Expanded Space-Mapping EM-Based Design Framework Exploiting Preassigned Parameters

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***Abstract*—We present a novel design framework for microwave circuits. We calibrate coarse models (circuit based models) to align with fine models (full-wave electromagnetic simulations) by allowing some preassigned parameters (which are not used in optimization) to change in some components of the coarse model. Our expanded space-mapping design-framework (ESMDF) algorithm establishes a sparse mapping from optimizable to preassigned parameters. We illustrate our approach through two microstrip design examples.**

***Index Terms*—Design automation, electromagnetic (EM) optimization, microstrip filters, microwave circuits, optimization methods, preassigned parameters, space mapping.**

I. Introduction

The concept of calibrating coarse models (computationally fast circuit based models) to align with fine models [typically CPU intensive full-wave electromagnetic (EM) simulations] in microwave circuit design has been exploited by several authors [1]–[4]. In [1]–[3], this calibration is performed through a mapping between the optimizable parameters of the coarse model and those of the fine model such that the corresponding responses match. In [4], the coarse model is calibrated by adding circuit components to nonadjacent individual coarse-model elements.

Here, we expand the original space-mapping technique [1]. We calibrate the coarse model by allowing "preassigned" parameters to change. For example, the coarse model of the three-section microstrip transformer in Fig. 1(b) consists of five components: three microstrip lines and two step junctions. The line lengths and widths (Fig. 1(a)) are optimizable. Preassigned parameters are substrate height H and dielectric constant ε_r. The coarse model is calibrated w.r.t. Sonnet's ***em*** [5] by tuning selected H and ε_r.

The ESMDF algorithm calibrates the coarse model by extracting the preassigned parameters such that corresponding responses match. It establishes a mapping from optimizable to preassigned parameters. The resulting mapped coarse model (the coarse model with the mapped preassigned parameters) is then optimized subject to a trust region size. The trust region size is updated [6]–[8] according to the match between the fine and mapped coarse model.

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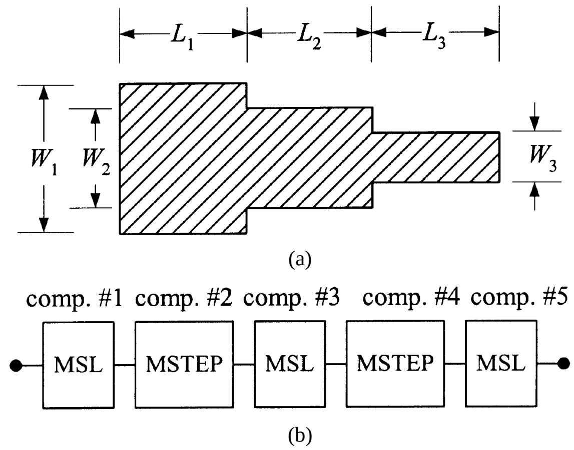

Fig. 1. Three-section microstrip transformer. (a) Physical structure; (b) Coarse model.

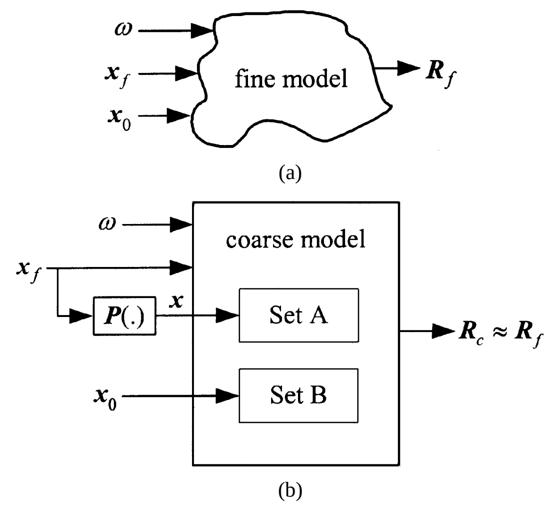

Fig. 2. Changing the preassigned parameters in some of the coarse-model components (the components in Set A) results in aligning the coarse model (b) with the fine model (a).

