COMPUTER-AIDED TUNING OF MICROWAVE FILTERS USING FUZZY LOGIC

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ABSTRACT – **The paper introduces an algorithm based on Fuzzy Logic for tuning microwave filters. The approach is demonstrated by considering two filters: one is slightly de-tuned and the other is highly de-tuned. In both cases the approach proved to be very efficient in identifying the filter elements that cause the de-tuning. The fuzzy rules are extracted from sampled data. The expert rules could be also added. The algorithm can be applied to any microwave circuit tuning problem.**

I. INTRODUCTION

Computer-aided diagnosis and tuning is very essential in the fabrication of complex microwave filters. Tuning is almost necessary for any manufactured microwave circuit due to lack of highly accurate design models, manufacturing tolerances and design uncertainties. Computer-aided tuning helps to speed up the tuning process and can be incorporated to improve the design model.

For most real-world control/tuning problems, the information regarding design, evaluation, realization, etc., can be classified into two types: numerical information obtained from mathematical models or measurements, and linguistic information obtained from human experts. Most current intelligent control approaches combine the standard processing methods using the numerical data with expert systems. Fuzzy logic theory allows us to incorporate the expert information into the control/tuning problem.

Fuzzy Set Theory (FST) was first introduced by Zadeh [1]. In classical logic, sets are defined in a crisp manner, i.e. an element either belongs to a set or does not belong to it. In fuzzy logic, a membership value between '0' and '1' is assigned to each element of the set. '0' means the element does not belong to the set at all, whereas '1' means the element totally belongs to that set. Fuzzy logic interprets the numerical data as linguistic rules. Then the extracted rules will be used as a kind of system specification to calculate the output values of the system. The procedure of creating fuzzy sets from numerical data is called "fuzzification", and the process of calculating the output values from the output fuzzy sets based on some linguistic rules is called "defuzzification". More details about these procedures are described in [1],[8].

Over the past two years, several papers [2]-[6] have been published on computer-aided tuning of microwave filters employing different techniques. These techniques can be basically divided into two main categories: time domain techniques and frequency domain techniques. Filter tuning using time domain is described by Dunsmore [2]-[4], while different theoretical and computational frequency domain techniques were proposed in [5]-[6].

All the above techniques are based on implementing a mathematical model that is capable of interpreting the measured data. The Fuzzy Logic approach also allows a mathematical model to be used in generating the fuzzy rules, which in turn are used to interpret the measured data. The approach however has the additional flexibility of allowing the integration of the mathematical model with information obtained from human experts. In addition, the fuzzy logic approach is very efficient computationally, since it requires only few measured data points to identify the filter elements that cause the de-tuning. In particular, the approach is useful in cases where the filter is highly de-tuned.

II. THE FILTER TUNING PROBLEM

Consider the generalized filter network shown in Fig. 1. The filter performance can be described by a coupling matrix **M** whose elements are identified in Fig. 1. To minimize the tuning effort, accurate determination of individual resonant frequencies and coupling coefficients is essential. Tuning the filter by adjusting each parameter individually as proposed in [4]-[5] may not lead to a convergent solution in some filters, particularly in structures, where the resonant frequency of the resonator is strongly dependent on the coupling values to the adjacent resonators. The fuzzy logic approach deals with the adjustment of all filter parameters taking into consideration the dependency of the parameters on each others.

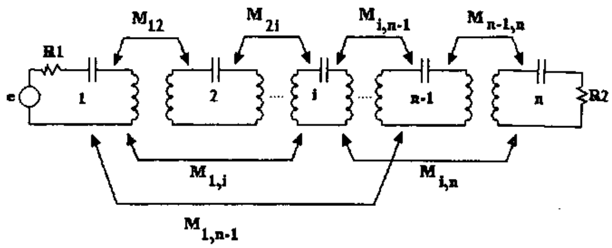

Fig. 1 A generalized model for coupled resonator filters

To illustrate the proposed fuzzy logic approach we consider in this paper the tuning of a 4-pole band-pass Chebyshev filter. The coupling matrix (M-matrix) is a symmetrical 4×4 matrix with all elements zero except m_{12}, m_{23} and m_{34}. Fig. 2 shows S_{21} versus frequency of two de-tuned filters; one with a slight deviation and the other with a high deviation from the ideal filter performance. These two examples represent the experimental data of two de-tuned filters. In order to use the tuning procedure, we need to extract the M-matrix elements associated with the experimental results. Then, with the knowledge of the ideal coupling matrix one can identify the elements that caused the de-tuning.

