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Parallel Space-Mapping Based Yield-Driven EM Optimization Incorporating Trust Region Algorithm and Polynomial Chaos Expansion

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ABSTRACT Space mapping (SM) methodology has been recognized as a powerful tool for accelerating electromagnetic (EM)-based yield optimization. This paper proposes a novel parallel space-mapping based yield-driven EM optimization technique incorporating trust region algorithm and polynomial chaos expansion (PCE). In this technique, a novel trust region algorithm is proposed to increase the robustness of the SM surrogate in each iteration during yield optimization. The proposed algorithm updates the trust radius of each design parameter based on the effectiveness of minimizing the l_1 objective function using the surrogate, thereby increasing the robustness of the SM surrogate. Moreover, for the first time, parallel computation method is incorporated into SM-based yield-driven design to accelerate the overall yield optimization process of microwave structures. The use of parallel computation allows the surrogate developed in the proposed technique to be valid in a larger neighborhood than that in standard SM, consequently increasing the speed of finding the optimal yield solution in SM-based yield-driven design. Lastly, the PCE approach is incorporated into the proposed technique to further speed up yield verification on the fine model. Compared with the standard SM-based yield optimization technique with sequential computation, the proposed technique achieves a higher yield increase with shorter CPU time by reducing the number of SM iterations. The proposed technique is illustrated by two microwave examples.

INDEX TERMS Electromagnetic optimization, parallel computation, polynomial chaos expansion, space mapping, trust region, yield optimization.

I. INTRODUCTION

Yield optimization, also called design centering, is an optimization process that aims to find a nominal design solution with the maximum yield [1]. Direct electromagnetic (EM)-based yield optimization does not appear to be feasible as a significantly large number of EM simulations are typically required during the whole optimization process [2]. As a recognized engineering optimization methodology, space

mapping (SM) holds a great potential to accelerate yield-driven EM optimization [3]–[5]. The basic concept of SM is to replace EM-based fine models with fast yet not so accurate coarse models and calibrate the coarse models with certain mapping (linear or nonlinear) structures in each iteration during optimization. Such mapping structures construct a mathematical link between a coarse model and a fine model. Through SM, the original CPU-intensive evaluations on the fine model are replaced by fast computations on the coarse model, while the accuracy of the fine model is still maintained [3].

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In the last two decades, a great amount of research efforts have been devoted to developing SM-based approaches to facilitate yield optimization of microwave structures [6], [11]. For example, neural space-mapping models have been exploited in [6] to perform EM-based yield optimization efficiently. The sensitivity formulas of the surrogate model responses have also been derived, which are then used in approximating the sensitivities of the fine model responses. In [7], a tuning space-mapping surrogate based yield estimation and optimization technique has been presented. The responses of the surrogate are further corrected to obtain improved yield accuracy, facilitating the overall yield optimization process. However, in these two methods, the SM surrogate is not updated during yield optimization, which means that a large amount of EM data are required to train the surrogate to be valid in a large region. Some other research works exist in the literature that update the SM surrogate in each iteration during yield optimization. For example, in [8], a modified ellipsoidal technique has been incorporated into space mapping and then applied to the yield optimization problem of microwave circuits. The mapping structure between coarse and fine models is updated iteratively in yield optimization using the EM responses at all the nominal points in the preceding iterations. In [9], a derivative-free trust region approach has been presented to maximize the yield of microwave circuits, where the generalized SM surrogate is used and updated at each SM iteration in yield optimization. For both [8] and [9], Jacobian matrices of the fine model responses are also used in the parameter extraction process to enhance the accuracy of the surrogate model. Recently, SM approaches exploiting response features have also been investigated with the objective of achieving more efficient yield estimation and/or optimization of microwave structures [10], [11].

All the aforementioned SM-based methods do not use parallel computation, which holds a great potential to speed up EM design optimization. Parallel computation is an efficient technique to speed up EM optimization by accelerating EM data generation [12] and surrogate model training [13]. Recently, a parallel SM approach has been presented in [14], where the parallel computation mechanism has been combined with SM, to facilitate EM-based nominal optimization. It has been shown that with parallel computation, the SM surrogate can be trained to be valid in a relatively larger neighborhood and the optimal nominal design can be obtained in shorter time and fewer SM iterations [14].

Yield estimation is an indispensable component of yield optimization. Traditional Monte Carlo (MC) method for EM-based yield estimation is computationally expensive as a large number of EM simulations are required to achieve desired yield estimation accuracy. Recently, the polynomial chaos expansion (PCE) approach [15] has emerged as a powerful tool for statistical analysis and yield estimation in microwave design [16]–[20]. Existing studies have shown that PCE has significant benefits over the traditional Monte Carlo analysis in terms of reduced computational costs and shorter

CPU time for yield estimation of microwave structures [20]. In [2], a PCE-based approach has been presented to solve the challenging problem of EM-based yield optimization. In this paper, we explore the possibility of combining SM and PCE to solve the EM-based yield optimization problem.

This paper proposes a novel parallel space-mapping based yield-driven EM optimization technique incorporating trust region algorithm and PCE. In this technique, a novel trust region algorithm designed specifically for EM-based yield-driven design is proposed to increase the robustness of the SM surrogate. The proposed algorithm updates the trust radius of each design parameter in each SM iteration based on the effectiveness of minimizing the l_1 objective function using the surrogate. Moreover, for the first time, we incorporate the parallel computation method to SM-based yield optimization of microwave structures. Specifically, parallel computation method is used to generate fine model EM responses at multiple geometrical samples simultaneously and to train the surrogate model to match the fine model over multiple geometrical samples. The use of parallel computation allows the surrogate to be trained in a larger neighborhood in the design parameter space than that in standard SM, consequently increasing the speed of finding the optimal yield solution in yield-driven design. Lastly, we propose to incorporate the PCE approach, which is an efficient alternative method for EM-based yield estimation, into the proposed technique to further accelerate the overall yield optimization process. Compared with the standard SM-based yield optimization technique, the proposed technique reduces the number of SM iterations to achieve a desired yield value, thereby accelerating the overall EM-based yield optimization process.

This paper is organized as follows. In Section II, we review the formulations of the original EM-based yield optimization problem. In Section III, the proposed parallel space-mapping based yield optimization technique is presented in detail. In Section IV, we perform yield optimization on two microwave examples to demonstrate the advantages of the proposed technique. In Section V, we conclude the paper.

