MEFiSTo-Based Microwave Filter Design Exploiting Space Mapping

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***Abstract*—We utilize space mapping within the MEFiSTo environment. We employ a coarse-grid MEFiSTo solver to achieve an optimal design of a fine-grid MEFiSTo model. Our algorithm exploits the implicit space mapping and output space mapping approaches. Dielectric constant, an expedient preassigned parameter, is first calibrated to roughly align the coarse and fine MEFiSTo models. Our output space mapping scheme absorbs the remaining deviation between the "implicitly" mapped coarse-grid and fine-grid MEFiSTo responses. The surrogate is then available for design. Our optimization routine employs a trust region methodology. A database system is also utilized to accelerate the design process. Our approach is illustrated through the design of a six-section H-plane waveguide filter. The rubber cell feature in MEFiSTo is employed to perform a response interpolation.**

***Index Terms*—CAD, electromagnetic simulation, microwave filters, optimization methods, space mapping, TLM.**

I. Introduction

Space mapping (SM) is becoming widely used in RF and microwave modeling and design. The SM process calibrates an enhanced coarse model to permit acceptable, near optimal design of a computationally expensive fine model with a minimal number of fine model function evaluations [1]–[2]. It makes effective use of the surrogate's fast evaluation to sparingly manipulate the iterations of the fine model [1].

In previous implementations of SM technology, an "idealized" empirically based coarse model provides a target optimal response with respect to the predefined design specifications. SM algorithms aim to achieve a satisfactory "space-mapped" design of the fine model $\bar{\boldsymbol{x}}_f$.

In this paper, we explore the SM methodology in the MEFiSTo simulation environment [3]. We design a CPU intensive fine-grid MEFiSTo structure utilizing a coarse-grid MEFiSTo model. Such a coarse model may not satisfy the original design specifications. Hence, SM techniques such as the aggressive SM [2] may fail to reach a satisfactory solution.

Here we propose a technique combining the implicit SM (ISM) [4] and output SM (OSM) [5] approaches. The parameter extraction (PE) process is utilized in constructing a surrogate of the fine model. We first calibrate the MEFiSTo coarse-grid model's dielectric constant. Then, an output SM scheme absorbs the response deviation between the two MEFiSTo models to make the updated surrogate is more representative of the fine-grid MEFiSTo model. The subsequent surrogate optimization step is governed by a trust region (TR) strategy to assure convergence [6]. A database subsystem is also created to avoid repeatedly invoking the simulator, to calculate the responses and derivatives, for a previously visited point [7]. The technique is illustrated by the design of a six-section H-plane waveguide filter using the commercial time domain simulator MEFiSTo [3]. We employ the TLM conformal (rubber) cell [8] in MEFiSTo to perform a linear response interpolation.

II. Background

The MEFiSTo time-domain full-wave solver is a "Multi-purpose Electromagnetic Field Simulation Tool" for modeling electromagnetic (EM) structures [3]. It explicitly solves Maxwell's equations in space and time with the Transmission Line Modeling (TLM) method. The TLM method is a discrete method that utilizes a mesh of interconnected transmission lines to model the propagation space. Its main advantage is its ability to model EM structures with arbitrary geometry and material properties [9].

The design problem for a fine-grid MEFiSTo model is

$$\boldsymbol{x}_f^* = \arg\min_{\boldsymbol{x}_f} U(\boldsymbol{R}_f(\boldsymbol{x}_f)) \tag{1}$$

where $\boldsymbol{R}_f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a vector of m responses of the model, e.g., $|S_{11}|$ at m selected frequency points. $\boldsymbol{x}_f \in \mathbb{R}^n$ is the vector of n design parameters and U is a suitable objective function. $\boldsymbol{x}_f^*$ is the optimal solution to be determined.

