Topology-Agnostic Antennas: Surrogate-Assisted Optimization of Fabrication Yield in a Distributed Setup

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Abstract. Maximization of yield is essential for reducing the cost of *en masse* manufactured antennas. Conventional approaches to the problem, based on Monte Carlo (MC) analysis, are impractical due to overwhelming cost associated with simulations of modern structures. In this work, a surrogate-assisted optimization of yield for multi-dimensional antennas is considered. The method shifts expensive MC to an approximation surrogate that is iteratively re-set in the course of optimization. The algorithm embeds a mechanism for automatic tuning of yield for nominal designs that violate the specifications. The method has been demonstrated using two topology-agnostic radiators represented using 22 and 52 parameters, respectively. To ensure low optimization cost (time-wise) training designs for surrogate identification are evaluated using an in-house distributed computing system. The maximized yields for both considered antenna designs amount to 97% and 79%, respectively. Validation of the results against yield estimated based on direct EM simulations is also provided.

Keywords: topology-agnostic antennas, distributed computing, yield optimization, surrogate-based methods, Monte Carlo.

1 Introduction

Antenna design is a challenging task that involves determination of topology and its tuning in order to fulfill the performance requirements. An additional step of the process—crucial for *en masse* manufacturing—involves evaluation of sensitivity to tolerances, i.e., small, random deviations of the optimized (also referred to as nominal) structure dimensions that stem from the fabrication processes [1]. Sensitivity of nominal design to tolerances might result in violation of specifications. The undesirable outcome is reduced yield and increased production cost (due to waste of resources used for fabrication of components that violate requirements and thus are rejected).

Yield can be estimated using geometrical methods, or approaches based on Monte Carlo (MC) simulations [2]-[5]. The latter boil down to performance evaluation for a

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large set of random perturbations w.r.t. the nominal design. Yield represents a ratio of designs that fulfill specifications to all samples [3]. Geometrical methods generate convex approximations to a feasible region of the search space (i.e., where specifications are met) [4]. Shifting the nominal design to the center of such region maximizes yield [5]. Unfortunately, these approaches require thousands of simulations for accuracy. which is impractical for modern antennas that can be evaluated only using numerically expensive electromagnetic (EM) simulations [4]. Cost-acceptable alternative involves worst-case analysis which, however, is overly pessimistic [6].

The cost of yield optimization can be reduced using surrogate methods [3], [4], [7], [8]. The latter shift the burden associated with antenna EM simulations to cheap, iteratively updated models [3], [7]. Surrogate-based optimization coupled with geometric and/or MC-based techniques proved to be useful for maximization of yield at a manageable cost. In [4], a cost-efficient design centering based on space mapping enhanced data-driven model has been proposed. In [3], yield optimization has been performed by shifting MC analyses to iteratively re-set feature-based models. Owing to less non-linear mapping between geometry and structure performance, feature models can be constructed using a low number of samples. A variant of the technique, where the surrogate is derived from low-fidelity simulations, has been presented in [9]. Despite proved usefulness, all the considered techniques have been validated using structures with well-defined, low-dimensional topologies.

Recently, an increased effort towards generation of antennas without engineering inference can be observed [10]. In such a setup, topology development is formulated as a specification-oriented optimization problem, which represents a significant departure from cognitive, experience-driven approaches. It has been demonstrated that the approach is useful for generation of high-performance radiators with non-intuitive geometries [10]. Evaluation of the effects of manufacturing tolerances on performance of topology-agnostic structures is difficult. The main problem is representation of geometries using dozens of parameters, as well as unknown relations between them. From this perspective, the problem associated with yield optimization for such structures remains open.

In this work, a cost-aware optimization of topology-agnostic antennas for maximization of fabrication yield is considered. The method involves a series of local optimizations where MC analyses are shifted to feature-based data-driven models. The latter are re-set after each iteration around the best nominal design. To enable optimization from infeasible nominal designs (i.e., the ones for which none of the perturbed solutions fulfills the defined specifications), the algorithm embeds a mechanism that adjusts the threshold for calculation of yield. The framework has been demonstrated using two topology-agnostic radiators with 22 and 52 design parameters, respectively. The computational cost (time-wise) associated with evaluation of the samples required for feature models identification has been reduced using distributed EM simulations. The method has been compared in terms of cost and accuracy against direct EM-based MC performed at the optimized nominal designs. Overall, nearly 21000 EM simulations (associated with ~10 days of CPU-time) have been performed to generate the results. Error for the estimated yield obtained using the discussed surrogate method is below 4% of the direct estimation based on EM simulations.

