An Implementable Space Mapping Design Framework

John W. Bandler, *Fellow, IEEE*, Qingsha S. Cheng, *Student Member, IEEE*,
Daniel M. Hailu, *Student Member, IEEE*, and Natalia K. Nikolova, *Member, IEEE*

McMaster University, Hamilton, Canada L8S 4K1, www.sos.mcmaster.ca

***Abstract* — We present a microwave design framework for implementing an implicit and response residual space mapping (RRSM) approach. The RRSM surrogate is matched to the fine model. An intuitive "multiple cheese-cutting" example demonstrates the concept. For the first time, an ADS framework implements the space mapping (SM) steps interactively. A six-section H-plane waveguide filter design emerges after four iterations, using the implicit SM and RRSM optimization entirely within the design framework. We use sparse frequency sweeps and do not use the Jacobian of the fine model.**

***Index Terms* — CAD, filter design, space mapping (SM), surrogate modeling, parameter extraction (PE).**

I. Introduction

Space mapping (SM) effectively connects fast coarse models to align with CPU-intensive fine models [1]-[4] in the design parameter space. The output space mapping (OSM) [5] addresses the residual misalignment of coarse and fine models in the response space.

We describe a new design framework implementing OSM, specifically, a response residual space mapping (RRSM) approach. It differs from the approach described in [5]. Here, we match the response residual SM surrogate with the fine model in a parameter extraction (PE) process. A novel and simple "multiple cheese-cutting" problem illustrates the technique. An ADS [6] design framework exploiting explicit, implicit, and output SM is presented. Entirely in ADS, a good six-section H-plane waveguide filter [7][8] design is achieved after only five EM simulations (Agilent HFSS [9]) or four iterations.

This work was supported in part by the Natural Sciences and Engineering Research Council of Canada under Grants OGP0007239, STR 234854 and STPGP 269760, through the Micronet Network of Centres of Excellence and Bandler Corporation.

J.W. Bandler is with the Simulation Optimization Systems Research Laboratory, Department of Electrical and Computer Engineering, McMaster University, Hamilton, ON, Canada L8S 4K1 and also with Bandler Corporation, P.O. Box 8083, Dundas, Ontario, Canada L9H 5E7.

Q.S. Cheng and D.M. Hailu are with the Simulation Optimization Systems Research Laboratory, and N.K. Nikolova is with the Computational Electromagnetics Laboratory, McMaster University, Hamilton, ON, Canada L8S 4K1.

II. Response Residual Space Mapping Approach

A. Surrogate

The response residual surrogate is a calibrated (implicitly or explicitly space mapped) coarse model plus an output or response residual. The residual is a vector whose elements are the differences between the calibrated coarse model response and the fine model response at each sample point after parameter extraction. The surrogate is shown in Fig. 1. Each residual element (sample point) may be weighted using a weighting parameter λ_i, $i = 1 \ldots m$, where m is the number of sample points.

In the parameter extraction, we match the previous response residual SM surrogate (instead of the calibrated coarse model of [5]) to the fine model at each sample point.

B. Multiple Cheese-cutting Problem

We develop a physical example suitable for illustrating space mapping optimization. Our "responses" are the *weights* of individual cheese slices. The designable parameter is the *length* of the top slice [see Fig. 2(a)]. A density of one is assumed. The goal is to cut through the slices to obtain a *weight* for each one as close to a desired *weight* s as possible. Note that we measure the *length* from the right-hand end. We cut on the left-hand side.

The coarse model involves 3 slices of the same *height* x,

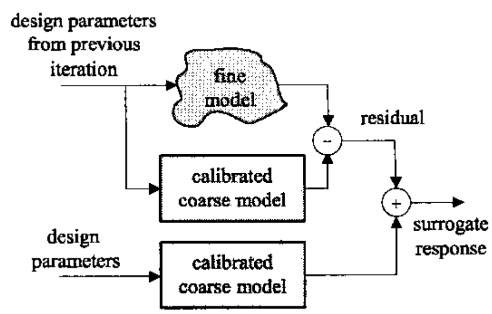


Fig. 1. Illustration of the response residual SM surrogate.

namely, the preassigned parameter shown in Fig. 2(a). The lengths of the two lower slices are c units shorter than the top one. The optimal *length* x_c^* can be calculated to minimize the differences between the weights of the slices and the desired *weight* s. We use minimax optimization. The responses of the coarse model are given by $R_{c1} = x \cdot x_c \cdot 1$, $R_{c2} = x \cdot (x_c - c) \cdot 1$ and $R_{c3} = x \cdot (x_c - c) \cdot 1$.

