On the Design of Complex EM Devices and Systems Through the System-by-Design Paradigm: A Framework for Dealing With the Computational Complexity

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Abstract—The system-by-design (SbD) is an emerging engineering framework for the optimization-driven design of complex electromagnetic (EM) devices and systems. More specifically, the computational complexity of the design problem at hand is addressed by means of a suitable selection and integration of functional blocks comprising problem-dependent and computationally efficient modeling and analysis tools as well as reliable prediction and optimization strategies. Due to the suitable reformulation of the problem at hand as an optimization one, the profitable minimum-size coding of the degrees of freedom (DoFs), and the “smart” replacement of expensive full-wave (FW) simulators with proper surrogate models (SMs), which yield fast yet accurate predictions starting from minimum size/reduced CPU-costs training sets, a favorable “environment” for optimal exploitation of the features of global optimization tools in sampling wide/complex/nonlinear solution spaces is built. This research summary is then aimed at: 1) providing a comprehensive description of the SbD framework and of its pillar concepts and strategies; 2) giving useful guidelines for its successful customization and application to different EM design problems characterized by different levels of computational complexity; and 3) envisaging future trends and advances in this fascinating and high-interest (because of its relevant and topical industrial and commercial implications) topic. Representative benchmarks concerned with the synthesis of complex EM systems are presented to highlight advantages and potentials as well as current limitations of the SbD paradigm.

Index Terms—Complex EM problems, learning-by-examples (LBEs), optimization, surrogate modeling (SM), system-by-design (SbD).

I. INTRODUCTION

In the last years, there have been many and significant progresses in the development of numerical techniques—denoted as full-wave (FW) solvers—for the accurate analysis of complex electromagnetic (EM) devices and systems (see [1]–[8] and the reference therein). Although highly reliable, FW solvers are generally time-consuming [8] and their exploitation to solve complex EM synthesis problems often implies “local” refinements of an initial/reference solution based on parametric sweeps and/or trial-and-error steps. Otherwise, design strategies involving analytic/semianalytic methods (AMs) (e.g., [9], [10]) are generally less computationally demanding, thus allowing the use of more effective and complex synthesis strategies (e.g., global optimization or gradient-based deterministic and iterative methods), but they may be unreliable when dealing with high-complexity systems since they typically approximate or even neglect nonlinear EM phenomena that require the FW solution of Maxwell’s equations. Moreover, AMs cannot deal with whatever EM device or system since they are generally suitable for canonical or rather “simple” structures [10]. Therefore, the “holy-grail” in synthesizing complex EM systems is, on the one hand, to take advantage of the modeling accuracy of FW solvers, on the other, to exploit global optimization strategies for finding the global optimum (or the closest one) of the cost function that quantifies the mismatch between user requirements and design outcomes. As a matter of fact, global optimization strategies, based, for example, on nature-inspired evolutionary algorithms (EAs) [11]–[15], have been widely applied in many EM engineering problems since they allow an efficient exploration of the whole solution space and, unlike deterministic algorithms,
they require neither the analytic knowledge nor the differentiation of the cost function. Moreover, a priori information (e.g., physical requirements or already available suboptimal solutions) can be introduced in a straightforward manner as additional constraints on the iterative process of selecting trial solutions [13]. Of course, global optimizers require the evaluation of many solutions (typically hundreds or thousands) to ensure an effective sampling of the solution space and to find a solution fitting all user requirements, and thus, the "bare" integration of an FW solver in an iterative optimization tool will imply unrealistic/unaffordable computational costs. Such a problem is even worse when implementing robust design techniques that require the evaluation of an additional set of "perturbed guesses" to guarantee, for instance, the a priori stability of the optimized devices over a wide frequency band. In this framework, an interesting approach has been proposed in [16] to enable the computationally efficient robust synthesis of microstrip antennas without extra computational overhead. However, such a strategy still needs evaluating each trial solution during the global optimization, implying an overall cost equal to standard/less robust approaches [16]. In order to overcome EAs computational issues, different approaches have been proposed ranging from: 1) the improvement of the convergence rate of EAs by (i.1) using a set of "good" (i.e., close to the global optimum) trial solutions at the initialization of the optimization process [17], [18] and/or by (i.2) identifying a minimum set of representative solution parameters [19], [20] up to 2) the reduction of the time for evaluating (i.e., the computation of the mismatch cost function) a single solution [21]–[25] also integrating suitable coarse-to-fine space mapping strategies [26], [27].

Within this context, the system-by-design (SbD) recently emerged as an innovative paradigm able to exploit such strategies in a more integrated and seamless fashion [28]–[35]. As a matter of fact, the SbD enables an effective, reliable, and computationally efficient use of global optimizers for addressing complex EM design problems since it is aimed at the "task-oriented design, definition, and integration of system components to yield EM devices with user-desired performance having the minimum costs, the maximum scalability, and suitable reconfigurability properties." Applications of the SbD to the synthesis of innovative meta-materials [28]–[30], fractal antennas [31], electrically large airborne radomes [32], wide angle impedance matching (WAIM) layers [33], [34], and reflectarray antennas [35] have been recently documented.

The aim of this work is: 1) to provide a comprehensive description of the SbD framework and of its pillar concepts and strategies; 2) to give useful guidelines for its successful customization and application to different EM design problems that share the common issue of the computational complexity; and 3) to envisage future trends and advances in this fascinating and high-interest (because of its relevant and topical industrial and commercial implications) topic.

The outline of this article is as follows. The general principles of the SbD are pointed out in Section II, while the description of the functional blocks of the SbD is given in Section III. Two novel advanced SbD-based synthesis strategies are presented in Section IV. Representative synthesis benchmarks are illustrated (see Section V) to show the SbD working as well as to give some proofs of the method effectiveness and efficiency when dealing with computational complexity issues. Some concluding remarks are finally drawn also envisaging future trends (see Section VI).

II. SbD PARADIGM

By denoting with $\Omega (\Omega = \{\Omega_k; k = 1, \ldots, K\})$ the set of $K$ descriptive parameters [i.e., the degrees of freedom (DoFs)] of the design problem at hand, the goal of the SbD is to yield, in a reasonable time frame, the setup of the DoFs, $\Omega^{(\text{end})}$, so that the corresponding cost function value, $\Phi(\Omega^{(\text{end})})$, differs from that of the global optimum, $\Phi(\Omega^{(\text{opt})})$, at most for a maximum deviation $\xi$.

\[
\Phi(\Omega^{(\text{end})}) = \Phi(\Omega^{(\text{opt})}) \leq \xi
\]  

(1)

$\Phi$ being a metric that quantifies the mismatch of a problem solution, $\Omega$, from the project/user requirements, $\Gamma^{(\text{th})}$, where $\Gamma$ is the mapping function between the solution space, $\mathcal{R}(\Omega)$, and the requirements space, $\mathcal{R}(\Gamma) : \mathcal{R}(\Omega) \rightarrow \mathcal{R}(\Gamma)$, being $\mathcal{R}(\Gamma) \equiv \mathcal{R}(\Phi)$.

To find a computationally efficient solution of such a design problem (1), the SbD exploits four interconnected functional blocks devoted to the following subtasks (see Fig. 1).

1) **Requirements and Constraints Definition (RCD):** Mathematical definition of the project requirements, $\Gamma^{(\text{th})}$, and of a set of physical-admissibility constraints, $G_{a}^{\min} \leq G_a(\Omega) \leq G_{a}^{\max}$ ($a = 1, \ldots, A$), starting from specifications, guidelines, and objectives provided by the end-users in the statement of work (SoW).

2) **Problem Formulation (PF):** Mathematical reformulation of the synthesis problem as an optimization one by: 1) selecting/defining a parametric model of the solution; 2) identifying the corresponding DoFs, $\Omega$, that is the minimum number of univocally representative model descriptors; and 3) choosing the cost function, $\Phi(\Omega)$, which mathematically codes the mismatch between the project requirements/constraints and the performance of the model, $\Gamma(\Omega)$, whose global optimum corresponds to the best admissible physical solution of the problem at hand.

3) **Cost Function Computation (CFC):** Evaluation, in the most efficient and accurate way, of the cost function

![Fig. 1. SbD paradigm—functional scheme of the SbD.](image-url)
value $\Phi(\Omega^{(p)})$ of a trial solution $\Omega^{(p)}$ in order to “quantify” the optimality of the $p$th ($p = 1, \ldots, P$) trial physical solution (i.e., the fitness of this solution to the problem at hand).

4) Solution Space Exploration (SSE): Dealing with an optimization problem, the task to carry out is the sampling of the solution space, $\Omega(\Omega)$, bounded by $G_{\text{min}}^{(a)} \leq G_a(\Omega) \leq G_{\text{max}}^{(a)} (a = 1, \ldots, A)$, to look for the global optimum of the cost function $\Phi(\Omega)$ [i.e., $\Omega^{(\text{end})}$ in (1)]. Therefore, the SSE block is aimed at generating a succession of $I$ trial solutions $\Omega_{i}^{(p)}; i = 1, \ldots, I \hspace{1mm} (p = 1, \ldots, P)$ and $I$ being the number of agents and of iterations, respectively, by means of a suitable optimization algorithm so that $\Omega_{i}^{(\text{end})} = \arg\{\min_{i=1,\ldots,I}[\Phi_{i}^{(\text{best})}]\} (\Phi_{i}^{(\text{best})} \equiv \Phi(\Omega_{i}^{(\text{best})}))$ being $\Omega_{i}^{(\text{best})} = \arg\{\min_{p=1,\ldots,P}[\Phi(\Omega^{(p)})]\} (\Phi(\Omega^{(p)}) \equiv \Phi(\Omega^{(p)}))$. Generally speaking, $\Omega_{i}^{(p)} = \{\omega_{i}^{(p)}; k = 1, \ldots, K\}$ is a vectorial increment defined on the basis of a suitable set of operators $\mathcal{L}$, $\Omega_{i}^{(p)} = \mathcal{L}[\Omega_{i}^{(q)}, \omega_{i}^{(j)}; j = 1, \ldots, (i-1); q = 1, \ldots, P]$ depending on the optimization strategy at hand.

