Design Optimization of Microwave Structures Using Low-Order Local Cauchy-Approximation Surrogates

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Abstract **─** A robust and computationally efficient microwave design optimization procedure is presented. This procedure integrates low-order Cauchy-approximation surrogate models with coarse-discretization EM simulations. The optimization engine is space mapping (SM). Instead of setting up a single surrogate model valid for the entire design variable space, a sequence of surrogate models is established in small hyper-cubes containing the optimization path. This allows us to substantially limit the number of training points necessary to create the surrogates and, therefore, reduce the cost of the optimization process. Moreover, our approach eliminates the need for circuit-equivalent coarse models traditionally used by SM algorithms. Our algorithm is successfully illustrated through the efficient design of a number of microwave filters.

Index Terms **─** Cauchy approximation, computer-aided design (CAD), EM optimization, space mapping, surrogate modeling.

I. INTRODUCTION

Accurate evaluation of microwave devices can be realized using CPU-intensive electromagnetic (EM) simulation. These simulators may require extensive simulation time for complex structures. It is, thus, prohibitive to utilize these simulators in optimizing complex structures. On the other hand, analytical models can only be used to yield initial designs that need to be further tuned to meet the given performance specifications. This is particularly true for some emerging classes of circuits such as ultra wideband (UWB) antennas [1] or substrate integrated circuits [2] where no systematic design procedures exist that would lead to designs satisfying the prescribed specifications. Therefore, EM-simulation-driven design optimization becomes increasingly important.

The computational cost of simulation-based optimization can be partially reduced by using co-simulation [3-5], where the EM model is split into smaller parts that are subsequently combined in a circuit simulator. However, the EM-embedded co-simulation model is still subjected to direct optimization. Also, application of this approach is limited and cannot be directly applied in case of radiating structures such as antennas.

Computationally efficient simulation-based optimization can be realized using surrogate-based optimization (SBO) [6, 7], where the optimization burden is shifted to a surrogate model, a computationally cheap representation of the structure being optimized (referred to as the fine model). Probably the most successful approaches of this kind are space mapping (SM) [8-19], simulation-based tuning [20-22] and tuning SM [23-26], and various response correction techniques [27-30], as well as methods utilizing variable-fidelity models [31, 32]. Using these techniques, the direct optimization of expensive (or "fine") EM-based models is replaced by iterative optimization of less accurate but fast representations ("coarse" models). The coarse model should be physically-based (to have a good prediction capability) and it should be computationally cheap. In practice, equivalent-circuit models or models exploiting analytical formulas are preferred [6]. Unfortunately, reliable equivalent-circuit models may lack accuracy, which is critical for the SM algorithm performance [33-35]. These models may also be difficult to develop for certain types of microwave devices including antennas, substrate integrated circuits, and waveguide structures. Also, an extra simulator is involved in the optimization process.

An alternative way of creating the coarse model for SM algorithm was proposed in [36, 37] using Cauchy approximation [38] of the coarse-discretization EM simulation data of the microwave structure under consideration. The coarse model built in this way is fast and easy to optimize but the approach described in [36] can work efficiently only when the number of design variables n is small (up to 3 or 4). As the number of coarse-discretization simulations necessary to set up the coarse model grows exponentially with n, their computational cost becomes impracticably high for large n. Also, the coarse model of [36] is set up once for the entire optimization process. Thus, it should be valid in the relatively large neighborhood of the initial design which increases the required order of the Cauchy model, and consequently, the number of coarse-discretization simulations necessary to produce the training data [36].

Here, an alternative technique for creating the coarse model is described. This technique extends the work presented in [39] to problems with larger number of parameters. We exploit low-order Cauchy approximation of coarse-discretization simulation data set up in small regions enclosing the optimization path. This allows us to reduce the number of training points necessary to set up the coarse model when compared with [36]. Moreover, as the number of training points is proportional to n^2 (in particular, it does not grow exponentially with n as in [36]), our method can be applied for problems with a larger number of design variables. The efficiency of our approach is demonstrated through the design of three microstrip filters.

II. DESIGN OPTIMIZATION USING CAUCHY-BASED SURROGATES

In this section, we formulate the microwave design optimization problem, recall the standard space mapping optimization technique, and provide some general considerations regarding coarse models – the most important component of the SM algorithm. We also discuss the coarse models created by Cauchy approximation of the coarse-discretization EM-simulation data as well as describe the proposed technique exploiting low-order Cauchy approximation models.

A. Formulation of the design problem

Let $\boldsymbol{R}_f(\boldsymbol{x}) \in R^m$ denotes the response vector of the device of interest (fine model), where $\boldsymbol{x}$ is a vector of design variables (e.g., geometry parameters). $\boldsymbol{R}_f(\boldsymbol{x})$ can be, e.g., S-parameters of a device evaluated over a certain frequency band.

