Computer-Aided Tuning of Microwave Filters Using Fuzzy Logic

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***Abstract*—This paper introduces an algorithm based on fuzzy logic for tuning microwave filters. The approach is demonstrated by considering two filters: a four-pole Chebyshev filter and an eight-pole elliptic filter. Each filter is then detuned to perform two examples: one is slightly detuned and the other is highly detuned. In both cases, the approach has proven to be very efficient in identifying the filter elements that cause the detuning. The fuzzy rules are extracted from sampled data. The expert rules could also be added. The algorithm can be applied to any microwave circuit tuning problem.**

***Index Terms*—Circuit tuning, computer-aided design (CAD), computer-aided tuning, fuzzy logic (FL), fuzzy-logic systems (FLS), microwave circuits, microwave filters.**

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 (FL), 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. The extracted rules will then 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] and [8].

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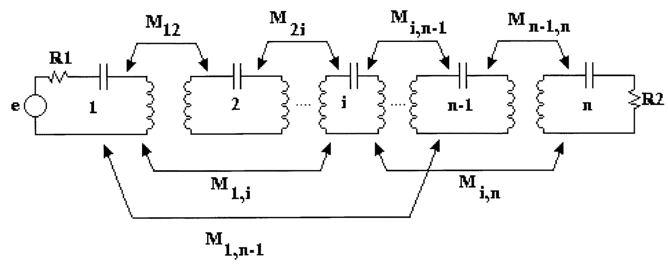


Fig. 1. Generalized model for coupled resonator filters.

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- and frequency-domain techniques. Filter tuning using the time-domain technique is described in [2]–[4], while different theoretical and computational frequency-domain techniques were proposed in [5] and [6].

All the above techniques are based on implementing a mathematical model that is capable of interpreting the measured data. The FL 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 FL approach is very efficient computationally since it requires only a few measured data points to identify the filter elements that cause the detuning. In particular, the approach is useful in cases where the filter is highly detuned.

II. Filter Tuning Problem

Consider the generalized filter network shown in Fig. 1. The filter performance can be described by a coupling matrix $\mathbf{M}$ whose elements are identified in Fig. 1. The generalized matrix is shown in (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] and [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 FL approach deals with the adjustment of all filter parameters taking into consideration the dependency of the parameters on each other as follows:

$$M = \begin{bmatrix} m_{11} & m_{12} & \cdot & \cdot & \cdot & m_{1n} \\ m_{21} & m_{22} & \cdot & \cdot & \cdot & m_{2n} \\ \cdot & & & & & \cdot \\ \cdot & & & & & \cdot \\ \cdot & & & & & \cdot \\ m_{n1} & m_{n2} & \cdot & \cdot & \cdot & m_{nn} \end{bmatrix}. \quad (1)$$

The typical structure shown in Fig. 1 consists of n coupled lossless resonators. $M_{\rm ij} = M_{\rm ji}$ denotes the frequency-independent coupling between resonator i and j. Following the analysis in [12], we can get the scattering parameters in terms of the coupling elements

$$S_{21} = -2j\sqrt{R_1 R_2}\left[A^{-1}\right]_{n1} \quad (2)$$

$$S_{11} = 1 + 2jR_1\left[A^{-1}\right]_{11} \quad (3)$$

where

$$A = \lambda I - jR + M \quad (4)$$

$$\lambda = \frac{f_0}{\rm BW}\left(\frac{f}{f_0} - \frac{f_0}{f}\right) \quad (5)$$

where I is the unity matrix and R is a matrix with all elements zero, except $R_{11} = R_1$ and $R_{nn} = R_2$.

The importance of the coupling elements in filter tuning is that the coupling elements are directly related to the position of adjustable screws. Once one of these elements deviate from the desired value, we can easily turn it back to the desired value by turning the corresponding screw.

In case of a detuned filter, we have access to the S-parameters of the detuned filter. The extraction of the coupling elements with the knowledge of scattering parameters will help us find the corresponding screws to be adjusted for tuning.

In the following sections, we will show how by using this mathematical model, we can extract the coupling elements using the FL approach.

III. FLSs

The first paper on FL was written by Zadeh [1], who is considered to be the founding father of the entire field of FL. He introduces FST as a formal way to represent uncertainty mathematically.

Recall that a crisp set A in a universe of discourse U can be defined as $A = \{x \mid x \text{ meets some condition}\}$. This tells us that if x meets the specific condition, then it belongs to set A; otherwise it does not belong to set A. Alternatively, we can introduce a "0"–"1" membership function $\mu_A(x)$ to describe the membership of x to A. If $x \in A$, then $\mu_A(x) = 1$; and if $x \notin A$, then $\mu_A(x) = 0$.

A fuzzy set F in a universe of discourse U is characterized by a membership function $\mu_F(x)$, which can take values in the interval $[0, 1]$. A fuzzy set is a generalization of a crisp set whose membership function can only accept 0 or 1. A membership function in this case measures the degree of similarity of an element in U to a fuzzy subset.

