IEEE Journal of Microwaves

Received 31 August 2020; revised 16 October 2020; accepted 24 October 2020.
Date of current version 7 January 2021.

*Digital Object Identifier 10.1109/JMW.2020.3034263*

# Advanced RF and Microwave Design Optimization: A Journey and a Vision of Future Trends

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*(Invited Paper)*

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**ABSTRACT** In this paper, we outline the historical evolution of RF and microwave design optimization and envisage imminent and future challenges that will be addressed by the next generation of optimization developments. Our journey starts in the 1960s, with the emergence of formal numerical optimization algorithms for circuit design. In our fast historical analysis, we emphasize the last two decades of documented microwave design optimization problems and solutions. From that retrospective, we identify a number of prominent scientific and engineering challenges: 1) the reliable and computationally efficient optimization of highly accurate system-level complex models subject to statistical uncertainty and varying operating or environmental conditions; 2) the computationally-efficient EM-driven multi-objective design optimization in high-dimensional design spaces including categorical, conditional, or combinatorial variables; and 3) the manufacturability assessment, statistical design, and yield optimization of high-frequency structures based on high-fidelity multi-physical representations. To address these major challenges, we venture into the development of sophisticated optimization approaches, exploiting confined and dimensionally reduced surrogate vehicles, automated feature-engineering-based optimization, and formal cognition-driven space mapping approaches, assisted by Bayesian and machine learning techniques.

**INDEX TERMS** ANN, Bayesian, Broyden, CAD, cognition, design automation, EDA, features, Gaussian process, Kriging, machine learning, multi-objective, multi-physics, optimization, Pareto, polynomial chaos, sensitivity, space mapping, statistical, surrogate, tolerances, uncertainty quantification, yield.

## I. INTRODUCTION

Formal numerical optimization procedures as applied to circuit design started in the 1960s [1], with RF and microwave passive filter design being perhaps the most fertile application area for the pioneering design optimization techniques [1]. That decade [2] saw the advent of several then-called heuristic optimization methods relying solely on objective function values, e.g., pattern search [2]. The 1970s followed with the rapid adoption of powerful gradient-based optimization methods, typically based on quasi-Newton methodologies [2], [3], where the underlying model exploits information contained in available derivatives. By that time, automatic optimization was identified as the most significant advance in microwave CAD [4]. Design centering and tolerance-driven design entered the microwave arena also in the 1970s [5]. Powerful minimax algorithms emerged from the Technical University of Denmark [6] in the 1970s and 1980s, consolidating quasi-Newton gradient methods. Early applications involving a large number of design variables and error functions include the optimization of waveguide multiplexers for satellite applications [7], [8]. These nonlinear minimax algorithms have stood the test of time, finding their way into modern commercial design automation software. The early 1990s saw the first industrial implementation of gradient-based, direct EM optimization applied to microwave filter design. Response surface techniques involved interpolation, gradient estimation, and on-the-fly database updates [9].

Discovered in 1993, published in 1994 [10], the space mapping concept surprised the engineering community. EM-based optimization immediately took off when the first implementation demonstrated EM-validated design solutions obtained in only a handful of full-wave EM simulations [10].

In 2002, Steer, Bandler, and Snowden [11] provided a solid forecast for EM-based design optimization, predicting that knowledge-based approaches would allow us to directly incorporate full-wave EM simulators into the linear and nonlinear microwave design process [11].

Sailing from the historical evolution of microwave design optimization, and with emphasis on the first two decades of the current century, this paper highlights the most promising current and future trends in advanced design optimization techniques. In particular, we venture on projecting that space mapping, machine learning, Bayesian, feature- and surrogate-based, as well as cognition-driven approaches, will address current and future challenges in optimizing RF and microwave devices, circuits, and systems, including multi-objective and multi-physics design optimization.

## II. SPACE MAPPING, MACHINE LEARNING, AND BAYESIAN APPROACHES: TOWARDS HIGH-FIDELITY SYSTEM-LEVEL AND MULTI-PHYSICS DESIGN OPTIMIZATION

Space Mapping (SM) is one of the most powerful and computationally efficient optimization approaches for RF and microwave engineering. SM methods belong to the general class of surrogate-based optimization (SBO) algorithms [12]. SBO approaches are specialized for the efficient optimization of computationally expensive objective functions [13]. A distinctive feature of SM, reflected in its origin as clearly described by its inventor [14], lies in its intriguing relationship to the human cognition process.

