Optimization of High-Speed Electromagnetic Systems with Accurate Parametric Macromodels Generated using Sequential Sampling of the Design Space.

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Abstract — **This paper presents a design optimization approach for electromagnetic systems using parametric macromodels. The parametric macromodels are generated using an efficient sequential sampling of the design space of interest which ensures optimal sample selection for a required level of accuracy. The proposed method is validated on a microwave notch filter example for which the parametric macromodel is used in a minimax optimization algorithm so that the design parameters are optimized for some specific electrical design performances.**

1 INTRODUCTION

Design optimization of high-speed microwave systems focuses on calculating the optimal values of the design variables for which the system responses satisfy the design specifications. Optimal values of the design variables are often determined using optimization algorithms (optimizers) which drive the electromagnetic (EM) simulator to obtain the responses and their sensitivities in consecutive optimization iteration. Unfortunately, multiple consecutive EM simulations are often computationally expensive.

In recent years, design optimization of high-speed microwave systems using parametric macromodels attained considerable interest [1, 2]. These parametric macromodels accurately describe the parameterized frequency behavior of EM systems for the entire design space of interest, thereby acting as a replacement model for the original and expensive EM simulators [3, 4, 5, 6, 7]. However, as pointed out in [2], one of the key issues in these modeling approaches, rarely addressed in the literature, is the optimal selection of data samples in order to limit the total number of expensive EM simulations.

In this work, we focus on using efficient sequential sampling schemes to generate parametric macromodels which are used in design optimization of microwave systems. Parametric macromodels are used in conjunction with standard optimization algorithms [8], resulting in an optimal design such that all the design specifications are satisfied.

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2 PROPOSED METHOD

The flowchart of Fig. 1 describes the main idea of the proposed optimization method based on parametric macromodels generated by means of sequential sampling. The method begins by identifying the design parameters $\vec{g} = (g^{(n)})_{n=1}^{N}$, which are tuned to optimize certain cost functions or performance indexes. Once the ranges of the design parameters are defined, some initial design sample points $\vec{g}_k$, $k = 1, 2, ...K$ and the corresponding frequency response $H(s_i, \vec{g}_k)$, $i = 1, 2, ...N_s$ are generated. Here s_i represents the complex Laplace variable. The Vector Fitting (VF) method [9, 10] is used to build frequency-dependent rational models called *root macromodels* $R(s, \vec{g}_k)$ at each initial sample points.

Once the *root macromodels* are built at the initial design sample points, the next step is to parameterize them with respect to the design parameters $\vec{g}$. In [4], a parametric macromodel is built by interpolating a set of *root macromodels* at an input-output level, while in [5, 6], both poles and residues are parameterized by interpolating the internal state-space matrices, resulting in a higher modeling capability with respect to [4]. In [7], a novel enhanced interpolation of *root macromodels* at an input/output level is described, which is based on the use of some coefficients: one coefficient as a multiplicative factor at the input/output level of the system and the other coefficient as a compression or expansion term for the Laplace variable s. It results in high modeling capability and robustness and it is used in this paper.

After generating an initial parametric macromodel, the accuracy of this parametric macromodel is checked using some predefined error criteria at carefully chosen locations of the design space. If the accuracy is found to be inadequate, additional

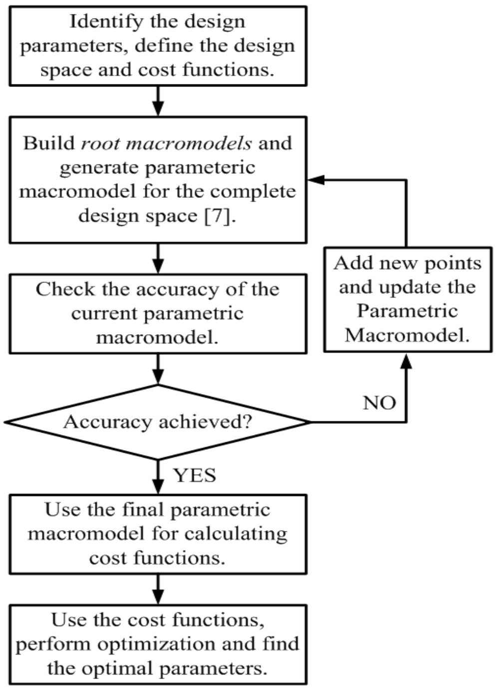

Figure 1: Flowchart of the proposed optimization.

samples are generated in the design space and the parametric macromodel is updated with the generation of *root macromodels* on the new samples followed by a parameterization using [7]. This process continues until the required level of accuracy is achieved.

The efficient and accurate parametric macromodel generated is used in a minimax optimization algorithm which finds the optimal values of the design parameters such that certain performance indexes are minimized.

