

Cost-Efficient Microwave Design Optimization Using Adaptive Response Scaling

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Abstract

In this paper, a novel technique for cost-efficient design optimization of microwave structures has been proposed. Our approach exploits an adaptive response scaling that ensures good alignment between an equivalent circuit (used as an underlying low-fidelity model) and an electromagnetic (EM) simulation model of the structure under design. As the adaptive scaling tracks the low-fidelity model changes both in terms of frequency and the response level, it exhibits better generalization capability than traditional (e.g., space mapping) surrogates. This translates into improved design reliability and reduced design cost. Our methodology is demonstrated using two examples of microstrip filters and compared to several variations of conventional space mapping.

Keywords: Computer-aided design, microwave filters, EM-driven design, surrogate-based optimization, space mapping, adaptive response scaling

1 Introduction

Electromagnetic (EM)-simulation-driven design closure is an important step of the microwave design process. It typically aims at adjustment of geometry parameters of the structure at hand (e.g., a filter) to ensure that given design specifications (concerning, e.g., return loss) are met (Koziel and Bekasiewicz, 2015). Deviations from the ideal/required characteristics are normally due to inaccuracies of the simplified representations—such as equivalent circuit models—utilized to obtain the initial (or pre-tuning) design.

For the sake of automation, it is advantageous that the EM-based design closure is conducted through numerical optimization. This, however, may be computationally expensive when conventional off-the-shelf algorithms are utilized. Numerous techniques have been proposed to speed up EM-driven

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design, most of which rely on surrogate-based optimization (SBO) paradigm (Koziel, Yang and Zhang, 2013). These include many variations of space mapping (SM), e.g., (Bandler et al. 2004; Koziel, Bekasiewicz and Kurgan, 2014; Sans *et al.* 2014) response correction techniques (Echeverria and Hemker, 2005; Koziel 2010; Koziel and Leifsson, 2013) utilization of artificial neural networks (Gorissen *et al.* 2011), as well as simulation-based tuning and tuning space mapping (Cheng, Bandler and Koziel, 2012). Furthermore, availability of cheap adjoint sensitivities (Bast, Bakr and Nikolova, 2008; Koziel and Bekasiewicz, 2015) revived, to some extent, the interest in gradient-based optimization (Toivanen *et al.* 2010), also in connection with SBO (Koziel *et al.* 2013; Koziel and Leifsson, 2013). On the other hand, the utilization of adjoints is not yet widespread in the microwave engineering community.

Majority of SBO techniques require a rather careful implementation as well as certain engineering insight into the problem. One of the issues pertinent to, for example, SM, is the necessity of appropriate selection of the type and parameters of the surrogate model (such as preassigned parameters for implicit space mapping (Bandler *et al.* 2004; Bekasiewicz, Kurgan and Kitlinski, 2012)). Straightforward application of such methods may lead to unpromising results, including convergence issues (Koziel, Bandler and Madsen, 2009). Methods such as simulation-based tuning are much more robust yet limited in terms of application scope and software requirements. Other techniques, such as the shape-preserving response prediction (SPRP) (Koziel, 2010), require the fulfillment of specific assumptions concerning the response shape of the structure of interest and as well as relatively complex implementation.

In this paper, we propose a simple adaptive scaling technique for fast design optimization of microwave devices. It is based on tracking the changes (both frequency- and level-wise) of the underlying low-fidelity model (e.g., an equivalent circuit) to ensure good generalization capability of the surrogate model constructed with it. Our approach is demonstrated using two examples of microstrip bandpass filters and compared to several variations of space mapping algorithms.

2 Surrogate-Based Optimization Basics

Let $\mathbf{R}_f(\mathbf{x})$ be a response of the EM-simulated (high-fidelity) model of a device (e.g., filter) under design, where $\mathbf{x}$ is a vector of adjustable (geometry) parameters, and $\mathbf{R}_f$ represents relevant responses such as S -parameters versus frequency. Let $\mathbf{R}_c(\mathbf{x})$ denote the low-fidelity model of the same device, e.g., an equivalent circuit. The problem to be solved is

$$\mathbf{x}^* = \arg \min_{\mathbf{x}} U(\mathbf{R}_f(\mathbf{x})) \quad (1)$$

where U encodes given design specifications, and $\mathbf{x}^*$ is the optimum design to be found.