Since its first appearance in 1994 [10], space mapping has experienced an impressive evolution in terms of variations, improvements, and engineering/scientific applications. Comprehensive reviews of the first generations of SM methods for modeling and design optimization are available in [15] and [16]. A specific review of SM-based optimization exploiting artificial neural networks is in [17]. An updated and schematically summarized overview of the evolution of space mapping is shown in Fig. 1 [18]. Clearly, the most recent optimization techniques originating from the space mapping concept are also the most sophisticated and robust formulations. From those, feature-based and cognition-driven design developments are perhaps the most promising techniques to address future design automation challenges.

On a different perspective, a historical narrative of the original, simplest, and most widely adopted space mapping algorithmic approach to design optimization is in [18], where the Broyden-based input space mapping algorithm, better known as aggressive space mapping (ASM), is reviewed over more

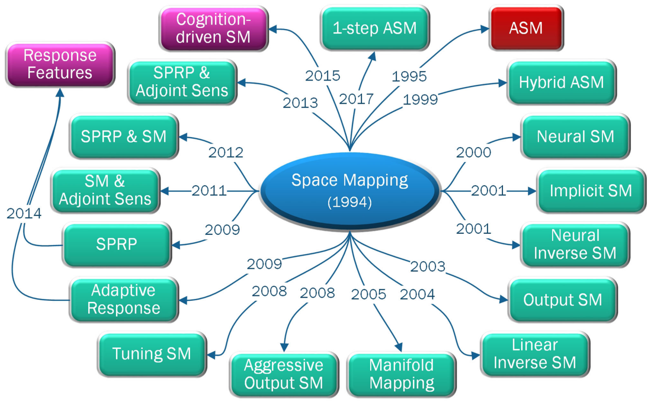


**FIGURE 1.** **Design optimization methods emerged from the space mapping (SM) concept: aggressive SM [19]; hybrid ASM [20]; neural SM [21]–[23]; implicit SM [24]–[28]; neural inverse SM [29], [30]; output SM [31], [32]; linear inverse SM [33]–[36]; manifold mapping [37][39]; aggressive output SM [40]; tuning SM [41]–[48]; adaptive response correction (ARC) [49], [50]; shape-preserving response prediction (SPRP) [51], [52]; SM with adjoint sensitivities [53], [54]; SPRP exploiting SM [55]; SPRP using adjoint sensitivities [56], [57]; response features [58]–[61] (emerged from ARC and SPRP); cognition-driven SM [62]–[65]; one-step ASM [66], [67].**

than two decades of academic and industrial applications [68]. Significant successes include the ASM design of a 10-channel dielectric resonator output multiplexer with 140 variables [69].

Along with ASM, tuning space mapping (see Fig. 1) is among the most intuitive approaches to SM-based design. Tuning SM in its various manifestations of port tuning, has demonstrated profound success in shortening the design cycles for filter design [41]–[48], allowing filters to be tuned with EM accuracy at circuit theory speed.

Space mapping emerged from the need to perform efficient numerical optimization of microwave circuits using full-wave EM simulators [14]. However, SM optimization has now been applied to a diversity of engineering disciplines, well beyond RF and microwave engineering. For instance, the Broyden-based input space mapping algorithm has been applied in areas such as magnetic circuits, materials design, environmental sciences, medical instrumentation, biomedical, chemical, civil, mechanical, aerodynamic, aeronautical, and aerospace engineering [18]. Models of the optimized structures have been implemented using a variety of numerical simulators, including commercially available EDA systems and internal CAD tools. More recently, measurement-based physical platforms have also been incorporated as "fine models" [70]–[73].

