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Physics-Based Surrogates for Low-Cost Modeling of Microwave Structures

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Abstract

High-fidelity electromagnetic (EM) simulation is a very accurate but computationally expensive way of evaluating the performance of microwave structures. In many situations, it has to be done multiple times when conducting various design tasks, such as parametric optimization or statistical analysis. Fast and accurate models, so-called surrogates, are therefore indispensable in contemporary microwave engineering. The most popular way of creating such models is by approximation of sampled EM-simulation data using, for example, low-order polynomials, support vector regression or neural networks. Unfortunately, initial cost of creating such models may be extremely high because of a large number of samples necessary to ensure reasonable accuracy. An alternative approach is to use physics-based models, where the surrogate is created by correcting an auxiliary low-fidelity model, e.g., equivalent circuit. In this paper, we review several modeling techniques exploiting this idea, including some variations of space mapping as well as shape-preserving response prediction. Our considerations are illustrated using examples of typical microwave components such as filters and antennas.

Keywords: Microwave engineering, surrogate modeling, electromagnetic simulation, space mapping, shape-preserving response prediction.

1. Introduction

Accurate evaluation of microwave components and structures can be obtained using full-wave electromagnetic (EM) simulation which became one of the fundamental design tools of contemporary microwave engineering. For certain structures (e.g., filters), there exist simple theoretical models that can be used to obtain initial designs, however, in many situations, EM-simulation-driven design is actually a must (substrate-integrated circuits [1], ultrawideband antennas [2], or dielectric resonator antennas [3]). Unfortunately, a high-fidelity EM simulation is computationally expensive, which might be a serious bottleneck for EM-simulation-based design tasks that require numerous evaluations of the structure of interest, such as parametric optimization or statistical analysis. Therefore, accurate and computationally cheap models of microwave structures are indispensable.

One of the most popular ways of constructing computationally cheap models is by using approximation techniques such as polynomial regression [4], radial basis functions [5], kriging [6], [7], support vector regression [8]-[11], fuzzy systems [12], [13], rational approximation [14], or artificial neural networks [15]-[18]. Approximation models, once created, are fast, but a large number of training points obtained through massive EM simulations is necessary for good accuracy over the entire design space. Moreover, contemporary approximation

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models rely on uniform data sampling [6], which results in an exponential growth of the number of training points with respect to the dimensionality of the design space—known as *the curse of dimensionality*. As a result, the aforementioned approximation techniques are suitable for creating multiple-use library models rather than ad-hoc models for solving design tasks such as parametric optimization.

This difficulty can be alleviated by exploiting physics-based models. In this approach, the surrogate model is created by a suitable correction of the underlying low-fidelity model. One of the most popular techniques of this kind in microwave engineering is space mapping (SM) [19]–[23]. A space mapping surrogate is constructed using a simplified representation (low-fidelity or coarse model) of the microwave structure in question (high-fidelity or fine model), e.g., an equivalent circuit, and some auxiliary mappings that “reshape” the parameter space and/or response of the coarse model. The enhancement of the coarse model is typically realized through suitable analytical formulas, which allows the surrogate model to be almost as computationally cheap as the coarse model. However, because the coarse model is supposedly physics-based, the accuracy of the space mapping surrogate is considerably better than the accuracy of possible function approximation models using a comparable amount of fine model data [24].

One of the problems of space mapping is that the low-fidelity model has to be substantially faster than the high-fidelity model because each evaluation of the SM surrogate involves an evaluation of the coarse model. Therefore, equivalent circuit or analytical coarse models are preferred. However, for many structures, such models are not available (e.g., wideband antennas, substrate integrated circuits) and the only alternative is coarse-discretization EM simulation. Simulation models are relatively expensive (typically, only 5 to 50 times faster than the corresponding high-fidelity models). To extend the applicability of SM to these cases, a modification of the standard SM has been proposed [25], where the coarse model to be used by the SM surrogate is constructed through an approximation of the coarse-discretization EM simulation data. This approach gives a reasonable tradeoff between the computational cost and the accuracy of the surrogate model.

Another technique exploiting physics-based low-fidelity models, shape-preserving response prediction (SPRP), has been reported in [26]. Similarly as SM, SPRP utilizes a computationally cheap coarse model of the microwave structure in question. However, in contrast to SM, no extractable parameters are necessary, which makes it easy to implement. Also, SPRP is based on modeling of the so-called characteristic points describing the response (e.g., S -parameters versus frequency) of the structure of interest rather than the response itself. In many cases, the dependence between the location of the characteristic points and the design variables is much simpler than the dependence of the original response. As a result, SPRP usually ensures better accuracy than SM [26]. On the other hand, SPRP has certain limitations; in particular, it requires that the sets of characteristic points for any two sets of design variables are in one-to-one correspondence throughout the region of surrogate model validity [27], which may not always be possible to satisfy.

In this paper, we briefly review and illustrate, using examples of typical microwave devices, a few physics-based surrogate modeling techniques, including standard space mapping, space mapping with kriging interpolation, as well as shape-preserving response prediction. We also discuss the advantages and disadvantages of the presented techniques.

