Antenna Optimization Through Space Mapping

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***Abstract*—We apply space mapping to antenna design for the first time. We exploit a coarse-mesh method of moments (MoM) solver as the coarse model and align it with the fine-mesh MoM solution through space mapping. We employ two plans: (I) implicit and output space mapping, and (II) input and output space mapping. We propose a local meshing method which avoids inconsistencies in the coarse model. The proposed techniques are implemented through our user-friendly space mapping framework (SMF) system. In a double annular ring antenna example, the S-parameter is optimized. The finite ground size effect for the MoM is efficiently solved by space mapping plan I and the design specification is satisfied after only three iterations. In a patch antenna example, we optimize the impedance using both plans in separate optimization processes. Comparisons are made. Coarseness in the coarse model and its effect on the space mapping performance are also discussed.**

***Index Terms*—Antenna design, CAD, EM optimization, method of moments (MoM), space mapping (SM).**

I. Introduction

The method of moments (MoM) is one of the most often used numerical techniques for antenna and microwave device analysis. Accurate MoM simulations of practical structures are memory and CPU intensive. This computational cost could become prohibitive in complex design problems, which may require anywhere between tens and thousands of system analyses. The electromagnetics-based antenna design remains a challenging task and ongoing research is pursuing acceleration of the numerical analysis on the one hand and improving the efficiency of the optimization algorithms on the other. The space mapping approach proposed here addresses the latter problem in conjunction with MoM-based analysis.

Common classifications of optimization algorithms include gradient-based (e.g., steepest-descent, conjugate-gradient, Newton and quasi-Newton), stochastic (e.g., random-search, genetic, simulated-annealing, particle-swarm), and neural-based approaches [1]. Some of these have already been incorporated into commercial electromagnetic CAD packages. Only recently, the space mapping (SM) and surrogate-based optimization have been recognized in the mathematical and engineering community as a distinct class of approaches, e.g., [2]–[5]. They promise unprecedented efficiency in problems where two system models are available: a coarse model, which is not accurate but is fast (e.g., approximate analytical models, empirical formulas, equivalent circuits), and a fine model, which is very accurate but is expensive to evaluate (e.g., electromagnetic simulations, a set of measurements). The SM technique takes advantage of the efficiency of the coarse model and the accuracy of the fine model. It aligns the coarse model with the fine model in an iterative optimization process where most of the burden of the multiple system analyses is placed on the coarse model [6]–[10].

So far, SM has been successfully applied to the electromagnetics-based design of microwave filters, impedance-matching networks, multiplexers, etc.; see, e.g., [6]–[10]. There, equivalent-circuit, empirical, and semianalytical models and combinations thereof have been linked to full-wave electromagnetic simulators.

The application of SM to antenna design, on the other hand, proves to be more challenging. This is due to the fact that, with few exceptions, the radiating structures are too complex to lend themselves to analytical and/or circuit modeling. Examples of exceptions include printed patches of standard shapes and some standard horn designs. In the former case, fast analytical models include transmission-line and cavity representations loaded with the aperture admittances [11], [12]. In the latter case, complete design procedures exist [13] based on analysis where the edge diffraction is ignored. Such fast models are good candidates for coarse models in an SM optimization process. Unfortunately, for the vast majority of modern antenna types, coarse models are not available. This limits the applicability of the SM and surrogate-based optimization in antenna design.

Here, we propose an approach, which allows the construction of a coarse model for any radiating structure, which can be modeled by an MoM solver. The same solver is used for the coarse and the fine model. The fine model is an accurate MoM solution whose mesh satisfies rigorous convergence criteria, e.g., the convergence error is below 1%. The coarse model uses a coarse mesh, which normally would satisfy very relaxed requirements, e.g., a convergence error below 15%. Some MoM analysis engines may have additional features allowing for other types of approximations, which can speed up the system analysis significantly. A good example is the use of a specialized Green's function in the case of a ground plane and an N-layered substrate of infinite extent (N is finite), which is much faster than

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the analysis of a structure with a finite-size ground plane where all interfaces are meshed.

When employing coarse-mesh coarse models, the mesh topology must remain unchanged throughout the optimization iterations in order to keep the coarse-model response smooth and consistent in the design-parameter space. For that, local mesh control is employed. This is not necessary for the fine model, which can be remeshed at each optimization iteration.

We implement two SM plans: (I) implicit and output SM, and (II) input and output SM, [14], [15]. The aim of implicit and input SM is to roughly align the responses of the coarse and fine models through parameter extraction in the coarse-model design-parameter space. Then output SM performs response-level adjustments to achieve a perfect local match between the coarse and fine model responses.

