Reduced-Cost Surrogate Modeling of Input Characteristics and Design Optimization of Dual-Band Antennas Using Response Features

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Abstract

In this paper, a procedure for low-cost surrogate modeling of input characteristics of dual-band antennas has been discussed. The number of training data required for construction of an accurate model has been reduced by representing the antenna reflection response to the level of suitably defined feature points. The points are allocated to capture the critical features of the reflection characteristic, such as the frequencies and the levels of the resonances, and supplemented by the additions (infill) points, which is necessary to provide sufficient data that allows restoring the entire response through interpolation. Because the coordinates of the feature points exhibit less nonlinear behavior (as a function of antenna geometry parameters) compared to *S*-parameters as a function of frequency, surrogate model construction can be realized with a smaller number of data points. The presented modeling approach is demonstrated using an example of a planar dipole antenna. Also, the feature-based method is favorably compared to direct modeling of reflection characteristics using kriging. The relevance of the technique is further verified by its application for design optimization.

1. Introduction

Electromagnetic (EM) solvers are vital tools for design of modern antenna structures due to unprecedented development and availability of computational resources (both in terms of hardware and software) but also because EM analysis is the only way of accurate performance evaluation of modern antenna structures. This is particularly the case when the evaluation requires inclusion of environmental components (connectors, housing, etc.) as those may considerably affect the antenna operation, e.g., for compact structures [1]. Ensuring sufficient accuracy of realistic antenna models requires dense discretization of the structure which leads to high cost of EM simulation. Consequently, design approaches based on multiple evaluations of EM models (e.g., optimization or robust design) are impractical from computational standpoint.

The above problem can be addressed through development of more efficient optimization methods. In this context, there are two classes of approaches that are worth mentioning, specifically, surrogate-assisted techniques (both local [2], [3], and global [4], [5]), as well as gradient-based methods with adjoint sensitivities [6], [7]. Nevertheless, from the point of view of repeated handling of the same structure, utilization of fast replacement models (surrogates) that may accurately represent a given antenna structure in a larger portion of the design space appears to be a better solution. Two categories of models, i.e., functional (or data-driven) and physics-based surrogates are utilized for expedited design. Functional models mimic the behavior of the structure by approximation of the EM training data acquired across the search space. The most popular data-driven techniques include, among others, artificial neural networks [9], radial-basis functions [10], kriging [11], and support vector regression [12]. Although functional models benefit from fast evaluation, they require large training sets to achieve acceptable accuracy. Also, the number of required data samples grows very quickly with the increased number of geometry parameters and their ranges.

The main advantage of physics-based surrogates is that the knowledge about the structure at hand is embedded in their underlying low-fidelity models. Consequently, they offer better generalization than functional surrogates [13], [14]. For the same reason, they do not require as many training samples as the data-driven models. On the other hand, physics-based surrogates are normally constructed based on the low-fidelity EM models with relaxed discretization density. Consequently, their numerical cost is relatively high. A possible workaround is combination of data-driven modeling at the low-fidelity model level with further correction using sparsely-sampled high-fidelity EM data using, e.g., co-kriging [15] or space mapping [13], or response features [16]-[18].

In this work, a method for accurate modeling of dual-band antenna structures input characteristics using reduced number of training samples has been considered. Accurate modeling of such radiators using conventional methods (e.g., kriging [11], or artificial neural-networks [9]) is difficult due to their highly nonlinear responses (as a function of frequency and geometry parameters). Here, this problem is addressed using feature-based method where the original response of the structure (reflection versus frequency) is expressed in terms of points which characterize its key properties. The response features are less nonlinear functions of geometry than the frequency characteristics. here, response feature sets are built around the coordinates (frequencies and levels) of antenna resonances and supplemented with additional (infill) points, necessary to cover the entire frequency range of interest. Therefore, suitable accuracy of the model can be achieved using smaller number of training samples as compared to conventional techniques. The proposed approach is demonstrated using a two-band single-layer dipole antenna. The method has been favorably compared to direct modeling of reflection using kriging interpolation. Furthermore, application of the proposed feature-based surrogate for antenna design is discussed providing additional confirmation of the usefulness and relevance of our technique.