A fuzzy set F in U can be represented as $F = \{(x, \mu_F(x)) \mid x \in U\}$. When U is continuous, F is usually written as $F = \int_U \mu_F(x)/x$. In this equation, the integral sign does not mean integration; it denotes a collection of all points x associated with their related membership functions $\mu_F(x)$. When x is discrete, F is written as $F = \sum_U \mu_F(x)/x$. In this equation, the summation sign does not mean summation; it denotes the collection of all points x associated with their membership functions $\mu_F(x)$.

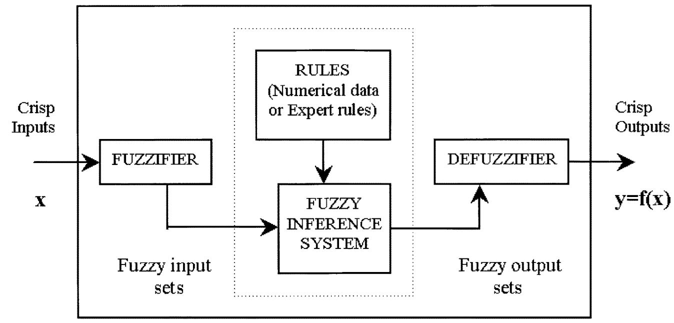


Fig. 2. Block diagram of an FLS.

An FLS, in general, is a nonlinear mapping of an input data vector into a scalar output. Fig. 2 depicts the block diagram of such a system. If we have a vector output, we can decompose it into a collection of independent multiinput/single-output systems. An FLS can also be described as a function approximator.

Here, we briefly describe different blocks in an FLS. The *fuzzifier* maps the crisp input numbers into fuzzy sets. The *rules* are in the form of IF–THEN rules that relate input fuzzy sets to output fuzzy sets at different conditions and are also called *fuzzy associative memory*. The *inference system* maps the input fuzzy sets into output fuzzy sets. This block combines the rules in a specific way to obtain the output fuzzy sets. The *defuzzifier* maps fuzzy output sets into crisp output numbers. This step is necessary since we need to obtain crisp numbers in most engineering applications.

It can be shown that an FLS can be represented as a fuzzy basis function (FBF) expansion in the following form [11]:

$$y = f(\mathbf{x}) = \sum_{l=1}^{M} \bar{y}^l \phi_l(\mathbf{x}) \quad (6)$$

where $\phi_l(\mathbf{x})$ is called an FBF, M is the number of rules, and $\bar{y}^l$ is the coefficient corresponding to each rule. It has been proven for many types of FLSs that they can be treated as *universal function approximators*. Therefore, an FLS can approximate any real continuous nonlinear function to arbitrary degree of accuracy [11].

IV. Generating Fuzzy Rules From Numerical Data

Many approaches were proposed for generating fuzzy rules from numerical data (i.e., Takagi and Sugeno in 1985 [7], Wang and Mendel in 1992 [8], Sugeno and Yasukawa in 1993 [9], and Leondes in 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 $\mathbf{M}$-matrix coupling coefficients as outputs, whereas the S-parameters of the filter at different frequencies considered as inputs. Suppose we have p frequency sampling points, i.e., p inputs and q unknown coupling coefficients as outputs. We can either extract the input information from S_{21} or S_{11}. The inputs then will be in the form $S(f_1), \ldots, S(f_p)$, which can be written in the form $x_1, x_2, \ldots, x_p$ for simplicity. The outputs, which are the coupling coefficients, could also be written in the form $y_1, y_2, \ldots, y_q$ for simplicity. We can now alter each coupling coefficient around the ideal design depending on the degree of mistuning and generate a number of input–output data pairs

$$\begin{aligned}&\left(x_1^{(1)}, x_2^{(1)}, \ldots, x_p^{(1)}; y_1^{(1)}, y_2^{(1)}, \ldots, y_q^{(1)}\right)\\&\left(x_1^{(2)}, x_2^{(2)}, \ldots, x_p^{(2)}; y_1^{(2)}, y_2^{(2)}, \ldots, y_q^{(2)}\right)\\&\ldots\\&\left(x_1^{(n)}, x_2^{(n)}, \ldots, x_p^{(n)}; y_1^{(n)}, y_2^{(n)}, \ldots, y_q^{(n)}\right).\end{aligned} \tag{7}$$

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

$$\begin{aligned}&\text{IF } (x_1 \text{ is } fs_{x1}) \text{ and } (x_2 \text{ is } fs_{x2}) \ldots\\&\text{and } (x_p \text{ is } fs_{xp}), \text{ THEN}\\&(y_1 \text{ is } fs_{y1}) \ldots \text{ and } (y_q \text{ is } fs_{yq})\end{aligned} \tag{8}$$

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 choose among the conflicting rules the rule with maximum degree based on the membership values of input–output data pairs [8]. 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 identifies the range that the variable could possibly take. Note that the variables are also allowed to lie outside their domain intervals. If a data pair fits in all of the input intervals corresponding to inputs, then that data pair will take effect in output calculation. In other words, the corresponding rule to the data pair will be fired. The output domain intervals are also selected based on the same approach. The firing rules correspond to different data pairs that resemble the experimental performance of the circuit, i.e., in this case, S-parameters. The defuzzification part of the FLS will combine the fired rules information to calculate the output of the system.