The optimization is carried out with the space mapping framework (SMF) system [16]. SMF is a prototype GUI-oriented software package that implements a number of SM optimization algorithms. The system provides sockets to popular simulators (e.g., MEFiSTo, FEKO, Sonnet ***em***, ADS). It allows for automatic fine and coarse model data acquisition and, consequently, for fully automatic SM optimization. SMF also provides interfaces for modeling and statistical analysis.

Our examples are implemented with a commercial MoM solver [17]. We consider a double annular ring antenna and a patch antenna. In the first example, we exploit the CPU-intensive surface equivalence principle as a fine model and the special Green's function with a coarse mesh as a coarse model. The S-parameter response is optimized in three iterations. In the second example, we optimize the input impedance at a single frequency using two SM plans. The comparisons show larger time saving in SM plan I. Last, we discuss the coarseness in the coarse model and its effect on the SM performance.

II. Basics of Space Mapping Optimization

Space mapping (SM) technology is a recognized engineering optimization paradigm, consisting of a number of efficient optimization approaches, e.g., [5]–[10]. The main feature is that the direct optimization of the high-fidelity computationally expensive fine model is replaced by the iterative optimization and update of the fast coarse model. Provided that the misalignment between the fine and coarse models is not significant, SM-based algorithms typically provide excellent results after only a few evaluations of the fine model. In contrast, direct optimization typically requires dozens or hundreds of evaluations and may fail to provide acceptable results.

Let $\boldsymbol{R}_f : X_f \to R^m$ denote the response vector of the fine model of a given device, where $X_f \subseteq R^n$ is the design-parameter domain of the fine model. Our goal is to solve

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

where $U : R^m \to R$ is a given objective function and $\boldsymbol{x}$ is the vector of fine-model design parameters. In many engineering problems, we are concerned with the so-called minimax objective function. If we denote the fine model response components by $\boldsymbol{R}_f = [R_{f.1} \cdots R_{f.m}]^T$, the lower specification vector by $\boldsymbol{R}_l = [R_{l.1} \cdots R_{l.m}]^T$, and the upper specification vector by $\boldsymbol{R}_u = [R_{u.1} \cdots R_{u.m}]^T$, then we require that $R_{f.i} \leq R_{u.i}$ for $I \in I_u$ and $R_{f.i} \geq R_{l.i}$ for $I \in I_l$, where I_l, $I_u \subset \{1, 2, \ldots, m\}$. The minimax objective function is defined as

$$U(\boldsymbol{R}_f) = \max\left\{\max_{i \in I_u}(R_{f.i} - R_{u.i}), \max_{i \in I_l}(R_{l.i} - R_{f.i})\right\}. \tag{2}$$

In some problems, U may be defined by a norm, i.e.

$$U(\boldsymbol{R}_f) = \|\boldsymbol{R}_f - \boldsymbol{R}_{spec}\| \tag{3}$$

where $\boldsymbol{R}_{spec} = [R_{spec.1} \cdots R_{spec.m}]^T$ is the target response.

We consider the fine model to be expensive to compute and solving (1) by direct optimization to be impractical. Instead, we use surrogate models, i.e., computationally cheap models that are supposed to be acceptable local representations of the fine model.

According to the SM approach, the basis of the surrogate is the coarse model. Let $\boldsymbol{R}_c : X_c \times X_p \to R^m$ denote the response vectors of the coarse model. Here, $X_c \subseteq R^n$ is the coarse-model design-parameter domain (we assume that $X_c \subseteq X_f$) and $X_p \subseteq R_q$ is the domain of auxiliary (preassigned) coarse model parameters. We emphasize that the preassigned parameters $\boldsymbol{x}_p$ are outside of X_f and X_c. They are used to align the coarse and fine model responses in the parameter-extraction step of the SM procedure; however, they remain fixed during the optimization process aiming at an optimum surrogate with respect to the design specifications. Typical preassigned parameters in a layered structure are the dielectric constant and the height of a dielectric layer.

The optimal solution of the coarse model $\boldsymbol{x}_c^*$ is

$$\boldsymbol{x}_c^* \triangleq \arg \min_{\boldsymbol{x} \in X_c} U\left(\boldsymbol{R}_c\left(\boldsymbol{x}, \boldsymbol{x}_p^{(0)}\right)\right) \tag{4}$$

where $\boldsymbol{x}_p^{(0)}$ denotes the initial preassigned parameter values. Solving (4) is a necessary step in initializing the SM optimization process.