2. Case Study: Two-Band Dipole Antenna

The considered technique for modeling of input characteristics will be explained and, subsequently, verified, using the example of a single-layer two-band dipole antenna shown in Fig. 1 [19]. The structure is implemented on a 0.762 mm thick Taconic RF-35 dielectric substrate with relative permittivity of 3.5. Dual-band operation of the structure is ensured by two separated slots. The antenna is fed through a 50 ohm coplanar waveguide (CPW). The vector of adjustable parameters is: $\boldsymbol{x} = [l_1\ l_2\ l_3\ w_1\ w_2\ w_3]^T$, whereas parameters $l_0 = 30$, $w_0 = 3$, $s_0 = 0.15$ and $o = 5$ remain fixed. The unit for all dimensions is mm. The EM antenna model $\boldsymbol{R}$ is implemented in CST Microwave Studio [20]. It consists of about 100,000 hexahedral cells and its average simulation time on a dual Intel Xeon E5540 machine is 60 seconds.

3. Feature-Based Modeling for Two-Band Antennas

In this work, we are interested in modeling input characteristics of the antenna. The EM model $\boldsymbol{R}(\boldsymbol{x})$ represents the modulus of the reflection response, $|S_{11}|$, at m frequencies, ω_1 to ω_m, i.e., $\boldsymbol{R}(\boldsymbol{x}) = [R(\boldsymbol{x},\omega_1)\ \ldots\ R(\boldsymbol{x},\omega_m)]^T$. The goal is to construct a surrogate model $\boldsymbol{R}_s$ which is a representation of $\boldsymbol{R}$ in a given subset X of the search space. Let $X_T = \{\boldsymbol{x}^1, \boldsymbol{x}^2, \ldots, \boldsymbol{x}^N\} \subset X$ be the training set for which responses of the antenna model are known. Conventional approaches aim at direct modeling of $\boldsymbol{R}(\boldsymbol{x},\omega_j)$, $j = 1, \ldots, m$, which is challenging because frequency responses of narrow-band antennas are highly nonlinear (cf. Fig. 2).

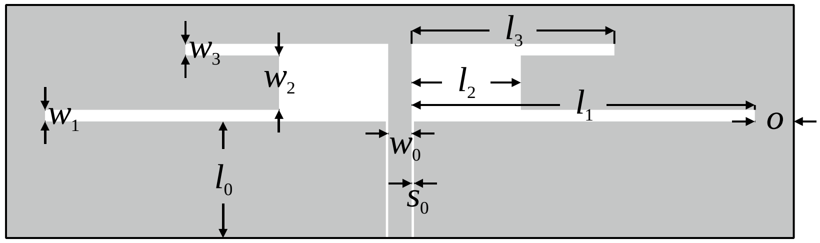
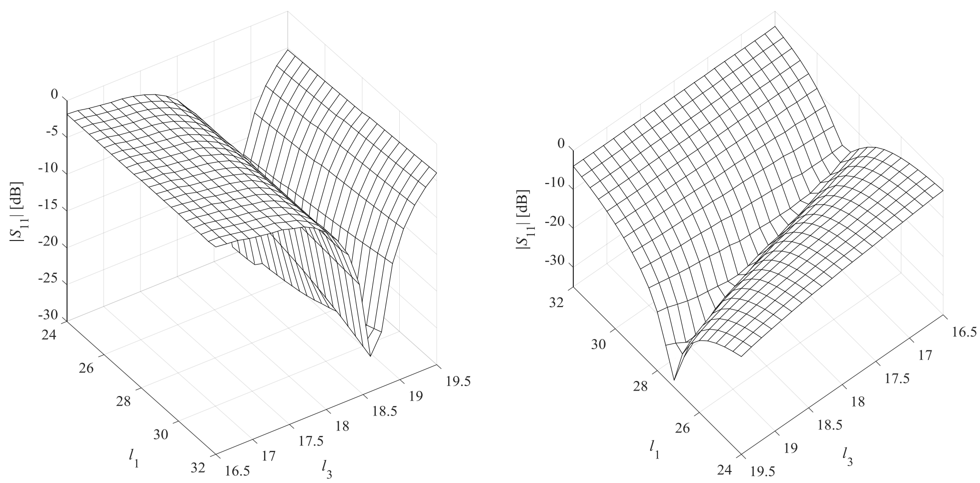


