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EM-Driven Tolerance Optimization of Compact Microwave Components Using Response Feature Surrogates

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***Abstract*—Improving microwave component immunity to parameter deviations is of high importance, especially in the case of stringent performance specifications. This paper proposes a computationally efficient algorithm for robustness enhancement of compact microwave circuits. The objective is to increase the acceptable levels of geometry parameter deviations under which the prescribed performance specifications are still fulfilled. Our approach incorporates feature-based surrogate models utilized for low-cost prediction of the fabrication yield, as well as the trust-region framework for adaptive control of design relocation and ensuring convergence of the optimization process. The efficacy of our technique is demonstrated using a broadband microstrip filter.**

***Keywords*— fabrication tolerances, tolerance, optimization, statistical analysis, robust design, response features, EM-driven design, compact components.**

I. Introduction

Most microwave design optimization procedures still do not account for the inevitable deviations in geometry parameters from nominal values. Yet manufacturing processes are never perfect and knowledge about material parameters, e.g., substrate permittivity, and operating conditions, e.g., input power level, is uncertain. Such uncertainties and parameter tolerances affect system performance and are best accounted for at the design stage.

Quantification of uncertainties is computationally expensive, as it is usually carried out at the level of full-wave electromagnetic (EM) analysis. The latter is imperative for compact microwave components, where strong EM cross-coupling effects cannot be adequately represented using simpler methods, e.g., equivalent networks. Conventional uncertainty quantification (UQ) procedures, such as EM-driven Monte Carlo simulation, may incur impractical CPU expenses, whereas robust design (e.g., yield optimization [1], design centering [2]) often turns prohibitive. Acceleration thereof can be achieved by means of surrogate modeling methods, both data-driven [3], and physics-based [4]. Popular techniques employed for UQ include kriging [5], neural networks [6], [7] and polynomial chaos expansion (PCE) [8]. Utilization of surrogates may lead to considerable computational savings, but is hindered by the curse of dimensionality [9]. This can be mitigated by approaches such as dimensionality reduction [10], or incorporation of variable-fidelity simulations [11].

An alternative approach to utilize surrogate models for EM-driven design purposes, including statistical analysis, involves the response feature technology [12]-[14]. Therein, the surrogate model is set up to represent selected characteristic (feature) points of the system responses, which allows for 'flattening' the functional landscape to be handled. As a result, reformulating the modeling or optimization process in terms of response features leads to considerable computational savings [12], [15], [16].

This paper describes a novel technique for reduced-cost robust design of compact microwave passives. The design problem is to maximize input parameter tolerances for which the design specifications are still satisfied, i.e., 100-percent yield can be achieved. The yield estimation is carried out using feature-based regression surrogates, whereas the optimization process is embedded in a trust-region framework to ensure convergence. Verification conducted for a broadband filter demonstrates that robustness enhancement can be accomplished using only a few dozen EM analyses. At the same time, feature-based metamodels reliably account for system yield, as corroborated through EM-based Monte Carlo simulation.

II. Robustness Optimization Using Response Features

This section formulates our robustness enhancement procedure. It is explained using a specific case study of a bandpass filter.

A. Performance Requirements. Nominal Design

We denote by $\boldsymbol{x} = [x_1 \ldots x_n]^T$ a vector of design parameters of the circuit at hand. The symbol f stands for the frequency. To conduct the optimization process, one needs to quantify the system performance. As an example, consider a bandpass filter with f_L and f_R being the frequencies determining the target operating bandwidth. Further, let $S_{\max}$ denote the maximum acceptable in-band reflection level. The filter satisfies the specs if

$$\max\left\{f \in [f_L, f_R] : |S_{11}(\boldsymbol{x}, f)|\right\} \le S_{\max} \qquad (1)$$

In practice, additional requirements may be imposed on both the reflection and transmission response (e.g., maximum in-band ripple level, etc.). Here, this is omitted for simplicity.