We consider an optimization algorithm that generates a sequence of points $\boldsymbol{x}_f^{(i)} \in X_f$, $i = 1, 2, \ldots$, so that

$$\boldsymbol{x}_f^{(i+1)} = \arg \min_{\boldsymbol{x} \in X_s^{(i)}} U\left(\boldsymbol{R}_s^{(i)}(\boldsymbol{x})\right). \tag{5}$$

Here, $\boldsymbol{R}_s^{(i)} : X_s^{(i)} \to R^m$ is the surrogate model at iteration i. We assume that $X_f \cap X_s^{(i)} \neq \emptyset$ for $i = 0, 1, 2, \ldots$. In the SM framework, the family of surrogate models is constructed from the coarse model in such a way that each $\boldsymbol{R}_s^{(i)}$ is a suitable distortion of $\boldsymbol{R}_c$, such that the response of the surrogate model matches the response of the fine model as well as possible.

In this work, we use a surrogate model based on input SM [6], implicit SM [7] and output SM [18]. The surrogate model at iteration i is defined as

$$\boldsymbol{R}_s^{(i)}(\boldsymbol{x}) = \boldsymbol{R}_c\left(\boldsymbol{B}^{(i)}\boldsymbol{x} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)}\right) + \boldsymbol{\Delta R}^{(i)} \tag{6}$$

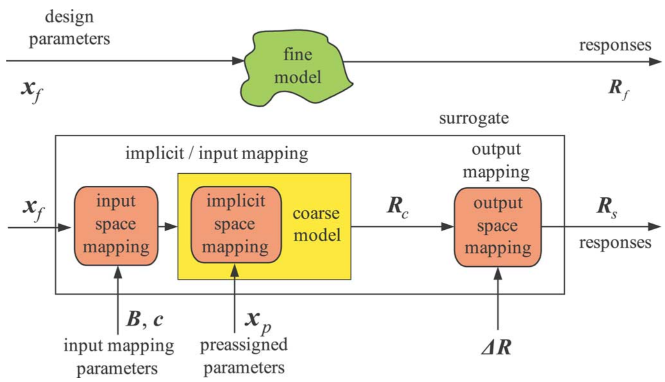

Fig. 1. Illustration of our approach to implicit, input, and output SM.

where

$$\left(\boldsymbol{B}^{(i)}, \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)}\right) = \arg \min_{(\boldsymbol{B}, \boldsymbol{c}, \boldsymbol{x}_p)} \varepsilon^{(i)}(\boldsymbol{B}, \boldsymbol{c}, \boldsymbol{x}_p) \tag{7}$$

and

$$\boldsymbol{\Delta R}^{(i)} = \boldsymbol{R}_f^{(i)}\left(\boldsymbol{x}_f^{(i)}\right) - \boldsymbol{R}_c\left(\boldsymbol{B}^{(i)}\boldsymbol{x}_f^{(i)} + \boldsymbol{c}^{(i)}, \boldsymbol{x}_p^{(i)}\right). \tag{8}$$

The matrices $\boldsymbol{B}^{(i)} \in M_{n \times n}$, $\boldsymbol{c}^{(i)} \in M_{n \times 1}$, and the vector $\boldsymbol{x}_p^{(i)}$ are obtained using parameter extraction applied to the matching condition $\varepsilon^{(i)}$ as per (7). The vector $\boldsymbol{\Delta R}^{(i)} \in M_{m \times 1}$ is calculated using (8) after $\boldsymbol{B}^{(i)}$, $\boldsymbol{c}^{(i)}$, and $\boldsymbol{x}_p^{(i)}$ are determined.

A matching condition that we use in this work is defined as

$$\varepsilon^{(i)}(\boldsymbol{B}, \boldsymbol{c}, \boldsymbol{x}_p) = \left\| \boldsymbol{R}_f\left(\boldsymbol{x}_f^{(i)}\right) - \boldsymbol{R}_c\left(\boldsymbol{B} \cdot \boldsymbol{x}_f^{(i)} + \boldsymbol{c}, \boldsymbol{x}_p\right) \right\|. \tag{9}$$

As follows from (7) and (9), we tune the values of the preassigned parameters $\boldsymbol{x}_p^{(i)}$ of the coarse model (implicit SM) and/or $\boldsymbol{B}$ and $\boldsymbol{c}$ (linear input SM) in order to reduce the misalignment between the fine model and the current surrogate model using the fine model data from the latest iteration. More general matching conditions can be found in [19].

It is now clear that implicit and input SM exploit the physics-based similarity of the models and tune their shape, material or equivalent-circuit parameters, while the output SM ensures perfect local alignment between their responses at the current iteration point. As follows from (6)–(9), we implement implicit/input SM and output SM sequentially. This is illustrated in Fig. 1.

Having defined the surrogate model, we can define the optimization algorithm. It is, in fact, an implementation of the generic surrogate model-based optimization problem (5).