Fig. 1. Two-band single-layer dipole antenna: topology.



(a) (b)

Fig. 2. Reflection characteristics of the dipole obtained for $24.0 \le l_1 \le 32.0$ and $16.5 \le l_3 \le 19.5$ at: (a) 3 GHz frequency, and (b) 6 GHz frequency. The remaining parameters are $l_2 = 12.5$ $w_1 = 0.4$ $w_2 = 2.5$ $w_3 = 0.75$.

In this work, the modeling of input characteristics is carried out at the level of appropriately defined response features. The feature points selected for the considered antenna are shown in Fig. 3. The most important are the main and supplemental points that define the location of the antenna resonances and the reflection response shape around them. The supplemental points are allocated in equal distance on the slopes between the resonance and nearest local maxima of the response. Since the absolute value of reflection is modeled, ten supplemental points per slope is considered as sufficient representation of the response shape. It should be noted that sufficiently large number of points has to be selected to permit accurate interpolation and recreate the frequency response of the structure. Therefore, additional (infill) points are introduced that are allocated uniformly in between the supplemental points, either with respect to the level (for the steep parts of the response) or with respect to the frequency (for more flat parts of the response). Here, the jth feature point of the response is defined as $\boldsymbol{R}(\boldsymbol{x}^k)$: $\boldsymbol{f}_k^j = [\omega_k^j\ l_k^j]^T$, $j = 1, \ldots, K$, and $k = 1, \ldots, N$, where ω_k^j and l_k^j represent the frequency and the magnitude (level) components of $\boldsymbol{f}_k^j$.

Figure 4 shows the landscapes of the selected feature points derived from the antenna reflection characteristics. They have been obtained in the same search space region as in Fig. 2. It should be noted that responses in Fig. 4 are much less nonlinear, particularly for the frequency component, which is a close-to-linear function of the geometry parameters. Consequently, it is expected that modeling of antenna responses expressed in terms of the feature points would involve a smaller number of data samples compared to direct modeling of the reflection characteristic.

