OPTIMAL PROCESSING OF MICROWAVE MEASUREMENTS FOR MODEL PARAMETER IDENTIFICATION

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J.W. Bandler*+, S.H. Chen*, S. Daijavad* and W. Kellermann*

Abstract

A powerful model parameter identification technique employing the ℓ_1 norm is described. The technique is based on a novel approach which utilizes multiple sets of measurements on microwave devices. Each new set of measurements corresponds to a circuit model with one or a few parameters changed as a result of deliberate adjustments on the device under consideration. The technique has been tested on realistic examples of multi-coupled cavity filters.

Introduction

Consider a microwave device modelled by a two-port equivalent for which measurements are performed at the input and output ports. Typical responses, in practice, are input or output reflection coefficients and corresponding return losses, insertion loss and group delay between source and load. As an example, here we consider input reflection coefficient denoted by R, insertion loss denoted by L and group delay represented by D. The responses are functions of the parameters of the network model.

The motivation for the development of the approach presented in this paper is that using input and output port measurements, it may be difficult, if not impossible, to identify model parameters uniquely. The choice of an optimal set of frequency points at which measurements are to be performed becomes critical. Since the approaches for such a selection are heuristic and usually difficult to achieve, we develop and formulate a new method for identification which intuitively makes the problem better-conditioned and more independent of frequency points selected.

The approach can be summarized as follows. After taking measurements on the device at a number of frequency points, from which the model parameters can not be identified successfully, we vary one or a few of the model parameters by physically making an easy-to-achieve adjustment on the device, and take another set of measurements. The amount by which the model parameters have changed due to such a physical adjustment may not be known, however, in practice it is not a restriction to assume that it is known which parameters have changed. Adding a complete new set of measurements with the addition of only one or a few new variables should facilitate the identification. If not successful, we keep making adjustments one or a few at a time and record measurements until the model parameters are uniquely identified.

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* Simulation Optimization Systems Research Laboratory, Department of Electrical and Computer Engineering, McMaster University, Hamilton, Canada L8S 4L7.

\+ President, Optimization Systems Associates, Dundas, Ontario, Canada L9H 6L1.

The ℓ_1 Approximation Problem

The problem of approximating a measured (or specified) response by a network or system response can be formulated as an optimization problem.

Let

$$\mathbf{f}^{m}(\omega) \triangleq [f_1^{m} \;\; f_2^{m} \;\; \dots \;\; f_k^{m}]^T \tag{1}$$

be a measured or specified response corresponding to measurements (or observations) at data (frequency) points ω_i, $i = 1, 2, \dots, k$, where

$$f_i^{m} \triangleq f^{m}(\omega_i), \quad i = 1, 2, \dots, k \, . \tag{2}$$

Let

$$\mathbf{f}^{c}(\mathbf{x},\omega) \triangleq [f_1^{c}(\mathbf{x}) \;\; f_2^{c}(\mathbf{x}) \;\; \dots \;\; f_k^{c}(\mathbf{x})]^T \tag{3}$$

be the response of an appropriate model which depends nonlinearly on a vector of parameters $\mathbf{x} \triangleq [x_1 \;\; x_2 \;\; \dots \;\; x_n]^T$, where

$$f_i^{c}(\mathbf{x}) \triangleq f^{c}(\mathbf{x}, \omega_i), \quad i = 1, 2, \dots, k \, . \tag{4}$$

The approximation problem may be stated as follows

$$\underset{\mathbf{x}}{\text{minimize}} \; \|\mathbf{f}\| \, , \tag{5}$$

where

$$\mathbf{f} \triangleq [f_1 \;\; f_2 \;\; \dots \;\; f_k]^T \text{ and} \tag{6}$$

$$f_i \triangleq f_i^{c}(\mathbf{x}) - f_i^{m}, \quad i = 1, 2, \dots, k \, . \tag{7}$$

It is usually assumed that the expected values of the components of **f** are zero, but due to the presence of measurement errors in observing $\mathbf{f}^m$, this cannot be realized in practice. The particular norm to be used depends on the distribution of these errors, represented by the components of **f** [1]. It is commonly supposed that the values of f_i are independent and normally distributed, when the maximum likelihood estimate of the data is given by choosing the norm to be the least squares norm. The data, however, might contain some wild points or isolated gross errors, and in this case, minimization of the ℓ_1 norm residual is superior to using other norms ℓ_p with $p > 1$ [2]. The larger the value of p, the more focus is put on the data points with largest deviation from the approximating function. With ℓ_∞ the maximum deviation will be minimized.

