Managing Model Fidelity for Efficient Optimization of Antennas using Variable-resolution Electromagnetic Simulations

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Abstract: Electromagnetic (EM) simulation has become an important tool in the design of contemporary antenna structures. However, accurate simulations of realistic antenna models are expensive and therefore design automation by employing EM solver within an optimization loop may be prohibitive because of its high computational cost. Efficient EM-driven antenna design can be performed using surrogate-based optimization (SBO). A generic approach to construct surrogate models of antennas involves the use of coarse-discretization EM simulations (low-fidelity models). A proper selection of the surrogate model fidelity is a key factor that influences both the performance of the design optimization process and its computational cost. Despite its importance, this issue has not yet been investigated in the literature. Here, we focus on a problem of proper surrogate model management. More specifically, we carry out a numerical study that aims at finding a trade-off between the design cost and reliability of the SBO algorithms. Our considerations are illustrated using several antenna design cases. Furthermore, we demonstrate that the use of multiple models of different fidelity may be beneficial to reduce the design cost while maintaining the robustness of the optimization process.

1 INTRODUCTION

Design of contemporary antennas strongly relies on electromagnetic (EM) simulations. For many structures, including ultra-wideband (UWB) antennas of non-canonical shapes (Shantz, 2005) or dielectric resonator antennas (DRAs) (Petosa, 2007), EM-based design is the only possibility to adjust geometry and/or material parameters so that given performance specifications are met. Typically, this is performed through laborious parameter sweeps guided by engineering experience, which does not guarantee optimum results.

Automation of the antenna design process by using numerical optimization routines is challenging as high-fidelity EM simulation is computationally expensive and conventional algorithms (e.g., gradient-based ones) require large number of such simulations. Population-based techniques (metaheuristics) have recently become popular in the solving certain antenna-design-related tasks (Haupt, 2007); (Kerkhoff and Ling, 2007). Methods such as genetic algorithms (Pantoja et al., 2007), particle swarm optimizers (Jin and Rahmat-Samii, 2005) or ant colony optimization (Halehdar et al., 2009), can alleviate certain problems (e.g., getting stuck in a local optimum); however, these methods are mainly applicable if the objective function evaluation is very fast, for example, for synthesis of antenna array patterns (Jin and Rahmat-Samii, 2008). The use of such techniques for simulation-based antenna design is questionable due to the large number of model evaluations required by metaheuristics.

In recent years, there has been a growing interest in surrogate-based optimization (SBO) methods (Bandler et al., 2004); (Koziel et al., 2006); (Koziel et al., 2011), where direct optimization of a CPU-intensive full-wave EM model is replaced by iterative updating and re-optimization of a cheap and yet reasonably accurate representation of the antenna structure under consideration, by so-called surrogate model. There are many techniques exploiting both approximation surrogates, e.g., neural networks (Rayas-Sánchez, 2004; Kabir et al., 2008), support vector regression (Smola and Schölkopf, 2004); (Meng and Xia, 2007), radial-basis functions (Buhmann and Ablowitz, 2003), kriging (Simpson et al., 2001); (Forrester and Keane, 2009), as well as

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physics-based surrogates (space mapping (Bandler et al., 2004); (Amari et al., 2006); (Koziel et al., 2008), simulation-based tuning (Swanson and Macchiarella, 2007); (Rautio, 2008); (Cheng et al., 2010), manifold mapping (Echeverria and Hemker, 2005), shape-preserving response prediction (Koziel, 2010a). Approximation models are fast and universal, however, they are associated with the high initial cost, which is due to sampling of the design space and acquiring EM simulation data, and they are typically not suitable for ad-hoc optimization. Techniques exploiting physics-based surrogates are particularly attractive because they are capable to yield a satisfactory design using a very limited number of expensive high-fidelity EM simulations (Bandler et al., 2004).

One of the important assumptions to ensure efficiency of the SBO techniques exploiting physics-based surrogates is that the underlying low-fidelity model is computationally cheap. The most prominent technique of this kind is space mapping (Koziel, 2010a). It is originated in the area of microwave filter design where this assumption is naturally satisfied by circuit equivalents (Bandler et al., 2004) serving as low-fidelity models for filters. In case of antennas, physics-based surrogates can be obtained from coarse-discretization EM simulations as this is the only versatile way to create lower-fidelity antenna models. Unfortunately, such models may be relatively expensive. As a result, their evaluation cost cannot be neglected and may contribute considerably to the overall design expenses.