Step 1) Choose coarse model and preassigned parameters $\boldsymbol{x}_p$. Set $i = 0$.

Step 2) Solve (4) to find coarse-model optimal solution $\boldsymbol{x}_c^*$; set $\boldsymbol{x}_f^{(0)} = \boldsymbol{x}_c^*$.

Step 3) Evaluate fine model to obtain $\boldsymbol{R}_f(\boldsymbol{x}_f^{(i)})$.

Step 4) Update $\boldsymbol{B}^{(i)}$, $\boldsymbol{c}^{(i)}$, $\boldsymbol{x}_p^{(i)}$ through parameter extraction using (7).

Step 5) Compute $\boldsymbol{\Delta R}^{(i)}$ using (8) and update surrogate model using (6).

Step 6) Solve (5) to obtain $\boldsymbol{x}_f^{(i+1)}$.

Step 7) If termination condition is satisfied (convergence achieved or design specification satisfied), stop; otherwise, set $i = i + 1$, go to Step 3.

III. Coarse-Mesh Coarse Models

In the numerical examples discussed in Section V, both fine and coarse models are implemented using the same MoM-based simulator [17]. The fine model uses a fine mesh satisfying mesh convergence so that the results are accurate. The fine model evaluation is computationally demanding. The coarse model uses a coarse MoM mesh which, as indicated here, results in significant speed-up at the expense of the response accuracy.

A. CPU Time Cost Versus Mesh Density

The CPU time for an MoM simulation can be expressed as [20]

$$T_{\text{CPU}} = A + BN + CN^2 + DN^3 \tag{10}$$

where N is the number of unknowns. A, B, C, and D are constants independent of N. A accounts for the simulation setup. The meshing of the structure leads to the linear term BN. The filling of the system matrix is responsible for the quadratic term, and solving the matrix equation for the cubic term. The values of A, B, C and D depend on the problem at hand and the type of the MoM discretization procedure.

The quadratic and cubic terms dominate. For small to medium size problems, as the constant C is much larger than D, the solution time is dominated by the matrix fill. For large-scale problems, the matrix solving time with its cubic term will eventually dominate the CPU-time cost. Thus, for medium to large scale problems, the time saving offered by coarse-mesh coarse models will be significant.

B. Mesh Convergence and Meshing Method

The mesh convergence needs to be checked to get an accurate simulation result. This is done by refining the mesh from one simulation to the next, and keeping all other parameters the same. If the results are significantly different, the surfaces are not adequately discretized and we need to refine the mesh.

The coarse-mesh coarse model does not need to achieve mesh convergence. Consequently, if the mesh topology and number of mesh elements vary due to the variation of geometrical design parameters during optimization, inconsistent results are obtained. To overcome this problem, we force the mesh topology to remain unchanged during the optimization. This is done by local meshing in FEKO [21]. In effect, for a given part of the structure, the user can fix the number of mesh lines along its contours. This enforces the same mesh topology regardless of variations in some of the shape parameters of the part.

In the fine model, where mesh convergence is satisfied, we use global meshing where the minimum mesh density is determined by the number of mesh lines per wavelength. At each iteration, remeshing is allowed.

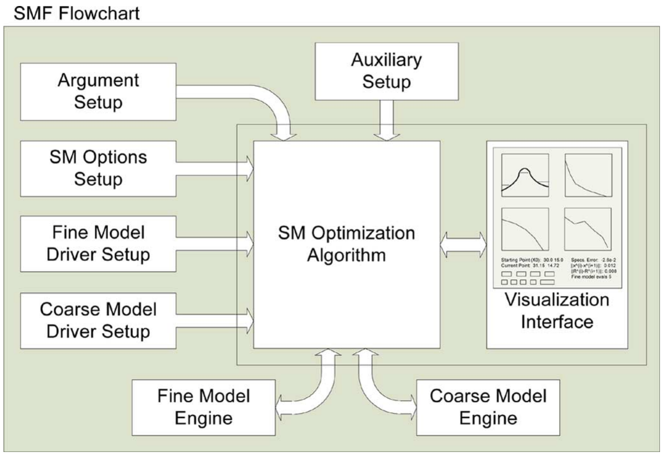

Fig. 2. Flowchart of the optimization module in SMF [16].

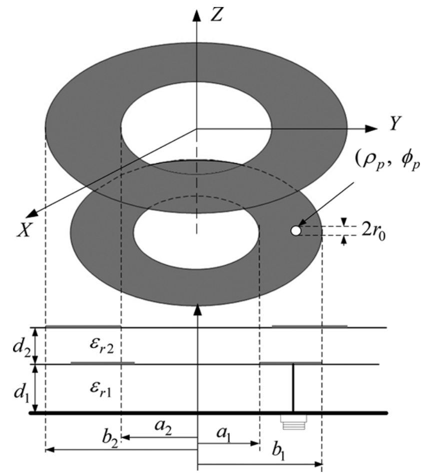

Fig. 3. Geometry of a stacked probe-fed printed double annular ring antenna example.