II. FORMULATION OF THE ORIGINAL EM-BASED YIELD OPTIMIZATION PROBLEM

Let \mathbf{x} be a n -dimensional vector containing n design parameters (e.g., geometrical/physical parameters) of the microwave structure under consideration. Let \mathbf{x}^0 denote the nominal point of \mathbf{x} . In the approaches to statistical design of microwave structures, the uncertainties introduced by the manufacturing process make the actual values of \mathbf{x} be distributed around \mathbf{x}^0 . The distribution is usually considered to follow some kind of distribution, e.g., uniform, Gaussian, etc.

Microwave design typically involves goals in terms of a number of design specifications applied on the responses of microwave structures. In practice, the design specifications are sampled at a number of frequency points in the whole frequency bands of interest. Let N_s denote the total number of design specification samples, which usually consist of both the upper and the lower ones. Let the j th design specification

sample be denoted by S_j , where $j = 1, \dots, N_s$. Let N_s^u and N_s^l ($N_s^l = N_s - N_s^u$) be the number of upper specification samples and the number of lower specification samples, respectively. Without the loss of generality, we assume that the first N_s^u samples, $S_1, \dots, S_{N_s^u}$, represent upper design specification samples, and that the remaining N_s^l samples, $S_{N_s^u+1}, \dots, S_{N_s}$, are lower design specification samples. Let $R_j^f(\mathbf{x})$ represent the response of the fine model at the frequency of interest corresponding to S_j . Let $\mathbf{e}(\mathbf{x})$ be an error vector used to indicate how well the response vector of the fine model satisfies the design specifications. Specifically, $\mathbf{e}(\mathbf{x})$ is defined as follows:

$$\mathbf{e}(\mathbf{x}) = [e_1 \ e_2 \ \dots \ e_{N_s^u} \ \dots \ e_{N_s}]^T, \quad (1)$$

where the j th element in the above vector, $e_j(\mathbf{x})$, is given by

$$e_j(\mathbf{x}) = \begin{cases} R_j^f(\mathbf{x}) - S_j, & \text{if } 1 \leq j \leq N_s^u, \\ S_j - R_j^f(\mathbf{x}), & \text{if } N_s^u < j \leq N_s. \end{cases} \quad (2)$$

Yield refers to the percentage of non-defective designs of all produced designs. To realize EM-based yield analysis and optimization, a sufficiently large number of random outcomes of the design parameters are typically generated, represented by

$$\mathbf{x}^m = \mathbf{x}^0 + \Delta\mathbf{x}^m, \quad m = 1, 2, \dots, N_{mc}, \quad (3)$$

where \mathbf{x}^m represents the deviation between the m th outcome and the nominal point, and N_{mc} is the total number of random outcomes for yield analysis. In this paper, m ($m = 1, \dots, N_{mc}$) is used to represent the index of random outcomes in Monte Carlo analysis. Due to the uncertainties in the manufacturing process, the EM responses at some outcomes may satisfy design specifications while others may not. Let the yield at nominal point \mathbf{x}^0 be denoted as $Y(\mathbf{x}^0)$. Then, $Y(\mathbf{x}^0)$ can be approximated as the number of acceptable designs over the total number of design outcomes, i.e.,

$$Y(\mathbf{x}^0) \approx N_{acpt}/N_{mc}, \quad (4)$$

where N_{acpt} represents the total number of acceptable designs.

Let $H_p(\cdot)$ represent the one-sided least p th function. According to [1], the following objective function $U(\mathbf{x}^0)$ can be used to solve the original EM-based yield optimization problem

$$U(\mathbf{x}^0) = H_p(\mathbf{u}(\mathbf{x}^0)), \quad (5)$$

where $\mathbf{u} = [u_1, u_2, \dots, u_{N_{mc}}]^T$. The m th component in \mathbf{u} is found from

$$u_m = \alpha_m H_q(\mathbf{e}(\mathbf{x}^m)), \quad m = 1, \dots, N_{mc}, \quad (6)$$

where q and p are two parameters indicating the norms used for \mathbf{e} and \mathbf{u} , respectively. A smaller value of $U(\mathbf{x}^0)$ indicates a higher yield. Following the suggestion in [1], we set $p = q = 1$ and the weighting factor $\alpha_m = 1$ in this paper.

These settings lead to an objective function in the following form [2]:

$$U(\mathbf{x}^0) = \sum_{m \in M} \sum_{j \in J(\mathbf{x}^m)} e_j(\mathbf{x}^m). \quad (7)$$

$$J(\mathbf{x}^m) = \{j | e_j(\mathbf{x}^m) > 0\} \quad (8)$$

$$M = \{m | J(\mathbf{x}^m) \neq \emptyset\} \quad (9)$$

In most practical cases, a reasonably large number of random comes are required to achieve an effective minimization of the objective function defined in (1)-(9).

III. PROPOSED PARALLEL SPACE-MAPPING BASED YIELD OPTIMIZATION TECHNIQUE INCORPORATING TRUST REGION ALGORITHM AND PCE

A direct application of the objective function $U(\mathbf{x}^0)$ is feasible if the responses are computed by circuit simulations. When the responses are obtained from EM simulations, it appears to be computationally expensive to apply $U(\mathbf{x}^0)$ to EM-based yield optimization directly [2]. Therefore, in this paper, for the first time, we propose a parallel SM based yield-driven EM optimization technique incorporating trust region algorithm and PCE. In the following section, we describe the proposed yield optimization technique in detail.

The proposed technique mainly consists of five parts, namely, fine model data generation with parallel computational method, surrogate modeling over multiple geometrical samples with parallel computation method, the l_1 design centering algorithm to optimize the yield using the surrogate model, a novel trust region algorithm to update the trust region of the surrogate, and the PCE approach to yield verification on the fine model. We provide the descriptions for these five parts in the subsequent sections.