II. Basic Concepts and Notation

A. Preassigned Parameter Mapping

Consider a microwave circuit represented by a fine model and a coarse model. We decompose the coarse model into two sets of components: a Set A and Set B. See Fig. 2. In Set A, we allow preassigned parameters to change throughout the design process. In Set B, we keep the preassigned parameters intact. The vector $\boldsymbol{x}_0 \in \Re^{n_0}$ represents the original values of the preassigned parameters. Assume that the total number of coarse-model components is N, the number of components in Set A is $m \leq N$ and the set I is defined by

$$I = \{1, 2, \ldots, N\}. \tag{1}$$

Let $j_1, j_2, \ldots, j_m \in I$ represent the indices of the components in Set A. The vector of corresponding preassigned parameters

$$\boldsymbol{x} = [\boldsymbol{x}_{j_1}^T \quad \boldsymbol{x}_{j_2}^T \quad \ldots \quad \boldsymbol{x}_{j_m}^T]^T \in \Re^{mn_0} \tag{2}$$

where $\boldsymbol{x}_{j_i} \in \Re^{n_0}$, $i = 1, 2, \ldots, m$ is the ith component. The vector $\boldsymbol{x}_f \in \Re^n$ represents the original optimization variables.

We assume that we can establish a mapping from some elements of $\boldsymbol{x}_f$ to $\boldsymbol{x}$ such that the coarse model aligns with the fine model. This mapping is given by

$$\boldsymbol{x} = \boldsymbol{P}(\boldsymbol{x}_r)\colon \Re^{n_r} \mapsto \Re^{mn_0} \tag{3}$$
$$\boldsymbol{x}_f = [\,\boldsymbol{x}_r^T \quad \boldsymbol{x}_s^T\,]^T. \tag{4}$$

Decomposition of $\boldsymbol{x}_f$ into $\boldsymbol{x}_r$ and $\boldsymbol{x}_s$ (introduced and justified by Bandler *et al.* [2] as "partial space mapping") allows a reduction of the mapping $\boldsymbol{P}$. We approximate (3) and consider the difference form

$$\Delta\boldsymbol{x} = \boldsymbol{B}_r \Delta\boldsymbol{x}_r \tag{5}$$

where $\boldsymbol{B}_r \in \Re^{(mn_0)\mathrm{x}n_r}$ is a matrix to be determined.

B. Responses

The vectors $\boldsymbol{R}_f$, $\boldsymbol{R}_c$, defined over the frequency set Ω_p, represent responses of the fine model and coarse model, respectively, used for coarse-model calibration. The vectors $\boldsymbol{R}_{fs}$, $\boldsymbol{R}_{cs}$, defined over the frequency set Ω_s, represent specific responses used to define the objective function for design optimization in terms of design specifications.

C. Illustrative Example

Consider the microstrip transformer in Fig. 1. The source and load impedances are 50 and 150 Ω, respectively. The design specifications are

$$|S_{11}| \le -20 \text{ dB}, \qquad \text{for } 5 \text{ GHz} \le \omega \le 15 \text{ GHz}.$$

The fine model is analyzed by Sonnet's ***em*** [5]. The coarse model in Fig. 1(b) is analyzed by OSA90/hope [9]. The optimization variables are the widths and the lengths of the microstrip transmission lines in Fig. 1(a). That is

$$\boldsymbol{x}_f = [\,W_1 \quad W_2 \quad W_3 \quad L_1 \quad L_2 \quad L_3\,]^T.$$

The preassigned parameters are the dielectric constant $\varepsilon_r = 9.7$ and the substrate height $H = 25$ mil. Therefore, the vector $\boldsymbol{x}_0 = [25 \text{ mil}\; 9.7]^T$. The coarse model consists of five components $(N = 5)$ as shown in Fig. 1(b). The algorithm applies the coarse-model decomposition technique in Section III and chooses the components 1, 3, and 5. Thus, Set A consists of the three transmission lines in Fig. 1(b) and Set B consists of components 2 and 4 (the step junctions). The vector of preassigned parameters (in Set A) is

$$\boldsymbol{x} = [\,\boldsymbol{x}_1^T \quad \boldsymbol{x}_3^T \quad \boldsymbol{x}_5^T\,]^T$$

where $\boldsymbol{x}_i = [\,\varepsilon_{ri} \quad H_i\,]^T$, $i = 1, 3, 5$. The vector $\boldsymbol{x}_r$ in (3) is given by

$$\boldsymbol{x}_r = [\,W_1 \quad W_2 \quad W_3\,]^T.$$

The matrix $\boldsymbol{B}_r$ is chosen to have the sparsity structure

$$\boldsymbol{B}_r = \begin{bmatrix} \mathrm{x} & 0 & 0 \\ \mathrm{x} & 0 & 0 \\ 0 & \mathrm{x} & 0 \\ 0 & \mathrm{x} & 0 \\ 0 & 0 & \mathrm{x} \\ 0 & 0 & \mathrm{x} \end{bmatrix}$$

TABLE I
RESPONSE SENSITIVITY MEASURES W.R.T. PREASSIGNED PARAMETERS OF MICROSTRIP TRANSFORMER COARSE-MODEL COMPONENTS

Component #	$\hat{S}_i$
1	1.00
2	0.05
3	0.39
4	0.04
5	0.77

where x denotes a nonzero entry. This structure reflects an association between preassigned parameters and the design parameters of the corresponding component. For example, the preassigned parameters are functions only of W_1, W_2, and W_3, respectively.