2. Formulation of the Microwave Modeling Problem. Physics-Based Surrogate Models

Let $\mathbf{R}_f: X_f \rightarrow R^m$, $X_f \subseteq R^n$ denote the response vector of the microwave device of interest (high-fidelity or fine model). In particular, $\mathbf{R}_f(\mathbf{x})$ may represent the magnitude of a transfer function of a filter or a reflection coefficient of an antenna at m chosen frequencies. The task is to build the surrogate model $\mathbf{R}_s$ of $\mathbf{R}_f$ so that the match between the two models is as good as possible in the region of interest $X_R \subseteq X_f$. Typically, X_R is an n -dimensional interval in R^n with center at the reference point $\mathbf{x}^0 = [x_{0,1} \dots x_{0,n}]^T \in R^n$ and size $\boldsymbol{\delta} = [\delta_1 \dots \delta_n]$ [23]. Figure 1 shows the conceptual illustration of the fine and the surrogate models.

The quality of the surrogate can be assessed using a suitable error measure. Here, we use the relative error measure $\|\mathbf{R}_f(\mathbf{x}) - \mathbf{R}_s(\mathbf{x})\|/\|\mathbf{R}_f(\mathbf{x})\|$ expressed in percent, where $\mathbf{R}_f(\mathbf{x})$ and $\mathbf{R}_s(\mathbf{x})$ denote the fine and the respective surrogate model response at a given test point (design) $\mathbf{x}$. The figures of interest are average and maximum error over a set of test points. Typically, the test points are allocated in X_R using a uniform probability distribution.

One of the important characteristics of the surrogate is that it should be computationally much cheaper than the high-fidelity model. Another desirable feature is analytical tractability (particularly smoothness) so that the surrogate can be easily processed (e.g., optimized) in the design-related tasks.

In this paper, we focus the so-called physics-based modeling, i.e., methods that construct the surrogate by correcting the underlying low-fidelity model. There are several possibilities to obtain the physics-based low-fidelity models in microwave engineering. In some cases, models based on explicit analytical or semi-empirical formulas are available. Such models are normally very fast, however, they are usually of limited accuracy. For certain structures, particularly filters, low-fidelity models can be implemented as equivalent circuits, see Fig. 2 [28]. Equivalent circuit models are also very fast although not as convenient as analytical ones as an extra simulator has to be used for their evaluation. Their accuracy may also be limited, particularly for more complex structures. The most versatile type of low-fidelity model, available for any microwave structure, can be obtained through a coarse-discretization EM simulation (cf. Fig. 3). This type of a model is usually quite accurate; however, it might be relatively expensive. Unfortunately, selecting a good trade-off between the model accuracy and speed is not obvious. It is worth mentioning that coarsening the mesh is not the only way of creating an EM-based low-fidelity model. Other options include reducing the distance from the simulated structure to the absorbing boundary conditions, in the case of finite-volume electromagnetic simulators [29]; the lower order of the basis functions, in the case of finite-element and integral equation solvers [30]; simplified excitation, e.g., the discrete source of the coarse model versus the waveguide port of the fine model; zero thickness of metallization; the use of perfect electric conductor in place of finite-conductivity metals.

3. Surrogate Modeling Using Space Mapping

Space mapping (SM) [23] is a simple way of constructing the surrogate of a microwave structure by correcting the underlying coarse model. The coarse model should be computationally cheap and physically-based so that a good alignment between the surrogate and the fine model can be obtained by using a limited number of fine model evaluations [23]. For these reasons, a preferred choice for the coarse model is an equivalent circuit.

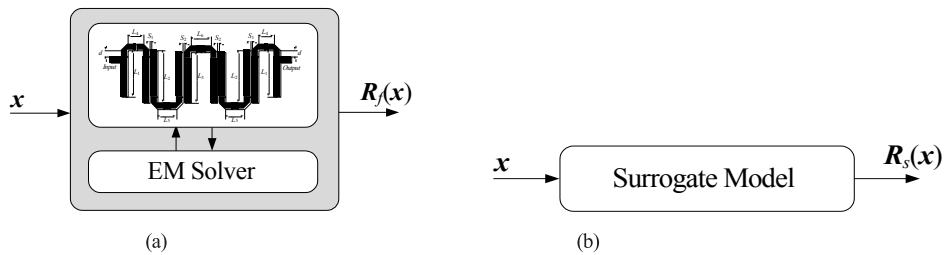


Fig. 1. Conceptual illustration of (a) the EM-simulated fine model, and (b) the surrogate model.

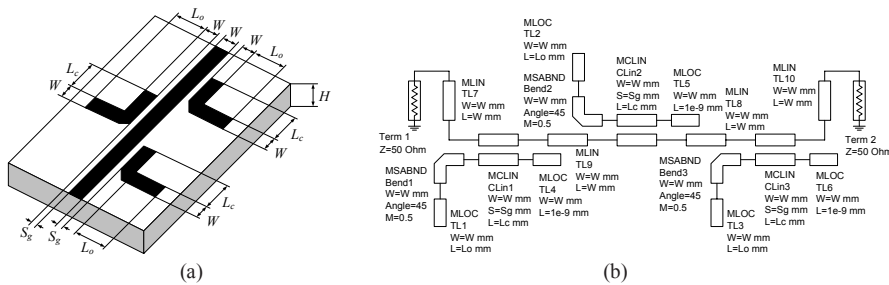


Fig. 2. Microstrip filter: (a) geometry, and (b) equivalent circuit.