Therefore, the proper choice of the surrogate model fidelity is of great significance. On one hand, using a coarser low-fidelity model allows us to reduce its evaluation time. On the other hand, the coarser models are less accurate. As a result, a large number of iterations of the SBO algorithm may be necessary to yield a satisfactory design so that the total cost may be about the same or even higher than the total cost of an optimization algorithm employing only the finer model. Moreover, the surrogate-based optimization process may simply fail if the underlying low-fidelity model is not sufficiently accurate. For finer models, the individual evaluation time may be higher, but this is not directly translated into a higher total design cost because a smaller number of iterations may be sufficient to find a good design. In general, finding a good trade-off between the low-fidelity model speed and accuracy is not obvious.

Computational expenses of the low-fidelity models which are built from coarse-mesh discrete simulations can be alleviated to some extent on the algorithmic level. For example, in space mapping, the surrogate model parameters are repeatedly extracted with nonlinear regression at every iteration of the optimization algorithm (Koziel et al., 2006), which results in a large number of low-fidelity model evaluations and consequently in high total costs. Unlike space mapping, response correction techniques, e.g., manifold mapping (Echeverria and Hemker, 2005), shape-preserving response prediction (Koziel, 2010a), or adaptively adjusted design specification method (Koziel, 2010b) do not have these issues because no extractable parameters are utilized there.

Here, we study the importance of the proper selection of the antenna model fidelity and its influence on performance of the surrogate-based design process in terms of the computational cost and design quality. We also investigate the potential benefits of using several models of different fidelity in the same optimization run. Our considerations are based on several antenna design cases. The presented results can be helpful to formulate recommendations regarding the surrogate model selection for simulation-based antenna design.

2 LOW-FIDELITY ANTENNA MODELS

In this section, we formulate the antenna design task, recall the generic surrogate-based optimization (SBO) scheme, as well as discuss the issues regarding the selection of the low-fidelity antenna model that is a key component of physics-based SBO methods.

2.1 Design Problem Formulation

The antenna design task can be formulated as a nonlinear minimization problem

$$\boldsymbol{x}_f^* \in \arg\min_{\boldsymbol{x}} U\left(\boldsymbol{R}_f(\boldsymbol{x})\right) \quad (1)$$

where Rf ∈ Rm denotes the response vector of a high-fidelity (or fine) model of the antenna of interest evaluated through expensive high-fidelity EM simulation; x ∈ Rn is a vector of designable variables. Typically, these are geometry and/or material parameters. The response Rf(x) might be, e.g., the modulus of the reflection coefficient |S11| evaluated at m different frequencies. In some cases, Rf may consists of several vectors representing, e.g., antenna reflection, gain, etc. U is a given scalar merit function, e.g., a norm, or a minimax function with upper and lower specifications. U is formulated so that a better design corresponds to a smaller value of U. xf* is the optimal design to be determined.

2.2 Surrogate-based Optimization

In this work we consider surrogate-based optimization (SBO) techniques (Koziel et al., 2011) that aim at reducing the cost of EM-driven design by shifting the optimization burden into a cheap and yet reasonably accurate representation of the high-fidelity model, a surrogate.

A generic SBO algorithm produced a series of approximate solutions to (1), x(i), i = 0, 1, …, as follows (Koziel, et al., 2011):

$$\boldsymbol{x}^{(i+1)} = \arg\min_{\boldsymbol{x}} U(\boldsymbol{R}_s^{(i)}(\boldsymbol{x})) \quad (2)$$

where Rs(i) is the surrogate model at iteration i; x(0) is the initial design Typically, the surrogate model is updated after each iteration using the high-fidelity model data accumulated during the optimization process. Normally, the high-fidelity model is referred to rarely, in many cases only once per iteration, at a newly found design vector x(i+1). For a well working algorithm, the number of iterations necessary to find a satisfactory design is rather low. This, in conjunction with the assumption of the surrogate model being fast, allows us to significantly reduce the computational cost of the design process when compared with direct solving of the original problem (1).

