EM-BASED DESIGN TOOLS FOR MICROWAVE CIRCUITS USING FUZZY LOGIC TECHNIQUES

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ABSTRACT – **This paper introduces a new approach based on fuzzy logic techniques for microwave circuit design. The Fuzzy Logic System (FLS) is constructed using data pairs generated from an EM simulator. A 3-pole microstrip filter is used to demonstrate the concept. The FLS is employed as a design tool to directly synthesize the filter physical dimensions for a required filter response. Theoretical results for three filters having different bandwidths are presented to demonstrate the validity of the proposed approach.**

Index Terms—**CAD, fuzzy logic, fuzzy logic systems, microwave filters, circuit design, computer-aided design, microwave circuits.**

I. INTRODUCTION

Over the past years, several techniques based on neural networks [1]-[2] and Cauchy methods [3]-[4] have been introduced as fast and flexible EM- based tools for microwave modeling. With the use of training data generated from the EM simulator, these techniques have been successful in building a model that can be used to replace the EM simulator. However, the role of these models has been limited to simulation allowing the prediction of the scattering parameters of the circuit for given physical dimensions, i.e. the forward problem. While these models [1]-[4] are fast and accurate they still need to be integrated with optimization tools to complete the design process.

More recently, the feasibility of using Fuzzy Logic Systems (FLS) in diagnosis and tuning of microwave filters has been demonstrated in [5]-[6]. FLS techniques can be implemented to deal directly with the reverse problem i.e. for given filter scattering parameters, the FLS model would predict the physical dimensions. In fact, the filter design problem and the filter diagnosis problem can be basically viewed as the same problem where the de-tuned filter response is replaced by the required ideal filter response while the coupling elements are replaced by the filter circuit physical dimensions. In the diagnosis problem, a theoretical coupling matrix model can be combined with measured data as well as expert information to generate the if-then rules of the FLS, while in the design problem, the if-then rules are generated using an EM simulator.

In this paper, we demonstrate how fuzzy logic techniques can be used in the design of microwave circuits. A 3-pole microstrip filter is used as an example to demonstrate the proposed approach. Data pairs were generated using HPADS, which are then grouped using subtractive clustering technique [9] to minimize the number of rules. With the use of Sugeno fuzzy logic techniques [7], the fuzzy membership functions were optimized using the initial set of data pairs as well as a set of checking data pairs.

In this paper, the fuzzy logic model was built to synthesize the dimensions of filters having different bandwidths and return loss specifications but with the same center frequency. The model can be extended to build a FLS system that can synthesis dimensions of filters having any center frequency over a limited frequency range.

II. DEFINITION OF THE PROBLEM

We consider designing a 3-pole Chebyshev microstrip filter having the layout shown in Fig. 1. As can be seen from Fig. 1, there are 4 key parameters in the design of this filter structure. These parameters are: d_1, d_2, l_1, and l_2.

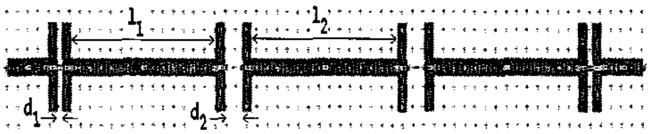

Figure 1. The 3-pole Chebyshev filter structure

To start the design process, we need to generate the proper data pairs to build our FLS. For this problem, we take some frequency samples at different frequencies of our desired performance to capture the most important features of the filter. These scattering values at the sampled frequencies are considered as inputs to our fuzzy logic system. Once we alter the 4 dimensions in Fig. 1, the scattering values at sampled frequencies also change. The outputs of our fuzzy logic system are set to be the design dimensions including the resonator lengths l_1, l_2, and gap spacings d_1, d_2, which represent the sequential couplings of the filter. With the use of this information, we obtain a record of input-output data pairs for building our fuzzy logic system. The data pairs are in the form:

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$$
\begin{aligned}
&(x_1^{(1)}, x_2^{(1)} \ldots, x_p^{(1)}; y_1^{(1)}, y_2^{(1)} \ldots, y_q^{(1)}),\\
&(x_1^{(2)}, x_2^{(2)} \ldots, x_p^{(2)}; y_1^{(2)}, y_2^{(2)} \ldots, y_q^{(2)}),\\
&\ldots\\
&(x_1^{(n)}, x_2^{(n)} \ldots, x_p^{(n)}; y_1^{(n)}, y_2^{(n)} \ldots, y_q^{(n)})
\end{aligned}
\tag{1}
$$

where we have n data pairs for a system with p sampled scattering parameters as inputs, and q unknown physical dimensions as outputs. The above-mentioned data pairs are obtained using HP-ADS. For our design problem, we consider here designing filters with a center frequency of 2 GHz. We also consider bandwidth variations of 0.6-1.2 percent. The desired return loss for this problem is 15 dB. Fig. 2 shows 3 different examples with 0.6, 0.8, and 1.13 percent bandwidths respectively. Our goal is to build a fuzzy logic system to extract the physical dimensions of the filter for different bandwidths.

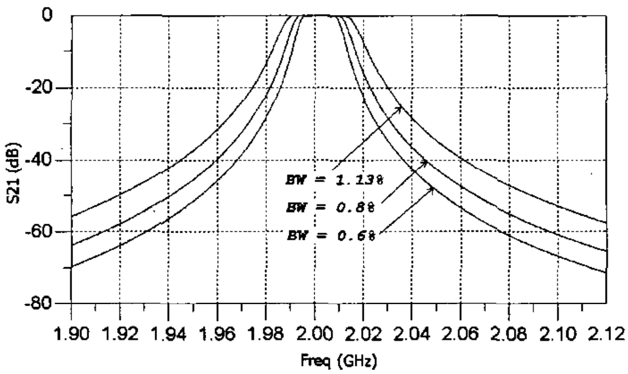

Figure 2. Filter design responses with different bandwidths

In next sections, we will show how we can get a fuzzy logic system to directly extract the design dimensions, and will compare the results with regular filter synthesis results.

III. BUILDING THE FUZZY LOGIC SYSTEM

In this paper, we use a method based on Sugeno fuzzy inference system [7]. Models that employ the Sugeno type rules have been shown to be able to accurately represent complex behavior with only a few rules [8], and therefore the complexity of the system decreases dramatically.

The consequent of rules are no longer fuzzy sets as in [5-6], but mathematical functions. The most commonly used type of these systems has rules with linear functions:

$$
\begin{aligned}
&IF\ X_1\ is\ A_1\ \&\ X_2\ is\ A_2\ \& \ldots THEN\\
&Y_1\ is\ B_1\ \&\ Y_2\ is\ B_2 \ldots
\end{aligned}
\tag{2}
$$

where X_j is the j^{th} input variable and Y_j is the j^{th} output variable, and B_j is in the form:

$$B_j = a_0 + a_1 x_1 + a_2 x_2 + \cdots \tag{3}$$

The input fuzzy sets, A_j, are characterized by Gaussian membership functions as depicted in Fig. 3.

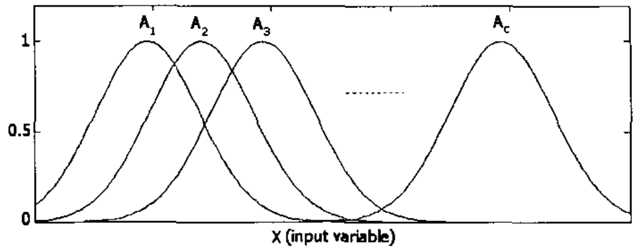

Figure 3. Typical Gaussian membership functions for inputs

Each membership function has a function of the form:

$$\mu_{A_j}(x) = \exp\left[-\frac{1}{2}\left(\frac{x-\bar{x}_j}{\sigma_j}\right)^2\right] \tag{4}$$

where $\bar{x}_j$ is the center of the membership function for fuzzy set A_j, and σ_j is the standard deviation of the Gaussian function. We need to determine the center and standard deviation of the Gaussian functions, along with the fuzzy rules to build the FLS.

