A Surrogate Modeling Space Definition Method for Efficient Filter Yield Optimization

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***Abstract*—Surrogate models are widely used in filter yield optimization methods to improve efficiency, which can be divided into online and offline. State-of-the-art offline surrogate model-based filter yield optimization methods are shown to be effective for filter cases with more than 10 sensitive design variables. In these methods, a keystone is the appropriate definition of the space for building the surrogate model, deciding success/failure or at least the efficiency of the yield optimization. However, there is a lack of systematic methods to achieve it. To address this challenge, a new method, called pattern search optimization-based surrogate modeling space definition method (PSOMSD), is proposed. The performance of PSOMSD is demonstrated by a real-world filter case with 14 sensitive design variables. Analysis shows the appropriateness of the defined surrogate modeling space and advantages compared to empirical methods.**

***Index Terms*—Microwave filter; Yield optimization; Surrogate modeling domain; Optimization domain.**

I. Introduction

Fabrication error degrades the filter performance significantly [1], [2]. In many cases, although the initial filter design (without considering fabrication error) shows high performance, many fabricated filters cannot meet the design requirements and are not qualified to be used. Hence, obtaining a filter design near the initial design that is robust to fabrication error is important, and this process is called filter yield maximization or optimization [3], [4], [5]. Yield refers to the ratio between the number of fabricated filters meeting the design requirements and the total number of fabricated filters under fabrication error [4], [6]. A high-yield filter design indicates the saving of much filter tuning time and effort. Filter yield optimization is therefore attracting much attention.

The major challenge of filter yield optimization is efficiency. To obtain a reasonably accurate estimation of the yield for a candidate filter design, many Monte-Carlo (MC) samples around the candidate design are often needed [7]. For each sample, full-wave electromagnetic (EM) simulation is often unavoidable, which is computationally expensive. Depending on the method, many such candidate designs may be visited and estimated, costing a long time.

To address this challenge, surrogate models are employed. Surrogate models are computationally cheap approximation models mapping the filter design parameters to the filter responses or features extracted from filter responses [4], [8]. Hence, surrogate model-assisted filter yield optimization methods become routine. Widely used surrogate models include polynomial chaos [9], [10], [11], Gaussian process regression [12], and neural network [13], [14]. Particularly, filter design knowledge (e.g., transfer function, features extracted from filter response) is considered in the surrogate models to increasingly improve the efficiency [15], [16], [17].

Surrogate model-assisted filter yield optimization methods can be divided into online and offline. In online methods, local optimization starts from the initial design, and the surrogate modeling space is the fabrication error range with the current candidate design as the center. Once the algorithm iterates to a new candidate design, the previous surrogate model is discarded and a new surrogate model is rebuilt through MC sampling. Online methods mainly target filters with a small number of sensitive design variables due to the significant growth of necessary MC samples (i.e., computationally expensive EM simulations) when the number of sensitive design variables grows to more than 10 [18]. Offline methods, on the other hand, build a single surrogate model for a "certain" design space near the initial design and use this model to replace EM simulations in the global optimization process. Due to the affordable surrogate modeling process and enabling global optimization, offline methods show effectiveness for filter cases with more than 10 sensitive design variables [14].

However, a challenge in offline methods that does not exist in online methods is the determination of the surrogate modeling space. An appropriate definition of the surrogate modeling space is the keystone for offline yield optimization methods for most EM devices (e.g., [19]). For filters, this is even more challenging. A small surrogate modeling space may not include the aimed robust design, leading to minor yield improvement. A relatively large surrogate modeling space may work for some EM devices (e.g., antennas [20], [21]), but not for filters. As said above, filter responses often degrade significantly even when a small deviation is added to an optimal design [22]. Therefore, a slightly large surrogate modeling space may cause the MC samples satisfying the design requirements to become very few (e.g., $< 1\%$ of the

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MC samples according to our pilot experiments), leading to insufficient information for surrogate modeling of the design subspaces meeting the requirements. To the best of our knowledge, unlike antennas where successful methods exist (e.g., [19]), there is no systematic method for surrogate modeling space definition for filters. The only available method is the empirical method by the authors, i.e., using $\pm 0.05\%\lambda$, where λ is the wavelength of the center frequency of the filter [14].