The great majority of design optimization cases solved by the fundamental methods summarized in Fig. 1 have been applied at the device-, component-, or circuit-level. However, the application of SM, including cognition-driven and feature-based techniques, to high-fidelity system-level design optimization is in its infancy. A few preliminary emerging demonstrations [72], [74] have been reported in the area of post-silicon electrical validation of high-speed computer platforms, as illustrated in Fig. 2 [74], where the optimal

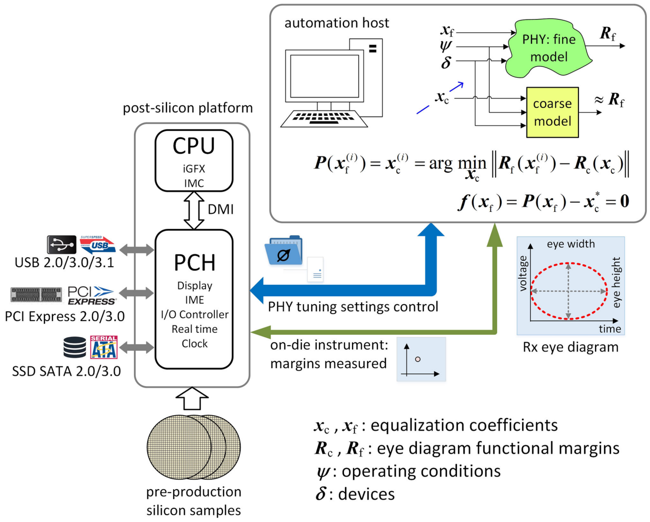


**FIGURE 2. Optimizing equalization coefficients of high-speed input/output links in a computer platform to maximize eye diagram functional margins under varying operating conditions (e.g., voltage, temperature) and devices (e.g., silicon skew, external devices). Broyden-based input SM is applied [74], with a coarse metamodel built from a frugal amount of physical platform measurements.**

equalization coefficients of a physical platform that maximize the receiver eye diagram functional margins (so called PHY tuning process) are found following a Broyden-based input space mapping approach, reducing the PHY tuning process from several days to a few hours [74]. Design optimization of highly accurate system-level complex models is particularly challenging, especially when those models are based on physical measurements subject to statistical uncertainty and varying operating or environmental conditions. A promising strategy to deal with such a challenging scenario consists of complementing advanced feature-based and cognition-driven SM approaches with Bayesian [75] and machine learning techniques [76]–[78]. Bayesian optimization is inherently adequate to deal with stochastic or noise-corrupted responses, in high-dimensional design spaces that can be even categorical, conditional, or combinatorial [76], making it a natural candidate to address high-frequency system-level expensive industrial optimization problems, such as those typically found in signal- and power-integrity [79]–[84].

Highly accurate multi-physics microwave design optimization is another very challenging application area, even at the device-, component-, or circuit-level. RF and microwave design automation considering multi-scale modeling combined with multi-physics simulation remains a "grand scientific and engineering challenge" [85]. Ultimately, the multi-physics approach to design optimization aims at intelligently coupling the most relevant physical domains, typically including transport phenomena, full-wave electromagnetics (EM), electrical, thermal and mechanical domains. Pioneering work on multi-physics optimization of RF and microwave circuits has been reported [86]–[90]. Manufacturability assessment, statistical design and yield optimization of high-frequency structures considering high-fidelity multi-physical performance is still absent in the scientific literature.

## III. FEATURE-BASED STATISTICAL DESIGN

Engineering systems are affected by several types of uncertainties, including fabrication tolerances [5], [8], technological spread (e.g., the lack of precise knowledge of substrate parameters), as well as varying operating conditions (e.g., input power level, temperature) [91]. For microwave passive components, the most relevant types of uncertainties are geometry parameter deviations with respect to their nominal values [5], [8]. These are caused by imperfect manufacturing procedures, e.g., chemical etching in the case of microstrip devices, and can be quantified by means of probability distributions. The primary detrimental effect of the tolerances may be an inability of the circuit to fulfill the performance requirements imposed upon it. Hence, reliable quantification of the circuit sensitivity to uncertainties and its reduction during the design process is important to ensure circuit robustness [92]. In practice, this is realized by lessening the statistical moments of the circuit performance figures, particularly their variances [93]. Notwithstanding, design specifications for microwave components are often formulated in a minimax form (i.e., through lower and upper bounds for the figures of interest) [94], in which case a more suitable statistical performance metric is a yield [95].