The response vectors $\boldsymbol{R}_{fs}$, $\boldsymbol{R}_{cs}$ contain $|S_{11}|$. The vectors $\boldsymbol{R}_f$, $\boldsymbol{R}_c$ contain the real and imaginary parts of S_{11}. Set Ω_s contains 21 evenly spaced frequencies while Ω_p contains 11 evenly spaced frequencies from 5 to 15 GHz.

III. Coarse Model Decomposition

We present a method based on sensitivity analysis to decompose the coarse-model components. Set A contains those for which the response is sensitive to changes in preassigned parameters, while Set B contains those for which the response is insensitive.

Step 1) For all $i \in I$ in (1) evaluate

$$S_i = \left\| \left(\frac{\partial \boldsymbol{R}_{cs}^T}{\partial \boldsymbol{x}_i} \boldsymbol{D} \right)^T \right\|_F \tag{6}$$

where Si represents a measure of the sensitivity of the coarse-model response to preassigned parameters of the ith component, the matrix $\boldsymbol{D}$ is for scaling and $\|\|_F$ denotes Frobenius norm.

Comment: The Jacobian in (6) is evaluated by perturbation at $\boldsymbol{x}_i = \boldsymbol{x}_0$, $i \in I$. The matrix $\boldsymbol{D}$ is diagonal. It consists of the elements of $\boldsymbol{x}_0$. For the microstrip transformer in Fig. 1(b), (see Section II), $D = \mathrm{diag}\{25 \text{ mil}, 9.7\}$.

Step 2) Evaluate

$$\hat{S}_i = \frac{S_i}{\max_{j \in I}\{S_j\}}, \qquad i \in I \tag{7}$$

Comment: For the example, in Section II, the values of $\hat{S}_i$ are given in Table I, where we notice that $\boldsymbol{R}_{cs}$ is most sensitive to the first transmission line.

Step 3) Put the ith component in Set A if $\hat{S}_i \ge \beta$ otherwise put it in Set B.

Comment: The scalar β is a small positive number less than 1. In our examples $\beta = 0.2$. For the microstrip transformer, we place components 1, 3, and 5 in Set A (see Table I) and components 2 and 4 in Set B.

IV. ESMDF Algorithm

The ESMDF algorithm decomposes the coarse model into two sets of components as in Section III. Then, it obtains the optimal solution of the coarse model. If the fine-model response at that solution satisfies the specifications and (or) is very close to the optimal coarse-model response, (i.e, the coarse model is already very good) the algorithm terminates. Otherwise, the algorithm calibrates the coarse model by extracting the preassigned parameters at the optimal coarse-model solution and updating the matrix $\boldsymbol{B}_r$. At each iteration, the algorithm obtains the optimal solution of the mapped coarse model subject to a certain trust region [6], [8]. This solution is accepted if it results in a reduction in the fine-model objective function. The trust region size is adaptively updated according to the relative improvement of the fine-model objective function to that of the coarse model. The algorithm performs four main tasks: mapped coarse-model optimization, extraction of preassigned parameters, checking some stopping criteria and updating the mapping parameters and the trust region size.

A. Mapped Coarse-Model Optimization

A trust region methodology controls the optimization of the mapped coarse model to insure improvement in the fine-model objective function. Let $\boldsymbol{h}$ denote the prospective step $\Delta \boldsymbol{x}_f$ and $\boldsymbol{h}_r$ denote the corresponding step $\Delta \boldsymbol{x}_r$. At the ith iteration the algorithm obtains the step $\boldsymbol{h}^{(i)}$ by solving the optimization problem

$$\begin{aligned}\boldsymbol{h}^{(i)} &= \arg\min_{h} U\left(\boldsymbol{R}_{cs}\left(\boldsymbol{x}_f^{(i)} + \boldsymbol{h}, \boldsymbol{x}^{(i)} + \boldsymbol{B}_r^{(i)}\boldsymbol{h}_r\right)\right)\\ &\text{subject to } \|\boldsymbol{\Lambda}_i \boldsymbol{h}\| \le \delta_i \end{aligned} \tag{8}$$

where U is a suitable objective function, δ_i is the trust region radius and the matrix $\boldsymbol{\Lambda}_i$ is for scaling [7]. We set $\boldsymbol{\Lambda}_i$ as a diagonal matrix whose elements are the reciprocal of the elements of $\boldsymbol{x}_f^{(i)}$. Therefore, the trust region radius δ_i represents the maximum allowable relative change in the design variables at the ith iteration. The norm used in (8) is the ℓ_∞ norm. The algorithm decides whether to accept the prospective step $\boldsymbol{h}^{(i)}$, as shown in (9) at the bottom of the page. The ith iteration is successful if $\boldsymbol{h}^{(i)}$ results in an improvement in the fine-model objective function. The algorithm updates the trust region radius according to the criteria in [7] and [8].

