Multi-Fidelity Multi-Grid Design Optimization of Planar Microwave Structures with Sonnet

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Abstract: Simple and reliable algorithm for design optimization of microwave structures with Sonnet ***em*** is introduced. The presented methodology exploits coarse-discretization models of the structure of interest, starting from a very coarse grid, and gradually increasing the discretization density. Each model is optimized using a grid-search routine. The optimal design of the current model is used as an initial design for the finer-discretization one. Our methodology is computationally efficient as most of the operations are performed on coarse-discretization models. Two examples of microstrip filter design are given.

Keywords: Computer-aided design (CAD), electromagnetic simulation, grid search, microwave design

1. Introduction

Due to the complexity of microwave structures and a growing demand for accuracy, theoretical models can only be used to yield initial designs that need to be further tuned to meet given performance specifications. Therefore, EM-simulation-based design closure becomes increasingly important. A serious bottleneck of simulation-driven optimization is its high computational cost, which makes straightforward approaches such as employing EM solver directly in an optimization loop impractical. Co-simulation [1], [2] is only a partial solution because the circuit models with embedded EM components are still directly optimized. Efficient simulation-driven design can be realized using surrogate-based optimization (SBO) principle [3], where the optimization burden is shifted to a surrogate model, computationally cheap representation of the structure being optimized (referred to as the fine model). The successful SBO approaches used in microwave area are space mapping (SM) [4-7] and various forms of tuning [8-10] and tuning SM [11,12]. Unfortunately, their implementation is not always straightforward: substantial modification of the optimized structure may be required (tuning), or additional mapping and more or less complicated interaction between auxiliary models is necessary (SM). Also, space mapping performance heavily depends on the surrogate model selection.

Here, a simple yet efficient design optimization methodology to be used for structures simulated using Sonnet ***em*** [13] is introduced. Our technique is based on iterative optimization of coarse-discretization models using a simple grid-search algorithm. The optimal design of the current model is used as an initial design for the finer-discretization one. The final design can be refined using a second-order polynomial approximation of the available Sonnet-simulation data. The proposed methodology is very simple to implement, unlike space mapping or other surrogate-based approaches does not require a circuit-equivalent coarse model nor any modification of the structure being optimized. It is also computationally efficient because the optimization burden is shifted to the coarse-discretization models.

2. Multi-Fidelity Multi-Grid Design Optimization Procedure

In this section, we formulate the optimization problem (Section 2.*A*), describe the building blocks of the proposed optimization procedure (Sections 2.*B*-2.*E*) and formulate the procedure itself (Section 2.*F*).

A. Design Optimization Problem

The design optimization problem is formulated as follows

$$\boldsymbol{x}_f^* \in \arg\min_{\boldsymbol{x}} U(\boldsymbol{R}_f(\boldsymbol{x})) \,. \tag{1}$$

where $\boldsymbol{R}_f(\boldsymbol{x}) \in R^m$ is a response vector of a structure of interest, e.g., $|S_{21}|$ at m frequencies; $\boldsymbol{x} \in R^n$ is a design variable vector; U is a scalar merit function, e.g., a minimax function with upper/lower specifications; $\boldsymbol{x}_f^*$ is the optimal design to be determined. Here, $\boldsymbol{R}_f$ is evaluated using Sonnet ***em*** with a $g_{h.f} \times g_{v.f}$ grid.

B. Coarse-Discretization Models

The optimization technique introduced here exploits a family of coarse-discretization models $\{\boldsymbol{R}_{c.j}\}$, $j = 1, \ldots, K$, all evaluated using Sonnet ***em***. The model $\boldsymbol{R}_{c.j}$ exploits a grid $g_{h.j} \times g_{h.j}$. It is assumed that $g_{h.j} > g_{h.j+1}$ and $g_{v.j} > g_{v.j+1}$ for $j = 1, \ldots, K-1$, and $g_{h.K} > g_{h.f}$ and $g_{v.K} > g_{v.f}$. In other words, discretization of $\boldsymbol{R}_{c.j+1}$ is finer than that of $\boldsymbol{R}_{c.j}$. In practice, the number K of coarse-discretization models is two or three.