The fine model is similar but the lower two slices are f_1 and f_2 units shorter, respectively, than the top slice [Fig. 2(b)]. The *heights* of the slices are x_1, x_2 and x_3, respectively. The corresponding responses of the fine model are $R_{f1} = x_1 \cdot x_f \cdot 1$, $R_{f2} = x_2 \cdot (x_f - f_1) \cdot 1$, and $R_{f3} = x_3 \cdot (x_f - f_2) \cdot 1$.

We demonstrate the implicit and response residual SM optimization process. We set $c = 2$ and $f_1 = f_2 = 4$. The specification s is set to 10. The *heights* of the slices are fixed at unity for the fine model, i.e., $x_1 = x_2 = x_3 = 1$. The coarse model preassigned parameter x is initially unity. Fig. 3 shows the first two iterations of the algorithm, step by step. The RRSM algorithm converges to the optimal fine model solution as shown in Fig. 4.

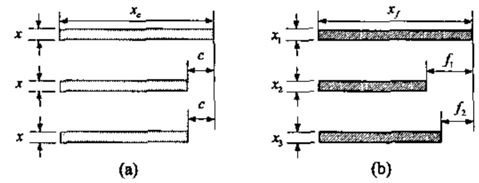


Fig. 2. Multiple cheese-cutting problem: (a) the coarse model and (b) fine model.

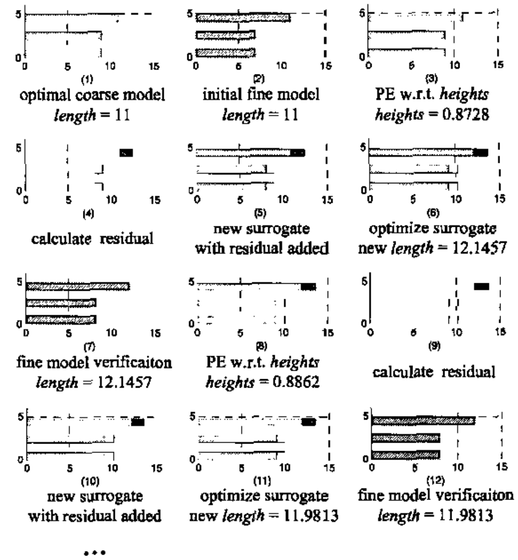


Fig. 3. "Multiple cheese-cutting" problem: step-by-step implicit SM and RRSM optimization.

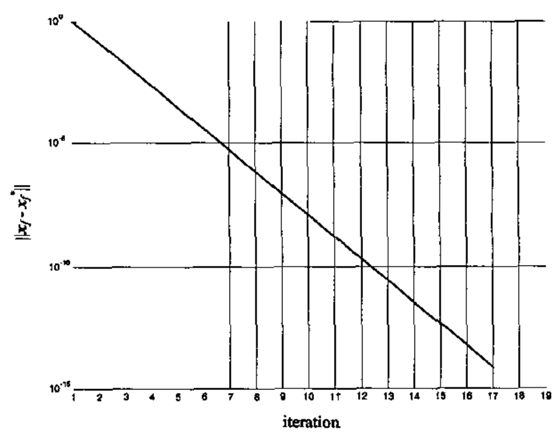


Fig. 4. Parameter difference between the RRSM design and minimax direct optimization. Finally, $x_f = x_f^* = 12$.