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2 Methodology

2.1 Problem Formulation

Let $\boldsymbol{R}(\boldsymbol{x}_0)$ be the reflection response obtained (over the frequency $\boldsymbol{f}$) from EM simulation of the topology-agnostic antenna model at the nominal design $\boldsymbol{x}_0$. Then, let $\boldsymbol{X} = \delta_0\{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_m\}$ and $U(\boldsymbol{x}) = U(\boldsymbol{R}(\boldsymbol{x}))$ be a set of $m = 1, \ldots, M$ random designs generated according to the assumed probability distribution and scaled w.r.t. δ_0 and the objective function. The manufacturing yield is a ratio of designs that met the specifications to all perturbations around $\boldsymbol{x}_0$. It is given as follows [3]:

$$Y\left(\boldsymbol{x}_0, \boldsymbol{X}\right) = \frac{1}{M}\sum_{m=1}^{M} H\left(U\left(\boldsymbol{x}_0 + \delta \boldsymbol{x}_m\right)\right) \tag{1}$$

Note that $H(\boldsymbol{x}) = H(U(\boldsymbol{x})) = 1$ when $U(\boldsymbol{x}) \leq U_0$ (i.e., when $U_0 = 0$, the specifications are fulfilled); otherwise, $H(\boldsymbol{x}) = 0$. Note that the accuracy of MC-based yield depends on the number M of evaluated random designs (preferably, hundreds or thousands), which is impractical when EM antenna models are used.

The problem pertinent to unacceptable computational cost can be mitigated by shifting the burden associated with MC to a cheap data-driven surrogate constructed around $\boldsymbol{x}_0$ using a limited number of EM-based training samples.

2.2 Representation of Antenna Characteristics Using Response Features

The accuracy of surrogate-assisted yield estimation is subject to fidelity of data-driven model used for MC simulations. For topology-agnostic antennas, the frequency responses are highly non-linear functions of geometry [10]. Given that the considered structures are characterized by dozens of parameters, a large number of training samples would be needed for construction of accurate frequency-based models. Instead, the antenna behavior can be represented in the form of carefully selected features. In such a setup, the properties are first extracted from the frequency responses of training designs and then used for identification of auxiliary data-driven surrogate.

Let $\boldsymbol{F} = \boldsymbol{F}(\boldsymbol{x}) = P(\boldsymbol{R}(\boldsymbol{x}))$ be the feature-based antenna response extracted using function P. The matrix $\boldsymbol{F} = [\boldsymbol{\omega}\ \boldsymbol{L}]^T$ comprises $q = 1, \ldots, Q$ pairs of frequency- and level-related points $\boldsymbol{\omega} = [\omega_1 \ldots \omega_q]^T$ and $\boldsymbol{L} = [L_1 \ldots L_q]^T$. Each pair can be extracted either w.r.t. selected frequency point, or reflection level. Compared to $\boldsymbol{R}(\boldsymbol{x})$, $\boldsymbol{F}(\boldsymbol{x})$ is much less non-linear function of design parameters. Hence, response features are useful for construction of a simple, yet accurate approximation models (see Fig. 1). For more detailed discussion on the concept, see [1], [9], [11].

