Space-Mapping Optimization With Adaptive Surrogate Model

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***Abstract*—The proper choice of mapping used in space-mapping optimization algorithms is typically problem dependent. The number of parameters of the space-mapping surrogate model must be adjusted so that the model is flexible enough to reflect the features of the fine model, but at the same time is not over flexible. Its extrapolation capability should allow the prediction of the fine model response in the neighborhood of the current iteration point. A wrong choice of space-mapping type may lead to poor performance of the space-mapping optimization algorithm. In this paper, we consider a space-mapping optimization algorithm with an adaptive surrogate model. This allows us to adjust the type of space-mapping surrogate model used in a given iteration based on the approximation/extrapolation capability of the model. The technique does not require any additional fine model evaluations.**

***Index Terms*—Adaptive surrogate model, engineering optimization, microwave design, space mapping, space-mapping optimization.**

I. Introduction

SPACE MAPPING is a recognized engineering optimization methodology [1]–[5]. It shifts the optimization burden from an expensive "fine" (or high fidelity) model to a cheap "coarse" (or low fidelity) model by iterative optimization and updating of the surrogate model, which is built using the coarse model and available fine model data. A similar idea is exploited by other surrogate-based methods [6]–[12], although many of them construct a surrogate model by direct approximation of the fine model data with no underlying coarse model.

Space mapping was originally applied to the optimization of microwave devices [1], where fine models are often based on full-wave electromagnetic simulators, whereas coarse models are physically based circuit models. Recently, space-mapping techniques have been applied to design problems in a growing number of areas (see, e.g., [13]–[15]). A review of advances in space-mapping technology is contained in [4].

Recent efforts have focused in several areas, which are: 1) the development of new algorithms that use different space-mapping techniques such as implicit space mapping [2] and output space mapping [3]; 2) the development of new space-mapping-based models [16]; 3) theoretical justification of space mapping and convergence theory for space-mapping optimization algorithms [17], [18]; 4) neuro-space mapping [19]–[22]; and 5) applications of space mapping (e.g., [23]–[26]).

The common problem in space-mapping-based optimization is the proper choice of type of mapping. Space-mapping techniques available include input, implicit, and different variations of output space mapping, as well as customized mappings such as frequency space mapping [3]. By combining these mappings in different configurations, one can adjust the flexibility of the space-mapping surrogate model, which is correlated with the number and type of space-mapping parameters. The space-mapping surrogate model cannot be too simple, otherwise it will not properly reflect the features of the fine model. The surrogate model cannot be over-flexible because its extrapolation properties would then be too poor to allow accurate prediction of the fine model response in the neighborhood of the current iteration point. Unfortunately, it is difficult to tell beforehand which combination of mappings may be optimal for a given problem. A wrong choice of space-mapping type may lead to poor performance of the space-mapping optimization algorithm. Another issue is that surrogate models that are flexible and theoretically suitable for a given problem may exhibit poor performance due to difficulties in the extraction of the model parameters.

In this paper, we present a space-mapping-based optimization algorithm with an adaptive surrogate model. Our technique allows us to adjust the type of space-mapping surrogate model used in a given iteration based on the approximation/extrapolation capability of the model. This capability is estimated by comparing properly chosen quality factors that measure the ability of the surrogate model to match the fine model and to extrapolate its response at points not used in parameter extraction. The technique does not require any additional fine model evaluations because the quality factor calculation is based on already available data.

II. Basics of Space-Mapping Optimization

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

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

where $U : R^m \rightarrow R$ is a given objective function. To solve (1), we use an optimization algorithm that generates a sequence

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of points $\boldsymbol{x}^{(i)} \in X_f$, $i = 0, 1, 2, \ldots$, and a family of surrogate models $\boldsymbol{R}_s^{(i)} : X_s^{(i)} \to R^m$, $i = 0, 1, \ldots$, so that

$$\boldsymbol{x}^{(i+1)} = \arg \min_{\boldsymbol{x} \in X_f \cap X_s^{(i)}, \left\|\boldsymbol{x}-\boldsymbol{x}^{(i)}\right\| \le \delta^{(i)}} U\left(\boldsymbol{R}_s^{(i)}(\boldsymbol{x})\right) \quad (2)$$

where $\delta^{(i)}$ denotes the trust region radius at iteration i. We use a trust region method [27], [28] to improve the convergence properties of the algorithm.

Let $\boldsymbol{R}_c : X_c \to R^m$, $X_c \subseteq R^n$, denote the response vectors of the coarse model. The surrogate models $\boldsymbol{R}_s^{(i)}$ are constructed from the coarse model so that proper matching conditions are satisfied. A variety of space-mapping-based surrogate models are available [1]–[5], [17], [18]. Here, we use a surrogate model that incorporates both input [1] and output [3] space mapping. We define $\boldsymbol{R}_s^{(0)} = \boldsymbol{R}_c$ and

$$\boldsymbol{R}_s^{(i)}(\boldsymbol{x}) = \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c\left(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x} + \boldsymbol{c}^{(i)}\right) + \boldsymbol{d}^{(i)} \quad (3)$$

