Improving Efficiency of Space Mapping Optimization of Microwave Structures and Devices

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***Abstract*—A new implementation of space mapping optimization and modeling procedures for microwave design is presented. We use the optimization capability of the "coarse model" simulator, Agilent ADS, to significantly reduce the computational cost of solving the parameter extraction and surrogate optimization sub-problems. This allows substantial reduction of the overall optimization time for the space mapping algorithm. Illustration examples are provided.**

***Index Terms*—Computer-aided design (CAD), EM optimization, space mapping, surrogate modeling.**

I. Introduction

Space mapping (SM) has been widely used for optimization and modeling of microwave devices and structures [1]-[4]. SM assumes "fine" and "coarse" models. In the microwave area, the "fine" model is typically implemented with a high fidelity CPU-intensive EM simulator. The "coarse" model can be a simplified representation of the corresponding device, e.g., an equivalent circuit. SM exploits the speed of the coarse model and the accuracy of the fine model by iterative optimization and updating of the surrogate model which is built using the coarse model and available fine model data.

The coarse model is assumed to be much faster than the fine model. In order to neglect the cost related to creating and optimizing the surrogate model, the coarse model should be at least three orders of magnitude faster than the fine model. In the microwave area, the coarse model is often implemented using a circuit simulator such as Agilent ADS [5] because many microwave devices, in particular filters, transformers, etc., have straightforward equivalent circuit representations.

A problem arises while using simulators such as Agilent ADS as a "black box" in a space mapping optimization loop. Although actual simulation time might be very short (e.g., a couple of milliseconds), the whole process of evaluating the coarse model is much longer (e.g., a couple of seconds) because of additional cost related to preparing input data, loading the simulator into memory and retrieving the model response. This substantially increases the computational cost of the two optimization tasks, solved during each iteration of the SM algorithm: extraction of the surrogate model parameters and surrogate model optimization. The additional cost may increase the total optimization cost of the SM algorithm so that the time-saving advantages of space mapping are lost.

In this paper we describe a new implementation of an SM algorithm in which both the parameter extraction and surrogate optimization are carried out inside the available coarse model simulator using its internal optimization capabilities. This allows significant reduction of the total optimization time in comparison with the standard way of evaluating the coarse model as a "black box".

II. Space Mapping Optimization Algorithm

Let $R_f : X_f \to R^m$, $X_f \subseteq R^n$, denote the response vector of a fine model of the device of interest. Our goal is to solve

$$x_f^* = \arg\min_{x \in X_f} U\left(R_f(x)\right) \tag{1}$$

where $U : R^m \to R$ is a given objective function. We consider solving (1) by direct optimization to be impractical. Instead, we consider an optimization algorithm that generates a sequence of points $x^{(i)} \in X_f$, $i = 0, 1, 2, \ldots$, and surrogate models $R_s^{(i)} : X_s^{(i)} \to R^m$, $X_s^{(i)} \subseteq R^n$, $i = 0, 1, \ldots$, so that

$$x^{(i+1)} = \arg\min_{x \in X_f \cap X_s^{(i)}} U\left(R_s^{(i)}(x)\right) \tag{2}$$

and $R_s^{(i+1)}$ is constructed using suitable matching conditions with the fine model at $x^{(k)}$, $k = 0, 1, \ldots, i$.

Space mapping assumes the existence of a coarse model that describes the same object as the fine model: less accurate but much faster to evaluate. Let $R_c : X_c \to R^m$ denote the response vectors of the coarse model, where $X_c \subseteq R^n$. The family of surrogate models is constructed from the coarse model in such a way that the misalignment between $R_s^{(i)}$ and the fine model is minimized. A variety of SM-based surrogate models are available [1]-[4]. Below, we show a surrogate model that incorporates both input and output SM. At iteration i, $i = 0, 1, 2, \ldots$ the surrogate model $R_s^{(i)}$ is defined as

$$R_s^{(i)}(x) = A^{(i)} \cdot R_c(B^{(i)} \cdot x + c^{(i)}) + d^{(i)} \tag{3}$$

where

$$(A^{(i)}, B^{(i)}, c^{(i)}) = \arg\min_{(A,B,c)} \sum_{k=0}^{i} \| R_f(x^{(k)}) - A \cdot R_c(B \cdot x^{(k)} + c) \| \tag{4}$$

$$d^{(i)} = R_f(x^{(i)}) - A^{(i)} \cdot R_c(B^{(i)} \cdot x^{(i)} + c^{(i)}) \tag{5}$$