2.3 Distributed Framework for Feature-Assisted Yield Estimation

To ensure cost-efficient evaluation of yield, MC analyses are executed using a second order polynomial model. Let $\boldsymbol{X}_t = [\boldsymbol{x}_{t.0}\ \boldsymbol{x}_{t.1} \ldots \boldsymbol{x}_{t.n}]$, $n = 0, 1, \ldots, 2D$, be a $D \times N$ matrix of training designs ($N = 2D + 1$, where D is the number of antenna geometry parameters). When $n = 2d$ ($d = 1, \ldots, D$), the vector $\boldsymbol{x}_{t.n} = \boldsymbol{x}_0 - \boldsymbol{\delta}_d$, whereas for $n = 2d - 1$, $\boldsymbol{x}_{t.n}$

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$= \boldsymbol{x}_0 + \boldsymbol{\delta}_d$; $\boldsymbol{x}_{t.0} = \boldsymbol{x}_0$. The elements of $\boldsymbol{\delta}_d$ are zero for all but dth parameter, i.e., $\boldsymbol{\delta}_d = [\delta_1 \ldots \delta_d \ldots \delta_D]^T = [0 \ldots \delta \ldots 0]^T$ (δ is the user-defined) [3], [9]. The surrogate is a composition of models defined according to frequency and level features: $\boldsymbol{G} = [\boldsymbol{G}_\omega\ \boldsymbol{G}_L] = [\boldsymbol{G}_\omega(\boldsymbol{x})\ \boldsymbol{G}_L(\boldsymbol{x})]$. Let $\boldsymbol{A}_\omega$ be the matrix of polynomial model $\boldsymbol{G}_\omega(\boldsymbol{x})$ coefficients given as:

$$\boldsymbol{A}_\omega = \begin{bmatrix} \boldsymbol{\alpha}_0 & \boldsymbol{\alpha}_1 & \cdots & \boldsymbol{\alpha}_n \end{bmatrix} = \begin{bmatrix} \alpha_{1.0} & \cdots & \alpha_{1.n} \\ \vdots & \ddots & \vdots \\ \alpha_{q.0} & \cdots & \alpha_{q.n} \end{bmatrix} \tag{2}$$

Also, let $\boldsymbol{\alpha}_q = [\alpha_{q.0}\ \alpha_{q.1} \ldots \alpha_{q.n}]$ be a vector that represents qth row of $\boldsymbol{A}_\omega$ obtained as $\boldsymbol{\alpha}_q = \boldsymbol{\beta}\boldsymbol{\omega}_q$, where $\boldsymbol{\omega}_q = [\omega_{q.0}\ \omega_{q.1} \ldots \omega_{q.n}]^T = [\omega_q(\boldsymbol{x}_{t.0})\ \omega_q(\boldsymbol{x}_{t.1}) \ldots \omega_q(\boldsymbol{x}_{t.n})]^T$ is a vector containing qth feature points extracted from EM-based responses of training designs from $\boldsymbol{X}_t$; $\boldsymbol{\beta} = (\boldsymbol{V}^T\boldsymbol{V})^{+}\boldsymbol{V}^T$ and $\boldsymbol{V}$ is a Vandermonde matrix constructed from $\boldsymbol{X}_t$ (note that "$+$" is a pseudo-inverse). The surrogate response at $\boldsymbol{x}$ (constrained to the $\boldsymbol{l}_b = -\boldsymbol{1}^T\delta$, $\boldsymbol{u}_b = \boldsymbol{1}^T\delta$ bounds, where $\boldsymbol{1}^T$ is a D-dimensional vector of ones) is given as:

$$\boldsymbol{G}_\omega(\boldsymbol{x}) = \boldsymbol{\alpha}_{\omega.1} + \boldsymbol{x}^T\boldsymbol{\alpha}_{\omega.2} + (\boldsymbol{x} \circ \boldsymbol{x})^T \boldsymbol{\alpha}_{\omega.3} \tag{3}$$

The coefficients in (3) are extracted from columns of $\boldsymbol{A}_\omega$ as $\boldsymbol{\alpha}_{\omega.1} = \boldsymbol{\alpha}_0 = [\alpha_{1.0} \ldots \alpha_{q.0}]^T$, $\boldsymbol{\alpha}_{\omega.2} = [\boldsymbol{\alpha}_1 \ldots \boldsymbol{\alpha}_{n1}]$, and $\boldsymbol{\alpha}_{\omega.0} = [\boldsymbol{\alpha}_{n1+1} \ldots \boldsymbol{\alpha}_{n2}]$, respectively. Note that $n_1 = D$, $n_2 = 2D$, whereas the symbol "$\circ$" in (3) is a Hadamard product. The model $\boldsymbol{G}_L(\boldsymbol{x})$ is derived accordingly. Finally, the surrogate is used to obtain $\boldsymbol{G}(\boldsymbol{x}_0 + \delta_0\boldsymbol{x}_m)$ response features for all $\boldsymbol{x}_m \in \boldsymbol{X}$ designs (cf. Section 2.1). The responses are then evaluated using (1)—with $U(\boldsymbol{x}) = U(\boldsymbol{G}(\boldsymbol{x}))$—to provide approximated yield at $\boldsymbol{x}_0$ design.