To address this challenge, this paper proposes a systematic method, called pattern search optimization-based surrogate modeling space definition method (PSOMSD), to obtain the appropriate surrogate modeling space. PSOMSD defines an objective function in terms of a relaxed S-parameter performance metric and carries our pattern search optimization to each design variable, in order to obtain the surrogate modeling space systematically. Its effectiveness is demonstrated by a practical filter with 14 sensitive design variables.

II. The PSOMSD Method

The offline surrogate model-assisted filter yield optimization flow is shown in Fig. 1. All three stages are critical. This paper focuses on the first stage. An alternative of the second and third stages (i.e., the machine learning methods for surrogate modeling and evolutionary algorithms for global optimization) is described in [14], which is directly employed in the next section. Note that the MC samples for surrogate modeling are bounded by the space defined in the first stage and in global optimization when some generated candidate designs by evolutionary operators are out of the defined space, they are set to the nearest bound. Hence, the first stage, on which this paper focuses, is a keystone.

Like every filter yield optimization method, PSOMSD starts from an initial design $\boldsymbol{x}^{init}$ which overly satisfies the design requirements (e.g., max($|S_{11}|$) ≤ -19 dB in the passband for the design requirement of max($|S_{11}|$) ≤ -16 dB). PSOMSD aims to find the appropriate vector $\boldsymbol{\delta}$ to define the surrogate modeling space $[\boldsymbol{x}^{init} - \boldsymbol{\delta}, \boldsymbol{x}^{init} + \boldsymbol{\delta}]$, which will be used for surrogate modeling and global optimization. The appropriateness of $\boldsymbol{\delta}$ is determined by two factors: (1) It is sufficient to contain a robust design near $\boldsymbol{x}^{init}$ with a significantly improved yield value if it exists; and (2) It is compact to avoid unnecessary MC samples to subspaces without robust designs, so as to save the EM simulations for data preparation of the surrogate modeling, making the offline filter yield optimization efficient. The PSOMSD method works as follows.

Step 1: Define the objective function, $\min_{x_i} g(\boldsymbol{x})$, for pattern search optimization. For each $x_i (i = 1, 2, \ldots, d)$, where d is the number of sensitive design variables, initialize the step size m to a value much larger than the fabrication error (e.g., 0.1 mm for a fabrication error of 0.005 mm) and carry out Steps 2 to 5.

Step 2: If the step size is large than 0.001 mm, add pattern vectors $\boldsymbol{p_1}$ and $\boldsymbol{p_2}$ to $\boldsymbol{x}$, where only the i^{th} dimension of $\boldsymbol{p_1}$ and $\boldsymbol{p_2}$ are $\pm m$, respectively, and all other dimensions are 0. Compare $g(\boldsymbol{x}+\boldsymbol{p_1})$ and $g(\boldsymbol{x}+\boldsymbol{p_2})$ and the better one is $\boldsymbol{x}'$. Otherwise, save the current x_i and go to Step 5.

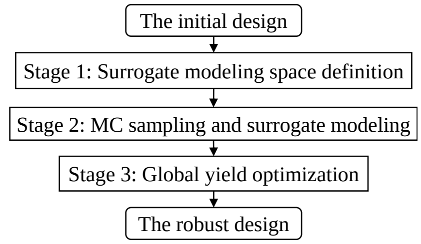


Fig. 1. The flow diagram of offline surrogate model-assisted filter yield optimization methods.

Step 3: If $g(\boldsymbol{x}')$ is better than $g(\boldsymbol{x})$, use $\boldsymbol{x}'$ to replace $\boldsymbol{x}$ and set $m = m \times 2$. Go to Step 2. Otherwise, go to Step 4.

Step 4: Keep $\boldsymbol{x}$ and set $m = m \times 0.5$. Go to Step 2.

Step 5: Set $\delta_i = |x_i - x_i^{init}|$, $(i = 1, 2, \ldots, d)$.

Some clarifications for PSOMSD are as follows.