Let $\boldsymbol{x}^{(0)}$ be the nominal design, obtained by optimizing the filter using the objective function based on (1). We have

$$\boldsymbol{x}^{(0)} = \arg\min_{\boldsymbol{x}} \left\{ \max\left\{ f \in [f_L, f_R] : |S_{11}(\boldsymbol{x}, f)| \right\} \right\} \quad (2)$$

Note that $\boldsymbol{x}^{(0)}$ does not account for any parameter uncertainties.

B. Fabrication Yield

The statistical performance metric utilized in this work is yield Y [2], defined as

$$Y(\boldsymbol{x}^{(0)}) = \int_{X_f} p(\boldsymbol{x}, \boldsymbol{x}^{(0)}) d\boldsymbol{x} \quad (3)$$

where $p(\boldsymbol{x},\boldsymbol{x}^{(0)})$ is a probability density function describing variations of the design $\boldsymbol{x}$ w.r.t. $\boldsymbol{x}^{(0)}$; X_f is the feasible space, i.e., the set of designs satisfying the specs (e.g., (1) for a filter).

A practical way of evaluating (3) is Monte Carlo (MC) simulation, where the yield is estimated as

$$Y(\boldsymbol{x}^{(0)}) = N_r^{-1} \sum_{k=1}^{N_r} H(\boldsymbol{x}^{(0)} + d\boldsymbol{x}^{(k)}) \quad (4)$$

with $d\boldsymbol{x}^{(k)}$, $k = 1, \ldots, N_r$, being random deviations generated according to the density function $p(\cdot)$, and the function $H(\boldsymbol{x}) = 1$ if the condition (1) is met, otherwise $H(\boldsymbol{x}) = 0$. In our verification experiments, p is assumed to be joint Gaussian distribution with zero mean and a variance σ. Observe that running MC directly at the level of EM simulation models is CPU intensive.

C. Tolerance Optimization. Problem Formulation

Statistical design of high-frequency components is usually concerned with maximization of yield. The task is to find

$$\boldsymbol{x}^* = \arg\min_{\boldsymbol{x}} \{-Y(\boldsymbol{x})\} \quad (5)$$

In this work, robustness improvement is formulated from the perspective of input tolerances. We aim at maximizing the acceptable levels of parameter deviations for which the yield is still equal to unity. For simplicity, we assume a single parameter to control the tolerances, which is the variance σ of independent Gaussian probability distributions describing the deviations. The robustness enhancement task is formulated as

$$\boldsymbol{x}^* = \arg\min \left\{ \boldsymbol{x} : U_Y(\boldsymbol{x}) \right\} \quad (6)$$

where

$$U_Y(\boldsymbol{x}) = \arg\max_{\sigma} \left\{ Y(\boldsymbol{x}, \sigma) = 1 \right\} \quad (7)$$

The value of the objective function (7) at $\boldsymbol{x}$ is the largest σ for which the yield Y is still equal to one. Section II.*E* will elaborate on numerical evaluation of (7). The robustness enhancement concept is illustrated in Fig. 1.

D. Feature-Based Regression Surrogates

To improve cost-efficiency of the optimization process, here, yield evaluation is executed using response feature surrogates. Reformulating the design task in terms of appropriately chosen characteristic (feature) points of the system responses allows for linearizing the relationships between the system parameters and objective function variations [12]. The selection of the feature points depends on the problem. A prerequisite is that their coordinates should allow for evaluating the performance specifications imposed upon the circuit (cf. Fig. 2).

The feature points at design $\boldsymbol{x}$ are written as

$$\boldsymbol{P}(\boldsymbol{x}) = [p_1(\boldsymbol{x})\ p_2(\boldsymbol{x}) \ldots p_{N_p}(\boldsymbol{x})]^T \quad (8)$$