The implicit SM (ISM) approach employs an auxiliary set of parameters, such as dielectric constant, to calibrate the surrogate against the fine model. The surrogate can then be

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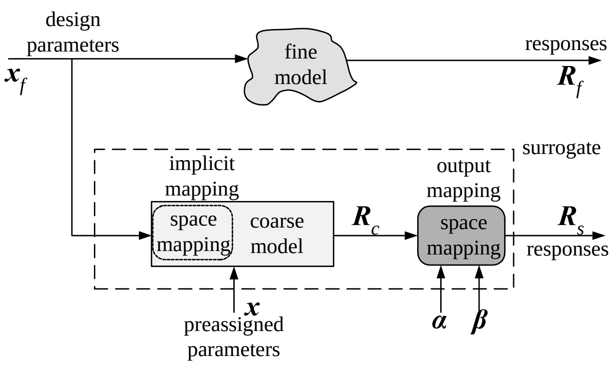


Fig. 1. The implicit and output SM concepts [10]. We calibrate the surrogate against the fine model utilizing the preassigned parameters $\boldsymbol{x}$, e.g., dielectric constant, and the output response mapping parameters: the scaling matrix $\boldsymbol{\alpha}$ and the shifting vector $\boldsymbol{\beta}$.

optimized to predict the next fine model iterate [4].

Output SM (OSM) $\boldsymbol{O}:\mathbb{R}^m \to \mathbb{R}^m$ is originally proposed to fine-tune the residual response deviation [5] between the fine model and its surrogate, in the final stages.

III. A Proposed Approach

We exploit the ISM and OSM concepts to construct a surrogate of the fine model iteratively [10]

$$\boldsymbol{R}_s(\boldsymbol{x}_f, \boldsymbol{x}^{(j+1)}, \boldsymbol{\alpha}^{(j+1)}, \boldsymbol{\beta}^{(j+1)}) \triangleq \boldsymbol{\alpha}^{(j+1)} \boldsymbol{R}_c\left(\boldsymbol{x}_f, \boldsymbol{x}^{(j+1)}\right) + \boldsymbol{\beta}^{(j+1)} \tag{2}$$

where, at the jth iteration, the preassigned parameter vector is $\boldsymbol{x}^{(j+1)} \in \mathbb{R}^p$. The scaling diagonal matrix $\boldsymbol{\alpha}^{(j+1)} \in \mathbb{R}^{m\times m}$ and the shifting vector $\boldsymbol{\beta}^{(j+1)} \in \mathbb{R}^m$ are the output mapping parameters. The surrogate and the coarse model responses are denoted by $\boldsymbol{R}_s$ and $\boldsymbol{R}_c \in \mathbb{R}^m$, respectively. Fig. 1 describes a conceptual scheme for combining an input parameter mapping (implicit in our case) with an output response mapping [10].

A. Parameter Extraction (Surrogate Calibration)

The parameter extraction (PE) optimization process aligns the surrogate (2) with the fine model by calibrating the mapping(s) parameters. At the jth iteration, the PE step is

$$\begin{gathered}\left[\boldsymbol{x}^{(j+1)}, \boldsymbol{\alpha}^{(j+1)}, \boldsymbol{\beta}^{(j+1)}\right] \triangleq \arg\min_{\boldsymbol{x},\boldsymbol{\alpha},\boldsymbol{\beta}} \left\| \boldsymbol{r}\left(\boldsymbol{x}_f^{(j)}, \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{\beta}\right)\right\|, \\ \boldsymbol{r}\left(\boldsymbol{x}_f^{(j)}, \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{\beta}\right) = \boldsymbol{R}_s\left(\boldsymbol{x}_f^{(j)}, \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{\beta}\right) - \boldsymbol{R}_f\left(\boldsymbol{x}_f^{(j)}\right)\end{gathered} \tag{3}$$

Here, the PE is executed in two steps. Firstly, $\boldsymbol{x}^{(j+1)}$ is extracted keeping the output mapping parameters $\boldsymbol{\alpha}^{(j)}$ and $\boldsymbol{\beta}^{(j)}$ fixed to have a rough alignment between the fine and surrogate models. Then, we calibrate the surrogate by manipulating $\boldsymbol{\alpha}^{(j)}$ and $\boldsymbol{\beta}^{(j)}$ at $\boldsymbol{x}_f^{(j)}$ and $\boldsymbol{x}^{(j+1)}$ to absorb the response deviation [10].