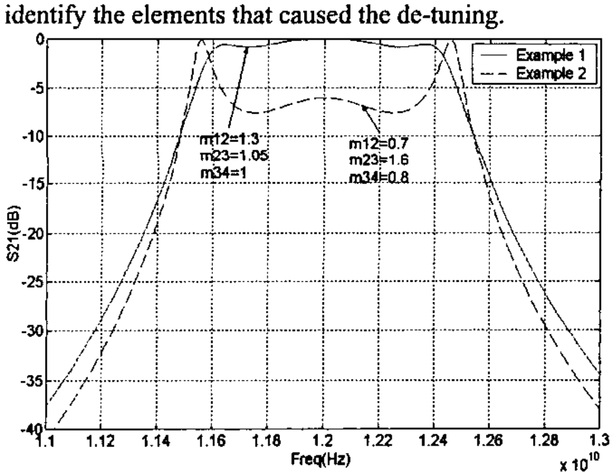

Fig. 2. Two examples of slightly de-tuned and highly de-tuned filter characteristics

III. GENERATING FUZZY RULES FROM NUMERICAL DATA

Many approaches were proposed for generating fuzzy rules from numerical data (Takagi & Sugeno 1985 [7], Wang & Mendel 1992 [8], Sugeno & Yasukawa 1993 [9], Leondes 1999 [10]).

In this paper, the fuzzy rules are generated using the method proposed by Wang and Mendel, since it allows to combine both numerical and linguistic information into a common framework—a fuzzy rule base [8]. We consider the **M**-Matrix coupling coefficients as outputs, whereas the S-parameters of the filter at different frequencies considered as inputs. We use 9 frequency points, therefore 9 inputs, $S_{21}(f_1)\ldots S_{21}(f_9)$, and 3 outputs, m_{12}, m_{23} and m_{34}. We call the inputs $x_1, x_2 \ldots x_9$, and the outputs y_1, y_2, y_3. Then we generate a set of desired input-output data pairs:

$$\begin{gathered}(x_1^{(1)}, x_2^{(1)} \ldots, x_9^{(1)}; y_1^{(1)}, y_2^{(1)}, y_3^{(1)}),\\ (x_1^{(2)}, x_2^{(2)} \ldots, x_9^{(2)}; y_1^{(2)}, y_2^{(2)}, y_3^{(2)}),\\ \ldots\\ (x_1^{(n)}, x_2^{(n)} \ldots, x_9^{(n)}; y_1^{(n)}, y_2^{(n)}, y_3^{(n)})\end{gathered} \tag{1}$$

For each input and output, we define a membership function. Using the membership functions, for each data pair we obtain a rule in the format:

$$\begin{gathered}IF\ (x_1\ is\ fs_{x1})\ and\ (x_2\ is\ fs_{x2})\ \ldots\\ and\ (x_9\ is\ fs_{x9}),\ THEN\\ (y_1\ is\ fs_{y1})\ldots and\ (y_3\ is\ fs_{y3})\end{gathered} \tag{2}$$

where fs is a fuzzy set among the fuzzy sets of each input/output variable.

Basically, we get n rules corresponding to n data pairs. However, in practice it is highly probable that there will be some conflicting rules, i.e., rules that have the same **IF** part but a different **THEN** part. To resolve the conflict, we will choose the rule with maximum degree, i.e. most probable one, among the conflicting rules. In this way, not only the conflict problem is resolved, but also the number of rules is greatly reduced.