For the bandpass filter considered before, the feature vector will take the form of

$$\begin{aligned} \boldsymbol{P}(\boldsymbol{x}) &= [p_1(\boldsymbol{x})\ p_2(\boldsymbol{x}) \ldots p_{N+1}(\boldsymbol{x})]^T = \\ &= [f_1(\boldsymbol{x})\ f_2(\boldsymbol{x})\ l_1(\boldsymbol{x}) \ \ldots \ l_{N-1}(\boldsymbol{x})]^T \end{aligned} \quad (9)$$

where f_1 and f_2 are the frequencies corresponding to $S_{\max}$ (e.g., –15 dB level of $|S_{11}|$, and l_k are the reflection levels corresponding to local in-band maxima of $|S_{11}|$, cf. Fig. 2. The performance requirements (1) can be expressed using (9) as

$$f_1(\boldsymbol{x}) \le f_L,\ f_2(\boldsymbol{x}) \ge f_R,\ \text{and}\ l_k(\boldsymbol{x}) \le S_{\max},\ k = 1, \ldots, N-1 \quad (10)$$

The feature points are used for low-cost evaluation of the system yield. Let $\boldsymbol{x}^{(i)}$ be the ith iteration point produced by the robustness enhancement algorithm. We consider the feature-based surrogate model $\boldsymbol{L}_P^{(i)}(\boldsymbol{x})$ established at $\boldsymbol{x}^{(i)}$, and defined as

$$\boldsymbol{L}_P^{(i)}(\boldsymbol{x}) = [p_{L.1}(\boldsymbol{x}) \ldots p_{L.N_p}(\boldsymbol{x})]^T = \begin{bmatrix} l_{0.1} + \boldsymbol{L}_1^T(\boldsymbol{x} - \boldsymbol{x}^{(i)}) \\ \vdots \\ l_{0.N_p} + \boldsymbol{L}_{2N_p}^T(\boldsymbol{x} - \boldsymbol{x}^{(i)}) \end{bmatrix} \quad (11)$$

The model coefficients can be found analytically as

$$\begin{bmatrix} l_{0.j} \\ \boldsymbol{L}_j \end{bmatrix} = \begin{bmatrix} 1 & (\boldsymbol{x}_B^{(1)} - \boldsymbol{x}^{(i)})^T \\ & \vdots \\ 1 & (\boldsymbol{x}_B^{(n+1)} - \boldsymbol{x}^{(i)})^T \end{bmatrix}^{-1} \begin{bmatrix} p_j(\boldsymbol{x}_B^{(1)}) \\ \vdots \\ p_j(\boldsymbol{x}_B^{(n+1)}) \end{bmatrix},\ j = 1, \ldots, N_p \quad (12)$$

where $\boldsymbol{x}_B^{(k)}$, $k = 1, \ldots, n + 1$, are the training points, and $p_j(\boldsymbol{x}_B^{(k)})$ are the entries of the feature vectors $\boldsymbol{P}(\boldsymbol{x}_B^{(k)})$ extracted from EM-simulated circuit responses. The training vectors are $\boldsymbol{x}_B^{(1)} = \boldsymbol{x}^{(i)}$, and $\boldsymbol{x}_B^{(k)} = \boldsymbol{x}^{(i)} + [0 \ldots 0\ d\ 0 \ldots 0]^T$ with d at the $(k–1)$th position.

E. Evaluating Objective Function U_Y

The function $U_Y(\boldsymbol{x})$ of (7) is evaluated through numerical integration of the density function $p(\cdot)$, using the feature-based surrogate (11). This involves computation of $Y(\boldsymbol{x},\sigma)$ for a given σ, which is realized with a large number of random observables $\boldsymbol{x}_r^{(j)}$ (here, N_r= 100,000) allocated using p, according the variance σ. The yield estimation procedure is the following:

1. For given σ, generate the observable set $\{\boldsymbol{x}_r^{(j)}\}_{j = 1, \ldots, Nr}$;
2. Evaluate $\boldsymbol{L}_P^{(i)}(\boldsymbol{x}_r^{(j)})$ for $j = 1, \ldots, N_r$;
3. Evaluate design specs (e.g., (1) for a filter) for all $\boldsymbol{x}_r^{(j)}$ using surrogate-predicted features $p_{L.k}(\boldsymbol{x}_r^{(j)})$, $j = 1, \ldots, N_r$;
4. Compute $Y(\boldsymbol{x},\sigma)$ according to (4).

Note that using large N_r reduces the yield estimation variance. The function $U_Y(\boldsymbol{x})$ is calculated by solving (7), here, using a golden ratio search. The symbol $U_Y^{(i)}(\boldsymbol{x})$ will be used to denote the objective function evaluated for feature based model $\boldsymbol{L}_P^{(i)}$.