III. SbD Functional Blocks Implementation

To provide the readers with a general description of the SbD framework and implementation strategies, let us now focus on the PF, CFC, and SSE functional blocks, postponing the details of the first block (RCD) to the illustrative examples discussed later on.

A. Problem Formulation (PF)

In order to synthesize satisfactory and reliable solutions, all project requirements/constraints defined by the end-user must be carefully “translated” into a proper mathematical framework, as detailed in the following.

1) Solution Model and DoFs Identification: In global search strategies, such as EAs, the number $P$ of agents/trial solutions evaluated at each $i$th ($i = 1, \ldots, I$) iteration is proportional to the number of DoFs, $K$ [13], [14]. Accordingly, a suitable formulation of the problem at hand must be made so that: 1) $K$ is as low as possible to minimize the computational burden for a more efficient design, but at the same time, and 2) the choice of the $K$ DoFs, $\Omega$, guarantees the existence of a solution fitting the SbD goal (1) as well as its careful correspondence with a feasible physical solution. Toward this end, parametric studies are a valid approach to perform a sensitivity analysis and to identify which descriptors (varied within suitable bounds) have the highest impact on the performance indexes, $\gamma(\Omega)$, and are the most representative to define the minimum set of $K$ descriptors. On the other hand, a key factor in the “representation” of the actual physical solution is the choice of the basis functions to be exploited for defining smarter solution models, which are characterized by a reduced dimensionality, $K$, while ensuring high flexibility in the solution representation. This is the case, for instance, when synthesizing the shape/profile of an EM device as in [28] where linear arrays have been miniaturized by means of isotropic covering metasurfaces. More in detail, the goal has been that of determining the optimal transformation-optics (TOs) 2-D profile, $\gamma(x, y)$, such that the lens-enclosed antenna mimics a reference one

\[
\Omega_{k}^{(\text{pix})} = 1, \quad \Omega_{k}^{(\text{pix})} = 0
\]

with larger aperture. By describing $\gamma(x, y)$ with a pixel-basis representation

\[
\gamma^{(\text{pix})}(x, y) = \sum_{k=1}^{K^{(\text{pix})}} \Omega_{k}^{(\text{pix})} B_{k}^{(\text{pix})}(x, y)
\]

where $B_{k}^{(\text{pix})}(x, y) = 1$ if $(x, y) \in \rho_{k}$, while $B_{k}^{(\text{pix})}(x, y) = 0$ otherwise, $\rho_{k}$ being the $k$th discretization cell of the lens, and the arising number of DoFs was equal to the number of pixels, $K^{(\text{pix})}$ [see Fig. 2(a)]. Differently, a spline-based representation has been adopted in [28] to describe the lens profile in terms of Bézier quadratic curves by means of second-order polynomials, $B_{k}^{(\text{spl})}(x, y, \Omega^{(\text{spl})}) (k = 1, \ldots, K^{(\text{spl})})$ [19], [20] [32] so that the DoFs coincide with the control points of the spline curve, $\Omega^{(\text{spl})} = \{(x_{k}^{(\text{spl})}, y_{k}^{(\text{spl})}); k = 1, \ldots, K^{(\text{spl})}\}$ [see Fig. 2(b)]. It is worth pointing out that while the pixel-based representation (3) needs a significantly larger number of descriptors, $K^{(\text{pix})} \gg K^{(\text{spl})}$, to yield a detailed model of $\gamma(x, y)$, the use of spline bases allows one to model a continuous profile with a limited number of control points (e.g., $K^{(\text{spl})} = 5$ [28]). Of course, using a spline-based representation is not always the best solution, but certainly, a careful study on the representation properties of a set of basis functions is a “golden” rule for having a competitive SbD-based design approach.

2) Cost Function Definition: The cost function $\Phi(\Omega)$ is the unique link between the optimization strategy and the physics of the EM problem. Therefore, it must be carefully defined to guarantee the correct sampling of the solution space and the achievement of feasible solutions [13]. Moreover, the choice of the cost function determines the overall complexity of the $K$-dimensional landscape explored by the SSE block. To the best of authors’ knowledge, there is not a general guideline to optimally select $\Phi(\Omega)$ as well as to have the arising cost function with suitable properties, for instance, to limit the occurrence of local minima/false solutions. However, similar to what is done in inverse scattering [36], [37], its behavior can be roughly estimated by analyzing the functional cuts along some directions of the solution space

\[
\Phi\{t, \Omega^{(1)}, \Omega^{(2)}\} = \Phi\{(1 - t) \times \Omega^{(1)} + t \times \Omega^{(2)}\},
\]

$\Omega^{(1)}$ and $\Omega^{(2)}$ being two user-chosen positions within the solution space, while $t$ is a real variable. From (4), it turns out that $\Phi\{t, \Omega^{(1)}, \Omega^{(2)}\} = \Phi(\Omega^{(1)})$ if $t = 0$ and $\Phi\{t, \Omega^{(1)}, \Omega^{(2)}\} = \Phi(\Omega^{(2)})$ if $t = 1$ while sweeping $t$ within suitable bounds.
gives some insights on the behavior of the cost function along a 1-D cut passing through $\Omega^{(1)}$ and $\Omega^{(2)}$. What is the reason for doing it? On the one hand, such evaluations allows one to have some indications (not analytic proofs) on the degree of complexity/nonlinearity of the functional space at hand. On the other hand, they can provide a valid support for the optimal choice and implementation of the CFC and SSE blocks.

B. Cost Function Computation (CFC)

The computation of $\Phi(\Omega)$ requires the evaluation of specific performance indexes of the synthesized EM device. Toward this aim, several numerical techniques are available for performing accurate FW analyses [1]–[3]. By formulating forward EM problems by means of properly discretized sets of integral and/or differential equations, the corresponding numerical solution needs the computation of thousands or millions of unknowns. Therefore, a repeated evaluation of the cost function $\Phi(\Omega)$ is the real bottleneck of standard (StD) optimization-based designs whose computational burden is

$$\Delta_{\text{fw}} = (P \times I) \times \Delta_{\text{fw}}.$$  (5)

$\Delta_{\text{fw}}$ being the CPU time for a single FW simulation. Unless reliable analytic model are available, learning by examples (LBE) techniques are exploited by the SbD to significantly reduce the computational burden, while keeping a reliable prediction of the performance of the synthesized device/system. In short, LBEs are devoted to build fast surrogate models (SMs) able to predict, in a computationally efficient fashion, the outcome of high-fidelity EM simulations [38]. From an architectural viewpoint, LBE strategies are two-step implementations composed by: 1) a training and 2) a testing phase. The training phase is typically performed offline and it is devoted to build an accurate and fast surrogate of the cost function $\Phi(\Omega)$, $\Phi(\Omega)$, starting from a training set of $S$ examples/observations of the input–output (I/O) relationship, $\mathcal{D}_S = \{\{\Omega^{(s)}\}, \Phi^{(s)}\}; s = 1, \ldots, S$, where $\Phi^{(s)}$ stands for $\Phi(\Omega^{(s)})$ (see Fig. 3). During the test phase, online predictions of the cost function value are then outputted for previously unseen inputs [38].

Among several LBE strategies, let us focus in the following on the most commonly adopted ones in EM engineering

$^3$The feasibility of such analyses clearly depends on the computational complexity and CPU time of each evaluation of the cost function. Of course, careful a priori analyses must be performed case-by-case to infer about their worthiness and proper setup.

Fig. 3. Training set generation. Pictorial representation of the DoFs, reduced features, and cost function spaces and their interconnections for the generation of the training sets $\mathcal{D}_S = \{\{\Omega^{(s)}\}, \Phi^{(s)}\}; s = 1, \ldots, S$ and/or $\mathcal{D}_S = \{\{\Omega^{(s)}\}, \Phi^{(s)}\}; s = 1, \ldots, S$.

![Diagram of training set generation](image)

Fig. 4. CFC—actual function value and predictions made by the RBFN, SVR, and ordinary kriging (OK) SMs for (a) Levy’s, (b) Schwefel’s, and (c) Ackley’s 1-D ($K = 1$) benchmark functions when using $S = 6$ training samples.

[38] Radial basis function networks (RBFNs) are popular artificial neural networks (ANNs) computing the surrogate $\Phi(\Omega)$ as a linear combination, through suitable real expansion coefficients, $\{w^{(s)}; s = 1, \ldots, S\}$, of $S$ Gaussian functions

$$\Phi^*(\Omega) = \sum_{s=1}^{S} \Phi^{(s)}(\Omega) w^{(s)}.$$  (6)

Otherwise, support vector regressors (SVRs) define the SM as follows:

$$\Phi^*(\Omega) = \sum_{s=1}^{S} \left((a^{(s)} - \beta^{(s)}) \mathcal{K}(\Omega^{(s)}, \Omega) + \varsigma\right).$$  (7)

where $a^{(s)}$ and $\beta^{(s)} (s = 1, \ldots, S)$ are the SVR weights, while $\mathcal{K}(\Omega^{(s)}, \Omega)$ is the kernel function, $\varsigma$ being a bias [38]. A main difference between RBFNs and SVRs is the intrinsic capability of RBFNs to exactly fit/interpolate the training samples (i.e., $\Phi^*(\Omega^{(s)}) = \Phi(\Omega^{(s)}); s = 1, \ldots, S$). Otherwise, the SVR tolerates/neglects deviations of the surrogate prediction $\Phi^*(\Omega)$ from the actual cost function $\Phi(\Omega)$ smaller than a threshold $\epsilon$ by defining an “$\epsilon$-insensitive tube” [38].

