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LOW-COST PARAMETER EXTRACTION AND SURROGATE OPTIMIZATION FOR SPACE MAPPING DESIGN USING EM-BASED COARSE MODELS

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Abstract—Space mapping (SM) is one of the most popular surrogate-based optimization techniques in microwave engineering. The most critical component in SM is the low-fidelity (or coarse) model — a physically-based representation of the structure being optimized (high-fidelity or fine model), typically evaluated using CPU-intensive electromagnetic (EM) simulation. The coarse model should be fast and reasonably accurate. A popular choice for the coarse models are equivalent circuits, which are computationally cheap, but not always accurate, and in many cases even not available, limiting the practical range of applications of SM. Relatively accurate coarse models that are available for all structures can be obtained through coarsely-discretized EM simulations. Unfortunately, such models are typically computationally too expensive to be efficiently used in SM algorithms. Here, a study of SM algorithms with coarsely-discretized EM coarse models is presented. More specifically, novel and efficient parameter extraction and surrogate optimization schemes are proposed that make the use of coarsely-discretized EM models feasible for SM algorithms. Robustness of our approach is demonstrated through the design of three microstrip filters and one double annular ring antenna.

1. INTRODUCTION

Accurate and reliable performance prediction of microwave devices requires electromagnetic (EM) simulation. In particular, EM simulation is the only option when interactions of the microwave device and its environment, such as the antenna housing, the

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connectors, and the feeding structure, are to be taken into account. Nowadays, EM simulation is central in microwave engineering design and optimization [1, 2]. There are problems associated with exploiting EM simulation in design optimization, e.g., accurate EM simulation is computationally expensive, and, typically, the results obtained include numerical noise. Moreover, conventional optimization algorithms normally require large number of objective function calls. Consequently, direct EM-simulation-driven optimization is — in many cases — impractical. Due to this, design improvement is often carried out through parameter sweeps (usually, one parameter at a time), which is time consuming and may not yield an optimized design.

Efficient EM-simulation-driven design can be realized using surrogate-based optimization (SBO) [3]. The SBO techniques employed in microwave engineering are either based on approximation models (such as neural networks [4–6], support-vector regression [7–9], fuzzy systems [10–12], Cauchy approximation [13]), or physically-based surrogates (such as space mapping [1, 14–17] or simulation-based tuning [18–20]). Methods exploiting approximation models are quite versatile, but a large set of training samples is normally necessary to create the surrogate, which requires a substantial computational effort. These approaches are, therefore, more suitable for creating library models for multiple uses, such as the design of a specific class of devices. The methods exploiting physically-based surrogates, on the other hand, normally require a rather limited number of simulation runs to yield an optimized design, and, therefore, are more attractive for ad-hoc optimization. The physically-based surrogates are constructed by correcting an underlying low-fidelity model, which can be based on one of, or a combination of (1) simplified physics, (2) coarse discretization, and (3) relaxed convergence criteria [3]. The surrogate then serves as a prediction tool of the performance of the structure under consideration in the optimization loop in place of the CPU-intensive high-fidelity (or fine) model [1]. The key points here are that such a correction may be relatively cheap (in extreme cases, it can be based on a single high-fidelity model evaluation), and the number of correction-prediction cycles necessary to find a satisfactory design may be small, yielding a computationally efficient design process [14].

The focus of this paper is on space mapping (SM) [14], which is probably the most popular surrogate-based [3] design optimization methodology in microwave engineering to date. Compared to other methods utilizing physically-based surrogates, SM seems to be the most general. In particular, unlike tuning, SM is not invasive [19], i.e., it does not require any modification of the structure of interest, and, unlike shape-preserving response prediction [21], SM does not make any assumptions about the relationships between the low- and high-fidelity model responses.

The low-fidelity (or coarse) model is critical for SM performance [22]. It should be computationally cheap (so that its multiple evaluations do not affect the optimization cost significantly) and, at the same time, relatively accurate. The latter ensures that the SM surrogate model — constructed from the coarse model — is reliable, which allows the SM algorithm to yield a satisfactory design after a few fine model evaluations.

Equivalent circuit models are typically favored as coarse models due to their low computational cost [1]. However, circuit models are not always sufficiently accurate, and, more importantly, they are not available for many structures, such as antennas, and substrate-integrated circuits. Coarsely-discretized EM models are the most generic types of coarse models and are available for all kinds of microwave structures. Coarsely-discretized EM models can be made as accurate as required by controlling the discretization density. However, they are rather expensive with typical evaluation time ratio between the fine and coarsely-discretized EM coarse model between 5 to 50. Consequently, the total evaluation time for the coarse model (due to parameter extraction and surrogate model optimization) may determine the space mapping optimization cost.

In this paper, we formulate a specific surrogate model setup for the SM algorithm working with coarsely-discretized EM coarse models, including schemes for an efficient parameter extraction and surrogate model optimization. By making use of relatively accurate and expensive coarse models, our approach allows for a substantial reduction of the number of coarse model evaluations. The efficiency of the proposed technique is demonstrated through the design of several microwave structures.

2. SPACE MAPPING OPTIMIZATION

In this section, we briefly review the basics of space mapping optimization, and discuss various aspects of its most important component: the coarse model.

2.1. Space Mapping Optimization Algorithm

The microwave design can be formulated as a nonlinear minimization problem of the form

$$\mathbf{x}_f^* \in \arg\min_{\mathbf{x}} U\left(\mathbf{R}_f(\mathbf{x})\right), \tag{1}$$

where $\mathbf{R}_f \in R^m$ denotes the response vector of a high-fidelity (or fine) model of the device of interest, e.g., the modulus of the reflection coefficient $|S_{21}|$ evaluated at m different frequencies. U is a given scalar merit function, a minimax function with upper and lower specifications. The vector $\mathbf{x}_f^*$ is the optimal design to be determined. The fine model is assumed to be CPU-intensive so that solving (1) directly (e.g., using gradient-based algorithm) is usually prohibitive.