Using the ℓ_1 norm we wish to solve the problem,

$$\underset{\mathbf{x}}{\text{minimize}}, \quad \|\mathbf{f}(\mathbf{x})\| \triangleq \sum_{i=1}^{k} |f_i(\mathbf{x})| \tag{8}$$

The necessary conditions for optimality of the nonlinear ℓ_1 problem [3] indicate that zeros of the nonlinear functions $f_i(x)$ play an important role in the characteristics of the ℓ_1

objective function. This fact has been used in fault isolation techniques for linear analog circuits [4]. The ℓ_1 norm is used to isolate the most likely faulty elements.

Another important application of the ℓ_1 norm is the functional approach to post-production tuning [5], where the ℓ_1 norm is used to select the number of tunable parameters needed to tune all possible outcomes of a manufactured design.

In this paper the ℓ_1 norm is employed in a general model parameter identification technique.

The ℓ_1 Algorithm

The unconstrained ℓ_1 optimization problem is formulated in (8). In this paper we use an iterative algorithm for solving (8) which requires the user to supply function and gradient values of the nonlinear functions $f_i(\mathbf{x})$. The algorithm is also using some second-order information, which is approximated from the user supplied gradients.

The algorithm is similar to that of Hald and Madsen in [6]. It has been reported by Hald in [7], which describes and lists a Fortran program implementing a version of the algorithm. Hald and Madsen [8] have proved that the algorithm has sure convergence properties.

The algorithm is a two stage one. It always starts in Stage 1, which is a first-order trust region method similar to that of Madsen [9]. Often this method has quadratic final convergence, but in some cases (called singular, see Madsen and Schjaer-Jacobsen [10]) the final convergence is slow. Therefore, Stage 2 is introduced. Here, a quasi-Newton method is used to solve a set of nonlinear equations which express the necessary conditions for a local minimum of (8).

If the Stage 2 iteration is unsuccessful, then a switch is made back to Stage 1. Several switches between the two stages are allowed. The switching criteria ensure that the global convergence properties of the Stage 1 iteration are not wasted by the Stage 2 iteration. Experiments show that usually very few switches are performed.

Formulation Using Multiple Sets of Measurements

The problem of model parameter identification using multiple sets of measurements is formulated as follows. We use superscript 1 to denote the original circuit model and superscript j to denote the model after the (j−1)th set of adjustments, i.e., the jth circuit. Consider vector $\mathbf{x}^1 = [x_1^1 \; x_2^1 \; \ldots \; x_n^1]^T$ representing the parameters of the original circuit model. We have measurements on reflection coefficient, insertion loss and group delay denoted by $\mathbf{R}^{m1}$, $\mathbf{L}^{m1}$ and $\mathbf{D}^{m1}$, where taking reflection coefficient for instance, we have

$$\mathbf{R}^{m1} = [\ldots \; R_i^{m1} \; \ldots]^T, \quad i \in \{1, \ldots, M^{R1}\}, \tag{9}$$

with i identifying the frequency point at which the measurement is taken. M^{R1} is the total number of frequency points at which reflection coefficient of the first (original) circuit has been measured. $\mathbf{L}^{m1}$, $\mathbf{D}^{m1}$, M^{L1} and M^{D1} are defined in a similar way. The identification based on <u>one</u> set of measurements is formulated as the following optimization problem