Of course, there is not an optimal and unique choice for the best prediction technique, but this depends on the design problem at hand as well as on the selection of the remaining SbD blocks. Indeed, exactly performing like high-fidelity FW simulators when processing previously explored solutions may be a desirable feature since the I/O relationship, $\mathcal{K}(\Omega)$, is purely deterministic. However, the SM should not be regarded in the SbD framework as a highly reliable computationally efficient alternative to FW solvers, but rather as a sufficiently accurate estimator of the behavior of the cost function to guide the solution-space sampling/exploration toward the attraction basin of $\Omega^{(opt)}$. In order to better understand this latter concept, let us consider some simple yet intuitive examples on well-known 1-D ($K = 1$) benchmark cost functions, $\Phi(\Omega) \triangleq \Phi(\Omega_1)$. Fig. 4(a) shows the 1D Levy’s cost function within the range $\Omega_1 \in [-10, 10]$ [39] along with the predictions made
by the RBFN and the SVR surrogates starting from $S = 6$ randomly chosen training samples. As it can be observed, the SVR correctly identifies the presence of a valley centered at the global minimum of the actual cost function, $\Omega_{\text{levy}}^{\text{opt}} = 1$, while a significantly worse prediction of the cost function behavior is given by the RBFN even though this latter perfectly fits all training observations. However, the SVR may lead to an oversmoothed surrogate of $\Phi$ failing to “understand” the overall trend of the actual cost function as shown in Fig. 4(b) for Schwefel’s function [39] ($\Omega_1 \in [-500, 500]$ and $\Omega_{\text{Schwefel}}^{\text{opt}} = 420.9687$). The two surrogates perform similarly when dealing with Ackley’s function [39] ($\Omega_1 \in [-5, 5]$ and $\Omega_{\text{Ackley}}^{\text{opt}} = 0$—Fig. 4(c)).

Another widely used LBE method is the ordinary kriging (OK) whose remarkable advantage over the RBFN and the SVR is the straightforward capability of providing a measure, $\Psi(\overline{\Omega})$, of the degree of reliability/confidence associated with any prediction $\Phi(\overline{\Omega})$ [38], [41]. As it will be explained in the next sections, such an additional output is a powerful source of information to be profitably exploited to enhance the effectiveness of the whole SbD synthesis. More in detail, the surrogate model generated by the OK is given by [40], [41]

$$\Phi(\overline{\Omega}) = \mu + \eta^T \mathcal{R}^{-1}(\overline{\Phi} - \mathcal{L}\mu)$$

where $\mu$ is a real constant, $\Phi = \{\Phi(s); s = 1, \ldots, S\}^T$, $\mathcal{L}$ being the transpose operator, $\mathcal{R} = \{(p, q); p, q = 1, \ldots, S\}$ is the ($S \times S$) training correlation matrix, and $\eta = \{\eta_s; s = 1, \ldots, S\}$ is the correlation vector of $\Phi$ [41]. As for the prediction reliability metric, its meaning is quite intuitive since it is defined as the weighted distance between $\overline{\Omega}$ and the $S$ training samples (i.e., $\Psi(\overline{\Omega}) \propto (\sum_{s=1}^{S} \|\overline{\Omega} - \overline{\Phi}^{(s)}\|_2)/S$) being $\Psi(\overline{\Omega}) = 0$ and $\Phi(\overline{\Omega}) = \Phi(\overline{\Omega})$ only if $\overline{\Omega} = \overline{\Phi}^{(s)}$ ($s = 1, \ldots, S$) (see Fig. 5). More specifically, the OK uncertainty is modeled starting from the assumption that the cost function value $\Phi(\overline{\Omega})$ is the realization of a normally distributed random variable with mean $\Phi(\overline{\Omega})$ and standard deviation equal to $\Psi(\overline{\Omega})$ [40], [41] (see Fig. 5). For the sake of completeness, the predictions made by the OK for Levy’s, Schwefel’s, and Ackley’s functions are reported in Fig. 4.

1) SbD-Driven Training Set Generation : In order to yield a reliable SM, the training set must be properly built. Hypothetically, only a very large (ideally infinite) number, $S$, of I/O pairs would allow to exactly predict the cost function value $\Phi(\overline{\Omega})$ (i.e., $\Phi(\overline{\Omega}) \rightarrow \Phi(\overline{\Omega})$ when $S \rightarrow \infty$). Practically, strategies for the selection of the minimum number of representative samples guaranteeing the SM prediction error is below a desired threshold are needed. Toward this aim, the SbD toolkit deals with LBE strategies from a different perspective and in terms of a three-step approach where only the last one is finalized at defining the SM [42]. More in detail, the first step is concerned with the reduction of the dimension of the input (solution) space $\Psi(\overline{\Omega})$ to mitigate the negative effects of the curse of dimensionality [43]. It is worth pointing out that such a task is partially/preliminarily addressed by the PF block when choosing the smallest set of the most representative DoFs that guarantees the existence of a physically admissible solution (see Section III-A1). However, whether $K$ is still high (e.g., $K > 20$) lower cardinality yet highly informative training sets can be built by means of space reduction techniques. These latter determine a reduced set of $K' (K' \ll K)$ DoFs, called reduced features, $\chi^{(s)} = \{\chi^{(s)}; k = 1, \ldots, K'\}$ by means of a linear/nonlinear transformation operator $\Lambda$ so that a reduced database, $\overline{D}_S = \{\chi^{(s)}; \Phi(\overline{\Omega})^{(s)}; s = 1, \ldots, S\}$ (see Fig. 3), is built. The $\Lambda$-based mapping can be function-independent (i.e., $\chi^{(s)} = \Lambda(\overline{\Omega}^{(s)})$), as in the principal component analysis (PCA) [42] and in the Sammon mapping (SAM) [24], or function-dependent (i.e., $\chi^{(s)} = \Lambda(\overline{\Omega}^{(s)\Phi})$) as for the partial least squares (PLSs) [42]. Although the exploitation of such techniques within the SbD needs further investigation, a simple and intuitive recipe for the application of the PLS algorithm to the design of EM devices with a large number of DoFs is given in the following.4

1) Generate the training set of $S$ I/O pairs $\overline{D}_S$ by sampling the original $K$-dimensional DoFs space and computing the corresponding output by means of the FW solver.
2) Apply the SIMPLS algorithm [42] to $\overline{D}_S$ in order to compute the $(K \times K')$ PLS transformation matrix $\mathcal{W}$ allowing to compute the set of extracted features as

$$\chi = \overline{\Omega} \times \mathcal{W}$$

where $\chi = \{\chi^{(s)}; s = 1, \ldots, S\} \in \mathbb{R}^{S \times K'}$ and $\overline{\Omega} = \{\overline{\Omega}^{(s)}; s = 1, \ldots, S\} \in \mathbb{R}^{S \times K}$.

The PLS is particularly suitable to deal with prediction problems since, unlike PCA and SAM, it performs a feature extraction based on the relation between input and output training samples. Moreover, it has been already successfully applied in other contexts as a powerful tool to reduce the dimensionality of the input space and to enable the generation of low-cardinality/highly informative training sets [42].
3) Train an SM using the reduced database $\hat{D}_S$ to build a fast predictor $\hat{\Phi}(\chi)$ of $\Phi(\chi) = \Phi(\Omega)$. 
4) During the online test phase, project every new/ Previously unseen test sample $\Omega$ onto the PLS-reduced space by computing its lower-dimensionality version $\chi$ as follows:

$$\chi = \Omega \times W$$  \hspace{1cm} (10)

then input $\chi$ to the SM to make it predict the corresponding output/cost function value.

To provide a proof of concept of the effectiveness of the above procedure, let us consider a $K = 50$-dimensionality problem with a cost function defined as $\Phi(\Omega) = (\sum_{k=1}^{33} k \times \Omega_k) + (\sum_{k=33}^{49} \Omega_k) + (1/2)\Omega_{44} \times \Omega_{50}$. Due to the high dimensionality of the input space, a training database $D_S$ of $S = 200$ I/O samples ($\Omega_k \in [-5, 5], k = 1, \ldots, K$) is insufficient for building an accurate predictor of $\Phi(\chi)$. As a matter of fact, the scatter plot of the actual, $\Phi(m) = \Phi(\Omega(m))$, versus the predicted, $\hat{\Phi}(m) = \hat{\Phi}(\Omega(m))$, cost function $(m = 1, \ldots, M, M = 1000$ being the number of test samples) when using $D_S$ to train an OK model, shows that the predictor is completely unreliable (i.e., $\hat{\Phi}(\Omega(m)) \approx 0 \forall m = 1, \ldots, M$—Fig. 6(a)).

Otherwise, a remarkable accuracy improvement is yielded when applying the PLS to “shrink” the original $K = 50$ DoFs to only $K' = 4$ extracted features (see Fig. 6(a)).

Quantitatively, the computed prediction error

$$E = \frac{\sum_{m=1}^{M}(\Phi(m) - \hat{\Phi}(m))^2}{\sum_{m=1}^{M}(\Phi(m) - \bar{\Phi})^2}$$  \hspace{1cm} (11)

where $\Phi_{av} = (1/M) \sum_{m=1}^{M} \Phi(m)$ is equal to $E|_{S=50} = 9.98 \times 10^{-2}$ and $E|_{K=200} = 7.67 \times 10^{-2}$. Similar outcomes are verified also when increasing the training set cardinality to $S = 2000$, with almost no benefit over the curse of dimensionality using the original high-dimensionality features [i.e., $E|_{S=50} = 9.72 \times 10^{-1}$ and $E|_{K=200} = 2.04 \times 10^{-2}$—Fig. 6(b)].

The second step is aimed at an “exhaustive” representation of the input space $\Omega(\chi)$ by properly selecting the $S$ I/O pairs. The available sampling strategies can be classified into two main categories: 1) one-shot/noniterative and 2) adaptive strategies [44]–[48].