As indicated above, identification of polynomial model coefficients $\boldsymbol{A}_\omega$ (and $\boldsymbol{A}_L$) involves EM simulations of the antenna at nominal design $\boldsymbol{x}_0$ and $2D$ perturbations around it. For multi-dimensional structures (as in this work), the cost associated with sequential evaluation of $\boldsymbol{X}_t$ can be inacceptable. Here, the problem is mitigated through parallelization of EM simulations using an in-house developed distributed computing system that comprises a few heterogenic nodes (machines) with EM simulation software. The system implements a client-server architecture. For construction of model $\boldsymbol{G}$, the server generates a set of N simulation packages (one for each $\boldsymbol{x}_{t.n} \in \boldsymbol{X}_t$ design) and uploads them to a shared repository. The latter is accessed by the clients which download data, evaluate the design and send the responses back to the repository. Finally, the server aggregates the designs and EM responses within a common database. The computational speed-up resulting from the use of the outlined distributed system is proportional to the number of nodes. In practice, it is bounded from above by the number of available licenses for the EM-simulation software.

2.4 Yield Optimization Algorithm

Let $Y_S(\boldsymbol{x}_0, \boldsymbol{X}) = Y_S(\boldsymbol{x}_0, \boldsymbol{X}, U_0)$ be the yield obtained using the feature-based surrogate model of Section 2.3. Now, let $\boldsymbol{U}_X = [U(\boldsymbol{G}^{(i)}(\boldsymbol{x}^{(i)} + \delta_0\boldsymbol{x}_1)) \ldots U(\boldsymbol{G}^{(i)}(\boldsymbol{x}^{(i)} + \delta_0\boldsymbol{x}_m))]$ be a vector of objective function responses obtained for all $\boldsymbol{X}$ perturbations around $\boldsymbol{x}^{(i)}$;

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$U_{X.l} = \min(\boldsymbol{U}_X)$ and $U_{X.u} = \max(\boldsymbol{U}_X)$. The optimization involves iterative ($i = 0, 1, \ldots$) tuning of the nominal design to maximize the yield by solving [3]:

$$\boldsymbol{x}^{(i+1)} = \arg\min_{\boldsymbol{x}} \left(-Y_S^{(i)} \left(\boldsymbol{x}^{(i)}, \boldsymbol{X} \right) \right) \quad (4)$$

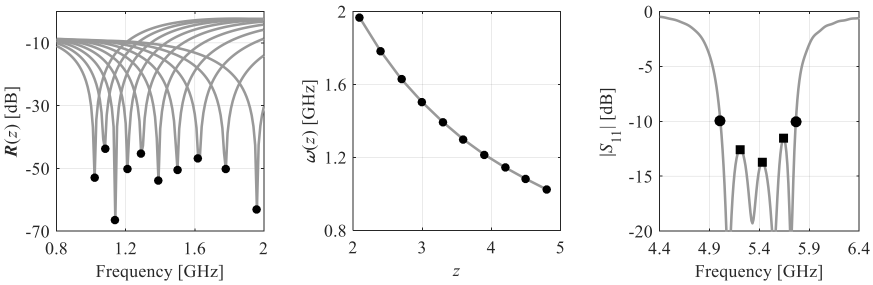
where $Y_S^{(i)}$ is obtained from the $\boldsymbol{G}^{(i)}$ responses. The algorithm is as follows:

1. Set $i = 0$, $\boldsymbol{x}^{(i)} = \boldsymbol{x}_0$, $\delta = 2\delta_0$, $U_0 = 0$ and generate $\boldsymbol{X}$;
2. Generate $\boldsymbol{G}^{(i)}$ model around $\boldsymbol{x}^{(i)}$ design as explained in Section 2.3;
3. Set $E^{(i)} = -Y_S(\boldsymbol{x}^{(i)}, \boldsymbol{X})$; If $E^{(i)} = 0$, go to Step 4; otherwise go to Step 5;
4. Calculate $U_{X.l}^{(i)}$, $U_{X.u}^{(i)}$, and find $U_0 = U_0(\gamma)$ that shifts yield according to Y_0;
5. If $i > 0$, $E^{(i)} < 0$, $E^{(i-1)} \leq E^{(i)}$, set $\boldsymbol{x}_0^* = \boldsymbol{x}^{(i-1)}$ and END; otherwise go to Step 6;
6. Generate $\boldsymbol{x}^{(i+1)}$ by solving (4), set $U_0 = 0$, $i = i + 1$, and go to Step 2.

It should be reiterated that $U_0(\gamma) = \gamma U_{X.u}^{(i)} + (1 - \gamma)U_{X.l}^{(i)}$ in Step 4 is identified only if $E^{(i)} = 0$, i.e., when all perturbations around currently best design $\boldsymbol{x}^{(i)}$ violate the performance specifications. The coefficient γ is obtained by solving:

$$\gamma^* = \arg\min_{\gamma} \left(\left| Y_S \left(\boldsymbol{x}^{(i)}, \boldsymbol{X}, U_0(\gamma) \right) - Y_0 \right| \right) \quad (5)$$

Here, $Y_0 = 0.3$ is selected as target value. The consequence of adjusting U_0 using (5) is that yield can be minimized using (4) even from the nominal designs that violate the specifications. The latter might be the case, e.g., for structures with highly selective responses. The method, however, should not be considered as a generic yield-oriented optimization from poor starting points as it does not embed mechanisms for adjusting $\boldsymbol{X}_t$ perturbations used for construction of $\boldsymbol{G}^{(i)}$ surrogate. At each iteration, nominal design is tuned within $\boldsymbol{l}_{b0} = -\boldsymbol{1}^T\delta_0$, $\boldsymbol{u}_{b0} = \boldsymbol{1}^T\delta_0$ bounds. Also, given that $\boldsymbol{G}^{(i)}$ is constrained to a $\delta = 2\delta_0$ range around $\boldsymbol{x}^{(i)}$, evaluation of $\boldsymbol{x}^{(i)} + \boldsymbol{X}$ does not involve extrapolation. For conceptual illustration of yield optimization, see Fig. 2.



(a) (b) (c)

Fig. 1. Feature-assisted design: (a) frequency and (b) feature responses as a function of some parameter z [10], as well as (c) features ($Q = 5$) extracted from the frequency data (—) that represent response levels (■) at local maxima and frequencies in GHz (●) at bandwidth edges (defined at –10 dB level). Note that changes of $\boldsymbol{\omega}(z)$ are much less non-linear compared to $\boldsymbol{R}(z)$.

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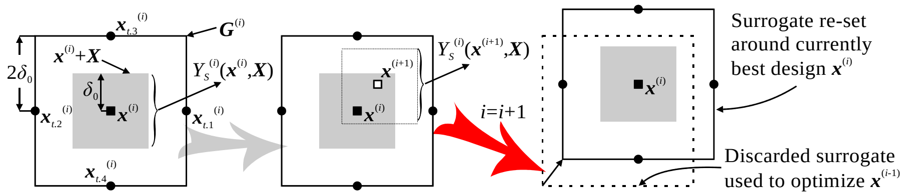

Fig. 2. Surrogate-based yield optimization at *i*th algorithm iteration: a conceptual illustration.

3 Results

The considered yield optimization methodology is demonstrated using two topology-agnostic antennas represented using 22 and 52 independent design parameters, respectively. For each antenna, the numerical experiments are performed using a total of M = 10000 random designs with Gaussian distribution (σ = 0.03). The scale for perturbations is set to $\delta_0 = 3\sigma$ [3], [9]. A comparison of manufacturing yield calculated, for the optimized nominal designs, using surrogate model and directly from EM simulations is also provided. A total of five nodes have been used to perform distributed computations. Note that the number is limited by availability of licenses for EM simulation software.

