a mean square error (MSE) method. The aim of the training process is to minimize the training error between the ANFIS output and the actual (desired) target. This allows a fuzzy system to learn features from the data it observes, and implements these features in the system rules. When testing the model, a new data set that is not presented in the training set is introduced to the system. If the test error is sufficiently small, this will indicate that the system can generalize and that the system did not memorize or over-fit the training data. In order to obtain output with high accuracy, we

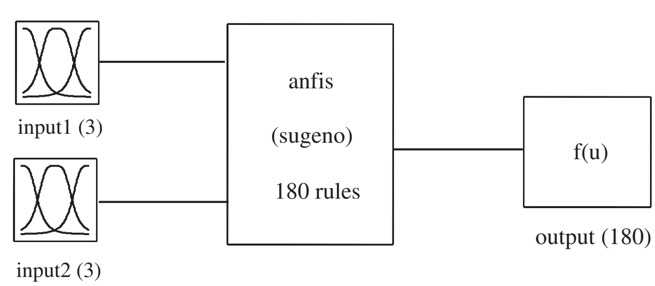

Fig. 4. Fuzzy rule architecture of the ANFIS models. System first ANFIS: 2 inputs, 1 output (characteristic impedance), 180 rules. System second ANFIS: 2 inputs, 1 output (cavity capacitance sensitivity), 180 rules.

evaluated different ANFIS models and then the best ANFIS model results were presented. It should be emphasized that better and more robust results may be obtained from the proposed model if more input data set values are supplied for training.

The first ANFIS model was developed to compute the characteristic impedance (in Ω) of a practical air-suspended microshield line when the values of angle (β) and the geometrical ratio ($2b/W$) of the microshield line (Fig. 2) were given as input. The characteristic impedance was computed for $a/h = 0.1$, $a/b = 0.8$. The CMT was used to generate data for $0.5 \leqslant 2b/W \leqslant 0.9$ and $-45 \leqslant \beta \leqslant 5$. In order to compute the characteristic impedance of the microshield line 4000 data set, consisting of input parameters and the corresponding computed values of the characteristic impedance, were generated for the first ANFIS model. The data set was divided into two separate data sets—the training data set and the testing data set. The training data set was used to train the ANFIS, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for the computation of the characteristic impedance of the microshield line. There are a total of 180 fuzzy rules in the architecture.

The first ANFIS model used 2000 training data in 500 training periods and the step size for parameter adaptation had an initial value of 0.0110. The steps of parameter adaptation are shown in Fig. 5. At the end of 500 training periods, the network error convergence curve was derived as shown in Fig. 6. From the curve, the final convergence value (MSE) is 4.9537×10^{-5}. In these applications, changes of the final (after training) generalized bell shaped membership functions with respect to the initial (before training) generalized bell shaped membership functions of the input parameters were examined. Figs. 7 and 8 show the initial (before training) and final (after training) membership functions of the two input parameters using the generalized bell shaped membership function. The examination of initial and final membership functions

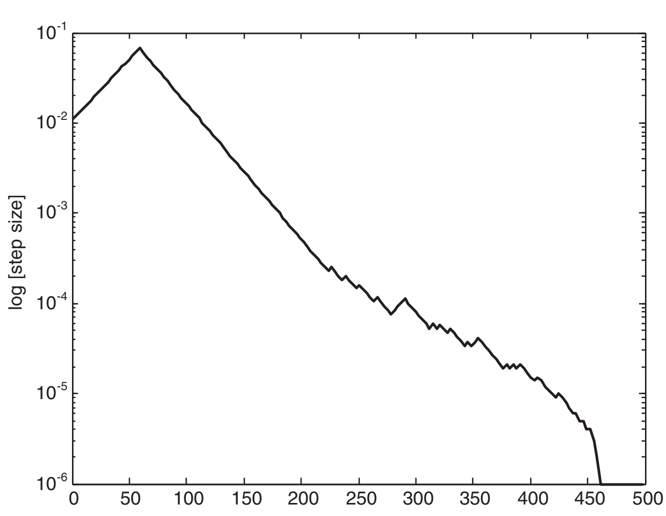

Fig. 5. Adaptation of parameter steps of the first ANFIS.