In this paper, a microwave design task is formulated as a nonlinear minimization problem with respect to $\boldsymbol{x}$. Design specifications are translated into a scalar merit function U, so that a better design corresponds to a smaller value of $U(\boldsymbol{R}_f(\boldsymbol{x}))$. Typically, U is a minimax function with upper and/or lower specifications [8].

The goal is to solve the following optimization problem:

$$\boldsymbol{x}_f^* \in \arg\min_{\boldsymbol{x}} U\left(\boldsymbol{R}_f(\boldsymbol{x})\right). \qquad (1)$$

Here, $\boldsymbol{x}_f^*$ is the optimal design to be determined. The fine model is assumed to be computationally expensive so that handling the problem (1) directly by employing EM simulator in the optimization loop is impractical.

B. Surrogate-based optimization

Surrogate-based optimization (SBO) [6] avoids solving (1) directly for computationally expensive models. Instead, the following algorithm is considered [14]:

$$\boldsymbol{x}^{(i+1)} = \arg\min_{\boldsymbol{x}} U\left(\boldsymbol{R}_s^{(i)}(\boldsymbol{x})\right), \qquad (2)$$

where $\boldsymbol{x}^{(i)}$, $i = 0, 1, \ldots$, is a series of approximate solutions to (1) with $\boldsymbol{x}^{(0)}$ being the initial design. The surrogate model $\boldsymbol{R}_s^{(i)}$ is a representation of $\boldsymbol{R}_f$ created using available fine model data, and updated after each iteration.

The construction of the surrogate model depends on the specific SBO approach. In the case of SM [8, 9], the surrogate model is a composition of the coarse model $\boldsymbol{R}_c$ (a less accurate but computationally cheap representation of $\boldsymbol{R}_f$) and simple mappings, e.g., $\boldsymbol{R}_s^{(i)} = \boldsymbol{R}_c(\boldsymbol{B}^{(i)}\cdot\boldsymbol{x}+\boldsymbol{c}^{(i)})$ (input SM [8]) or $\boldsymbol{R}_s^{(i)} = \boldsymbol{A}^{(i)}\cdot\boldsymbol{R}_c(\boldsymbol{x}) + \boldsymbol{d}^{(i)}$ (output SM [9]). Other approaches include implicit SM [40, 41] and frequency SM [9]. The mapping parameters are determined to minimize the misalignment between the surrogate and $\boldsymbol{R}_f$, usually in a least-square sense [8].

One of the recent SBO techniques developed for microwave engineering is shape-preserving response prediction (SPRP) [30], where the surrogate model is constructed using a set of so-called characteristic points of the fine and coarse model response as well as corresponding translation vectors that describe the change of the coarse model response that is a result of the model optimization [30]. These translation vectors are subsequently applied to the fine model response at certain reference design (typically, the latest iteration point $\boldsymbol{x}^{(i)}$) in order to predict the $\boldsymbol{R}_f$ response at the current design.

Other SBO techniques, in particular, manifold mapping [27] or adaptive response correction [29], can be considered as generalizations of output SM and construct the surrogate through enhancing the coarse model by a suitable design-variable-dependent additive correction term.

C. Coarse models – general remarks

In order to ensure good performance of the SBO algorithm, regardless of whether it is space mapping, SPRP, or other technique, the coarse model should be physically-based, i.e., describe the same phenomena as the fine model which would ensure good prediction capability of the surrogate [9]. Also, $\boldsymbol{R}_c$ should be computationally cheap so that the numerous coarse model evaluations utilized while optimizing the surrogate model (2) and—in case of space mapping—solving the parameter extraction problem [8] do not seriously affect the computational cost of the algorithm.

For these reasons, the preferred choice for the coarse model is an equivalent circuit. In some cases, however, circuit-based coarse models are not available (antennas, substrate integrated circuits). Also, accuracy of such models is often insufficient, which may affect the performance of the SBO algorithm.

D. Coarse models using Cauchy approximation of coarse-discretization EM simulations

The coarse model can be implemented as a coarsely discretized EM model exploiting the same EM solver as the one used to evaluate $\boldsymbol{R}_f$ [36]. In this case, however, it is difficult to find a satisfactory trade-off between accuracy and evaluation time of $\boldsymbol{R}_c$, as well as to ensure its good analytical properties (e.g., smoothness) [42].

To overcome this problem, the coarse model can be created by approximating the data from the coarsely discretized EM model (referred to here as $\boldsymbol{R}_{f\text{-}c}$) using a suitable approximation technique. It is only necessary to evaluate the coarse EM model at a predefined set of training points. The resulting coarse model is computationally cheap.