3.1 Antenna Model

Consider a topology-agnostic planar antenna of Fig. 3(a) [10]. It is implemented on a Rogers AD255C substrate (ε_r = 2.55, h = 1.52 mm). The radiator is in the form of a polygon fed through a concentric probe. The antenna is defined by a D-dimensional vector $\boldsymbol{x}$ = $[x_{c.1}\ y_{c.1}\ x_{c.2}\ \ldots\ x_{c.D/2}\ y_{c.2}\ \ldots\ y_{c.D/2}]^T$ comprising xy coordinates of points defined in a Cartesian system (here, D is set to 22 and 52 for the first and second test case, respectively). Parameters: o = 5, r_1 = 1.27, and r_2 = 2.84 are fixed (all dimensions are in mm); B = 2(max(|$\boldsymbol{x}$|) + o). The antenna is implemented in CST Microwave Studio. The EM model $\boldsymbol{R}$ is discretized using ~400,000 cells and computational cost (averaged across the available distributed nodes) amounts to 200 s. The objective function is defined as $U = \max(\{U_1, U_2, U_3\})$, where $U_1 = \max([L_2\ \ldots\ L_{Q-1}]) - L_{\rm thd}$, $U_2 = \omega_1 - f_L$, $U_3 = f_H - \omega_Q$ (cf. Section 2.2). The feature coordinates used to represent the structure performance are specified w.r.t. levels at local maxima located between corner frequencies specified at the target level of $L_{\rm thd}$ = –10 dB (see Fig. 1(c) for illustration).

3.2 Topology-Agnostic WiFi Antenna

Consider a WiFi antenna (cf. Fig. 3(b)) defined using a 22-parameter nominal design $\boldsymbol{x}_0$ = [–0.17 –1.88 6.89 13.18 –4.22 –4.34 –22.75 –12.31 –3.31 7.83 22.75 6.89 –0.67 14.08 19.45 7.92 0.74 –15.99 –7.30 –19.45 –7.25 –0.67]^T. The corner frequencies are f_L = 5.25 GHz and f_H = 5.85 GHz. The initial design violates the requirements (see Fig. 3(b)), hence $Y_S(\boldsymbol{x}_0, \boldsymbol{X}) = 0$. The optimized nominal design $\boldsymbol{x}_0^*$ = [–0.28 –1.74 6.76 12.96 –3.73 –4.25 –22.43 –12.61 –3.62 7.16 22.43 6.76 –0.61 14.07 19.32 7.80 1.15 –15.4 –7.21 –

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19.32 –8.03 –0.61]^T is obtained after 8 iterations of the algorithm (cf. Section 2.4). Note that the first 3 steps are associated with shifting the design w.r.t. the specifications. The final yield is $Y_S(\boldsymbol{x}_0^*, \boldsymbol{X}) = 0.966$. The computational cost of optimization corresponds to 344 EM simulation (~3.8 hours of CPU-time using all available nodes). For the sake of comparison, EM-based evaluations of all $\boldsymbol{X}$ perturbations around $\boldsymbol{x}_0^*$ are also performed for direct estimation of yield. The final response is $Y(\boldsymbol{x}_0^*, \boldsymbol{X}) = 0.989$, which represents a 2.3% discrepancy w.r.t. $Y_S(\boldsymbol{x}_0^*, \boldsymbol{X})$. Note that direct yield evaluation required 10000 EM simulations (~111.1 hours of CPU-time, or over 4.6 days for all nodes). Given that EM-driven minimization of (4) is infeasible as it would require evaluations of (1) per iteration, the algorithm of Section 2.4 offers acceptable accuracy. Responses at $\boldsymbol{x}_0$, $\boldsymbol{x}_0^*$, and selected perturbations around $\boldsymbol{x}_0^*$ (feature- and frequency-based) are shown in Fig. 3(b).