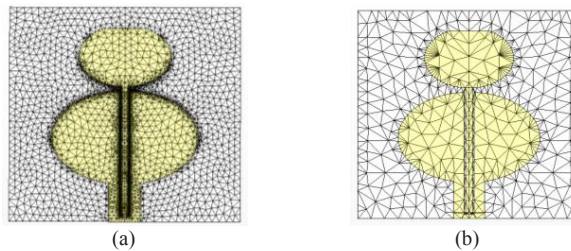


Fig. 3. Ultrawideband monopole antenna: finely- (a) and coarsely-discretized (b) geometry.

Let $\mathbf{R}_c : X_c \rightarrow R^m$, $X_c \subseteq R^n$, denote the coarse model response vector. $\mathbf{R}_c(\mathbf{x})$ represents the same physical characteristic of the system of interest as $\mathbf{R}_f(\mathbf{x})$. Let $X_{B,SM} = \{\mathbf{x}_{SM}^1, \mathbf{x}_{SM}^2, \dots, \mathbf{x}_{SM}^{N_{SM}}\} \subset X_R$ be the base set, such that the fine model response is known at all points $\mathbf{x}^j$, $j = 1, 2, \dots, N_{SM}$. In this work, the base set is chosen to be a factorial design, the so-called star distribution [23], consisting of $2n + 1$ points located at the center and all the faces of X_R .

The SM surrogate $\mathbf{R}_{s,SM}$ is defined as

$$\mathbf{R}_{s,SM}(\mathbf{x}) = \mathbf{A} \cdot \mathbf{R}_c(\mathbf{B} \cdot \mathbf{x} + \mathbf{c}) \quad (1)$$

where $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{c}$ are $m \times m$, $n \times n$, and $n \times 1$ matrices determined through a parameter extraction process, defined as

$$[\mathbf{A}, \mathbf{B}, \mathbf{c}] = \arg \min_{[\alpha, \beta, \gamma]} \sum_{k=1}^{N_{SM}} \|\mathbf{R}_f(\mathbf{x}_{SM}^k) - \alpha \cdot \mathbf{R}_c(\beta \cdot \mathbf{x}_{SM}^k + \gamma)\| \quad (2)$$

The flexibility of the model represented by (1)-(2) can be enhanced in many ways, e.g., by exploiting the so-called “pre-assigned” or “implicit” parameters. These parameters (e.g., dielectric constants, substrate height) are fixed in the fine model but can be freely modified in the coarse model in order to allow better alignment between the fine model and the surrogate [31]-[33]. Other types of SM surrogates can be found in [31].

Space mapping typically ensures reasonable accuracy while using a limited amount of fine model data. Moreover, as the parameter extraction process (2) is independent of the evaluation point $\mathbf{x}$ of the surrogate model, the accuracy of the model (1)-(2) is barely dependent on the number of the base points N_{SM} .

As an example, consider the fourth-order ring resonator bandpass filter [34] shown in Fig. 4(a). The filter is simulated using electromagnetic solver FEKO [35]. The space mapping surrogate model is constructed by correcting the low-fidelity model which is an equivalent circuits shown in Fig. 4(b). The low-fidelity model is implemented in Agilent ADS [36]. The design variables and the region of interest for our filter are the following (all sizes in mm): $\mathbf{x} = [L_1 \ L_2 \ L_3 \ S_1 \ S_2 \ W_1 \ W_2]^T$, $\mathbf{x}^0 = [24 \ 20 \ 26 \ 0.1 \ 0.1 \ 1.2 \ 0.8]^T$, $\boldsymbol{\delta} = [2 \ 2 \ 2 \ 0.05 \ 0.05 \ 0.1 \ 0.1]^T$. The surrogate model was set up using 20 base points allocated within the region of interest using Latin Hypercube Sampling [37]. The average modeling error measured as indicated in Section 2 using 50 random test points is 3.1 percent. Figure 5 shows the high-fidelity and the SM surrogate model responses at selected test points.

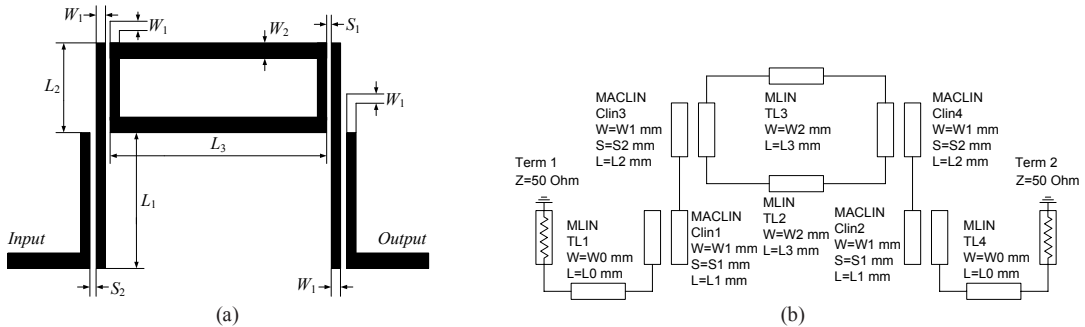


Fig. 4. Forth-order ring-resonator bandpass filter: (a) geometry [34], (b) equivalent circuit (Agilent ADS).

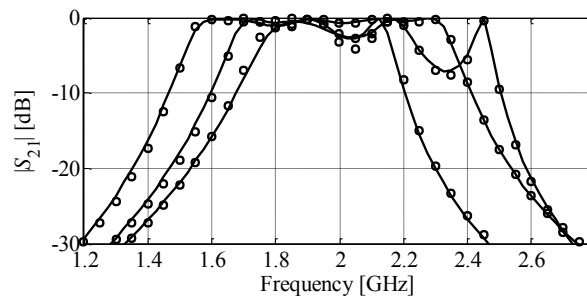


Fig. 5. Fourth-order ring resonator filter: responses of the high-fidelity (solid line) and SM surrogate model $\mathbf{R}_{s,SM}$ (circles) at selected test points.