Space mapping [1] replaces solving the problem (1) directly by generating a sequence of approximate solutions, denoted as $\mathbf{x}^{(i)}$, $i = 0, 1, 2, \ldots$, and a family of surrogate models $\mathbf{R}_s^{(i)}$, as follows [14]:

$$\mathbf{x}^{(i+1)} = \arg\min_{\mathbf{x}} U\left(\mathbf{R}_s^{(i)}(\mathbf{x})\right). \tag{2}$$

Here, $\mathbf{x}^{(0)}$ is the initial design. The surrogate model $\mathbf{R}_s^{(i)}$ is a representation of $\mathbf{R}_f$ created using available fine model data, and updated after each iteration.

Space mapping constructs a surrogate model based on the low-fidelity (or coarse) model $\mathbf{R}_c$: a less accurate but computationally cheap representation of the fine model. Let $\bar{\mathbf{R}}_s$ be a generic SM surrogate model, i.e., $\mathbf{R}_c$ composed with suitable (usually linear) transformations. At the ith iteration, the surrogate model $\mathbf{R}_s^{(i)}$ is defined as

$$\mathbf{R}_s^{(i)}(\mathbf{x}) = \bar{\mathbf{R}}_s\left(\mathbf{x}, \mathbf{p}^{(i)}\right), \tag{3}$$

where

$$\mathbf{p}^{(i)} = \arg\min_{\mathbf{p}} \sum\nolimits_{k=0}^{i} w_{i.k} \left\|\mathbf{R}_f\left(\mathbf{x}^{(k)}\right) - \bar{\mathbf{R}}_s\left(\mathbf{x}^{(k)}, \mathbf{p}\right)\right\| \tag{4}$$

is a vector of model parameters and $w_{i.k}$ are weighting factors; a common choice of $w_{i.k}$ is $w_{i.k} = 1$ for all i and all k (all previous designs contribute to the parameter extraction process) or $w_{i.i} = 1$ and $w_{i.k} = 0$ for $k < i$ (the surrogate model depends on the most recent design only). In this work, the latter setup is used. The space mapping optimization algorithm flow is shown in Fig. 1.

Various space mapping surrogate models are available [1, 14]. They can be categorized into four groups: (i) models based on a (usually linear) distortion of the coarse model parameter space, e.g., input SM of the form $\bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{p}) = \bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{B}, \mathbf{c}) = \mathbf{R}_c(\mathbf{B} \cdot \mathbf{x} + \mathbf{c})$ [1]; (ii) models based on a distortion of the coarse model response, e.g., output space mapping of the form $\bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{p}) = \bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{d}) = \mathbf{R}_c(\mathbf{x}) + \mathbf{d}$; other versions of coarse model response correction can be found in [14] (output space mapping with sensitivity) and [31] (manifold mapping); (iii) implicit space mapping [23], where the parameters used to align the

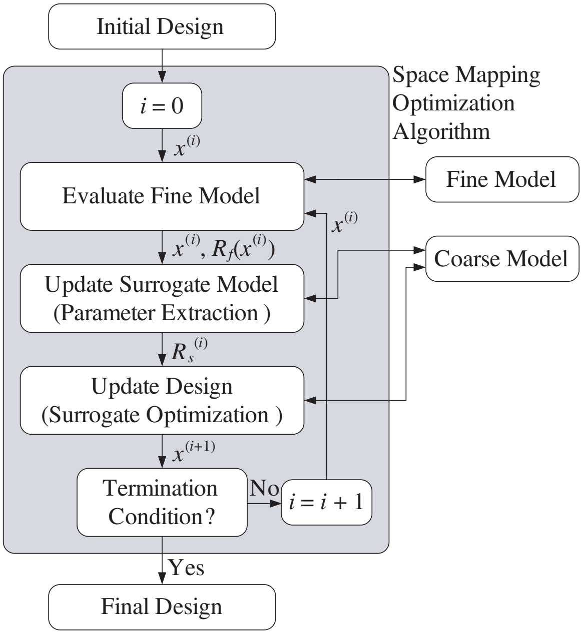


Figure 1. Flowchart of the space mapping algorithm. An approximate fine model optimum is obtained iteratively by optimizing the surrogate model. The fine model is evaluated at each new design for verification purposes. Parameter extraction and surrogate model optimization only involve coarse model.

surrogate and the fine model are different from the design variables, i.e., $\bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{p}) = \bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{x}_p) = \mathbf{R}_{c.i}(\mathbf{x}, \mathbf{x}_p)$, with $\mathbf{R}_{c.i}$ being the coarse model dependent on both the design variables $\mathbf{x}$ and the so-called preassigned parameters $\mathbf{x}_p$ (e.g., dielectric constant, substrate height) that are normally fixed in the fine model but can be freely altered in the coarse model [23]; (iv) custom models exploiting parameters characteristic to a given design problem; the most characteristic example is the so-called frequency space mapping $\bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{p}) = \bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{F}) = \mathbf{R}_{c.f}(\mathbf{x}, \mathbf{F})$ [14], where $\mathbf{R}_{c.f}$ is a frequency-mapped coarse model, i.e., the coarse model evaluated at frequencies different from the original frequency sweep for the fine model, according to the mapping $\omega \rightarrow f_1 + f_2\omega$, with $\boldsymbol{F} = [f_1 f_2]^T$. Fig. 2 shows the block diagrams of the basic surrogate models types.

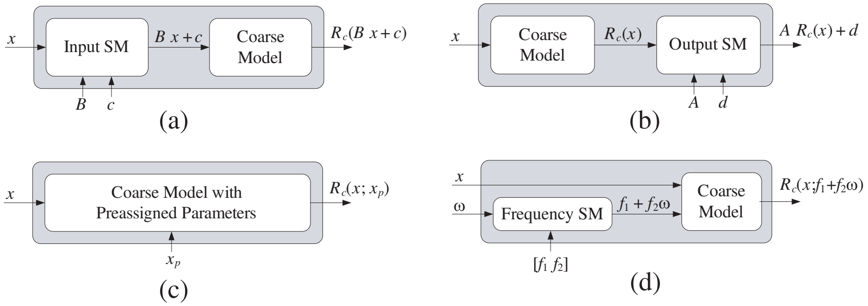


Figure 2. Basic space mapping surrogate types: (a) input SM, (b) output SM, (c) implicit SM, (d) frequency SM.