A. FINE MODEL DATA GENERATION WITH PARALLEL COMPUTATION METHOD

Parallel computation is a powerful tool to speed up the EM data generation process. Here, we propose to use parallel computational method to evaluate the fine model responses using multiple processors in parallel, thereby reducing the total CPU time of EM-based yield optimization. Let N be the number of data points generated using the fine model. The fine model responses at N data points are evaluated using N parallel processors. Let S_p and η represent the parallel speedup factor and the parallel efficiency, respectively. The communication time between multiple processors running in parallel produces an overhead cost to the EM data generation process in each iteration. The speedup is defined as the ratio of the data generation time on a single processor over that on N processors running in parallel [14], i.e.,

$$S_p = \frac{\sum_{j=1}^N T_j}{T_o + \max_{1 \leq j \leq N} T_j}, \quad (10)$$

where T_o represents the additional communication time for data generation using N processors, and T_j denotes the time for each fine model evaluation on the j th processor.

The parallel efficiency η is defined as the ratio of the speedup factor over the total number of processors [14], i.e.,

$$\eta = \frac{S_p}{N}. \quad (11)$$

Obviously, when all the N processors have similar evaluation time T_j and the overhead cost T_o is much smaller than T_j , a large speedup and a high parallel efficiency can be achieved.

B. SURROGATE MODELING OVER MULTIPLE GEOMETRICAL SAMPLES USING PARALLEL COMPUTATION METHOD

Direct EM-based yield optimization with accurate full-wave EM simulations is computationally prohibitive. Therefore, the first step in the proposed technique is to develop a surrogate model to replace the fine model to achieve high-quality yield optimization solutions in an efficient manner. Same as all the SM-based approaches, we assume the availability of a computationally fast but not so accurate coarse model and an accurate but computationally expensive fine model. Let $\mathbf{R}^c(\mathbf{x})$ and $\mathbf{R}^f(\mathbf{x})$ denote the response vectors of the coarse and fine models corresponding to \mathbf{x} , respectively. We first establish a surrogate model combining the coarse model with a linear input mapping as follows:

$$\mathbf{x}_c = \mathbf{B}\mathbf{x}_f + \mathbf{c}, \quad (12)$$

$$\mathbf{R}^s(\mathbf{x}_f, \mathbf{w}) = \mathbf{R}^c(\mathbf{x}_c) = \mathbf{R}^c(\mathbf{B}\mathbf{x}_f + \mathbf{c}), \quad (13)$$

where \mathbf{x}_c and \mathbf{x}_f are two vectors containing all the design variables of the coarse model and the fine model, respectively. $\mathbf{R}^c(\mathbf{x}_c)$ is the response vector of the coarse model corresponding to \mathbf{x}_c , while $\mathbf{R}^s(\mathbf{x}_f, \mathbf{w})$ represents the response vector of the SM surrogate. \mathbf{w} is a vector of mapping parameters which contain all the elements in \mathbf{B} and \mathbf{c} , where \mathbf{B} and \mathbf{c} represent the coefficients in the linear mapping function.

The surrogate in the proposed technique is trained over multiple geometrical samples. The purpose is to make the surrogate valid in a relatively larger neighborhood in the design parameter space, thereby reducing the SM iterations in the whole optimization process. Let the nominal point at the k th ($k = 1, 2, \dots$) iteration during yield optimization be denoted by $\mathbf{x}^{0,k}$, where $\mathbf{x}^{0,1}$ is initialized as the optimal solution from nominal optimization. In each iteration, a set of geometrical samples are generated in the neighborhood of $\mathbf{x}^{0,k}$ in the design parameter space. The fine model responses at these geometrical samples are to be used to train the surrogate model. In this paper, star distribution is used as the sampling method to generate the geometrical samples around $\mathbf{x}^{0,k}$ in the design parameter space. Let X_{Tr}^k represent the set of geometrical samples in iteration k , then,

$$X_{Tr}^k = \{\mathbf{x}^{(1),k}, \mathbf{x}^{(2),k}, \dots, \mathbf{x}^{(2n+1),k}\}. \quad (14)$$

Next, the fine model are evaluated at all these $2n + 1$ geometrical samples by using $2n + 1$ processors in parallel

$$\{\mathbf{R}^f(\mathbf{x}^{(i),k}) | i = 1, 2, \dots, 2n + 1\} \\ = \{\mathbf{R}^f(\mathbf{x}^{(1),k}), \mathbf{R}^f(\mathbf{x}^{(2),k}), \dots, \mathbf{R}^f(\mathbf{x}^{(2n+1),k})\}. \quad (15)$$

In each iteration (say iteration k), the surrogate model is trained by using an optimization formulation with the objective of minimizing an error function. Let $E(\mathbf{w})$ be the error function. $E(\mathbf{w})$ is defined as the sum of the squared differences between the responses of the fine model and those of the surrogate at all the $2n + 1$ geometrical samples, i.e.,

$$E(\mathbf{w}) = \sum_{l=1}^{2n+1} e^{(l),k}(\mathbf{w}) \\ = \sum_{l=1}^{2n+1} \left\| \mathbf{R}^f(\mathbf{x}^{(l),k}) - \mathbf{R}^s(\mathbf{x}^{(l),k}, \mathbf{w}) \right\|^2, \quad (16)$$

where $\mathbf{R}^f(\mathbf{x}^{(l),k})$ and $\mathbf{R}^s(\mathbf{x}^{(l),k})$ denote the response vectors of the fine and coarse models corresponding to the l th ($l = 1, 2, \dots, 2n + 1$) training sample $\mathbf{x}^{(l),k}$, respectively. The training process of the surrogate model can be denoted by

$$\mathbf{w}_k = \arg \min_{\mathbf{w}} E(\mathbf{w}), \quad (17)$$

where \mathbf{w}_k contains the optimal parameters of the mapping function after training. Similar to the fine model data generation process, in this paper, the training process of the surrogate model to match the fine model at $2n + 1$ data points also uses the parallel computation method [14]. This reduces the surrogate modeling time in each iteration, thereby further accelerating the overall yield optimization process. Once the training procedure is finished, a new set of mapping parameters is obtained. Next, we perform yield optimization using the updated surrogate to obtain the next optimal yield solution $\mathbf{x}^{0,k+1}$.

C. THE ONE-SIDED l_1 CENTERING ALGORITHM FOR YIELD OPTIMIZATION USING THE PARALLEL SM SURROGATE

Once the development of the surrogate is done, we next perform yield optimization on the surrogate model with the same statistical distributions and design specifications as those in the original EM-based yield optimization problem. The yield optimization on the surrogate is effective provided that the surrogate model is well trained over a number of geometrical samples and that a suitable region of interest is defined for the surrogate.