In [34], $\boldsymbol{R}_c$ was built using a multi-dimensional Cauchy rational approximation that can be summarized as follows [38]. Let $R_s(\boldsymbol{x})$ be a scalar system response where $\boldsymbol{x} = [x_1\ x_2\ \ldots\ x_n]^T$ is the vector of design variables. The response R_s can be modeled as:

$$\overline{R}_s(\boldsymbol{x}) = \frac{a_0 + a_1x_1 + a_2x_2 + a_3x_1^2 + a_4x_1x_2 + a_5x_2^2 + .}{b_0 + b_1x_1 + b_2x_2 + b_3x_1^2 + b_4x_1x_2 + b_5x_2^2 + ..}, \quad (3)$$

where $\boldsymbol{a} = [a_0\ a_1\ \ldots\ a_M]^T$ and $\boldsymbol{b} = [b_0\ b_1\ \ldots\ b_M]^T$ are the unknown coefficients. The globally-optimal model coefficients can be found using a robust algorithm for the extraction of the parameterized Cauchy model introduced in [38]. This algorithm allows for an error margin in the given response data resulting in a stable formulation that is less sensitive to errors. It also implements safeguard constraints that eliminate spurious solutions. The model coefficients can be found by solving a linear program of the form [38]:

$$\min_{\boldsymbol{v}} \boldsymbol{c}^T\boldsymbol{v} \quad \text{subject to} \quad \boldsymbol{A}(\boldsymbol{\delta})\boldsymbol{v} \le \boldsymbol{d}, \quad (4)$$

where $\boldsymbol{v} = [t\ \ \boldsymbol{a}^T\ \boldsymbol{b}^T]^T$ is the vector of unknowns with t being an auxiliary variable introduced by the linear program. The matrix $\boldsymbol{A}$ depends on the set of data pairs S whose cardinality is N_s. The number of rows in the matrix $\boldsymbol{A}$ depends linearly on N_s, the vectors $\boldsymbol{c}$ and $\boldsymbol{d}$ are constant vectors whose dimensions also depend on N_s. The global optimum of the linear program (4) can always be found [38]. The vector $\boldsymbol{\delta} = [\delta_1\ \delta_2\ \ldots\ \delta_{N_s}]^T$ is the vector of tolerances defined as $R_i - \delta_i \le \overline{R}_s(\boldsymbol{x}^i) \le R_i + \delta_i$, where δ_i is the allowed tolerance for the ith data sample. In this work, the tolerances are identical for all samples and preset to a small value (typically 10^{-3}).

Let $X_B = \{\boldsymbol{x}^1, \boldsymbol{x}^2, \ldots, \boldsymbol{x}^N\}$ be a base set and $\boldsymbol{R}_{f\text{-}c}(\boldsymbol{x}) = [R_{f\text{-}c.1}(\boldsymbol{x}) \ldots R_{f\text{-}c.m}(\boldsymbol{x})]^T$. The vector $\boldsymbol{R}_{f\text{-}c}(\boldsymbol{x}^j)$ is known for $j = 1, 2, \ldots, N$.. The coarse model $\boldsymbol{R}_c$ is defined as:

$$\boldsymbol{R}_c(\boldsymbol{x}) = [\overline{R}_{f-c.1}(\boldsymbol{x}) \quad \overline{R}_{f-c.2}(\boldsymbol{x}) \quad \ldots \quad \overline{R}_{f-c.m}(\boldsymbol{x})]^T, \quad (5)$$

where $\overline{R}_{f-c.i}(\boldsymbol{x})$ is the Cauchy model of the ith component of $\boldsymbol{R}_{f\text{-}c}(\boldsymbol{x})$ constructed as described in (5).

III. LOW-ORDER LOCAL CAUCHY-APPROXIMATION SURROGATES

The coarse model (3)-(5) has a number of advantages. It is computationally cheap and easy to optimize, there is no need for a circuit-equivalent model, and the same EM solver can be used to implement both the fine and coarse model. Also, the initial design obtained through optimization of the coarse-mesh EM model is usually better than the initial design that could be possibly obtained using other methods. Unfortunately, the Cauchy-approximation model of Section II. *B* has some practical limitations. To overcome these, we propose low-order local approximation technique described in Section III. *B*.

A. Limitations of the Cauchy-approximation coarse models

The Cauchy-approximation coarse model can be used efficiently only when the number of design variables n is small (up to 3 or 4). For larger n, the required number of evaluations of $\boldsymbol{R}_{f\text{-}c}$ becomes too large (the number of training points increases exponentially with n) so that the computational cost of creating the coarse model is too high. Also, because the coarse model is set up only once for the entire optimization process, it has to have a relatively large region of validity, which results in a high (required) order of the model. This has two consequences: (i) large number of model parameters (which again increases the number of necessary training points), and (ii) difficulty in ensuring the required accuracy of the Cauchy approximation (high order rational-function approximation are highly nonlinear and their generalization capability is limited).

B. Low-order local Cauchy-approximation models

The Cauchy-based coarse model is typically set up in the neighborhood of the initial design defined by 10% to 20% deviation around the initial design. A substantial reduction of the training data can be obtained if the low-order Cauchy models are set up in smaller regions and the additional models are generated as necessary following the optimization path as explained in Fig. 1 for $n = 2$.