F. Robustness Enhancement Algorithm

The tolerance optimization task (6) is solved iteratively using the trust-region (TR) framework [17], which produces a series of $\boldsymbol{x}^{(i)}$, $i = 0, 1, \ldots$, approximating $\boldsymbol{x}^*$ ($\boldsymbol{x}^{(0)}$ is the nominal design) as

$$\boldsymbol{x}^{(i+1)} = \arg\min_{\|\boldsymbol{x}-\boldsymbol{x}^{(i)}\| \le d^{(i)}} U_Y^{(i)}(\boldsymbol{x}) \quad (13)$$

Solving of (14) is constrained to the trust region defined as $\|\boldsymbol{x} - \boldsymbol{x}^{(i)}\| \le d^{(i)}$. The TR size $d^{(i)}$ is adjusted based on the gain ratio

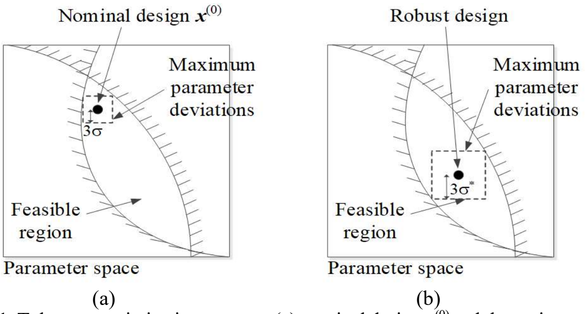

Fig. 1. Tolerance optimization concept: (a) nominal design $\boldsymbol{x}^{(0)}$ and the region corresponding to the maximum values of parameter deviations that ensure 100-percent yield; (b) robust design, featuring enlarged acceptable parameter deviations.

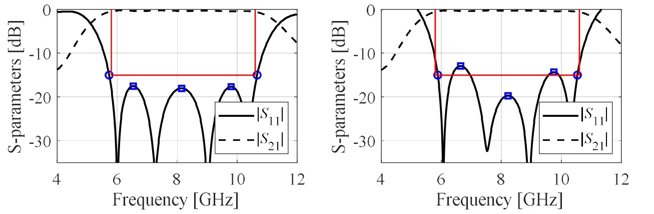

Fig. 2. Response features for a bandpass filter. Shown are the S-parameters and the feature points corresponding to –15 dB level of $|S_{11}|$ and local maxima of $|S_{11}|$ within the filter operating band; the feature points permit determination of whether the return loss characteristic satisfies the matching conditions over the operating bandwidth. The left- and right-hand-side panels correspond to designs satisfying and violating the performance specifications, respectively.

$$r = \left(U_Y^{\#(i)}(\boldsymbol{x}^{(i+1)}) - U_Y^{(i)}(\boldsymbol{x}^{(i)})\right) / \left(U_Y^{(i)}(\boldsymbol{x}^{(i+1)}) - U_Y^{(i)}(\boldsymbol{x}^{(i)})\right) \quad (14)$$

The denominator in (14) is the objective function improvement predicted using the regression model. The numerator is calculated using $U_Y^{\#(i)}$, defined as in Section II.*C* but using the feature-based model $\boldsymbol{L}_P^{\#(i)}$, in which the coefficient vector $[l_{0.1} \ldots l_{0.Np}]^T$ is replaced by $\boldsymbol{P}(\boldsymbol{x}^{(i+1)})$, extracted from EM simulation data at $\boldsymbol{x}^{(i+1)}$. Using $U_Y^{\#(i)}$ is a cheap yet approximate way of validating $\boldsymbol{x}^{(i+1)}$ (only one EM analysis is involved).

The vector $\boldsymbol{x}^{(i+1)}$ is accepted if $r > 0$. Otherwise, the iteration is repeated with a reduced $d^{(i)}$. The termination condition is $\|\boldsymbol{x}^{(i+1)} - \boldsymbol{x}^{(i)}\| < \varepsilon$ (convergence in argument) OR $d(i) < \varepsilon$ (reducing the TR radius), with $\varepsilon = 10^{-3}$.

