



Expedited Dimension Scaling of Microwave and Antenna Structures Using Inverse Surrogates

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Abstract

Re-designing circuits for various sets of performance specifications is an important problem in microwave and antenna engineering. Unfortunately, this is a difficult task that is normally realized as a separate design process, which is often as expensive (in computational terms) as obtaining the original design. In this work, we consider the application of inverse surrogate modeling for fast geometry scaling of microwave and antenna structures. Computational efficiency of the discussed procedure is ensured by representing the structure at the low-fidelity model level. The explicit relation between design specifications (here, operating frequency) of the structure and its geometry dimensions is determined based on a set of predetermined reference designs. Subsequently, the model is corrected to elevate the re-designed geometry to the high-fidelity electromagnetic (EM) model level. Our approach is demonstrated through a compact rat-race coupler and a patch antenna with enhanced bandwidth.

Keywords: Surrogate modeling, inverse modeling, geometry scaling, computer-aided design (CAD), simulation-driven design, microwave structures, antennas.

1 Introduction

Computer simulation models are the key tools utilized in modern microwave and antenna engineering (Qing and Chen, 2009). High-fidelity computational models yield accurate responses of the structure at hand, accounting for environmental effects (Bekasiewicz and Koziel, 2015a; Koziel and Bekasiewicz, 2014) and various second-order effects (Koziel and Yang, 2011) that may affect the performance. On the other hand, high-fidelity electromagnetic (EM) simulations are numerically expensive, which is a fundamental problem for automated design of microwave and antenna structures exploiting numerical optimization procedures. The reason is that conventional algorithms require hundreds or even thousands of objective function evaluations to converge to the optimal design.

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Therefore, automated determination of the optimal solutions may be computationally prohibitive for expensive models (Kuwahara, 2005; Chamaani, Abrishamian and Mirtaheeri, 2010). This is the case for most conventional methods including both gradient-based algorithms with numerical derivatives (Nocedal and Wright, 2006), and derivative-free procedures (Conn, Scheinberg and Vicente, 2009) especially population-based global search algorithms. Consequently, in many areas, design techniques based on parameter sweeps guided by engineering insight (typically, one parameter at a time) are industrial standard. Although such an approach is very laborious, it may lead to satisfactory results, especially if the search is guided by engineering experience and problem-specific knowledge. Nevertheless, hands-on design approaches cannot provide truly optimum designs (Koziel and Bekasiewicz, 2015a).

Automated design of microwave and antenna components can be accelerated by means of adjoint sensitivities (Ghassemi, Bakr and Sangary, 2013; Nomura *et al.* 2013; Koziel and Bekasiewicz, 2015a) which allows for evaluation of the system response and its derivatives at a cost of single simulation (Koziel and Bekasiewicz, 2014; Koziel and Bekasiewicz, 2015a). Unfortunately, adjoint sensitivities are supported by only a few commercial EM solvers (CST, 2013; ANSYS, 2012). Another approach to achieving a design speedup is by using surrogate-based optimization (SBO) (Queipo *et al.* 2005; Bandler *et al.* 2004a; Koziel, Bekasiewicz and Kurgan, 2014), where direct optimization of the high-fidelity simulation model is replaced by an iterative procedure of correcting and re-optimizing a cheaper representation of the system of interest (a so-called surrogate model). The most efficient SBO techniques are those exploiting physics-based models (Bekasiewicz and Koziel, 2015a; Koziel, Bekasiewicz and Kurgan, 2014; Leifsson and Koziel, 2011; Leifsson *et al.*, 2008), where the surrogate is constructed by appropriate enhancement/correction of an underlying low-fidelity model of the structure at hand, e.g., coarse-discretization EM model or equivalent network representation. The state-of-the art SBO methods include, among others, space mapping (SM) (Bandler *et al.* 2004a; Bandler *et al.* 2004b; Koziel, Bekasiewicz and Kurgan, 2014), various response correction approaches (Koziel, Leifsson and Ogurtsov, 2013; Koziel, Ogurtsov and Szczepanski, 2012), feature-based optimization techniques (Koziel and Bandler 2015), as well as—in microwave and antenna engineering—adaptively adjusted design specifications (Bekasiewicz and Koziel, 2015b).