for $i = 1, 2, \ldots$, where

$$\left(\boldsymbol{A}^{(i)}, \boldsymbol{B}^{(i)}, \boldsymbol{c}^{(i)}\right) = \arg \min_{(\boldsymbol{A},\boldsymbol{B},\boldsymbol{c})} \sum_{k=0}^{i} \left\|\boldsymbol{R}_f\left(\boldsymbol{x}^{(k)}\right) - \boldsymbol{A} \cdot \boldsymbol{R}_c\left(\boldsymbol{B} \cdot \boldsymbol{x}^{(k)} + \boldsymbol{c}\right)\right\| \quad (4)$$

$$\boldsymbol{d}^{(i)} = \boldsymbol{R}_f\left(\boldsymbol{x}^{(i)}\right) - \boldsymbol{A}^{(i)} \cdot \boldsymbol{R}_c\left(\boldsymbol{B}^{(i)} \cdot \boldsymbol{x}^{(i)} + \boldsymbol{c}^{(i)}\right). \quad (5)$$

Apart from model (3)–(5), there is an optional frequency scaling that works in such a way that the coarse model is evaluated at a different frequency than the fine model using the transformation: $\omega \to f_0^{(i)} + f_1^{(i)}\omega$, where $\boldsymbol{F} = [f_0^{(i)}\ f_1^{(i)}] \in R^2$ is obtained in a parameter-extraction process similar to (4).

Flexibility of the surrogate model can be adjusted by disabling some of the parameters, i.e., constraining them to their initial values. We shall use the following naming convention for the surrogate models: the presence of any of the letters $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{c}$, and $\boldsymbol{F}$ is equivalent to enabling (not constraining) the corresponding model component, e.g., surrogate model $\boldsymbol{Bc}$ denotes the model that uses nontrivial components $\boldsymbol{B}$ and $\boldsymbol{c}$.

III. Space Mapping With Adaptive Surrogate Model

The general space-mapping model (3) allows us to use different combinations of space mapping. However, an optimal choice of mapping is usually problem dependent and may also be iteration dependent. We do not want the surrogate model to be too simple because, in that case, it cannot properly reflect the features of the fine model. We do not want the surrogate to be over flexible because its extrapolation properties, i.e., its capability to properly model the fine model response in the neighborhood of the current iteration point, may be lost. In general, a suitable choice requires both knowledge of the problem and engineering experience.

Here, we describe a simple algorithm that makes the process of choosing a good space mapping automatic. The algorithm is adaptive in the sense that it can change the space mapping used from iteration to iteration based on the estimated performance of space mapping both with respect to approximation and extrapolation quality.

Let $R_S = \{\boldsymbol{R}_{s.1}, \ldots, \boldsymbol{R}_{s.K_i}\}$ be a set of candidate surrogate models considered at iteration i. Each of $\boldsymbol{R}_{s.j}$ is a special case of (3). For simplicity, we assume the following compact way of writing the surrogate models: $\boldsymbol{R}_{s.j} : X_{s.j} \times X_{p.j} \to R^m$, where $X_{p.j}$ is a parameter domain of the model. We shall denote by $\boldsymbol{p}_j^0$ the set of initial values of the parameters of candidate model $\boldsymbol{R}_{s.j}$. The model $\boldsymbol{R}_{s.j}^{(i)}(\cdot) = \boldsymbol{R}_{s.j}(\cdot, \boldsymbol{p}_j^{(i)})$ is set up by proper choice of its parameter values $\boldsymbol{p}_j^{(i)}$, which are determined using the parameter-extraction procedure

$$\boldsymbol{p}_j^{(i)} = \arg \min_{\boldsymbol{p} \in X_{p.j}} \sum_{\boldsymbol{y} \in X_{\mathrm{APP}}^{(i)}} \|\boldsymbol{R}_f(\boldsymbol{y}) - \boldsymbol{R}_{s.j}(\boldsymbol{y}, \boldsymbol{p})\| \quad (6)$$

where $X_{\mathrm{APP}}^{(i)}$ is a subset of $X^{(i)} = \{x^{(0)}, x^{(1)}, \ldots, x^{(i)}\}$, the set of all previous iteration points. Let $X_{\mathrm{EXT}}^{(i)} \subset X^{(i)}$, such that $X_{\mathrm{APP}}^{(i)} \cap X_{\mathrm{EXT}}^{(i)} = \varnothing$. Now, let us define the following two quantities:

$$F_{\mathrm{APP}.j}^{(i)} = \frac{\sum_{\boldsymbol{y} \in X_{\mathrm{APP}}^{(i)}} \left\|\boldsymbol{R}_f(\boldsymbol{y}) - \boldsymbol{R}_{s.j}\left(\boldsymbol{y}, \boldsymbol{p}_j^0\right)\right\|^2}{\sum_{\boldsymbol{y} \in X_{\mathrm{APP}}^{(i)}} \left\|\boldsymbol{R}_f(\boldsymbol{y}) - \boldsymbol{R}_{s.j}^{(i)}(\boldsymbol{y})\right\|^2} \quad (7)$$

and

$$F_{\mathrm{EXT}.j}^{(i)} = \frac{\sum_{\boldsymbol{y} \in X_{\mathrm{EXT}}^{(i)}} \left\|\boldsymbol{R}_f(\boldsymbol{y}) - \boldsymbol{R}_{s.j}\left(\boldsymbol{y}, \boldsymbol{p}_j^0\right)\right\|^2}{\sum_{\boldsymbol{y} \in X_{\mathrm{EXT}}^{(i)}} \left\|\boldsymbol{R}_f(\boldsymbol{y}) - \boldsymbol{R}_{s.j}^{(i)}(\boldsymbol{y})\right\|^2}. \quad (8)$$