In this paper, we use the one-sided l_1 design centering algorithm [6] to optimize the yield of the surrogate. Let $\mathbf{e}^s(\mathbf{x})$ represent the error vector used to indicate how well the response vector of the surrogate model satisfies the design specifications. Similar to (1), we have

$$\mathbf{e}^s(\mathbf{x}) = [e_1^s, e_2^s, \dots, e_{N_s^u}^s, \dots, e_{N_s}^s]^T. \quad (18)$$

For each random outcome \mathbf{x}^m , we have a corresponding error vector $\mathbf{e}^s(\mathbf{x}^m)$. The value of $e_j^s(\mathbf{x}^m)$, where $j = 1, \dots, N_s$, indicates the violation degree of the surrogate model response for the j th design specification sample (S_j). A larger value of $e_j^s(\mathbf{x}^m)$ implies that S_j is violated to a larger degree.

To optimize the yield of the microwave structure at \mathbf{x}^0 , the l_1 design centering algorithm minimizes the following objective function using a certain gradient-based optimization algorithm:

$$\begin{aligned} U^s(\mathbf{x}^0) &= \sum_{m \in M} \sum_{j \in J(\mathbf{x}^m)} e_j^s(\mathbf{x}^m), \\ J(\mathbf{x}^m) &= \{j | e_j^s(\mathbf{x}^m) > 0\} \\ M &= \{m | J(\mathbf{x}^m) \neq \emptyset\} \end{aligned} \quad (19)$$

where $e_j^s(\mathbf{x}^m)$ is defined in the same way as that in (2), but this time the responses are evaluated from the surrogate model instead of the fine model, i.e.,

$$e_j^s(\mathbf{x}) = \begin{cases} R_j^s(\mathbf{x}, \mathbf{w}) - S_j, & \text{if } 1 \leq j \leq N_s^u, \\ S_j - R_j^s(\mathbf{x}, \mathbf{w}), & \text{if } N_s^u < j \leq N_s. \end{cases} \quad (20)$$

It is seen that the yield objective function defined in (19) is closely related to the number of failed designs. By minimizing (19), the yield of the fine model is expected to be increased. Therefore, the new nominal point used for yield verification on the fine model, $\mathbf{x}^{0,k+1}$, is obtained as follows:

$$\mathbf{x}^{0,k+1} = \arg \min_{\mathbf{x}^0} U^s(\mathbf{x}^0). \quad (21)$$

Note that by replacing the EM-based fine model by a computationally efficient surrogate model, and applying (19)-(21) on the surrogate, we avoid the large number of computationally expensive EM simulations and thus the EM-based yield optimization procedure is greatly accelerated.

D. PROPOSED TRUST REGION ALGORITHM FOR PARALLEL SM BASED YIELD OPTIMIZATION

Since the surrogate model can only learn the EM behavior of the fine model in a certain region in the design parameter space, a trust region has to be defined for the surrogate in each iteration during yield optimization. The trust region is a region in the design parameter space beyond which the surrogate become unreliable and cannot represent the behavior of the fine model well. Therefore, the l_1 design centering algorithm should only explore the parameter space inside the trust region in order to have an effective minimization of the objective function defined in (19). Based on this idea, we propose a novel trust region algorithm to update the trust radius of each design parameter in each iteration in yield-driven design.

Let Ω^k be the trust region of the surrogate model in iteration k , defined as follows:

$$\Omega^k = \{\mathbf{x} | x_i^{0,k} - \delta_i^k \leq x_i \leq x_i^{0,k} + \delta_i^k, \forall i = 1, \dots, n\}, \quad (22)$$

where δ_i^k represents the trust radius for the i th design variable in iteration k . Let $\delta^k = \{\delta_1^k, \delta_2^k, \dots, \delta_n^k\}$ be the set containing the trust radii for all the design variables. The update of the trust radius for each design parameter depends on the ratio of yield improvements of the surrogate model over that of the fine model between two consecutive iterations. Specifically, between iteration k and iteration $k + 1$, we evaluate the yield

values of the fine model (denoted by $Y_f(\mathbf{x}^{0,k})$ and $Y_f(\mathbf{x}^{0,k+1})$) and the yield value of the surrogate model (denoted by $Y_s(\mathbf{x}^{0,k+1})$) via the PCE approach. Define a parameter r to be the ratio of yield increase on the surrogate model over that on the fine model as follows:

$$r = \begin{cases} \frac{Y_f(\mathbf{x}^{0,k+1}) - Y_f(\mathbf{x}^{0,k})}{Y_s(\mathbf{x}^{0,k+1}) - Y_f(\mathbf{x}^{0,k})}, & \text{if } Y_f(\mathbf{x}^{0,k+1}) \geq Y_f(\mathbf{x}^{0,k}), \\ -1, & \text{otherwise.} \end{cases} \quad (23)$$

The parameter r can be used as an indicator to update the trust radius of each design parameter due to the following reasons: 1) when $Y_f(\mathbf{x}^{0,k+1}) < Y_f(\mathbf{x}^{0,k})$, this means that yield optimization on the surrogate is not effective, i.e., it cannot increase the yield of the fine model. Therefore, the trust radius of each design parameter should shrink; 2) when $Y_f(\mathbf{x}^{0,k+1}) \geq Y_f(\mathbf{x}^{0,k})$, this implies that the yield of the fine model is increased after performing yield optimization on the surrogate. Depending on how large the yield improvement on the fine model is, one can choose to keep, enlarge, or shrink the current trust radius. In this paper, we use the following formulas to update the trust radii of the design parameters in the k th iteration [21]:

$$\delta^{k+1} = \begin{cases} 0.69\delta^k, & \text{if } r < 0.1, \\ \min\{1.3\delta^k, \Delta_{max}\}, & \text{if } r > 0.75, \\ \delta^k, & \text{otherwise,} \end{cases} \quad (24)$$

where Δ_{max} denotes the maximal allowed trust radii for the design variables. In this paper, Δ_{max} is set as 50% of the initial nominal values of the design variables.