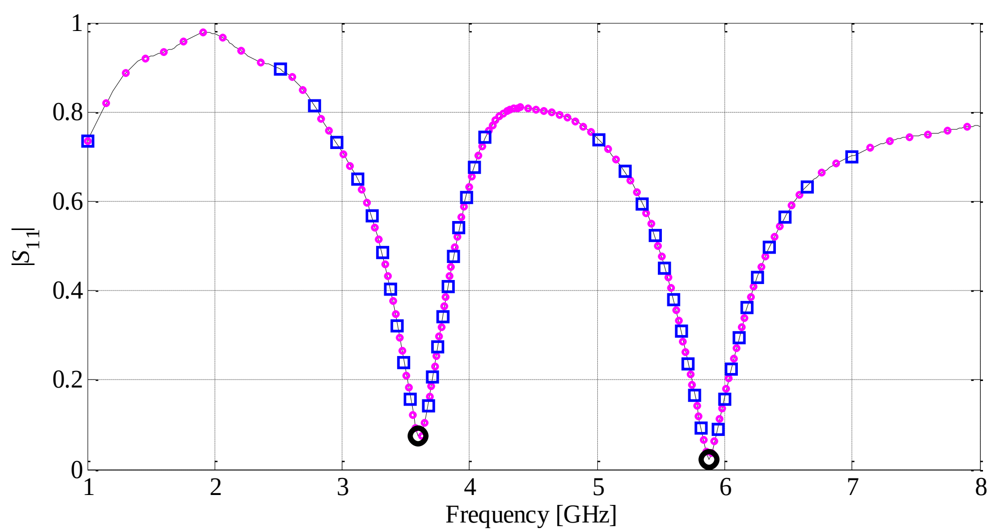


Fig. 3. Feature points selected for the two-band dipole antenna: (**O**) main points (frequency and reflection level of resonances), (□) supplemental points allocated equally with respect to $|S_{11}|$ (intervals between points at the left- and the right-hand-side of the resonances are independent), (○) infill points allocated equally with respect to frequency between the remaining points (their number may vary for various intervals).

The discussed method exploits two functional models $s_{\omega.j}(\boldsymbol{x})$ and $s_{l.j}(\boldsymbol{x})$ (j = 1, …, K) composed of the data sets of corresponding feature points defined for frequency and level of the reflection responses. The points are extracted from N training designs, $\{\boldsymbol{f}_1^j, \boldsymbol{f}_2^j, \ldots, \boldsymbol{f}_N^j\}$, $j = 1, \ldots, K$ [18]. Both models are constructed using kriging interpolation [11]. The surrogate is given by [18]

$$\boldsymbol{R}_s(\boldsymbol{x}) = \left[R_s(\boldsymbol{x},\omega_1)\ \ldots\ R_s(\boldsymbol{x},\omega_m)\right]^T \tag{1}$$

where

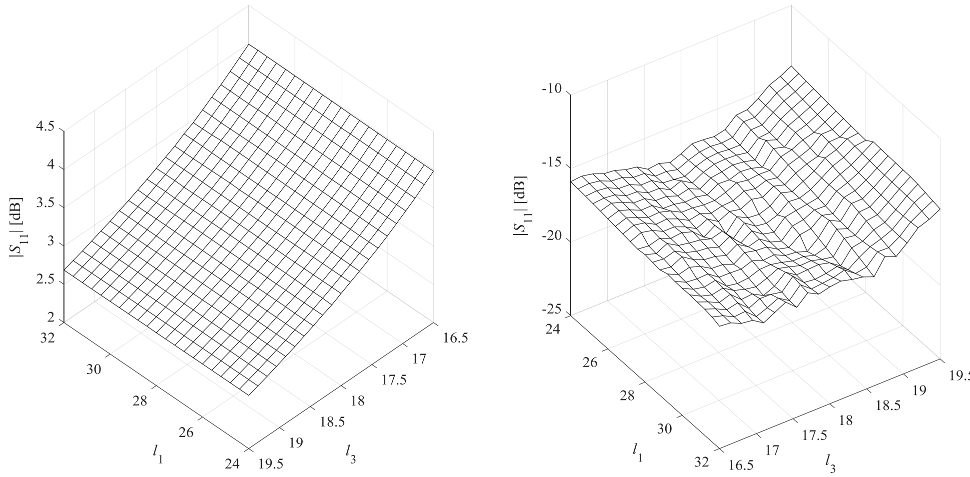
$$R_s(\boldsymbol{x},\omega_j) = I(\Omega(\boldsymbol{x}),L(\boldsymbol{x}),\omega_j) \tag{2}$$

$$L(\boldsymbol{x}) = [s_{l.1}(\boldsymbol{x})\ \ldots\ s_{l.K}(\boldsymbol{x})] \tag{3}$$

and $\Omega(\boldsymbol{x}) = [s_{\omega.1}(\boldsymbol{x})\ \ldots\ s_{\omega.K}(\boldsymbol{x})]$ are the locations of the feature points at the given design $\boldsymbol{x}$. The function $I(\Omega,L,\omega)$ denotes interpolation of the level vector L and frequency vector Ω into the response at a given frequency ω_j. This interpolation is necessary in order to yield the predicted model response at the original frequency sweep, i.e., at the frequencies ω_1 to ω_m. In other words, responses produced by both kriging models are characterized by non-uniform frequency step and thus they need to be re-interpolated to the original (uniform) frequency sweep.