C. Grid-Search Algorithm

To optimize the coarse-discretization model $\boldsymbol{R}_{c.j}$ we use the following simple grid-search procedure (here, $\boldsymbol{x}^{(j-1)} = [x_1^{(j-1)} \ldots x_n^{(j-1)}]^T$ is the initial design, i.e., the optimal design of $\boldsymbol{R}_{c.j-1}$, s is a function that "rounds" $\boldsymbol{x}$ to the nearest grid point $s(\boldsymbol{x})$):

```
x^(j) = s(x^(j–1));                                  // Snap x^(j) to the nearest grid point
U_min = U(R_c.j(x^(j)));                             // Evaluate objective function
do
    U_0 = U_min;                                     // Update the reference objective function value
    for k = 1 to n                                   // Evaluating objective function at perturbed designs
        U_k = U(R_c.j([x_1^(j) … x_k^(j) + d_k … x_n^(j)]^T));   // (here, d_k = g_h.j or g_v.j (depends on orientation of x_k^(j)))
    end
    h = – [(U_1 – U_0)/d_1 … [(U_n – U_0)/d_n]^T;    // Search direction estimation
    h = h·(||[d_1 … d_n]^T||/||h||);                 // Search direction normalization
    do                                               // Line search:
        x_tmp = s(x^(j) + h);                        // Set the trial design and "snap" it to the grid
        U_tmp = U(R_c.j(x_tmp));                     // Evaluate objective function at the trial design
        if U_tmp < U_min                             // If the trial is successful:
            x^(j) = x_tmp;                           // 1. Update the design
            U_min = U_tmp;                           // 2. Store the best result
            h = 2·h;                                 // 3. Increase the search step
        else
            break;                                   // Otherwise, exit the line search algorithm
        end
    while 1
    if U_min ≥ U_0                                   // Line search failed => perform local search
        for k = 1 to n
            U_–k = U(R_c.j([x_1^(j) … x_k^(j) – d_k … x_n^(j)]^T));   // Evaluate the remaining neighbours of x^(j)
        end
        U_tmp = min{U_–k, U_–k+1, …, U_k–1, U_k};    // Find the best design
        k_tmp = argmin{–n ≤ k ≤ n : U_k};            // Fine the corresponding perturbation index
        if U_min < U_0                               // If local search is successful:
            x^(j) = [x_1^(j) … x_k^(j) + sign(k_tmp)·d_k … x_n^(j)]^T;   // 1. Update the design
            U_min = U_k_tmp;                         // 2. Store the best value
        end
    end
while U_min < U_0                                    // Continue if further improvement was possible
return x^(j);                                        // Otherwise, return x^(j) as the optimal design of R_c.j
```

For simplicity, the unconstrained version of the grid-search algorithm is described above. Generalization for constrained optimization is straightforward. Operation of the algorithm is illustrated in Fig. 1.

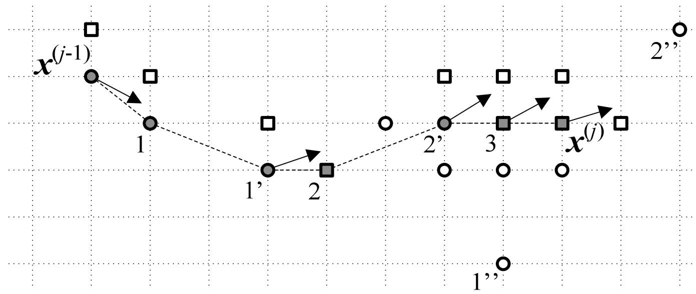


Fig. 1. Illustration of the grid-search algorithm for two design variables (n = 2). The search direction (→) at the initial design $\boldsymbol{x}^{(j-1)}$ is obtained using two perturbed designs marked as squares. The trial points for the line search are denoted as 1, 1' and 1''. The last successful trial design is 1'. At this design, a new search direction is found, and a new line search is launched with designs 2, 2' and 2'' (the last of which is unsuccessful). The next line search starting from 2' is unsuccessful and the new design 3 is obtained using a local search, similarly as the final design $\boldsymbol{x}^{(j)}$ that cannot be further improved even by a local search, which terminates the algorithm.