There are many ways of constructing surrogate models that can be roughly split into approximation-based and physics-based ones. Approximation models are obtained by approximating sampled high-fidelity model data using, e.g., neural networks (Rayas-Sánchez, 2004)), kriging (Forrester and Keane, 2009), or support-vector regression (Smola and Schölkopf, 2004). This type of models are fast and generic, and, therefore, easily transferrable from one problem to another. There are several strategies of allocating new samples and updating the model and the one mentioned above (evaluating Rf at the surrogate model optimum) is just one of them, commonly used in local search. These, so-called infill criteria (Forrester and Keane, 2009); (Couckuyt et al., 2010), may be either focused on exploration of the design space (aiming at improving global accuracy of the model) or exploitation (local search). Approximation model have one significant disadvantage though: the initial cost of setting up the surrogate is typically high because a large number of samples may be necessary to ensure decent model accuracy. This cost may not be justifiable for a one-time design optimization of a given antenna structure.

Here, we focus on physics-based surrogates created from an underlying low-fidelity model Rc, faster and yet reasonably representation of Rf. The surrogate Rs(i) is obtained by aligning Rc with Rf at the current design x(i) using Rf data accumulated in previous iterations. Because the low-fidelity model embeds some “knowledge” about the structure under consideration, only a limited amount of high-fidelity model data is necessary to correct Rc and the generalization capability of the physics-based surrogates (i.e., the ability to represent the high-fidelity model outside the training set) is also much better than for the approximation models.

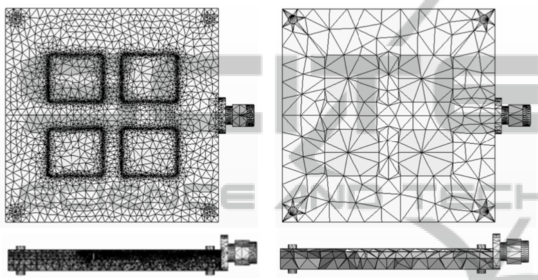
2.3 Low-Fidelity Antenna Models

The only universal way of creating physics-based low-fidelity antenna models is through coarse-discretization EM simulation. This is particularly the case for wideband and ultra-wideband (UWB) antennas (Schantz, 2005), as well as dielectric resonator antennas (DRAs) (Petosa, 2007) to name just a few. In this paper, we assume that the low-fidelity model Rc is evaluated with the same EM solver as the high-fidelity model. The low-fidelity model can be created by reducing the mesh density compared to the high-fidelity one as illustrated with Fig. 1. Other options of the low-fidelity model may include, among others: using smaller computational domain with the finite-volume methods, using low order basis functions with the finite-element and moment methods, applying simple absorbing boundaries, modelling metals with the perfect electric conductor, neglecting metallization thickness of traces, strips, and patches, ignoring dielectric losses and dispersion.

Because of the possible simplifications, the low-fidelity model Rc is (typically 10 to 50 times) faster than Rf but not as accurate. Therefore, it cannot substitute the high-fidelity model in design optimization. Obviously, making the low-fidelity model mesh coarser (and, perhaps, introducing other simplifications) results in loss of accuracy but also in a shorter computational time. Figure 2 shows the plots illustrating the high- and low-fidelity model responses at a specific design for the antenna structure in Fig. 1, as well as the relationship between the mesh coarseness and the simulation time.

The selection of the low-fidelity model coarseness is important for the computational cost and performance of the design optimization process. Coarser models are faster, which translates into lower cost of per design iteration. However, coarser models are also less accurate, which may results in a larger number of iterations necessary to yield a satisfactory design. Also, there is an increased risk that the optimization algorithm will fail to find a good design. Finer models, on the other hand, are more expensive but they are more likely to produce a useful design in a smaller number of iteration.

As mentioned in the introduction, the main focus of this paper is to investigate the relationship between the performance of the surrogate-based antenna design process and the underlying coarse model fidelity.



(a) (b)

Figure 1: A microstrip antenna (Chen, 2008): (a) a high-fidelity EM model with a fine tetrahedral mesh; and (b) a low-fidelity EM model with a coarse tetrahedral mesh.