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Matrices $A^{(i)} = diag\{a_1^{(i)}, \ldots, a_m^{(i)}\}$, $B^{(i)} \in M_{n\times n}$ and $c^{(i)} \in M_{n\times 1}$ are obtained by parameter extraction (PE), as defined in (4). Matrix $d^{(i)} \in M_{m\times 1}$ is calculated using formula (5) after having determined $A^{(i)}$, $B^{(i)}$, $c^{(i)}$. The SM optimization algorithm can be summarized as follows.

Step 0 Set $i = 0$ and choose starting point $x^{(0)}$;
Step 1 Evaluate the fine model at $x^{(i)}$;
Step 2 Obtain $R_s^{(i)}$ using (4) and (5);
Step 3 Optimize $R_s^{(i)}$ and obtain $x^{(i+1)}$ as in (2); (6)
Step 4 If the termination condition[1] is not satisfied set $i = i + 1$ and go to Step 1; else END;

[1] The algorithm is terminated if (i) $||x^{(i)}-x^{(i-1)}||\leq TolX$ and $||R_f^{(i)}-R_f^{(i-1)}||\leq TolFun$ (convergence of the algorithm; *TolX* and *TolFun* are user specified tolerances), or (ii) i>MaxIter (user-specified maximum number of iterations)

As we can see, the two important steps of the SM optimization algorithm are parameter extraction (4) and surrogate model optimization (2). Both sub-problems involve multiple evaluations of the coarse model and may substantially affect the computational cost of the optimization process if the coarse model evaluation is not fast enough. Moreover, although increasing the flexibility of the SM surrogate model (i.e., adding more parameters) usually improves the performance of the SM algorithm in terms of its ability of finding a good solution, it actually increases the computational cost of PE as more parameters result in more coarse model evaluations required to extract these parameters.

III. New Implementations of Parameter Extraction and Surrogate Optimization

We shall assume that the coarse model is to be simulated using Agilent ADS [5]. ADS can be considered as the primary coarse model evaluator in the microwave area because it is widely used and it allows convenient and straightforward creation of coarse models for many microwave structures and devices. Below, we describe three implementations of SM optimization algorithm that make use of multipoint simulation and optimization capabilities of the coarse model simulator in order to reduce the computational cost of SM optimization.

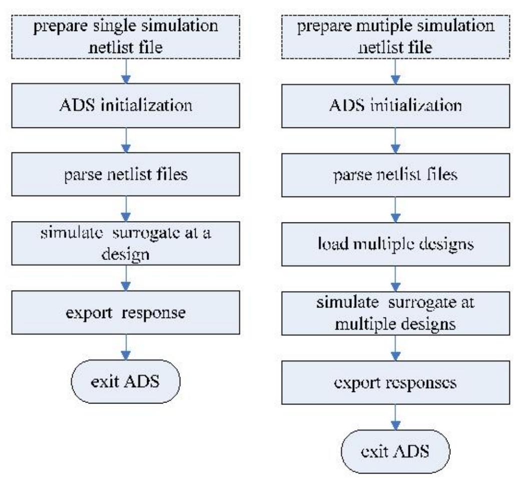
A. Traditional Implementation (Method 1)

Standard implementation of the SM optimization algorithm assumes that both the PE and surrogate model optimization sub-problems are solved using appropriate optimization routines that make calls to the coarse model simulator each time the coarse model has to be evaluated. Each time we invoke an ADS simulation, CPU clock cycles are consumed on allocating memory, loading the simulator, verifying license, loading the input file, parsing the input file, simulating the circuit, exporting the response, etc. While the circuit simulation is usually fast for a single design, calling ADS simulation repeatedly will generate a huge amount of overhead that cannot be neglected in the SM optimization process. The flowchart of evaluating the coarse model is shown in Fig. 1(a).