2.2. Coarse Models

The coarse model is the critical component of SM algorithms. As the parameter extraction (4) and surrogate model optimization (2) require numerous evaluations of the surrogate, the coarse model should be computationally cheap. The coarse model should also be reasonably accurate, otherwise, the SM optimization process may require many iterations (2)–(4), or may even fail to find a design satisfying given specification requirements [22]. A qualitative comparison of various coarse models used in microwave engineering is presented in Table 1.

Analytical models are extremely fast, but reliable ones are hardly available, except for simple components. Equivalent-circuit models are also computationally cheap, which, in many cases, allows us to neglect the computational cost of the parameter extraction and surrogate optimization. For that reason, many SM-related papers (e.g., [1, 14, 15, 23]) deal with circuit coarse models; also, they are easy to construct for structures such as filters, as well as many microstrip devices. However, both analytical and circuit models may lack accuracy, and they are typically not available for structures such as antennas and substrate-integrated circuits.

A generic coarse model is obtained through EM simulation of the structure of interest with a coarse discretization. These coarse models are typically more accurate, but computationally more expensive than the coarse models based on the analytical methods or circuit theory. Therefore, the computational cost is a major bottleneck in adopting the coarsely-discretized EM models to SM optimization. A workaround is to build a function-approximation model using coarse-discretization EM-simulation data (using, e.g., kriging [24]). This, however, requires dense sampling of the design space, and should only be done locally to avoid excessive CPU cost [24].

Table 1. Coarse models and their characteristics.

Model Type	CPU Cost	Accuracy	Availability
Analytical	Very cheap	Low	Rather limited
Equivalent circuit	Cheap	Low to decent	Limited (mostly filters)
Coarsely-discretized EM simulation	Relatively Expensive	Good to very good	Generic: available for all structures

3. SPACE MAPPING WITH COARSELY-DISCRETIZED EM MODELS

In order to facilitate the use of coarse-discretization EM coarse models with SM algorithms, a careful choice of the surrogate model type has to be made. Also, efficient algorithms for extracting the surrogate model parameters and optimizing the surrogate are necessary to reduce the number of coarse model evaluations required to complete both processes.

3.1. Surrogate Model

Selecting a proper surrogate model is a non-trivial problem by itself [22], and can have major influence on the algorithm performance. When considering SM with coarsely-discretized EM models, one has to take into account the following factors:

- The number of surrogate model parameters should be limited in order to reduce the cost of parameter extraction,
- The major discrepancy between the fine and coarsely-discretized EM models is typically a frequency shift between the model responses.

Having this in mind, we recommend constructing the surrogate using frequency SM [1] and implicit SM [14]. Frequency SM exploits only two parameters regardless of the number of design variables and is typically able to remove substantial part of the mismatch between the coarse and fine model.

Let us assume that the components of $\mathbf{R}_c$ correspond to the model evaluations (e.g., $|S_{21}|$) at m different frequency points, i.e., $\Omega = [\omega_1\ \omega_2\ \ldots\ \omega_m]^T$, i.e., $\mathbf{R}_c(\mathbf{x}) = \mathbf{R}_c(\mathbf{x};\Omega) = [R_c(\mathbf{x},\omega_1)\ \ldots\ R_c(\mathbf{x},\omega_m)]^T$, where $R_c(\mathbf{x},\omega_j)$ is a component of $\mathbf{R}_c$ corresponding to frequency ω_j. Frequency SM scales the frequency sweep Ω for the coarse model so that we have $\mathbf{R}_c(\mathbf{x}; f_1 + f_2 \cdot \Omega)$, with f_1 and f_2 being extractable parameters.

Implicit SM can be used as auxiliary mapping. In this paper, we only consider planar structures and parameters of dielectric layers (e.g., permittivity and thickness) can be utilized as additional degrees of freedom (preassigned parameters [14, 23]) to match the coarse and fine models. The coarse model with preassigned parameters $\mathbf{x}_p$ will be referred to as $\mathbf{R}_c(\mathbf{x}, \mathbf{x}_p; \Omega)$. The frequency and implicit SM surrogate model is then $\mathbf{R}_s(\mathbf{x}, \boldsymbol{p}) = \mathbf{R}_s(\mathbf{x}, [\mathbf{x}_p^T\ f_1\ f_2]^T) = \mathbf{R}_c(\mathbf{x}, \mathbf{x}_p;\ f_1 + f_2 \cdot \Omega)$.

It should be mentioned that response correction techniques such as output space mapping [14] and manifold mapping [31] (see also Section 2.1) do not require parameter extraction at all. Nevertheless, particularly if the coarse model is obtained through coarse-discretization EM simulation, the relationship between the coarse and fine model responses (e.g., their relative frequency shift) is, more or less, similar across the design space, so that both the frequency and implicit SM are capable of greatly reducing the misalignment between the models, and thus improving the generalization capability of the SM surrogate. On the other hand, response correction is normally local and it does not improve the surrogate's prediction capability. In fact, it can introduce the response distortion while moving away from the design at which it was established [32].

3.2. No-cost Frequency Scaling

Surrogate model parameters are obtained in the parameter extraction process (4) that involves multiple evaluations of the coarse model. Here, parameters of the frequency SM are determined without involving $\mathbf{R}_c$ (except $\mathbf{R}_c$ $(\mathbf{x}^{(i)})$) as follows:

$$\left[f_1^{(i)}, f_2^{(i)}\right] = \arg\min_{(f_1, f_2)} \left\| \mathbf{R}_f\left(\mathbf{x}^{(i)}\right) - I\left(\mathbf{R}_c\left(\mathbf{x}^{(i)}; \Omega\right), \Omega, f_1 + f_2 \cdot \Omega\right) \right\|, \quad (5)$$

where I: $R^m \times \Omega \times [\omega_{\min}, \omega_{\max}] \rightarrow R^m$ is an interpolation function such that $I(\mathbf{R}, \Omega, \cdot)$ interpolates the response $\mathbf{R}$ defined on Ω onto $[\omega_1, \omega_m]$ and extrapolates $\mathbf{R}$ onto $[\omega_{\min}, \omega_1)$ and $(\omega_m, \omega_{\max}]$; $\omega_{\min} < \omega_1$ ($\omega_{\max} > \omega_m$) to allow sufficient "room" for response matching. In particular, $I(\mathbf{R}, \Omega, f_1 + f_2 \cdot \Omega)$ is the evaluation of the interpolated/extrapolated response $\mathbf{R}$ (originally defined on Ω) at a "scaled" frequency sweep $f_1 + f_2 \cdot \Omega$. Here, I is implemented as piecewise cubic splines.