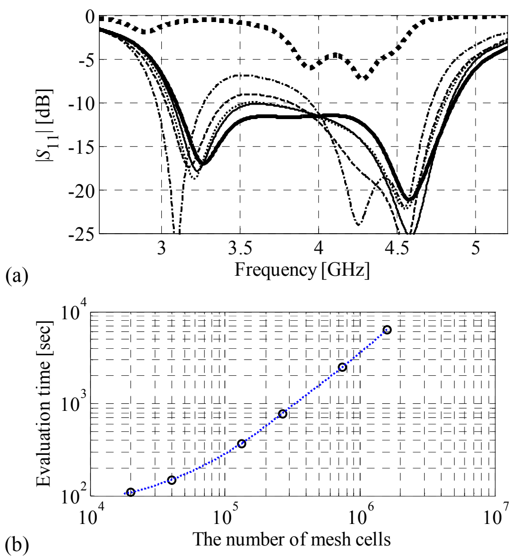


Figure 2: An antenna of Fig. 1 evaluated with the CST MWS transient solver (CST, 2011) at a selected design: (a) the reflection response with different discretization density, 19,866 cells (▪▪▪), 40,068 cells (· — ·), 266,396 cells (– –), 413,946 cells (···), 740,740 cells (—), and 1,588,608 cells (▬); and (b) the antenna evaluation time versus the number of mesh cells.

Our considerations will be based on numerical study; however, it should be stressed that, at the present stage or research, visual inspection of the model responses and the relationship between the high- and low-fidelity models is an important step in the model selection process. In particular, it is essential that the low-fidelity model captures all important features present in the high-fidelity one.

Going back to Fig. 2, one can observe that the two "finest" coarse-discretization models (with ~400,000 and ~740,000 cells) are properly representing the high-fidelity model response (shown as a thick solid line). The model with ~270,000 cells can be considered as a borderline one. The two remaining models could be considered as too coarse, particularly the one with ~20,000 cells; its response is substantially deviated from that of the high-fidelity model.

2.4 Surrogate Model Construction

There are many techniques for constructing the surrogate from a physics-based low-fidelity model, however, we are interested here in those where the surrogate model parameters can be obtained without involving multiple evaluations of the low-fidelity one. The reason is that we aim at minimizing both the number of high- and low-fidelity model evaluations during the design process. There are several more or less involved techniques of this kind, such as manifold mapping (Echeverria and Hemker, 2005), adaptive response correction (Koziel et al., 2009), or shape-preserving response prediction (Koziel, 2010a). However, here, we focus on the two basic methods which are sufficient for our considerations, response correction and frequency scaling.

The response correction technique assumes that the surrogate model is constructed by composing the low-fidelity model response with a suitable correction function as follows:

$$\boldsymbol{R}_s(\boldsymbol{x}) = \boldsymbol{C}(\boldsymbol{R}_c(\boldsymbol{x})) \tag{3}$$

where $C : Rm \rightarrow Rm$ is a response correction function. Here, the surrogate model at iteration i of the optimization process (2) is defined as Rs(i)(x) = C(i)(Rc(x)), where C(i) is the correction function at iteration i. For surrogates constructed using response correction, we typically request that at least zero-order consistency between the surrogate and the fine model is satisfied, i.e., Rs(i)(x(i)) = Rf(x(i)). It can be shown (Alexandrov et al., 1998) that satisfaction of first-order consistency, i.e., J[Rs(i)(x(i))] = J[Rf(x(i))] (here, J[·] denotes the Jacobian of the respective model), guarantees convergence of {x(i)} to a local optimum of Rf assuming that (3) is enhanced by the trust region mechanism (Conn et al., 2000) and the functions involved are sufficiently smooth.

In this paper, we only consider a basic response correction, i.e.,

$$\boldsymbol{C}(\boldsymbol{R}_c(\boldsymbol{x})) = \boldsymbol{R}_c(\boldsymbol{x}) + [\boldsymbol{R}_f(\boldsymbol{x}^{(i)}) - \boldsymbol{R}_c(\boldsymbol{x}^{(i)})] \tag{4}$$

This type of correction ensures a zero-order consistency, i.e., Rs(i)(x(i)) = Rf(x(i)).