B. Multipoint Model Evaluation (Method 2)

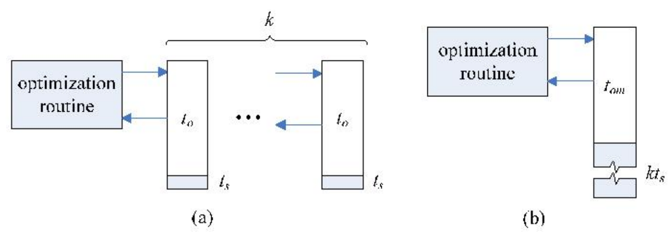
The computational cost of the parameter extraction process can be reduced by evaluating the coarse model at several points in a single ADS simulator call while evaluating the matching error (see (4)). In order to do that, the original ADS netlist is modified by adding a data access component (DAC) that imports multiple designs and corresponding fine model responses. The method allows us to perform coarse model evaluation at multiple points in one shot and avoids the overhead related to loading the simulator. The coarse model evaluation flowchart is shown in Fig. 1(b). Fig. 2 shows the difference in computational cost between Method 1 and 2 for evaluating the coarse model at k points (designs). A traditional call takes $k(t_o+t_s)$ and our new implementation takes $t_{om}+kt_s$, where t_o and t_{om} are the overhead time for a one-simulation call and for a multiple-simulation call respectively, k is the number of desgins. t_s is the circuit simulation time for a single design. Note that $t_o \approx t_{om}$ and $t_s << t_o$ in our ADS examples. Note also that in parameter extraction we typically use all available fine model data so that $k = i$, where i is the SM iteration index. Thus, the benefit of this approach is that PE time cost remains roughly constant in each iteration, while according to the standard approach, it grows linearly with i and can be large for large i.

Note that this approach does not affect the surrogate optimization process because the optimization routine is not evaluating the coarse model at multiple points in this case.



(a) (b)

Fig. 1 Call to ADS for single-point (a) and multi-point simulation (b).



(a) (b)

Fig. 2. Time cost of k coarse model simulations using a standard single-point evaluation (a), and multi-point evaluation (b).

C. Inside-ADS Optimization (Method 3)

The third approach takes advantage of the ADS multipoint simulation and built-in optimization capabilities. In particular, it is possible to solve the whole PE and surrogate optimization sub-problems inside the ADS simulator. Fig. 3(a) shows the ADS optimization procedure in the PE process. Compared with the traditional way, the optimization loop is moved into ADS. Since the loop is inside ADS, the SM algorithm only prepares the modified ADS netlist and initiates one call to ADS for the entire optimization process. Since the optimization takes a lot of surrogate model simulations, a large amount of time is saved. The netlist originally containing only the coarse model implementation in Method 1, is enhanced by DAC components importing multiple designs and corresponding fine model responses, by VAR components incorporating space mapping equations and matrices, by optimization GOAL components specifying matching goals between fine and surrogate models, and, finally, by optimization engine OPTIM that searches for the optimal solution for PE.

Fig. 3(b) shows the surrogate optimization in ADS. For the reason discussed earlier, the surrogate model optimization routine incurs an overhead for each ADS call. The overhead is largely removed by shifting the optimization burden from the SM algorithm to ADS. The way of modifying the ADS netlist is similar as in the case of parameter extraction.

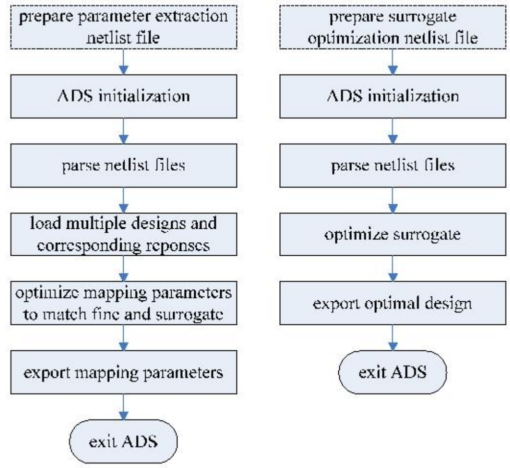
Both approaches, multi-point model evaluation and inside-ADS optimization are implemented in our space mapping software, the SMF system [6].

IV. Examples

In this section we consider two examples of microwave design problems. For each problem we run the SM optimization using Method 1, 2, and 3 (as in Section III) for the parameter extraction and surrogate model optimization.