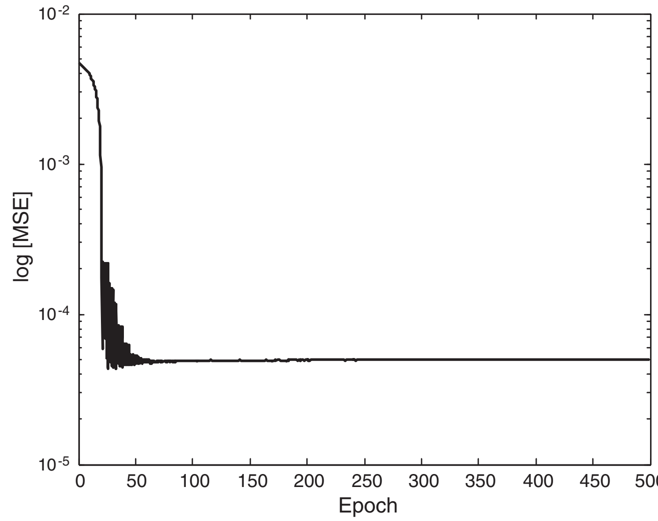

Fig. 6. The curve of network error convergence of the first ANFIS.

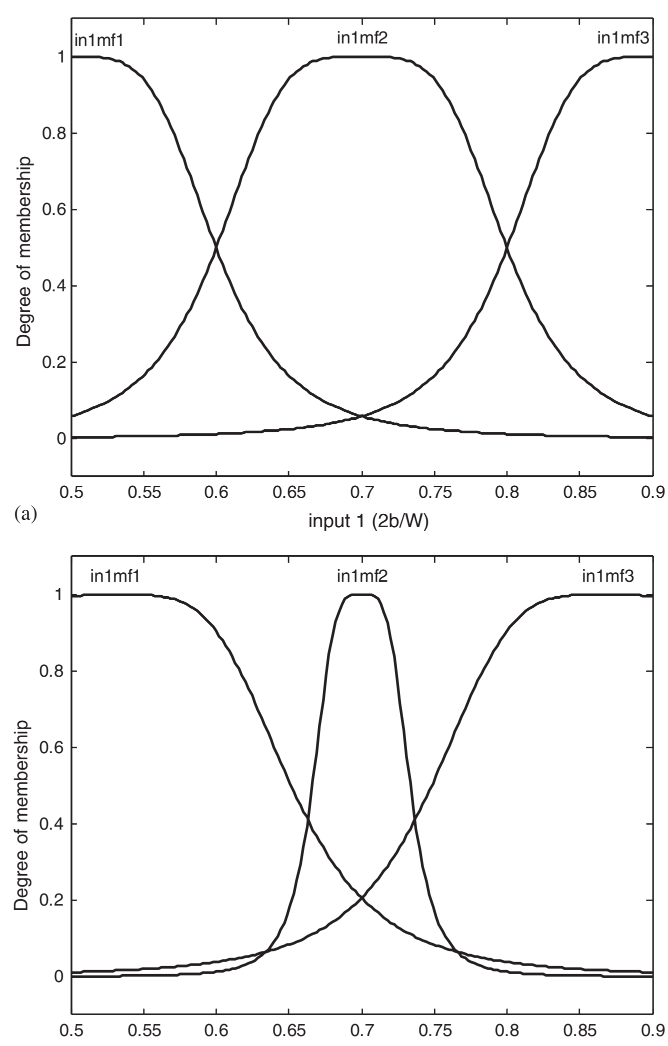

Fig. 7. (a) Initial and (b) final generalized bell shaped membership function of the geometrical ratio ($2b/W$).