An important problem in microwave and antenna engineering is to re-design a given structure for various sets of performance requirements. Typically, the structures are designed for a given operating frequency and their re-design for other frequencies is realized as a separate task the cost of which is just as high as getting the original design. Due to the high-cost of simulation-driven optimization, reusing the results obtained for a given set of requirements to accelerate the design for new specifications seems to be an attractive idea that may significantly speed up the design process. Frequency of the structure operation can be adjusted by means of scaling its dimensions (Koziel and Bekasiewicz, 2015b; Koziel, Bekasiewicz, and Leifsson, 2015). Unfortunately, the relationships between the operating frequency and the dimensions are nonlinear which makes the scaling process a nontrivial task.

In this paper, we utilize inverse surrogate modeling for rapid geometry scaling of microwave and antenna structures. The considered algorithm exploits low-fidelity model to optimize the design for several operating frequencies. Subsequently, an inverse surrogate model which establishes an explicit relationship between the operating frequency of the structure and its geometrical parameters is extracted. The model is then corrected to enable reliable scaling of the high-fidelity EM model. Our approach has been demonstrated using two examples: a compact folded microwave coupler, and a patch antenna with enhanced operational bandwidth.

2 Microwave Device Scaling Using Inverse Surrogates

In this section, formulate the dimension scaling problem and outline of the considered scaling procedure. Its main component is an inverse surrogate model describing the relations between the structure parameters and its operating frequency. We describe the surrogate model construction and

discuss the problem of design uniqueness. The latter is particularly important when the design process involves handling several design objectives at a time.

2.1 Scaling Problem Formulation

Let $\mathbf{x} \in R^n$ be a vector representing design parameters and $\mathbf{R}_f(\mathbf{x})$ be the response vector of the high-fidelity EM model of the structure at hand. Then, assume that the structure is designed for a given center frequency f_0 for which performance specifications are fulfilled. Dimensions of such a circuit will be referred to as the reference design $\mathbf{x}_f^*(f_0)$. The optimum design of the structure obtained for any given frequency f is referred to as $\mathbf{x}_f^*(f)$.

The considered problem is to scale dimensions of the design to a different frequency of operation f , so that they are optimal (or close-to-optimal) with respect to specifications at f . In other words, given $\mathbf{x}_f^*(f_0)$, the problem is to find $\mathbf{x}_f^*(f)$ for frequencies within a specified range around f_0 . Dimension scaling of topologically complex structures with compact geometries and/or multiple parameters is a challenging task, because the relations between their dimensions and responses are usually highly nonlinear and sometimes counter-intuitive (Koziel, Bekasiewicz, and Leifsson, 2015). In general, re-designing a structure to operate at higher frequencies typically reduces its dimensions. However, as demonstrated in Section 4, the opposite can happen, i.e., increasing the antenna operational frequency may yield a structure with some of geometrical dimensions being larger. Similar effects can be observed for compact microwave structures (cf. Section 3). Notwithstanding, the possibility of rapid dimension scaling seems to be attractive from a practical standpoint. Figure 1 shows example responses of miniaturized rat-race coupler optimized for a certain frequency and then redesigned for a different frequency.

2.2 Inverse Model Construction

An inverse surrogate model of the structure at hand is the core component of the discussed dimension scaling procedure (Koziel and Bekasiewicz, 2015b; Koziel, Bekasiewicz, and Leifsson, 2015). The model determines the relationship $\mathbf{x}_c(f)$ between the structure dimensions and its frequency of operation. The surrogate is constructed at the low-fidelity model level which ensures numerical efficiency of the process. The inverse model is given by

$$\mathbf{x}_c(f, \mathbf{P}) = [x_{c,1}(f, \mathbf{p}_1) \dots x_{c,n}(f, \mathbf{p}_n)]^T, \quad (1)$$

where $x_{c,k}(f, \mathbf{p}_k)$ is a model of the k th independent design variable, $\mathbf{p}_k$ are coefficients of the model and $\mathbf{P} = [\mathbf{p}_1 \dots \mathbf{p}_n]$ is the aggregated coefficient vector for the entire model. Clearly, there is a lot of freedom in selecting a particular analytical form of $x_{c,k}$.