If $X_{\mathrm{EXT}}^{(i)}$ is empty, we set $F_{\mathrm{EXT}.j}^{(i)} = F_{\mathrm{APP}.j}^{(i)}$.

The first factor, i.e., $F_{\mathrm{APP}.j}^{(i)}$, measures the quality of the approximation properties of model $\boldsymbol{R}_{s.j}$ because it is the ratio of the matching error before and after parameter extraction, calculated for the points which were used in parameter extraction. The second factor, i.e., $F_{\mathrm{EXT}.j}^{(i)}$, measures the quality of the extrapolation properties of model $\boldsymbol{R}_{s.j}$ because it is the ratio of the matching error before and after parameter extraction, calculated for the points which were not used in extraction.

At iteration i, we select the surrogate model based on the combined quality factor

$$F_j^{(i)} = \alpha F_{\mathrm{APP}.j}^{(i)} + (1-\alpha) F_{\mathrm{EXT}.j}^{(i)}. \quad (9)$$

In particular, we set

$$\boldsymbol{R}_s^{(i)} = \boldsymbol{R}_{s.j_{\max}}^{(i)} \quad (10)$$

where

$$j_{\max} = \arg \max_{j \in \{1,2,\ldots,K_i\}} F_j^{(i)}. \quad (11)$$

A good surrogate model exhibits high values for both $F_{\mathrm{APP}.j}^{(i)}$ and $F_{\mathrm{EXT}.j}^{(i)}$; however, we consider extrapolation properties as even more important than approximation properties because $F_{\mathrm{EXT}.j}^{(i)}$ indicates the capability of modeling the fine model outside the points at which the surrogate was created. This factor also indicates potential over flexibility of the surrogate model. Therefore, in practice, we use small values of α (e.g., $\alpha = 0.1$).

The space-mapping algorithm with an adaptive surrogate model selection scheme can be summarized as follows.

Step 0: Set $i = 0$; Choose the candidate model set R_S;

Step 1: Given $X^{(i)} = \{\boldsymbol{x}^{(0)}, \boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(i)}\}$, set $X_{\text{APP}}^{(i)}$ and $X_{\text{EXT}}^{(i)}$;

Step 2: Perform parameter extraction and calculate quality factors $F_{\text{APP}.j}^{(i)}$ and $F_{\text{EXT}.j}^{(i)}$; Choose the current surrogate model $\boldsymbol{R}_s^{(i)}$;

Step 3: Optimize $\boldsymbol{R}_s^{(i)}$ and obtain $\boldsymbol{x}^{(i+1)}$ using (2);

Step 4: Update $\delta^{(i)}$;

Step 5: If $\boldsymbol{x}^{(i+1)}$ is accepted set $i = i + 1$, $\delta^{(i)} = \delta^{(i-1)}$;

Step 6: If the termination condition is not satisfied go to *Step 1*; else terminate the algorithm.

The proposed adaptive scheme does not require any extra fine model evaluations because the surrogate model assessment is based on already existing fine model data. Additional computational effort concerns the coarse model only, and because we assume that the coarse model evaluation is significantly cheaper than the fine model evaluation, this additional effort does not substantially affect the total execution time of the optimization algorithm. In order to further reduce the execution time, unsuccessful candidate models can be gradually eliminated from R_S (based, for example, on the ranking of $F_j^{(i)}$). In our numerical experiment, however, we keep R_S fixed throughout the algorithm.

The proposed adaptive scheme alleviates certain problems in parameter extraction. In particular, the space-mapping surrogate model $\boldsymbol{R}_{s.q}$, which is potentially better than another model, say, $\boldsymbol{R}_{s.p}$, may appear worse at a given iteration because of parameter-extraction problems, e.g., a large number of parameters or the wrong starting point may prevent the parameter-extraction process from finding optimal values of the space-mapping parameters.

A possible extension of the proposed method is to exploit more than one coarse model so that the candidate surrogate models are combinations of both different space-mapping types and different coarse models. In particular, our method can be used for the adaptive selection of the coarse model.

IV. Examples

A. Test Problem Description

Problem 1: Six-section H-plane waveguide filter [29] (Fig. 1). The fine model is simulated using MEFiSTo [30] in a 2-D mode. The MATLAB coarse model (Fig. 2) has lumped inductances and dispersive transmission line sections. We simplify formulas due to Marcuvitz for the inductive susceptances corresponding to the H-plane septa. Design parameters are $\boldsymbol{x} = [L_1\ L_2\ L_3\ W_1\ W_2\ W_3\ W_4]^T$. The design specifications are $|S_{11}| \le 0.16$ for 5.4 GHz $\le \omega \le$ 9.0 GHz, $|S_{11}| \ge 0.85$ for 5.0 GHz $\le \omega \le$ 5.2 GHz, and $|S_{11}| \ge 0.5$ for 9.5 GHz $\le \omega \le$ 10.0 GHz. The starting point is $\boldsymbol{x}^{(0)}$ =[16.16 16.16 16.63 12.78 11.79 11.24 11.16]^T mm (coarse model optimal solution).