D. Design Refinement

Having optimized the finest of the coarse-discretization models, $\boldsymbol{R}_{c.K}$, we also have its evaluations at $\boldsymbol{x}^{(K)}$ and at all perturbed designs around it $\boldsymbol{x}_k^{(K)} = [x_1^{(K)} \ldots x_k^{(K)} + \mathrm{sign}(k)\cdot d_k \ldots x_n^{(K)}]^T$, i.e., $\boldsymbol{R}^{(k)} = \boldsymbol{R}_{c.K}(\boldsymbol{x}_k^{(K)})$, $k = -n, -n+1, \ldots, n-1, n$. This data can be used to refine the final design without directly optimizing $\boldsymbol{R}_f$. Instead, one can set up an approximation model involving $\boldsymbol{R}^{(k)}$ and optimize it in the neighbourhood of $\boldsymbol{x}^{(K)}$ defined as $[\boldsymbol{x}^{(K)} - \boldsymbol{d}, \boldsymbol{x}^{(K)} + \boldsymbol{d}]$, where $\boldsymbol{d} = [d_1\ d_2 \ldots d_n]^T$. In this work, we use a reduced quadratic model $\boldsymbol{q}(\boldsymbol{x}) = [q_1\ q_2 \ldots q_m]^T$, defined as

$$q_j(\boldsymbol{x}) = q_j([x_1 \ldots x_n]^T) = \lambda_{j.0} + \lambda_{j.1}x_1 + \ldots + \lambda_{j.n}x_n + \lambda_{j.n+1}x_1^2 + \ldots + \lambda_{j.2n}x_n^2 . \tag{2}$$

Coefficients $\lambda_{j.r}$, $j = 1, \ldots, m$, $r = 0, 1, \ldots, 2n$, can be uniquely obtained by solving the linear regression problems $q_j(\boldsymbol{x}_k^{(K)}) = R_j^{(k)}$, $k = -n, -n+1, \ldots, n-1, n$, where $R_j^{(k)}$ is a jth component of the vector $\boldsymbol{R}^{(k)}$.

In order to account for possible misalignment between $\boldsymbol{R}_{c.K}$ and $\boldsymbol{R}_f$, instead optimizing the quadratic model $\boldsymbol{q}$ it is recommended to optimize a corrected model $\boldsymbol{q}(\boldsymbol{x}) + [\boldsymbol{R}_f(\boldsymbol{x}^{(K)}) - \boldsymbol{R}_{c.K}(\boldsymbol{x}^{(K)})]$ that ensures a zero-order consistency [14] between $\boldsymbol{R}_{c.K}$ and $\boldsymbol{R}_f$. The refined design can be then found as

$$\boldsymbol{x}^* = \arg \min_{\boldsymbol{x}^{(K)} - \boldsymbol{d} \le \boldsymbol{x} \le \boldsymbol{x}^{(K)} + \boldsymbol{d}} U(\boldsymbol{q}(\boldsymbol{x}) + [\boldsymbol{R}_f(\boldsymbol{x}^{(K)}) - \boldsymbol{R}_{c.K}(\boldsymbol{x}^{(K)})]) . \tag{3}$$

If necessary, the step (3) can be performed a few times starting from a refined design, i.e., $\boldsymbol{x}^* = \mathrm{argmin}\{\boldsymbol{x}^{(K)} - \boldsymbol{d} \le \boldsymbol{x} \le \boldsymbol{x}^{(K)} + \boldsymbol{d} : U(\boldsymbol{q}(\boldsymbol{x}) + [\boldsymbol{R}_f(\boldsymbol{x}^*) - \boldsymbol{R}_{c.K}(\boldsymbol{x}^*)])\}$ (each iteration requires only one evaluation of $\boldsymbol{R}_f$).

E. Optional Design Specifications Adjustments

Typically, the major difference between the responses of $\boldsymbol{R}_f$ and coarse-discretization models $\boldsymbol{R}_{c.j}$ is that they are shifted in frequency. This difference can be easily absorbed by frequency-shifting the design specifications while optimizing a model $\boldsymbol{R}_{c.j}$. More specifically, suppose that the design specifications are described as $\{\omega_{k.L}, \omega_{k.H}; s_k\}$, $k = 1, \ldots, n_s$, (e.g., specifications $|S_{21}| \ge -3$ dB for 3 GHz $\le \omega \le$ 4 GHz, $|S_{21}| \le -20$ dB for 1 GHz $\le \omega \le$ 2 GHz and $|S_{21}| \le -20$ dB for 5 GHz $\le \omega \le$ 7 GHz would be described as {3, 4; –3}, {1, 2; –20}, and {5, 7; –20}). If the average frequency shift between responses of $\boldsymbol{R}_{c.j}$ and $\boldsymbol{R}_{c.j+1}$ is $\Delta\omega$, this difference can be absorbed by modifying the design specifications to $\{\omega_{k.L} - \Delta\omega, \omega_{k.H} - \Delta\omega; s_k\}$, $k = 1, \ldots, n_s$.