Here, it is decided based on visual inspection of the training data. The model is obtained in a two-step procedure that works as follows:

1. Optimize the low-fidelity model of the structure for a set of operating frequencies $f_j, j = 1, \dots, N$, to find its optimum designs $\mathbf{x}_{c,j} = [x_{c,j,1} \dots x_{c,j,n}]^T$;
2. Perform curve fitting by solving nonlinear regression problems to find coefficients of the inverse model, for $k = 1, \dots, n$:

$$\mathbf{p}_k = \arg \min_{\mathbf{p}} \sum_{j=1}^N (x_{c,k}(f_j, \mathbf{p}) - x_{c,j,k})^2. \quad (2)$$

The inverse modeling concept is illustrated in Fig. 2. Note that $\mathbf{x}_c(f)$ directly returns the parameters of the structure scaled to the given center frequency f . However, the model (1) operates at the low-fidelity model level and thus its further correction is required to obtain the dimensions of the high-fidelity EM structure (cf. Section 2.3).

An important aspect of the dimension scaling process is that the optimized low-fidelity model designs are only approximations of the “ideal” geometry parameter values corresponding to any given

operating frequency. At the same time, the parameters obtained by means of direct optimization of the model are normally different from these “ideal” values. This is mostly due to imperfections of the optimization process (e.g., true optimum is unattainable due to the specific termination conditions used, deficiencies of the utilized optimization approach, numerical noise issues, etc.). Another reason is certain ambiguity concerning the definition of the good design. This is illustrated in Fig. 2 where the sequence of the optimized designs is “noisy” and thus does not follow any smooth curve. These factors indicate that the analytical form of the inverse model should be relatively simple (i.e., contain just a few degrees of freedom) so that it allows modeling the relationship between the frequency of operation and the circuit dimensions while smoothing the numerical “noise”.

2.3 Scaling Algorithm

As mentioned before, the inverse surrogate is constructed using the low-fidelity model responses so that it has to be corrected in order to be applied for scaling of the high-fidelity (EM-simulation) model of the structure at hand. The described correction procedure assumes that the low- and high-fidelity models are well correlated.

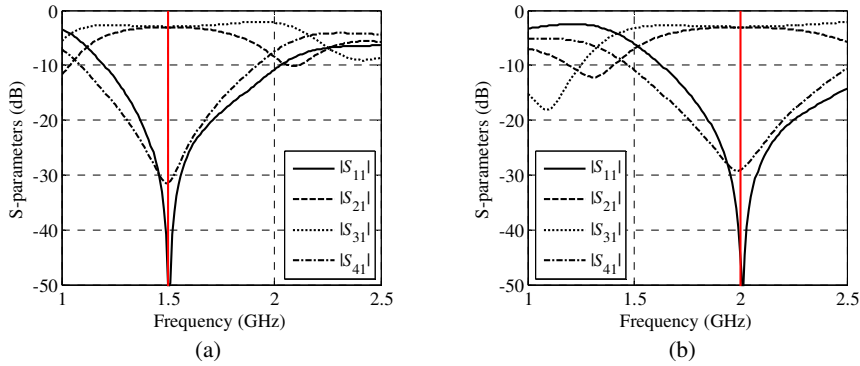


Figure 1: Dimension scaling of a miniaturized rat-race coupler (Koziel, Bekasiewicz, and Kurgan, 2015): (a) circuit response at a reference frequency $f_0 = 1.5$ GHz; (b) response of a scaled circuit at the frequency $f = 2.0$ GHz. For consistency of the scaling process a “good” response should be possibly unique which may involve arbitrary choices with respect to design specifications.

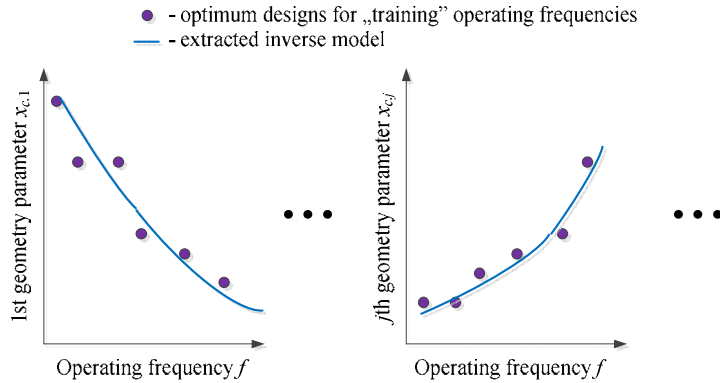


Figure 2: Extraction of the inverse model $x_c(f)$. The training data is obtained from optimizations of the low-fidelity model at the operating frequencies f_j , $j = 1, \dots, N$, which cover the desired frequency range for scaling. The parameters of the inverse model are obtained individually for each geometry variable by solving (2).

