An Implicit Space Mapping Technique for Component Modeling

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Abstract—We present an implicit Space Mapping (ISM) technique for modeling microwave and RF components, the first attempt to employ ISM-based surrogates specifically for modeling. The proposed technique calibrates the surrogate by mapping certain preassigned parameters. This surrogate employs linearly interpolated preassigned parameters. Using a three-section transformer, we demonstrate that our technique is simple to apply within Agilent ADS. We show that we can easily enhance an HTS filter empirical model to the accuracy of an electromagnetic model, Sonnet's *em*.

Index Terms—CAD, optimization, EM modeling, microstrip modeling, microwave filters, space mapping, surrogate modeling.

I. INTRODUCTION

Space Mapping (SM) technology [1] addresses the issue of reducing unnecessary time-consuming full-wave electromagnetic (EM) simulations of microwave structures in device modeling and design optimization.

SM assumes the existence of "fine" and "coarse" models. The "fine" model may be a CPU-intensive EM simulator that provides high accuracy. The "coarse" model is a simplified representation, typically an equivalent circuit with empirical formulas. Modeling techniques [1], space derivative mapping [2], the so-called generalized SM [3] and SM-based neuro-modeling [4] exploit the computational efficiency of coarse models and the accuracy of corresponding fine models so as to realize fast, accurate (enhanced) models valid over wide parameter ranges.

The SM-based modeling [5], our previous development, was designed to satisfy the desire of engineers to set up and use SM-based models in connection with (or even within) available commercial software. A family of models was implemented entirely in the Agilent ADS [6] framework.

The expanded SM design framework (ESMDF) [7] and implicit space mapping (ISM) [8] optimization techniques exploit preassigned parameters. In this paper, we present ISM specifically for modeling. We calibrate the mapping of the preassigned parameters simultaneously at multiple on-grid points in the design parameter space in the region of interest. We extract the mapping by matching the surrogate to the corresponding fine model data. Through the mapping, the preassigned parameters are then interpolated linearly by the design parameters. Our technique is simple to apply within Agilent ADS. We show that we can easily enhance an HTS filter empirical model to the accuracy of an EM model.

II. IMPLICIT SPACE MAPPING MODELING

In our approach, design parameters are linearly mapped to preassigned parameters through the mapping parameters B_p and c_p. We optimize B_p and c_p (parameter extraction) to match the surrogate to given fine model data.

More generally, we consider input SM (B and c), implicit SM (B_p and c_p.) and output SM (A and d). The surrogate formulation is written as

$$R_s(x_f, A, B, c, B_p, c_p, d) = A \cdot R_c(B \cdot x_f + c, B_p \cdot x_f + c_p) + d \tag{1}$$

with matrices $A = diag\{a_1, \ldots, a_m\}$, $B \in M_{n \times n}$, $c \in M_{n \times 1}$, $B_p \in M_{n \times p}$, $c_p \in M_{p \times 1}$ and $d \in M_{m \times 1}$, where $M_{k \times l}$ denotes the set of $k \times l$ real matrices. B and c account for the input mapping, B_p and c_p account for the linear interpolation of preassigned parameters. A and d provide an output mapping [9]. R_c represents the coarse model response vector. x_f denotes design parameters.

The parameter extraction procedure for q training points is

$$(\overline{A}, \overline{B}, \overline{c}, \overline{B}_p, \overline{c}_p, \overline{d}) =$$

$$\arg \min_{(A, B, c, B_p, c_p, d)} \sum_{k=1}^{q} \| R_f(x_f^{(k)}) - R_s(x_f^{(k)}, A, B, c, B_p, c_p, d) \| \tag{2}$$

The enhanced model (surrogate) is

$$R_s(x_f) = R_s(x_f, \overline{A}, \overline{B}, \overline{c}, \overline{B}_p, \overline{c}_p, \overline{d}) \tag{3}$$