In order to find the rules, there is another step, which is to assign membership functions to any of the input/output variables. The input membership functions are selected considering the difference between the ideal and experimental input values to get proper domain intervals for each input. "Domain interval" of a variable means that most probably the variable will lie in that interval. Note that the variables are also allowed to lie outside their domain intervals. We should also choose the output domain intervals such that most probably the output values will lie in those intervals. As an example, Fig. 3 shows the selected membership functions for x_3 at 11.67 GHz, and membership functions for y_1 i.e. m_{12}.

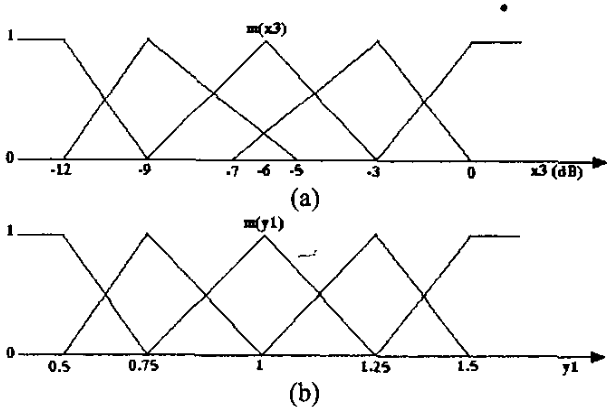

Fig.3. Membership functions a) for x_3 b) for y1

IV. CALCULATION OF OUTPUT PARMETERS

To calculate any of the outputs, we use the centroid defuzzification formula:

$$y_i = \frac{\sum_{j=1}^{K} m_j y_i^j}{\sum_{j=1}^{K} m_j} \qquad (3)$$

$$m_j = m_j(x_1) m_j(x_2) \ldots\ m_j(x_9) \qquad (4)$$

Where y_i^j denotes the center value of the fuzzy set corresponding to rule j, and output y_i. The x_k values are the input values at which the output is desired. The term $m_j(x_k)$ is the membership value of x_k to the fuzzy set corresponding to the rule j, and input x_k. K is the number of rules.

IV. TUNING RESULTS FOR THE SLIGHTLY DE-TUNED FILTER

The ideal coupling matrix of the filter is given in equation (5), while the coupling matrix of the slightly de-tuned filter (example 1) is given in equation (6). The performance associated with this coupling matrix represents the experimental performance of a slightly de-tuned filter.

By defining all membership functions for inputs and outputs, extracting the rules from the generated data, and using the defuzzification formula, we extracted the coupling matrix of the slightly de-tuned filter. The fuzzy logic approach required 70 rules and only 9 frequency sampling points i.e. 9 inputs to perform the extraction.

The extracted coupling matrix is given in equation (7), while Fig. 4 shows the extracted performance calculated using equation (7). The extracted coupling matrix provides a response that is fairly close to the experimental filter response.

$$M_{ideal} = \begin{bmatrix} 0 & 1.2 & 0 & 0 \\ 1.2 & 0 & 0.95 & 0 \\ 0 & 0.95 & 0 & 1.2 \\ 0 & 0 & 1.2 & 0 \end{bmatrix} \qquad (5)$$

$$M_{example1} = \begin{bmatrix} 0 & 1.3 & 0 & 0 \\ 1.3 & 0 & 1.05 & 0 \\ 0 & 1.05 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \qquad (6)$$

$$M_{extracted} = \begin{bmatrix} 0 & 1.28 & 0 & 0 \\ 1.28 & 0 & 1.03 & 0 \\ 0 & 1.03 & 0 & 1.118 \\ 0 & 0 & 1.118 & 0 \end{bmatrix} \qquad (7)$$

V. TUNING RESULTS FOR THE HIGHLY DE-TUNED FILTER

The coupling matrix of the highly de-tuned filter (example 2) is given in equation (8). We also used only 9 frequency points and the same 70 rules for this example. Equation (9) gives the extracted coupling matrix, while Fig. 5 illustrates a comparison between the fuzzy logic extracted performance and the experimental performance for both S_{21} and S_{11}. A very good match between the two filter characteristics is achieved.