Let $\mathbf{x}_c^*(f_0)$ and $\mathbf{x}_f^*(f_0)$ denote the optimum designs of the low- and high-fidelity model at the reference frequency f_0 . The scaled dimensions for the high-fidelity model are obtained as follows:

$$\mathbf{x}_f(f) = \mathbf{x}_c(f, \mathbf{P}) + [\mathbf{x}_f^*(f_0) - \mathbf{x}_c^*(f_0)]. \quad (3)$$

The correction term in brackets is used to shift the inverse model $\mathbf{x}_c$ so that we have $\mathbf{x}_f(f_0) = \mathbf{x}_f^*(f_0)$.

In practice, the geometry scaling process introduces some residual errors. As a consequence, the actual operating frequency of the design $\mathbf{x}_f(f)$ may be slightly different from f and equal to $f + \Delta f$ (Δf may be positive or negative). In other words, Δf is a frequency scaling error resulting from imperfections of the inverse surrogate derived from fluctuations of the training data (cf. Section 2.2). They can be accounted for by means of the following correction term:

$$\mathbf{x}_f(f) \leftarrow \mathbf{x}_c(f - \Delta f, \mathbf{P}) + [\mathbf{x}_f^*(f_0) - \mathbf{x}_c^*(f_0)]. \quad (4)$$

More specifically, given the scaling error of $+\Delta f$, the corrected design should be obtained by evaluating the inverse model (3) at the operating frequency $f - \Delta f$ to compensate for the Δf error. It should be noted that correction (4) is not mandatory because, in many cases the quality of design obtained from the inverse surrogate is reasonably good. The cost of scaling the structure to an arbitrarily selected frequency f is only one high-fidelity model simulation. Assuming that correction (4) is necessary, the overall cost increases to two evaluations of the high-fidelity model.

It should be noted that a successful operation of the scaling algorithm requires that the low- and high-fidelity models are well correlated. Although the frequency misalignment between the models is not critical (it can be accounted for by the correction procedure), both models should exhibit similar response changes under comparable geometry parameter modifications. Although not much freedom exists in the case of equivalent circuit models, the discretization density of the low-fidelity EM models should ensure its good correlation with the high-fidelity representation.

3 Case Study I: Miniaturized Rat-Race Coupler

Our first design example is a miniaturized microstrip rat-race coupler (RRC) shown in Fig. 3 (Koziel, Bekasiewicz and Kurgan, 2015). The structure is composed of four 70.7-ohm folded sections (three of quarter-wavelength and one having three quarters of a wavelength; Pozar 2012). The circuit is fed through four 50 Ohm ports. The RRC is implemented on a 0.762 mm Taconic RF-35 substrate ($\epsilon_r = 3.5$, $\tan\delta = 0.018$). The center frequency of the reference designs is $f_0 = 1.5$ GHz. The RRC parameter vector is: $\mathbf{x} = [l_1 \ l_2 \ l_3 \ d \ w]^T$, with $w_0 = 1.7$, $l_0 = 15$ fixed. The unit for all dimensions is mm. The high-fidelity model of the structure is implemented in CST Microwave Studio and simulated using its frequency domain EM solver (CST, 2013). The model consists of ~210,000 mesh cells and its typical simulation time is 20 minutes. The low-fidelity (circuit) representation of a coupler is prepared in Agilent ADS simulator (Agilent, 2011).

The aim is to scale the RRC in a frequency range from 0.5 GHz to 2 GHz. The dimensions of the reference design are $\mathbf{x}_f^* = [0.753 \ 7.41 \ 12.09 \ 1.00 \ 0.772]^T$. The procedure of Section 2.2 has been utilized to extract the inverse surrogate model. The process has been completed after a total of 13 optimizations of the low-fidelity model with respect to frequencies divided by 125 MHz steps. The typical misalignment between responses of the low- and high-fidelity models at f_0 frequency is shown in Fig. 4. The reference circuit design at f_0 is $\mathbf{x}_c^* = [0.738 \ 4.94 \ 12.51 \ 0.917 \ 0.885]^T$. It should be noted that, due to relatively simple topology of the RRC, the discrepancies between responses of both models are noticeable yet not very significant.