The uniform grid sampling belongs to the first class and it performs a full-factorial exploration of the input space by uniformly sampling each $k$th ($k = 1, \ldots, K'$) dimension and considering all existing combinations. Clearly, it becomes rapidly unfeasible when increasing the solution space dimensionality $K'$ and/or the number of quantization levels, $Q$ (e.g., $Q = 10^3$ when $K' = 5$ and $Q = 10$). To overcome such a drawback, other strategies such as the Latin hypercube sampling (LHS) [47] and the orthogonal arrays (OAs) method [17], [31] can be exploited. As for the adaptive sampling strategies 2), they are based on the iterative selection of the $S$ training samples to reach a profitable balancing between exploration (i.e., new samples in the regions of $\Omega(\chi)$ where the sampling rate is low) and exploitation (i.e., new samples where the cost function $\Phi$ is more nonlinear as it can be inferred from the cuts-analysis (4)) [47].

2) SbD Time Saving: When using a SM instead of the FW solver, the total cost of the SbD-based synthesis turns out to be

$$\Delta t_{SbD} = \Delta t_{SM}(S) + (P \times I) \times \Delta t_{test}$$  \hspace{1cm} (12)

where $\Delta t_{test}$ is the CPU time to yield a single $\Phi$-prediction and $\Delta t_{SM}(S) = (S \times \Delta t_{FW}) + \Delta t_{train}$ is the CPU time to perform the $S$ training simulations and to generate the SM.\footnote{It should be noticed that also the training/test times are functions of $S$ [i.e., $\Delta t_{train/test} = \Delta t_{train/test}(S)$]. However, $S$ is kept quite small ($S < 10^3$) in practical applications to guarantee a significant time saving. Therefore, the dependence on the training set size $S$ can be neglected since $\Delta t_{train/test}(S) \ll (S \times \Delta t_{FW})$.}

Accordingly, the SbD becomes profitable and very competitive when $\Delta t_{SbD} \ll \Delta t_{SbD}$, being

$$\Delta t_{SbD} = (P \times I) \times \Delta t_{FW}$$  \hspace{1cm} (13)

To provide a simple, although rigorous, indication of the overall time saving of the SbD with respect to a trivial integration of an FW solver within an optimization loop, let us consider that in practical situations ($\Delta t_{train} \ll \Delta t_{test}$), and thus, the following approximation generally holds true: $\Delta t_{SbD} \approx S \times \Delta t_{FW}$. Accordingly, the time saving percentage due to the SbD (i.e., $\Delta t_{sav} = ((\Delta t_{SbD} - \Delta t_{SbD}(S))/\Delta t_{SbD})$) is equal to

$$\Delta t_{sav} \approx \frac{(P \times I) - S}{(P \times I)} \times 100$$  \hspace{1cm} (14)

and thus, the rule-of-thumb applicability condition for the SbD is $S < (P \times I)$.

The percentage saving in (14) can be even higher in case of massive parallel computing. With reference to the computational scenario where $O (O \geq P)$ processors are available, while the effects of multiple and parallel computational capabilities can be exploited by a standard approach only to reduce the optimization time

$$\Delta t_{sav}^P = \frac{\Delta t_{SbD}}{P}$$  \hspace{1cm} (15)

by sharing among the $O$ CPUs, the evaluation of the cost function of the $P$ multiple agents/trial solutions at each $i$th ($i = 1, \ldots, I$) iteration, the SbD benefits of this computational overboost also for reducing the training time

$$\Delta t_{SbD}^P = \frac{\Delta t_{SM}(S)}{O} + \frac{(P \times I) \times \Delta t_{test}}{P}$$  \hspace{1cm} (16)

Therefore, the percentage time saving is roughly around

$$\Delta t_{sav}^P \approx \left(1 - \frac{S}{O \times I}\right) \times 100$$  \hspace{1cm} (17)

[i.e., $\Delta t_{sav}^P > 0$ if $S < (O \times I)$] and it further reduces to $\Delta t_{sav}^P \approx (1 - (1/I)) \times 100$ [i.e., $\Delta t_{sav} > 0$ always since $I > 1$ by definition of iterative optimization loop], if $O \geq S$ since $\Delta t_{SM}(S) \approx \Delta t_{FW}$. It is worth pointing out that such considerations are quite general and they are intentionally not customized to specific parallel computing architectures or solvers/simulation tools, their choice and optimal setup being strongly dependent on the design at hand as well as on the available computing facilities.

\footnote{\textsuperscript{4}Indeed, the number of CPUs that can be used in parallel in standard optimization algorithms is bounded by the number of trial solutions $P$ since the generation of new solutions depends on the outcomes of the previous iteration.}
Many global optimization methods exist and the choice of the most effective algorithm for the synthesis problem under study is a key issue and not trivial task at all. From a theoretical viewpoint, the “no free-lunch theorem” (NFL) of optimization [49] states that: 1) “the average performance of any pair of algorithms across all problems is identical” and 2) “no matter what the cost function, by simply observing how well the algorithm has done so far tells us nothing about how well it would do if we continue to use it on the same cost function.” This implies that “whether an optimization algorithm performs better than random search on some class of problems, then it must perform worse than random search on another class” [49]. Therefore, the application of an arbitrary algorithm to an optimization problem without understanding the nature and the properties/features of the cost function $\Phi$ as well as of $\Omega$ is on average equivalent to perform a random search. Indeed, it is well proven that each optimizer has its own “optimal niche” of application where it outperforms other alternatives or vice versa a suitable reformulation of the synthesis problem at hand allows one to use a particular optimization tool. By extension, the NFL principles hold true for the SbD, as well, since this latter formulates a synthesis problem as an optimization one. More specifically, the NFL rules apply to the SbD framework as follows “it is not possible to a priori identify the best combination of the functional blocks of the SbD able to perform well on every possible problem.”

To give some insights on this concept and its consequences, let us focus our attention to the integration of two representative blocks, namely the SM and the optimization tool. Toward this end, let us consider the optimization of the three benchmark functions in Fig. 4, but with $K = 6$, performed with the “bare” integration of the RBFN, the SVR, and the OK models with two state-of-the-art evolutionary optimizers, namely the particle swarm optimizer (PSO) and the differential evolution (DE) [13], [14]. Given the stochastic nature of both the SMs (i.e., the LHS) and the optimizers, the median realization over $R = 20$ executions with $P = 10$ agents for $I = 200$ iterations is reported to yield statistically meaningful results. Fig. 7 reports the cost function values at the last iteration ($i$) of the different BARE-SbD algorithms versus the $(S/K)$ ratio. Dealing with Levy’s function [see Fig. 7(a)], the choice of the SVR to generate the SM turns out to be successful for the arising SbD implementation since both the PSO-SVR and the DE-SVR integrations yield the best results, provided that a sufficient number of training samples are available (i.e., $(S/K) \geq 20 \rightarrow S \geq 120$ being $K = 6$). Otherwise, the SVR-based methods are the worse ones for the minimization of Schwefel’s function [see Fig. 7(b)] because of the oversmoothing in approximating the actual cost function [see Fig. 4(b)]. On the contrary, the OK enables a proper exploration of the solution space when integrated with the PSO [see Fig. 7(b)]. This latter choice is suboptimal when dealing with Ackley’s function, while both SVR-based strategies perform very well whatever the cardinality $S$ of the training set [see Fig. 7(c)].

### IV. Advanced SbD Strategies

Totally replacing the FW solver with an SM, as done in BARE-SbD approaches (see Section III-C), may lead to suboptimal designs [50]. This holds true especially when nonnegligible time savings are required to permit the synthesis of high-complexity and computationally demanding devices/systems, thus setting a low size, $S$, for the training set because of the very limited number of affordable simulations within a reasonable amount of time. As a matter of fact, treating the SM as a “magic black box” could produce undesired effects such as: 1) the convergence toward false solutions/local minima and/or 2) the prediction of unfeasible cost function values (e.g., negative values, $\Phi(\Omega) < 0$). Moreover, simply increasing $S$ to globally improve the prediction accuracy could be not enough to prevent such issues and advanced SbD strategies are necessary. They are mainly based on the following basic recipes: 1) the local refinement of the SM within the attraction basin of $\Phi^{(\text{opt})}$ and/or 2) the interactive collaboration between the optimizer and the predictor. By following those guidelines, two advanced SbD implementations are described in the following.

#### A. Optimization-Driven “Smart” SM Generation

Unlike state-of-the-art adaptive sampling strategies (see Section III-B1), the accuracy of the SM is locally enhanced in the neighborhood of $\Omega^{(\text{opt})}$. Toward this end, an optimization-driven adaptive sampling strategy can be adopted to build the training set $\mathcal{D}_{s}$ by iteratively adding new samples to an initial dataset $\mathcal{D}_{0}$ with $S_{0} \rightarrow S = \frac{S}{J}$ $I/O$ pairs. Such a strategy belongs to the class of the “output space filling” (OSF) techniques [51] and it is aimed at uniformly exploring the output/cost function space for which $\Phi(\Omega^{(\text{opt})}) < \Phi_{\text{th}}, \Phi_{\text{th}}$ being a user-specified threshold. It is performed within the CFC block (see Fig. 1) and it consists of the following procedural steps.