More specifically, the proposed approach assumes that $\boldsymbol{R}_c$ is set up locally in the neighborhood of the initial design $\boldsymbol{x}^{(0)}$ (neighborhood size $\delta_1 \times \delta_2$) and the surrogate model optimization is constrained to this neighborhood. If the new design is on the border of this neighborhood, a new $\boldsymbol{R}_c$ is created in the adjacent region. Each (local) $\boldsymbol{R}_c$ requires a small number of training data.

Setting $\boldsymbol{R}_c$ in the region of size $\Delta_1 \times \Delta_2$ enclosing the entire optimization path would require a substantially larger amount of training data (here, coarse-discretization EM simulations). For example, if $\Delta_1 = \Delta_2 = 10\%$ of $\|\boldsymbol{x}^{(0)}\|$ (relative size) and $\delta_1 = \delta_2 = 2\%$ of $\|\boldsymbol{x}^{(0)}\|$, the size of $\Delta_1 \times \Delta_2$ is 25 times larger than the size of $\delta_1 \times \delta_2$.

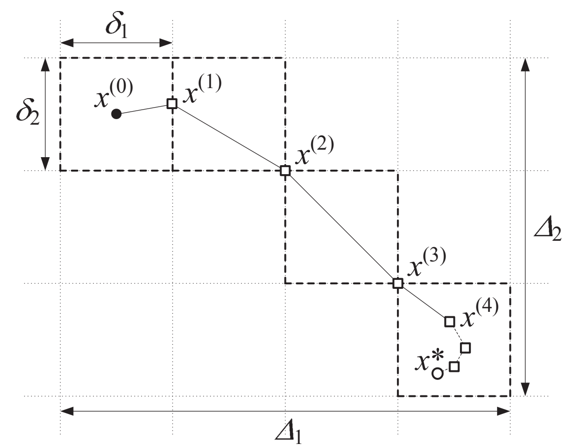

Fig. 1. Local versus quasi-global Cauchy-approximation-based coarse models (two dimensional illustration): the proposed approach assumes that the coarse model is set up locally in the neighborhood of the initial design $\boldsymbol{x}^{(0)}$ (neighborhood size $\delta_1 \times \delta_2$). The surrogate model optimization is constrained to this neighborhood. If the new design reaches the border, a new coarse model is created in the adjacent region. Each (local) coarse model requires small number of training data.

A typical optimization path that spans the entire $\Delta_1 \times \Delta_2$ region contains five $\delta_1 \times \delta_2$ cells so that the number of training points (assuming comparable model accuracy) will be 5 times smaller for the proposed approach than for the original method [36]. For example, at n = 5, the region size ratio would be 625, and the training point number ratio 125 which shows a tremendous savings when using local models. It should also be noted that the proper values of Δ_i are not known beforehand. Therefore, the proposed approach is more flexible as no initial region size estimate is necessary.

In all numerical experiments presented here, we use second-order Cauchy models that only have $(n+1)(n+2)$ unknown coefficients. We choose the number of training points to be also equal to $(n+1)(n+2)$. This is yet another advantage of the proposed technique because the number of unknown parameters (and, consequently, the number of training points) for high-order Cauchy models grows exponentially with n.

IV. VERIFICATION EXAMPLES

The performance of our technique exploiting local low-order Cauchy models is verified using three examples of microstrip filters. The number of design variables in these examples ranges from five to nine and cannot be handled by a "traditional" Cauchy model being set up for the entire search space.

A. 4th-order ring resonator bandpass filter [43]

Consider the fourth-order ring resonator bandpass filter [43] shown in Fig. 2. The design parameters are $\boldsymbol{x} = [L_1\ L_2\ L_3\ S_1\ S_2]^T$ mm. Other parameters are W_1 = 1.2 mm and W_2 = 0.8 mm. The fine model is simulated in FEKO [44]. The total mesh number (i.e., the total number of mesh elements) for $\boldsymbol{R}_f$ is 1334. Simulation time for $\boldsymbol{R}_f$ is 84 min. The total mesh number for the coarse-mesh FEKO model $\boldsymbol{R}_{f\text{-}c}$ is 180 (evaluation time 112 s). The design $\boldsymbol{R}_{f\text{-}c}$ specifications are $|S_{21}| \geq -1$ dB for 1.75 GHz $\leq \omega \leq$ 2.25 GHz, and $|S_{21}| \leq -20$ dB for 1.0 GHz $\leq \omega \leq$ 1.5GHz and 2.5 GHz $\leq \omega \leq$ 3.0 GHz. The initial design is $\boldsymbol{x}^{init}$ = [25.0 20.0 25.0 0.12 0.1]^T mm. The fine model specification error at $\boldsymbol{x}^{(0)}$ is +4.3 dB. The response of the fine model at $\boldsymbol{x}^{init}$ is shown in Fig. 3.