V. Setting up the Tuning Problems

To illustrate the proposed FL approach in this paper, we first consider the tuning of a four-pole bandpass Chebyshev filter. The coupling matrix ($\mathbf{M}$-matrix) is a symmetrical 4×4 matrix with all elements zero, except m_{12}, m_{23}, and m_{34}.

Fig. 3 depicts S_{21} versus the frequency of two detuned filters: one with a slight deviation and the other with a high deviation from the ideal filter performance.

As a more complicated example, we consider an eight-pole bandpass elliptic filter, which also has coupling between non-adjacent resonators. The coupling matrix for this example is a symmetrical 8×8 matrix with all elements 0, except the ones

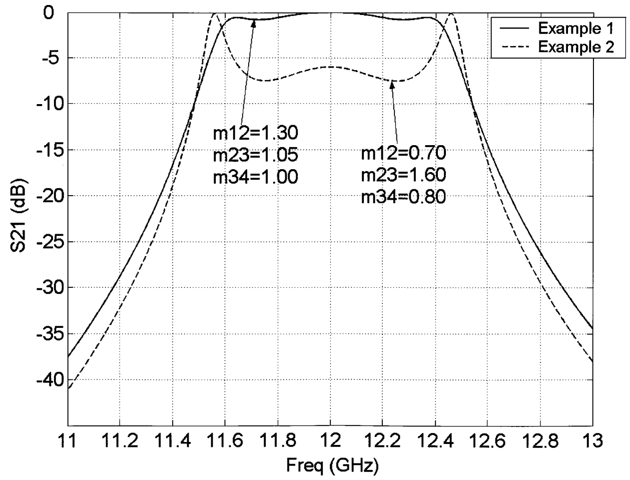


Fig. 3. Two examples of slightly detuned and highly detuned four-pole Chebyshev filter characteristics.

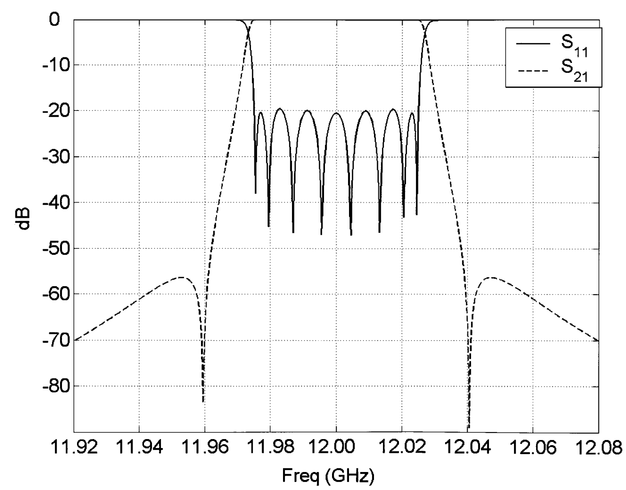


Fig. 4. Ideal eight-pole elliptic-filter characteristic.

shown in (9). Fig. 4 shows S_{11} and S_{22} of the ideal design filter with the center frequency of 12 GHz as follows:

$$M = \begin{bmatrix} 0 & m_{12} & 0 & 0 & 0 & 0 & 0 & 0 \\ m_{12} & 0 & m_{23} & 0 & 0 & 0 & m_{27} & 0 \\ 0 & m_{23} & 0 & m_{34} & 0 & m_{36} & 0 & 0 \\ 0 & 0 & m_{34} & 0 & m_{45} & 0 & 0 & 0 \\ 0 & 0 & 0 & m_{45} & 0 & m_{34} & 0 & 0 \\ 0 & 0 & m_{36} & 0 & m_{34} & 0 & m_{23} & 0 \\ 0 & m_{27} & 0 & 0 & 0 & m_{23} & 0 & m_{12} \\ 0 & 0 & 0 & 0 & 0 & 0 & m_{12} & 0 \end{bmatrix}. \tag{9}$$

We also assume that the filter is symmetrical, thus,

$$m_{i,j} = m_{(n+1-i),(n+1-j)}. \tag{10}$$

As a result, the nonzero variables in the $\mathbf{M}$-matrix are m_{12}, m_{23}, m_{34}, m_{45}, m_{36}, and m_{27}. Fig. 5 depicts the frequency response of the eight-pole filter in two cases of slightly detuned and highly detuned.

These two examples represent the experimental data of two detuned filters each with two different deviations. In order to use the tuning procedure, we need to extract the $\mathbf{M}$-matrix elements associated with the experimental results. With the knowledge of

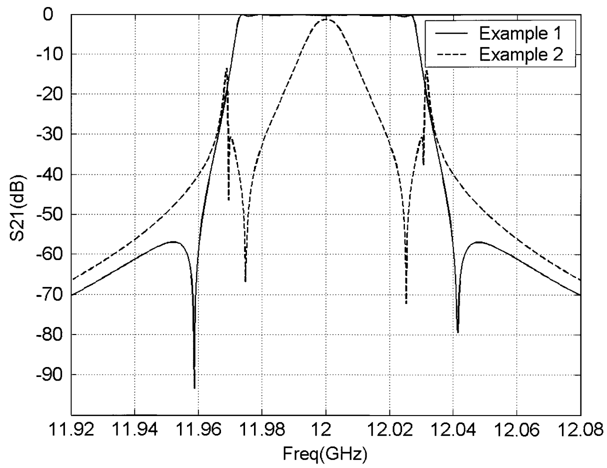


Fig. 5. Two examples of slightly detuned and highly detuned eight-pole elliptic-filter characteristics.