According to the SBO paradigm (Koziel, Yang and Zhang, 2013), direct solving of (1) is replaced by an iterative procedure

$$\mathbf{x}^{(i+1)} = \arg \min_{\mathbf{x}} U(\mathbf{R}_s^{(i)}(\mathbf{x})) \quad (2)$$

where $\mathbf{x}^{(i)}$, $i = 0, 1, \dots$, is a sequence of approximations to $\mathbf{x}^*$, and $\mathbf{R}_s^{(i)}$ is a surrogate model at iteration i , which is a fast representation of the high-fidelity constructed using $\mathbf{R}_c$.

The most important differences between various realizations of SBO algorithms are in the methodologies for constructing the surrogate model. The most popular SBO approach in microwave engineering is space mapping, where the surrogate is obtained by usually simple correction of the low-fidelity model of the form $\mathbf{R}_s(\mathbf{x}) = \mathbf{R}_c(\mathbf{x}; \mathbf{p})$, where $\mathbf{p}$ are the SM parameters extracted or calculated to

reduce the misalignment between the surrogate and the low-fidelity model at the most recent design or at several previous designs encountered at the optimization patch. Examples include input SM with $\mathbf{R}_s(\mathbf{x}) = \mathbf{R}_c(\mathbf{B}\mathbf{x} + \mathbf{c})$, implicit SM ($\mathbf{R}_s(\mathbf{x}) = \mathbf{R}_c(\mathbf{x}; \mathbf{p})$ where $\mathbf{p}$ are so-called preassigned parameters, e.g., the substrate height and permittivity (Bandler et al. 2004)), or output SM ($\mathbf{R}_s(\mathbf{x}) = \mathbf{R}_c(\mathbf{x}) + \Delta$, where Δ is typically a constant vector, e.g., $\Delta = \mathbf{R}_f(\mathbf{x}^{(i)}) - \mathbf{R}_c(\mathbf{x}^{(i)})$).

Satisfaction of at least zero-order consistency between the surrogate and the high-fidelity model (i.e., $\mathbf{R}_f(\mathbf{x}^{(i)}) = \mathbf{R}_s^{(i)}(\mathbf{x}^{(i)})$) is critical for the algorithm convergence (Alexandrov and Lewis, 2001; Koziel, Bandler and Madsen, 2009). Ensuring it by output SM as in the previous paragraph, may not work well for highly nonlinear (e.g., filter) responses (Koziel, Bandler and Madsen, 2008).

3 Surrogate Construction By Adaptive Response Scaling

Here, we introduce an adaptive response scaling (ARS) technique that aims at constructing the surrogate model that (i) preserves zero-order consistency $\mathbf{R}_s^{(i)}(\mathbf{x}^{(i)}) = \mathbf{R}_f(\mathbf{x}^{(i)})$, and (ii) exhibits good generalization capability by accounting for both frequency and amplitude changes of the low-fidelity model responses during the optimization process.

Figure 1 shows the high- and low-fidelity model responses (here, $|S_{11}|$) at the reference design $\mathbf{x}^{(i)}$ and another design $\mathbf{x}$. It can be observed that the models are significantly misaligned yet relatively well correlated. The adaptive response scaling attempts to explore these correlations using the procedure described below.

The response scaling is realized at the level of complex S -parameter responses, separately for the respective real and imaginary parts. In the first step, frequency relationship is between the low- and high-fidelity model at the reference design $\mathbf{x}^{(i)}$ (i.e., the design being the starting point for the subsequent iteration of (2)) is retrieved by solving

$$F^{(i)}(\omega) = \arg \min_F \int_{\omega_{\min}}^{\omega_{\max}} |r_f(\mathbf{x}^{(i)}, \omega) - r_c(\mathbf{x}^{(i)}, F(\omega))| d\omega, \quad (3)$$

where F is a nonlinear frequency scaling function, here, implemented using cubic splines with 20 control points within the frequency range of interest; r_f/r_c are high-/low-fidelity responses of interest (e.g., $\text{Re}(S_{11})$, etc.). $F^{(i)}$ minimizes the discrepancy between the responses within the frequency range of interest $\omega_{\min}$ to $\omega_{\max}$.