III. VERIFICATION CASE STUDY

For the sake of illustration, consider an upper UWB-band microstrip filter shown in Fig. 3 [18], and implemented on RO4003C substrate ($\varepsilon_r = 3.55$, $h = 0.305$ mm); $W_0 = 0.66$ mm. The performance specifications are to ensure $|S_{11}| \leq -15$ dB for the operating band from 5.8 GHz to 10.6 GHz. The design parameters are $\boldsymbol{x} = [L_1\ L_2\ L_3\ W_1\ W_2\ W_3]^T$, whereas the nominal design (optimized to minimize the in-band reflection level) is $\boldsymbol{x}^{(0)} = [4.25\ 5.20\ 4.04\ 6.69\ 1.07\ 0.47]^T$.

The procedure of Section II has been applied to maximize the input tolerance level (represented by the variance σ) so that 100-percent fabrication yields is still ensured. The final design obtained through optimization is $\boldsymbol{x}^* = [4.24\ 5.17\ 4.02\ 6.71\ 1.06\ 0.47]^T$. Table 1 provides numerical data concerning the acceptable tolerance levels at the nominal design and upon optimization. It can be observed that the improvement factor is almost 1.6. At the same time, the CPU cost of the robustness enhancement process is only 40 EM analyses of the circuit.

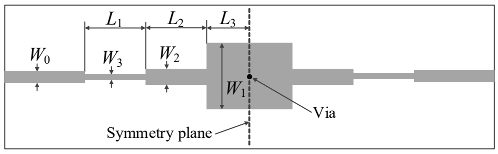

Fig. 3. Verification circuit: ultra-wideband (UWB) filter using stepped-impedance resonator [13].

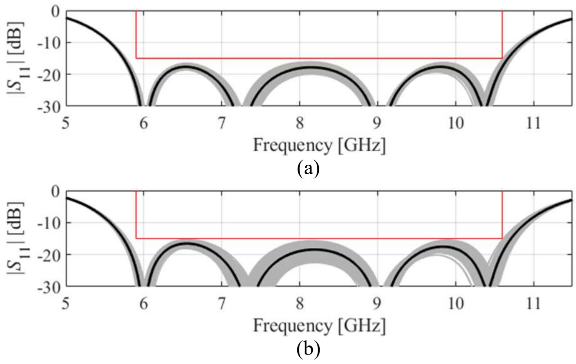

Fig. 4. EM-driven Monte Carlo analysis of the circuit of Fig. 2: (a) nominal design, (b) design found using the proposed algorithm. Black plots represent the circuit responses at the nominal and the optimized designs, respectively, gray plots stand for EM data at the random observables generated during the MC analysis.

Table 1. Robustness enhancement results.

Nominal design	Maximum variance σ ensuring 100-percent yield[@]	5.6 μm
	Maximum parameter deviations ensuring 100% yield	16.7 μm
	EM-based yield estimation[#]	100 %
Tolerance-optimized design	Maximum variance σ ensuring 100-percent yield[@]	8.7 μm
	Maximum parameter deviations ensuring 100% yield	26.1 μm
	EM-based yield estimation[#]	100 %
Optimization cost[$]		40

[@] σ refers to the variance of the independent zero-mean Gaussian distributions assumed to describe the fabrication tolerances. Maximum parameter deviations are assumed to be 3σ.
[#] Estimation obtained using Monte Carlo simulation based on 500 random samples.
[$] Optimization cost in terms of the number of EM analyses of the circuit under design.

Figure 4 shows visualization of the Monte Carlo simulation at the nominal and the robust design. Note a considerable enlargement in the spread of circuit responses corresponding to random observables, which indicates an improved immunity of the circuit to geometry parameter deviations.

IV. CONCLUSION

This paper proposed a novel approach to cost-efficient robustness enhancement of microwave passives. Our technique relies on fast feature-based regression surrogates. It allows for maximizing the input tolerance levels ensuring perfect fabrication yield at low CPU expenses, corresponding to a few dozen EM simulations of the circuit at hand.

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