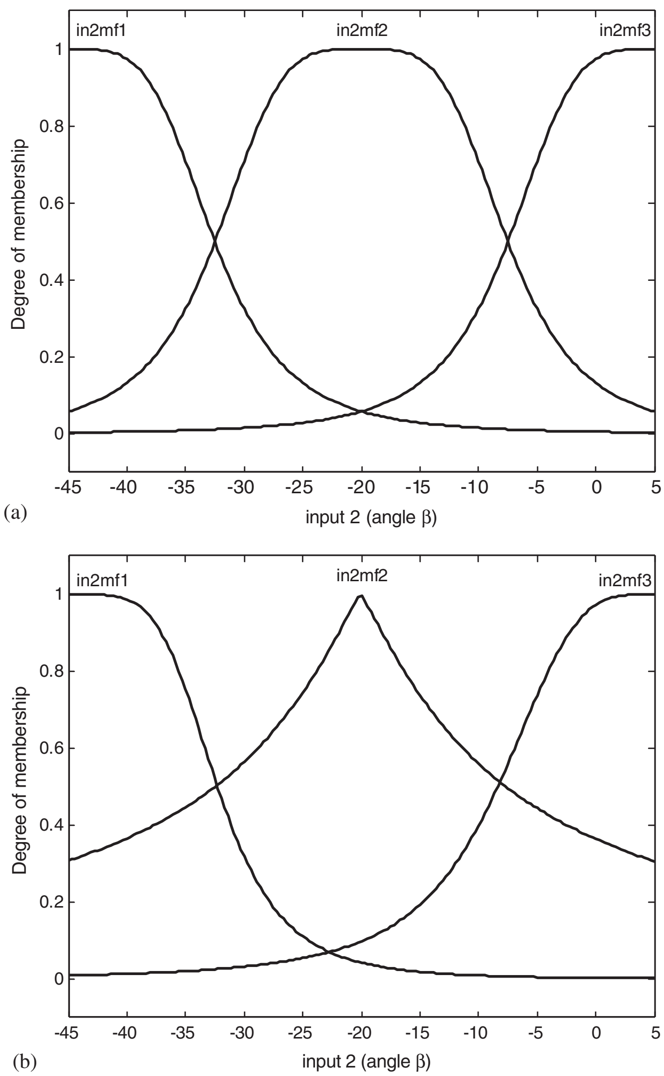

Fig. 8. (a) Initial and (b) final generalized bell shaped membership function of the angle (β).

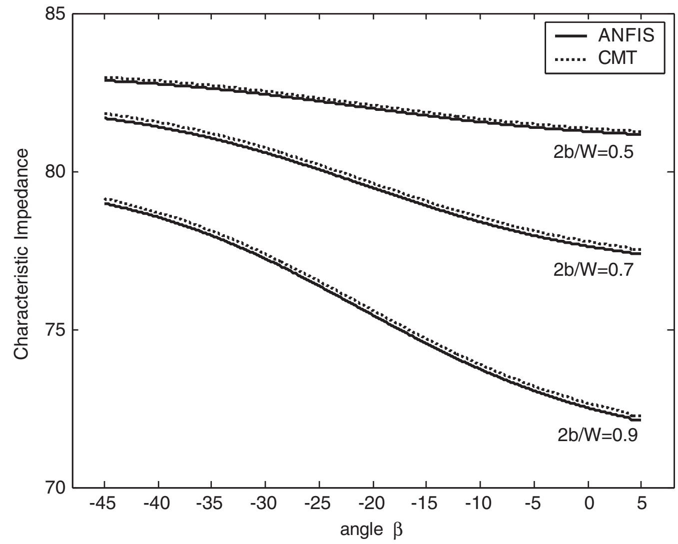

Fig. 9. Characteristic impedance (in Ω) of a practical air-suspended microshield line versus angle β (in degree) as a function of geometrical ratios $2b/W$, $a/h = 0.1$, $a/b = 0.8$.