E. INCORPORATING THE PCE APPROACH FOR YIELD VERIFICATION ON THE FINE MODEL

In each iteration, after the yield optimization on the surrogate is done and a new nominal point is found, the yield value on the fine model at the new nominal point has to be verified. To further speed up the overall optimization process, we propose to use the PCE approach to verify the yield of the fine model in each iteration during yield optimization. To realize PCE-based yield estimation, one has to first transform the original random parameters \mathbf{x} to independent standard random parameters ξ . Next, the stochastic expansion has to be applied in the “ ξ -space” [22] to express the function between the stochastic quantity and ξ . In the k th iteration, let $R_j^f(\mathbf{x}^{0,k}, \xi)$ be the response of the fine model at the frequency point where the j th design specification sample exists. Via PCE, the relationship between $R_j^f(\mathbf{x}^{0,k}, \xi)$ and ξ is represented by the weighted sum of a set of orthogonal basis functions as follows:

$$R_j^f(\mathbf{x}^{0,k}, \xi) = \sum_{i=0}^P a_{ij}(\mathbf{x}^{0,k}) \Phi_i(\xi), \quad (25)$$

where $\Phi_i(\cdot)$ represents the generalized basis function in PCE. The total number of terms in (25) is $P + 1$. a_{ij} represents the PCE coefficients, which are also the weighting coefficients for different basis functions at different EM responses.

Given that the basis functions $\Phi_i(\xi)$ are orthogonal to each other, the coefficients of PCE, a_{ij} , are evaluated as follows:

$$a_{ij}(x^{0,k}) = \frac{\int_{\Omega^n} R_j^f(x^{0,k}, \xi) \Phi_i(\xi) \rho(\xi) d\xi}{\int_{\Omega^n} \Phi_i^2(\xi) \rho(\xi) d\xi}, \quad (26)$$

where Ω^n represents the n -dimensional random space of ξ . $\rho(\xi)$ represents the joint probability density function (PDF) of the transformed parameters ξ . Numerical quadrature based on sparse grid techniques [20] are typically used to evaluate the multi-dimensional integrations in (26). Let N_{sg} be the number of samples in sparse grid techniques.

To perform yield estimation of the fine model, a number of PCE models have to be constructed at all the frequencies of interest. More specifically, a single PCE model has to be constructed for each frequency point under consideration. In other words, the total number of PCE models is equal to the total number of frequency points in the whole frequency range of interest. Then, an MC analysis needs to be performed on the PCE models taking into consideration all the design specifications [20]. We summarize the yield verification on the fine model via PCE at iteration k as follows:

- Step 1) Generate N_{sg} samples of the transformed parameters ξ , i.e., $\{\xi^{(1)}, \xi^{(2)}, \dots, \xi^{(N_{sg})}\}$, in the “ ξ -space” following the rules of the sparse grid technique.
- Step 2) Transform the N_{sg} samples in the “ ξ -space” back into the “ x -space”, to obtain a set of geometrical parameter samples around the nominal point $x^{0,k}$.
- Step 3) Evaluate the responses of the fine model at the N_{sg} geometrical parameter samples in parallel.
- Step 4) Numerically evaluate the PC coefficients a_{ij} using numerical quadrature based on the sparse grid technique [2].
- Step 5) Perform an MC analysis on the PCE models taking into consideration all the design specifications to obtain the yield verification result on the fine model at $x^{0,k}$.

As demonstrated in [17], the PCE approach to EM-based yield estimation is much more computationally efficient than traditional MC analysis, since an accurate evaluation of PCE coefficients typically requires much fewer EM samples than the MC analysis does.

F. THE PROPOSED YIELD OPTIMIZATION ALGORITHM

The overall yield optimization procedure terminates if the difference of $x^{0,k}$ between subsequent iterations is sufficiently small or the yield value of the fine model at the new nominal point is higher than a user-defined threshold, i.e.,

$$\|x^{0,k+1} - x^{0,k}\| \leq \varepsilon, \quad (27)$$

$$\text{or } Y(x^{0,k+1}) \geq Y_{th}, \quad (28)$$

where ε and Y_{th} are both user-defined criteria. The flow chart of the proposed yield optimization algorithm is shown in Fig. 1, which can also be summarized as follows:

- Step 1) Set iteration counter $k = 1$. Initialize the termination criteria ε and Y_{th} (the desired yield value).

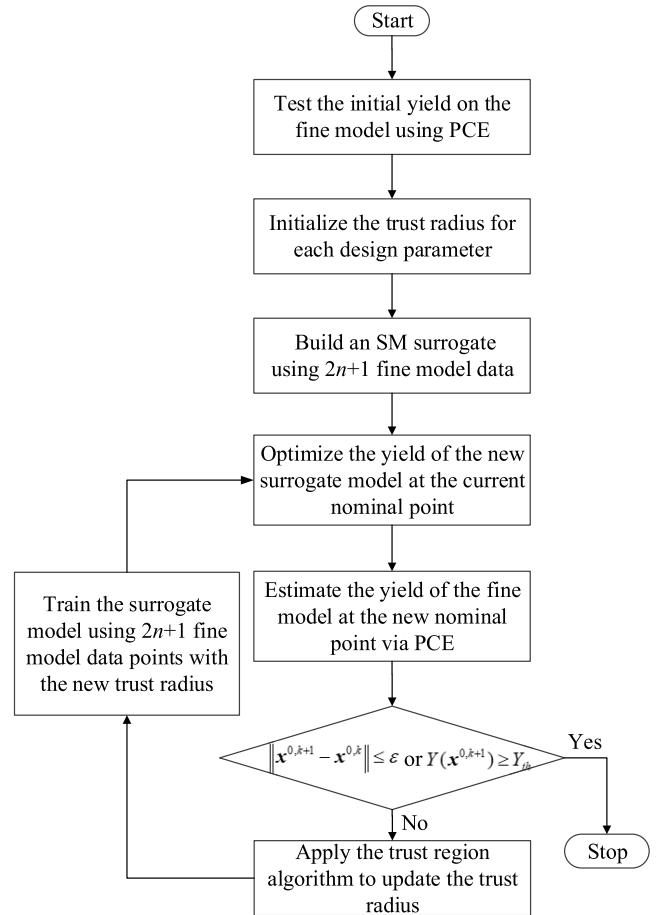


FIGURE 1. Flow chart of the proposed yield optimization technique.