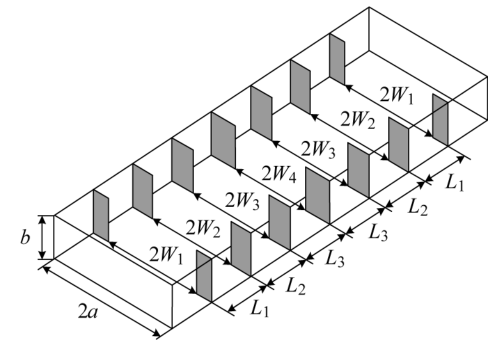

Fig. 1. Six-section H-plane waveguide filter: the 3-D view [29].

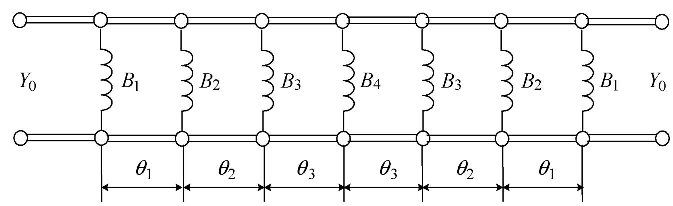

Fig. 2. Six-section H-plane waveguide filter: the equivalent empirical circuit model [29].

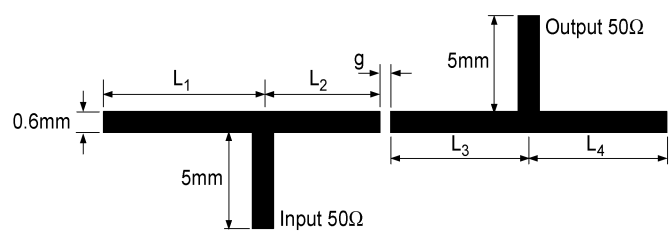

Fig. 3. Geometry of the microstrip bandpass filter [31].

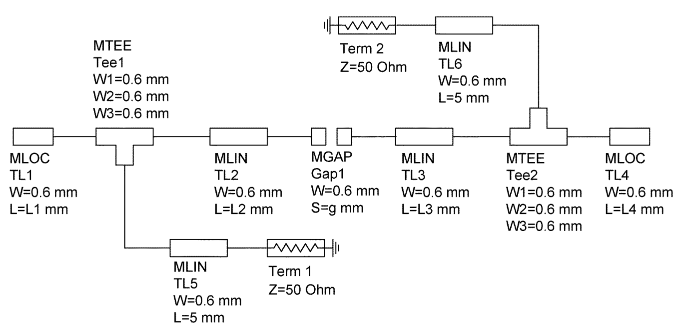

Fig. 4. Coarse model of microstrip bandpass filter (Agilent ADS).

Problem 2: Microstrip bandpass filter [31] (Fig. 3). The design parameters are $\boldsymbol{x} = [L_1\ L_2\ L_3\ L_4\ g]^T$. The fine model is simulated in FEKO [32], the coarse model is the circuit model implemented in Agilent ADS [33] (Fig. 4). The design specifications are $|S_{21}| \le -20$ dB for 4.5 GHz $\le \omega \le$ 4.7 GHz, $|S_{21}| \ge -3$ dB for 4.9 GHz $\le \omega \le$ 5.1 GHz, and $|S_{21}| \le -20$ dB for 5.3 GHz $\le \omega \le$ 5.5 GHz. The initial design is the coarse model optimal solution $\boldsymbol{x}^{(0)} = [6.712\ 4.950\ 6.399\ 5.147\ 0.0846]^T$ mm.

Problem 3: Microstrip bandpass filter with double-coupled resonators [31] (Fig. 5). The design parameters are $\boldsymbol{x} = [L_1\ L_2\ L_3\ g]^T$. The fine model is simulated in FEKO [32], the coarse model is the circuit model implemented

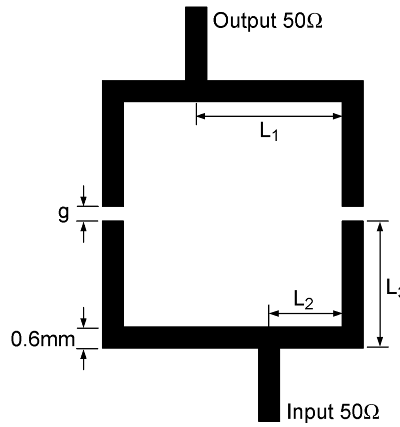

Fig. 5. Geometry of the microstrip bandpass filter with double-coupled resonators [31].