B. Surrogate Optimization (Prediction)

We optimize a suitable objective function of the surrogate (2) in an effort to obtain a solution of (1). We utilize the trust region (TR) methodology to find a step in the fine space [10]

$$\begin{gathered}\boldsymbol{h}^{(j)} \triangleq \arg\min_{\boldsymbol{h}} U(\boldsymbol{R}_s(\boldsymbol{x}_f^{(j)} + \boldsymbol{h}, \boldsymbol{x}^{(j+1)}, \boldsymbol{\alpha}^{(j+1)}, \boldsymbol{\beta}^{(j+1)})), \\ \|\boldsymbol{h}\|_\infty \le \delta^{(j)}\end{gathered} \tag{4}$$

where $\delta^{(j)}$ is the TR size at the jth iteration. The tentative step $\boldsymbol{h}^{(j)}$ is accepted as a successful step in the fine space if there is a reduction of the objective function of the fine model otherwise it is rejected. The TR radius is updated according to [6]. The proposed algorithm is given in detail in [10].

C. Design Procedure

We summarize our design procedure in the following steps:

1. Obtain a suitable starting point for the design process, e.g., by analyzing an equivalent circuit model.
2. Solve (4) to find the initial surrogate (coarse-grid MEFiSTo model) optimizer.
3. Evaluate the fine-grid MEFiSTo model response.
4. Perform PE step (3) to find the mapping parameters.
5. Solve (4) to obtain $\boldsymbol{h}^{(j)}$ and evaluate $\boldsymbol{R}_f(\boldsymbol{x}_f^{(j)} + \boldsymbol{h}^{(j)})$.
6. Update $\boldsymbol{x}_f^{(j+1)}$ and $\delta^{(j+1)}$.

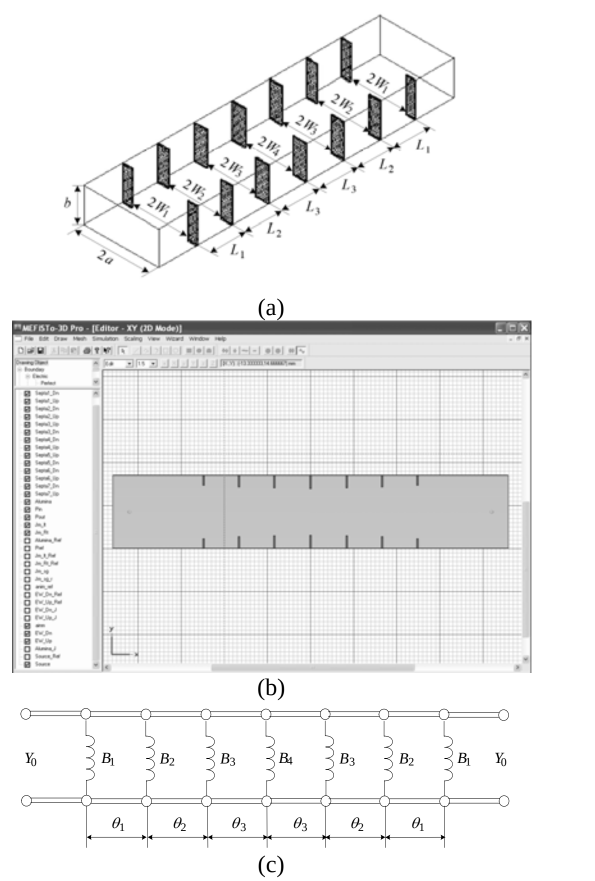


Fig. 2. The six-section H-plane waveguide filter: (a) the 3D view [10]. (b) MEFiSTo snapshot of the cross section. (c) the equivalent empirical circuit model [10].