Note that (5) does not involve any coarse model evaluations so that it is of no-cost in terms of electromagnetic simulation. Note also that the scheme (5) can be easily extended assuming, e.g., higher-order polynomial or any other scaling function.

3.3. Low-cost Parameter Extraction

Preassigned parameters $\mathbf{x}_p$ of the implicit SM can be found, after determining the frequency SM coefficients, using a first-order approximation of $\mathbf{R}_c$ with respect to $\mathbf{x}_p$:

$$\begin{aligned}\mathbf{H}^{(i)}\left(\mathbf{x}_p\right) &= \mathbf{R}_c\left(\mathbf{x}^{(i)}, \mathbf{x}_p^{(i-1)}; f_1 + f_2 \cdot \Omega\right) \\ &\quad + \left[\mathbf{J}_{\mathbf{R}_c\left(\mathbf{x}^{(i)}, \,\cdot\,; f_1+f_2\cdot\Omega\right)}\left(\mathbf{x}_p^{(i-1)}\right)\right] \cdot \left(\mathbf{x}_p - \mathbf{x}_p^{(i-1)}\right), \quad (6)\end{aligned}$$

where $\mathbf{J}_{\mathbf{R}_c(\mathbf{x}^{(i)}, \,\cdot\,; f_1+f_2\cdot\Omega)}(\mathbf{x}_p^{(i-1)})$ is an estimated Jacobian of $\mathbf{R}_c$ with respect to $\mathbf{x}_p$ at $\mathbf{x}^{(i)}$ and $\mathbf{x}_p^{(i-1)}$ obtained using finite differentiation (or, adjoint sensitivities, if available). In order to reduce the effect of possible numerical noise present in the coarse model response, the finite differentiation is performed using relatively large steps. Let $\delta^{(i)}$ be the parameter extraction search radius at iteration i. For $\delta_k = \delta^{(i)} \cdot 2^{k-2}$, $k = 1, 2, 3$, we solve the following sub-problem:

$$\mathbf{x}_p^k = \arg \min_{\mathbf{x}_p : \left\|\mathbf{x}_p - \mathbf{x}_p^{(i-1)}\right\| \le \delta_k} \left\|\mathbf{R}_f(\mathbf{x}^{(i)}) - \mathbf{H}^{(i)}(\mathbf{x}_p)\right\|. \quad (7)$$

Then, the values of δ_k and $E_k = ||\mathbf{R}_f(\mathbf{x}^{(i)}) - \mathbf{R}_c(\mathbf{x}^{(i)}, \mathbf{x}_{pk}; f_1 + f_2 \cdot \Omega)||$ are interpolated using second-order polynomial to find δ^* that gives the smallest (estimated) value of the matching error (δ^* is then set to be $\delta^{(i+1)}$). Having δ^*, the preassigned parameters are found as

$$\mathbf{x}_p^{(i)} = \arg \min_{\mathbf{x}_p : \left\|\mathbf{x}_p - \mathbf{x}_p^{(i-1)}\right\| \le \delta^*} \left\|\mathbf{R}_f(\mathbf{x}^{(i)}) - \mathbf{H}^{(i)}(\mathbf{x}_p)\right\|. \quad (8)$$

Due to a good accuracy of the coarsely-discretized EM model, the procedure (7), (8) exploiting the first-order approximation (6) typically gives satisfactory results. The cost of the parameter extraction is low: only $n_p + 4$ evaluations of $\mathbf{R}_c$, where n_p is the number of preassigned parameters ($n_p = 2$ for test cases of Section 4). Frequency SM parameters f_1 and f_2 can also be included in the extraction procedure (6)–(8), which allows better matching at the additional cost of 2 coarse model evaluations.

3.4. Low-cost Surrogate Optimization

Efficiency of the surrogate model optimization can also be improved by using the scheme similar to (6)–(8). More specifically, we use a 1st-order expansion of $\mathbf{R}_c$ with respect to $\mathbf{x}$:

$$\begin{aligned}\mathbf{G}^{(i)}(\mathbf{x}) &= \mathbf{R}_c\left(\mathbf{x}^{(i)}, \mathbf{x}_p^{(i)}; f_1 + f_2 \cdot \Omega\right) \\ &\quad + \left[\mathbf{J}_{\mathbf{R}_c\left(\,\cdot\,, \mathbf{x}_p^{(i)}; f_1+f_2\cdot\Omega\right)}(\mathbf{x}^{(i)})\right] \cdot \left(\mathbf{x} - \mathbf{x}^{(i)}\right), \quad (9)\end{aligned}$$

where $\mathbf{J}_{\mathbf{R}_c(\,\cdot\,,\mathbf{x}_p^{(i)};f_1+f_2\cdot\Omega)}(\mathbf{x}^{(i)})$ is an estimated Jacobian of $\mathbf{R}_c$ with respect to $\mathbf{x}$. Let $\lambda^{(i)}$ be the surrogate optimization search radius at iteration i. For $\lambda_k = \lambda^{(i)} \cdot 2^{k-2}$, $k = 1, 2, 3$, we solve (note that the model $\mathbf{G}$ is corrected by output SM term $\mathbf{R}_f(\mathbf{x}^{(i)}) - \mathbf{G}^{(i)}(\mathbf{x}^{(i)})$ to make it consistent with the fine model at $\mathbf{x}^{(i)}$):

$$\mathbf{x}^k = \arg \min_{\mathbf{x}:\left\|\mathbf{x}-\mathbf{x}^{(i)}\right\|\leq\lambda_k} U\left(\mathbf{G}^{(i)}(\mathbf{x}) + \mathbf{R}_f\left(\mathbf{x}^{(i)}\right) - \mathbf{G}^{(i)}\left(\mathbf{x}^{(i)}\right)\right). \quad (10)$$