B. Stopping Criteria

At the ith iteration, the algorithm simulates the fine model at the optimal mapped coarse-model solution and stops if one of the following stopping criteria is satisfied.

1) Predefined maximum number of iterations $i_{\max}$ is reached. This puts a limit on the number of fine-model evaluations the designer can afford.
2) Algorithm reaches a solution that just satisfies the specifications.
3) Mapped coarse-model response is very close to the fine-model response

$$\left\|\boldsymbol{R}_{fs}\left(\boldsymbol{x}_f^{(i)}, \Omega_p\right) - \boldsymbol{R}_{cs}\left(\boldsymbol{x}_f^{(i)}, \boldsymbol{x}^{(i-1)} + \boldsymbol{B}_r^{(i-1)}\boldsymbol{h}_r^{(i)}, \Omega_p\right)\right\| \le \varepsilon_1. \tag{10}$$

4) The solutions obtained in two successive successful iterations are very close [3]

$$\left\|\boldsymbol{x}_f^{(i)} - \boldsymbol{x}_f^{(i-1)}\right\|_\infty \le \varepsilon_2. \tag{11}$$

5) The radius of the trust region is very small

$$\delta_i < \delta_{\min} \tag{12}$$

where $\delta_{\min}$ is the smallest allowable trust region radius.

C. Extraction of Preassigned Parameters

At the ith iteration, if the algorithm accepts the prospective step $\boldsymbol{h}^{(i)}$ (9) and the stopping criteria are not satisfied, it extracts the vector of the preassigned parameters $\boldsymbol{x}^{(i+1)}$ corresponding to $\boldsymbol{x}_f^{(i+1)}$

$$\boldsymbol{x}^{(i+1)} = \arg\min_{x} \left\|\boldsymbol{R}_f\left(\boldsymbol{x}_f^{(i+1)}, \Omega_p\right) - \boldsymbol{R}_c\left(\boldsymbol{x}_f^{(i+1)}, \boldsymbol{x}, \Omega_p\right)\right\| \tag{13}$$

where the norm used in (13) is the Huber norm [10]. The optimization problem (13) may get trapped in a poor local minimum if the coarse and fine-model responses are severely misaligned. Possible ways to overcome this is to use frequency mapping [11] or statistical parameter extraction [12]. Here, we present another technique. Instead of solving (13) directly, we try to roughly align the responses first. We do that by minimizing the difference between the center frequency and the bandwidth of the coarse-model and the fine-model responses. We use this solution as a starting point to solve (13). If this procedure fails to produce a good match the algorithm uses the statistical parameter extraction approach in [12]. That is, it tries to solve (13) from different random starting points until it obtains a good match.

D. Updating the Mapping Parameters

After extracting the preassigned parameters at the ith iteration the algorithm updates $\boldsymbol{B}_r$ in (5). In the early iterations we have an under-determined system. We choose the minimum norm solution to render the preassigned parameters close to their original values. That is, we choose $\boldsymbol{B}_r$ close to $\boldsymbol{0}$. At the ith iteration we have

$$\begin{aligned}&[\,\Delta\boldsymbol{x}^{(1)} \quad \Delta\boldsymbol{x}^{(2)} \quad \ldots \quad \Delta\boldsymbol{x}^{(i)}\,]\\ &\qquad = \boldsymbol{B}_r\,[\,\Delta\boldsymbol{x}_r^{(1)} \quad \Delta\boldsymbol{x}_r^{(2)} \quad \ldots \quad \Delta\boldsymbol{x}_r^{(i)}\,]\end{aligned} \tag{14}$$

where

$$\Delta\boldsymbol{x}^{(j)} = \boldsymbol{x}^{(j)} - \boldsymbol{x}^{(j-1)}, \qquad j \in 1, 2, \ldots, i \tag{15a}$$
$$\Delta\boldsymbol{x}_r^{(j)} = \boldsymbol{x}_r^{(j)} - \boldsymbol{x}_r^{(j-1)}, \qquad j \in 1, 2, \ldots, i. \tag{15b}$$