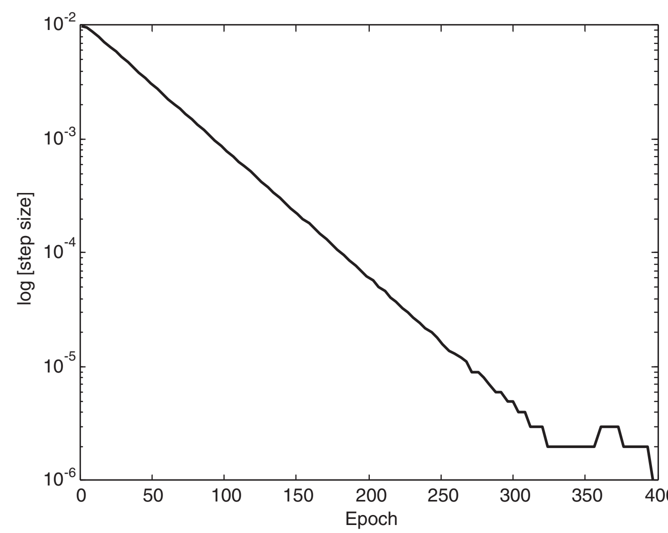

Fig. 10. Adaptation of parameter steps of the second ANFIS.

indicates that there is a considerable change in the final membership functions of the two input parameters. Analysis of Figs. 7 and 8 shows that the two input parameters have considerable impacts on the computation of the characteristic impedance of the microshield line.

After training, 2000 testing data was used to validate the accuracy of the first ANFIS model for the computation of the characteristic impedance of the microshield line. The test results of the ANFIS are compared with the results of CMT in Fig. 9 for the characteristic impedance. From this figure one can see that the results of the ANFIS presented for this application are in very good agreement with the results of CMT. The CPU times (for Pentium 4, 3.00 GHz) for computation of the characteristic impedance by CMT and ANFIS are 16:03(min:s) and 5:42(min:s), respectively. The CPU times of the models demonstrated that application of the ANFIS is useful, especially for real-time applications, for the computation of the characteristic impedance of microshield lines.

In order to to compute the cavity capacitance sensitivity of a rectangular-shaped microshield line, the second ANFIS model was developed. The values of the geometrical ratios (a/h and $2b/W$) of the microshield line were given as input. The cavity capacitance sensitivity was computed for $a/b = 0.5$. Data was generated for $0.1 \leqslant a/h \leqslant 0.5$ and $0.5 \leqslant 2b/W \leqslant 1.0$ by the usage of the CMT. For computation of the cavity capacitance sensitivity of the microshield line 4000 data set, consisting of input parameters and the corresponding computed values of the cavity capacitance sensitivity, were generated. The data set was divided into two separate data sets—the training data set and the testing data set.

The second ANFIS model used 2000 training data in 400 training periods and the step size for parameter adaptation had an initial value of 0.0099. Fig. 10 shows the steps of

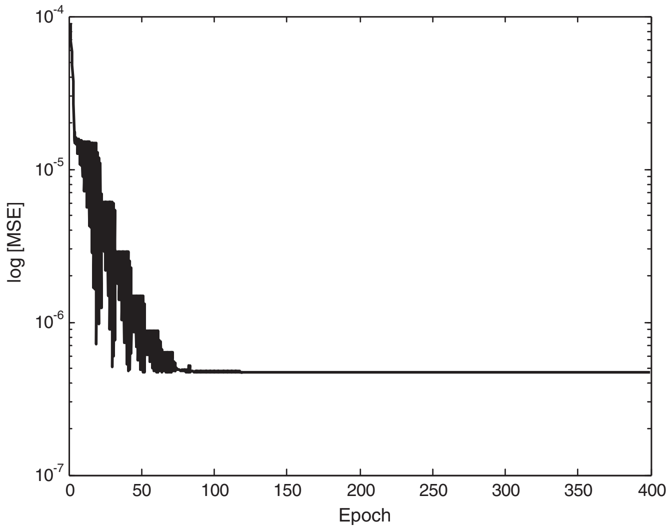

Fig. 11. The curve of network error convergence of the second ANFIS.