III. ADS Schematic Design Framework

Agilent ADS has a huge library of circuit models that can be used as "coarse" models. ADS also has a suite of easy-to-use optimization tools, e.g., random search, gradient search, Quasi-Newton search, discrete search, genetic algorithm. An *S*-parameter file S*n*P in ADS can import data files (*S*-parameters) in Dataset or Touchstone format. Here, *n* is the port number. Fig. 5 is a symbol of 2-port S-Parameter File component S2P with terminals. Many EM simulators ("fine" model) such as Sonnet's ***em*** [10], Agilent Momentum [11], and Agilent HFSS [9] support Touchstone file format. Using this file, we import *S*-parameters and match them with the ADS circuit model (coarse model) responses in the PE procedure. The residual between the calibrated coarse model and fine model can also be obtained using the S*n*P file and MeasEqn (Measurement Equation) component. These major steps of SM are friendly for engineers to apply.

ADS Schematic Design Framework for SM

Step 1 Set up the coarse model in ADS schematic.

Step 2 Optimize the coarse model using the ADS optimizer.

Step 3 Copy and paste the parameters into the parameterized fine model (Agilent Momentum, HFSS/Empipe3D [12], or Sonnet's ***em***). In Momentum, the fine model can also be generated using the *Generate/Update Layout* command.

Step 4 Simulate the fine model and save the responses in Touchstone format (Agilent Momentum,

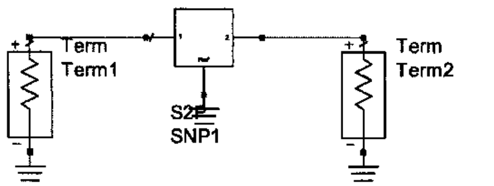


Fig. 5. S2P (2-Port *S*-Parameter File) symbol with terminals.

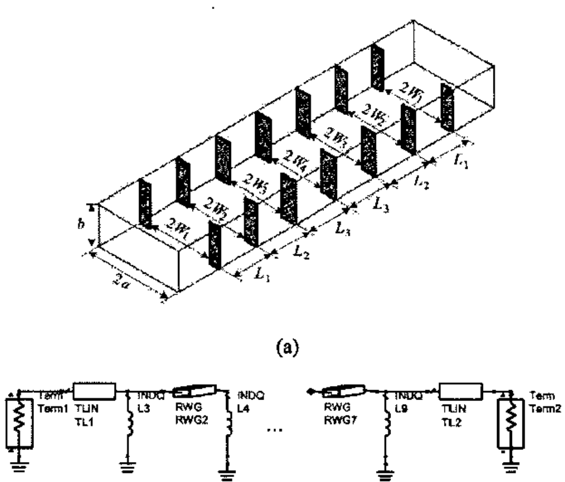
HFSS, or Sonnet's ***em***) or Dataset (Momentum); check the stopping criteria; if satisfied, stop.

Step 5 Import the responses to the ADS schematic using S*n*P component under *Data Items*. Set up ADS (calibrated) coarse model or response residual SM surrogate to match the S*n*P component and run ADS optimizer to perform parameter extraction. Here, you may extract the coarse model design parameter or the preassigned parameters to implement explicit (original or aggressive SM) or implicit space mapping, respectively.

Step 6 Predict the next fine model solution by
(a) Explicit SM: transfer extracted parameters to MATLAB [12] (or other scientific computing tool) and calculate a prediction based on the algorithm in [1][2], or,
(b) Implicit SM: reoptimize the calibrated coarse model w.r.t. design parameters to predict the next fine model design, and/or,
(c) RRSM: reoptimize the surrogate (calibrated coarse model plus response residual) w.r.t. design parameters to predict the next fine model design.

Step 7 Update the fine model design and go to Step 4.

We implement implicit and response residual SM optimization in the ADS schematic framework in an interactive way. The fine model is Agilent momentum, HFSS, or Sonnet's ***em***.



(a)

(b)

Fig. 6. (a) Six-section H-plane waveguide filter (b) ADS coarse model.

IV. H-PLANE FILTER DESIGN

A. Implicit and Response Residual SM Optimization Steps

We use the ADS framework exploiting implicit SM and RRSM to design an H-plane filter. The following iterations are employed: two iterations of implicit SM to drive the design to be close to the optimal solution; one implicit SM and RRSM iteration using weighting parameters $\lambda_i = 0.5$, $i = 1...m$ ($\lambda_i \leq 1$ because the optimization algorithm has difficulty reoptimizing the surrogate with the full residual added); a second implicit SM and RRSM iteration with the full residual added.