IV. SMF: Implementation of SM Optimization Algorithms

In order to make SM accessible to engineers not experienced in this technology, a prototype user-oriented software package was created. SMF [16] is a GUI-based Matlab system that can perform SM-based constrained optimization, modeling and statistical analysis. It implements existing SM approaches, including input, output, implicit and frequency SM. It contains drivers for commercial simulators that allow linking the fine and coarse model to the algorithm and make the optimization process fully automatic. In this paper, we use SMF to validate the antenna design based on SM optimization and MoM coarse and fine models.

Fig. 2 shows a block diagram of the optimization module in SMF. Optimization is performed in several steps. First, the user enters problem arguments, including starting point, frequency sweep, optimization type and specifications. Next, the user sets up space mapping itself, i.e., the kind of space mapping to be used (e.g., input, output, implicit), specifies the termination condition, parameter extraction options, and optional constrains.

The next step is to link the fine and coarse models to SMF by setting up the data that will be used to create model drivers. Using the user-provided data (e.g., simulator input files and design-parameter identification data), SMF creates drivers that automatically invoke fine and coarse model evaluations as required by the SM algorithm.

Parameter extraction, surrogate model optimization, and optional trust-region specific options are set in the next step using auxiliary interfaces.

Having done the setup, the user runs the execution interface, which invokes the SM optimization algorithm and the output visualization. The latter includes model responses, specification error plots as well as convergence plots, all updated at each SM iteration.

V. Examples

We use: (I) implicit and output SM, or (II) input and output SM. As explained in Section III, the implicit SM operates on the preassigned parameters while the input SM operates on the mapping parameters $\boldsymbol{B}$ and $\boldsymbol{c}$. Both approaches can be used separately (as done in the examples below) or simultaneously. When implicit SM is used alone, the input mapping parameters are fixed at $\boldsymbol{B} = \boldsymbol{I}$ and $\boldsymbol{c} = \boldsymbol{0}$, where $\boldsymbol{I}$ is the identity matrix. When input SM is used alone, $\boldsymbol{x}_p$ is empty.

A. Double Annular Ring Antenna

We consider the stacked probe-fed printed annular ring antenna [22] shown in Fig. 3. The antenna is printed on a printed circuit board (PCB) with $\varepsilon_{r1} = 2.2$, $d_1 = 6.096$ mm for the lower substrate, and $\varepsilon_{r2} = 1.07$, $d_2 = 8.0$ mm for the upper substrate. The dielectric loss tangent is 0.001 for both layers.

The finite ground size is 100 × 100 mm. The radius of the feed pin is $r_0 = 0.325$ mm. The design parameters are the outer and inner radius of each ring and the feed position, namely, $[a_1\ a_2\ b_1\ b_2\ \rho_p]^T$. The design specification is

$$|S_{11}| \leq -10 \text{ dB for } 1.75 \text{ GHz} \leq \omega \leq 2.15 \text{ GHz}. \quad (11)$$

In the MoM solver used here, special Green's functions are available to model multilayer substrates where the ground plane and the substrate are assumed infinite in extent. The method is efficient since only the finite metallic surfaces are discretized. However, in many applications, the infinite ground plane assumption is not accurate. It is well known that the ground-plane size has a strong effect on the performance of microstrip antennas [23], [24].

The surface equivalence principle (SEP) allows the analysis of layered structures with a finite-size ground plane. In this case, however, the surfaces of all dielectric interfaces are discretized for the electric and magnetic current densities. All sides of a dielectric have to be meshed, making a closed solid. Thus, the number of unknowns is many times larger in comparison with the analogous structure of infinite ground plane analyzed with the special Green's function.

We choose the SEP model as the fine model and the special Green's function analysis as the coarse model. To further reduce the simulation time in the coarse model, we apply a coarser mesh

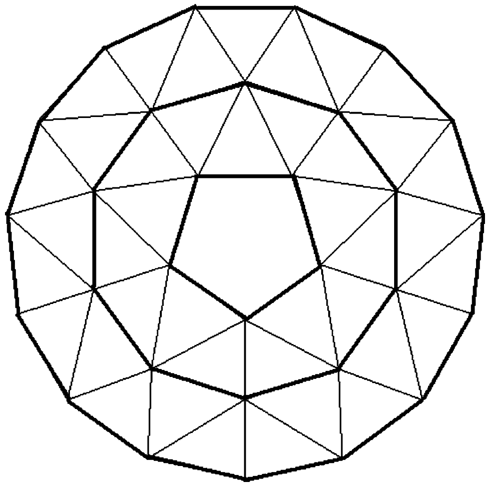

Fig. 4. Demonstration of local meshing of the annular ring in the coarse-mesh coarse model for a stacked ring antenna example.