The values of λ_k and $U_k = U(\mathbf{G}^{(i)}(\mathbf{x}^k) + \mathbf{R}_f(\mathbf{x}^{(i)}) - \mathbf{G}^{(i)}(\mathbf{x}^{(i)}))$ are interpolated using second-order polynomial to find λ^* that gives the smallest (estimated) value of the specification error (λ^* is then set to be $\lambda^{(i+1)}$). The new design is then found as

$$\mathbf{x}^{(i+1)} = \arg \min_{\mathbf{x}:\left\|\mathbf{x}-\mathbf{x}^{(i)}\right\|\leq\lambda^*} U\left(\mathbf{G}^{(i)}(\mathbf{x}) + \mathbf{R}_f\left(\mathbf{x}^{(i)}\right) - \mathbf{G}^{(i)}\left(\mathbf{x}^{(i)}\right)\right). \quad (11)$$

Note that computational cost of the surrogate model optimization process is only $n + 4$ coarse model evaluations.

4. EXAMPLES

In this section, we present several examples demonstrating the operation and efficiency of space mapping using our parameter extraction (PE) and surrogate optimization (SO) algorithms described in Section 3. We compare its performance with conventional space mapping implementation. More efficient PE and SO results in substantial reduction of the optimization cost, from 40 to 70 percent, depending on the test case.

4.1. Microstrip Bandpass Filter [25]

Consider the microstrip bandpass filter [25] shown in Fig. 3. The design parameters are $\mathbf{x} = [L_1\ L_2\ L_3\ L_4\ g]^T$. The other parameters are $L_0 = 5\,\text{mm}$ and $W = 0.6\,\text{mm}$. The fine model simulated in FEKO [26]. The total mesh number for $\mathbf{R}_f$ is 882 (simulation time 13 min). The total mesh number for the coarsely-discretized FEKO model $\mathbf{R}_c$ is 100 (evaluation time 30 seconds). The design specifications are $|S_{21}| \leq -20\,\text{dB}$ for $4.5\,\text{GHz} \leq \omega \leq 4.7\,\text{GHz}$, $|S_{21}| \geq -3\,\text{dB}$ for $4.9\,\text{GHz} \leq \omega \leq 5.1\,\text{GHz}$ and $|S_{21}| \leq -20\,\text{dB}$ for $5.3\,\text{GHz} \leq \omega \leq 5.5\,\text{GHz}$. The initial design is $\mathbf{x}^{(0)} = [6.6\ 4.7\ 6.2\ 5.0\ 0.05]^T\,\text{mm}$.

SM optimization uses the frequency and implicit SM surrogate with substrate height and dielectric constant as preassigned parameters. The cost of parameter extraction (cf. Sections 3.2 and 3.3) is 8

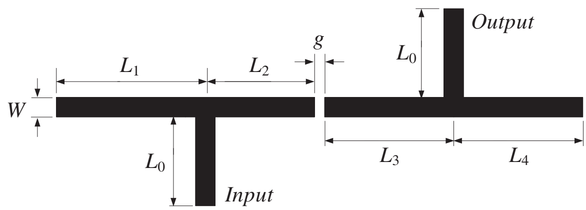


Figure 3. Microstrip bandpass filter: geometry [25].

Table 2. Microstrip bandpass filter: optimization cost.

Algorithm	Algorithm Component[1]	Model Evaluations		Total Cost	
		Number & Time	Relative Cost	Absolute [min]	Relative[4]
Standard[2]	PE	$180 \times \mathbf{R}_c$ (90 min)	80%	266	20.4
	SO	$248 \times \mathbf{R}_c$ (124 min)			
	$\mathbf{R}_f$ evaluations[3]	$4 \times \mathbf{R}_f$ (52 min)	20%		
This work	PE	$24 \times \mathbf{R}_c$ (12 min)	33%	78	6.0
	SO	$27 \times \mathbf{R}_c$ (14 min)			
	$\mathbf{R}_f$ evaluations[3]	$4 \times \mathbf{R}_f$ (52 min)	67%		

[1] PE = Parameter extraction, SO = Surrogate model optimization.
[2] PE and SO realized using *lsqnonlin* and *fminimax* [27], respectively.
[3] Includes: three SM iterations and fine model evaluation at $\mathbf{x}^{(0)}$.
[4] Equivalent number of fine model evaluations.

coarse model evaluations per iteration. Surrogate model optimization is performed as described in Section 3.4 (9 $\mathbf{R}_c$ evaluations per iteration). The optimized design, $\mathbf{x}^{(2)} = [6.43\ 4.78\ 6.17\ 4.89\ 0.094]^T$ mm (specification error -1.4 dB), is obtained after three SM iterations. The total cost corresponds to about 6 evaluations of the fine model (Table 2). The relative cost of parameter extraction and surrogate optimization is 33%. Fig. 4(a) shows the fine model at the initial and at the final designs. Fig. 4(b) shows $\mathbf{R}_f$ at $\mathbf{x}^{(0)}$ as well as the surrogate model at $\mathbf{x}^{(0)}$ before and after parameter extraction.