$$\underset{\text{w.r.t. } \mathbf{x}^1}{\text{minimize}}, \quad \sum_{i=1}^{M^{R1}} w_i^{R1} |R_i^{c1} - R_i^{m1}| + \sum_{i=1}^{M^{L1}} w_i^{L1} |L_i^{c1} - L_i^{m1}| + \sum_{i=1}^{M^{D1}} w_i^{D1} |D_i^{c1} - D_i^{m1}|, \tag{10}$$

where R^c, L^c and D^c represent calculated (based on the model) responses and w denotes the weighting factor. After making the first set of adjustments we have model parameter vector $\mathbf{x}^2 = [x_1^2 \; x_2^2 \; \ldots \; x_n^2]$, however, since some of the parameters in $\mathbf{x}^2$ have the same values as the ones in $\mathbf{x}^1$, we introduce a new vector $\mathbf{x}_a^2$ which contains the values of only those parameters that have changed after the first set of adjustments. Therefore, $\mathbf{x}_a^2$ has only one or a few elements compared to n elements in $\mathbf{x}^2$. Generalizing the idea to t circuits, i.e., t–1 adjustments on the original circuit model, the optimization problem is

$$\underset{\text{w.r.t. } \mathbf{x}}{\text{minimize}}, \quad \sum_{j=1}^{t} \left\{ \sum_{i=1}^{M^{Rj}} w_i^{Rj} |R_i^{cj} - R_i^{mj}| + \sum_{i=1}^{M^{Lj}} w_i^{Lj} |L_i^{cj} - L_i^{mj}| + \sum_{i=1}^{M^{Dj}} w_i^{Dj} |D_i^{cj} - D_i^{mj}| \right\}, \tag{11}$$

where

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}^1 \\ -- \\ \mathbf{x}_a^2 \\ -- \\ \cdot \\ \cdot \\ \cdot \\ -- \\ \mathbf{x}_a^t \end{bmatrix} \tag{12}$$

Examples

We consider multi-coupled cavity filters used in modern communication systems, e.g., satellite multiplexing networks. The symmetrical impedance matrix for a narrow-band lumped model of an unterminated filter is given by [11-12]

$$j\,\mathbf{Z} \triangleq j(s\mathbf{1} + \mathbf{M}) + r\mathbf{1}\;, \tag{13}$$

where $\mathbf{1}$ denotes an nxn identity matrix and s is the normalized frequency variable given by $s \triangleq (\omega_0/\Delta\omega)(\omega/\omega_0 - \omega_0/\omega)$, ω_0 and $\Delta\omega$ being the synchronously tuned cavity resonant frequency and the bandwidth parameter, respectively. Uniform dissipation by all cavities is indicated by parameter r. $\mathbf{M}$ is the coupling matrix whose (i,j) element represents the normalized coupling between the ith and jth cavities and the diagonal entries M_{ii} represent the deviations from synchronous tuning. Element M_{ij} does not necessarily correspond to a desirable and designable coupling. It may as well represent a stray coupling which is excluded from the nominal electrical equivalent circuit. Dispersion effects on the filter can be modelled by a frequency dependent M matrix.

As applications for our identification technique, we have considered the identification of coupling parameters from simulated measurements on reflection coefficient for multi-cavity filters centred at 4 GHz with a bandwidth of 40 MHz.

Case 1

A 10th order detuned filter with Q = 10,000 has the reflection coefficient response as shown in Fig. 1(a) where the response has been deliberately contaminated by a Gaussian noise having a maximum value of 0.01. This is to emulate the limits on accuracy of measurement equipment. By varying M_{12} and $M_{9,10}$ the response of Fig. 1(b) is obtained and a further adjustment on M_{23} and M_{89} results in the response of Fig. 1(c). Both responses of Figs. 1(b) and 1(c) have also been contaminated. Selecting 20 frequency points between 3960 and 4000 MHz from the response of Fig. 1(a) and using the same frequencies for responses of Figs. 1(b) and 1(c), we identify the non-zero parameters of the filter as