- The method to determine $\boldsymbol{\delta}$ must have generality considering different kinds of filter structures and working frequencies. Therefore, carrying out a low computing cost optimization is used to obtain the "self-adaptiveness" for various filters. In the optimization, the particular characteristics of the targeted filter are self-contained.
- The objective function for the optimization is set to $\min_{x_i} g(\boldsymbol{x}) = |f(\boldsymbol{x}) - (\boldsymbol{r}_0 + \xi)|$, where $f(\boldsymbol{x})$ is the function output (extracted from the response) of a candidate design $\boldsymbol{x}$ through EM simulations, $\boldsymbol{r}_0$ is the same function output of the initial design $\boldsymbol{x}^{init}$ (e.g., $r_0 = -20$ dB for max($|S_{11}|$) in the passband) and ξ is the margin value. The reason for setting such an objective function is to observe the neighborhood of $\boldsymbol{x}^{init}$ that leads to a reasonably small degradation ξ, which provides an important reference for setting $\boldsymbol{\delta}$. ξ is the only empirical parameter in PSOMSD and our recommended value is 3 dB according to experiments of various filters. Stopband specifications (e.g., S_{21}) follow the same margin.
- $\boldsymbol{\delta}$ is a vector since the appropriate space for each design variable is different. Hence, the design variables are separately optimized. Unlike other EM devices, filter design variables are more separable and each design variable corresponds to a value in the coupling matrix.
- Because the filter design landscape is rugged, derivative-based optimization methods often do not show good performance [23]. Hence, a derivative-free method is selected based on experimental comparisons, which is pattern search. The ratio value is 2, which is often the default setting. However, other derivative-free search methods and settings can be investigated.
- Experiments with various filters show that often a few hundred EM simulations are needed in the above optimization process. Compared with several thousand MC samples that are often used in the surrogate modeling process (Stage 2 in Fig. 1), this cost is reasonably low. Moreover, it should be noticed that many candidate designs visited by the above optimization that are within $[\boldsymbol{x}^{init} - \boldsymbol{\delta}, \boldsymbol{x}^{init} + \boldsymbol{\delta}]$ can be used in the surrogate modeling, which further saves the necessary EM simulations.

TABLE I
PSOMSD-OBTAINED SURROGATE MODELING SPACE AND THE YIELD OPTIMIZATION RESULT

design variables	$\boldsymbol{x}-\boldsymbol{\delta}$	$\boldsymbol{x}+\boldsymbol{\delta}$	$\boldsymbol{x}^{init}$	$\boldsymbol{x}^{robust}$	design variables	$\boldsymbol{x}-\boldsymbol{\delta}$	$\boldsymbol{x}+\boldsymbol{\delta}$	$\boldsymbol{x}^{init}$	$\boldsymbol{x}^{robust}$
$Qe1$	2.947	3.021	2.984	2.967	L_6	49.971	50.041	50.004	49.98
$Qe2$	2.766	2.834	2.802	2.818	K_{12}	2.667	2.736	2.702	2.687
L_1	50.228	50.294	50.262	50.261	K_{23}	3.272	3.338	3.308	3.306
L_2	43.746	43.818	43.786	43.805	K_{34}	21.223	21.299	21.261	21.297
L_3	41.418	41.485	41.451	41.449	K_{45}	2.883	2.965	2.925	2.943
L_4	86.605	86.631	86.643	86.629	K_{56}	2.394	2.468	2.432	2.431
L_5	43.129	43.202	43.167	43.170	K_{25}	12.001	12.073	12.036	12.039

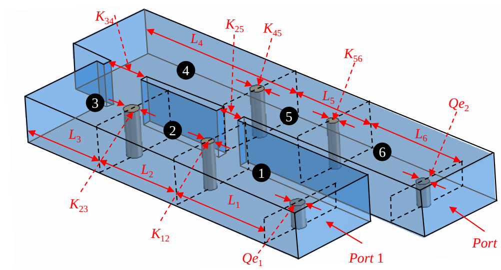
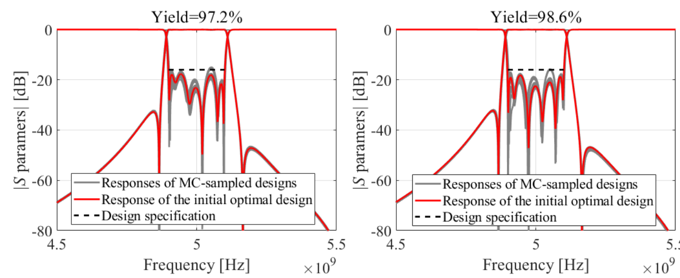


Fig. 2. Structure of the C-band filter.