The starting point for space mapping optimization stage, $\boldsymbol{x}^{(0)}$ = [24.47 19.76 26.61 0.125 0.1]^T mm, is an approximate optimum of the coarsely discretized model; $\boldsymbol{x}^{(0)}$ is found at the cost of 60 $\boldsymbol{R}_{f\text{-}c}$ evaluations (equivalent to about 1.3 evaluations of $\boldsymbol{R}_f$). The fine model specification error at $\boldsymbol{x}^{(0)}$ is +1.3 dB.

The region size for the local Cauchy model $\boldsymbol{R}_c$ is $\boldsymbol{\delta}$ = [1.0 1.0 1.0 0.1 0.1]^T mm. We use a second-order model that has 42 coefficients. The model is established using 42 base points allocated with the Latin hypercube sampling (LHS) algorithm [45]. The surrogate model for optimization algorithm (2) is created using frequency SM [8] and output SM [9]. Figure 4 shows the responses of $\boldsymbol{R}_f$, $\boldsymbol{R}_{f\text{-}c}$ and the frequency-space-mapped $\boldsymbol{R}_c$ at $\boldsymbol{x}^{(0)}$.

The design obtained after the first iteration of the SM algorithm, $\boldsymbol{x}^{(1)}$ = [23.97 19.58 27.11 0.16 0.05]^T mm, is located at the border of the region [$\boldsymbol{x}^{(0)} - \boldsymbol{\delta}/2$, $\boldsymbol{x}^{(0)} + \boldsymbol{\delta}/2$]. According to the methodology of Section 3.2, the new coarse model is set up in the adjacent region of size $\boldsymbol{\delta}$ with the center at [23.47 19.76 27.61 0.125 0.1]^T mm (the last component is not modified because 0.05 mm is set as the lower bound for the design variables S_1 and S_2). The space-mapped coarse model is then optimized. The procedure is continued for four iterations. The final design is $\boldsymbol{x}^{(4)}$ = [22.97 19.81 26.78 0.166 0.05]^T mm (specification error – 0.5 dB). Figure 5 shows the fine model response at $\boldsymbol{x}^{(4)}$. Table 1 summarizes the computational cost of the optimization: the total optimization time corresponds to less than 8 evaluations of $\boldsymbol{R}_f$.

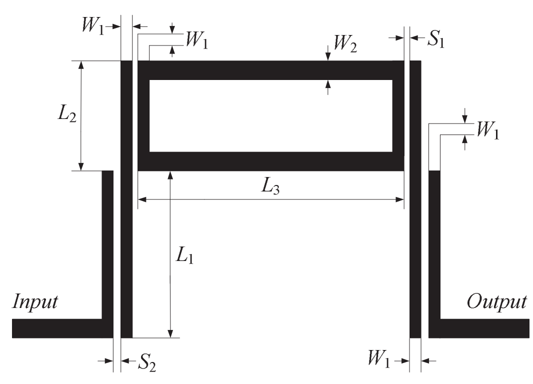

Fig. 2. Fourth-order ring resonator bandpass filter: geometry [43].

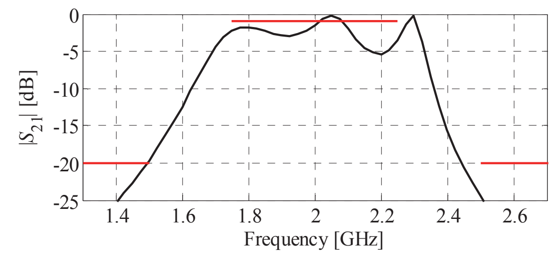

Fig. 3. Fourth-order ring resonator filter: response of the fine model $\boldsymbol{R}_f$ at the initial design $\boldsymbol{x}^{init}$.

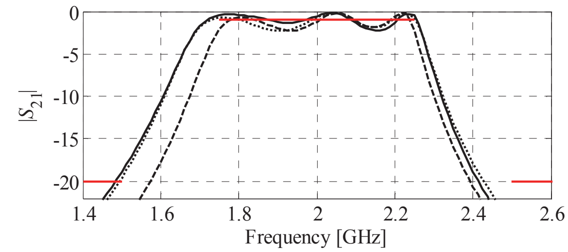

Fig. 4. Fourth-order ring resonator filter: response of the fine model $\boldsymbol{R}_f$ (solid line), coarse-mesh model $\boldsymbol{R}_{f\text{-}c}$ (dashed line) and the frequency-space-mapped coarse model (dotted line) at $\boldsymbol{x}^{(0)}$.

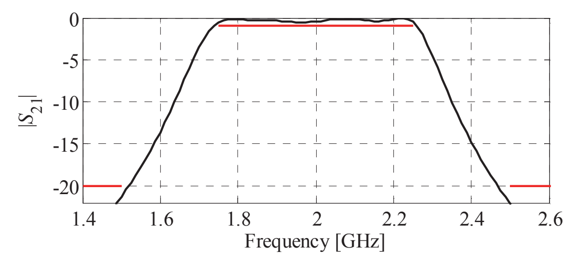

Fig. 5. Fourth-order ring resonator filter: fine model response at the final design.