1. **Initialization:** Generate $\mathcal{D}_{0} = \{\Omega^{(s)}; \Phi^{(s)}\}; s \in \{1, \ldots, S_{0}\}$ by sampling the input space via LHS and initialize the loop index ($j = 1$).
2. **SbD-OSF Loop** [$j = 1, \ldots, (S - S_{0})$].
   a. Train an SM using the $S_{j-1}$ samples of the dataset $\mathcal{D}_{j-1}$.
   b. Let $\mathcal{D}_{j}$ be the SM output, and $\mathcal{D}_{j}^{*}$ be the SM output with associated $\Phi_{\text{th}}$.
   c. Update $\mathcal{D}_{j-1}$ to $\mathcal{D}_{j}$ if $\Phi_{\text{th}} < \Phi(\Omega) < \Phi^{(\text{opt})}$; otherwise, continue without adding new samples.
   d. Increase the training set size to $S_{j} = S_{j-1} + 1$.
   e. Repeat steps a) through d) until the number of training samples meets a pre-defined threshold.

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**Fig. 7.** SSE—values of the cost function at the convergence, $\Phi_{\text{bD}}$, for different “bare” SbD algorithms versus the ratio between the training cardinality and the number of variables, $S/K$: (a) Levy’s, (b) Schwefel’s, and (c) Ackley’s functions with $K = 6$. 

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b) Sample the input space via LHS to generate $C$ candidates, $\{\mathbf{d}^{(c)}; c = 1, \ldots, C\}$, and predict the corresponding cost function values, $\{\Phi^{(c)} \triangleq \Phi(\mathbf{d}^{(c)}); c = 1, \ldots, C\}$.

c) Select the “best” candidate $\mathbf{d}^*$ as $\mathbf{d}^* = \arg\max_{c=1,\ldots,C}\{\min_{i=1,\ldots,S} (d_{c,i})\}$ subject to $\Phi^{(c)} \leq \Phi_{th}$ being $d_{c,i} \triangleq |\Phi^{(c)} - \Phi^{(i)}|$.

d) Compute the actual cost function value of $\mathbf{d}^*$, $\Phi^* \triangleq \Phi(\mathbf{d}^*)$, and update the training size, $S_j \leftarrow (S_{j-1} + 1)$, and dataset, $D_j \leftarrow D_{j-1} \cup \{\mathbf{d}^*, \Phi^*\}$ along with the loop index, $j \leftarrow (j + 1)$. Stop the procedure if $S_j = S$ or go to Step 2(a).

Fig. 8 shows the results of such a procedure when applied to the 1-D Ackley’s function. More specifically, the SbD-OSF has been run by setting $S_0 = 5$ and $S = 50$, while the OK-based SM model has been chosen to predict $C = 200$ candidates at each $j$th [$j = 1, \ldots, (S - S_0)$] loop. As it can be observed, there is an adaptive exploration of the region where $\Phi(\mathbf{d}) < \Phi_{th}$ [$\Phi_{th} = 6.0$—Fig. 8(a)] and, as a by-product, the accuracy of the OK has been enhanced only close to $\mathbf{d}^{(op)}$ [see Fig. 8(b)].

B. “Confidence-Enhanced” SbD Optimization

Another strategy to improve the effectiveness of the SbD is to implement a more interactive framework by enforcing a bilateral exchange of information between the CFC and the SSE blocks (see Fig. 1). Let us first notice that, on the one hand, the SM is a computationally cheap alternative to the FW solver, and on the other hand, the optimizer progressively localizes “promising” regions of the search space (i.e., the attraction basins of the landscape of the cost function) where the prediction accuracy should be enhanced to facilitate the convergence toward the global minimum, $\mathbf{d}^{(op)}$. In order to fully exploit these features, a novel SbD strategy is proposed hereinafter by profitably combining the global search/hill-climbing features of the PSO [13] with the capability of the OK to provide a reliability index (see Section III-B) of the SM predictions. The arising “confidence-enhanced” PSO-OK (PSO-OK/C) method is based on a “reinforced learning” (RL) strategy that updates the SM during the optimization by adaptively selecting trial solutions to be evaluated with the FW solver. It works as follows.

1) Initialization ($i = 0$): Train an OK-based SM starting from an initial training set of $S_0$ I/O pairs, $\mathcal{D}_{S_0}$. Compute the best cost function value of the solutions in $\mathcal{D}_{S_0}$, $\Phi^{train}_{best} = \min_{i=1,\ldots,S_0} (\Phi^{(i)})$. Given the desired time saving $\Delta t_{sav}$, set the maximum number of affordable simulations, $S$, accordingly [i.e., $S = P \times I \times (1 - (\Delta t_{sav}/100))$]. Define an initial swarm of $P$ particles with random positions $(\mathbf{d}_i^{(p)}; p = 1, \ldots, P)$ and velocities $(\mathbf{v}_i^{(p)}; p = 1, \ldots, P)$.

2) PSO-OK/C Optimization Loop ($i = 0, \ldots, I$):

a) For each $p$th ($p = 1, \ldots, P$) particle, predict the cost function value, $\Phi_i^{(p)} (\Phi^{(p)}_i \triangleq \Phi(\mathbf{d}_i^{(p)}))$, and compute the associated confidence index, $\Psi_i^{(p)} (\Psi^{(p)}_i \triangleq \Psi(\mathbf{d}_i^{(p)}))$. If $S_i < S$, then go to Step 2(b); otherwise, go to Step 2(c).

b) Select the “most promising” particle as $\mathbf{d}^* = \arg\min_{p=1,\ldots,P} (\mathcal{F}^{-}(\Phi_i^{(p)}))$, where $\mathcal{F}^{-}(\Phi_i^{(p)}) = \Phi_i^{(p)} - \zeta \Psi_i^{(p)}$ is the “lower confidence bound” (LCB) of the $p$th ($p = 1, \ldots, P$) trial solution, $1 \leq \zeta \leq 3$ being a real coefficient [24]. If $\mathcal{F}^{-}(\Phi_i^{(p)}) > \Phi^{train}_{best}$, then jump to Step 2(c) and otherwise perform the following RL operations.

i) Use the FW solver to compute the actual cost function of $\mathbf{d}^*$, $\Phi^* (\Phi^* \triangleq \Phi(\mathbf{d}^*))$.

ii) Update the training set, $\mathcal{D}_{S_i} \leftarrow \mathcal{D}_{S_{i-1}} \cup \{\mathbf{d}^*, \Phi^*\}$, and its size, $S_i \leftarrow (S_{i-1} + 1)$. If $\Phi^* < \Phi^{train}_{best}$, then update $\Phi^{train}_{best}$ ($\Phi^{train}_{best} \leftarrow \Phi^*$).

iii) Retrain the OK model with $\mathcal{D}_{S_i}$.

c) Update the personal best position of each $p$th ($p = 1, \ldots, P$) particle, $\mathbf{d}^{(p)}_i (\mathbf{d}^{(p)}_i \triangleq \arg\min_{j=1,\ldots,P} (\Phi^*_j))$, according to the rules summarized in Table I and sketched in Fig. 9. Such an updating process is based on the degree of reliability of each $p$th ($p = 1, \ldots, P$) trial solution, $\Psi^*_i$, and of its previous best position, $\Psi^{(p)}_i$. For instance, let us consider the case shown in Fig. 9(d) where the cost function value assigned to $\mathbf{d}^{(p)}_i$ and $\Phi^{(p)}_i$ and $\mathbf{d}^{(p)}_{i-1}$ and $\Phi^{(p)}_{i-1}$.

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7According to the reference literature [48], the number of candidates is set to a value in the range $C \in [50, 200] \times K$. 

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Fig. 8. Advanced SbD Strategies (ShD-OSF; Ackley’s function). (a) Training samples generated by the initial LHS sampling ($S_0 = 5$) along with those iteratively added by the ShD-OSF ($S = 50$). (b) OK predictions with the initial (LHS) or the ShD-OSF training set.
is affected by some uncertainty, both being predicted. Although $\tilde{\Phi}_i^{(p)} > \Phi_i^{(p)}$, it is profitable to update the $p$th ($p = 1, \ldots, P$) personal best (i.e., $\tilde{\Phi}^{(p)}_i \leftarrow \Phi_i^{(p)}$) since $\bar{\Phi}_i^{(p)}$ has a higher probability to have a smaller cost function value than $\tilde{\Phi}^{(p)}_i$ [i.e., $\mathcal{F}(\bar{\Phi}_i^{(p)}) < \mathcal{F}^{(p)}(\Phi_i^{(p)})$—Table I and Fig. 9(d)]. Otherwise, whether the previous personal best has been simulated [i.e., it is 100% reliable—Fig. 9(b)], it can be updated with the current particle position only if this latter has no chance to have a worse/higher cost function value (i.e., $\mathcal{F}(\bar{\Phi}_i^{(p)}) < \mathcal{F}(\Phi_i^{(p)})$) being the “upper confidence level” (UCB) associated with $\Phi_i^{(p)}$ given by $\mathcal{F}(\Phi_i^{(p)}) \equiv \Phi_i^{(p)} + \zeta \gamma_i^{(p)}$ [see Table I and Fig. 9(b)].

d) Update the global best position, $g_i$ ($g_i \equiv \Omega_{\text{best}}^{(p)}$) according to the confidence-based rules in Table II and shown in Fig. 10.

e) If $i = I$, then stop the optimization and output $g_i$ as the final design (i.e., $\Omega^{(\text{end})} = g_i$), and else, go to Step 2(f).

f) Use the standard PSO governing equations [13] to generate a new set of particles positions and velocities, update the iteration index, $i \leftarrow (i + 1)$, and go to Step 2(a).

As it can be inferred, the PSO-OK/C SbD method implements a surrogate-assisted evolutionary optimization by exploiting an “individual-based” model management strategy [50], but unlike state-of-the-art techniques, it gives the user a full control of the time saving $\Delta t_{\text{sim}}$ by letting him specify the total amount $S$ of feasible FW simulations [i.e., $S = P \times I \times (1 - (\Delta t_{\text{sim}}/100))$] in order to comply with specific computational/time constraints for the synthesis problem at hand.