The vector $\boldsymbol{x}^{(0)}$ contains the original values of the preassigned parameters. When solving (14) for $\boldsymbol{B}_r$ sparsity should be considered. Let $\boldsymbol{b} \in \Re^p$ contain the nonzero elements of $\boldsymbol{B}_r$. By rearranging (14) we can write the linear system as

$$\boldsymbol{y} = \boldsymbol{X}_r \boldsymbol{b} \tag{16}$$

where $\boldsymbol{y} = [\,(\Delta\boldsymbol{x}^{(1)})^T \quad (\Delta\boldsymbol{x}^{(2)})^T \quad \ldots \quad (\Delta\boldsymbol{x}^{(i)})^T\,]^T \in \Re^{mn_0 i}$ and $\boldsymbol{X}_r \in \Re^{mn_0 i \times p}$ is a sparse matrix whose nonzero elements are the elements of $\Delta\boldsymbol{x}_r^{(1)}, \Delta\boldsymbol{x}_r^{(2)}, \ldots \Delta\boldsymbol{x}_r^{(i)}$. The structure of the matrix $\boldsymbol{X}_r$ depends on the sparsity of $\boldsymbol{B}_r$. The solution of (16) is given by

$$\boldsymbol{b} = \boldsymbol{X}_r^{+} \boldsymbol{y} \tag{17}$$

$$\boldsymbol{x}_f^{(i+1)} = \begin{cases} \boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)}, & \text{if } U\left(\boldsymbol{R}_{fs}\left(\boldsymbol{x}_f^{(i)} + \boldsymbol{h}^{(i)}, \Omega_p\right)\right) < U\left(\boldsymbol{R}_{fs}\left(\boldsymbol{x}_f^{(i)}, \Omega_p\right)\right)\\ \boldsymbol{x}_f^{(i)}, & \text{otherwise.}\end{cases} \tag{9}$$

TABLE II
VALUES OF DESIGN PARAMETERS FOR MICROSTRIP TRANSFORMER

Parameter (mm)	Starting point	Optimal coarse model solution	Solution reached by our ESMDF algorithm
W_1	0.40	0.381	0.335
W_2	0.15	0.151	0.136
W_3	0.05	0.042	0.039
L_1	3.00	2.783	2.990
L_2	3.00	3.003	3.079
L_3	3.00	3.085	3.139

where X_r^+ is the pseudoinverse of X_r. A Matlab [13] function is written to construct the matrix X_r and the Matlab function pinv is used to evaluate X_r^+. The advantage of using the pseudoinverse is that it gives us the minimum norm solution for underdetermined systems.

E. Summary of the ESMDF Algorithm

Given δ_0 (the initial trust region radius), $\delta_{\min}, i_{\max}, \varepsilon_1, \varepsilon_2$ the algorithm performs the following steps.

Step 1: Decompose the coarse-model components into sets A and B as mentioned in **Section III**. Initialize $i = 0$, $B_r = 0$.
Step 2: Optimize the coarse model. Designate the optimal solution $x_f^{(0)}$.
Step 3: Simulate the fine model at $x_f^{(0)}$. Terminate if a stopping criterion is satisfied.
Step 4: Extract the preassigned parameters $x^{(i)}$ by solving **(13)**. Update B_r using **(17)**.
Step 5: Evaluate the prospective step $h^{(i)}$ by optimizing the mapped coarse model **(8)**.
Mark i as a successful iteration if
$U\left(R_{fs}\left(x_f^{(i)} + h^{(i)}, \Omega_p\right)\right) < U\left(R_{fs}\left(x_f^{(i)}, \Omega_p\right)\right)$.
Set $x_f^{(i+1)}$ according to **(9)**.
Comment: When $i = 0$ we disable the trust region, hence δ_0 can be small. For example, 0.05 is used in our design examples.
Step 6: Update δ and increment i.
Step 7: If a stopping criterion is satisfied terminate.
Step 8: If the ith iteration is successful go to Step 4, otherwise go to Step 5.

V. EXAMPLES

The ESMDF algorithm has been tested with $\delta_0 = 0.05$, $\delta_{\min} = 0.005$, $i_{\max} = 10$, and $\varepsilon_1 = 0.005$ on an IBM Aptiva (AMD Athlon, 650 MHz, 384 MB).

A. Three-Section Microstrip Transformer

This example (Section II) requires two iterations (three fine-model simulations) to reach the optimal solution in Table II in 17 min. The stopping criterion (10) terminates the algorithm, signifying excellent agreement between the mapped coarse model and fine model. The initial and final solutions are shown in Fig. 3(a) and (b). Table III shows corresponding preassigned parameters.

The final mapped coarse model can be utilized in yield estimation. We assume a uniform distribution with 0.25 mil tolerance on all six geometrical parameters. With 250 outcomes the estimated yield is 78% compared with 79% using the fine model directly.