The discussed modeling approach can be summarized as follows:

1. Acquire training data;
2. Identify main, supplemental and infill points for each training design (cf. Fig. 3);
3. Construct kriging models for the level- and the frequency- related features;
4. Interpolate kriging models responses (2) to obtain frequency response of the antenna surrogate.



(a) (b)

Fig. 4. Functional landscapes of feature points obtained for $24.0 \leq l_1 \leq 32.0$ and $16.5 \leq l_3 \leq 19.5$: (a) frequency, and (b) level components of the antenna response. It should be noted that the shapes of the responses are significantly less nonlinear compared to ones obtained in the frequency domain (cf. Fig. 2).

The model constructed using (1)-(3) is shown in Fig. 3. For more detailed discussion on kriging and feature-based methods see, e.g., [5], [11], [17], [18].

4. Results and Comparisons

Validation of the considered technique for modeling of input characteristics has been performed by constructing feature-based models for the training sets of 20, 50, 100, 200, 400, and 800 samples allocated using Latin Hypercube Sampling [21]. For the sake of comparison, the same training sets have been utilized for direct modeling of antenna reflection using kriging interpolation. The region of interest is defined by the following lower and upper bounds for design variables: $\boldsymbol{l} = [24.0\ 12.0\ 16.5\ 0.2\ 0.6\ 0.5]^T$, and $\boldsymbol{u} = [32.0\ 13.0\ 19.5\ 0.6\ 3.2\ 1.0]^T$. These ranges are sufficiently wide to allow the lower operating frequency to change from around 2.6 GHz to 4.2 GHz, and the upper operating frequency to change from 5.2 GHz to 6.8 GHz.

The accuracy of the models is validated using the test set composed of 100 randomly generated samples. The error measure $||\boldsymbol{R}(\boldsymbol{x}) - \boldsymbol{R}_s(\boldsymbol{x})||/||\boldsymbol{R}(\boldsymbol{x})||$ is expressed in percent. When calculating the errors, dB-valued responses are considered in order to emphasize the importance of appropriate representation of the antenna resonances.

The comparison of conventional and feature-based models in terms of the average error is shown in Table 1. The results indicate that, for the same data sets, the accuracy of the feature-based modeling is 50% to 70% higher than of the kriging-based one. Consequently, feature-based model with accuracy comparable to frequency-based model can be constructed using four- to eight-fold smaller training data set. This corresponds to reduction of the computational cost from 75 to over 85 percent with respect to conventional modeling.

A comparison of antenna responses obtained from simulation of the high-fidelity EM model and the feature-based surrogate generated using 400 training samples is shown in Fig. 5. The responses of both models are well aligned which indicates practically sufficient accuracy of the surrogate. Resonant frequencies for the selected designs are: 2.8 GHz and 5.45 GHz, 3.05 GHz and 5.8 GHz, 3.6 GHz and 6.2 GHz, as well as 4 GHz and 6.2 GHz. They have been selected so that the test designs are spread along the surrogate model.

5. Application Examples

Additional verification of the proposed modeling approach is provided in this section by applying the feature-based surrogate for antenna optimization. Three different sets of operating frequencies are considered: (i) f_1 = 3.0 and f_2 = 6.2 GHz, (ii) f_1 = 3.5 and f_2 = 6.5 GHz, and (iii) f_1 = 4.0 and f_2 = 5.5 GHz. In all cases, the objective is to minimize

$|S_{11}|$ in the frequency range of ±0.02 GHz around the operating frequencies. As the surrogate model is very fast, any optimization algorithm can be utilized. Here, sequential quadratic programming (specifically Matlab's *fmincon*) is exploited [22].