4. Surrogate Modeling Using Space Mapping and Kriging

As mentioned in the introduction, space mapping requires that the underlying low-fidelity model to be substantially faster than the high-fidelity one. In many situations, fast low-fidelity models, particularly equivalent circuits, are not available. On the other hand, low-fidelity models can always be obtained through coarse-discretization EM simulation. Such models are relatively expensive and usually quite noisy (mostly in the sense of the numerical noise present due to adaptive meshing techniques). In order to expand the applicability of space mapping to these situations, one can use intermediate response surface approximation models as suggested in [25]. More specifically, we construct the coarse model for the space mapping surrogate using functional approximation of the data obtained from the coarse-discretization EM simulation (referred to as $\mathbf{R}_{cd}$). In this way, an EM simulation is only performed while setting up the model; the subsequent evaluation of the SM surrogate will not invoke the EM simulator again.

Here, we use kriging [7] as the approximation method but other techniques such as radial basis function interpolation [7] or support vector regression [8] can also be utilized.

Let $X_B = \{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^N\}$ denote a base set, such that the responses $\mathbf{R}_{cd}(\mathbf{x}^j)$ are known for $j = 1, 2, \dots, N$. Let $\mathbf{R}_{cd}(\mathbf{x}) = [R_{cd,1}(\mathbf{x}) \dots R_{cd,m}(\mathbf{x})]^T$. Components of the model response vector may correspond to certain parameters, e.g., $|S_{21}|$ evaluated at m frequency points.

We focus on ordinary kriging [7] that estimates a deterministic function f as $f_p(\mathbf{x}) = \mu + \varepsilon(\mathbf{x})$, where μ is the mean of the response at the base points, and ε is the error with zero expected value, and with a correlation structure being a function of a generalized distance between the base points. We use a Gaussian correlation function of the form

$$R(\mathbf{x}^i, \mathbf{x}^j) = \exp \left[\sum_{k=1}^n \theta_k |x_k^i - x_k^j|^2 \right] \quad (3)$$

where the θ_k are unknown correlation parameters used to fit the model, while x_k^i and x_k^j are the k th components of the base points $\mathbf{x}^i$ and $\mathbf{x}^j$.

The kriging-based coarse model $\mathbf{R}_c$ is defined as

$$\mathbf{R}_c(\mathbf{x}) = [R_{c,1}(\mathbf{x}) \dots R_{c,m}(\mathbf{x})]^T \quad (4)$$

where

$$R_{c,j}(\mathbf{x}) = \mu_j + \mathbf{r}^T(\mathbf{x}) \mathbf{R}^{-1}(\mathbf{f}_j - \mathbf{I} \mu_j) \quad (5)$$

Here $\mathbf{I}$ denotes a column-vector of N ones,

$$\mathbf{f}_j = [R_{cd,j}(\mathbf{x}^1) \dots R_{cd,j}(\mathbf{x}^N)]^T \quad (6)$$

$\mathbf{r}$ is the correlation vector between the point $\mathbf{x}$ and base points

$$\mathbf{r}(\mathbf{x}) = [R(\mathbf{x}, \mathbf{x}^1) \dots R(\mathbf{x}, \mathbf{x}^N)]^T \quad (7)$$

whereas $\mathbf{R}$ is the correlation matrix between the base points, namely,

$$\mathbf{R} = \begin{bmatrix} R(\mathbf{x}^1, \mathbf{x}^1) & R(\mathbf{x}^1, \mathbf{x}^2) & \dots & R(\mathbf{x}^1, \mathbf{x}^N) \\ R(\mathbf{x}^2, \mathbf{x}^1) & R(\mathbf{x}^2, \mathbf{x}^2) & \dots & R(\mathbf{x}^2, \mathbf{x}^N) \\ \vdots & \vdots & \ddots & \vdots \\ R(\mathbf{x}^N, \mathbf{x}^1) & R(\mathbf{x}^N, \mathbf{x}^2) & \dots & R(\mathbf{x}^N, \mathbf{x}^N) \end{bmatrix} \quad (8)$$

The mean μ_j is given by $\mu_j = (\mathbf{I}^T \mathbf{R}^{-1} \mathbf{I})^{-1} \mathbf{I}^T \mathbf{R}^{-1} \mathbf{f}_j$. The correlation parameters θ_k are obtained by maximizing $-[M \ln(\sigma^2) + \ln |\mathbf{R}|]/2$ [7] in which the variance $\sigma_j^2 = (\mathbf{f}_j - \mathbf{I} \mu_j)^T \mathbf{R}^{-1} (\mathbf{f}_j - \mathbf{I} \mu_j)/N$ and $|\mathbf{R}|$ are both functions of θ_k .