F. Design Optimization Procedure

The optimization procedure proposed in this work can be summarized as follows (input arguments are: initial design $\boldsymbol{x}^{(0)}$ and the number of coarse-discretization models K):

1. Set $j = 1$;
2. Optimize $\boldsymbol{R}_{c.j}$ using the algorithm of Section 2.*B* to obtain a new design $\boldsymbol{x}^{(j)}$;
3. Set $j = j + 1$; if $j < K$ go to 2;
4. Set up a quadratic model $\boldsymbol{q}$ as in (2) and find a refined design $\boldsymbol{x}^*$ using (3).

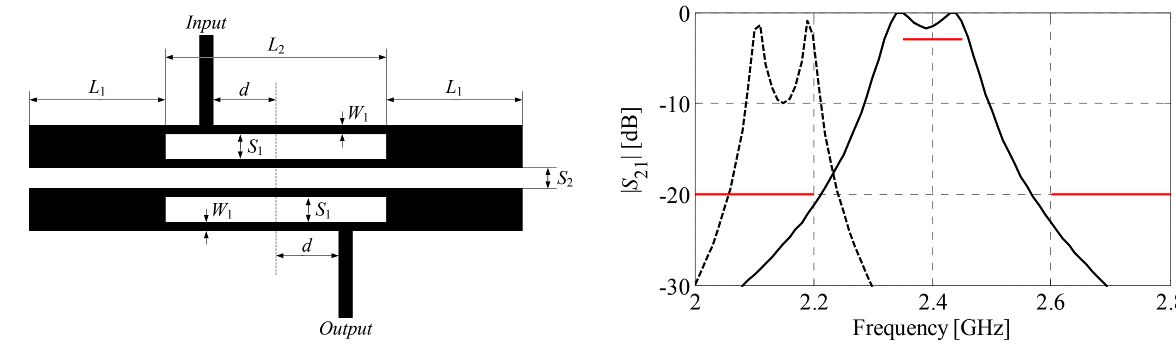
Note that the the original model $\boldsymbol{R}_f$ is only evaluated at the final stage (step 4) of the optimization process.

3. Illustration Examples

A. Compact Stacked Slotted Resonators Microstrip Bandpass Filter [15]

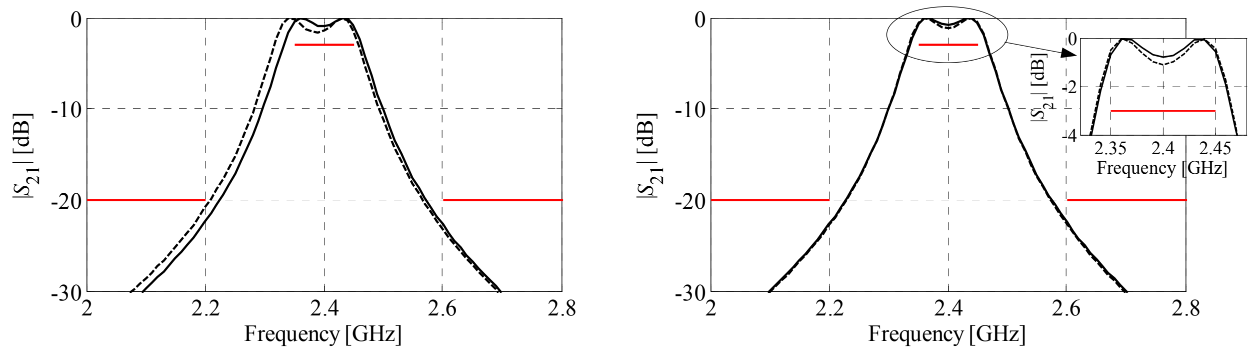
Consider the stacked slotted resonators bandpass filter [15] shown in Fig. 1. The design parameters are $\boldsymbol{x} = [L_1\ L_2\ W_1\ S_1\ S_2\ d]^T$ mm. The filter is simulated in Sonnet ***em*** [13] using a grid of 0.05 mm × 0.05 mm (model $\boldsymbol{R}_f$). The design specifications are $|S_{21}| \geq -3$ dB for 2.35 GHz $\leq \omega \leq$ 2.45 GHz, and $|S_{21}| \leq -20$ dB for 1.9 GHz $\leq \omega \leq$ 2.3GHz and 2.6 GHz $\leq \omega \leq$ 2.9 GHz. The initial design is $\boldsymbol{x}^{(0)} = [7\ 10\ 0.6\ 1\ 2\ 1]^T$ mm.