The high-fidelity model responses evaluated at the designs obtained through optimization of the feature-based surrogate are shown in Fig. 6. Due to good predictive power of the latter, acceptable reflection responses of the antenna are obtained without further correction. Table 2 shows the detailed dimensions of the designs of Fig. 6.

Table 1. Modeling Results of the Single-Layer Two-Band Dipole

Model/Cost	Average Error [%]					
	$N^{*} = 20$	$N = 50$	$N = 100$	$N = 200$	$N = 400$	$N = 800$
Feature-Based Surrogate	23.3	15.2	14.8	12.4	9.2	7.4
Kriging Interpolation[#]	43.2	28.4	22.1	18.2	16.9	13.3

[*] Size of the training set
[#] Direct kriging interpolation of antenna reflection.

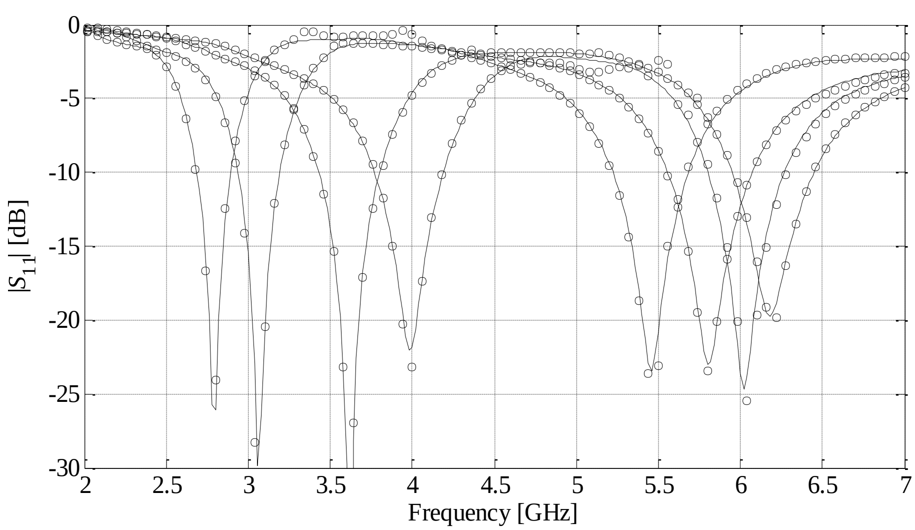
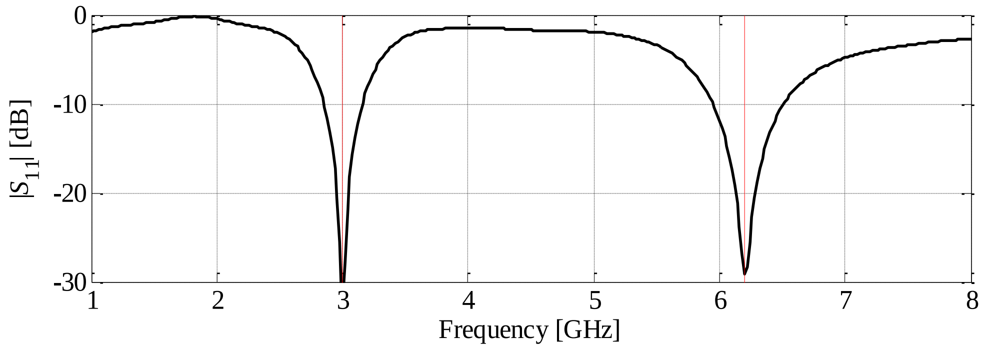
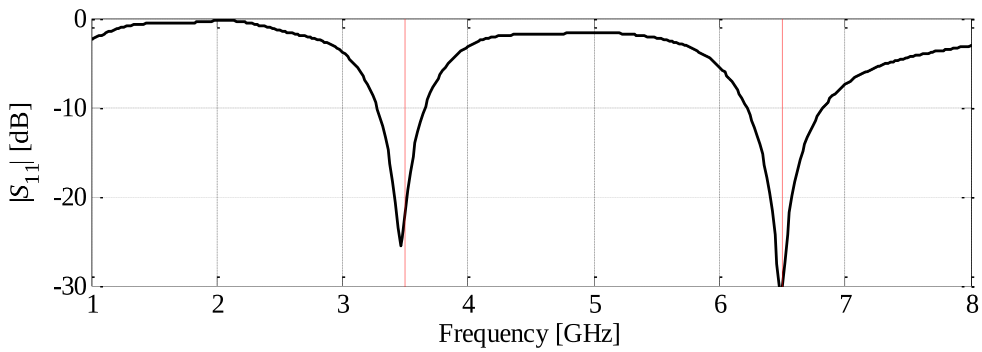