Function-approximation-based coarse models have a few important advantages: (i) they are fast and smooth, (ii) it is possible to build an SM model for problems where finding reliable and fast coarse models such as equivalent circuits is problematic (e.g., wideband antennas), and (iii) the accuracy of the function-approximation coarse model created from

coarse-discretization EM simulations is comparable to the accuracy of other possible coarse models (e.g., equivalent circuit). It should be emphasized that although the coarse model (3)-(8) uses function approximation, it retains the features of the physically-based model if the number of base points is sufficiently large. On the other hand, the computational cost of creating such models is low: assuming that the typical number of training points is $N = 100$ to 200, and the typical evaluation time ratio between R_f and R_{cd} varies between 20 to 50, the cost of creating R_c would be 2 to 10 high-fidelity model evaluations, which is much less than for any method based on a direct approximation of the fine model data only.

Consider a planar dipole antenna shown in Fig. 6. The antenna consists of the main radiator element and two parasitic strips [38]. The design variables are $x = [l_0 \ w_0 \ a_0 \ l_p \ w_p \ s_0]^T$. Other variables are: $a_1 = 0.5$ mm, $w_1 = 0.5$ mm. Rogers RT5880 laminate is used for the substrate dielectric (substrate height $h = 1.58$ mm). The high-fidelity antenna model R_f is simulated using the CST MWS transient solver [39] with evaluation time 44 minutes. The coarse-discretization model R_{cd} is also simulated in CST MWS (evaluation time 100 seconds). The region of interest is defined by the reference point $x^0 = [18.0 \ 12.0 \ 0.6 \ 13.0 \ 7.0 \ 1.5]^T$ mm, and the region size $\delta = [0.5 \ 0.5 \ 0.2 \ 0.5 \ 0.5 \ 0.5]^T$ mm. The kriging coarse model is created using $N = 100$ R_{cd} samples allocated using LHS [37]. The CPU-cost of establishing the coarse model corresponds to less than four evaluations of the fine model. The SM surrogate has been established using model (1) enhanced by frequency SM. Again, we considered two cases: (i) single-point base set $X_{B,SM} = \{x^0\}$, and (ii) a star distribution base set [23] with the center at x^0 . Modeling accuracy has been verified using 50 test points (Table 1). Figure 7 shows the fine and surrogate model responses at the selected test points. Note that the modeling accuracy is quite good even if only one base design is used to set up the surrogate model. A comparison with conventional kriging interpolation of the high-fidelity model data indicates that space mapping is much more efficient than direct kriging interpolation, i.e., similar level of modeling error is obtained for much smaller number of training samples.

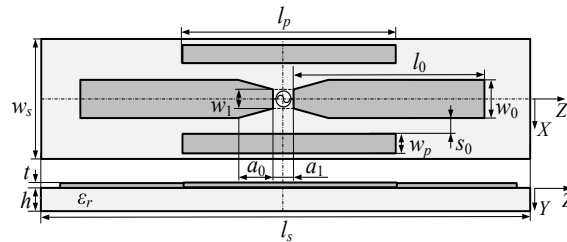


Fig. 6. Dipole antenna: geometry [32]: top and side views. The dash-dot lines show the magnetic (YOZ) and the electric (XOY) symmetry walls. The 50 ohm source impedance is not shown in this figure.

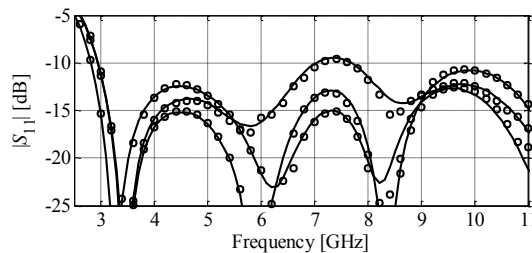


Fig. 7. Dipole antenna: fine (solid line) and SM-enhanced kriging coarse model responses (circles) at the selected test points.

Table 1. Dipole antenna: modeling results.

Surrogate Model	Base Set	Average Error	Computational cost [*]
SM-enhanced kriging R_c	1 point	7.6 %	5
	11 points (star distribution)	5.1 %	17
Kriging R_c	N/A	9.5 %	4
Kriging $R_f^{\#}$	20 points (LHS [§])	9.6 %	20
	50 points (LHS [§])	5.8 %	50
	100 points (LHS [§])	3.3 %	100
	200 points (LHS [§])	2.5 %	200
	400 points (LHS [§])	2.2 %	400

^{*} Cost of creating the surrogate in equivalent number of R_f evaluations.

[#] Kriging interpolation of sampled fine model data.

[§] Training points allocated using Latin Hypercube Sampling [30].

5. Surrogate Modeling Using Shape-Preserving Response Prediction

Similar to space mapping, the shape-preserving response prediction (SPRP) technique [27] exploits a low-fidelity model to create the surrogate. Versions of SPRP not relying on a low-fidelity model are also available [40]. In the SPRP technique, the surrogate is constructed by tracking the response of the low-fidelity model. The response change of $\mathbf{R}_c$ is described by the translation vectors corresponding to a finite number of the so-called characteristic points. These translation vectors are subsequently used to predict the change of the entire high-fidelity model response.

The SPRP concept is explained in Fig. 7(a) using the coarse model responses of a microstrip bandstop filter [27] at a certain design $\mathbf{x}^r$ as well as at some other design $\mathbf{x}$. Characteristic points of $\mathbf{R}_c(\mathbf{x}^r)$ are selected to represent $|S_{21}| = -3$ dB, $|S_{21}| = -20$ dB, and the local $|S_{21}|$ maximum (at about 13 GHz). The squares denote corresponding characteristic points for $\mathbf{R}_c(\mathbf{x})$, while the small pieces of lines represent the translation vectors that determine the “movement” of the characteristic points of $\mathbf{R}_c$ when changing the design variables from $\mathbf{x}^r$ to $\mathbf{x}$. Because of $\mathbf{R}_c$ being physically based, the fine model response at $\mathbf{x}$ can be predicted using the same translation vectors and the corresponding characteristic points of the fine model response at $\mathbf{x}^r$, $\mathbf{R}_f(\mathbf{x}^r)$ (Fig. 7(b)).