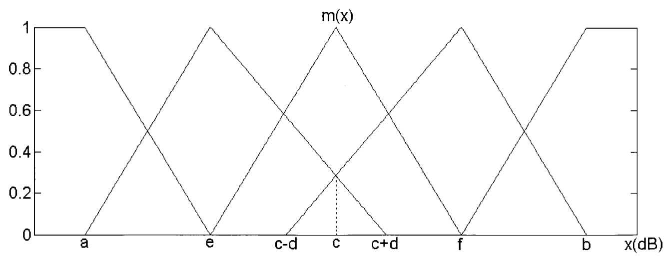


Fig. 6. General shape of input membership functions for four-pole Chebyshev filter example.

the ideal coupling matrix, one can then identify the elements that caused the detuning.

VI. Assigning the Membership Functions and Defuzzification Process

In assigning the membership functions or fuzzy sets, we use 4–5 input fuzzy sets, five output fuzzy sets, and triangular membership functions.

For the four-pole filter example, we choose five fuzzy sets for each input with the third fuzzy set centered on the measured value of the input. The membership functions are in the shape depicted in Fig. 6.

In Fig. 6, c is the measured value of S_{21} at a specific frequency. The domain interval $b-a$ is selected considering the difference between the measured and ideal S_{21}. The value d is usually a small fraction of the domain interval to let the measured input value belong to the three middle fuzzy sets at the same time. The values e and f are chosen around the middle of a, c and b, c, respectively.

The output membership functions are symmetrical triangular functions with centers at coupling element values by which the data pairs are generated. As an example, Fig. 7 depicts the output membership function of the coupling element y_1, i.e., m_{12}.

For the eight-pole filter example, we choose four fuzzy sets for each input with the measured value of the input at the middle of two centers of adjacent fuzzy sets, as shown in Fig. 8.

In Fig. 8, c is the measured value of S_{21} at a specific frequency. The domain interval $b-a$ is also selected considering

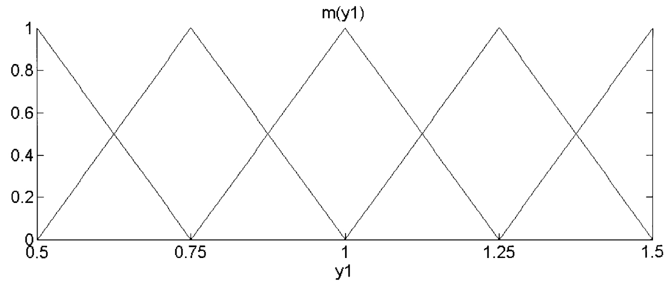


Fig. 7. Output membership functions for y_1 corresponding to the four-pole Chebyshev filter.

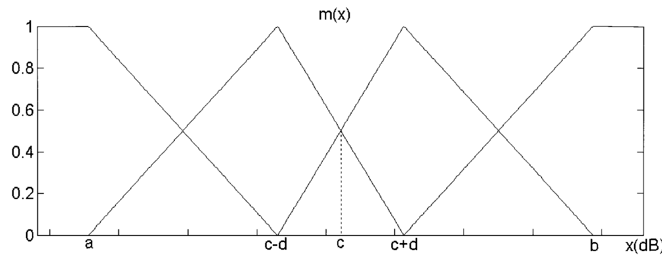


Fig. 8. General shape of input membership functions for eight-pole elliptic-filter example.

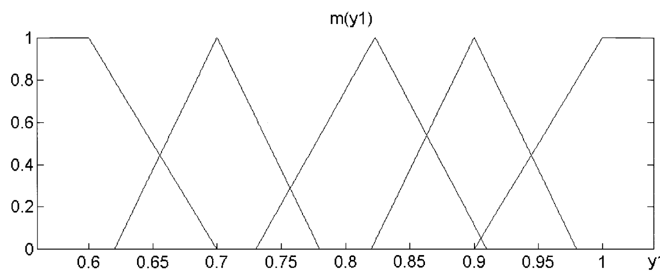


Fig. 9. Output membership functions for y_1 corresponding to the eight-pole elliptic filter.

the difference between the measured and ideal S_{21}. The value d is usually a small fraction of the domain interval to let the measured input value belong to the two middle fuzzy sets at the same time.

The output membership functions in this example are also chosen as symmetrical triangular functions each centered at the coupling element sampling points. As an example, Fig. 9 shows the output membership functions of the coupling element y_1, i.e., m_{12}.

Note that, in general, the choice of membership functions, as well as their location and spreads, is a related problem and can be adaptively implemented in our algorithm. This issue has been referred to as *tuning the parameters of an FLS using training data*, and is addressed in [13]–[15].