The analytical form of the inverse model was assumed to be $x_{c,k}(f) = p_1 + p_2 \exp(p_3 f)$, where $\mathbf{p} = [p_1 \ p_2 \ p_3]$ are the model parameters. The plots of the extracted inverse surrogate model are shown in Fig. 5. One should emphasize that the representation of the “training” designs provided by the inverse model is very accurate and only a minor fluctuations of dimensions with respect to the curves can be observed. The results indicate sufficient uniqueness of the optimized designs. The only noticeable departure from the model curve can be observed for variable x_5 (see Fig. 5). Nonetheless, the relative value of this deviation is small (the range of variability for x_5 is only from 0.87 mm to 0.89 mm). It should also be noted that parameter x_5 increases with frequency which is counterintuitive from the point of geometry scaling, because operational frequency of microwave structures is normally inversely proportional to their physical dimensions.

The extracted inverse model has been verified by scaling the dimensions for the following frequencies: 0.5 GHz, 0.7 GHz, 1 GHz, 1.2 GHz, 1.7 GHz, and 2.0 GHz. The results shown in Fig.6 indicate that the scaling procedure works properly as the responses of the high-fidelity model fulfill design specifications (equal power split and almost symmetric -20 dB bandwidth around the f). The correction step of (4) was required only for scaling the antenna at the 1.7 GHz frequency (shift by 50 MHz) which indicates very good generalization capability of the inverse model.

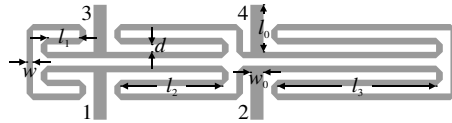


Figure 3: Geometry of the miniaturized rat-race coupler (Koziel, Bekasiewicz and Kurgan, 2015).

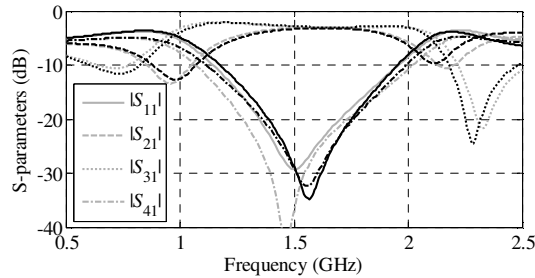


Figure 4: Comparison of the low- (gray lines) and high-fidelity (black lines) model responses of the miniaturized coupler at the design for $f_0 = 1.5$ GHz.

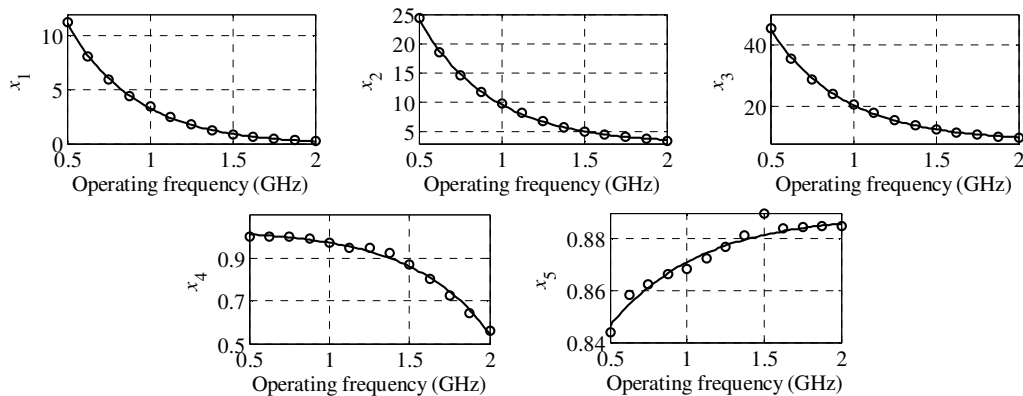


Figure 5. The inverse model (—) extracted from 13 low-fidelity model designs (○).