TABLE I
FINE MODEL AND COARSE MODEL IN THE DOUBLE ANNULAR RING ANTENNA

Model type	Technique	Meshing method	Mesh number	Frequency sweep time
Coarse model	Special Green's function + coarse mesh	Local meshing	83	8.721 seconds
Fine model	SEP	Global meshing density = 20	2661*	1 hour and 18 minutes*

*Number of mesh lines and time cost in the fine model are measured at the initial point.

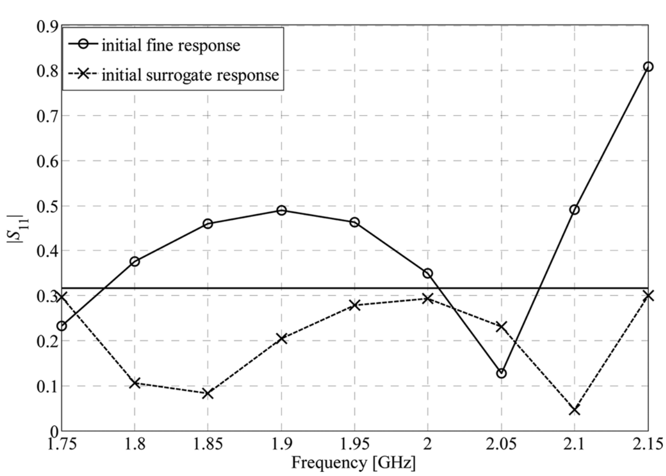

Fig. 5. Initial fine and surrogate responses corresponding to the coarse model optimal solution for the double annular ring antenna.

by local meshing. As shown in Fig. 4, the number of mesh lines along the three loops (thick lines) is topologically fixed at 5, 10, and 15, respectively, regardless of the variation in the design parameter values. The fine and coarse models are summarized in Table I.

This problem has been solved using implicit and output SM. The relative permittivities of the two layers, ε_{r1} and ε_{r2}, are used as preassigned parameters. The initial fine model, which takes its design-parameter values from the optimized coarse model (see Step 2 of the algorithm in Section II), exhibits a

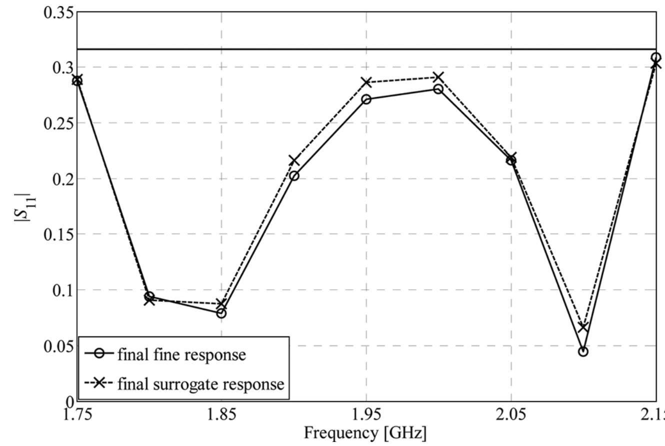

Fig. 6. Final fine and surrogate responses for the double annular ring antenna example.

TABLE II
INITIAL AND FINAL DESIGN OF THE DOUBLE ANNULAR RING ANTENNA

Design parameters	Initial design (mm)	Final design (mm)
a_1	9.2277	10.6735
a_2	8.7224	7.8088
b_1	30.7230	28.4621
b_2	34.1266	32.5043
ρ_p	18.2107	19.6817

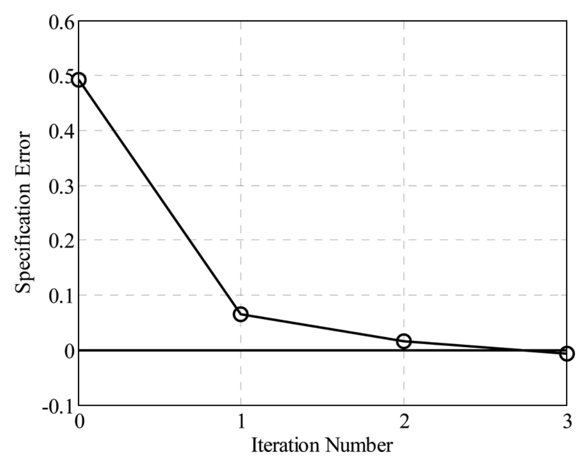

Fig. 7. Objective function value versus iteration number in the double annular ring antenna example.

poor response, shown in Fig. 5. In three iterations (four fine model simulations), the fine model is optimized and aligned with the surrogate very well. Both final responses are plotted in Fig. 6. The total time taken is 5 h 58 min (note that a single fine model simulation requires about 1 h 18 min). Fig. 7 shows the reduction of the objective function versus the number of the iterations. Table II summarizes the initial and final designs.