Another type of basic technique for surrogate model construction considered here is a frequency scaling. It is useful because, in many cases, the major discrepancy between the high- and low-fidelity model responses is a frequency shift, which can be easily reduced by means of simple scaling functions parameterized by just a few coefficients. Here, we consider an affine scaling defined as F(ω) = f0 + f1ω (Koziel et al., 2006), where f0 and f1 are unknown parameters to be determined. Assuming that the model responses correspond to evaluation of the figures of inteters (e.g., S-parameters) at a set of frequencies, i.e., Rc(x) = [Rc(x,ω1), …, Rc(x,ωm)]T. The frequency scaled model is then defined as

$$\boldsymbol{R}_{c.F}(\boldsymbol{x}) = [R_c(\boldsymbol{x}, F(\omega_1)), ..., R_c(\boldsymbol{x}, F(\omega_m))]^T \tag{5}$$

where the scaling parameters obtained by minimizing the matching error

$$\sum_{k=1}^{m} [R_f(\boldsymbol{x}^{(i)}, \omega_k) - R_c(\boldsymbol{x}^{(i)}, f_0 + f_1\omega_k)]^2 \tag{6}$$

It should be noted that the frequency scaling parameters can be obtained without referring to an EM simulation because all the necessary responses Rc(x(i),f0 + f1ωk) can be obtained by interpolating/ extrapolating the know values Rc(x(i),ωk), k = 1, …, m.

3 CASE STUDY I: SELECTING MODEL FIDELITY

We consider two antenna design cases with the optimized designs found using an SBO algorithm of the type (2). For each case, we consider three low-fidelity EM models of different mesh density. We investigate the performance of the SBO algorithm working with these models in terms of the computational cost and the quality of the final design.

3.1 Design of Broadband Slot Antenna

Consider a CPW-fed slot antenna shown in Fig. 3(a) (Jiao et al., 2007). The design variables are x = [ax ay a b s1]T; w0 = 4 mm, s0 = 0.3 mm. The substrate, 0.813 mm Rogers RO4003C (ε1 = 3.38 at 10 GHz), and the ground plane are of infinite lateral extends. The initial design is $\boldsymbol{x}^{(0)}$ = [40 25 10 20 2]^T mm. The design specifications are |S11| ≤ –12 dB for 2.3-to-7.6 GHz. The high-fidelity model Rf is evaluated with the CST MWS transient solver (CST, 2011) (3,556,224 mesh cells, simulated in 60 min). We consider three coarse models (all evaluated in CST MWS): Rc1 (110,208 mesh cells, 1.5 min), Rc2 (438,850, 5 min), and Rc3 (1,113,840, 8 min).

Figure 3(b) shows the responses of Rf and Rc1 through Rc3 at the initial design. Because of mostly the vertical shift between the low- and the high-fidelity model responses, the surrogate model for the algorithm (1) is created using output space mapping (OSM) (Bandler et al., 2004) so that Rs(i)(x) = Rck(x) + [Rf(x(i)) – Rck(x(i))] (k is an index of a respective low-fidelity model), cf. (4). Table 1 and Fig. 3(c) show the optimization results. All the low-fidelity models are relatively reliable here and the qualities of the final designs are comparable. The design cost is the smallest for the SBO algorithm working with Rc1 even though five design iterations are necessary. The algorithm working with Rc2 and Rc3 require only 3 and 2 iterations, respectively, but they are relatively expensive compared to Rf. Thus, in this case, using the coarsest model is the most advantageous.

3.2 Design of Microstrip Antenna

Consider a coax-fed microstrip antenna shown in Figs. 4(a) and 4(b) (Wi et al., 2007). Design variables are x = [a b c d e l0 a0 b0]T. The antenna is on 3.81 mm thick Rogers TMM4 (ε1 = 4.5 at 10 GHz); lx= ly= 6.75 mm. The ground plane is of infinite extends. The feed probe diameter is 0.8 mm. The connector's inner conductor is 1.27 mm in diameter. Design specifications are |S11| ≤ –10 dB for 5 GHz to 6 GHz. The high-fidelity model Rf is evaluated with CST MWS transient solver (CST, 2011) (704,165 mesh cells, evaluation time 60 min). We consider three coarse models: Rc1 (41,496, 1 min), Rc2 (96,096, 3 min), and Rc3 (180,480, 6 min). The initial design is x(0) = [6 12 15 1 1 1 1 –4]T mm. Figure 4(c) shows the responses of all the models at the approximate optimum of Rc1. The major misalignment between the responses is due to the frequency shift so that the surrogate is created here using frequency scaling (5), (6) (Koziel et al., 2006) as well as output SM (4) (Bandler et al., 2004). The results, Table 2 and Fig. 4(d), indicate that the model Rc1 is too inaccurate and the SBO design process using it fails to find a satisfactory design. The designs found with models Rc2 and Rc3 satisfy the specifications and the cost of the SBO process using Rc2 is slightly lower than while using Rc3.