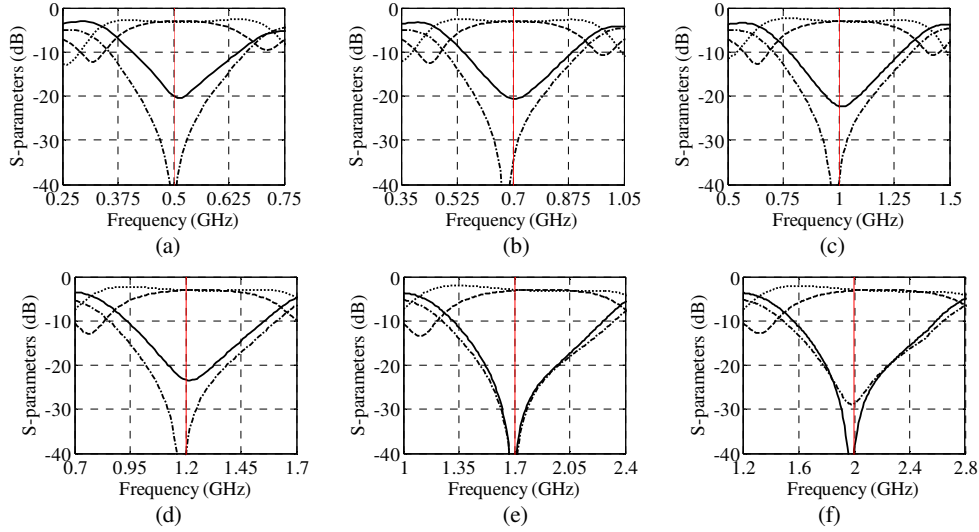


Figure 6: Frequency characteristics of the miniaturized coupler obtained using the technique of Section 2 for selected frequencies: (a) 0.5 GHz; (b) 0.7 GHz; (c) 1.0 GHz; (d) 1.2 GHz; (e) 1.7 GHz; and (f) 2.0 GHz. The vertical red lines denote operating frequencies, whereas the lines marked (—), (---), (····), and (- · - ·) represent matching, transmission, coupling and isolation, respectively.

4 Case Study II: Bandwidth-Enhanced Patch Antenna

Our second benchmark problem is a patch antenna with enhanced-bandwidth shown in Fig. 7 (Koziel, Bekasiewicz, and Leifsson, 2015). The structure is composed of a microstrip patch with inset feed excited through a microstrip line. Parasitic radiator introduces additional resonance and, consequently, enhances bandwidth. The impedance bandwidth of the antenna is further improved by means of the ground plane trim allocated below the radiator. The antenna is implemented on a 0.762 mm Taconic RF-35 substrate (cf. Section 4). The structure is represented by eight-parameter vector $\mathbf{x} = [L \ l_1 \ l_2 \ l_3 \ W \ w_1 \ w_2 \ g]^T$, whereas $o = 7$, $w_0 = 1.7$, $l_0 = 10$ and $s = 0.5$ remain fixed (all dimensions are in mm). The high- and low-fidelity models of the structure are both prepared in CST Microwave Studio (CST, 2013). The former consists of $\sim 1,900,000$ mesh cells and its average simulation time 12 min. The low-fidelity model is composed of $\sim 300,000$ cells and its typical simulation time is 60 s.

A total of five training designs, optimized to achieve 25% bandwidth for operational frequencies of 4 GHz, 5 GHz, 6 GHz, 7 GHz, and 8 GHz, respectively, have been utilized to extract the inverse surrogate model. Note that the numerical cost of low-fidelity antenna model is about 60 times higher compared to the equivalent circuit model exploited in Section 3 and thus the number of “training” designs has been reduced to five. The analytical form of the model is the same as in Section 3. The plots of extracted surrogate are shown in Fig. 8. Note that two of the variables (l_3 and w_1) are increasing with scaling the antenna up in frequency, which is rather counterintuitive from the point of typically inverse proportional relation between the operational frequency and the antenna size.

The obtained inverse surrogate has been validated for four designs designated to operate at 4.5 GHz, 5.5 GHz, 6.5 GHz and 7.5 GHz frequencies. The reflection responses of scaled antenna designs are shown in Fig. 9. The results indicate very good quality of the scaling model. The obtained designs feature 25-percent fractional bandwidth which fulfills the imposed design requirement.