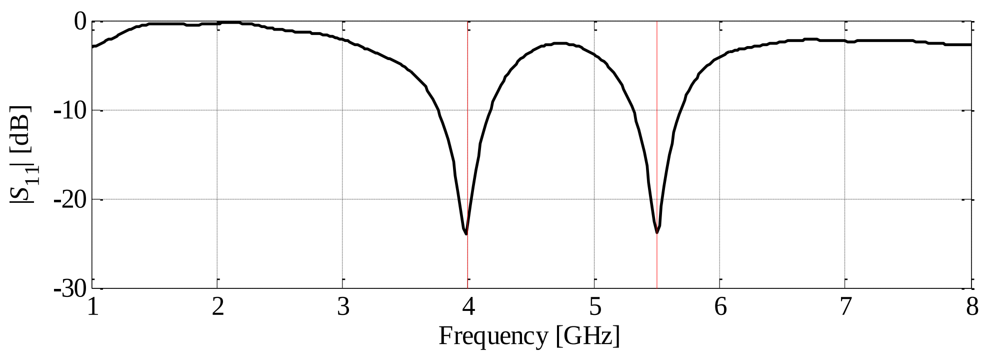
Fig. 5. Reflection characteristics of the high-fidelity (—) and feature-based models (400 training points) (○) at the selected test designs. Very good alignment between the results can be observed.



(a)



(b)



(c)

Fig. 6. Two-band dipole optimization: responses of the EM model at the designs obtained through optimization of the feature-based surrogate. The selected operating frequencies: (a) 3.0/6.2 GHz, (b), 3.5/6.5 GHz, (c) 4.0/5.5 GHz.

Table 2. Dimensions of the Optimized Two-Band Dipole Antenna Designs

Frequencies [GHz]		Parameters [mm]					
f_1	f_2	l_1	l_2	l_3	w_1	w_2	w_3
3.0	6.2	30.32	17.72	17.45	0.51	2.46	0.71
3.5	6.5	26.91	12.24	16.92	0.48	2.22	0.68
4.0	5.5	24.54	12.50	19.50	0.53	2.23	0.67

6. Conclusion

In this paper, a technique for reduced cost and accurate surrogate modeling of input characteristics of two-band antennas has been presented. Our methodology exploits the responses of the two-band antenna structure (specifically, the existence of two distinct resonances) to shift the modeling process from the conventional response space (*S*-parameters versus frequency) to so-called feature space of suitably selected characteristic points of the antenna responses. The feature points have been defined with respect to frequencies and levels of the antenna resonances as well as a number of infill points allocated in between. Our approach has been verified for a two-band single-layer dipole antenna example. Applications for the antenna design have also been discussed. As demonstrated, the dependence of the feature point coordinates on geometry parameters of the antenna is much less nonlinear than for the original responses. For the considered antenna, this allows for construction of 50 to 70 percent more accurate surrogates as compared to conventional modeling approaches (here, kriging interpolation). For similar accuracy of the approximation model, compared to conventional kriging modeling, the considered method requires 75 to over 85 percent less training samples. Future work will focus on utilization of the method for modeling of both the field and the electrical properties of the antennas.

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