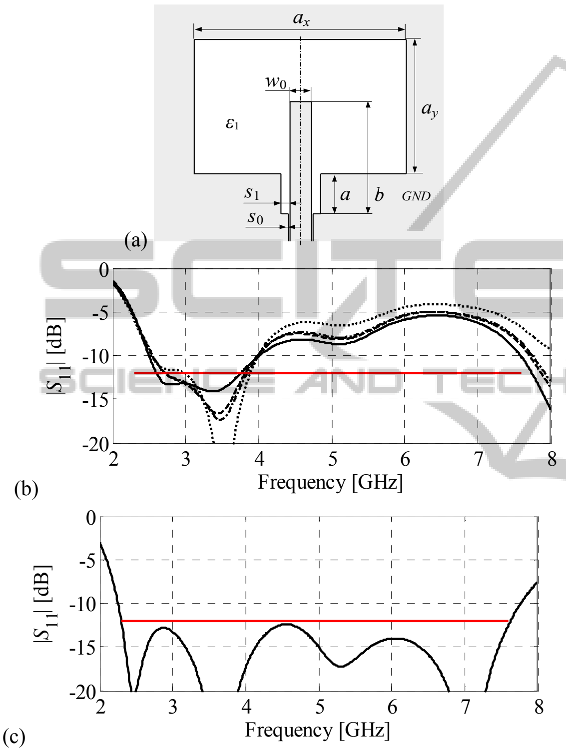


Figure 3: CPW-fed broadband slot antenna: (a) geometry (Jiao et al., 2007), (b) model responses at the initial design, Rc1 (···), Rc2 (-·-·-), Rc3 (- - -), and Rf (—), (c) high-fidelity model response at the final design found using the low-fidelity model Rc3.

Table 1: CPW-fed slot antenna – design results.

Low-Fidelity Model	Design Cost: Number of Model Evaluations1		Relative Design Cost2	max|S11| for 2 GHz to 8 GHz at Final Design
	Rc	Rf		
Rc1	287	5	12.2	–12.1 dB
Rc2	159	3	16.2	–12.0 dB
Rc3	107	2	16.3	–12.3 dB

1 Number of Rf evaluations is equal to the number of SBO iterations in (2).
2 Equivalent number of Rf evaluations.

4 CASE STUDY II: MODEL MANAGEMENT DRA DESIGN

In this section, we again consider the use of low-fidelity models of various mesh density for surrogate-based design optimization of the dielectric resonator antenna. We also investigate potential benefits of using two models of different fidelity within a single optimization run.

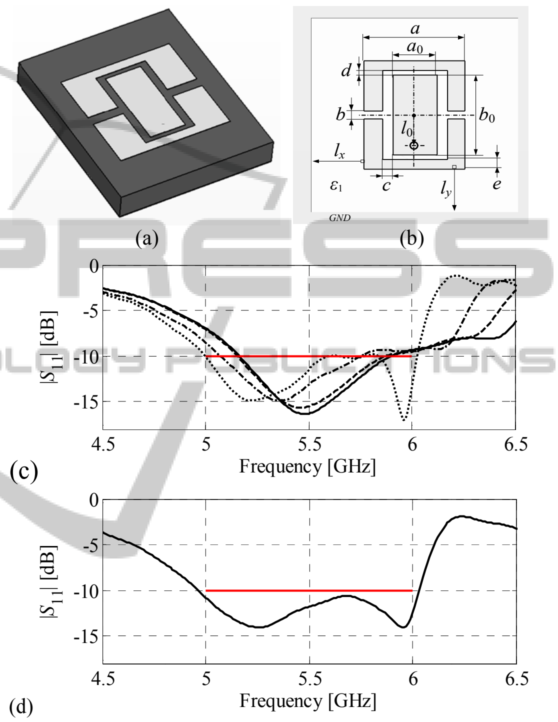


Figure 4: Coax-fed microstrip antenna (Wi et al., 2007): (a) 3D view; (b) top view, (c) model responses at the initial design, Rc1 (···), Rc2 (-·-·-), Rc3 (- - -), and Rf (—), (d) high-fidelity model response at the final design found using the low-fidelity model Rc3.