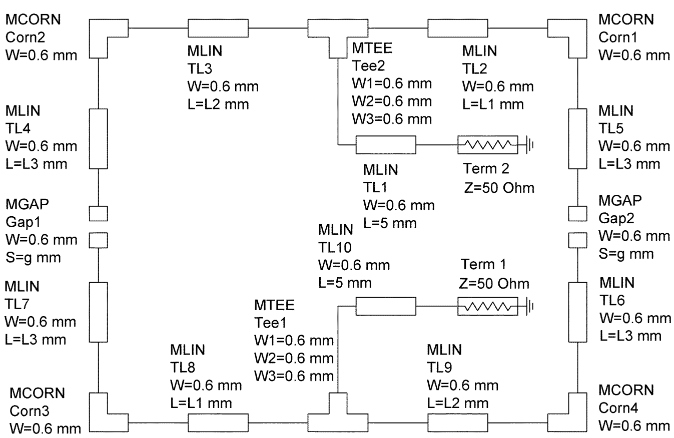

Fig. 6. Coarse model of microstrip bandpass filter with double-coupled resonators (Agilent ADS).

in Agilent ADS [33] (Fig. 6). The design specifications are $|S_{21}| \le -20$ dB for 4.5 GHz $\le \omega \le$ 4.85 GHz, $|S_{21}| \ge -3$ dB for 4.95 GHz $\le \omega \le$ 5.05 GHz, and $|S_{21}| \le -20$ dB for 5.15 GHz $\le \omega \le$ 5.5 GHz. The initial design is $\boldsymbol{x}^{(0)} = [3.0\ 1.5\ 3.0\ 0.25]^T$ mm.

B. Experimental Setup

For each of the test problems, we performed space-mapping optimization using the adaptive surrogate model selection scheme and the algorithm described in Section III. Table I shows the candidate model sets for each of the problems. For the sake of comparison, we also solved our problems using each of the candidate surrogate models separately.

For all the problems, we have set $X_{\text{APP}}^{(i)} = \{\boldsymbol{x}^{(I_i)}, \boldsymbol{x}^{(I_i+1)}, \ldots, \boldsymbol{x}^{(i)}\}$, where $I_i = \lfloor (i+1)/3 \rfloor$, and $X_{\text{EXT}}^{(i)} = \{\boldsymbol{x}^{(0)}, \boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(I_i-1)}\}$ ($X_{\text{EXT}}^{(i)}$ is empty if $I_i < 1$, i.e., $i < 2$). Thus, roughly 2/3 of the available points are used to assess approximation quality, as well as to determine the next surrogate model, while 1/3 of the points are used to assess extrapolation capability of the model. Obviously, there is a number of other choices available; the above is just one of many reasonable ones. Among other benefits, it allows reuse of space-mapping parameters for the winning candidate model without performing additional parameter extraction.

TABLE I
DESCRIPTION OF CANDIDATE MODEL SETS*

Test Problem	Candidate Model Set R_S
1	{***dF***, ***cd***, ***cdF***, ***Bd***, ***Bcd***, ***BdF***, ***BcdF***}
2	{***dF***, ***cd***, ***cdF***, ***Bd***, ***Bcd***, ***BdF***, ***BcdF***}
3	{***dI***, ***dF***, ***dFI***, ***cd***, ***cdI***, ***cdF***, ***cdFI***} #

* the naming convention for surrogate models (e.g., ***Bcd***) is explained in Section II.
\# ***I*** denotes implicit space mapping with preassigned parameters being electrical permittivities (initial value 9) and heights (initial value 0.66 mm) of microstrip elements MLIN, MCORN, and MTEE (all these elements are grouped into five groups; there is a separate electrical permittivity and height for each group, which makes a total of ten preassigned parameters).

TABLE II
OPTIMIZATION RESULTS

Test Problem	Surrogate Model[1]	Specification Error[2]	Number of Fine Model Evaluations
1	***dF***	**–0.025**	23
	cd	–0.016	21
	cdF	**–0.030**	19
	Bd	–0.004	18
	Bcd	–0.003	19
	BdF	**–0.027**	15
	BcdF	**–0.033**	21
	Adaptive Model	**–0.038**	18
2	***dF***	–0.501	7
	cd	–0.562	12
	cdF	**–1.413**	16
	Bd	**–1.395**	13
	Bcd	14.315	7
	BdF	–0.551	7
	BcdF	2.790	9
	Adaptive Model	**–1.393**	6
3	***dI***	**–0.645**	14
	dF	0.270	4
	dFI	–0.105	4
	cd	1.101	15
	cdI	0.711	9
	cdF	–0.042	12
	cdFI	**–0.675**	27
	Adaptive Model	**–0.643**	11

[1] the naming convention for surrogate models (e.g., ***Bcd***) is explained in Section II.
[2] the results marked bold are acceptable solutions; the rest of the results are considered not acceptable with respect to the given specification.