SPRP can be rigorously formulated as follows [27]. Let $\mathbf{R}_f = [R_f(\mathbf{x}, \omega_1) \dots R_f(\mathbf{x}, \omega_m)]^T$ and $\mathbf{R}_c = [R_c(\mathbf{x}, \omega_1) \dots R_c(\mathbf{x}, \omega_m)]^T$ denote the response vectors of the fine and coarse models, respectively, where ω_j , $j = 1, \dots, m$, is the frequency sweep. Let $\mathbf{p}_j^f = [\omega_j^f r_j^f]^T$, $\mathbf{p}_j^{c0} = [\omega_j^{c0} r_j^{c0}]^T$, and $\mathbf{p}_j^c = [\omega_j^c r_j^c]^T$, $j = 1, \dots, K$, denote the sets of characteristic points of $\mathbf{R}_f(\mathbf{x}^r)$, $\mathbf{R}_c(\mathbf{x}^r)$ and $\mathbf{R}_c(\mathbf{x})$, respectively, where $\mathbf{x}^r$ is a reference vector and $\mathbf{x}$ is a vector at which we want to estimate the fine model response. Here, ω and r denote the frequency and magnitude components of the respective point. The selection of the characteristic points should be determined by the defining features of the response shape (e.g., local minima/maxima) as well as some other points (e.g., points corresponding to specific values like -3 dB, -20 dB, etc.). The translation vectors of the $\mathbf{R}_c$ response are defined as $\mathbf{t}_j = [\omega_j^f r_j^f]^T$, $j = 1, \dots, K$, where $\omega_j^f = \omega_j^c - \omega_j^{c0}$ and $r_j^f = r_j^c - r_j^{c0}$. The SPRP surrogate is defined at point $\mathbf{x}$ as

$$\bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{x}^r) = [\bar{R}_s(\mathbf{x}, \mathbf{x}^r, \omega_1) \dots \bar{R}_s(\mathbf{x}, \mathbf{x}^r, \omega_m)]^T \quad (9)$$

where $\bar{R}_s(\mathbf{x}, \mathbf{x}^r, \omega_j) = \bar{R}_f(\mathbf{x}^r, F(\omega_j, \{-\omega_k^f\}_{k=1}^K)) + R(\omega_j, \{r_k^f\}_{k=1}^K)$ for $j = 1, \dots, m$. $\bar{R}_f(\mathbf{x}, \omega)$ is an interpolation of $\{R_f(\mathbf{x}, \omega_1), \dots, R_f(\mathbf{x}, \omega_m)\}$ onto the frequency interval $[\omega_1, \omega_m]$. The scaling function F interpolates the data pairs $\{\omega_1, \omega_1\}$, $\{\omega_1^f, \omega_1^f - \omega_1^f\}$, $\dots$, $\{\omega_K^f, \omega_K^f - \omega_K^f\}$, $\{\omega_m, \omega_m\}$, onto the frequency interval $[\omega_1, \omega_m]$. The function R does a similar interpolation for data pairs $\{\omega_1, r_1\}$, $\{\omega_1^f, r_1^f - r_1^f\}$, $\dots$, $\{\omega_K^f, r_K^f - r_K^f\}$, $\{\omega_m, r_m\}$; here $r_1 = R_c(\mathbf{x}, \omega_1) - R_c(\mathbf{x}^r, \omega_1)$ and $r_m = R_c(\mathbf{x}, \omega_m) - R_c(\mathbf{x}^r, \omega_m)$. The function F translates the frequency components of the characteristic points of $\mathbf{R}_f(\mathbf{x}^r)$ into the frequencies where they should be according to the translation vectors $\mathbf{t}_j$, while the function R adds the necessary magnitude component. The interpolation onto $[\omega_1, \omega_m]$ is necessary because the original frequency sweep is a discrete set. All interpolations are implemented through cubic splines. Generalizations of SPRP that help defining the surrogate model in case when one-to-one correspondence between the sets of characteristic points of the model responses may not be easy to preserve (which is a fundamental prerequisite of SPRP) can be found in [27].

Constructing the SPRP surrogate model, valid in a certain region of interest, based on the set of training points $X_B = \{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^N\}$, is then straightforward. We define