$$\mathbf{x}^1 = \left[M^1_{12}\ M^1_{23}\ M^1_{34}\ M^1_{45}\ M^1_{56}\ M^1_{67}\ M^1_{78}\ M^1_{89}\ M^1_{9,10}\ M^1_{1,10}\ M^1_{29}\ M^1_{38}\ M^1_{47} \right]^T$$

$$= \left[0.8\ \ 0.6\ \ 0.5\ \ 0.5\ \ 0.5\ \ 0.5\ \ 0.5\ \ 0.6\ \ 0.8\ \ -0.1\ \ 0.1\ \ -0.2\ \ 0.1 \right]^T,$$

$$\mathbf{x}^2_a = \left[M^2_{12}\ M^2_{9,10} \right]^T = \left[0.7\ \ 0.7 \right]^T \text{ and } \mathbf{x}^3_a = \left[M^3_{23}\ M^3_{89} \right]^T = \left[0.7\ \ 0.7 \right]^T .$$

The problem involves 17 variables and an ℓ_1 sum of 60 functions. The solution is reached in about 8 minutes of CPU time on the VAX 11/780 system.

Case 2

A 4th-order detuned lossy filter with Q = 10,000 has the response shown in Fig. 2(a). Besides the dominant couplings M_{12}, M_{23}, M_{34} and M_{14}, stray coupling M_{13} and two diagonal elements M_{11} and M_{44} representing the deviations of electrical cavities 1 and 4 from synchronous tuning exist. By varying M_{12}, we obtain the response of Fig. 2(b). To prove the insensitivity of the ℓ_1 algorithm to few isolated gross errors or wild points, we deliberately change the measurement data as illustrated by the dashed lines in Figs. 2(a) and 2(b). Selecting 14 uniformly spaced frequencies between 3960 and 3999 MHz (error = 0.1 at 3993 MHz) from the response of Fig. 2(a), and another 14 points between 3961 and 4000MHz using the response of Fig. 2(b) (error = 0.07 at 3994 MHz), we identify the dominant and stray couplings and cavity resonant frequencies as

$$\mathbf{x}^1 = \left[M^1_{11}\ \ M^1_{44}\ \ M^1_{12}\ \ M^1_{23}\ \ M^1_{34}\ \ M^1_{14}\ \ M^1_{13} \right]^T$$

$$= \left[0.2\ \ 0.2\ \ 0.5\ \ 0.5\ \ 0.5\ \ -0.4\ \ 0.02 \right]^T$$

and

$$\mathbf{x}^2_a = \left[M^2_{12} \right]^T = \left[0.8 \right] .$$

A value of 0.2 for a diagonal element corresponds to a deviation of about 10% of the bandwidth from the synchronous tuning. The problem involves 8 variables and an ℓ_1 sum of 28 functions and the solution is reached in about 8 seconds.

Summary

A powerful and efficient model parameter identification procedure for microwave devices has been presented. A fast and robust gradient-based ℓ_1 algorithm has been employed to optimally process multiple sets of measurements.

This work is a part of a cooperative effort with ComDev. Ltd. of Cambridge, Ontario, Canada towards modelling and tuning of microwave filtering and multiplexing systems.