We are using two coarse-discretization models: $\boldsymbol{R}_{c.1}$ (grid of 0.2 mm × 0.2 mm) and $\boldsymbol{R}_{c.2}$ (grid of 0.05 mm × 0.2 mm). The evaluation times for $\boldsymbol{R}_{c.1}$, $\boldsymbol{R}_{c.2}$ and $\boldsymbol{R}_f$ are 72 s, 5 min and 16 min, respectively. Figure 2b shows the responses of $\boldsymbol{R}_{c.1}$ at $\boldsymbol{x}^{(0)}$ and at $\boldsymbol{x}^{(1)} = [6.4\ 9.6\ 0.6\ 0.6\ 2\ 1.8]^T$ mm, its optimal design found using a grid search. Figure 3a shows the responses of $\boldsymbol{R}_{c.2}$ at $\boldsymbol{x}^{(1)}$ and at its optimized design $\boldsymbol{x}^{(2)} = [6.35\ 9.6\ 0.6\ 0.6\ 2.2\ 1.8]^T$ mm. Figure 3b shows the responses of $\boldsymbol{R}_f$ at $\boldsymbol{x}^{(2)}$ (specification error –1.7 dB) and the refined design $\boldsymbol{x}^* = [6.35\ 9.6\ 0.6\ 0.6\ 2.25\ 1.85]^T$ mm (specification error –2.1 dB). The optimization cost (Table 1) is quite low and corresponds to only 13 evaluations of the original, fine-discretization model.



(a) (b)

Fig. 2. Stacked slotted resonators filter: (a) geometry [15]; (b) responses of the coarse-discretization model $\boldsymbol{R}_{c.1}$ (0.2 mm × 0.2 mm grid) at the initial design $\boldsymbol{x}^{(0)}$ (dashed line) and at the optimized design of $\boldsymbol{R}_{c.1}$, $\boldsymbol{x}^{(1)}$, (solid line).



(a) (b)

Fig. 3. Stacked slotted resonators filter: (a) responses of the coarse-discretization model $\boldsymbol{R}_{c.2}$ (0.05 mm × 0.2 mm grid) at $\boldsymbol{x}^{(1)}$ (dashed line) and at $\boldsymbol{x}^{(2)}$ (solid line), the optimized design of $\boldsymbol{R}_{c.2}$ found using a grid search; (b) responses of the original fine-discretization model $\boldsymbol{R}_f$ at $\boldsymbol{x}^{(2)}$ (dashed line) and at the refined final design $\boldsymbol{x}^*$ (solid line).

Table 1. Optimization cost of the stacked slotted resonators bandpass filter.

Algorithm Component	Number of Model Evaluations	Evaluation Time	
		Absolute [min]	Relative to $\boldsymbol{R}_f$
Optimization of the coarse-discretization model $\boldsymbol{R}_{c.1}$	41	49	3.1
Optimization of the coarse-discretization model $\boldsymbol{R}_{c.2}$	26	130	8.1
Evaluation of the original (fine-discretization) model $\boldsymbol{R}_f$	2	32	2.0
Total optimization time	N/A	211	13.2

B. High-Temperature Superconducting (HTS) Filter [16]

Consider the HTS filter shown in Fig. 4a [16]. The design parameters are $\boldsymbol{x} = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$. The width of all the sections is $W = 8$ mil. A substrate of lanthanum aluminate is used with $\varepsilon_r = 23.425$ $H = 20$ mil. The filter is simulated in Sonnet ***em*** [13] using a grid of 0.5 mil × 0.5 mil (the $\boldsymbol{R}_f$ model). The design specifications are $|S_{21}| \leq 0.05$ for $\omega \leq 3.966$ GHz, $|S_{21}| \geq 0.95$ for 4.008 GHz $\leq \omega \leq 4.058$ GHz, and $|S_{21}| \leq 0.05$ for $\omega \geq 4.100$ GHz. The initial design is $\boldsymbol{x}^{(0)} = [196\ 196\ 190\ 20\ 92\ 100]^T$ mil.