A scaling function similar to (3) is computed to account for the (frequency) changes of the low-fidelity model response between $\mathbf{x}^{(i)}$ and $\mathbf{x}$. In particular, we have

$$F(\mathbf{x}, \omega) = \arg \min_F \int_{\omega_{\min}}^{\omega_{\max}} |r_c(\mathbf{x}, \omega) - r_c(\mathbf{x}^{(i)}, F(\omega))| d\omega. \quad (4)$$

Additionally, the amplitude changes of the low-fidelity model are calculated as

$$A(\mathbf{x}, \omega) = [r_c(\mathbf{x}, \omega) + 1] \div [r_c(\mathbf{x}^{(i)}, F(\mathbf{x}, \omega)) + 1]. \quad (5)$$

Here, $\div$ denotes component-wise division with respect to frequency. The shift by +1 is introduced in order to avoid division by zero (for frequencies for which $r_c(\mathbf{x}^{(i)}, F(\mathbf{x}, \omega)) = 0$) and to avoid too large values of $|A|$ (for r_c close to zero).

The prediction phase of the surrogate model is realized as follows. First, the reference high-fidelity model response $r_f(\mathbf{x}^{(i)}, \omega)$ is scaled in frequency using $F(\mathbf{x}, \omega)$ in order to account for the changes of the low-fidelity model while moving from $\mathbf{x}^{(i)}$ to $\mathbf{x}$ (the low- and high-fidelity models are assumed to be

well correlated although perhaps misaligned in the absolute terms). Then, the amplitude scaling function $A(\mathbf{x}, \omega)$ is scaled in frequency using $F^{(i)}(\mathbf{x}, \omega)$ in order to accommodate the frequency relationships between the low- and high-fidelity model at the reference design; finally, it is applied to correct the surrogate response in amplitude. Formally, the surrogate model is defined as

$$r_s(\mathbf{x}, \omega) = A(\mathbf{x}, F^{(i)}(\omega)) \circ [r_f(\mathbf{x}^{(i)}, F(\mathbf{x}, \omega)) + 1] - 1 \quad (6)$$

where $\circ$ denotes component-wise multiplication.

Note that the scaling function $F^{(i)}$ is only calculated once per iteration (2), whereas (4) and (5) are computed for each evaluation of the surrogate model.

For the sake of example, Fig. 2 shows $\text{Re}(S_{11})$ of the responses shown in Fig. 1, as well as the response of the surrogate model constructed according to ARS. It can be observed that the prediction power of the model is very good, especially given considerable misalignment between the low- and high-fidelity models as well as considerable change of the responses between the designs $\mathbf{x}^{(0)}$ and $\mathbf{x}$. Figure 3 shows how this translates to $|S_{11}|$ prediction. At the same time, the quality of the conventional output SM prediction is poor as it does not account for model response changes in frequency.

4 Verification Examples

In this section, we present numerical verification of the proposed design optimization approach. It is demonstrated using two examples of microstrip filters, a sixth- and an eight-order ones. Comparison with benchmark optimization algorithms (all surrogate-based) is also provided.

4.1 Sixth-Order Microstrip Bandpass Filter

Consider the 6th-order bandpass filter shown in Fig. 4, implemented on a Taconic RF-35 substrate ($\epsilon_r = 3.5$, $\tan \delta = 0.0018$, $h = 0.762$ mm). The design variables are $\mathbf{x} = [w_1 \ w_2 \ w_3 \ d_1 \ d_2 \ d_3 \ l_1 \ l_2 \ l_3]^T$.