C. Experimental Results

Table II shows the results of our experiments, i.e., the objective function value (minimax error) and the number of fine model evaluations necessary to obtain the solution for problems 1–3. As an illustration, Table III shows, for test problem 3, the actual sequence of surrogate models used in subsequent iterations of the algorithm, as well as the corresponding combined quality factors compared to quality factors averaged over the whole set of candidate models. Note that the number of iterations does not correspond to the number of fine model evaluations shown in Table II because we use a trust region approach and there may be more than one fine model evaluation per iteration. Figs. 7–9 show the fine model responses at the initial solution $\boldsymbol{x}^{(0)}$ and final solution obtained using our space-mapping algorithm with adaptive model selection for problems 1–3, respectively.

TABLE III
SURROGATE MODEL EVOLUTION FOR TEST PROBLEM 3

Iteration Number	Surrogate Model *	$F_{j_{\max}}^{(i)}$	$\overline{F^{(i)}}$ #
1	***dFI***	14.8	6.0
2	***dI***	11.9	6.5
3	***cdFI***	8.4	5.9
4	***dFI***	11.4	7.7
5	***dI***	13.2	8.5
6	***dI***	14.5	9.1
7	***dFI***	16.1	10.8
8	***dFI***	16.3	10.6

* the naming convention for surrogate models (e.g., $\boldsymbol{Bcd}$) is explained in Section II.
# $\overline{F^{(i)}} = K_j^{-1} \sum_{j=1}^{K_j} F_j^{(i)}$ is the average combined quality factor (i.e., the combined quality factor averaged over all candidate surrogate models).

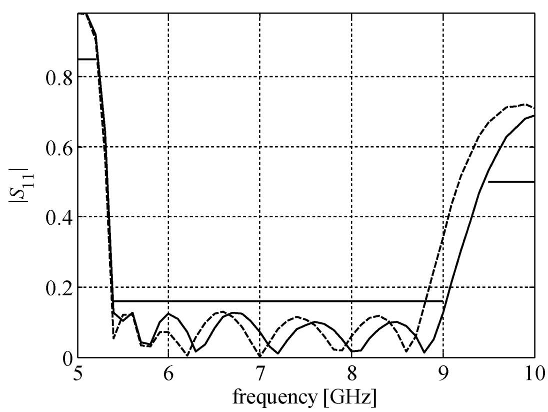

Fig. 7. Optimization results for the six-section H-plane waveguide filter problem using adaptive surrogate model selection: initial solution (dashed line) and final solution (solid line).

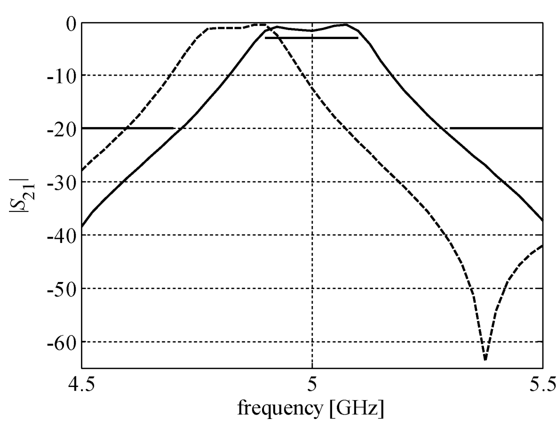

Fig. 8. Optimization results for the microstrip bandpass filter problem using adaptive surrogate model selection: initial solution (dashed line) and final solution (solid line).

D. Discussion

The results shown in Table II indicate that the algorithm working with adaptive model selection performs either better than the algorithm using any fixed surrogate model (problem 1) or almost as good as the best algorithms using a fixed surrogate model (problems 2 and 3). In the latter case, our space-mapping algorithm with adaptive model selection requires fewer fine model evaluations than the best fixed-model algorithms to obtain a solution of similar quality.

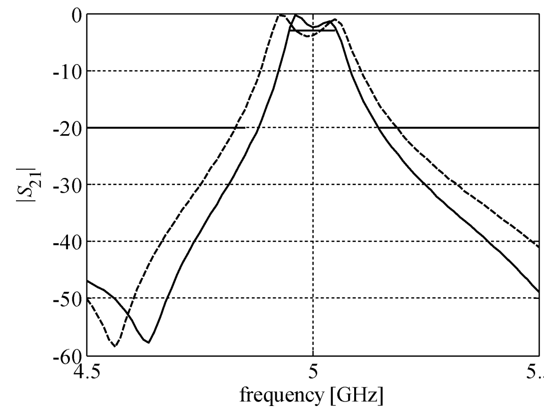

Fig. 9. Optimization results for the microstrip bandpass filter with double-coupled resonators problem using adaptive surrogate model selection: initial solution (dashed line) and final solution (solid line).

TABLE IV
PERFORMANCE COMPARISON: ADAPTIVE SPACE MAPPING VERSUS FIXED SURROGATE MODEL

Test Problem	Specification Error		Number of Fine Model Evals.	
	Adaptive Space Mapping	Fixed Space Mapping #	Adaptive Space Mapping	Fixed Space Mapping #
1	–0.038	–0.020	18	19.5
2	–1.393	+1.812	6	10.2
3	–0.643	+0.088	11	12.2

Values averaged over the whole candidate set for a given test problem.