Table 2: Coax-fed microstrip antenna – design results.

Low-Fidelity Model	Design Cost: Number of Model Evaluations1		Relative Design Cost2	max|S11| for 2 GHz to 8 GHz at Final Design
	Rc	Rf		
Rc1	385	6	12.4	–8.0 dB
Rc2	185	3	12.3	–10.0 dB
Rc3	121	2	14.1	–10.7 dB

1 Number of Rf evaluations is equal to the number of SBO iterations in (2).
2 Equivalent number of Rf evaluations.

Consider a hybrid DRA shown in Fig. 5. The DRA is fed by a 50 ohm microstrip terminated with an open ended section. Microstrip substrate is 0.787 mm thick Rogers RT5880. The design variables are x = [h0 r1 h1 u l1 r2]T. Other dimensions are fixed:

r0=0.635, h2=2, d=1, r3= 6, all in mm. Permittivity of the DRA core is 36, and the loss tangent is 10-4, both at 10 GHz. The DRA support material is Teflon ($\varepsilon 2=2.1$), and the radome is of polycarbonate ($\varepsilon 3 = 2.7$ and $\tan\delta = 0.01$). The radius of the ground plane opening, shown in Fig. 5(b), is 2 mm.

The high-fidelity antenna model Rf(x) is evaluated using the time-domain solver of CST Microwave Studio (CST, 2011) (~1,400,000 meshes, evaluation time 60 minutes). The goal is to adjust geometry parameters so that the following specifications are met: $|S11| \leq -12$ dB for 5.15 GHz to 5.8 GHz. The initial design is x(0) = [7.0 7.0 5.0 2.0 2.0 2.0]T mm.

We consider two auxiliary models of different fidelity, Rc1 (~45,000 meshes, evaluation time 1 min), and Rc2 (~300,000 meshes, evaluation time 3 min). We investigate the algorithm (2) using either one of these models or both (Rc1 at the initial state and Rc2 in the later stages). The surrogate model is constructed using both output SM (4) and the frequency scaling (5), (6). Figure 6(a) shows the importance of the frequency scaling, which, due to the shape similarity of the high- and low-fidelity model responses allows substantial reduction of the misalignment between them.

The DRA design optimization has been performed three times: (i) the surrogate constructed using Rc1 – cheaper but less accurate (Case 1), (ii) the surrogate constructed using Rc2 – more expensive but also more accurate (Case 2), and (iii) the surrogate constructed with Rc1 at the first iteration and with Rc2 for subsequent iterations (Case 3). The last option allows us to faster locate the approximate high-fidelity model optimum and then refine it using the more accurate model. The number of surrogate model evaluations was limited to 100 (which involves the largest design change) in the first iteration and to 50 in the subsequent iterations (smaller design modifications are required).

Table 3 shows the optimization results for all three cases. Figure 6(b) shows the high-fidelity model response at the final design obtained using the SBO algorithm working with low-fidelity model Rc2. The quality of the final designs found in all cases is the same. However, the SBO algorithm using the low-fidelity model Rc1 (Case 1) requires more iterations than the algorithm using the model Rc2 (Case 3), which is because the latter is more accurate. In this particular case, the overall computational cost of the design process is still lower for Rc1 than for Rc2. On the other hand, the cheapest approach is Case 2 when the model Rc1 is utilized in the first iteration that requires the largest number of EM analyses, whereas the algorithm switches to Rc2 in the second iteration, which allows us to both reduce the number of iterations and number of evaluations of Rc2 at the same time. The total design cost is the lowest overall.

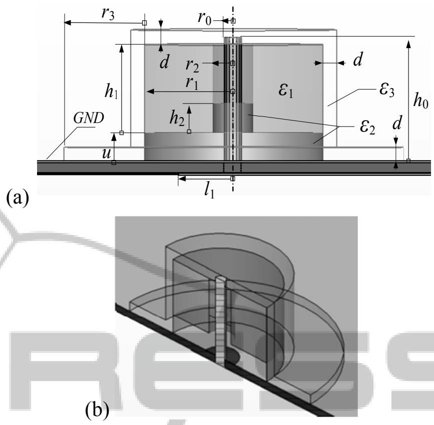


Figure 5: Hybrid DRA: (a) side view; (b) 3D-cut view.