V. SbD As Applied to the Synthesis of Complex EM Systems

This section is aimed at assessing the effectiveness, the potentialities, and the current limitations of the SbD as applied to the design of complex EM systems. Toward this end, three representative benchmarks of increasing complexity, concerned with the synthesis of: 1) time modulated arrays (TMAs) (see Section V-A); 2) microstrip patch arrays for 5G applications (see Section V-B); and 3) antennas for automotive radar systems (see Section V-C) will be discussed.

A. Benchmark 1: Synthesis of TMAs

The first benchmark problem deals with the synthesis of TMAs comprising real radiators and nonlinear switching beam-forming networks (BFNs). To model the mutual coupling effects among the $N$ antennas as well as the complex nonlinear/dynamic behavior of the BFN, the harmonic-balance (HB) technique [52], [53] has been used. The goal is to determine the optimal setup of the switch-on instants, $t_{\text{on}}^m = \{t_{\text{on}}^m; n = 1, \ldots, N\}$, $t_{\text{on}}^m$ being the $T$-normalized rise time of the $n$th ($n = 1, \ldots, N$) element subject to the physical-admissibility constraint $0 \leq t_{\text{on}}^m < 1$ (ROD Block), that minimizes the fluctuations of the instantaneous directivity $\mathcal{D}$ within the modulation period $T$ [52]. Following the guidelines in Section III-A1 (PF Block), the cardinality of the solution space (i.e., the number of DoFs) has been reduced to $K = (N/2)$ by considering symmetric excitation sequences [i.e., $t_{\text{on}}^m = t_{\text{on}}^{N-(N-n+1)}$; $n = ((N/2) + 1), \ldots, N$] so that $\Omega = \{t_{\text{on}}^m; n = 1, \ldots, (N/2)\}$, while the cost function has been defined as

$$\Phi(\Omega) = \frac{1}{\mathcal{D}(\Omega,t_p)} \int_0^T \mathcal{D}(\Omega,t_p) dt_p \quad (18)$$

where $\mathcal{D}$ is the average value of the instantaneous directivity over $T$.

As a representative numerical test, a TMA with $N = 16$ monopoles resonating at $f_0 = 2.45$ GHz printed over an RF60-A Taconic substrate with relative permittivity $\varepsilon_r = 6.15$, loss tangent $\tan \delta = 0.0028$, and thickness $h = 0.655$ mm [52] has been considered. Moreover, the duration of the modulation period has been set to $T = 10 \mu s$, while the durations of the driving pulses, $\tau = \{\tau_n; n = 1, \ldots, N\}$, have been chosen to afford a Dolph–Chebyshev pattern with a sidelobe level of $SLL = -30$ dB at $f_0$.

In order to define the most suitable implementation of the CFC and SSE blocks, a preliminary study has been carried out to: 1) estimate the nature of the cost function (18) and 2) assess the accuracy of different SMs. More specifically, the plots of the 1-D cuts of $\Phi$ (4) have been evaluated and an example is reported in Fig. 11(a). In this latter, the trial solution $\Omega = \Omega(t = 0)$ corresponds to a randomly chosen position within the search space $\Omega(\Omega)$, while $\Omega = \Omega(t = 1)$ is the solution found by a state-of-the-art StD approach based on a PSO run of $I = 200$ iterations with $P = 10$ particles [52] $[\Phi_{\text{std}} = 3.2 \times 10^{-2} \Phi_{\text{std}} \equiv \Phi_{\text{std}}^{(\text{end})}]$—Fig. 11(a). As it can be observed, the cost function (18) has a highly oscillating multimodal behavior with the occurrence of many local minima and the presence of steep/ nonsymmetric valleys [see Fig. 11(a)]. Those features imply that the SSE block cannot be a deterministic optimizer, but a stochastic hill-climbing technique is mandatory.

Next, the accuracy of different SMs (namely, the RBFN, the SVR, and the OK models) has been preliminary analyzed by checking the dependence of the prediction accuracy on the number of training samples, $S$. Toward this aim, a set of $U = (P \times I) = 2000$ HB-FW simulations has been performed by LHS-sampling the solution space, then the SMs have been trained with a subset of $S < U$ samples and their accuracy has been evaluated on the remaining $M = (U - S)$ samples. Fig. 11(b) reports the values of the SM error

$$\Xi(S) = \sum_{m=1}^{M=(U-S)} \Phi_i(\Omega_i^{(m)} - \Phi_i(\Omega_i^{(m)})) \sum_{m=1}^{M=(U-S)} \Phi_i(\Omega_i^{(m)})^2$$

(19)
versus $S$ along with the time saving $\Delta t_{\text{sav}}$ of the SbD [see Fig. 11(b)]. As expected, $\Delta t_{\text{sav}}$ (linearly) decreases with $S$ independently on the adopted SM, while the OK-based surrogate always outperforms the other SMs in terms of prediction performance, the SVR generally providing the worse values of $\Xi$ [see Fig. 11(b)]. It is also worth pointing out that, no matter what the training set size within the range $0.1 \leq (S/U) \leq 0.75$, the value of $\Xi$ of each method is almost constant and smaller than $10^{-1}$.

Moving to the solution of the TMA design problem with standard SbD approaches using LHS training sets of different sizes, let us analyze the case of very high time saving (i.e., $\Delta t_{\text{sav}} \geq 90\% \rightarrow S \leq 200$). By computing the “design quality index”, $\Delta \Phi \triangleq (((\Phi_{\text{StD}} - \Phi_{\text{SbD}})/\Phi_{\text{StD}})$, as the normalized difference between the cost function of the StD solution, $\Phi_{\text{StD}}$, and that from the SbD, $\Phi_{\text{SbD}} \triangleq \Phi_{\text{SbD}}^{(\text{end})}$, it turns out that both the DE-OK and the PSO-OK always yield the best results [see Fig. 11(c)]. The performance of the advanced SbD approaches presented in Section IV have been assessed as well. They allow remarkable improvements with respect to all bare SbD implementations. Indeed, Fig. 12 shows that the “smart” sampling performed by the SbD-OSF technique (here initialized with $S_0 = 40$ samples) results in a significant reduction of $\Delta \Phi$ when applying, later on, the PSO-OK. Even more significant is the positive effect of the PSO-OK/C (still initialized with $S_0 = 40$ samples). For instance, the PSO-OK/C obtains a solution very close to that of the StD approach ($\Delta \Phi_{\text{PSO-OK/C}} = 6.2\%$—Fig. 12), but with an impressive time saving of $\Delta t_{\text{sav}} = 95\%$. In order to better appreciate such an outcome, let us consider that $\Delta t_{\text{trw}} = 13$ s on a desktop PC with 3.6-GHz CPU and 32 GB of RAM memory, and thus, the time required by the StD approach and the PSO-OK/C to complete the optimization ($i = I$) was $\Delta t_{\text{StD}} = 7.2$ h and $\Delta t_{\text{PSO-OK/C}}^{(I=100)} = 21.2$ min, respectively. Moreover, it is worth noticing that the training and testing times are equal to $\Delta t_{\text{trw}}$ (SSU) $= 2.5 \times 10^{-2}$ s and $\Delta t_{\text{test}}$ (SSU) $= 2.0 \times 10^{-3}$ s, respectively, so that the condition $\Delta t_{\text{train/teu}} < (S \times \Delta t_{\text{trw}})$ holds true (see Section III-B).

The effectiveness of the PSO-OK/C in exploring the solution space is confirmed by the evolution of the optimal value of the cost function during the iterative optimization process.
OK, Fig. 15 compares the predicted values of the cost function, \( \Phi_{\text{best}} \), versus the iteration index, \( i \) \((i = 1, \ldots, I)\), and cost function values at the \( i \)-th control-iterations, \( \{\Phi[g_j]\} \), with the corresponding actual ones, \( \{\Phi[g_j]\} \), at some intermediate “control points” \( j = 1, \ldots, J \) (see Fig. 13(a)). As a matter of fact, there is perfect matching between the PSO-OK/C predictions and the actual cost function values due to the adaptive addition of training samples during the minimization.

As for the improvement of the PSO-OK/C over the PSO-OK, Fig. 15 compares the predicted values of the cost function, \( \Phi[g_j] \), with the corresponding actual ones, \( \Phi[g_j] \), at some intermediate “control points” \( j = 1, \ldots, J \) (see Fig. 13(a)). As a matter of fact, there is perfect matching between the PSO-OK/C predictions and the actual cost function values due to the adaptive addition of training samples during the minimization.

Fig. 14. SbD-synthesis (benchmark 1: \( K = 8, P = 10, I = 200, S_0 = 40, \) and \( S = 100) \) —1D cut of \( S_{\text{bD}} \) and OK predictions when applying the PSO-OK/C.

Quantitatively, it turns out that \( \Phi_{\text{SbD(PSO-OK)}} = 9.4 \times 10^{-2} \) versus \( \Phi_{\text{SbD(PSO-OK/C)}} = 3.4 \times 10^{-2} \) (see Fig. 15).

Finally, the SbD has been compared with competitive state-of-the-art approaches. First, the surrogate-assisted DE (SADE) algorithm [24] has been considered and Fig. 12 proves that the PSO-OK/C positively compares with such an optimization approach always providing good tradeoffs between design quality and time saving. Moreover, a comparison between the PSO-OK/C performance and those from a space mapping technique [26] has been carried out as well. Toward this end, the additive-input/multiplicative-output (AIMO) space mapping approach [27] has been implemented by considering an analytic model for the TMA composed by isotropic radiators and ideal switches (\( \Delta t_{\text{coarse}} = 0.02 \) sec). It turns out that, despite a lightly better time saving with just \( S = 6 \) HB-FW simulations and \( S_{\text{coarse}} = 2200 \) coarse-model evaluations (i.e., \( \Delta t_{\text{AIMO}} = 97.9\% \)), the final solution is slightly less accurate than the PSO-OK/C one (i.e., \( \Phi_{\text{AIMO}} = 5.9 \times 10^{-2} \)).