(a) (b)

Fig. 3. Responses using 500 MC samples considering fabrication error: (a) the result in [14] and (b) the result of the proposed method.

III. Numerical Results

Several filter cases are used to verify PSOMSD and the performance is similar. In this section, a C-band waveguide bandpass filter [14] is used, which is shown in Fig. 2. The passband is 4.9 GHz to 5.1 GHz. The section of the waveguide is 42.00 mm × 17.00 mm (WR-42). The sensitive design variables are $\boldsymbol{x}$=[$Qe1$, $Qe2$, L_1, L_2, L_3, L_4, L_5, L_6, K_{12}, K_{23}, K_{34}, K_{45}, K_{56}, K_{25}] (see Fig. 2). The fabrication error of each design variable is 0.005 mm. The filter is modeled in CST Microwave Studio with about 14,000 meshes, and each simulation costs about 2 minutes. The initial design is $\boldsymbol{x}^{init}$=[2.984, 2.802, 50.262, 43.786, 41.451, 86.643, 43.167, 50.004, 2.702, 3.308, 21.261, 2.925, 2.432, 12.036] (mm) with a passband $max(|S_{11}|)$ of -17.1 dB. The requirement for a fabricated filter to be qualified is the passband max($|S_{11}|$)≤ −16 dB. Based on this, the yield value of the initial design estimated by $40\times d$ (d is the number of sensitive design variables) EM simulations is 56%.

Table I lists the surrogate modeling space obtained by PSOMSD. A direct verification method is to use the obtained space to carry out yield optimization. For surrogate modeling and global optimization (Fig. 1), the YSMA (yield optimization for filters based on offline surrogate model-assisted evolutionary algorithm) method [14] is employed. The obtained robust optimal design is also shown in Table I with a yield value of 98.6% (by $40\times d$ EM simulation verification as in [14]), improving the initial yield by 42.4%. In the whole process, PSOMSD used 651 EM simulations, and the MC sampling used 1549 EM simulations. The total time consumption is 73.3 hours. Hence, the obtained surrogate modeling space is appropriate due to the successful yield result and the efficiency. Compare to [14] which uses the same YSMA method but uses the empirical method of 5% of the wavelength at the central frequency to define the surrogate modeling space, the yield value is improved by 1.4% and the number of EM simulations is reduced by 22% (Fig. 3).

The necessary number of MC samples needed for an offline surrogate model-assisted yield optimization method is not only decided by the surrogate modeling space, but also by the machine learning method in surrogate modeling. For example, to make the neural network in YSMA obtain a reasonably accurate regression, the number of MC samples cannot be smaller than a certain threshold. Hence, to further verify the compactness of the surrogate modeling space obtained by PSOMSD, more analysis is carried out.

The volume of the hyperspace obtained by PSOMSD and the above empirical method are compared. The volume ratio between PSOMSD and the empirical method is 27.5%, showing the significant advantage of PSOMSD. A follow-up experiment is to decrease the obtained surrogate modeling space by 2 times (i.e., proportional scaling of each design variable) and carry out yield optimization using YSMA. When using 50% of the PSOMSD-obtained space, the optimal yield value is 79.6%. This shows that 50% of the space is insufficient because the optimal robust design with sufficient yield improvement is not included. It can also be found from Table I that some of the design variables (i.e., L_2, L_4, L_6 and K_{34}) are close to the bound of the PSOMSD-obtained space.

IV. Conclusion

Surrogate modeling space definition is a keystone for offline surrogate model-assisted filter yield optimization methods, highly affecting the yield optimization result and efficiency. Therefore, the PSOMSD method has been proposed, providing sufficient and compact surrogate modeling space systematically. Its advantages compared to empirical methods are also shown. Future research will focus on filter yield optimization software tools combining PSOMSD and YSMA.

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