As the first example, consider the microstrip band-pass filter [7] shown in Fig. 4. The design parameters are $\boldsymbol{x} = [L_1\ L_2\ L_3\ L_4\ g]^T$. The fine model is simulated in FEKO [8], the coarse model is the circuit model implemented in Agilent ADS [5] (Fig. 5). The design specifications are $|S_{21}| \leq -20$dB for $4.5\text{GHz} \leq \omega \leq 4.7\text{GHz}$ and $5.3\text{GHz} \leq \omega \leq 5.5\text{GHz}$, and $|S_{21}| \geq -3$dB for $4.9\text{GHz} \leq \omega \leq 5.1\text{GHz}$. The initial design is the coarse model optimal solution $\boldsymbol{x}^{(0)} = [6.784\ 4.890\ 6.256\ 5.28\ 0.0956]^T$ mm. For this problem we use simplified input space mapping with shift parameter $\boldsymbol{c}$ and output space mapping ($\boldsymbol{d}$ term). The fine model initial and optimized responses after 6 SM iterations ($\boldsymbol{x}^{(6)}$=[6.431 4.760 6.175 4.886 0.0604]^T mm) are shown in Fig. 6.

Table I shows a comparison of the optimization time for the three implementations of the SM algorithm. For the standard implementation, most of the computational cost comes from the surrogate evaluation in PE and surrogate optimization. Method 2 (multi-point model evaluation) improves the situation. However, only Method 3 (inside-ADS optimization) makes the computational overhead of the coarse model evaluation insignificant. The total Method 3 optimization time cost is about 2.5 times lower than Method 1.



(a) (b)

Fig. 3. Inside-ADS parameter extraction (a) and surrogate optimization (b).

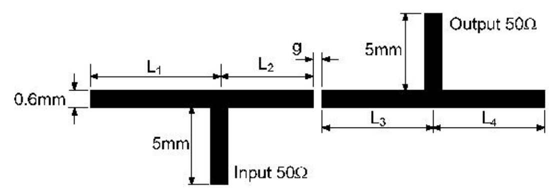


Fig. 4. Geometry of the microstrip band-pass filter [7].

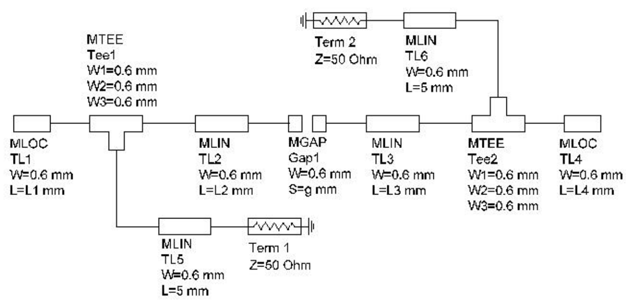


Fig. 5. Coarse model of microstrip band-pass filter (Agilent ADS).

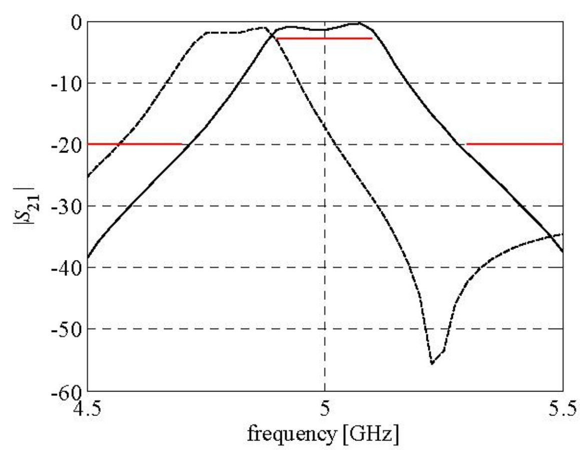


Fig. 6. Initial (dashed line) and optimized (solid line) $|S_{21}|$ versus frequency for the microstrip band-pass filter.