- Initialize the trust radius for each design parameter. Set the perturbation sizes in star distribution for the design parameters the same as their trust radius.
- Step 2) Initialize the nominal point $x^{0,k}$ to be the optimal solution from nominal optimization x_{ini}^0 . Estimate the yield of the fine model at $x^{0,k}$ using the PCE approach described in Section III-E.
- Step 3) If $k \geq 2$, update the trust radius for each design parameter using (23) and (24), and update the perturbation size to be the same as the updated trust radius.
- Step 4) Generate $2n+1$ geometrical samples, X_{Tr}^k , following star distribution based on the updated trust region for training the surrogate.
- Step 5) Build a new surrogate model $R^s(x, w)$ using (14)-(17) and obtain the optimal mapping parameters B and c .
- Step 6) Perform yield optimization on the new surrogate by solving (21) using a gradient-based algorithm, e.g., the quasi-Newton method, to find the next optimal yield solution $x^{0,k+1}$.
- Step 7) Estimate the yield of the fine model at the new nominal point $x^{0,k+1}$ using the PCE approach.
- Step 8) If $\|x^{0,k+1} - x^{0,k}\| \leq \varepsilon$ or $Y(x^{0,k+1}) \geq Y_{th}$ is satisfied, go to Step 9), otherwise, set $k = k + 1$ and go to Step 3).

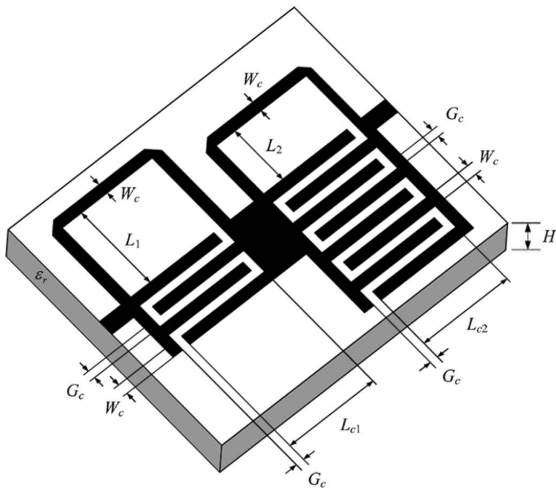


FIGURE 2. The structure of the low-pass elliptic microstrip filter used in EM simulation and yield optimization, from [14].

Step 9) Output the final optimal yield solution $\mathbf{x}^* = \mathbf{x}^{0,k}$ and the final yield value $Y^* = Y_f(\mathbf{x}^{0,k})$.

G. DISCUSSION

In this paper, we choose to use the PCE approach to verify the yield of the fine model during the overall yield optimization process. The PCE approach serves as an efficient vehicle to further speed up the proposed technique. There also exist some other methods in the literature that can avoid the high computational costs in traditional Monte Carlo based analysis, such as the stochastic testing method [23], the polynomial chaos-Kriging (PC-Kriging) method [24], and the neural network based technique [25]. They all perform well for statistical analysis and/or yield estimation in different applications. Considering that the main focus of this work is yield-driven EM optimization, a comprehensive comparison between these methods and the PCE approach is beyond the scope of this paper. However, upon being used properly, other efficient methods such as those in [23]–[25] can also be incorporated in the proposed technique to achieve efficient yield optimization of microwave structures.

IV. APPLICATION EXAMPLES

A. YIELD OPTIMIZATION OF A LOW-PASS ELLIPTIC MICROSTRIP FILTER

In this example, we aim to perform yield optimization for a two-section low-pass elliptic microstrip filter [14], as shown in Fig. 2. We consider six design variables, i.e., $\mathbf{x} = [L_1, L_2, L_{c1}, L_{c2}, W_c, G_c]^T$ (mil), and assume that the variables have independent normal distributions to allow yield optimization. The initial nominal point obtained from nominal EM optimization is $\mathbf{x}_{ini}^0 = [44.79825, 171.68189, 165.44252, 45.05873, 6.06197, 3.36753]^T$ (mil). The standard deviation of each design variable is 0.5% of its mean value. The design specifications for the filter are

defined as

$$\begin{aligned} |S_{21}| &\geq 0.9, & \text{for } 1.0 \text{ GHz} \leq \omega \leq 2.0 \text{ GHz} \\ |S_{21}| &\leq 0.1, & \text{for } 2.3 \text{ GHz} \leq \omega \leq 4.0 \text{ GHz} \end{aligned}$$

The HFSS EM simulator with a fast simulation feature is used to perform fine model evaluations. The coarse model is the equivalent circuit for the low-pass filter using simple transmission lines [14]. NeuroModelerPlus software is used to program the coarse model, implement surrogate model training over multiple geometrical samples, and perform yield optimization on the surrogate model. The initial yield value of the fine model at the initial nominal point is 36%. The initial trust radius of each design parameter is set as 5% of its nominal value, i.e., $\delta^1 = 0.05 \times \mathbf{x}_{ini}^0$. The stop criteria of the propose yield optimization algorithm are set as $\epsilon = 1.0e - 5$ and $Y_{th} = 90\%$. A cluster of computers is used to allow parallel processing for parallel data generation.

The proposed yield optimization technique stops after two SM iterations, meeting the user-defined yield criterion Y_{th} . The final optimal yield solution is $\mathbf{x}^* = [43.91140, 158.20101, 163.80511, 46.46544, 6.23598, 3.22687]^T$ (mil) with a yield value of 90% of the fine model. The yield value of the fine model during yield optimization is verified by the PCE approach. For a further verification, we evaluate the responses of the fine model at a sufficiently large number (N_{mc}) of random outcomes around the initial and final design solutions, and obtain the corresponding yield values using Monte Carlo analysis, as shown in Fig. 3. To obtain the reasonable value of N_{mc} in Monte Carlo analysis, the yield at the initial nominal point is estimated with different number of random samples. We gradually increase the value of N_{mc} until a convergence on the yield value is observed (which happens when $N_{mc} = 100$). The same value is used for the number of random outcomes during yield optimization on the surrogate model. It is observed from Fig. 3 that a significant increase on the yield value is obtained, which demonstrates the effectiveness of the proposed technique.