III. EXAMPLES

A. Three-Section Microstrip Transformer

We demonstrate the ADS modeling implementation for a three-section microstrip impedance transformer [Fig. 1(a)] [10]. The fine model is a Sonnet *em* [11] model. The coarse model, Fig. 1(b), comprises cascaded ADS microstrip empirical models. Three MSub components (MSub1, MSub2 and Msub3) introduce the preassigned parameters $\{\varepsilon_1, h_1, \varepsilon_2, h_2, \varepsilon_3, h_3\}$, the dielectric constant and the substrate height for each microstrip line. The design parameters are $x_f = [W_1 \, L_1 \, W_2 \, L_2 \, W_3 \, L_3]^T$. The region of interest is 12.7 mil $\leq W_1 \leq$ 15.5 mil, 105 mil $\leq L_1 \leq$ 129 mil, 5 mil $\leq W_2 \leq$ 6.2 mil, 108 mil $\leq L_2 \leq$ 132 mil, 1.5 mil $\leq W_3 \leq$ 1.9 mil, and 109 mil $\leq L_3 \leq$ 133 mil. The frequency range used is 5 GHz to 15 GHz with a step of 1 GHz (11 points). The reflection coefficient S_{11} is used to match the responses of the ISM-based surrogate and the fine model. The number of base points in the region of interest is 13. The reference point is $x^0 =$[14.1 117 5.6 120 1.7 121]^T. The thickness of the dielectric substrate is 0.635 mm (25 mil) and its relative permittivity is 9.7. The preassigned parameters are linearly associated with (mapped from) the design parameters. The approach of [5] is easily modified to implement our new mapping. To avoid tedious typing, the mapping equations can be imported from a pre-defined text file using a modified AEL program from Agilent EEsof Knowledge Center (Example ID 143047).

Table I shows a statistical analysis of the R_s modeling errors

of 20 random test points for both SM-based and ISM-based ($B = I$ and $c = 0$) modeling. The results are both good.

B. HTS Filter Example

We consider the HTS bandpass filter of [12]. The physical structure is shown in Fig. 2(a). Design parameters are the lengths of the coupled lines and the separation between them, namely, $x_f = [S_1 \, S_2 \, S_3 \, L_1 \, L_2 \, L_3]^T$. The substrate used is lanthanum aluminate with $\varepsilon_r =$ 23.425, $H=$ 20 mil and substrate dielectric loss tangent of 0.00003. The length of the input and output lines is $L_0 =$50 mil and the lines are of width $W=$ 7 mil.

We use an Agilent ADS coarse model as in [8] which consists of microstrip empirical models. See Fig. 2(b). Notice the symmetry in the HTS structure, i.e., coupled lines "CLin5" are identical to "CLin1" and "CLin4" to "CLin2". We exploit different dielectric constants for each pair of coupled lines. Three ADS MSub components feed the mapped preassigned parameters (equations using the VAR component) to the coarse model. We use dielectric constants as preassigned parameters to compensate for changes in L_1, L_2

(a)

(b)

Fig. 1. The three-section 3:1 microstrip impedance transformer [10]: (a) structure and dimensions; (b) ADS coarse model.

TABLE I SM AND ISM MODELING STATISTICS FOR THREE-SECTION TRANSFORMER USING 20 RANDOM TEST POINTS

model	mean error	maximum error
R_c	0.042	0.057
SM-based R_s	0.006	0.012
ISM-based R_s	0.004	0.008

(a)