An important stage of uncertainty quantification is statistical analysis [96], which is a computationally expensive endeavor when executed at the level of full-wave EM simulation models, otherwise required to ensure reliability. In particular, EM-based evaluation is imperative for many classes of modern microwave components including compact structures: considerable cross-coupling effects therein cannot be accounted for using, e.g., equivalent network models [97]. At the same time, the standard statistical procedures, such as Monte Carlo (MC) analysis, require massive system evaluations, the cost of which may be unmanageable.

Several methodologies have been developed to alleviate the aforementioned difficulties. Worst-case analysis is one of the simplest [5], [8], [98]; however, it assumes the most disadvantageous scenarios, which leads to overly pessimistic performance estimations. Perhaps the most efficient approaches today rely on surrogate modeling methods [99]. The popular techniques employed in this context include response surface approximations [100], neural networks [101], and polynomial chaos expansion (PCE) [102], [103]. The attractiveness of PCE comes from the possibility of computing the statistical moments of the system outputs directly from the expansion coefficients with no need to run the MC simulation [104]. Clearly, certain performance metrics such as the yield, still require MC for their evaluation. The bottleneck of surrogate-based statistical analysis is high computational cost of model construction, which becomes a problem for higher-dimensional spaces, but also when the model domain is large (e.g., to cover sufficiently broad ranges of the system parameters). To a certain extent, this can be mitigated by techniques such as PC Kriging [105], where more complex trend functions (e.g., PCE) are employed instead of low-order polynomials. The dimensionality issues can be also alleviated by the principal component analysis [106], the use of variable-resolution models (space mapping [107], co-Kriging [108], Bayesian model fusion [109]), or by combining surrogate modeling techniques with model order reduction methods [110].

Diminishing the effects of uncertainties is even more important than their quantification. The procedures that aim at reducing the sensitivity of the system outputs to manufacturing tolerances are referred to as robust design, tolerance-aware design or yield-driven design [111]–[113]. Practical implementation requires the adjustment of the system parameters directed towards maximization of suitably defined statistical performance metrics. For the most widely used case of minimax specifications, one normally aims at improving the yield, i.e., the probability of fulfilling design specifications for given deviations of geometry and material parameters. The latter are described by the assumed probability distributions, e.g., Gaussian. Tolerance-aware design is an expensive procedure because it requires numerous yield estimations. In particular, it is normally prohibitive when conducted directly at the level of EM simulation models. Practical EM-driven statistical design can be realized using surrogate modeling techniques [99]–[104]. Widely used methods include response surface approximations [100], neural networks [114], space mapping [115] and polynomial chaos expansion [116]. Although it is possible to set up a single surrogate valid for the entire region of interest (from the point of view of yield optimization), the bottleneck is the curse of dimensionality. From this perspective, iterative methods, especially sequential approximate optimization (SAO) [117], seem to be more attractive. Therein, the surrogate is constructed in a small domain defined as a vicinity of the current design; it is subsequently relocated along the optimization path. This approach requires a repeated construction of the surrogate but at a considerably lower cost due to restricted domain.

Recently reported feature-based optimization (FBO) [118] is an alternative method that relies on reformulating the design task in terms of appropriately defined characteristic points of the system outputs. The feature points are defined to be sufficient for evaluating the circuit performance. At the same time, their dependence on geometry parameters is less nonlinear than the dependence of the primary characteristics. As demonstrated (e.g., [119], [120]) modeling at the level of features is more efficient in computational terms as compared to traditional techniques. Feature selection is generally problem dependent and might be related to the circuit transfer function (e.g., pole and zero location) [121], or may be directly extracted from the circuit responses (e.g., locations of the resonances [122] or local maxima of the filter return loss characteristic in the passband [123]).

The response feature technology has been applied to statistical analysis and yield optimization of microwave filters [123], microstrip couplers [124], as well as multi-band antennas [125]. Fig. 3 shows a 5th-order waveguide filter along with the response features selected for the purpose of statistical design (Fig. 3(b)). The surrogate model constructed at the level of features is accurate and covers a sufficiently large region to enable yield optimization using SAO, despite being based on only 19 star-distributed training data samples. The total optimization cost is only 76 EM analysis of the filter. Fig. 4 shows the MC analysis at the nominal and the yield-optimized designs, whereas Table 1 compares the yield estimated using MC and the feature-based surrogate. The agreement between the two data sets is very good.