3 SEQUENTIAL SAMPLING ALGORITHM

Once the ranges of the design parameters $\vec{g}$ are defined, a sequential sampling algorithm is used to build an accurate parametric macromodel choosing the data samples at optimal locations in the design space. Here, the sequential sampling method is explained for a two design parameter case, though it is applicable to any number of design parameters. The design space of the two parameters $(g^{(1)}, g^{(2)})$ is defined by the four corners of a rectangular region as shown in Fig. 2.a. Using the corner points of the design space, a parametric macromodel is built. Please note that the sequential sampling algorithm described here is general so that several parametric macromodeling schemes based on the local N-box regions of the design space can be applied [4, 5, 6, 7]. Here, the method of [7] is selected because of its modeling capability and robustness.

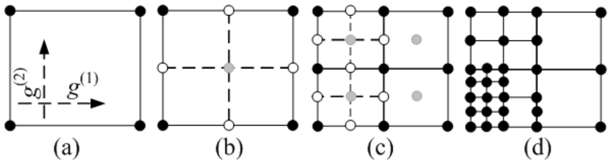

Figure 2: Design space during sequential sampling.

Next step is to check the accuracy of the generated parametric macromodel at the center of a particular subspace shown by the gray circle in Fig. 2.b. If the accuracy of the parametric macromodel is found to be not satisfactory, four new subspaces are generated, new sample points are added and the parametric macromodel is updated. This refinement step continues (Fig. 2.c) till the algorithm terminates by satisfying the accuracy at each local region of the design space as shown in Fig. 2.d.

4 DESIGN OPTIMIZATION

Once the parametric macromodel is built, it can be used in the optimization process of EM systems. Considering microwave filters, a typical optimization process begins by defining passband and stopband specifications in terms of the frequency responses, which are reformulated in the form of a cost function $F_i(\vec{g})$, to be minimized at optimization frequency samples s_i, $i = 1, 2, ..N_s$:

$$F_i(\vec{g}) = R^i_{\mathrm{L}} - R(s_i, \vec{g}) \;\text{ or }\; R(s_i, \vec{g}) - R^i_{\mathrm{U}}, \qquad (1)$$

In (1), R^i_{L} and R^i_{U} represents lower and upper frequency response thresholds, respectively, at frequency samples s_i, $i = 1, 2, ..., N_s$, spread over the frequency range of interest. A negative value for the cost function indicates that the corresponding specification is satisfied, while a positive value denotes that the specification is violated. The minimization (1) can be performed by several state-of-the-art optimization algorithms. In this paper, we use a minimax optimization algorithm [8] which uses the cost function (1) with respect to design parameter $\vec{g}$ giving the optimum design parameters $\vec{g^*}$ as

$$\vec{g^*} = \underset{\vec{g}}{\operatorname{argmin}}\{\max_i [F_i(\vec{g})]\}. \qquad (2)$$

5 NUMERICAL RESULTS

A folded stub microwave notch filter on a substrate with relative permitivity $\epsilon_r = 9.6$ and a thickness of 0.635 mm is modeled in this example. The layout of this filter is shown in Fig. 3. The spacing S and the length L of the stub are chosen as design variables in addition to frequency whose ranges are $S \in [0.5, 1.0]$ mm, $L \in [5.0, 10.0]$ mm and frequency $\in [2, 4]$ GHz. The design specifications of this notch filter are given in terms of the scattering parameter

$$|S_{21}| \leq -20\,\text{dB for } freq \in [2.925, 3.075]\,\text{GHz} \quad (3)$$

From the design specifications (3), considering a resonance frequency of 3 GHz, a cost function (1) is formulated in terms of S_{21} and $\vec{g} = (S, L)$.

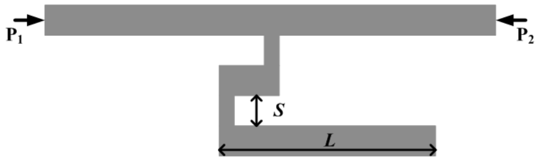

Figure 3: Layout of the folded stub notch filter.

The scattering matrix $\mathbf{S}(s, S, L)$ has been computed using the ADS Momentum[1] software. The sequential sampling algorithm has been implemented in Matlab R2010a[2] and used to drive the ADS Momentum simulations to generate $\mathbf{S}(s, S, L)$ at selected samples. The number of frequency samples were chosen to be equal to 41. The Mean Absolute Error (MAE) given by

$$E(\vec{g}) = \sum_{i=1}^{P_{in}} \sum_{j=1}^{P_{out}} \sum_{k=1}^{N_s} \frac{|R_{i,j}(s_k, \vec{g}) - H_{i,j}(s_k, \vec{g})|}{P_{in} P_{out} N_s} \quad (4)$$

with number of input ports P_{in}, output ports P_{out} and frequency samples N_s is used as an error measure to assess the accuracy at each region of the design space during the sequential sampling process. The final design space generated with the sequential sampling is shown in Fig. 4.