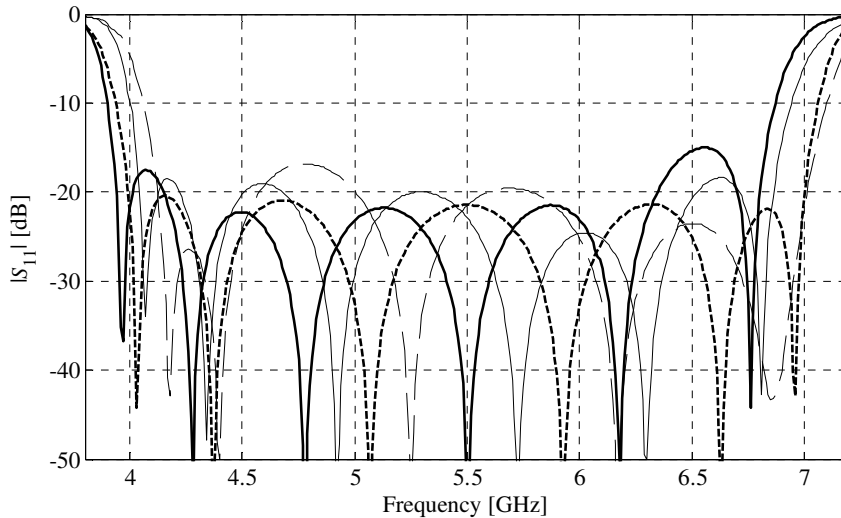


Figure 1: Responses of the 6th-order microstrip bandpass filter of Section IV.A: $|S_{11}|$ at a reference design $\mathbf{x}^{(i)}$ (—) and another design $\mathbf{x}$ (---); High- and low-fidelity models shown using thick and thin lines, respectively.

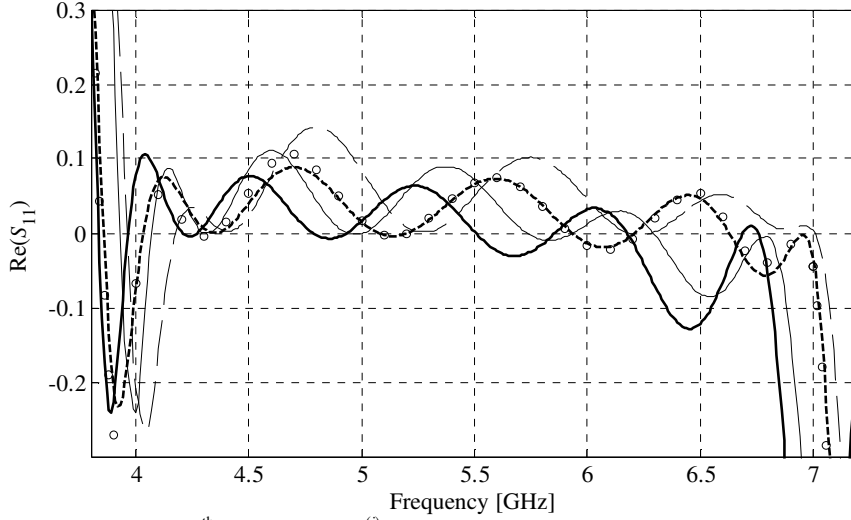


Figure 2: Responses of the 6th-order filter at $x^{(i)}$ (—) and x (---) (cf. Fig. 1): R_f (thick lines) and R_c (thin lines); surrogate model response determined by (6) shown using circles.

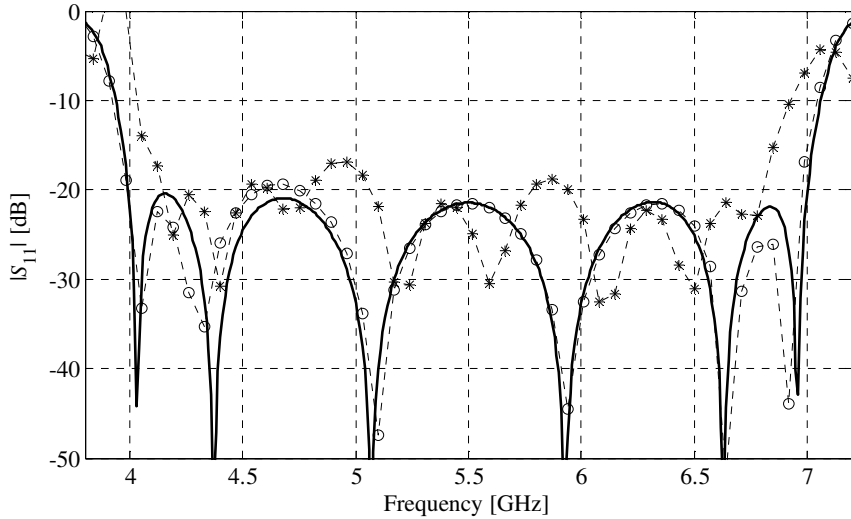


Figure 3: High-fidelity model response at x (thick line), and surrogate model responses obtained using adaptive response scaling (o) and conventional output SM (*).