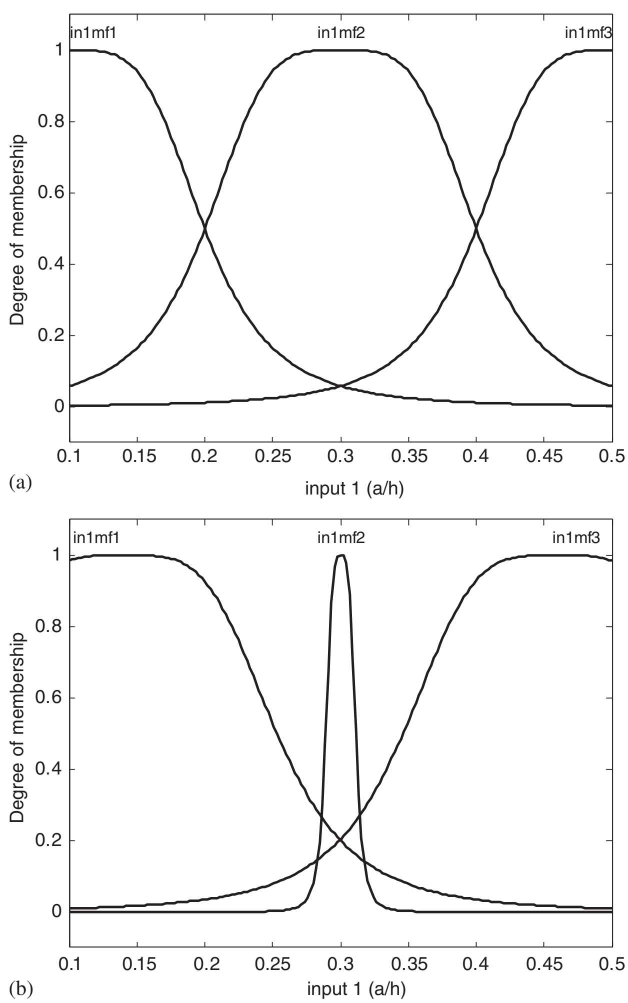

Fig. 12. (a) Initial and (b) final generalized bell shaped membership function of the geometrical ratio (a/h).

parameter adaptation. The network error convergence curve was derived as shown in Fig. 11 at the end of 400 training periods. As it is observed from the curve, the final convergence value is 4.7220×10^{-7}. The initial (before training) and final (after training) membership functions of the two input parameters using the generalized bell shaped membership function are shown in Figs. 12 and 13. From these figures, one can see that changes of the final membership functions of the two input parameters are similar. The examination of Figs. 12 and 13 indicates that the two input parameters have considerable impacts on the computation of the cavity capacitance sensitivity of the rectangular-shaped microshield line.

In order to validate the accuracy of the second ANFIS model for the computation of the cavity capacitance sensitivity of the rectangular-shaped microshield line, 2000 testing data was used. Fig. 14 presents the test results of the ANFIS and the results of CMT for the cavity capacitance sensitivity. This figure shows that the results of the ANFIS presented for this application are in very good agreement with the results of CMT. The CPU times (for Pentium 4, 3.00 GHz) for computation of the cavity capacitance sensitivity by CMT and ANFIS are 14:37(min:s) and 4:21(min:s), respectively. The comparison