Again, we are using two coarse-discretization models: $\boldsymbol{R}_{c.1}$ (grid of 2 mil × 4 mil) and $\boldsymbol{R}_{c.2}$ (grid of 1 mil × 2 mil). The evaluation times for $\boldsymbol{R}_{c.1}$, $\boldsymbol{R}_{c.2}$ and $\boldsymbol{R}_f$ are about 2 min, 6 min and 51 min, respectively. Figure 4b shows the responses of $\boldsymbol{R}_{c.1}$ at $\boldsymbol{x}^{(0)}$ and at $\boldsymbol{x}^{(1)} = [188\ 190\ 188\ 20\ 76\ 84]^T$ mil, its optimal design found using a grid search, as well as the response of $\boldsymbol{R}_{c.2}$ at $\boldsymbol{x}^{(0)}$. Because of noticeable frequency shift between $\boldsymbol{R}_{c.1}(\boldsymbol{x}^{(0)})$ and $\boldsymbol{R}_{c.2}(\boldsymbol{x}^{(0)})$ (7 MHz on average) the design specifications were adjusted as described in Section 2.*E* while optimizing $\boldsymbol{R}_{c.1}$. Figure 5a shows the responses of $\boldsymbol{R}_{c.2}$ at $\boldsymbol{x}^{(1)}$ and at its optimized design $\boldsymbol{x}^{(2)} = [188\ 189\ 188\ 20\ 76\ 86]^T$ mil, as well as the response of $\boldsymbol{R}_f$ at $\boldsymbol{x}^{(2)}$. Here, the average frequency shift between $\boldsymbol{R}_{c.2}(\boldsymbol{x}^{(1)})$ and $\boldsymbol{R}_f(\boldsymbol{x}^{(1)})$ is about 5 MHz and the design specifications are modified accordingly. Figure 5b shows the responses of $\boldsymbol{R}_f$ at $\boldsymbol{x}^{(2)}$ (specification error –0.01 dB) and the refined design $\boldsymbol{x}^* = [188\ 189\ 188\ 20.5\ 78\ 88]^T$ mm (specification error –0.02). Total optimization cost (Table 2) corresponds to only 10 evaluations of the fine-discretization model.