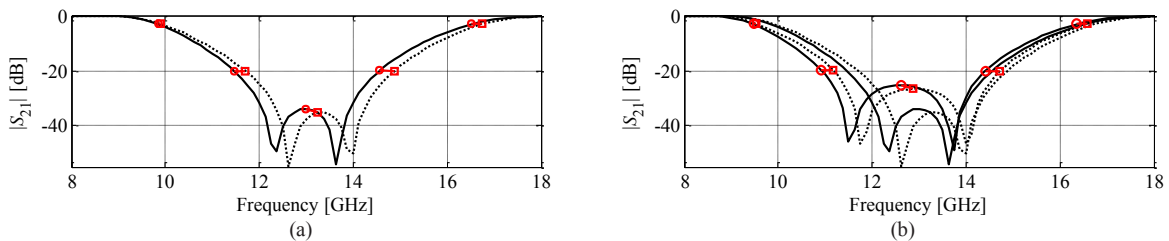


Fig. 8. (a) Coarse model response at the reference point $\mathbf{x}^0$, $\mathbf{R}_c(\mathbf{x}^0)$ (solid line), and at $\mathbf{x}$, $\mathbf{R}_c(\mathbf{x})$ (dotted line), characteristic points of $\mathbf{R}_c(\mathbf{x}^0)$ (circles) and $\mathbf{R}_c(\mathbf{x})$ (squares), and the translation vectors (short lines) [27]; (b) Fine model response at $\mathbf{x}^0$, $\mathbf{R}_f(\mathbf{x}^0)$ (solid line) and the predicted $\mathbf{R}_f$ response at $\mathbf{x}$ (dotted line) obtained using a SPRP based on characteristic points of Fig. 8(a); characteristic points of $\mathbf{R}_f(\mathbf{x}^0)$ (circles) and the translation vectors (short lines) were used to find the characteristic points (squares) of the predicted $\mathbf{R}_f$ response; responses $\mathbf{R}_c(\mathbf{x}^0)$ and $\mathbf{R}_c(\mathbf{x})$ are plotted using thin solid and dotted lines, respectively [27].

$$\mathbf{R}_s(\mathbf{x}) = \bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{x}') \quad (10)$$

where $\mathbf{x}'$ is the base point that is the closest to $\mathbf{x}$, i.e., $\mathbf{x}' = \operatorname{argmin}\{\mathbf{y} \in X_B : \|\mathbf{x} - \mathbf{y}\|\}$.

Although, as demonstrated in [26], this simple modeling approach proves to be more accurate than SM, it has some drawbacks. The model (10) utilizes only one base point at a time. As shown in Fig. 9(a), the region of interest is divided into regions of “attractions” of particular base points. For all evaluation points $\mathbf{x}$ located in a given region of “attraction”, the surrogate model (10) is determined using the same single base point as a reference design. Due to this, the surrogate does not utilize all available $\mathbf{R}_f$ data at a time. Also, the surrogate model is discontinuous at the borders of the areas of “attraction” because the solution to (10) is not unique at these points. This may cause some problems while using the surrogate for design optimization.

A modified SPRP modeling technique has been proposed in [26] that utilizes multiple reference designs and solves the discontinuity problem described in the previous section. Here, the base set is assumed to be allocated using star-distribution [23], however, the model can also be formulated for more general setups. The concept of the SPRP model exploiting multiple reference designs is explained in Fig. 9(b). For an evaluation point $\mathbf{x}$, we find a subset X_S of the base set X_B that defines a rectangular area (hypercube) of the region of interest containing $\mathbf{x}$. The surrogate model is set up using all points from X_S . The star-distribution base set contains $N = 2n + 1$ points as illustrated in Fig. 9(b) for $n = 2$. Without loss of generality, we can assume that $X_S = \{\mathbf{x}^0, \mathbf{x}^1, \dots, \mathbf{x}^n\}$. We have

$$\mathbf{x} = \mathbf{x}^0 + \beta_1 \mathbf{v}_1 + \beta_2 \mathbf{v}_2 + \dots + \beta_n \mathbf{v}_n \quad (11)$$

where $\beta_1, \dots, \beta_n$, determines a unique representation of $\mathbf{x} - \mathbf{x}^0$ using vectors $\mathbf{v}_i = \mathbf{x}^i - \mathbf{x}^0, i = 1, \dots, n$, and can be found as

$$[\beta_1 \ \beta_2 \ \dots \ \beta_n]^T = [\mathbf{v}_1 \ \mathbf{v}_2 \ \dots \ \mathbf{v}_n]^{-1} \cdot (\mathbf{x} - \mathbf{x}^0) \quad (12)$$

The vector $\mathbf{x}$ can be uniquely represented as $\mathbf{x} = \alpha_0 \mathbf{x}^0 + \alpha_1 \mathbf{x}^1 + \alpha_2 \mathbf{x}^2 + \dots + \alpha_n \mathbf{x}^n$, where $\alpha_0 = 1 - (\alpha_1 + \dots + \alpha_n)$, and $\alpha_i = \beta_i, i = 1, \dots, n$. The modified shape-preserving response prediction surrogate model is then defined as

$$\hat{\mathbf{R}}(\mathbf{x}) = \alpha_0 \bar{\mathbf{R}}(\mathbf{x}, \mathbf{x}^0) + \alpha_1 \bar{\mathbf{R}}(\mathbf{x}, \mathbf{x}^1) + \dots + \alpha_n \bar{\mathbf{R}}(\mathbf{x}, \mathbf{x}^n) \quad (13)$$

with $\bar{\mathbf{R}}_s(\mathbf{x}, \mathbf{x}^i), i = 0, 1, \dots, n$, being the shape-preserving response prediction models (1) determined using respective reference designs. It can be verified that the model (13) is continuous with respect to $\mathbf{x}$ provided that both $\mathbf{R}_f$ and $\mathbf{R}_c$ are continuous functions of $\mathbf{x}$. Also, it is expected to be more accurate than the model (10) because it exploits the available fine model data in a more comprehensive way.