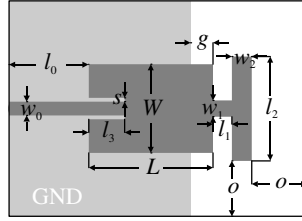


Figure 7: Geometry of the patch antenna with enhanced bandwidth (Koziel, Bekasiewicz and Leifsson 2015).

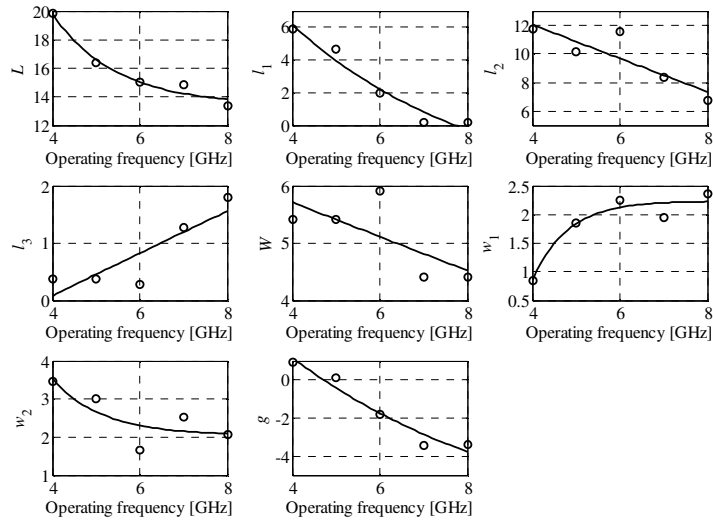


Figure 8: The inverse surrogate model (—) extracted from antenna dimensions obtained for the “training” designs (coarse-discretization EM model level) ($\circ$).

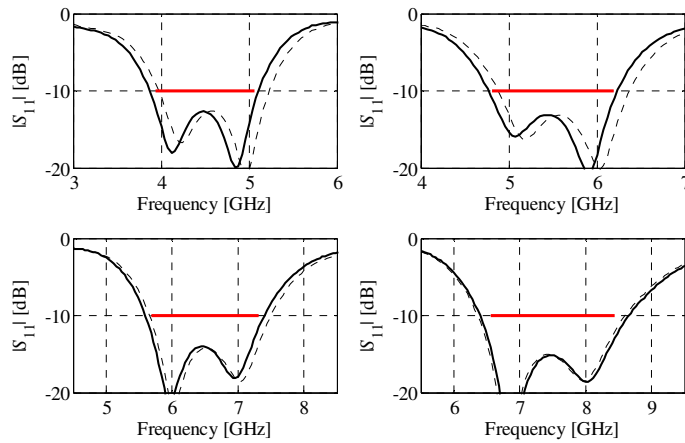


Figure 9: Responses of the bandwidth-enhanced patch antenna for: 4.5 GHz, 5.5 GHz, 6.5 GHz, and 7.5 GHz frequencies obtained using (3) (---), and the corrected using (4) (—).

5 Conclusion

In this work, a surrogate-assisted methodology for dimension scaling of microwave and antenna structures with respect to their operating frequency has been discussed. The scaling procedure exploits an inverse model that explicitly determines the relationships between the operating frequency and the structure geometry. The surrogate is obtained from the “training” designs optimized for a set of frequencies evenly selected along the frequency range of interest. Depending on the structure, the low-fidelity model may be an equivalent circuit or it can be obtained from coarse-discretization EM analysis. By exploiting correlations between the EM models of various fidelities, the inverse surrogate permits reliable prediction of the scaled dimensions at the high-fidelity model level. The cost of scaling procedure is just one high-fidelity simulation. Possible residual scaling errors can be accounted for by means of the correction procedure which requires only one additional EM simulation. The scaling algorithm considered in this work is a step towards efficient and automated reusing of the existing design results. The performance of the technique has been validated based on rat-race coupler structure and bandwidth-enhanced patch antenna. Possible enhancements of the approach such as an extension for multi-dimensional scaling (e.g., with respect to a few of operating parameters) will be considered in future work.

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