In our FLS, we use Singleton fuzzification, sum–product composition, and product inference [11]. To calculate any of the outputs, we use the centroid defuzzification formula

$$y_i = \frac{\sum_{j=1}^{K} m_j y_i^j}{\sum_{j=1}^{K} m_j} \tag{11}$$

$$m_j = m_j(x_1) m_j(x_2), \ldots, m_j(x_9) \tag{12}$$

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. Note that as long as the output membership functions are symmetrical, the shapes of the individual membership functions are arbitrary such as triangular, trapezoidal, and Gaussian functions, and y_i^j is simply the center of each membership function. If we chose a nonsymmetrical membership, then we would need to calculate the center of gravity of each membership function as y_i^j. By choosing symmetrical membership functions, we need less computation.

VII. Tuning Results for the Slightly Detuned Four-Pole Chebyshev Filter

The ideal coupling matrix of the filter is given in (13), while the coupling matrix of the slightly detuned filter (example 1) is given in (14). The performance associated with this coupling matrix represents the experimental performance of a slightly detuned filter.

By defining all membership functions for inputs and outputs, extracting the rules from the generated data, and using the defuzzification formula, one can easily extract the coupling matrix of the slightly detuned filter. The FL approach required 70 rules and only nine frequency sampling points, i.e., nine inputs to perform the extraction.

The extracted coupling matrix is given in (15), while Fig. 10 shows the extracted performance calculated using (2)–(5) and (15). The extracted coupling matrix provides a response that is fairly close to the experimental filter response

$$M_{\text{ideal}} = \begin{bmatrix} 0 & 1.2 & 0 & 0 \\ 1.2 & 0 & 0.95 & 0 \\ 0 & 0.95 & 0 & 1.2 \\ 0 & 0 & 1.2 & 0 \end{bmatrix} \tag{13}$$

$$M_{\text{example1}} = \begin{bmatrix} 0 & 1.3 & 0 & 0 \\ 1.3 & 0 & 1.05 & 0 \\ 0 & 1.05 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{14}$$

$$M_{\text{extracted}} = \begin{bmatrix} 0 & 1.28 & 0 & 0 \\ 1.28 & 0 & 1.03 & 0 \\ 0 & 1.03 & 0 & 1.118 \\ 0 & 0 & 1.118 & 0 \end{bmatrix}. \tag{15}$$

For this example, the inputs are selected to be the magnitude of S_{21} at different frequencies with seven frequencies inside the passband and the other two outside the passband.

VIII. Tuning Results for the Highly Detuned Four-Pole Chebyshev Filter

The coupling matrix of the highly detuned filter (example 2) is given in (16). We also used only nine frequency points and 70 rules for this example. Equation (17) gives the extracted coupling matrix, while Fig. 11 illustrates a comparison between the FL extracted performance and the experimental performance for both S_{21} and S_{11}. A very good match between the two filter characteristics is achieved.

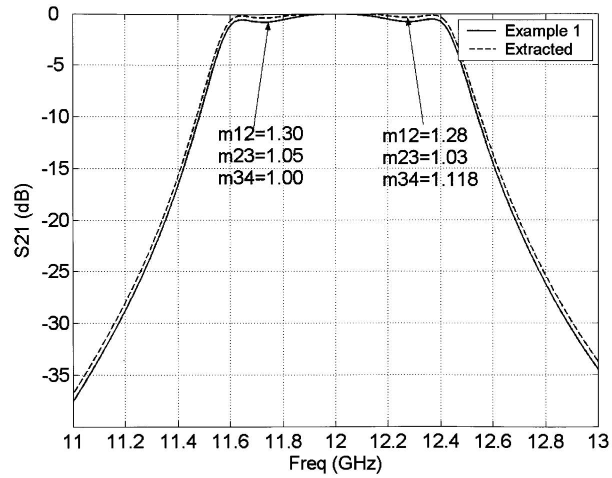


Fig. 10. Comparison between experimental and extracted performance using FL for the slightly detuned filter.

By comparing the ideal matrix given in (13) and the extracted matrix given in (17), one can easily identify the coupling coefficients that caused the detuning.

For this example, we used the same frequency sampling points as the slightly detuned example. We also used S_{21} as inputs as follows:

$$M_{\text{example2}} = \begin{bmatrix} 0 & 0.7 & 0 & 0 \\ 0.7 & 0 & 1.6 & 0 \\ 0 & 1.6 & 0 & 0.8 \\ 0 & 0 & 0.8 & 0 \end{bmatrix} \tag{16}$$

$$M_{\text{extracted}} = \begin{bmatrix} 0 & 0.75 & 0 & 0 \\ 0.75 & 0 & 1.645 & 0 \\ 0 & 1.645 & 0 & 0.759 \\ 0 & 0 & 0.759 & 0 \end{bmatrix}. \tag{17}$$

IX. Tuning Results for the Slightly Detuned Eight-Pole Elliptic Filter

The ideal coupling matrix of the filter is given in Table I, while the coupling matrix of the slightly detuned filter (example 1) is given in Table II. The performance associated with this coupling matrix represents the experimental performance of a slightly detuned filter.