Consider the coupled half-wavelength stepped impedance resonator (SIR) bandpass filter [41] (Fig. 10(a)). The design parameters are $\mathbf{x} = [L_1 \ L_2 \ L_3 \ L_4 \ S \ W_1 \ W_2]^T$ mm. The fine model is simulated in FEKO [35]. The coarse model (Fig. 10(b)) is implemented in Agilent ADS [36]. The region of interest is defined as $\mathbf{x}^0 = [3.0 \ 0.5 \ 13.0 \ 5.0 \ 0.5 \ 1.0 \ 1.0]^T$ mm $\boldsymbol{\delta} = [0.5 \ 0.2 \ 1.0 \ 0.5 \ 0.2 \ 0.2 \ 0.2]^T$ mm. For this example, the surrogate model was constructed three times, using (i) space mapping (cf. Section 3), (ii) standard SPRP, and (iii) modified SPRP. The comparison of the model accuracies is shown in Table 2 and Fig. 11.

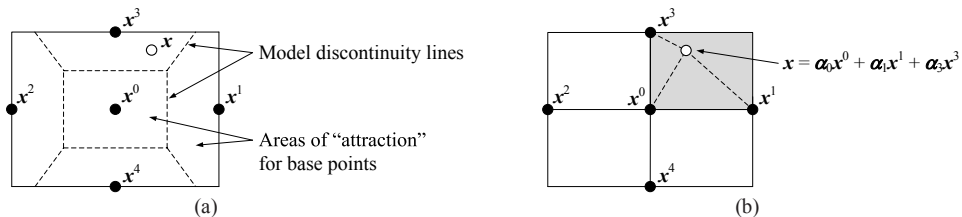


Fig. 9. SPRP modeling ($n = 2$): (a) Original: Star-distributed base points are denoted using black circles. The region of interest is divided into areas of “attraction” of particular base points, determined by the Euclidean distance. An example evaluation design $\mathbf{x}$ is close to the base design $\mathbf{x}^3$, and this point becomes a reference design for SPRP model; (b) Modified: Base points are denoted using black circles. A shaded area denotes a hypercube defined by a subset X_S of base points being the closest to an example evaluation design $\mathbf{x}$. The surrogate at $\mathbf{x}$ is defined as a linear combination of SPRP models using all base points from X_S as reference designs. Coefficients of this linear combination are calculated by representing $\mathbf{x}$ through all points from X_S .

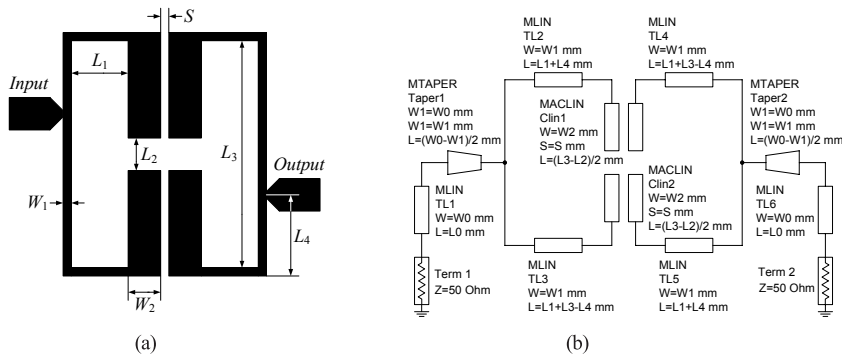


Fig. 10. Coupled half-wavelength SIR bandpass filter: (a) geometry [41]; (b) coarse model (Agilent ADS).

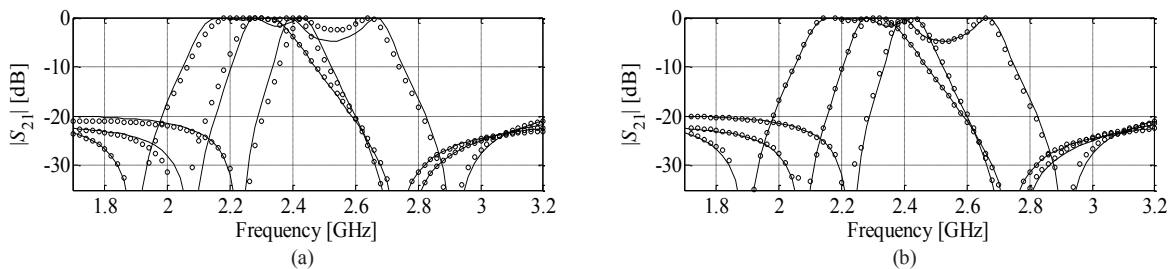


Fig. 11. Half-wavelength SIR bandpass filter: fine model (solid line) and surrogate model (circles) responses at three selected test points for: (a) standard SM model, (b) modified SPRP surrogate model.

Table 2. Coupled SIR Bandpass Filter: Modeling Results

Model	Average Error	Maximum Error
SM	5.9 %	11.5 %
SPRP (Basic Version)	4.7 %	9.7 %
SPRP (Modified Version)	1.5 %	3.5 %

6. Conclusions

Several methods for modeling of microwave components and structures exploiting physics-based surrogates have been discussed. Thanks to utilizing the knowledge embedded in the low-fidelity models, whether it is equivalent circuit or coarse-discretization EM simulation, techniques such as space mapping or shape-preserving response prediction can be used to create fast representations of the structures of interest at a low computational cost. The presented methods have been illustrated using examples of typical microwave components, including filters and an antenna. Modifications of both space mapping and shape-preserving response prediction that allows their application to a larger class of modeling problems or better utilization of available high-fidelity model data have also been discussed.

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