7. Check the stopping criteria to terminate, otherwise go to step 4.

IV. EXAMPLES

Six-Section H-plane Waveguide Filter

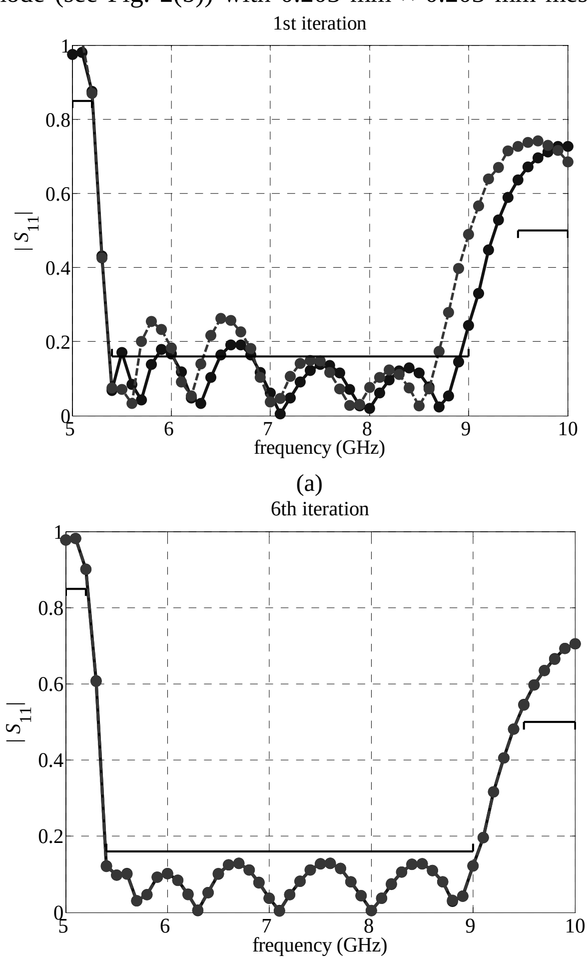
We consider the six-section H-plane waveguide filter [11] (see 3D view in Fig. 2(a)). A waveguide with a width 11.132 mm is used. The six-waveguide sections are separated by seven H-plane septa, which have a finite thickness of 0.203 mm. The waveguide is filled with alumina with a relative dielectric constant $\varepsilon_r = 9.4$. The design parameters are the three waveguide-section lengths L_1, L_2 and L_3 and the septa widths W_1, W_2, W_3 and W_4. A minimax objective function is employed with upper and lower design specifications

$$
\begin{aligned}
&|S_{11}| \le 0.16 \text{ for } 5.4 \text{ GHz } \le \omega \le 9.0 \text{ GHz} \\
&|S_{11}| \ge 0.85 \text{ for } \omega \le 5.2 \text{ GHz} \\
&|S_{11}| \ge 0.5 \quad \text{for } \omega \ge 9.5 \text{ GHz}
\end{aligned} \tag{5}
$$

The fine model is simulated using MEFiSTo [3] in a 2D mode (see Fig. 2(b)) with 0.203 mm × 0.203 mm mesh size and 27000 time steps (148 sec simulation time). We utilize the rubber cell feature available in MEFiSTo to perform a response interpolation for the off-grid points. We utilize 51 points in the frequency range 5.0 GHz ≤ ω ≤ 10.0 GHz. We use the least-squares Levenberg-Marquardt algorithm in Matlab [12] for the PE. A database system is utilized for the surrogate optimization using the minimax routine given in [13].

We utilize an empirical circuit model, shown in Fig. 2(c), to obtain a reasonable starting point for our deign procedure. It consists of lumped inductances and dispersive transmission line sections. We simplify formulas due to Marcuvitz for the inductive susceptances corresponding to the H-plane septa. They are connected to the transmission line sections through circuit theory. The model is implemented in Matlab [12].

The coarse-grid MEFiSTo model is simulated using MEFiSTo with 0.406 mm × 0.406 mm grid size and with 5000 time steps (9 sec simulation time). The simulation time of the MEFiSTo coarse-grid model is reduced because of the coarser-grid and the reduced number of time steps versus the MEFiSTo-fine model.



(b)

Fig. 3. The surrogate response (--•--) and the corresponding fine model response (–•–) at: (a) the initial design, and (b) the final design for the six-section H-plane waveguide filter designed using the coarse-grid MEFiSTo model.