B. Six-Section H-plane Waveguide Filter

The six-section H-plane waveguide filter [7][8] is shown in Fig. 6(a). The design parameters are the lengths and widths: L_1, L_2, L_3, W_1, W_2, W_3, W_4. Design specifications are $|S_{11}| \leq 0.16$ for frequency range 5.4-9.0GHz; $|S_{11}| \geq 0.85$ for frequency $\omega \leq 5.2$GHz; $|S_{11}| \geq 0.5$, for frequency $\omega \geq 9.5$GHz. We use 23 sample points.

A waveguide with a cross-section of 1.372×0.622 inches (3.485×1.58 cm) is used. The six sections are separated by seven H-plane septa, which have a finite thickness of 0.02 inches (0.508 mm). The coarse model consists of lumped inductances and waveguide sections. There are various approaches to calculate the equivalent inductive susceptance corresponding to an H-plane septum. We utilize a simplified version of a formula due to Marcuvitz [14] in evaluating the inductances. The coarse model is simulated using ADS [6] as in Fig. 6(b).

We the select waveguide width of each section as the preassigned parameter to calibrate the coarse model. The frequency coefficient of each inductor, for convenience PI, is also harnessed as a preassigned parameter to compensate for the suceptance change. The fine model exploits Agilent HFSS [9]. One frequency sweep takes 2.5 minutes on an Intel Pentium 4 (3 GHz) computer with 1 GB RAM and running in Windows XP Pro. Fig. 7(a) shows the fine model response at the initial solution. Fig. 7(b) shows the fine model response after running the algorithm using the Agilent HFSS simulator. Since no Jacobian is needed, the total time taken for five fine model

TABLE I
OPTIMIZABLE PARAMETER VALUES OF THE SIX-SECTION H-PLANE WAVEGUIDE FILTER

Parameter	Initial solution	Solution reached via RRSM
W_1	0.555849	0.499802
W_2	0.519416	0.463828
W_3	0.5033	0.44544
W_4	0.49926	0.44168
L_1	0.591645	0.630762
L_2	0.660396	0.644953
L_3	0.67667	0.665449
all values are in inches		

simulations is 15 minutes on an Intel P4 3 GHz computer. Table I shows the initial and optimal design parameter values of the six-section H-plane waveguide filter.

V. CONCLUSIONS

We present a response residual SM (RRSM) modeling technique that matches the response residual SM surrogate with the fine model. A new "multiple cheese-cutting" design problem illustrates the concept. Our approach is implemented entirely in the ADS framework. A good H-plane filter design emerges after only five EM simulations using the implicit and RRSM with sparse frequency sweeps and no Jacobian calculations.

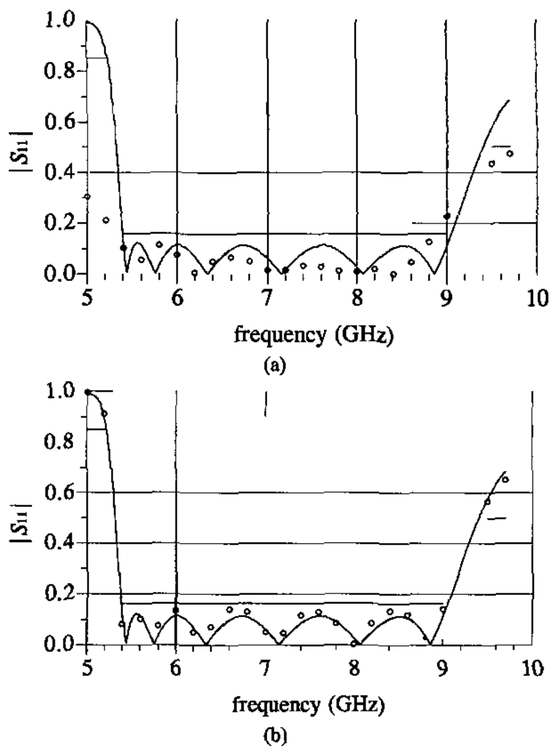


Fig. 7. H-plane filter optimal coarse model response (—), and the fine model response at: (a) initial solution (○); (b) solution reached via RRSM after 4 iterations (○).

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