In order to determine the fuzzy rules, we follow a procedure based on subtractive clustering techniques [9]. Using this procedure, we obtain the rules along with the membership function centers, with the assumption of knowing the standard deviation of the membership functions. The standard deviations for the simplest case are considered to be equal after the training data are normalized. If this assumption does not give us the desired fuzzy logic system, then theses parameters can be adjusted separately. We choose the optimal standard deviation, the one that gives us the minimum error.

The output of our is calculated using a weighted average of each rule's output similar to centroid defuzzification [6]:

$$y_j = \frac{\sum_{i=1}^{c} \mu_i y_{ij}}{\sum_{i=1}^{c} \mu_i} \tag{5}$$

where μ_i is the firing strength of each of the i^{th} rule, y_{ij} is the output value corresponding to the i^{th} rule, and c is the number of rules. In next sections, we will show the design results using our fuzzy logic system.

IV. INDENTIFICATION OF THE FUZZY LOGIC SYSTEM FOR THE 3-POLE MICROSTRIP FILTER DESIGN PROBLEM

Using the algorithm explained in previous sections, we design our FLS. For this purpose, we divide the data pairs into two different parts, one to build the fuzzy logic system, and the other to check the validity of the system function. We call the former *training data pairs*, and the latter *checking data pairs*. Using the training data pairs for different standard deviations, we obtain a set of fuzzy logic systems. To find the optimal value for standard deviations, we take advantage of the checking data pairs by making a comparison between training and checking errors for different standard deviations.

For this problem, we need to build a fuzzy system with 4 outputs, since we have 4 unknown dimensions. We use 15 frequency samples of S_{21} as inputs to our system. To generate the data, we first determine the range of the dimension values where the final design can take. Next, we use uniformly distributed random numbers for a set of input-output data. Then we obtain the sampled scattering parameters using an HP-ADS. To find the optimal fuzzy system, we separate the data pairs into training and checking pairs. The root square error has been used as a measure for checking and training data error.

For this problem, we generate 800 training data pairs to build the fuzzy system. We change the standard deviation (σ), and check the error for a checking data set consisting 200 data pairs. The error variation for training and checking data is depicted in Fig. 4.

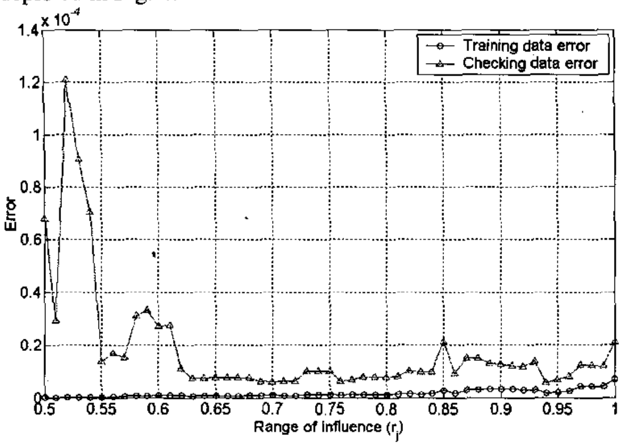

Figure. 4. Error variation for training and checking data

As can be seen from Fig. 4, the FLS is optimum, when we have the smallest error for checking data, which is corresponding to r_j=0.94, where r_j=2.83σ. The optimized fuzzy system has 12 rules.

V. RESULTS

To illustrate the performance of our FLS in the design of our 3-pole Chebyshev microstrip filter, we consider designing 3 different filters with the response plotted in Fig. 2. We also use the regular filter synthesis procedure [10] to design the same filters. Table 1 shows the physical dimensions extracted using filter synthesis, while Table 2 shows the extracted physical dimensions using our optimized fuzzy system for different bandwidths.