Note that some of the space-mapping algorithms with a fixed model fail to find an acceptable solution. In some cases (problem 2), this applies to the most flexible surrogate model ($\boldsymbol{BcdF}$). In some cases (problems 2 and 3), most of the fixed-model algorithms give results that are not acceptable. This means that choosing the surrogate model type "at random" may lead to inadequate performance of the algorithm.

On the other hand, because choosing the surrogate model without prior knowledge and experience is almost the same as a random choice, it is fair to make a comparison between the adaptive space-mapping approach and the average performance of the fixed-model algorithm. Table IV provides this kind of comparison. It shows, in particular, that the average performance of the fixed-model space-mapping algorithm is much worse than the performance of the space-mapping algorithm with adaptive surrogate model selection for all considered test problems.

V. CONCLUSION

A novel adaptive surrogate model selection procedure has been presented. The proposed technique allows us to adjust the type of space-mapping surrogate model used in a given iteration based on the approximation/extrapolation capability of the model. The technique does not require any extra fine model evaluations. Examples verifying the performance of our approach are provided. It follows that our adaptive surrogate model selection improves the performance of the space-mapping optimization algorithm. It prevents a bad choice of the space-mapping type. The algorithm working with our adaptive space mapping never failed to find a solution close to the optimal one. Failures happened to the algorithms working with a fixed space-mapping type, and this is exactly what may occur when the space-mapping type is wrongly chosen. The optimization results obtained with adaptive surrogate model selection are comparable to or better than the results obtained with a fixed space-mapping type.

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REFERENCES

[1] J. W. Bandler, R. M. Biernacki, S. H. Chen, P. A. Grobelny, and R. H. Hemmers, "Space mapping technique for electromagnetic optimization," *IEEE Trans. Microw. Theory Tech.*, vol. 4, no. 12, pp. 536–544, Dec. 1994.

[2] J. W. Bandler, Q. S. Cheng, N. K. Nikolova, and M. A. Ismail, "Implicit space mapping optimization exploiting preassigned parameters," *IEEE Trans. Microw. Theory Tech.*, vol. 52, no. 1, pp. 378–385, Jan. 2004.

[3] J. W. Bandler, Q. S. Cheng, D. H. Gebre-Mariam, K. Madsen, F. Pedersen, and J. Søndergaard, "EM-based surrogate modeling and design exploiting implicit, frequency and output space mappings," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Philadelphia, PA, Jun. 2003, pp. 1003–1006.

[4] J. W. Bandler, Q. S. Cheng, S. A. Dakroury, A. S. Mohamed, M. H. Bakr, K. Madsen, and J. Sondergaard, "Space mapping: The state of the art," *IEEE Trans. Microw. Theory Tech.*, vol. 52, no. 1, pp. 337–361, Jan. 2004.

[5] D. Echeverria and P. W. Hemker, "Space mapping and defect correction," *Int. Math. J. Comput. Methods Appl. Math.*, vol. 5, no. 2, pp. 107–136, 2005.

[6] N. M. Alexandrov and R. M. Lewis, "An overview of first-order model management for engineering optimization," *Optim. Eng.*, vol. 2, no. 4, pp. 413–430, Dec. 2001.

[7] A. J. Booker, J. E. Dennis, Jr., P. D. Frank, D. B. Serafini, V. Torczon, and M. W. Trosset, "A rigorous framework for optimization of expensive functions by surrogates," *Structural Optim.*, vol. 17, no. 1, pp. 1–13, Feb. 1999.

[8] J. E. Dennis and V. Torczon, "Managing approximation models in optimization," in *Multidisciplinary Design Optimization*, N. M. Alexandrov and M. Y. Hussaini, Eds. Philadelphia, PA: SIAM, 1997, pp. 330–374.

[9] S. J. Leary, A. Bhaskar, and A. J. Keane, "A knowledge-based approach to response surface modeling in multifidelity optimization," *Global Optim.*, vol. 26, no. 3, pp. 297–319, Jul. 2003.

[10] S. E. Gano, J. E. Renaud, and B. Sanders, "Variable fidelity optimization using a Kriging based scaling function," presented at the 10th AIAA/ISSMO Multidisciplinary Anal. Optim. Conf., Albany, NY, 2004, Paper AIAA-2004-4460.

[11] T. W. Simpson, J. Peplinski, P. N. Koch, and J. K. Allen, "Metamodels for computer-based engineering design: Survey and recommendations," *Eng. with Comput.*, vol. 17, no. 2, pp. 129–150, Jul. 2001.

[12] N. V. Queipo, R. T. Haftka, W. Shyy, T. Goel, R. Vaidynathan, and P. K. Tucker, "Surrogate-based analysis and optimization," *Progr. Aerosp. Sci.*, vol. 41, no. 1, pp. 1–28, Jan. 2005.

[13] S. J. Leary, A. Bhaskar, and A. J. Keane, "A constraint mapping approach to the structural optimization of an expensive model using surrogates," *Optim. Eng.*, vol. 2, no. 4, pp. 385–398, Dec. 2001.

[14] M. Redhe and L. Nilsson, "Using space mapping and surrogate models to optimize vehicle crashworthiness design," presented at the 9th AIAA/ISSMO Multidisciplinary Anal. Optim. Symp., Atlanta, GA, Sep. 2002, Paper AIAA-2002-5536.