B. Benchmark 2: Design of a Microstrip Array for 5G Applications

This second test case is devoted to further assess the advantages of the SbD when dealing with high-complexity EM design problems. Let us consider the synthesis of a planar microstrip array for 5G applications working at \( f_0 = 3.5 \) GHz (see Fig. 16). The antenna has been supposed to lie on the \((y, z)\) plane and composed by \( N = (4 \times 6) \) cavity-backed slot-fed square patches of side \( L_p = 2.73 \times 10^{-1} \) \( \lambda \). To enable \( \pm 45^\circ \) dual-polarization operation (\( J = 2 \) being the number of operating modes), each element has been rotated by \( 45^\circ \) and fed by two rectangular slots of dimensions \( (W_f, L_h) = (2.65 \times 10^{-2}, 1.31 \times 10^{-1}) \) \( \lambda \) (see Fig. 16(b)). The dimensions of the feeding lines have been set to \((W_f, L_f) = (1.69 \times 10^{-2}, 1.17 \times 10^{-1}) \) \( \lambda \), with an additional stub of length \( L_s = 5.25 \times 10^{-2} \) \( \lambda \) to reach a proper impedance matching. The following material and dielectric properties have been assumed: Arlon DiClad527 (\( \varepsilon_r = 2.5, \tan \delta = 0.0018 \)) with a total thickness of \( H = (h_1 + h_2 + h_z) = 1.24 \times 10^{-1} \) \( \lambda \) [see Fig. 16(a)], \( h_1 = 1.77 \times 10^{-2} \) \( \lambda \), \( h_2 = 5.93 \times 10^{-3} \) \( \lambda \), and \( h_c = 1.0 \times 10^{-1} \) \( \lambda \) being the height of the patch substrate, the feeding substrate, and the cavity, respectively. Starting from this reference setup, the set of DoFs \( \Omega = \{d_x, d_y, l_1, l_2\} \) (\( K = 4 \)) and \( d_x \) and \( d_y \) being the inter-element spacing along \( y \) and \( z \), respectively, while \( l_1 \) and \( l_2 \) locate the position of the feeding slot and microstrip line associated with
as a matter of fact, the PSO-OK/C performed only remarkable advantage in terms of computational efficiency.

\[ \Phi_j(\theta_i, \phi_i) = \frac{1}{2 \times V} \sum_{j=1}^{V} \sum_{i=1}^{N} G_j(\theta_i, \phi_i | \Omega)^2 \]  \quad \text{(20)}

where \( G_j(\theta_i, \phi_i | \Omega) \) is the realized gain of the \( j \)-th polarization when steering the main beam toward \( (\theta_1, \phi_1) = (90^\circ, 0^\circ) \) and \( (\theta_2, \phi_2) = (60^\circ, 75^\circ) \) (a); and \( (\theta_3, \phi_3) = (60^\circ, 75^\circ) \), \( (\theta_4, \phi_4) = (-60^\circ, 105^\circ) \), and \( (\theta_5, \phi_5) = (60^\circ, 105^\circ) \).

As for the computation of the actual value of the cost function \( \Phi \), the FW problem at hand has been solved with the Ansys HFSS EM simulator [54] by considering exactly the finite structure of the antenna (i.e., no periodic-infinite hypotheses) to take into account both the mutual coupling effects among the array elements as well as the fringing effects, the average simulation time being equal to \( \Delta t_{\text{FW}} = 5.64 \times 10^3 \text{ s} \).

Fig. 17 shows the evolution of the optimal value of the cost function for an SbD optimization based on the PSO executed with \( P = 4 \) agents for \( I = 50 \) iterations (\( P \times I = 200 \rightarrow \Delta t_{\text{SD}} = 1.13 \times 10^6 \text{ s} \sim 13 \text{ days} \)), \( \Phi_i(\Omega) \) (\( i = 1, \ldots, I \)), as well as the predicted curve outputted by the PSO-OK/C, \( \Phi_i \), along with the intermediate “control points.” The SbD converges to a solution whose cost function value is only \( \Delta \Phi = 2.64\% \) greater than that of the SbD, but with a remarkable advantage in terms of computational efficiency.

As a matter of fact, the PSO-OK/C performed only \( S = 40 \) FW simulations (comprising \( S_0 = 20 \) initial training samples before the optimization) enabling a time saving of \( \Delta t_{\text{san}} = 80\% \) (the training and testing times being equal to \( \Delta t_{\text{train}}(S)|_{S=40} = 1.45 \times 10^{-2} \text{ s} \) and \( \Delta t_{\text{test}}(S)|_{S=40} = 7.7 \times 10^{-4} \text{ s} \), respectively). For completeness, the plot of the arising realized gain patterns is shown in Fig. 18 when steering the main beam toward \( (\theta_1, \phi_1) = (90^\circ, 0^\circ) \) [see Fig. 18(a)] and \( (\theta_2, \phi_2) = (60^\circ, 105^\circ) \) [see Fig. 18(b)]. For completeness, the average realized gains along the steering direction are very close \( |G_{\text{SD}}[j=1] = 15.43 \text{ dB} \) versus \( G_{\text{SD}}[j=1] = 15.22 \text{ dB} \) and \( G_{\text{SD}}[j=2] = 15.53 \text{ dB} \) versus \( G_{\text{SD}}[j=2] = 15.36 \text{ dB} \), being \( G_j \triangleq (1/(2 \times V)) \sum_{i=1}^{V} G_j(\theta_i, \phi_i | \Omega) \), further confirming the similarity of the solutions at the convergence.

C. Benchmark 3: Design of a 77 GHz Automotive Radar Antenna

The last benchmark is aimed at providing a further proof that the SbD allows to manage very complex EM designs that are unaffordable using standard global optimization techniques. Toward this goal, the synthesis of a slotted substrate integrated waveguide (SIW) antenna for automotive radar applications at \( f_0 = 77 \text{ GHz} \) [55] is addressed in the following (see Fig. 19). The antenna is simulated with HFSS using a Rogers RO3003 substrate \( (\epsilon_r = 3.0 \text{ and } \tan \delta = 0.0013) \) of thickness \( h = 1.27 \times 10^{-1} \text{ mm} \) and comprises \( N = 18 \) uniformly spaced rectangular slots etched on the top conducting layer (see Fig. 19). In order to enable a robust design and to model all possible mutual coupling effects arising within linear arrangements (as required by the targeted radar application [55]), the design of the SIW antenna has been carried out by evaluating the EM features of the central embedded element within an array of \( N' = 7 \) equally spaced identical replicas, all \( (N' - 1) = 6 \) neighboring radiators being terminated on matched loads (see Fig. 19). The diameter of the vias, their spacing, as well as the width of the SIW, have been set following the guidelines in the reference literature [56] to \( d_{\text{via}} = 5.21 \times 10^{-2} \lambda \), \( s_{\text{via}} = 9.5 \times 10^{-2} \lambda \), \( s_{\text{via}} = 1.04 \times 10^{-1} \lambda \), and \( W_{\text{SIW}} = 0.47 \lambda \), respectively, so that the dominant \( TE_{10} \) mode propagates in the SIW (see Fig. 19). The set of optimized DoFs consists in \( K = 17 \) descriptors \( \Omega = \{a_1; a_2; a_3; b_1; b_2; \ell_x, \ell_y, \delta_i\} \cup \{\delta_k^n; n = 1, \ldots, (N/2)\} \).
DoFs (PF Block) as well as to enforce geometric/electric symmetry. Defining the input microstrip-to-SIW transition (a1, a2, and a3), the offset between the edges of the SIW and the initial (b1) and the final (b2) slots, the size of the slots (l1 and l2), their spacing (d1), as well as the x-offssets of the first (N/2) slots with respect to the SIW axis ([δ1n; n = 1, . . . , (N/2)], respectively.9 Accordingly, the synthesis problem at hand is aimed at minimizing the following multiobjective: cost function

\[
\Phi_\Omega = \sum_{\Theta \in \{S_{11}; \mathrm{SLL}; \mathrm{HPBW}; \mathrm{BDD}\}} \Phi(\Omega) = \frac{1}{N_f} \sum_{n=1}^{N_f} \mathcal{H}(\Theta(f_n; \Omega) - \Theta^0) \tag{21}
\]

where the four cost terms

\[
\Phi_\Omega = \frac{1}{N_f} \sum_{n=1}^{N_f} \mathcal{H}(\Theta(f_n; \Omega) - \Theta^0)
\]

\[\Theta \in \{S_{11}; \mathrm{SLL}; \mathrm{HPBW}; \mathrm{BDD}\}\] are related to the reflection coefficient at the input port of the SSIW (\(\Theta = S_{11}\)), the side-lobe level (\(\Theta = \mathrm{SLL}\)), the half-power beamwidth (\(\Theta = \mathrm{HPBW}\)), and the beam direction deviation (\(\Theta = \mathrm{BDD}\)) of the far-field pattern along the vertical (\(\phi = 90^\circ\)) plane. Moreover, \(N_f\) is the number of frequency samples \(\{f_n; n = 1, \ldots, N_f\}\) centered on \(f_0\), superscript \(\Omega\) indicates the target threshold, and \(\mathcal{H}(\Theta(f_n; \Omega) - \Theta^0) = \mathcal{H}(\Theta(f_n; \Omega) - \Theta^0)\) if \(\Theta(f_n; \Omega) > \Theta^0\), \(\mathcal{H}(\Theta(f_n; \Omega) - \Theta^0) = 0\) otherwise. By exploiting \(N_f = 21\) samples uniformly distributed over a \(\Delta f = 2\) GHz bandwidth \(f_n \in [76, 78]\) GHz, \(n = 1, \ldots, N_f\), a single FW assessment of the SSIW requires on average \(\Delta t_{\text{fw}} = 72\) min. As a consequence, it is quite immediate to verify the unfeasibility of a StD optimization (letting \(P = 20\) and \(I = 200\)), since \(\Delta t_{\text{st}} \approx 200\) days. Otherwise, a disruptive time saving of \(\Delta t_{\text{st}} = 92.87\%\) has been yielded by the SBD (run with \(S_0 = 85\) and \(S = 285 \rightarrow \Delta t_{\text{st}} \approx 14\) days). To verify

9The second half of the slots (n = (N/2) + 1, . . . , N) is obtained by mirroring the first half (n = 1, . . . , (N/2)—Fig. 19) to reduce the number of DoFs (PF Block) as well as to enforce geometric/electric symmetry.