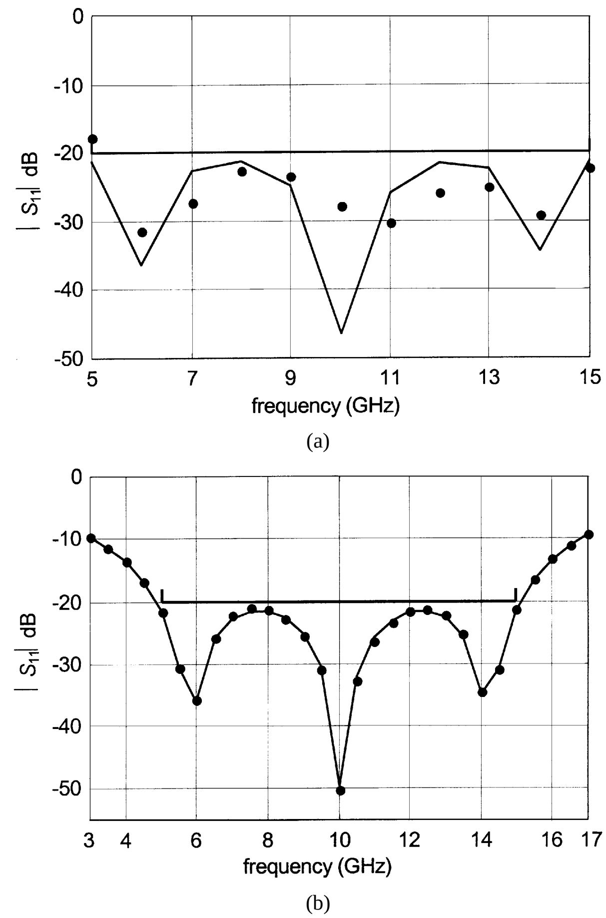

Fig. 3. The fine (●) and mapped coarse-model (—) responses of the microstrip transformer: (a) at the initial solution and (b) at the final solution (detailed frequency sweep).

TABLE III
VALUES OF PREASSIGNED PARAMETERS OF MICROSTRIP TRANSFORMER COARSE-MODEL DESIGNATED COMPONENTS AT INITIAL AND FINAL ITERATIONS

Preassigned parameters	Original value of the preassigned parameters	Preassigned parameters at the final iteration
H_1	25 mil	19.36 mil
H_3	25 mil	20.97 mil
H_5	25 mil	21.48 mil
ε_{r1}	9.7	8.57
ε_{r3}	9.7	9.17
ε_{r5}	9.7	9.31

B. HTS Filter (Fig. 4)

The design variables of the high-temperature superconducting (HTS) bandpass filter (Fig. 4(a)) [14] are the lengths of the coupled lines and the separation between them

$$x_f = [S_1 \quad S_2 \quad S_3 \quad L_1 \quad L_2 \quad L_3]^T$$

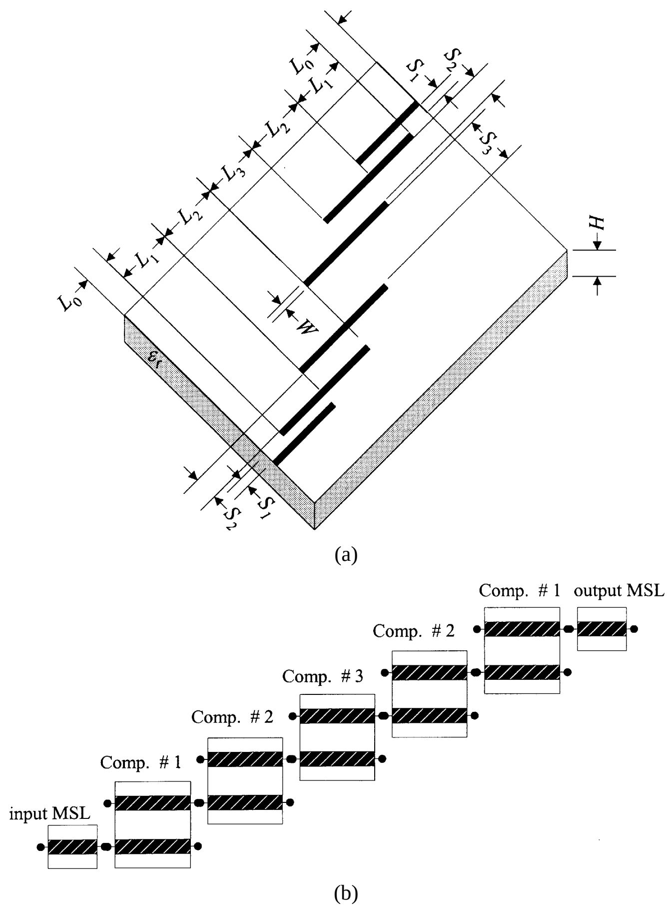

Fig. 4. HTS Filter. (a) Physical structure. (b) Coarse model.