For this example, we have $2n + 1 = 13$ data samples, so 13 processors are used to perform fine model evaluations in parallel. The time for fine model evaluations using the parallel computation method is 32 min, while that using the sequential computation method is 372 min. This results in a speedup of 11.6 and a parallel efficiency (η) of about 89.5%. This speedup contributes to the total CPU time reduction of the proposed yield optimization technique. For the purpose of comparison, we also apply the standard SM approach to optimize the yield for this example. For the standard SM, the surrogate model is built at only one geometrical sample in each SM iteration without using the parallel computation method. Specifically, in each iteration, the response of the fine model at the current nominal point is used to train the surrogate model. The comparison between the standard SM based yield optimization technique and the proposed yield optimization technique in terms of the yield improvement and total CPU time is shown in Table 1. Note that the CPU time for

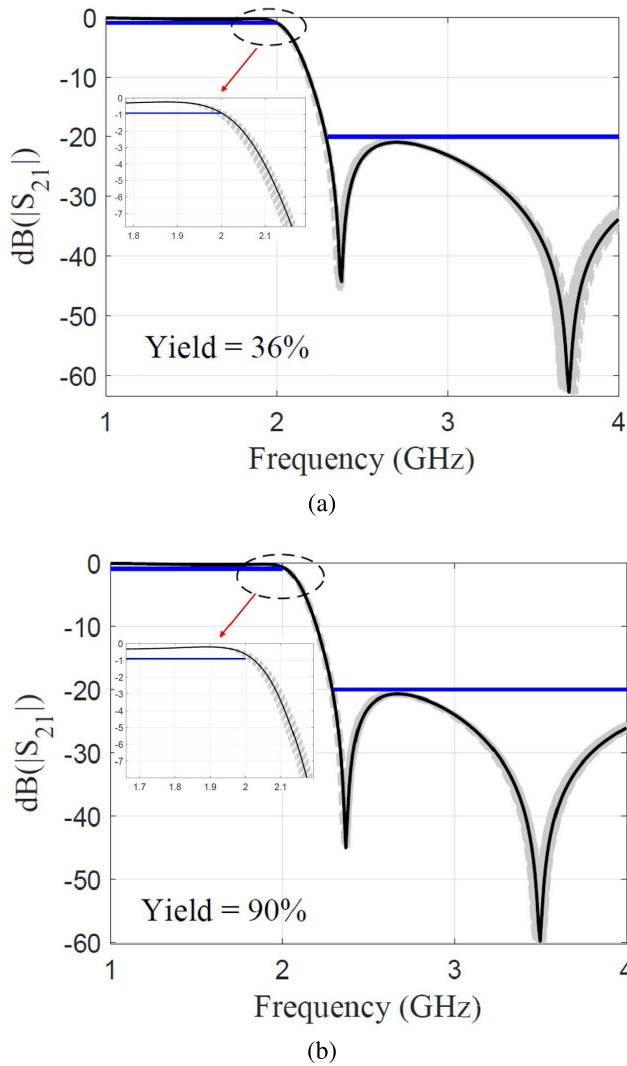


FIGURE 3. Yield optimization results of the low-pass microstrip filter using the proposed technique: (a) Before and (b) After yield optimization. In both figures, the grey dashed lines indicate 100 random samples in Monte Carlo analysis, while the black solid line indicates the nominal response.

yield verification on the fine model in each iteration is omitted for both methods. As can be seen in the table, the standard SM based yield optimization terminates after four iterations, achieving a small yield increase of the fine model. The reason behind this is that standard SM builds the surrogate model over a single point. Hence, the surrogate model is valid in a smaller region than that built with the parallel SM approach, making it difficult to achieve an effective yield optimization of the surrogate. It is also seen from the table that, compared with the standard SM based yield optimization technique, the proposed yield optimization technique achieves a much greater yield increase in shorter CPU time. This is because our proposed technique builds the surrogate model over multiple geometrical samples, which enables the surrogate to be valid in a larger neighborhood. Therefore, the proposed technique is able to find the optimal yield solution in fewer SM iterations, accelerating the overall yield optimization process.

TABLE 1. Comparison of standard SM based yield optimization technique and the proposed yield optimization technique for the lowpass microstrip filter.

Yield optimization technique	Standard SM based yield optimization technique	Proposed yield optimization technique
Initial yield of fine model	36%	36%
Number of SM iterations	4	2
Fine model evaluation time	29min × 4	32min × 2
Surrogate model training time	12s × 4	40s × 2
Total surrogate yield optimization time	24min	11min
Total CPU time	141min	76min
Final yield of fine model	40%	90%

B. YIELD OPTIMIZATION OF A BANDSTOP MICROSTRIP FILTER WITH OPEN STUBS

In the second example, we perform yield optimization for a bandstop microstrip filter with quarter-wave resonant open stubs [14], as shown in Fig. 4. The filter has five design variables, i.e., $\mathbf{x} = [W_1, W_2, L_0, L_1, L_2]^T$ (mil). We assume independent normal distributions for the design variables to realize yield estimation and optimization, with the standard deviation of each design variable being 0.5% of its mean value. The initial nominal point obtained from nominal EM optimization is $\mathbf{x}_{ini}^0 = [5.83198 \ 14.68157 \ 120.06024 \ 119.10691 \ 110.10827]^T$ (mil). The design specifications for the filter are defined as

$$\begin{aligned}
 |S_{21}| &\geq 0.9, & \text{for } 5.0 \text{ GHz} \leq \omega \leq 8.0 \text{ GHz} \\
 |S_{21}| &\leq 0.05, & \text{for } 9.3 \text{ GHz} \leq \omega \leq 10.7 \text{ GHz} \\
 |S_{21}| &\geq 0.9, & \text{for } 12.0 \text{ GHz} \leq \omega \leq 15.0 \text{ GHz}
 \end{aligned}$$

The HFSS EM simulator with a fast simulation feature is used to perform fine model evaluations. The coarse model is the equivalent circuit for the bandstop filter using simple transmission lines based on ADS [14]. NeuroModelerPlus software is used to program the coarse model, implement surrogate model training, and perform the yield optimization on the surrogate model. The yield value of the fine model at the initial nominal point is 22%. The initial trust radius of each design parameter is set as 5% of its nominal value, i.e., $\delta^1 = 0.05 \times \mathbf{x}_{ini}^0$. The stop criteria of the propose yield optimization algorithm is set as $\epsilon = 1.0e - 5$ and $Y_{th} = 90\%$. The proposed yield optimization technique terminates after two SM iterations, satisfying the user-defined stopping criterion $\|\mathbf{x}^{0,k+1} - \mathbf{x}^{0,k}\| \leq 1.0e - 5$. The final optimal yield solution is $\mathbf{x}^* = [5.86118 \ 14.59794$

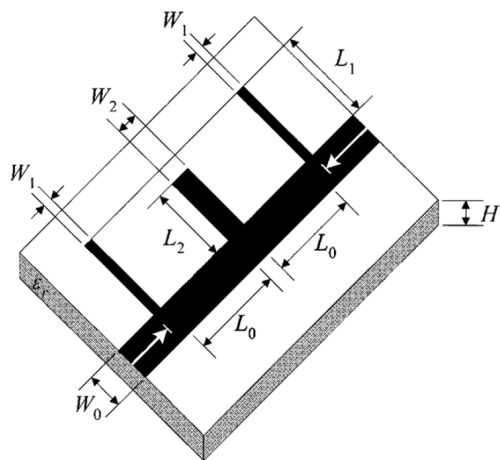


FIGURE 4. The structure of the bandstop microstrip filter defined for EM simulation and yield optimization, from [14].