Table 1: 4th-order ring resonator filter: optimization cost

Algorithm Component	Model Involved	Number of Model Evaluations	Absolute Time	Relative Cost*
Setting up Cauchy model	$\boldsymbol{R}_{f\text{-}c}$	168	5.2 h	3.7
Evaluation of the fine model	$\boldsymbol{R}_f$	4#	5.6 h	4.0
Total cost	-	-	10.8 h	7.7

* Equivalent number of fine model evaluations.
# Excluding fine model evaluation at the initial design.

B. Bandpass filter using microstrip resonators with open stub inverter [46]

Consider the bandpass microstrip filter with open stub inverter [46] shown in Fig. 6. The design parameters are $\boldsymbol{x} = [L_1\ L_2\ L_3\ S_1\ S_2\ W_1]^T$. The fine model simulated in FEKO [44]. The total mesh number for $\boldsymbol{R}_f$ is 1702. Simulation time for $\boldsymbol{R}_f$ is 132 min. The total mesh number for the coarse-discretization FEKO model $\boldsymbol{R}_{f\text{-}c}$ is 160 (evaluation time 89 s). The design specifications are $|S_{21}| \le -20$dB for 1.5 GHz $\le \omega \le$ 1.9 GHz, $|S_{21}| \ge -1$ dB for 1.98 GHz $\le \omega \le$ 2.02 GHz and $|S_{21}| \le -20$dB for 2.1GHz $\le \omega \le$ 2.5GHz. The initial design is $\boldsymbol{x}^{init} = [25.0\ \ 5.0\ \ 25.0\ \ 1.0\ \ 0.5\ \ 2.0]^T$ mm, which is quite poor (See Fig. 7). The fine model specification error at $\boldsymbol{x}^{(0)}$ is +43.3 dB.

The initial design for space mapping optimization, $\boldsymbol{x}^{(0)} = [23.0\ \ 5.0\ \ 25.0\ \ 0.7\ \ 0.1\ \ 1.0]^T$ mm, is a rough optimum of the coarsely discretized model obtained at the cost of 55 $\boldsymbol{R}_{f\text{-}c}$ evaluations (less than one evaluation of the fine model). The fine model specification error at $\boldsymbol{x}^{(0)}$ is +3.3 dB. The region size for the local Cauchy-approximation-based $\boldsymbol{R}_c$ is $\boldsymbol{\delta} = [0.2\ 0.2\ 0.2\ 0.2\ 0.1\ 0.2]^T$ mm. We use second-order model (56 unknown coefficients) that is established using 56 base points allocated with LHS [45]. As before, the surrogate model is created using frequency SM [8] and output SM [9]. The responses of $\boldsymbol{R}_f$, $\boldsymbol{R}_{f\text{-}c}$ and frequency-space-mapped $\boldsymbol{R}_c$ at $\boldsymbol{x}^{(0)}$ are shown in Fig. 8. For this example, a very good design, $\boldsymbol{x}^{(2)} = [22.90\ 4.915\ 25.10\ 0.799\ 0.139\ 0.826]^T$ mm, is obtained after two iterations with a specification error –0.7 dB. Figure 9 shows the fine model response at $\boldsymbol{x}^{(2)}$. As indicated in Table 2, the computational cost of the optimization is very low and corresponds to only 3.3 evaluations of $\boldsymbol{R}_f$.

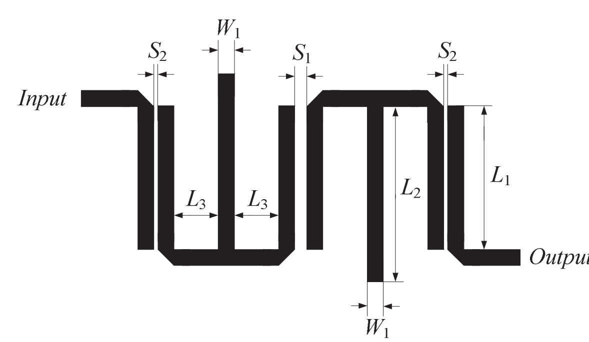

Fig. 6. Bandpass filter using microstrip resonators with open stub inverter: geometry [46].

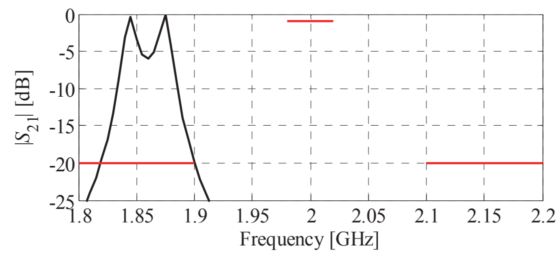

Fig. 7. Bandpass filter using microstrip resonators with with open stub inverter: response of the fine model at the initial design $\boldsymbol{x}^{init}$.