TABLE I
MICROSTRIP BANDPASS FILTER: OPTIMIZATION TIME FOR THE THREE IMPLEMENTATIONS OF SPACE MAPPING ALGORITHM

Method	Total Optimization Time	Total Fine Model Evaluation Time	Total PE and Surrogate Optimization Time	Optimization Time Savings	
				PE and Surrogate Opt.	Total
1	111 min	39 min (35%)	72 min (65%)	-	-
2	67 min	39 min (58%)	28 min (42%)	61%	40%
3	44 min	39 min (89%)	5 min (11%)	93%	60%

The second example is the three-section microstrip impedance transformer [9] shown in Fig. 7. The design parameters are $\boldsymbol{x} = [L_1\ L_2\ L_3\ \ W_1\ W_2\ W_3]^T$. The design specifications are $|S_{11}| \le 0.09$ for 5 GHz $\le \omega \le$ 15 GHz. The fine model is simulated in Sonnet ***em*** [10]. The coarse model is implemented in Agilent ADS [5] and shown in Fig. 8. The starting point is $\boldsymbol{x}^{(0)} = [117\ 121\ 124\ 15\ 6\ 2]^T$ mm.

For this problem we use input space mapping with parameters $\boldsymbol{B}$ and $\boldsymbol{c}$, and output space mapping ($\boldsymbol{d}$ term). The initial fine model response and the response at the solution obtained using the SM algorithm after 5 iterations ($\boldsymbol{x}^{(5)}$=[114.2 119.2 122.4 14.02 5.58 1.552]^T mm) are shown in Fig. 9.

Table II shows a comparison of the optimization time for the three implementations of the SM algorithm. As before, the standard implementation suffers from a considerable overhead due to parameter extraction and surrogate model optimization. The inside-ADS optimization approach makes this overhead negligible compared with the total fine model evaluation time.

It should be noted that techniques such as distributed evaluation of the fine model may significantly reduce the evaluation time for the fine model. This would increase the relative overhead of the PE and surrogate optimization compared with our demonstration in this section and make the techniques presented in the paper even more attractive.

V. CONCLUSION

A new implementation of the space mapping optimization algorithm that takes advantage of the optimization capability of a "black box" coarse model simulator is presented. By solving the two basic sub-problems of the SM algorithm, i.e., parameter extraction and surrogate model optimization inside the coarse model simulator, we are able to obtain substantial reduction of the computational cost of the whole optimization process. Examples utilizing Agilent ADS as a coarse model simulator confirm the effectiveness of our approach.

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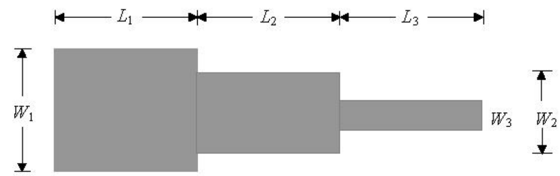

Fig. 7. The three-section impedance transformer [8].

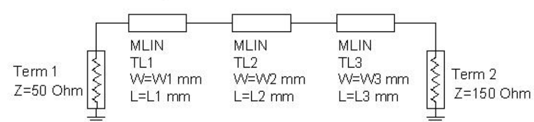

Fig. 8. The three-section impedance transformer: coarse model (Agilent ADS).

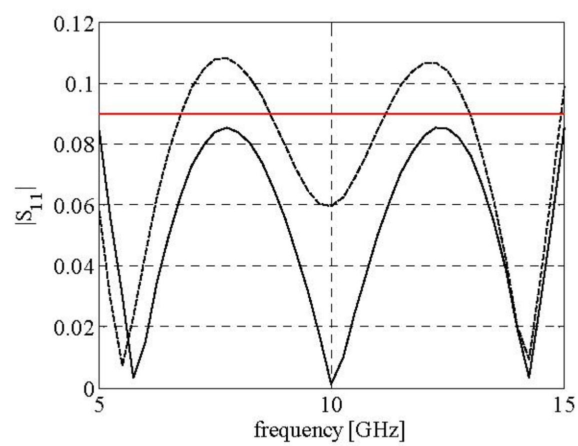

Fig. 9. Initial (dashed line) and optimized (solid line) $|S_{11}|$ versus frequency for the three-section microstrip impedance transformer.

TABLE II
THREE-SECTION TRANSFORMER: OPTIMIZATION TIME FOR THE THREE IMPLEMENTATIONS OF SPACE MAPPING ALGORITHM

Method	Total Optimization Time	Total Fine Model Evaluation Time	Total PE and Surrogate Optimization Time	Optimization Time Savings	
				PE and Surrogate Opt.	Total
1	193 min	102 min (53%)	91 min (47%)	-	-
2	149 min	102 min (68%)	47 min (32%)	48%	23%
3	109 min	102 min (94%)	7 min (6%)	92%	44%