The EM model is implemented in CST Microwave studio and simulated using its frequency domain solver (CST, 2013). The model consists of about 125,000 hexahedral mesh cells and its average simulation time is 3 min. The low-fidelity model is an equivalent circuit implemented in Agilent ADS (Agilent, 2011). The design specifications are $|S_{11}| \leq -20$ dB for $4 \text{ GHz} \leq \omega \leq 7 \text{ GHz}$, and $|S_{11}| \geq -3$ dB for $\omega \leq 3.85 \text{ GHz}$ and $\omega \geq 7.15 \text{ GHz}$. The filter was optimized using ARS (cf. Fig. 5), as well as—for the sake of comparison—several variations of space mapping algorithm (cf. Table 1). It can be observed that ARS ensured better reliability and lower design cost compared to

conventional SM. It is also important to note that some of the space mapping algorithms did not converge. It is well known that performance and computational cost of space mapping optimization depends on the choice of the underlying SM transformations (Koziel, Bandler and Madsen, 2008) and this choice is not trivial (Koziel and Bandler, 2007). This means, in particular, that the outcome of space mapping optimization is uncertain until the optimization run has actually been executed. ARS is free from these problems because of being parameter-less.

4.2 Eight-Order Microstrip Bandpass Filter

Our second example is the 8th-order bandpass filter shown in Fig. 6. The design variables are $\mathbf{x} = [w_1 \ w_2 \ w_3 \ w_4 \ d_1 \ d_2 \ d_3 \ d_4 \ l_1 \ l_2 \ l_3 \ l_4]^T$. The EM model is implemented in CST Microwave Studio (~160,000 mesh cells, simulation time 6 min). The low-fidelity model is implemented in Agilent ADS. The design specifications are $|S_{11}| \leq -20$ dB for $4 \text{ GHz} \leq \omega \leq 7 \text{ GHz}$, and $|S_{11}| \geq -3$ dB for $\omega \leq 3.92 \text{ GHz}$ and $\omega \geq 7.08 \text{ GHz}$. The filter optimized using ARS is shown in Fig. 7. Results of comparison with various SM algorithms are gathered in Table 1. The overall performance of the benchmark techniques is consistent with what was observed for the first example. Some of the SM variations did not work properly (the optimization algorithm diverged) but also, the overall optimization cost is much higher than for ARS.

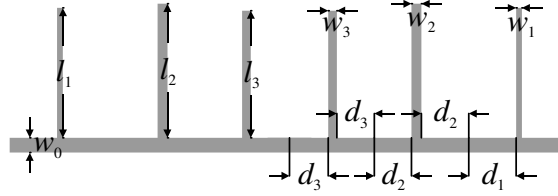


Figure 4: Geometry of the sixth-order bandpass filter.

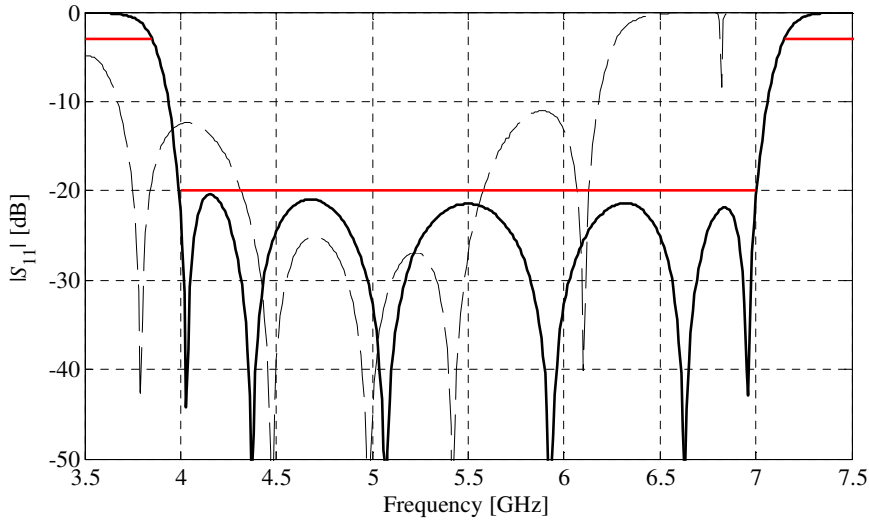


Figure 5: Sixth-order bandpass filter: initial (---) and final (—) filter responses obtained using adaptive response scaling technique.