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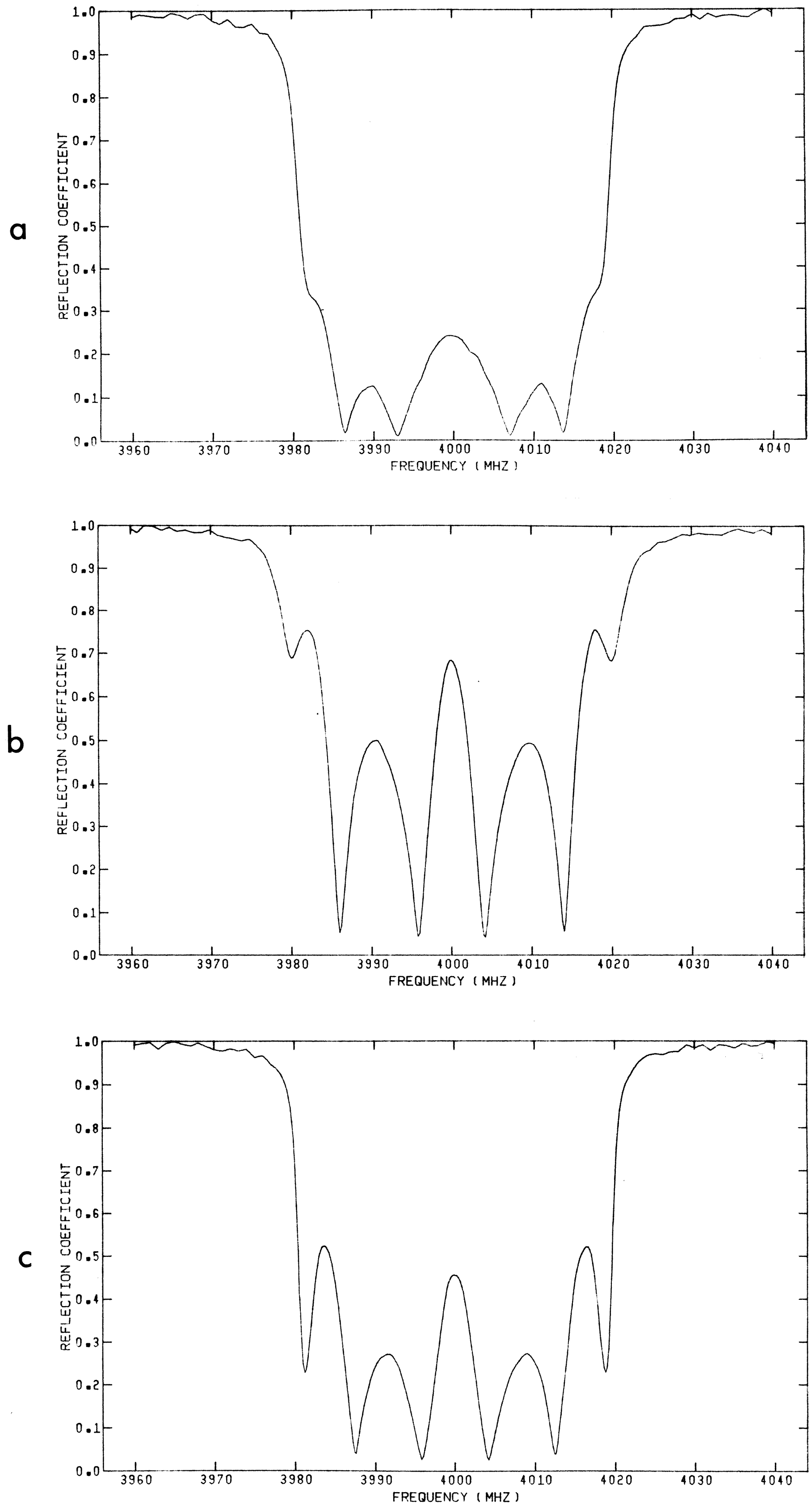
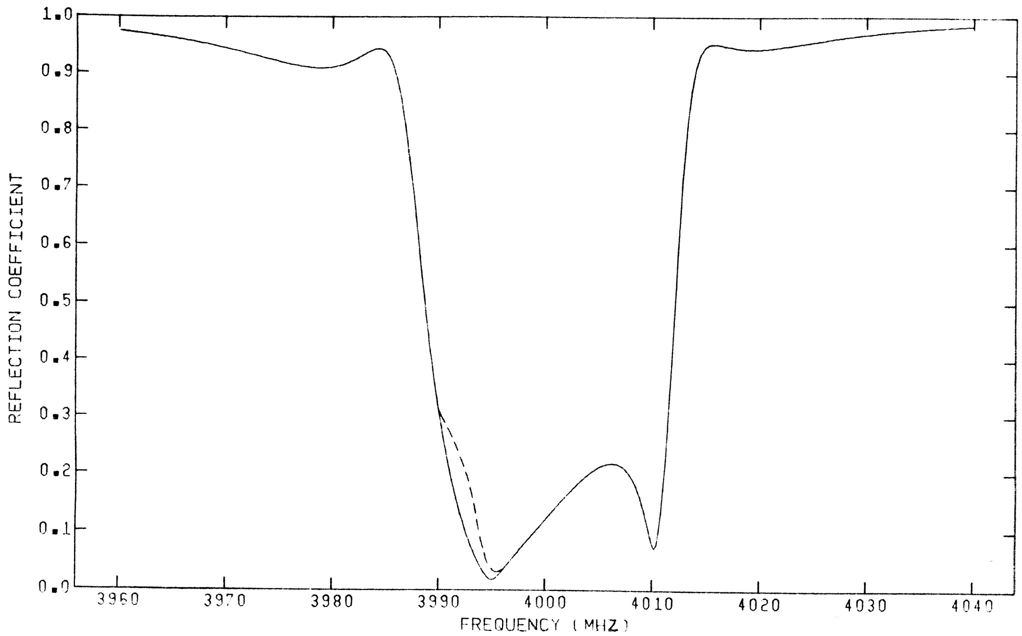