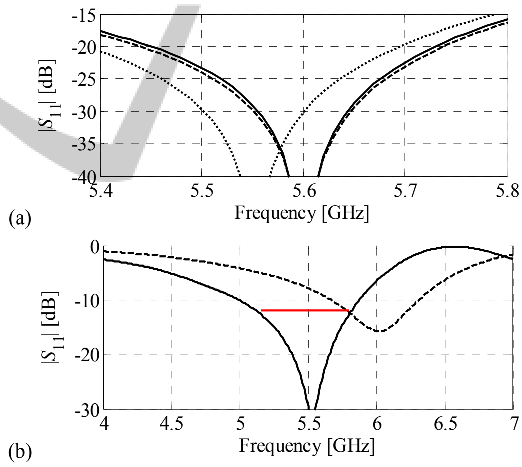


Figure 6: Hybrid DRA: (a) high- (—) and low-fidelity model Rc2 response at certain design before (····) and after (- - -) applying the frequency scaling, (b) high-fidelity model response at the initial design (- - -) and at the final design obtained using the SBO algorithm using with the low-fidelity model Rc2 (—).

Table 3: Hybrid DRA design results.

Case	Number of Iterations	Number of Model Evaluations1			Total Design Cost2	max|S11| for 5.15 GHz to 5.8 GHz at Final Design
		Rc1	Rc2	Rf		
1	4	250	0	4	8.2	–12.6 dB
2	2	0	150	2	9.5	–12.6 dB
3	2	100	50	2	6.2	–12.6 dB

1 Number of Rf evaluations is equal to the number of SBO iterations in (1).
2 Equivalent number of Rf evaluations.

5 DISCUSSION

Our results allow us to draw some conclusions regarding the selection of the model fidelity for surrogate-based antenna optimization. Using the cheaper (and less accurate) model may translate into lower design cost; however, it also increases the risk of failure. Using the higher-fidelity model may increase the cost but it definitely improves the robustness of the SBO design process and reduces the number of iterations necessary to find a satisfactory design. Visual inspection of the low- and high-fidelity model responses remains—so far—the most important way of accessing the model quality, which may also give a hint which type of model correction should be applied while creating the surrogate.

The following rules of thumb can be formulated in order to facilitate the model selection process:

- An initial parametric study of low-fidelity model fidelity should be performed at the initial design in order to find the "coarsest" model that still adequately represents all the important features of the high-fidelity model response. The assessment should be done by visual inspection of the model responses having in mind that the critical factor is not the absolute model discrepancy but the similarity of the response shape (e.g., even relatively large frequency shift can be easily reduced by a proper frequency scaling).
- When in doubt, it is safer to use a slightly finer low-fidelity model rather than a coarser one so that potential cost reduction is not lost due to a possible algorithm failure to find a satisfactory design.
- The type of misalignment between the low- and high-fidelity models should be observed in order to properly select the type of low-fidelity model correction while constructing the surrogate. The two methods considered in this paper (additive response correction and frequency scaling) can be considered as safe choices for most situations.

It should be emphasized that for some antenna structures, such as some narrow-band antennas or wideband travelling wave antennas, it is possible to obtain quite good ratio between the simulation times of the high- and low-fidelity models (e.g., up to 50), which is because even for relatively coarse mesh, the low-fidelity model may still be a good representation of the high-fidelity one. For some structures (e.g., multi-resonant antennas), only much lower ratios (e.g., 5 to 10) may be possible, which would translate into lower design cost savings while using the surrogate-based optimization techniques.

6 CONCLUSIONS

A problem EM simulation model management for surrogate-based optimization of antennas has been addressed. We have discussed a trade-off between the computational complexity and accuracy of the low-fidelity EM antenna models and their effects on the performance of the surrogate-based optimization process. Our considerations are illustrated using several antenna design cases. Recommendations regarding low-fidelity model selection are also formulated. We also demonstrate that by proper management of the models involved in the design process one can lower the overall optimization cost without compromising the final design quality.

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