TABLE 2. Comparison of standard SM based yield optimization technique and the proposed yield optimization technique for the bandstop microstrip filter.

Yield optimization algorithm	Standard SM approach to yield optimization	Proposed yield optimization technique
Initial yield of fine model	22%	22%
Number of iterations	5	2
Fine model evaluation time	14min × 5	16min × 2
Surrogate model training time	20s × 5	3min × 2
Total surrogate yield optimization time	22min	15min
Total CPU time	94min	53min
Final Yield of fine model	39%	46%

$117.55622 \ 121.90948 \ 107.62781]^T$ (mil) with a yield value of 46% of the fine model. The yield values at the initial nominal solution and the final optimal yield solution are both further verified by the Monte Carlo-based yield estimation, as shown in Fig. 5.

For this example, we have $2n + 1 = 11$ data samples, so 11 processors are used to perform fine model evaluations in parallel. The time for fine model evaluations using the parallel computation method is 16 min, while that using the sequential computation method is 157 min. This results in a speedup of 9.8 and a parallel efficiency (η) of about 89.2%. This speedup contributes to the total CPU time reduction of the proposed yield optimization technique. For comparison purposes, the standard SM approach is also applied to optimize the yield for this example. In each iteration during

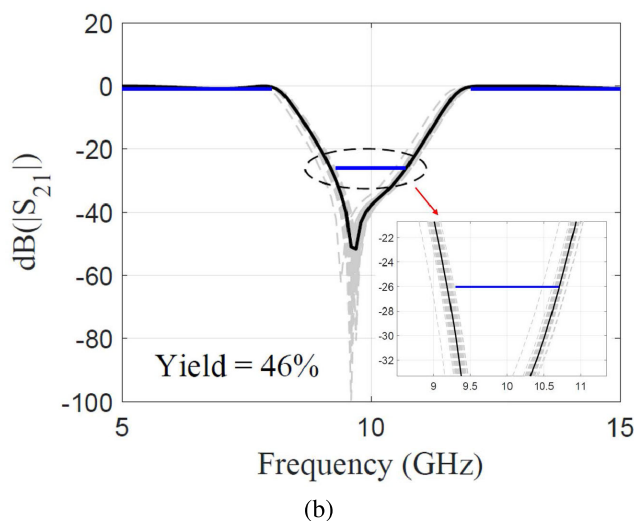
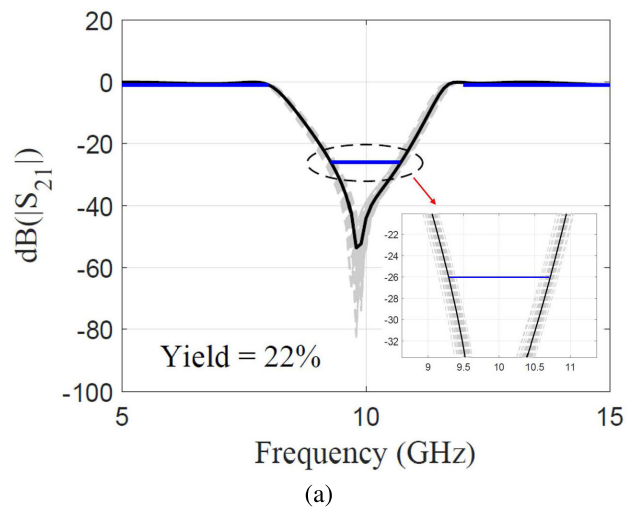


FIGURE 5. Yield optimization results of the bandstop microstrip filter using the proposed technique: (a) Before and (b) After yield optimization. In both figures, the grey dashed lines indicate 100 random samples in Monte Carlo analysis, while the black solid line indicates the nominal response.

yield optimization, the surrogate model is trained with the EM response at the current nominal point. Table 2 compares the standard SM based yield optimization technique and the proposed technique in terms of the yield improvement and the total CPU time. It is observed from the table that, the proposed yield optimization technique achieves a higher yield increase using fewer SM iterations compared with the standard SM based yield optimization technique. Specifically, the standard SM optimization terminates after five SM iterations with a yield value of 39% of the fine model, while the proposed technique terminates after two SM iterations with a yield value of 46% of the fine model. This is because the surrogate model in the proposed technique is trained to be valid in larger neighborhood than that in the standard SM. Therefore, the trust region defined for the surrogate in the proposed technique can be larger than that in the standard SM, which increases the ability of improving the yield of the fine model for the

proposed technique. These advantages ultimately allow the proposed technique to achieve a greater yield increase of the microwave structure in shorter CPU time compared with the standard SM based yield optimization technique.

V. CONCLUSION

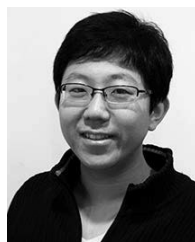
This paper has proposed a novel parallel space-mapping based yield-driven EM optimization technique incorporating trust region algorithm and PCE. A trust region algorithm has been proposed to update the trust radius of each design parameter in each space mapping iteration during optimization. Parallel computation method has been used to generate the EM data in parallel and enable surrogate modeling over multiple geometrical samples. The trained surrogate has been used to find the new yield optimal solution using the l_1 centering algorithm. The PCE approach has been incorporated to further speed up the yield verification on fine models. The proposed technique helps achieve high-quality solutions to the challenging problem of EM-based yield optimization in shorter time. As a possible future direction, we would like to apply the proposed technique to yield-driven design problems involving high-dimensional design parameter spaces.

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