10The BDD at the nth frequency sample \(f_n (n = 1, \ldots, N_f)\) is defined as

\[
BDD(f_n; \Omega) = |\theta_{\text{max}}(f_n; \Omega)|, \theta_{\text{max}}(f_n; \Omega)
\]

being the elevation direction of maximum gain in the considered plane.
the effectiveness of the advanced SSE block implementations (see Section IV), Fig. 20 shows the optimized frequency behavior of the $S_{11}$ [see Fig. 20(a)], the SLL [see Fig. 20(b)], the HPBW [see Fig. 20(c)], and the BDD [see Fig. 20(d)] yielded by the PSO-OK/C and the PSO-OK integrated with the SbD-OSF sampling. It can be observed that an almost perfect matching of all requirements has been achieved by both SbD methods [the threshold values in (22) being set to $S_{11} \text{th} = -10 \text{ dB}, \text{SLLth} = -15 \text{ dB}, \text{HPBWth} = 10^6$, and $\text{BDDth} = 0.5^2$, respectively], the PSO-OK/C providing the best fitting solution as it is also quantitatively verified by the corresponding cost functions, $\Phi_{\text{SDE}(\text{PSO-OK/C})} = 1.91 \times 10^{-2}$ versus $\Phi_{\text{SDE}(\text{PSO-OK/}\text{SbD-OSF})} = 2.57 \times 10^{-1}$ (see Table III). As a matter of fact, the PSO-OK/C design is the only one exhibiting a 100% compliancy with the bandwidth [see Fig. 20(a)], HPBW [see Fig. 20(c)], and BDD [see Fig. 20(d)] requirements, as verified by the null value assumed by the corresponding cost terms (see Table III). Otherwise, a sub-optimal solution has been obtained by the SbD at the same computational cost ($\Phi_{\text{SDE}} = 4.13 \times 10^{-1}$—Fig. 20 and Table III). For completeness, the optimized DoFs of the PSO-OK/C solution are reported in Table IV, while its gain pattern along the vertical [see Fig. 21(a)] and horizontal [$\phi = 0^\circ$—Fig. 21(b)] planes is shown in Fig. 21. Such results further assess the high robustness of the synthesized antenna, showing a very good stability of its radiation features over the complete frequency band of interest.

VI. CONCLUSION, FINAL REMARKS, AND FUTURE TRENDS

The SbD is an innovative paradigm for the computationally efficient solution of complex EM synthesis problems mainly devoted to properly deal with the “high-complexity” curse. Toward this purpose, the synthesis problems at hand are addressed through a suitable problem-driven selection and interconnection of functional blocks, each one implementing a rather “simple” and well-identified task, but all integrated to jointly fit, in an easier fashion, the required system functionality/performance. From a theoretical point of view, after summarizing the key features and the building blocks of the SbD-based synthesis framework, two innovative SbD implementations have been presented and applied to three challenging problems concerned with the design of realistic TMAs (see Section V-A), the synthesis of planar dual-polarization microstrip arrays for 5G applications (see Section V-B), and the design of SSIW radiators for 77 GHz automotive radar systems (see Section V-C). The purpose of such benchmarks is twofold. On the one hand, they provide representative examples of the potentialities and high flexibility of the SbD paradigm as applied to different antenna engineering problems. On the other hand, they complete the description of the RCD functional block (see Fig. 1) as customized to specific EM synthesis tasks. The main outcomes from these analyses are as follows.

1) The SbD enables the design of complex EM devices/systems in a suitable time frame due to the possibility to select the best (i.e., problem-oriented) tradeoff between time saving and prediction accuracy.

2) The accurate selection of the solution descriptors (i.e., the DoFs) allows one to reduce the number of required training samples and therefore the computational burden of the training phase.

3) The role of the SMs in the SbD is not only that of a reliable (i.e., accurate prediction of the cost function values) and computationally cheap alternative to the FW solver, but they are mainly devoted to map the landscape of the cost function to reliably drive the SSE algorithm toward the global optimum.

The main novelty of this manuscript over the existing literature consists in the following.

1) A detailed and comprehensive description of the SbD paradigm and pillar concepts only partially investigated in the previous works where it has been applied (i.e., customized) to specific target applications/designs without describing and detailing the general framework (see Sections II and III).

2) The definition of two new advanced SbD strategies overcoming current limitations of standard SbD approaches (see Section IV).

3) The comparative assessment of several SbD techniques when dealing with three different EM problems of increasing complexity (see Section V).

4) A careful investigation on the tradeoffs “time saving versus solution quality” with respect to competitive state-of-the-art approaches (see Section V).

Future activities, out of the scope of this work, will be aimed at customizing and applying the SbD to further challenging and high-complexity designs including unconventional phased arrays with real elements [57] and innovative meta-materials for smart EM environments applications [58]. Moreover, the development of SbD strategies that exploit deep learning [59] and/or multiobjective optimization algorithms [60], as well as feature extraction techniques [42] is under investigation. Finally, innovative optimization-driven methodologies based on the compressive sensing (CS) paradigm will be studied to build optimal training sets overcoming Nyquist’s theoretical limit so that it would possible to faithfully predict the cost function values using far fewer samples than traditional approaches [61].

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REFERENCES

[1] J. M. Jin, The Finite Element Method Electromagnetic. Hoboken, NJ, USA: Wiley, 2014.

[2] R. F. Harrington, Field Computational by Moment Methods. Hoboken, NJ, USA: Wiley, 1993.

[3] A. Tafove and S. C. Hagness, Computational Electrodynamics: The Finite-Difference Time-Domain Method. Norwood, MA, USA: Artech House, 2005.

[4] S. V. Savić, M. M. Ilić, and B. M. Kolundžija, “Maximally orthogonalized higher order basis functions in large-domain finite element modeling in electromagnetics,” IEEE Trans. Antennas Propag., vol. 68, no. 8, pp. 6455–6460, Aug. 2020. doi: 10.1109/TAP.2020.2970038.

[5] F. Vernini, M. Riglero, and G. Vecchi, “On the use of entire-domain basis functions and fast factorizations for the design of modulated metasurface,” IEEE Trans. Antennas Propag., vol. 68, no. 5, pp. 3824–3833, May 2020.
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[49] D. H. Wolper and W. G. Mcready, “No free lunch theorems for optimization,” IEEE Trans. Evol. Comput., vol. 1, no. 1, pp. 67–82, Apr. 1997.
[50] Y. Jin, “Surrogate-assisted evolutionary computation: Recent advances and future challenges,” Swarm Evol. Comput., vol. 1, no. 2, pp. 61–70, Jun. 2011.
[51] S. Bilicz, M. Lambert, and S. Gyimóthy, “Kriging-based generation of optimal databases as forward and inverse surrogate models,” Inverse Probl., vol. 27, no. 7, Jun. 2011, Art. no. 074012.
[52] D. Masotti, L. Poli, M. Salucci, P. Rocca, and A. Costanzo, “An effective procedure for nonlinear dynamic optimization of time-modulated arrays,” IEEE Antennas Wireless Propag. Lett., vol. 18, no. 10, pp. 2204–2208, Oct. 2019.
[53] V. Rizzoli, D. Masotti, F. Mastrì, and E. Montanari, “System-oriented harmonic-balance algorithms for circuit-level simulation,” IEEE Trans. Comput.-Aided Design Integr. Circuits Syst., vol. 30, no. 2, pp. 256–269, Feb. 2011.
[54] HFFS Suite V19, Ansys Corp., Pittsburg, PA, USA, 2019.
[55] Y. Yu, W. Hong, H. Zhang, J. Xu, and Z. H. Jiang, “Optimization and implementation of SIW slot array for both medium- and long-range 77 GHz automotive radar application,” IEEE Trans. Antennas Propag., vol. 66, no. 7, pp. 3769–3774, Jul. 2018.
[56] D. Deslandes and K. Wu, “Accurate modeling, wave mechanisms, and design considerations of a substrate integrated waveguide,” IEEE Trans. Microw. Theory Techn., vol. 54, no. 6, pp. 2516–2526, Jun. 2006.
[57] P. Rocca, G. Oliveri, R. J. Mailloux, and A. Massa, “Unconventional phased array architectures and design methodologies—A review,” Proc. IEEE, vol. 104, no. 3, pp. 544–560, Mar. 2016.
[58] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M.-S. Alouini, and R. Zhang, “Wireless communications through reconfigurable intelligent surfaces,” IEEE Access, vol. 7, pp. 116753–116773, Aug. 2019.
[59] A. Massa, D. Marcantonio, X. Chen, M. Li, and M. Salucci, “DNNs as applied to electromagnetics, antennas, and propagation—A review,” IEEE Antennas Wireless Propag. Lett., vol. 18, no. 11, pp. 2225–2229, Nov. 2019.
[60] P. Kadlec and Z. Raida, “Multi-objective self-organizing migrating algorithm applied to the design of electromagnetic components,” IEEE Antennas Propag. Mag., vol. 55, no. 6, pp. 50–68, Dec. 2013.
[61] A. Massa, P. Rocca, and G. Oliveri, “Compressive sensing in electromagnetics—A review,” IEEE Antennas Propag. Mag., vol. 57, no. 1, pp. 224–238, Feb. 2015.