Table 1. Physical dimensions extracted using filter synthesis

BW	d_1*(mm)*	d_2*(mm)*	l_1*(mm)*	l_2*(mm)*
0.6%	0.65859	2.19056	17.6153	17.7520
0.8%	0.525523	1.92048	17.5498	17.7492
1.13%	0.478957	1.79602	17.5210	17.7464

Table 2. Physical dimensions extracted using the optimized fuzzy logic system

BW	d_1*(mm)*	d_2*(mm)*	l_1*(mm)*	l_2*(mm)*
0.6%	0.510000	2.17100	17.6100	17.7600
0.8%	0.445100	2.00000	17.5801	17.7600
1.13%	0.329900	1.80000	17.5199	17.7600

Figures 5-8 show a comparison between the scattering parameters corresponding to the synthesized physical dimensions and those extracted using the fuzzy logic approach.

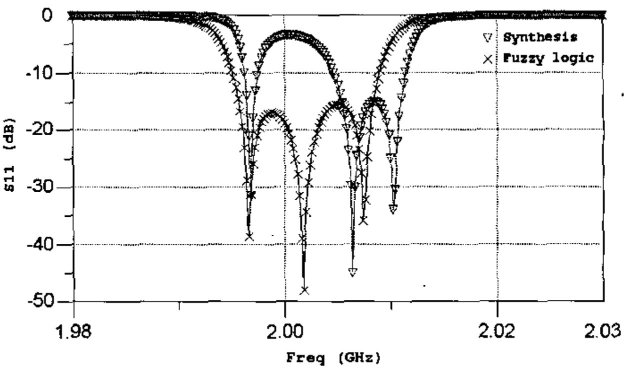

Figure 5. Comparison between the performances obtained from synthesis and the fuzzy logic system for *BW*=0.6%.

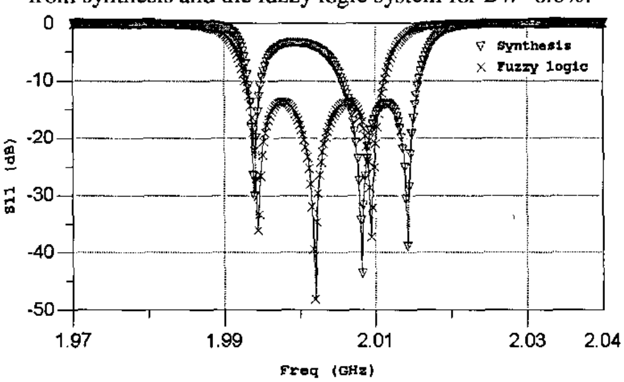

Figure 6. Comparison between the performances obtained from synthesis and the fuzzy logic system for *BW*=0.8%.

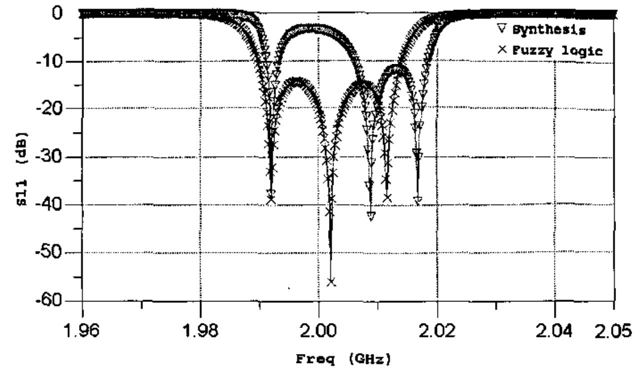

Figure 7. Comparison between the performances obtained from synthesis and the fuzzy logic system for BW=1.13%.

As it is evident from the results, the response obtained using synthesis is far from the desired response, while the fuzzy logic synthesis method gives the physical dimensions that correspond closely to our design specifications.

VI. CONCLUSION

In this paper, we have proposed a new approach for the design of microwave circuits based on fuzzy logic systems. The approach has been demonstrated by considering the design of 3-pole Chebyshev microstrip filters. The fuzzy logic system (FLS) is based on Sugeno-type rules, and subtractive clustering, which efficiently can model the performance of the system with only a few rules. The data pairs are based on EM simulation. The standard deviations of the membership functions are adjusted to find the optimal FLS with minimal error. The design dimensions extracted with the use of our optimized FLS satisfies the design requirements, while a regular filter synthesis gives a response, which is relatively far from the design goal. The fuzzy logic can be easily applied to other microwave design problems.

VII. REFERENCES

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