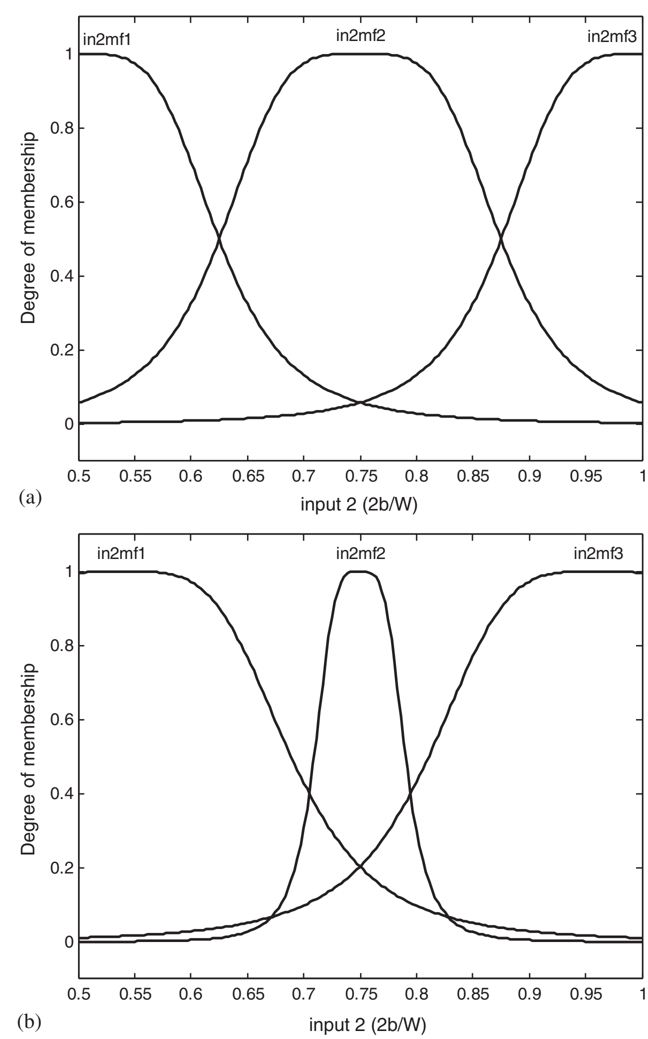

Fig. 13. (a) Initial and (b) final generalized bell shaped membership function of the geometrical ratio ($2b/W$).

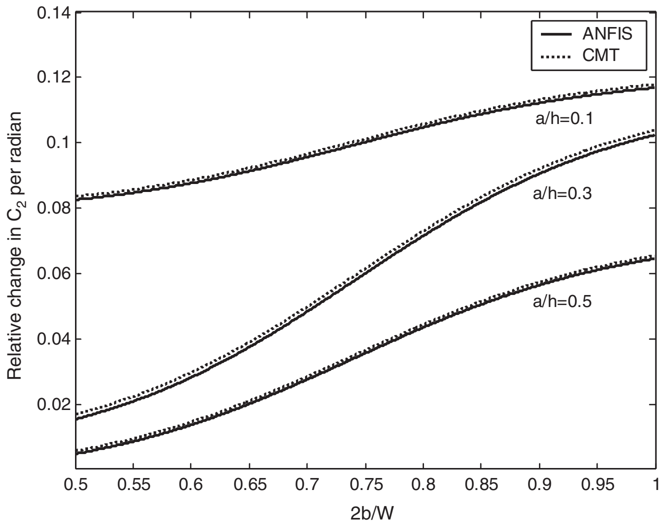

Fig. 14. Cavity capacitance sensitivity as a function of geometrical ratios $2b/W$, a/h, and $a/b = 0.5$.

of the CPU times indicated that the ANFIS model is faster than the CMT for the computation of the cavity capacitance sensitivity of the rectangular-shaped microshield lines.

5. Conclusion

We presented a new application of the ANFIS for evaluation of the quasi-TEM characteristic parameters of microshield line with practical cavity sidewall profiles. The ANFIS models are very powerful to build a complex and nonlinear relationship between inputs and outputs by learning among a set of given data. The results of the proposed ANFIS models for the characteristic impedance and the cavity capacitance sensitivity of microshield lines were in very good agreement with the results available in the literature obtained by using the CMT. Since the ANFIS models have high accuracy and require no complicated mathematical functions, they can be very useful for the development of fast CAD models. These CAD models, capable of accurately computing the characteristic impedance and the cavity capacitance sensitivity of microshield lines, are also very useful to microwave engineers. Based on the accuracy of the obtained results it can be mentioned that the ANFIS models can be used as an alternative to compute characteristic impedance and cavity capacitance sensitivity of microshield lines. This approach can be applied to many microwave components, since it is once trained, it can then be used during microwave design to provide instant answers to the task it learned.

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