Fig.1 Reflection coefficient responses of a detuned 10th order lossy filter with Q = 10,000. The responses have been contaminated by noise.

(a) Original or first response.
(b) Response after varying M_{12} and $M_{9,10}$.
(c) Response after varying M_{23} and M_{89} w.r.t. (b).

a



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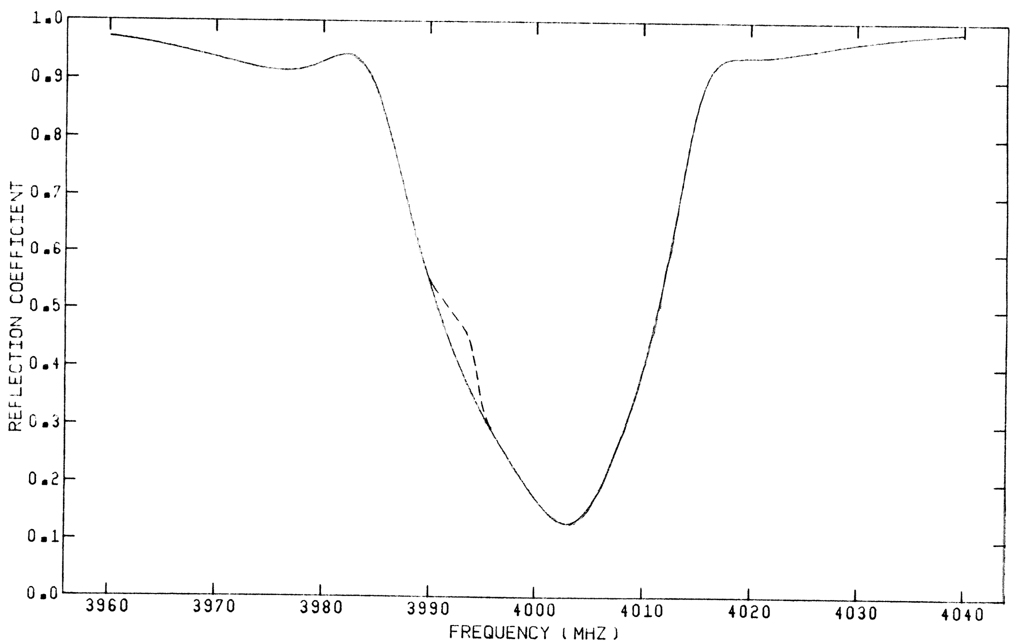

Fig. 2 Reflection coefficient responses of a detuned 4th order lossy filter. Stray couplings and deviations from synchronous tuning exist. Dashed lines indicate the responses after deliberate changes in measurement data.

(a) Original or first response.

(b) Response after varying M_{12}.