Surrogate modeling techniques appear to be amid very few approaches capable of carrying out EM-based statistical design in a computationally feasible manner. Among these,

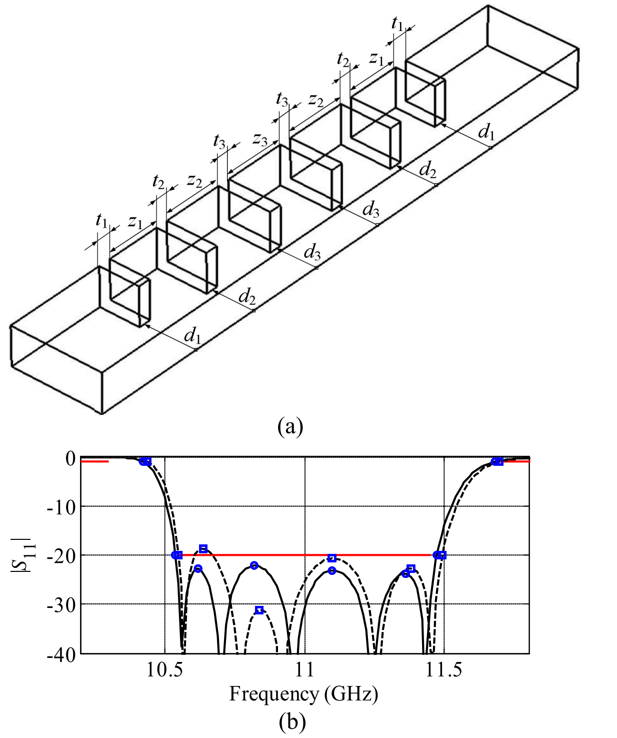


**FIGURE 3.** Fifth-order waveguide bandpass filter: a) parameterized filter geometry [123]; b) reflection response (—) at the optimum design with respect to minimax specifications marked with horizontal lines, and the response at a perturbed design (- - -). Circles and squares denote feature points for both responses corresponding to the −1 dB and −20 dB levels as well as the response maxima in the passband.

**TABLE 1.** Yield Optimization: 5th-Order Waveguide Filter

| Case | Yield Estimation Method | Estimated Yield* | CPU Cost# |
|---|---|---|---|
| Nominal design (minimax optimum) | Feature-based [123] | 0.25 | 19 |
| | EM-based Monte Carlo | 0.24 | 500 |
| Yield-optimized design | Feature-based [123] | 0.46 | 19 |
| | EM-based Monte Carlo | 0.47 | 500 |

∗.These particular yield values result from arbitrary assumptions concerning the geometry parameter deviations (see text).
#.Estimated cost in number of EM analyses.

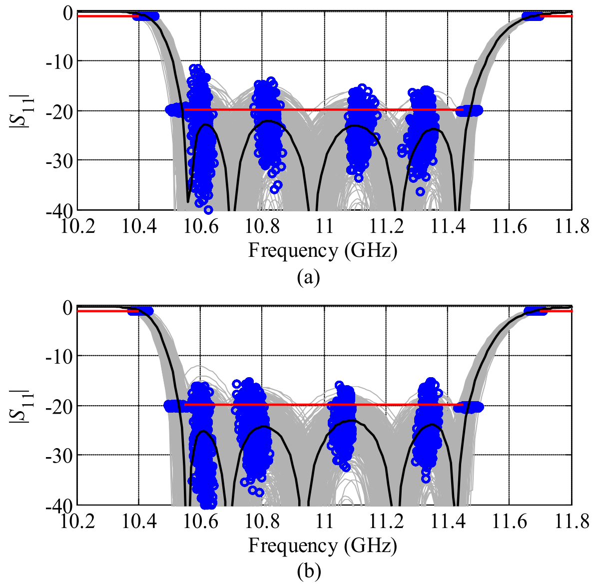


**FIGURE 4. Fifth-order waveguide filter [123]: yield estimation assuming a Gaussian probability distribution with standard deviations of 0.02 mm (Case 4) at (a) the nominal design (Y = 0.25), and (b) the optimized design (Y = 0.46). Gray lines correspond to 500 EM-simulated random samples for MC analysis, circles mark the feature points predicted by the surrogate.**