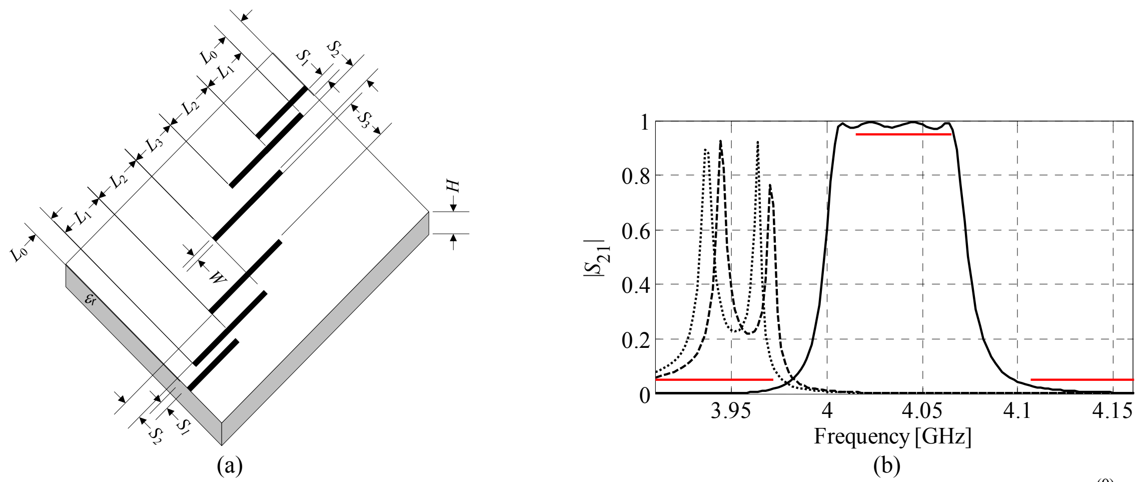


Fig. 4. HTS filter: (a) geometry [16], (b) responses of the coarse-discretization model $\boldsymbol{R}_{c.1}$ at the initial design $\boldsymbol{x}^{(0)}$ (dashed line) and at its optimized design $\boldsymbol{x}^{(1)}$ (solid line), as well as the response of $\boldsymbol{R}_{c.2}$ at $\boldsymbol{x}^{(0)}$ (dotted line); design specifications are shifted by 7 MHz toward higher frequencies to absorb the frequency shift between $\boldsymbol{R}_{c.1}(\boldsymbol{x}^{(0)})$ and $\boldsymbol{R}_{c.2}(\boldsymbol{x}^{(0)})$.

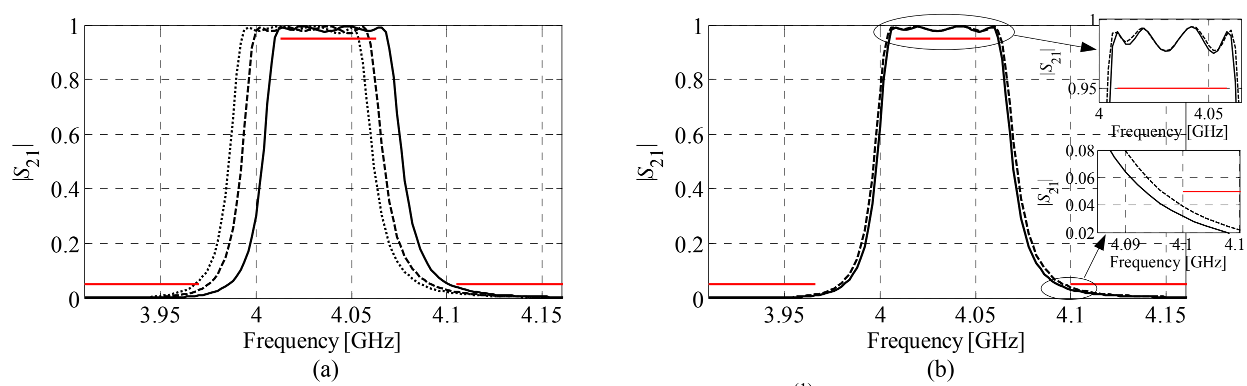


Fig. 5. HTS filter: (a) responses of the coarse-discretization model $\boldsymbol{R}_{c.2}$ at $\boldsymbol{x}^{(1)}$ (dashed line) and at its optimized design $\boldsymbol{x}^{(2)}$ (solid line), as well as the response of $\boldsymbol{R}_f$ at $\boldsymbol{x}^{(2)}$ (dotted line); design specifications are shifted by 5 MHz toward higher frequencies to absorb the frequency shift between $\boldsymbol{R}_{c.2}(\boldsymbol{x}^{(1)})$ and $\boldsymbol{R}_f(\boldsymbol{x}^{(1)})$; (b) responses of the fine-discretization model $\boldsymbol{R}_f$ at $\boldsymbol{x}^{(2)}$ (dashed line) and at the refined final design $\boldsymbol{x}^*$ (solid line); here the original design specifications are shown.

Table 2. Optimization cost of the HTS filter.

Algorithm Component	Number of Model Evaluations	Evaluation Time	
		Absolute [min]	Relative to $\boldsymbol{R}_f$
Optimization of the coarse-discretization model $\boldsymbol{R}_{c.1}$	104	195	3.8
Optimization of the coarse-discretization model $\boldsymbol{R}_{c.2}$	26	152	3.0
Evaluation of the original (fine-discretization) model $\boldsymbol{R}_f$	3	153	3.0
Total optimization time	N/A	500	9.8

4. Conclusion

Simple and robust algorithm for microwave design optimization with Sonnet is proposed that exploits sequential, multi-grid optimization of coarse-discretization Sonnet models and polynomial-approximation-based refinement of the final design. The presented method is easy to implement. It does not need an auxiliary equivalent-circuit model (which is typically used in space mapping) or any modifications to the original structure (such as cutting and inserting the tuning ports necessary by the tuning methodology). It is also computationally efficient as most of the operations are performed on the coarse-discretization models.

Acknowledgement

This work was supported in part by the Reykjavik University Development Fund under Grant T09009.

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