The filter was also optimized using conventional SM implementation with parameter extraction and surrogate optimization realized using Matlab routines (here, *lsqnonlin* and *fminmax* from Optimization Toolbox [27]). The final design — also obtained after two SM iterations — is comparable (specification error -1.3 dB), however, the optimization cost is much higher (Table 2) due to the much larger number of coarse model evaluations: the contribution of parameter ex-

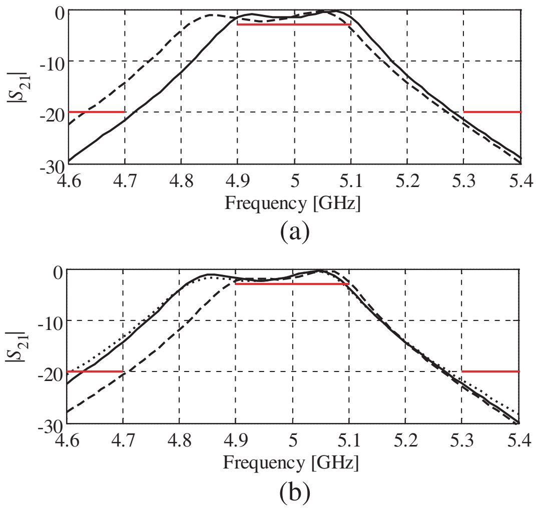


Figure 4. Microstrip bandpass filter: (a) Fine model response at the initial design (dashed line) and at the final design obtained using the SM algorithm presented here (solid line); (b) Fine model response at $\mathbf{x}^{(0)}$ (solid line), and the coarse model at $\mathbf{x}^{(0)}$ before (dashed line) and after (dotted line) parameter extraction.

traction and surrogate model optimization to the total design cost is 80%.

4.2. Microstrip Bandpass Filter with Open Stub Inverter [28]

Consider the bandpass microstrip filter with open stub inverter [28] shown in Fig. 5. The design parameters are $\mathbf{x} = [L_1\ L_2\ L_3\ S_1\ S_2\ W_1]^T$. The fine and coarse models are simulated in FEKO [26]. The total mesh number for $\mathbf{R}_f$ is 1702 (simulation time 50 min). The total mesh number for $\mathbf{R}_c$ is 160 (evaluation time 50 seconds). The design specifications are $|S_{21}| \leq -20\,\text{dB}$ for $1.8\,\text{GHz} \leq \omega \leq 1.9\,\text{GHz}$, $|S_{21}| \geq -1\,\text{dB}$ for $1.98\,\text{GHz} \leq \omega \leq 2.02\,\text{GHz}$ and $|S_{21}| \leq -20\,\text{dB}$ for $2.1\,\text{GHz} \leq \omega \leq 2.2\,\text{GHz}$. The initial design is the coarse model optimal solution $\mathbf{x}^{(0)} = [24.0\ 5.0\ 25.0\ 0.7\ 0.2\ 1.0]^T$ mm.

As before, the SM algorithm uses the frequency and implicit SM surrogate with substrate height and dielectric constant as preassigned parameters (parameter extraction cost is 8 coarse model evaluations per iteration). Surrogate model optimization is performed as described in Section 3.4 (10 $\mathbf{R}_c$ evaluations per iteration). The optimized

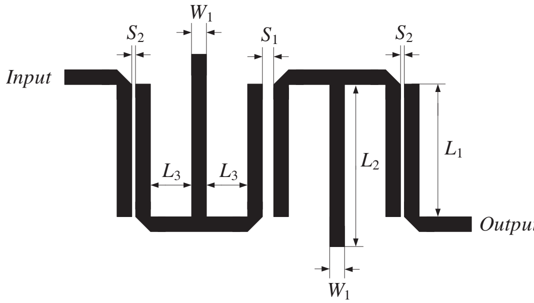


Figure 5. Geometry of the bandpass filter with open stub inverter [28].

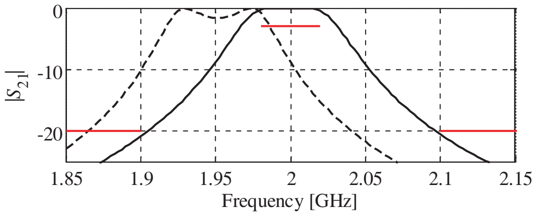
Table 3. Microstrip bandpass filter: optimization cost.

Algorithm	Algorithm Component[1]	Model Evaluations		Total Cost	
		Number & Time	Relative Cost	Absolute [min]	Relative[5]
Standard[2]	PE	$85 \times \mathbf{R}_c$ (71 min)	64%	416	8.3
	SO	$234 \times \mathbf{R}_c$ (195 min)			
	$\mathbf{R}_f$ evaluations[3]	$3 \times \mathbf{R}_f$ (150 min)	36%		
This work	PE	$24 \times \mathbf{R}_c$ (20 min)	18%	245	4.9
	SO	$30 \times \mathbf{R}_c$ (25 min)			
	$\mathbf{R}_f$ evaluations[4]	$4 \times \mathbf{R}_f$ (200 min)	82%		

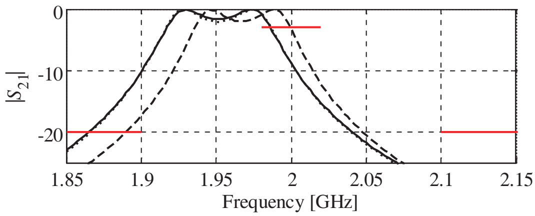
[1] PE = Parameter extraction, SO = Surrogate model optimization.
[2] PE and SO realized using *lsqnonlin* and *fminimax* [27], respectively.
[3] Includes: two SM iterations and fine model evaluation at $\mathbf{x}^{(0)}$.
[4] Includes: three SM iterations and fine model evaluation at $\mathbf{x}^{(0)}$.
[5] Equivalent number of fine model evaluations.

design, $\mathbf{x}^{(3)} = [23.76\ 2.87\ 24.74\ 0.82\ 0.13\ 0.59]^T$ mm (specification error -0.5 dB), is obtained after three SM iterations. The total cost corresponds to about 5 evaluations of the fine model (Table 3). The relative cost of parameter extraction and surrogate optimization is 18%. Fig. 6 shows the fine model at the initial and at the final designs, as well as $\mathbf{R}_f$ at $\mathbf{x}^{(0)}$ as well as the surrogate model at $\mathbf{x}^{(0)}$ before and after parameter extraction.