(b)
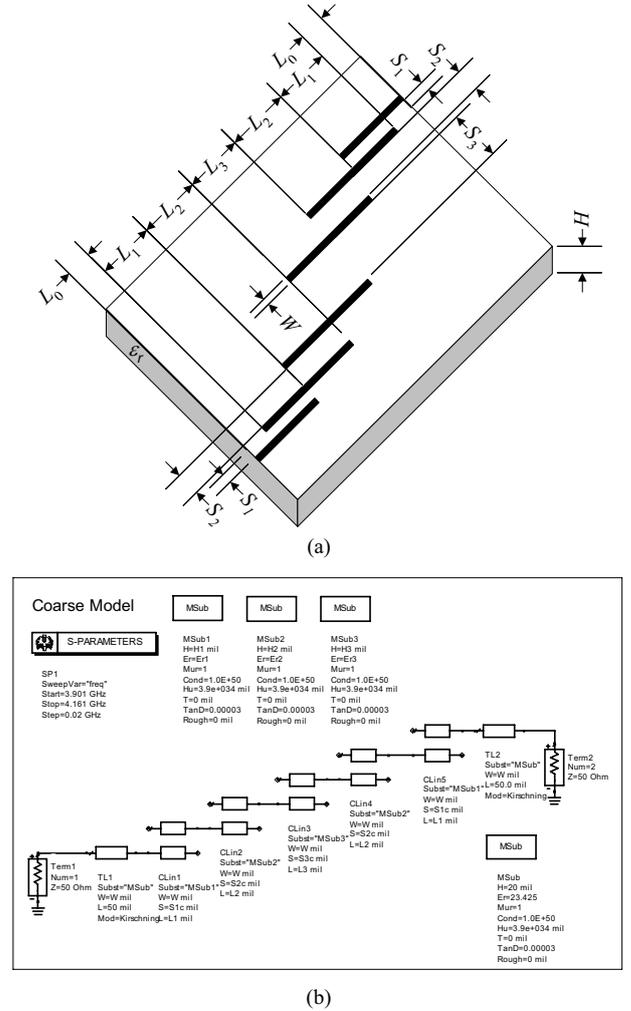
Fig. 2. The HTS filter (a) the physical structure [12], (b) the coarse model [5] as implemented in Agilent ADS.
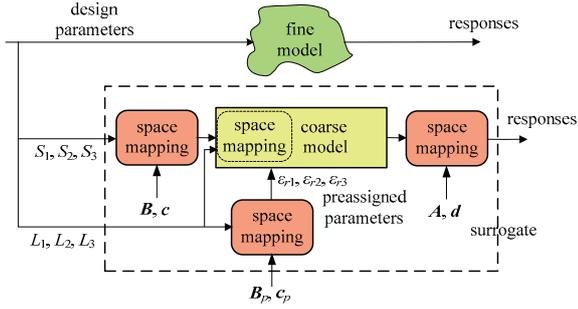
Fig. 3. ISM modeling for HTS filter configuration.

and L_3. S_1, S_2 and S_3 are still input mapped as shown in Fig. 3.

TABLE II HTS FILTER REGION OF INTEREST

parameters	reference point (x^0)	region 1 size ($\pm\delta_1$)	region 2 size ($\pm\delta_2$)	region 3 size ($\pm\delta_3$)	region 4 size ($\pm\delta_4$)	region 5 size ($\pm\delta_5$)
L_1	180	5	6	8	10	45
L_2	200	10	11	15	20	50
L_3	180	5	6	8	10	45
S_1	20	2	3	3	4	5
S_2	80	5	6	8	10	20
S_3	80	10	11	15	20	20

The fine model is simulated by Sonnet's *em* using 1mil × 1mil mesh size with 14 uniform frequency sweep points.

We use two groups of training or base points in the region of interest, the star distribution of $2n+1$ as in [5] and the star distribution plus 2^n corner points (vertices of the region). Since we have 24 mapping parameters, the system is better determined with more base points. We test both models (with 50 points) in expanded regions. Region 1 is the original region of interest. Regions 2 through 5 are expanded as in Table II. We are interested in the $|S_{21}|$. (The wider the range the closer to zero $|S_{21}|$ becomes since the passband can shift out of the sampling band). We show selected responses comparison in Fig. 4. Error statistics w.r.t. the fine model are