TABLE IV
RESPONSE SENSITIVITY MEASURES W.R.T. PREASSIGNED PARAMETERS OF HTS FILTER COARSE-MODEL COMPONENTS

Component #	$\hat{S}_i$
1	0.69
2	1.00
3	0.30

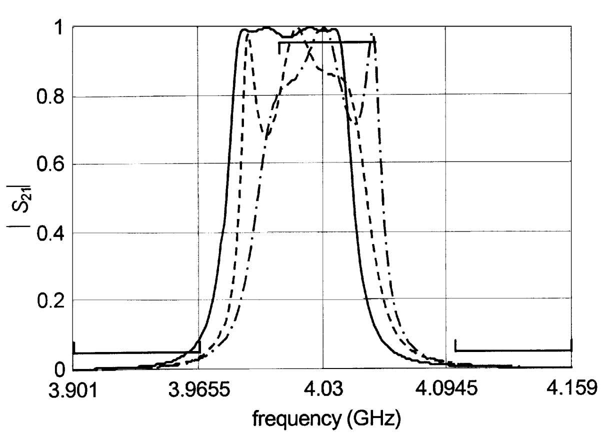

Fig. 5. The coarse-model response resulting from 2% perturbation in the preassigned parameters of: (a) the first component (— · — · —); (b) the second component (—), and (c) the third component (- - -).

$$\boldsymbol{x}_r = [\,S_1 \quad S_2 \quad S_3\,]^T.$$

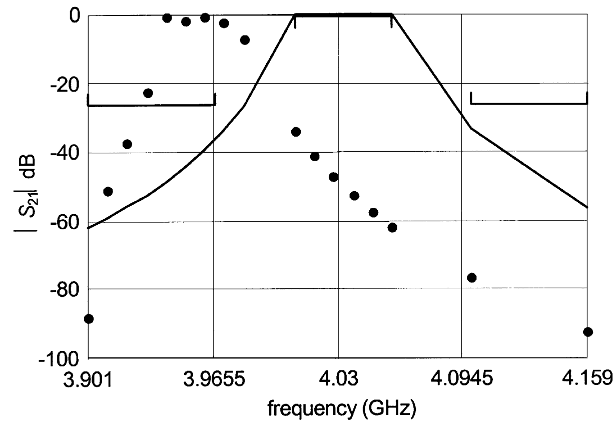

Fig. 6. Sonnet *em* fine-model response (●●) and the coarse-model response (—) of the HTS filter at the initial solution.

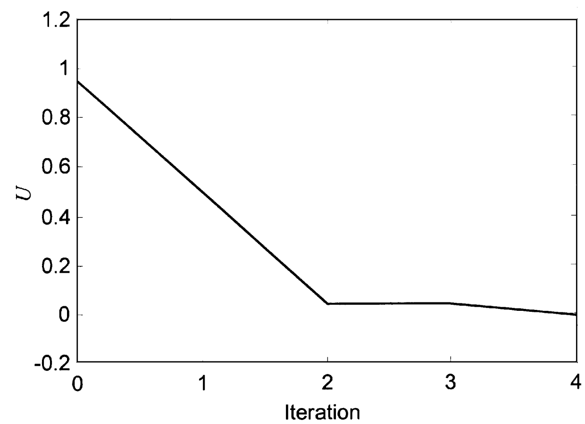

Fig. 7. Objective function of the HTS filter fine model.

TABLE V
VALUES OF DESIGN PARAMETERS FOR HTS FILTER

Parameter (mil)	Starting point	Optimal coarse model solution	Solution reached by our ESMDF algorithm
S_1	20.0	20.76	19.0
S_2	100	108.46	78.0
S_3	100	101.80	80.0
L_1	190	172.27	178.5
L_2	190	213.83	201.5
L_3	190	172.74	177.5

The substrate used is lanthanum aluminate with $\varepsilon_r = 23.425$, $H = 20$ mil and substrate dielectric loss tangent of 0.000 03. The length of the input and output lines is $L_0 = 50$ mil and the lines width $W = 7$ mil. We choose ε_r and H as preassigned parameters, thus $\boldsymbol{x}_0 = [20 \text{ mil } 23.425]^T$. The design specifications are

$$|S_{21}| \leq 0.05 \text{ for } \omega \geq 4.099 \text{ GHz and for } \omega \leq 3.967 \text{ GHz}$$
$$|S_{21}| \geq 0.95 \text{ for } 4.008 \text{ GHz} \leq \omega \leq 4.058 \text{ GHz}.$$