Direct optimization of the fine model in this example was not attempted. With a simulation time of 1 h and 18 min per system analysis, direct optimization would require about a week, which is not acceptable.

We also note that Fig. 3 shows a general layout of the stacked-ring structure, which represents the relative sizes of the rings before the preliminary coarse-model optimization. In it, $a_1 < a_2$ and $b_1 < b_2$. However, the coarse-model optimization as well as the subsequent SM optimization of the fine model resulted in a design where $a_1 > a_2$ while b_1 remained smaller than b_2.

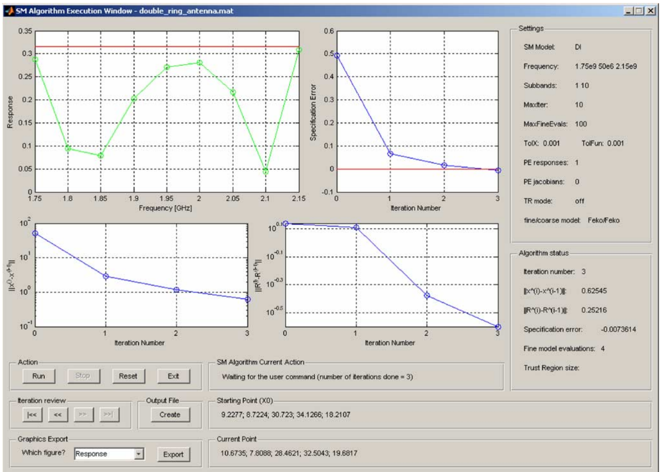

Fig. 8. Execution interface of SMF after the optimization procedure has stopped.

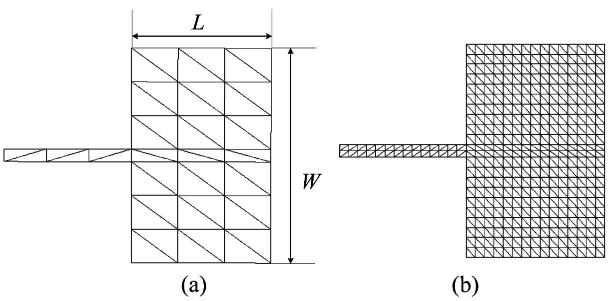

Fig. 9. Demonstration of the coarse model and the fine model. (a) The coarse model with three mesh lines along L and seven mesh lines along W. (b) The fine model with global mesh density of 30 mesh lines per wavelength.

Finally, we show the execution interface of the SMF system at the final iteration of the SM algorithm in Fig. 8. Plots in the interface correspond to the algorithm status after the last iteration. The top left plot shows the fine model response and the design specifications; the top right plot shows the specification error versus iteration number; the bottom left and bottom right plots are convergence plots that show $\|\boldsymbol{x}^{(i+1)} - \boldsymbol{x}^{(i)}\|$ and $\|\boldsymbol{R}_f^{(i+1)} - \boldsymbol{R}_f^{(i)}\|$ versus iteration number, respectively.

B. Patch Antenna

The antenna is printed on a substrate with relative dielectric constant $\varepsilon_r = 2.32$ and height $h = 1.59$ mm. The design parameters are the patch length and width, i.e., $\boldsymbol{x}_f = [L\, W]^T$. The objective is to obtain 50 Ω input impedance at 2 GHz. The objective function is $|Z_{in} - 50|$.

In the fine model, the global mesh density is 30 mesh lines per wavelength. In the coarse model, the mesh number and topology are fixed through local meshing. We choose three mesh lines along L and seven along W. The meshes of the two models are shown in Fig. 9. We use implicit SM and output SM (SM plan I) where the selected preassigned SM parameter is $\boldsymbol{x}_p = [\varepsilon_r]$. In the parameter extraction, we match the complex S_{11} instead of the input impedance.