3.3 Topology-Agnostic UWB Antenna

Consider ultra-wideband antenna (cf. Fig. 3(c)) design: $\boldsymbol{x}_0$ = [–0.06 –10.06 11.81 14.77 17.36 11.01 4.11 –1.92 –6.66 –9.14 –7.51 –11.09 –13.72 –12.47 –10.4 –10.87 –15.57 –17.36 –13.03 –6.32 –0.96 4.79 10.27 15.04 16.36 14.93 11.81 0.36 4.71 7.12 11.13 11.42 11.58 14.77 17.52 9.71 11.14 12.61 8.37 1.93 –2.63 –5.4 –8.7 –13.38 –13.24 –13.45 –17.52 –17.38 –16.84 –10.87 –5.02 0.36]^T. The yield is to be maximized within f_L = 5.95 GHz to f_H = 7.05 GHz, hence $\boldsymbol{x}_0$ violates specifications. The design $\boldsymbol{x}_0^*$ = [–0.14 –9.98 11.80 14.93 17.47 11.27 4.25 –1.78 –6.46 –8.88 –7.54 –10.92 –13.68 –12.43 –10.28 –10.72 –15.65 –17.47 –13.12 –6.27 –0.83 4.95 10.43 15.26 16.48 15.19 11.8 0.4 4.47 7.1 11.17 11.44 11.5 14.89 17.5 9.8 11.35 12.83 8.4 2.06 –2.69 –5.31 –8.75 –13.47 –13.09 –13.45 –17.51 –17.44 –16.9 –10.82 –4.96 0.4]^T is obtained after just 4 iterations (420 EM simulations; ~4.7 hours of CPU-time). The obtained yield is $Y_S(\boldsymbol{x}_0^*, \boldsymbol{X}) = 0.793$ which represents 3.6% discrepancy w.r.t. $Y(\boldsymbol{x}_0^*, \boldsymbol{X}) = 0.829$ (obtained based on 10000 EM simulations). Responses at $\boldsymbol{x}_0$, $\boldsymbol{x}_0^*$ and perturbations around $\boldsymbol{x}_0^*$ are shown in Fig. 3(c).

4 Conclusion

In this work, a surrogate-assisted yield optimization of topology-agnostic antennas has been considered. The algorithm sequentially generates feature-based data-driven surrogate that are used for local maximization of yield through a series of MC analyses that involve evaluations of random designs with the assumed probability distribution. To ensure acceptable cost of optimization for multi-parameter designs, generation of training designs for feature-based surrogates is handled by a distributed computing system. To enable optimization from designs that violate specifications, the algorithm embeds the mechanism that adjusts the threshold for yield evaluation. The method has been demonstrated based on two topology-agnostic patch antennas represented using 22 and 52 parameters, respectively. For the considered structures, the optimized yields of around 97% and 79% have been obtained, which represents up to 3.6% (more pessimistic) deviation from direct estimation. The cost of surrogate-assisted yield optimization is less than 5 hours of CPU-time per structure (two-fold lower compared to EM-based yield estimation around just a single nominal design).

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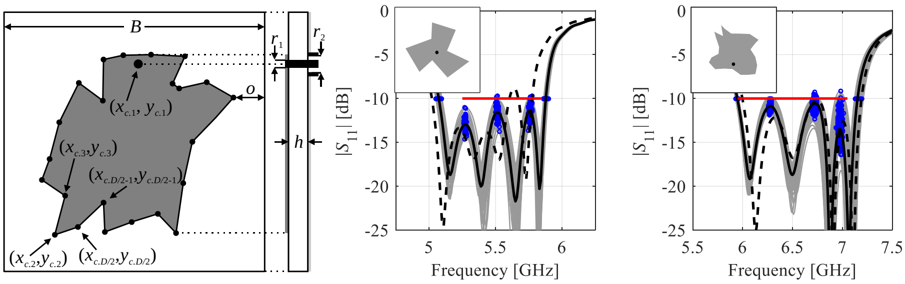

(a) (b) (c)

Fig. 3. Topology-agnostic radiator: (a) geometry with highlight on coordinates (●), as well as responses at $\boldsymbol{x}_0$ (– –), $\boldsymbol{x}_0^*$ (—), EM-based (gray), and feature-based (○) MC perturbations around $\boldsymbol{x}_0^*$ obtained for antennas with: (b) 22 (Section 3.2), and (b) 55 parameters (Section 3.3).

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