By defining all membership functions for inputs and outputs, extracting the rules from the generated data, and using the defuzzification formula, we can easily extract the coupling matrix of the slightly detuned filter. For each of the six unknowns i.e., coupling elements in (9), we chose five sampling points within the range of $\pm 10\%$ of the ideal coupling elements. We assume that the coupling elements to be extracted are within this range. Therefore, the number of data pairs in this case is $5^6 = 15\,625$. These data pairs are generated very fast using the center values of the fuzzy sets associated with the coupling elements incorporated into (2)–(5). We need to generate these data pairs only once. We first consider nine frequency points, i.e., nine inputs. To obtain a better selectivity in the case of a slightly detuned filter, we choose the magnitude of S_{11} at frequency points in the passband as inputs. After omitting the contradicting rules, the number of rules reduces to 1016 rules. For the inputs we have chosen, 24 of these rules are fired to extract the outputs.

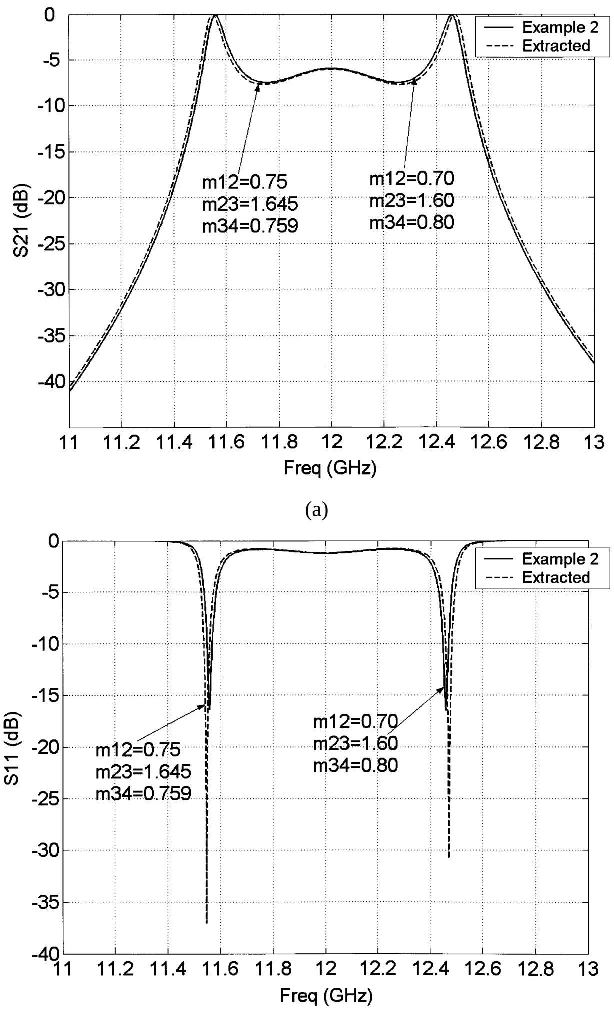


Fig. 11. Comparison between experimental and extracted performance using FL for the highly detuned filter. (a) S_{21}. (b) S_{11}.

TABLE I
$M_{\rm ideal}$ OF THE EIGHT-POLE ELLIPTIC-FILTER EXAMPLE

0	.8231	0	0	0	0	0	0
.8231	0	.5917	0	0	0	-.0251	0
0	.5917	0	.5516	0	.0781	0	0
0	0	.5516	0	.4925	0	0	0
0	0	0	.4925	0	.5516	0	0
0	0	.0781	0	.5516	0	.5917	0
0	-.0251	0	0	0	.5917	0	.8231
0	0	0	0	0	0	.8231	0

The extracted coupling matrix is given in Table III, while Fig. 12 shows the extracted performance calculated using the coupling matrix given in Table III and (2)–(5). The extracted coupling matrix provides a close response to the experimental filter response of S_{21}, as shown in Fig. 12(a), but not as much close response to the experimental response of S_{11}, as shown in Fig. 12(b).

To perform a better response, we increase the number of frequency points to 17. Increasing the number of frequency points

TABLE II
$M_{\rm example1}$ OF THE EIGHT-POLE ELLIPTIC-FILTER EXAMPLE (SLIGHTLY DETUNED)

0	.8000	0	0	0	0	0	0
.8000	0	.6000	0	0	0	-.0263	0
0	.6000	0	.6000	0	.0720	0	0
0	0	.6000	0	.5000	0	0	0
0	0	0	.5000	0	.6000	0	0
0	0	.0720	0	.6000	0	.6000	0
0	-.0263	0	0	0	.6000	0	.8000
0	0	0	0	0	0	.8000	0

TABLE III
$M_{\rm extracted}$ OF THE EIGHT-POLE FILTER EXAMPLE (SLIGHTLY DETUNED, NINE INPUTS)

0	.8004	0	0	0	0	0	0
.8004	0	.5762	0	0	0	-.0263	0
0	.5762	0	.5559	0	.0765	0	0
0	0	.5559	0	.4945	0	0	0
0	0	0	.4945	0	.5559	0	0
0	0	.0765	0	.5559	0	.5762	0
0	-.0263	0	0	0	.5762	0	.8004
0	0	0	0	0	0	.8004	0