The initial design point is the coarse model optimal solution $\boldsymbol{x}_f^{(0)} = [47.1285\ 100.470]^T$ mm. SM requires five iterations (six fine model simulations). Fig. 10 shows the reduction of the objective function versus number of iterations. The final design is $\boldsymbol{x}_f^* = \boldsymbol{x}_f^{(4)} = [46.7294\ 99.6875]^T$ mm. Table III shows the evolution of the design parameters, the objective function, the preassigned parameter and the output SM parameter at each iteration. The computation time is 341 s, compared with 2816 s for the direct fine model optimization.

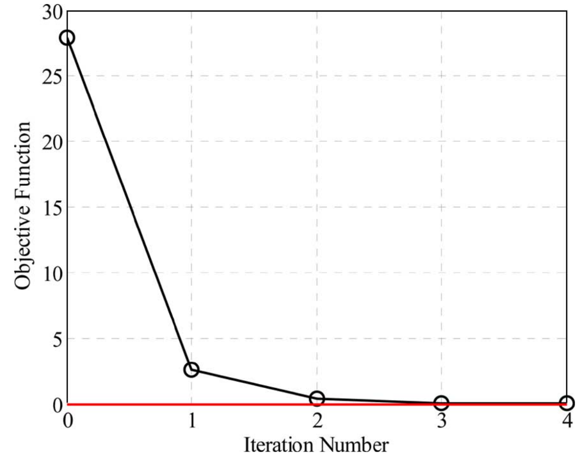

Fig. 10. Objective function value versus iteration number for the microstrip patch antenna example.

TABLE III
OPTIMIZATION RESULTS FOR THE PATCH ANTENNA EXAMPLE

Iteration	$\boldsymbol{x}_f$ (mm)	ε_r	$\Delta\boldsymbol{R}$	$\lvert Z_{in} - 50\rvert$
0	$\begin{bmatrix}47.1285\\100.470\end{bmatrix}$	2.3200	0.0000	27.941
1	$\begin{bmatrix}46.77743\\99.6922\end{bmatrix}$	2.3621	$0.0082-0.0461i$	2.5616
2	$\begin{bmatrix}46.7268\\99.6960\end{bmatrix}$	2.3589	$0.0145+0.0056i$	0.35956
3	$\begin{bmatrix}46.7294\\99.6883\end{bmatrix}$	2.3590	$0.0118+0.0054i$	2.4437×10^{-2}
4	$\begin{bmatrix}46.7294\\99.6875\end{bmatrix}$	2.3589	$0.0115+0.0059i$	1.1234×10^{-2}

An alternative way to solve this problem is through input and output SM (SM plan II). To save time in the parameter-extraction step, we extract only the variable vector $\boldsymbol{c}$ in the input mapping ($\boldsymbol{B}$ is fixed at $\boldsymbol{B} = \boldsymbol{I}$). The coarse model mesh is the same (100 mesh lines). The algorithm takes five iterations and 695 s to reach the specified error of 8.93×10^{-3}. As expected, it takes more time than the first SM option, because in the input SM, we tune two input SM variables in the parameter extraction rather than one as in the implicit SM.

Table IV summarizes the effect of the coarseness of the coarse model on the SM performance in the patch antenna example. The algorithm does not converge for 24 mesh elements (triangles). As the number of mesh elements increases, the function evaluation time increases while the SM iterations decrease. For SM plan I, we have the best SM performance in terms of total time cost for 100 mesh elements, which requires only 341 s. For SM plan II, we have the best SM performance with 48 mesh elements, which requires 479 s.

TABLE IV
THE EFFECT OF LOCAL MESHING ON SM PERFORMANCE FOR THE PATCH ANTENNA

Local meshing in the coarse model				SM Plan I		SM Plan II	
Mesh number along		Total mesh number	Function evaluation time (s)	Iteration number	Total time (s)	Iteration number	Total time (s)
L	W						
2	5	24	0.109	Not convergent		Not convergent	
3	7	48	0.219	6	364	9	479
5	9	100	0.438	4	341	5	695
9	20	400	4.063	4	1604	3	2659
11	22	528	8.375	3	2695	3	3220
Global meshing in the fine model				Direct optimization			
Mesh density=30		1032*	33.313*	2816 s			

*The number of mesh lines and function evaluation time for the fine model is measured at the starting point $[L\ W] = [55\ 85]$ mm.

VI. CONCLUSION

We have presented an effective space-mapping technique for antenna optimization based on a coarse model, which exploits a coarse nonconvergent mesh of fixed topology. Both coarse and fine models are implemented in the same MoM solver. A separate coarse model is not required. In the double annular ring example, our SMF system provides an efficient way to address the finite ground size problem. We solve the optimal impedance of a patch antenna problem using two SM plans. The coarseness in the coarse model and its effect on the space mapping performance are discussed. The approach is applicable to the design of antenna and microwave devices aided by method-of-moments models.

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