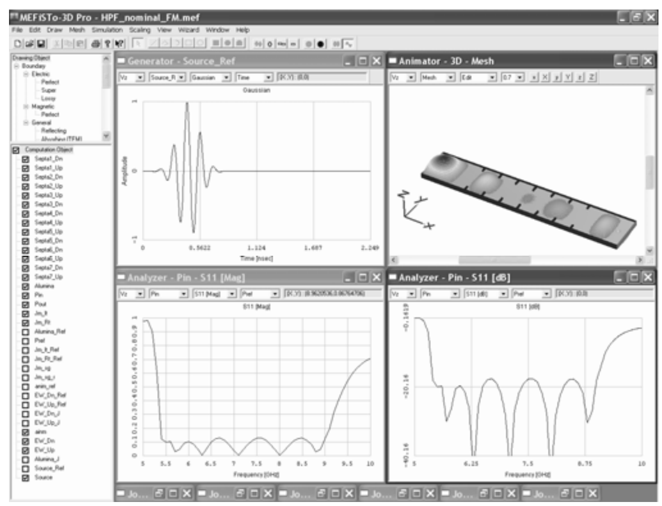
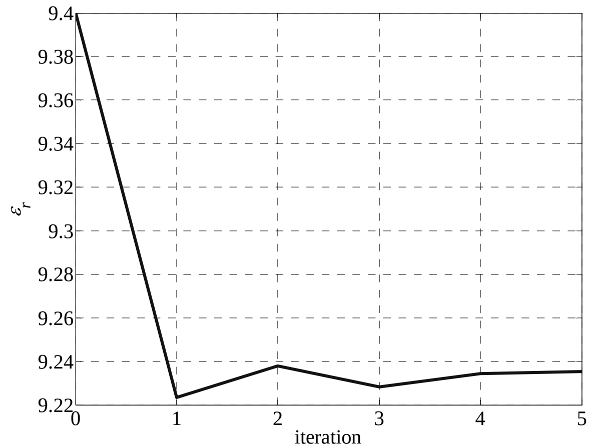


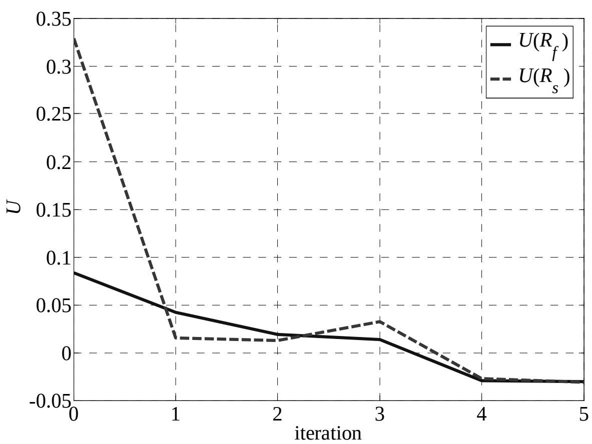
Fig. 4. A snapshot taken from MEFiSTo during the design process.

TABLE I
STARTING, INITIAL AND FINAL DESIGNS
FOR THE SIX-SECTION H-PLANE WAVEGUIDE FILTER

Parameter	Starting (optimal empirical model) design (mm)	Initial (optimal coarse-grid model) design (mm)	Final design (mm)
L_1	5.3780	5.3190	5.2838
L_2	5.4491	5.3893	5.2608
L_3	5.5983	5.5369	5.3947
W_1	4.1833	4.1374	4.1674
W_2	3.8414	3.8835	3.8827
W_3	3.6615	3.7017	3.7458
W_4	3.6168	3.6565	3.6287



(a)



(b)

Fig. 5. The change of the dielectric constant of the coarse-grid MEFiSTo model (a) and the reduction of the objective function (b) versus iterations for the six-section H-plane waveguide filter designed using the coarse-grid MEFiSTo model.

Despite the poor initial surrogate response (see Fig. 3(a)), the algorithm reaches an optimal solution in 6 iterations. The initial and final responses for the fine model and its surrogate are illustrated in Fig. 3. A snapshot of the design process executed in the MEFiSTo system is shown in Fig. 4. The change of the dielectric constant of the MEFiSTo coarse-grid model and the reduction of the objective function versus iterations are shown in Fig. 5. The optimal empirical model, the optimal coarse-grid MEFiSTo model and final designs are shown in Table I.

V. Conclusion

We utilize the SM technology in the MEFiSTo environment, exploiting the implicit SM and output SM concepts. The dielectric constant, acts as a preassigned parameter, is first calibrated for a rough (preprocessing) alignment between the coarse and fine MEFiSTo models. Output SM absorbs the remaining response deviation between the MEFiSTo fine-grid model and the implicitly mapped MEFiSTo coarse-grid model. Our approach is illustrated through the MEFiSTo-based design of a six-section H-plane waveguide filter filled with alumina. Our approach drives the commercial TLM-based simulator MEFiSTo. We employ the rubber cell feature in MEFiSTo to perform a response interpolation. Our algorithm converges to an optimal design of the fine-grid MEFiSTo waveguide filter in spite of a poor initial response of the coarse-grid MEFiSTo surrogate in a handful of iterations.

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