This corresponds to a 1.25% bandwidth. The coarse model consists of empirical models for single and coupled microstrip transmission lines [see Fig. 4(b)]. All open circuits are considered ideally open. Table IV

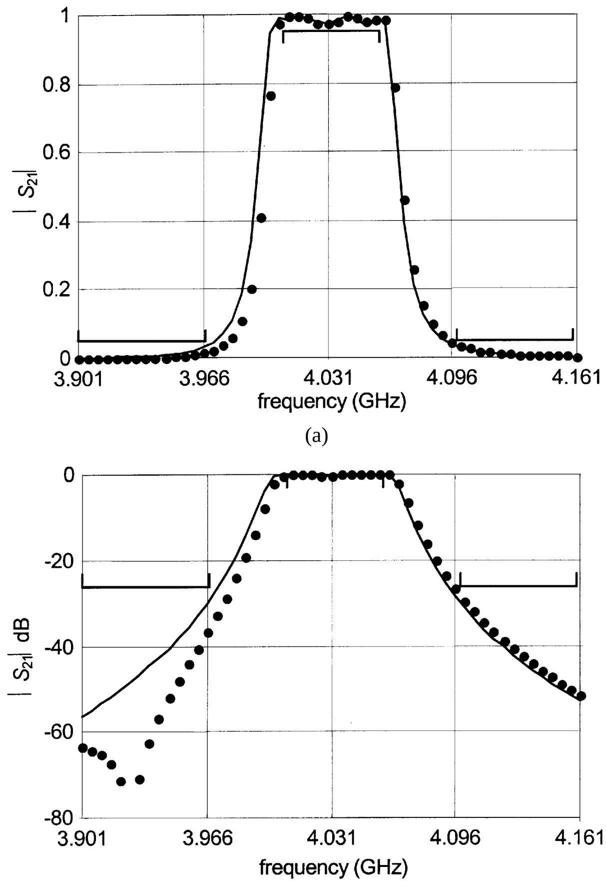

Fig. 8. Detailed frequency sweep of the fine- and coarse-model responses of the HTS filter at the final solution. (a) $|\boldsymbol{S}_{21}|$. (b) $|\boldsymbol{S}_{21}|$ in decibels.

shows the sensitivity measures for the coarse-model responses w.r.t. the preassigned parameters. Fig. 5 depicts significant changes in the coarse model response due to $+2\%$ perturbation in both preassigned parameters of each component. The preassigned parameter vector is $\boldsymbol{x} = [\,\boldsymbol{x}_1^T \quad \boldsymbol{x}_2^T \quad \boldsymbol{x}_3^T\,]^T$, where $\boldsymbol{x}_i = [\,\varepsilon_{ri} \quad H_i\,]$, for $i = 1, 2, 3$. Here

$$\boldsymbol{B}_r = \begin{bmatrix} \mathrm{x} & 0 & 0 \\ \mathrm{x} & 0 & 0 \\ 0 & \mathrm{x} & 0 \\ 0 & \mathrm{x} & 0 \\ 0 & \mathrm{x} & 0 \\ 0 & 0 & \mathrm{x} \\ 0 & 0 & \mathrm{x} \end{bmatrix}.$$

The fine model is parameterized by Empipe [15] and is simulated by Sonnet's ***em*** [5]. The cell size used is 0.5 mil by 1 mil. All parameter values are rounded to the nearest grid point. Ω_s contains 25 frequencies while Ω_p contains 17. The coarse and fine-model responses at the initial solution are shown in Fig. 6, where we notice severe misalignment. The remedy suggested in Section IV managed to get a good solution of (13). The algorithm needs four iterations (five fine-model simulations). The time taken is 6.2 h (one fine-model simulation takes 1.2 h). The fine-model objective function is shown in Fig. 7. Table V shows the starting point, the optimal coarse-model solution and the final solution. Detailed responses are shown in Fig. 8.

VI. Conclusion

We expand the original space-mapping technique for circuit design. We deliberately change some preassigned parameters in the coarse model to align it with the fine model. A mapping is established from the optimization variables to those preassigned parameters. This mapping is sparse and needs only few fine-model simulations to be established. Our algorithm calibrates the coarse model w.r.t. the fine model. It updates the mapping and exploits the resulting mapped (enhanced) coarse model with a trust region optimization methodology. For implementation details see [16]. We have successfully applied our approach to several design problems.

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