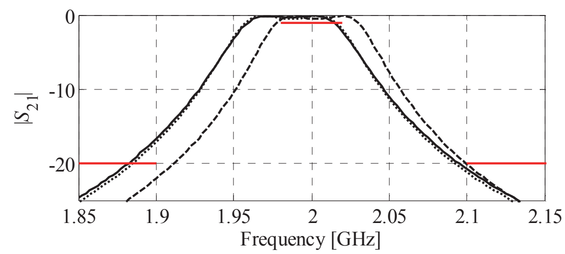

Fig. 8. Bandpass filter using microstrip resonators with with open stub inverter: response of the fine model $\boldsymbol{R}_f$ (solid line), coarse-mesh model $\boldsymbol{R}_{f\text{-}c}$ (dashed line) and the frequency-space-mapped coarse model (dotted line) at $\boldsymbol{x}^{(0)}$.

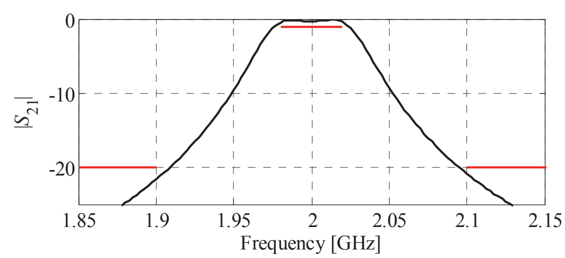

Fig. 9. Bandpass filter using microstrip resonators with with open stub inverter: fine model response at the final design.

Table 2: Bandpass filter using microstrip resonators with open stub inverter: optimization cost

Algorithm Component	Model Involved	Number of Model Evaluations	Absolute Time	Relative Cost*
Setting up Cauchy model	$\boldsymbol{R}_{f\text{-}c}$	112	2.8 h	1.3
Evaluation of the fine model	$\boldsymbol{R}_f$	2#	4.4 h	2.0
Total cost	-	-	7.2 h	3.3

* Equivalent number of fine model evaluations.
\# Excluding fine model evaluation at the initial design.

C. Microstrip hairpin filter [47]

Consider the microstrip hairpin filter [47] shown in Fig. 10. The design parameters are $\boldsymbol{x} = [L_1\ L_2\ L_3\ L_4\ L_5\ L_6\ S_1\ S_2\ d]^T$. The fine model is simulated in FEKO [44]. The total mesh number for $\boldsymbol{R}_f$ is 1424. Simulation time for $\boldsymbol{R}_f$ is 96 min. The total mesh number for the coarse-mesh FEKO model $\boldsymbol{R}_{f\text{-}c}$ is 176 (evaluation time 2 min). The design specifications are $|S_{21}| \leq -20$dB for 3.0 GHz $\leq \omega \leq$ 3.3 GHz, $|S_{21}| \geq -0.2$ dB for 3.6 GHz $\leq \omega \leq$ 4.3 GHz and $|S_{21}| \leq -20$dB for 4.7 GHz $\leq \omega \leq$ 5.0 GHz. The initial design is $\boldsymbol{x}^{init} = [10.0\ 10.0\ 10.0\ 0.5\ 1.0\ 0.5\ 0.1\ 0.2\ 0.1]^T$ mm. The fine model specification error at $\boldsymbol{x}^{init}$ is +20.6 dB. The response of the fine model at $\boldsymbol{x}^{init}$ is shown in Fig. 11.

Before performing space mapping optimization, an approximate optimum of the coarsely discretized model is found to be $\boldsymbol{x}^{(0)} = [9.9\ 11.2\ 11.35\ 0.875\ 0.75\ 0.5\ 0.125\ 0.2\ 0.8]^T$ mm. This step takes about 200 evaluations of $\boldsymbol{R}_{f\text{-}c}$ (≈ four evaluations of the fine model). The region size for the local Cauchy-approximation-based $\boldsymbol{R}_c$ is $\boldsymbol{\delta} = [0.05\ 0.05\ 0.05\ 0.05\ 0.05\ 0.05\ 0.025\ 0.025\ 0.05]^T$ mm. We use second-order model (110 unknown coefficients) that is established using 110 base points allocated with LHS [45]. Again, the surrogate model is created using frequency and output SM. The responses of $\boldsymbol{R}_f$, $\boldsymbol{R}_{f\text{-}c}$ and frequency-space-mapped $\boldsymbol{R}_c$ at $\boldsymbol{x}^{(0)}$ are shown in Fig. 12. The fine model specification error at $\boldsymbol{x}^{(0)}$ is +1.5dB. An optimized design, $\boldsymbol{x}^{(3)} = [9.9\ 11.2\ 11.325\ 0.925\ 0.7125\ 0.55\ 0.14375\ 0.2063\ 0.90]^T$ mm, is found after three iterations of our algorithm with a specification error of –0.04 dB. Figure 13 shows the fine model response at $\boldsymbol{x}^{(3)}$. The computational cost of the optimization corresponds to 10 evaluations of the fine model (Table 3).