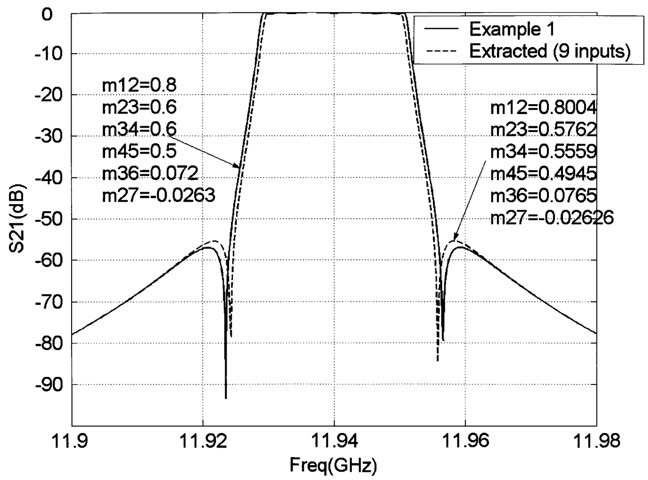
(inputs) can benefit us in the following two ways.

- The possibility of rule contradiction will decrease and, thus, we get more rules out of the basic rules extracted from the data pairs. More rules could give us a more accurate system. Note that by increasing the number of inputs, the number of rules cannot exceed the number of sampling points.
- For a rule to be fired, we need all the conditions of (8) at the antecedent to be satisfied. Therefore, more inputs lead to more conditions to be satisfied. This, in turn, reduces the probability for a rule to be fired. In other words, the rules will be more selective.

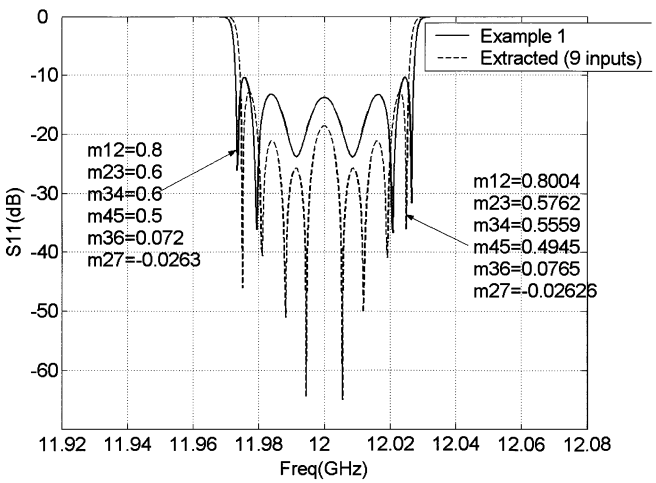
For this case, after omitting the contradicting rules, we get 2235 rules, which is about two times more than the number of rules for nine inputs. For the same input, in this case, 49 rules are fired to calculate the outputs. The extracted coupling matrix for 17 inputs is given in Table IV, while Fig. 13 shows the extracted performance calculated using the coupling matrix given in Table IV and (2)–(5). The extracted coupling matrix provides very close responses to the experimental responses of S_{21} and S_{11}, as shown in Fig. 13(a) and (b), respectively. A comparison between Figs. 12 and 13 demonstrates the effect of increasing the number of inputs, as it shows a better match for both S_{21} and S_{11} characteristics.

X. TUNING RESULTS FOR THE HIGHLY DETUNED EIGHT-POLE ELLIPTIC FILTER

The coupling matrix of the highly detuned filter (example 2) is given in Table V. We used 17 frequency points as well. The number of rules after resolving the contradictions becomes

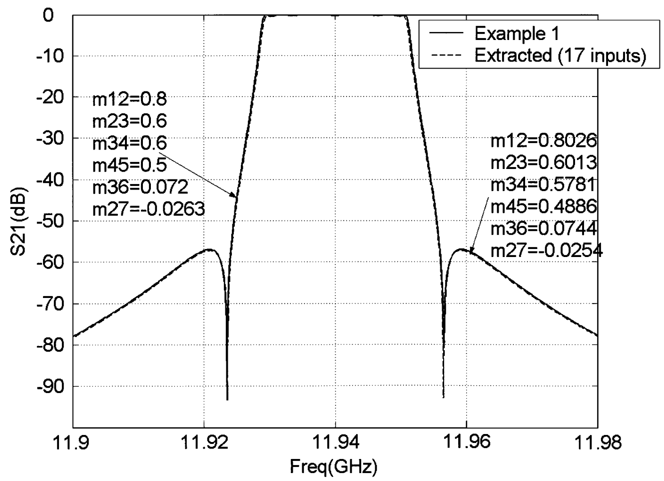


(a)

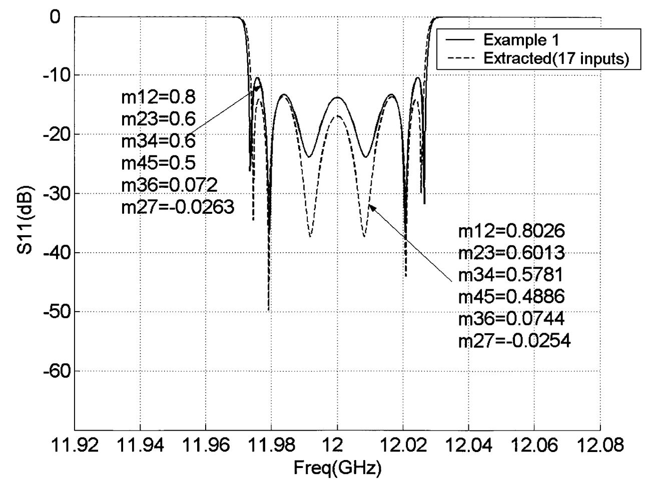


(b)

Fig. 12. Comparison between experimental and extracted performance of the eight-pole filter using FL with nine inputs for the slightly detuned filter. (a) S_{21}. (b) S_{11}.