As shown in Fig. 4, the algorithm selected 65 sample points in the design space of interest shown by the black dots. The validation samples are generated at each and every step of the sequential sampling and are used in further refinement, as shown in Fig. 2.b. However, for the terminal subspaces, since no further refinements are performed, the validation samples are not used in the modeling but stored in the data base for later use. Fig. 4 shows 46 validation sample points for the terminal subspaces, shown by gray asterisks. The average ADS Momentum simulation time for each design space point (S, L) has been found to be equal to $T_{SimAvg} = 127.70$ seconds on a Windows 7 platform on Intel(R) Core(TM)2 Duo P8700 2.53 GHz machine with 2 GB RAM. The total simulation time

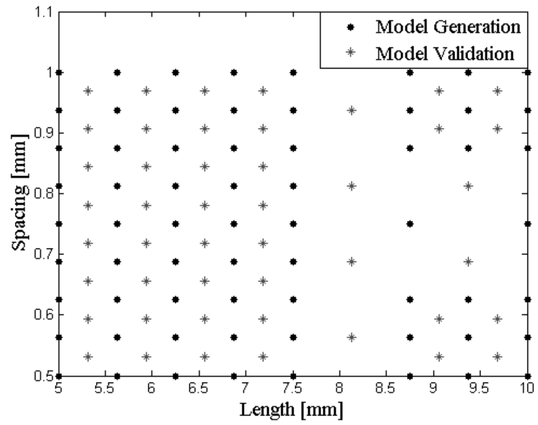

Figure 4: Design space generated using the sequential sampling algorithm.

to perform the ADS Momentum simulations and to build the parametric macromodel using the sequential sampling is found to be equal to $T_{tot} = 13966.21$ seconds of which $T_{\text{ADS}} = 13920.68$ seconds is spend on generation of data samples using ADS Momentum simulations. The target accuracy was set to -55 dB and the worst case accuracy was found to be -55.21 dB for the parametric macromodel.

Parameter		Value
Number of function evaluations		320
Initial design point (S^0, L^0)		(0.750 mm, 7.500 mm)
Optimal design point (S^*, L^*)		(0.995 mm, 6.089 mm)
Optimization time	Parametric macromodel	23.5 s
	ADS Momentum	35075.7 s

Table 1: Optimization results.

The cost function (1) calculated using the parametric macromodel generated, have been supplied to the minimax optimization algorithm (2), resulting in the optimum design parameter values S^* and L^*. Table 1 lists important parameters for the optimization. As seen in Table 1, there is a considerable gain in terms of the computation time. We note that the generation of the parametric macromodel requires some initial ADS Momentum simulations and therefore an initial computational effort. However, once the parametric macromodel is generated and validated, it acts as an accurate and efficient surrogate of the EM solver and can be used for multiple design optimization scenarios, for instance, changing filter specifications as well as

[1]Momentum EEsof EDA, Agilent Technologies, Santa Rosa, CA.

[2]The Mathworks, Inc., Natick, MA, USA

other design activities such as design space exploration and sensitivity analysis. Therefore, multiple uses of the parametric macromodel makes the initial computation effort negligible.

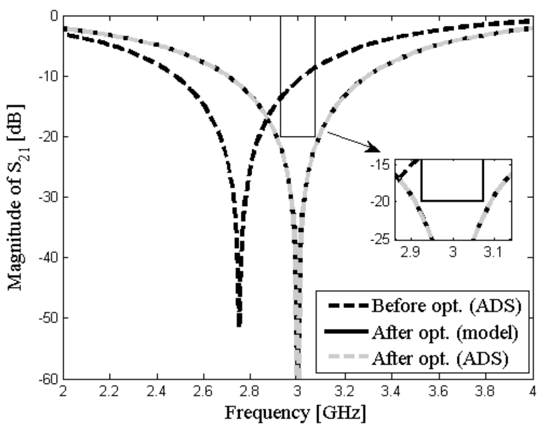

Figure 5: Magnitude of S_{21} with optimization.

Fig. 5 shows the magnitude of S_{21} as a function of frequency before and after optimization along with the design specifications for the filter. As seen in Fig. 5 , all the specifications are met for the optimal design parameter values (S^*, L^*). The actual ADS Momentum simulation is also compared with the parametric macromodel at the optimal solution and a good agreement between the two responses can be observed.

6 Conclusions

We have presented a new design optimization approach for EM systems using parametric macromodels, generated based on efficient sequential sampling of the design space. A minimax optimization was performed using the parametric macromodel on a microwave notch filter example for which the design parameters are optimized for some electrical performances. The presented numerical results validate the proposed method.

Acknowledgments

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