5 Conclusion

The adaptive response scaling (ARS) technique has been introduced for fast and reliable design optimization of microwave structures. It has been demonstrated using two microstrip bandpass filters of 6th and 8th orders. Numerical experiments indicate that ARS favorably compares with conventional space mapping techniques. The most important feature of ARS is that it fully exploits the knowledge about the problem embedded in the low-fidelity model. As opposed to space mapping approaches, where the model alignment is realized using the response of the low-fidelity model at a specific point (or points), ARS directly utilizes the changes of the low-fidelity model response under the change of the location in the design space. Owing to this, absolute discrepancies between the low- and high-fidelity models are not critical. For the same reason, generalization capability of the ARS surrogate is better than for other methods. The proposed methodology can be considered as an alternative approach to handle EM-driven design problems, particularly for structures with highly nonlinear responses such as filters.

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Table 1: Optimization cost: ARS versus benchmark methods

Filter	Optimization Algorithm	Design Optimization Cost ¹	
		# of EM Simulations	Total Cost ²
6 th -order	ARS (this work)	4	9.5
	Implicit SM ³	15 ⁶	76.4
	Implicit SM ⁴	6	27.6
	Frequency + Output SM	9 ⁶	22.7
	Input SM ⁵	3 ⁷	38.7
8 th -order	ARS (this work)	6	10.9
	Implicit SM ⁸	9 ⁷	26.2
	Implicit SM ⁹	8	23.7
	Frequency + Output SM	4 ⁷	13.8
	Input SM ¹⁰	9 ⁶	31.7

¹ Algorithm terminated upon satisfying design specifications.

² Cost including low-fidelity model evaluations, expressed in terms of the equivalent number of EM filter simulations.

³ Six implicit parameters related to substrate thickness.

⁴ Twelve implicit parameters related to substrate thickness and permittivity.

⁵ Six additive and six multiplicative parameters.

⁶ Algorithm converged, but the final response violates specifications.

⁷ Algorithm terminated due to divergence.

⁸ Eight implicit parameters related to substrate thickness.

⁹ Sixteen implicit parameters related to substrate thickness and permittivity.

¹⁰ Eight additive and eight multiplicative parameters.

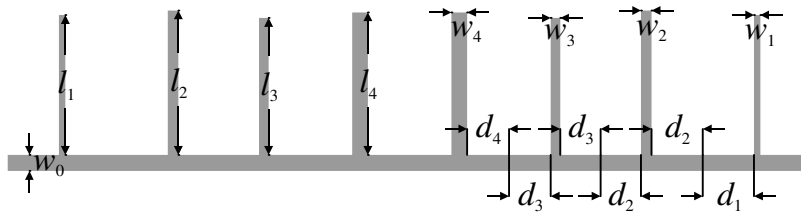


Figure 6: Geometry of the eight-order bandpass filter.

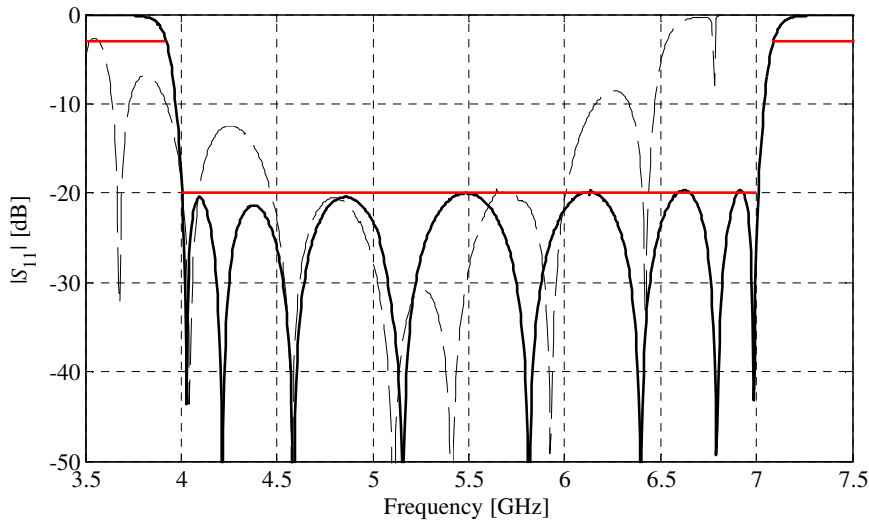


Figure 7: Eight-order bandpass filter: initial (---) and final (—) filter responses obtained using adaptive response scaling technique.

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