By comparing the ideal matrix given in equation (5) and the extracted matrix given in equation (9) one can easily identify the coupling coefficients, which caused the de-tuning.

$$M_{example2} = \begin{bmatrix} 0 & 0.7 & 0 & 0 \\ 0.7 & 0 & 1.6 & 0 \\ 0 & 1.6 & 0 & 0.8 \\ 0 & 0 & 0.8 & 0 \end{bmatrix} \quad (8)$$

$$M_{extracted} = \begin{bmatrix} 0 & 0.75 & 0 & 0 \\ 0.75 & 0 & 1.645 & 0 \\ 0 & 1.645 & 0 & 0.759 \\ 0 & 0 & 0.759 & 0 \end{bmatrix} \quad (9)$$

VI. CONCLUSION

The paper has introduced Fuzzy Logic tuning to the microwave community for the first time. The approach has been successfully applied to tune a 4-pole filter for two different cases. In both cases, a very small number of measured frequency points were required to identify the coupling coefficients that caused the de-tuning. The fuzzy logic approach can be easily applied to any microwave circuit tuning problem.

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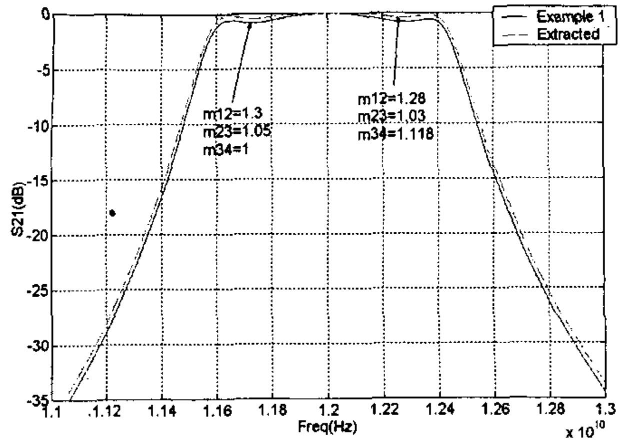
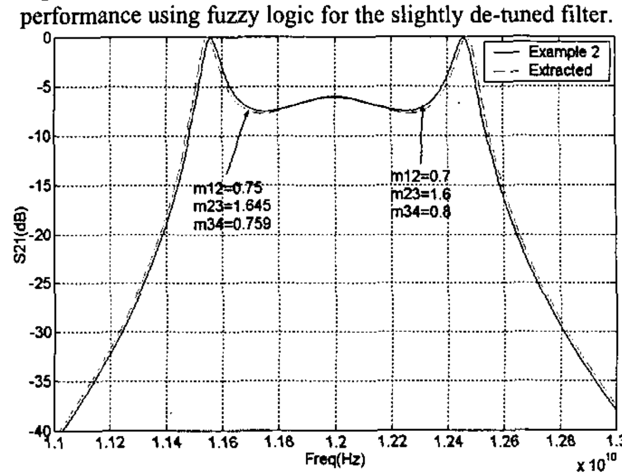
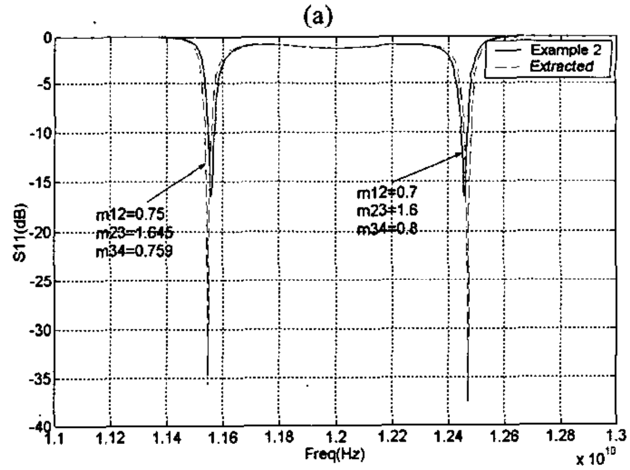


Figure 4. A Comparison between Experimental and extracted performance using fuzzy logic for the slightly de-tuned filter.



(a)



(b)

Figure 5. A Comparison between Experimental and extracted performance using fuzzy logic for the highly de-tuned filter a) S_{21} , b) S_{11}.