[15] H.-S. Choi, D. H. Kim, I. H. Park, and S. Y. Hahn, "A new design technique of magnetic systems using space mapping algorithm," *IEEE Trans. Magn.*, vol. 37, no. 5, pp. 3627–3630, Sep. 2001.

[16] S. Koziel, J. W. Bandler, A. S. Mohamed, and K. Madsen, "Enhanced surrogate models for statistical design exploiting space mapping technology," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Long Beach, CA, Jun. 2005, pp. 1609–1612.

[17] S. Koziel, J. W. Bandler, and K. Madsen, "Towards a rigorous formulation of the space mapping technique for engineering design," in *Proc. Int. Circuits Syst. Symp.*, Kobe, Japan, May 2005, pp. 5605–5608.

[18] ——, "Space mapping optimization algorithms for engineering design," in *IEEE MTT-S Int. Microw. Symp. Dig.*, San Francisco, CA, Jun. 2006, pp. 1601–1604.

[19] V. K. Devabhaktuni, B. Chattaraj, M. C. E. Yagoub, and Q.-J. Zhang, "Advanced microwave modeling framework exploiting automatic model generation, knowledge neural networks, and space mapping," *IEEE Trans. Microw. Theory Tech.*, vol. 51, no. 7, pp. 1822–1833, Jul. 2003.

[20] J. E. Rayas-Sanchez, "EM-based optimization of microwave circuits using artificial neural networks: The state-of-the-art," *IEEE Trans. Microw. Theory Tech.*, vol. 52, no. 1, pp. 420–435, Jan. 2004.

[21] J. E. Rayas-Sanchez, F. Lara-Rojo, and E. Martinez-Guerrero, "A linear inverse space-mapping (LISM) algorithm to design linear and nonlinear RF and microwave circuits," *IEEE Trans. Microw. Theory Tech.*, vol. 53, no. 3, pp. 960–968, Mar. 2005.

[22] L. Zhang, J. Xu, M. C. E. Yagoub, R. Ding, and Q.-J. Zhang, "Efficient analytical formulation and sensitivity analysis of neuro-space mapping for nonlinear microwave device modeling," *IEEE Trans. Microw. Theory Tech.*, vol. 53, no. 9, pp. 2752–2767, Sep. 2005.

[23] M. A. Ismail, D. Smith, A. Panariello, Y. Wang, and M. Yu, "EM-based design of large-scale dielectric-resonator filters and multiplexers by space mapping," *IEEE Trans. Microw. Theory Tech.*, vol. 52, no. 1, pp. 386–392, Jan. 2004.

[24] K.-L. Wu, Y.-J. Zhao, J. Wang, and M. K. K. Cheng, "An effective dynamic coarse model for optimization design of LTCC RF circuits with aggressive space mapping," *IEEE Trans. Microw. Theory Tech.*, vol. 52, no. 1, pp. 393–402, Jan. 2004.

[25] S. Amari, C. LeDrew, and W. Menzel, "Space-mapping optimization of planar coupled-resonator microwave filters," *IEEE Trans. Microw. Theory Tech.*, vol. 54, no. 5, pp. 2153–2159, May 2006.

[26] M. Dorica and D. D. Giannacopoulos, "Response surface space mapping for electromagnetic optimization," *IEEE Trans. Magn.*, vol. 42, no. 4, pp. 1123–1126, Apr. 2006.

[27] A. R. Conn, N. I. M. Gould, and P. L. Toint, *Trust Region Methods*, ser. MPS–SIAM Optim. Philadelphia, PA: SIAM, 2000.

[28] S. Koziel, J. W. Bandler, and K. Madsen, "Space-mapping based interpolation for engineering optimization," *IEEE Trans. Microw. Theory Tech.*, vol. 54, no. 6, pp. 2410–2421, Jun. 2006.

[29] M. H. Bakr, J. W. Bandler, N. Georgieva, and K. Madsen, "A hybrid aggressive space mapping algorithm for EM optimization," *IEEE Trans. Microw. Theory Tech.*, vol. 47, no. 12, pp. 2440–2449, Dec. 1999.

[30] *"MEFiSTo-3D Pro,"* ver. 4.0, Faustus Sci. Corporation, Victoria, BC, Canada, 2004.

[31] A. Hennings, E. Semouchkina, A. Baker, and G. Semouchkin, "Design optimization and implementation of bandpass filters with normally fed microstrip resonators loaded by high-permittivity dielectric," *IEEE Trans. Microw. Theory Tech.*, vol. 54, no. 3, pp. 1253–1261, Mar. 2006.

[32] *"FEKO User's Manual, Suite 4.2"* EM Softw. Syst. S.A. (Pty) Ltd., Stellenbosch, South Africa, 2004 [Online]. Available: http://www.feko.info

[33] Agilent ADS. ver. 2003C, Agilent Technol., Santa Rosa, CA, 2003.

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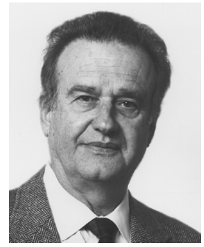

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