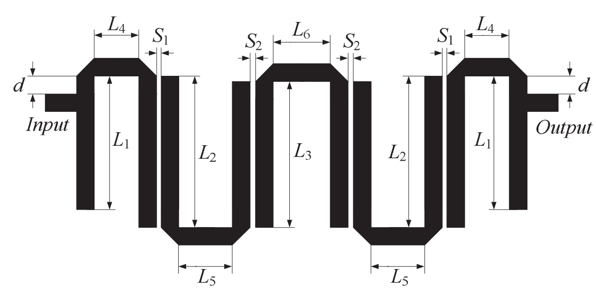

Fig. 10. The geometry of the microstrip hairpin filter [47].

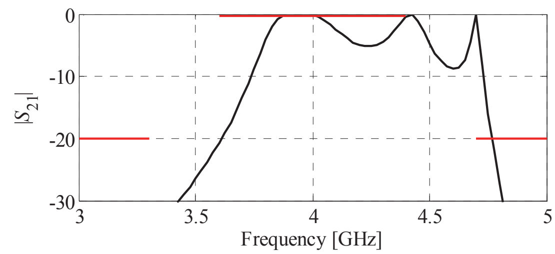

Fig. 11. Microstrip hairpin filter: response of the fine model $\boldsymbol{R}_f$ at the initial design $\boldsymbol{x}^{init}$.

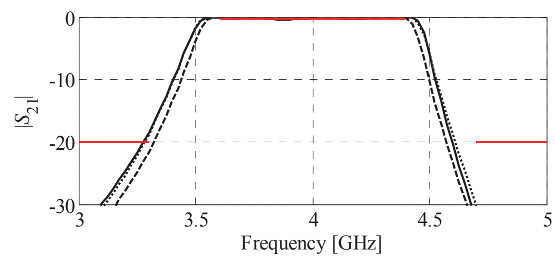

Fig. 12. Microstrip hairpin filter: response of the fine model $\boldsymbol{R}_f$ (solid line), coarse-mesh model $\boldsymbol{R}_{f\text{-}c}$ (dashed line) and the frequency-space-mapped coarse model (dotted line) at the approximate optimum of $\boldsymbol{R}_{f\text{-}c}$, $\boldsymbol{x}^{(0)}$.

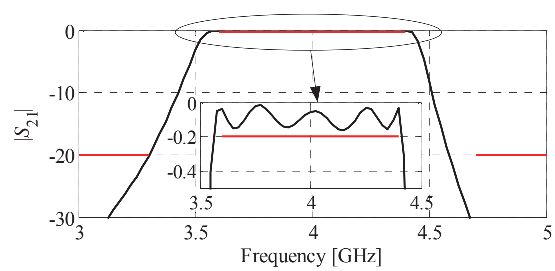

Fig. 13. Microstrip hairpin filter: fine model response at the final design.

Table 3: Microstrip hairpin filter: optimization cost

Algorithm Component	Model Involved	Number of Model Evaluations	Absolute Time	Relative Cost*
Setting up Cauchy model	$\boldsymbol{R}_{f\text{-}c}$	330	11.0 h	6.9
Evaluation of the fine model	$\boldsymbol{R}_f$	3#	4.8 h	3.0
Total cost	-	-	15.8 h	9.9

* Equivalent number of fine model evaluations.
# Excluding fine model evaluation at the initial design.

D. Discussion

The results presented in Sections IV. *A* through IV. *C* consistently demonstrate that a combination of coarse-discretization EM models, Cauchy approximation and space mapping can make a simulation-driven design very efficient.

It should be noted that the number of space mapping iterations necessary to complete the optimization process is low (no more than four for the presented examples). It is not dependent on the problem size. On the other hand, the cost of creating the Cauchy model is $(n+1)(n+2)$ coarse-discretization model evaluations. The aforementioned facts imply that the total optimization cost scales with n as n^2 (in worst case). This is much better than for the standard approach of [36], where, as explained in Section III, the cost generally grows exponentially with n, and, building a single Cauchy model is impractical for n larger than 4 or 5.

V. CONCLUSION

Computationally efficient design optimization algorithm exploiting space mapping and the coarse model based on local low-order Cauchy approximation of coarse-discretization EM simulation data is presented. The proposed approach does not require equivalent-circuit coarse model and is not limited to problems with small number of design variables. The robustness of our technique is demonstrated through the optimization of three microstrip filters with the number of design variables ranging from five to nine. Satisfactory designs are obtained at the cost of a few EM simulations of the filter structures.

ACKNOWLEDGEMENT

This work was supported in part by the Icelandic Centre for Research (RANNIS) Grant 110034021.

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