TABLE III HTS FILTER ERROR STATISTICS OF TEST REGIONS

	region	1	2	3	4	5
max error	R_c	2.396	2.258	2.175	2.297	1.404
	R_s[†]	0.279	0.320	0.217	0.582	0.188
	R_s[‡]	0.220	0.203	0.411 (0.187[◊])	0.275	0.180
mean error	R_c	1.594	1.374	1.219	1.009	0.116
	R_s[†]	0.123	0.121	0.109	0.131	0.051
	R_s[‡]	0.114	0.104	0.095	0.101	0.028

[†] with star distribution training set

[‡] with star distribution + corner training set

[◊] excluding one point with the largest error
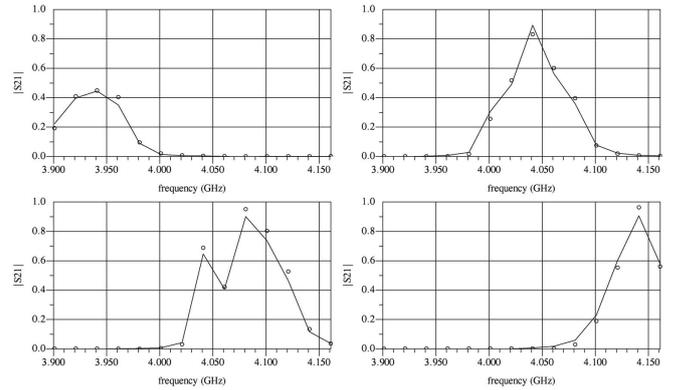
Fig. 4. HTS filter selected $|S_{21}|$ versus frequency for the fine model (o) and the R_s surrogate (—) in region 2.

shown in Table III for our surrogate R_s. The model trained in the expanded base set (2^n+2n+1 points) outperforms the star distribution model in all 5 regions in terms of mean error and max error (except for one sample). We interpolate the new surrogate using a linear frequency interpolation technique. The surrogate is then optimized to find an optimal solution to
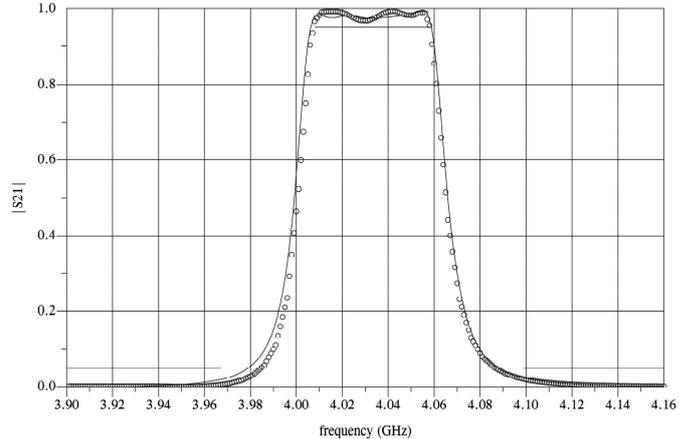
Fig. 5. HTS filter optimal $|S_{21}|$ versus frequency for the fine model (o) and the R_s surrogate (—) after only one surrogate model optimization.

satisfy the specification, $|S_{21}| \leq 0.05$ for $\omega \geq 4.099$ GHz and for $\omega \leq 3.967$ GHz; $|S_{21}| \geq 0.95$ for 4.008 GHz $\leq \omega \leq 4.058$ GHz.

Our design specification is satisfied in a single surrogate optimization. We verify the design using a finer frequency sweep of the fine model as shown in Fig. 5.

IV. CONCLUSIONS

We present an effective ISM-based surrogate methodology for RF and microwave CAD modeling exploiting linearly interpolated preassigned parameters. The surrogate permits relatively small mapping matrices B or B_p. We implement the technique in Agilent ADS in one step or one schematic. More base (training) points yield better surrogate models over extended regions. Our ISM-based surrogate provides a smooth model with high-accuracy similar to knowledge based

neural networks [13]. It is a simple substitute for an on-grid EM simulator.

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