(a)



(b)

Fig. 13. Comparison between experimental and extracted performance of the eight-pole filter using FL with 17 inputs for the slightly detuned filter. (a) S_{21}. (b) S_{11}.

TABLE IV
$M_{\text{extracted}}$ OF THE EIGHT-POLE ELLIPTIC-FILTER EXAMPLE
(SLIGHTLY DETUNED, 17 INPUTS)

0	.8026	0	0	0	0	0	0
.8026	0	.6013	0	0	0	-.0254	0
0	.6013	0	.5781	0	.0744	0	0
0	0	.5781	0	.4886	0	0	0
0	0	0	.4886	0	.5781	0	0
0	0	.0744	0	.5781	0	.6013	0
0	-.0254	0	0	0	.6013	0	.8026
0	0	0	0	0	0	.8026	0

TABLE V
M_{example1} OF THE EIGHT-POLE ELLIPTIC-FILTER EXAMPLE
(HIGHLY DETUNED)

0	.5000	0	0	0	0	0	0
.5000	0	.7000	0	0	0	.1000	0
0	.7000	0	1.0000	0	-.1000	0	0
0	0	1.0000	0	.1000	0	0	0
0	0	0	.1000	0	1.0000	0	0
0	0	-.1000	0	1.0000	0	.7000	0
0	.1000	0	0	0	.7000	0	.5000
0	0	0	0	0	0	.5000	0

3066. For the inputs we have chosen, ten of these rules are fired to extract the outputs. Table VI gives the extracted coupling matrix, while Fig. 14 illustrates a comparison between the FL extracted performance and the experimental performance for S_{21}. A very good match between the two filter characteristics is achieved. Comparing the number of firing rules in the case of the highly detuned filter with the case of the slightly detuned filter, we can observe that, although we have more rules in this example, the number of firing rules are less. The reason for this is that, in the case of the highly detuned filter, we need bigger domain intervals for inputs and outputs, while keeping the number of membership functions the same. This will result to having less data pairs that resemble the experimental performance of the filter or less firing rules.

By comparing the ideal matrix given in Table I and the extracted matrix given in Table VI, one can easily identify the coupling coefficients that caused the detuning.

TABLE VI
$M_{\mathrm{extracted}}$ OF THE EIGHT-POLE ELLIPTIC-FILTER EXAMPLE (HIGHLY DETUNED)

0	.4722	0	0	0	0	0	0
.4722	0	.6324	0	0	0	.0972	0
0	.6324	0	.9280	0	-.1222	0	0
0	0	.9280	0	.1222	0	0	0
0	0	0	.1222	0	.9280	0	0
0	0	-.1222	0	.9280	0	.6324	0
0	.0972	0	0	0	.6324	0	.4722
0	0	0	0	0	0	.4722	0

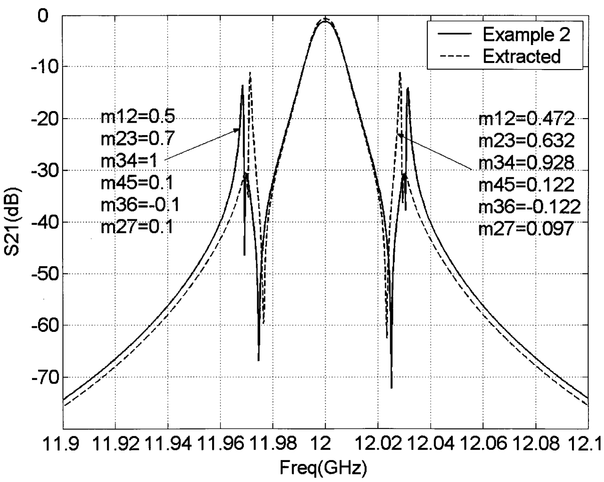


Fig. 14. Comparison between experimental and extracted performance of the eight-pole filter using FL with 17 inputs for the highly detuned filter.

XI. CONCLUSION

This paper has introduced FL tuning to the microwave community for the first time. The approach has been successfully applied to tune four-pole Chebyshev and eight-pole elliptic filters for two different cases of slightly detuned and highly detuned. In both cases, a very small number of measured frequency points were required to identify the coupling coefficients that caused the detuning. An FLS can be considered as a universal function approximator, with the extra capability of incorporating the human expert information, which makes it unique among other methods. Adding human experience to our model is one of our future objectives that is underway. Since all the tuning procedures for microwave problems need parameter extraction, FL can be applied to extract these parameters and, thus, can be easily applied to any microwave circuit tuning problem.

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