Optimization using conventional SM implementation (*lsqnonlin* for parameter extraction and *fminimax* for surrogate optimization) yields similar design in two SM iterations (specification error -0.6 dB) but the design cost is higher (Table 3); with the parameter extraction and surrogate model optimization being 64% of the total cost.



(a)



(b)

Figure 6. Microstrip bandpass filter: (a) Fine model response at the initial design (dashed line) and at the final design obtained using the SM algorithm presented here (solid line); (b) Fine model response at $\mathbf{x}^{(0)}$ (solid line), and the coarse model at $\mathbf{x}^{(0)}$ before (dashed line) and after (dotted line) parameter extraction.

4.3. Microstrip Hairpin Filter [29]

Consider the microstrip hairpin filter [29] shown in Fig. 7. The design parameters are $\mathbf{x} = [L_1\ L_2\ L_3\ L_4\ L_5\ L_6\ S_1\ S_2\ d]^T$. The fine model simulated in FEKO [26]. The total mesh number for $\mathbf{R}_f$ is 1080. Simulation time for $\mathbf{R}_f$ is 37 min. The total mesh number for the coarsely-discretized FEKO model $\mathbf{R}_c$ is 170 (evaluation time 1 min). The design specifications are $|S_{21}| \leq -20\,\text{dB}$ for $3.0\,\text{GHz} \leq \omega \leq 3.3\,\text{GHz}$, $|S_{21}| \geq -1\,\text{dB}$ for $3.6\,\text{GHz} \leq \omega \leq 4.4\,\text{GHz}$ and $|S_{21}| \leq -20\,\text{dB}$ for $4.7\,\text{GHz} \leq \omega \leq 5.0\,\text{GHz}$. The initial design is $\mathbf{x}^{init} = [9.0\ 9.0\ 9.0\ 2.0\ 2.0\ 2.0\ 0.2\ 0.4\ 0.5]^T$ mm.

The first step is the optimization of the coarse model, which is performed using the procedure similar to (9)–(11). The approximate optimum of the coarse model, $\mathbf{x}^{(0)} = [9.41\ 9.47\ 9.39\ 1.81\ 2.29\ 2.35\ 0.10\ 0.102\ 0.217]^T$ mm, is obtained at the cost of only 65 coarse model evaluations. SM optimization of the filter starts from $\mathbf{x}^{(0)}$, using the frequency and implicit SM surrogate with substrate height and dielectric constant as preassigned parameters. Parameter extraction is performed as described in Sections 3.2 and 3.3 (8 coarse model

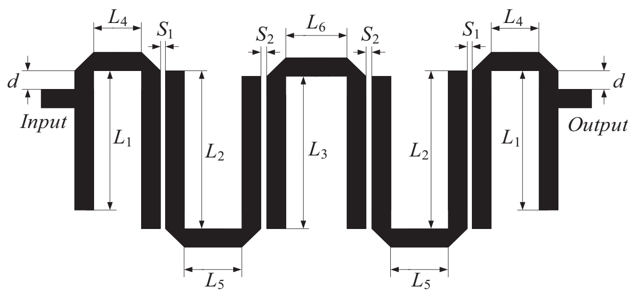


Figure 7. Microstrip hairpin filter: geometry [29].

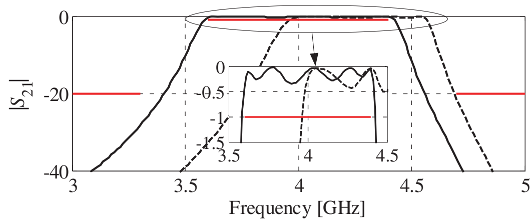
Table 4. Hairpin filter: optimization cost.

Algorithm	Algorithm Component[1]	Model Evaluations		Total Cost	
		Number & Time	Relative Cost	Absolute [min]	Relative[4]
Standard[2]	PE	$110 \times \mathbf{R}_c$ (110 min)			
	SO	$186 \times \mathbf{R}_c$ (186 min)	73%	407	11.0
	$\mathbf{R}_f$ evaluations[3]	$3 \times \mathbf{R}_f$ (111 min)	27%		
This work	PE	$16 \times \mathbf{R}_c$ (16 min)			
	SO	$26 \times \mathbf{R}_c$ (26 min)	27%	153	4.1
	$\mathbf{R}_f$ evaluations[3]	$3 \times \mathbf{R}_f$ (111 min)	73%		

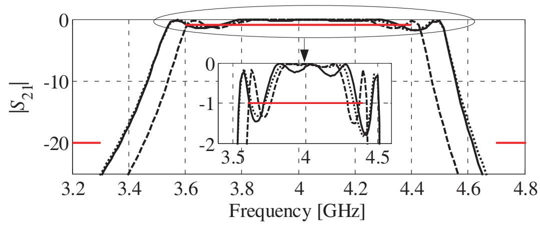
[1] PE = Parameter extraction, SO = Surrogate model optimization.
[2] PE and SO realized using *lsqnonlin* and *fminimax* [27], respectively.
[3] Includes: two SM iterations and fine model evaluation at $\mathbf{x}^{(0)}$.
[4] Equivalent number of fine model evaluations.

evaluations per iteration). Surrogate model optimization is performed as described in Section 3.4 (13 $\mathbf{R}_c$ evaluations per iteration). The optimized design, $\mathbf{x}^{(2)} = [9.363\ 9.507\ 9.479\ 1.884\ 2.433\ 2.284\ 0.10\ 0.196\ 0.321]^T$ mm (Fig. 8(a); specification error -0.6 dB), is obtained after two SM iterations. The total cost corresponds to about 4 evaluations of the fine model (Table 4), with the relative cost of parameter extraction and surrogate optimization being only 27%. Fig. 8(b) shows $\mathbf{R}_f$ at $\mathbf{x}^{(0)}$ as well as the surrogate model at $\mathbf{x}^{(0)}$ before and after parameter extraction.

As comparison, the filter was also optimized using Matlab routines for performing parameter extraction and surrogate optimization (here, *lsqnonlin* and *fminmax* from Optimization Toolbox [27]). Although the final design — also obtained after two SM iterations — is comparable (specification error -0.5 dB), the optimization cost is much higher



(a)



(b)

Figure 8. Hairpin filter: (a) Fine model respons e at the initial design (dashed line) and at the final design obtained using the SM algorithm presented here (solid line); (b) Fine model response at $\mathbf{x}^{(0)}$ (solid line), and the coarse model at $\mathbf{x}^{(0)}$ before (dashed line) and after (dotted line) parameter extraction.

(Table 4). In this case, the contribution of the parameter extraction and surrogate model optimization to the total cost is 73%.

4.4. Double Annular Ring Antenna [30]

Consider the stacked probe-fed printed annular ring antenna [30] shown in Fig. 9. The design parameters are $x = [a_1\ a_2\ b_1\ b_2\ \rho_1]^T$. The fine model is simulated in FEKO [26] (total mesh number 1480, simulation time 2 hours 5 minutes). The total mesh number for the coarsely-discretized FEKO model $\mathbf{R}_c$ is 300 (evaluation time 6.5 minutes). The design specifications are $|S_{11}| \leq -10\,\mathrm{dB}$ for $1.75\,\mathrm{GHz} \leq \omega \leq 2.15\,\mathrm{GHz}$. The initial design is $\mathbf{x}^{init} = [10.0\ 8.0\ 30.0\ 30.0\ 20.0]^T$ mm.

The optimum of the coarse model, $\mathbf{x}^{(0)} = [9.66\ 8.17\ 29.17\ 32.12\ 19.76]^T$ mm, is obtained using the procedure similar to (9)–(11) at the cost of only 18 coarse model evaluations. The SM algorithm exploits the frequency and implicit SM surrogate with dielectric constants ε_{r1} and ε_{r2} as preassigned parameters. Parameter extraction requires only 8 evaluations of $\mathbf{R}_c$; surrogate model optimization needs just 9 $\mathbf{R}_c$ evaluations (cf. Section 3).

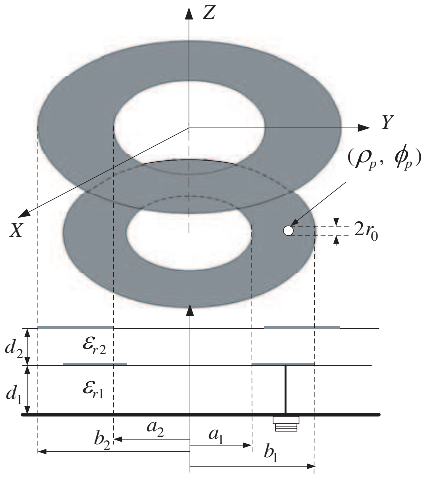


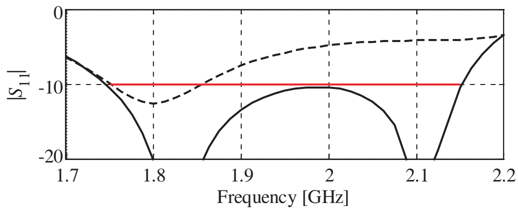
Figure 9. Geometry of a stacked probe-fed printed double annular ring antenna [30].

Table 5. Double annular ring antenna: optimization cost.

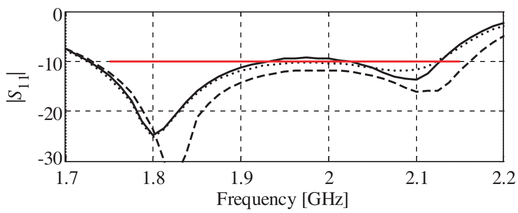
Algorithm	Algorithm Component[1]	Model Evaluations		Total Cost	
		Number & Time	Relative Cost	Absolute [min]	Relative[4]
Standard[2]	PE	$70 \times \mathbf{R}_c$ (455 min)	77%	1616	13.0
	SO	$121 \times \mathbf{R}_c$ (786 min)			
	$\mathbf{R}_f$ evaluations[3]	$3 \times \mathbf{R}_f$ (375 min)	23%		
This work	PE	$16 \times \mathbf{R}_c$ (104 min)	37%	596	4.7
	SO	$18 \times \mathbf{R}_c$ (117 min)			
	$\mathbf{R}_f$ evaluations[3]	$3 \times \mathbf{R}_f$ (375 min)	63%		

[1] PE = Parameter extraction, SO = Surrogate model optimization.
[2] PE and SO realized using *lsqnonlin* and *fminimax* [27], respectively.
[3] Includes: two SM iterations and fine model evaluation at $\mathbf{x}^{(0)}$.
[4] Equivalent number of fine model evaluations.

The final design shown in Fig. 10(a), $\mathbf{x}^{(2)} = [10.8\ 7.96\ 28.30\ 32.3\ 19.47]^T$ mm (specification error -0.4 dB), is obtained after two SM iterations with the total CPU cost of about four $\mathbf{R}_f$ evaluations (Table 5). The relative cost of parameter extraction and surrogate optimization is 37%. Fig. 10(b) shows the fine model at $\mathbf{x}^{(0)}$ and the surrogate model at $\mathbf{x}^{(0)}$ before and after parameter extraction.



(a)



(b)

Figure 10. Double annular ring antenna: (a) Fine model respons e at the initial design (dashed line) and at the final design obtained using the SM algorithm presented here (solid line); (b) Fine model response at $\mathbf{x}^{(0)}$ (solid line), and the coarse model at $\mathbf{x}^{(0)}$ before (dashed line) and after (dotted line) parameter extraction.

SM algorithm using standard setup (parameter extraction with *lsqnonlin* and surrogate optimization with *fminmax*) yielded comparable design in two iterations (specification error -0.2 dB), however, at a much larger cost (Table 5).

5. CONCLUSION

Novel parameter extraction and surrogate model optimization schemes are discussed that improve efficiency of SM algorithms while working with coarsely-discretized EM coarse models. Together with a proper selection of the surrogate model (here, frequency and implicit SM), our approach allows reduction of the computation overhead related to multiple coarse model evaluations as well as application of space mapping to problems where equivalent-circuit coarse models are not available.

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