the methods capable of addressing the traditional challenges of approximation surrogates (the issue of dimensionality and parameter ranges) seem to be particularly attractive. The response feature technology belongs to this group. Its further development, including automated feature definition and extending the application range to other types of high-frequency structures, may lead a way to set up generic frameworks for accelerated statistical design.

## IV. SIMULATION-DRIVEN SURROGATE-ASSISTED MULTI-OBJECTIVE DESIGN OPTIMIZATION

Practical design of high-frequency components, including microwave devices, requires accounting for several performance figures that are pertinent to both electrical properties (impedance matching, bandwidth, etc.), field properties (gain, radiation pattern for antenna arrays, etc.), as well as geometrical constraints (e.g., the circuit footprint). In other words, it is an inherently multi-objective task, and the goals are typically at least partially conflicting [126]. In particular, an improvement of a specific objective has, in general, detrimental effects on the remaining performance figures. Miniaturization of planar microwave passives or antennas is a representative example here: reduction of the circuit area normally results in difficulties in achieving satisfactory impedance matching or bandwidth [127], or in frequency misalignment of the transmission/matching responses of couplers [128], or in degradation of gain and efficiency of antennas [129]. Any realistic design is, in fact, a compromise (or a trade-off) between the considered goals.

Multi-objective (MO) design differs quantitatively from single-objective tasks already at the level of comparing the designs, which is most often realized using Pareto dominance relation [126]. This fosters reformulation of MO problems into single-criterial ones that can be solved using well-established numerical routines [130], [131]. Popular reformulation methods include objective aggregation (e.g., the weighted sum method [132]) or objective prioritization (selecting the primary objective and handling the remaining ones through constraints [133]). Having the designer's preferences clearly stated, such approaches might be effective. A representative example would be footprint reduction under hard acceptance thresholds set up for electrical performance figures [134].

Notwithstanding, proper MO design has a considerable advantage of yielding the entire set of trade-off solutions (also referred to as a Pareto set), which may be useful to evaluate suitability of a specific structure for a particular application or to compare competing circuit solutions in a conclusive manner. The most popular methods for solving MO problems are population-based metaheuristics, e.g., evolutionary algorithms [126], particle swarm optimizers [135], differential evolution [136], etc. Their major advantage is the ability of generating the entire Pareto set in a single algorithm run. Unfortunately, their computational complexity is high, which is a serious bottleneck whenever the structure under design needs to be evaluated using full-wave electromagnetic (EM) simulation, otherwise necessary for reliability reasons. Consequently, solving EM-driven MO problems directly is not a practical option.

Surrogate-assisted methods seem to be the most suitable approaches to alleviate the aforementioned difficulties. The main idea is to replace the expensive EM simulation model by the fast surrogate model, which allows for identification of the Pareto set using, e.g., population-based metaheuristic algorithms, at low computational cost. The popular modeling methods utilized in this context include response surfaces Kriging interpolation [137]–[141], Gaussian process regression [142], [143], artificial neural networks [144], [145], or combination of various techniques [146]. The application areas range from the design of microwave devices [142], and antennas [139], [146], through optimization of radar absorbers [141], to electromagnetic machine optimization [140], [144]. MO design combined with tolerance analysis is also considered [144], [146]. Typically, the surrogate model is rendered in the entire parameter space or its construction is interleaved with the optimization process using sequential sampling methods [142]. The major disadvantage of such approaches is a strong limitation on the number of the system parameters that may be considered in the optimization process, which is due to the curse of dimensionality, i.e., the rapid increase of the number of training samples necessary to build a reliable surrogate as a function of the number of parameters. The typical size of the test cases considered in the aforementioned works [137]–[146] is two or three variables, with the maximum of five [141] or six [144], [146]. Thus, the basic surrogate-assisted MO design is attractive as a concept

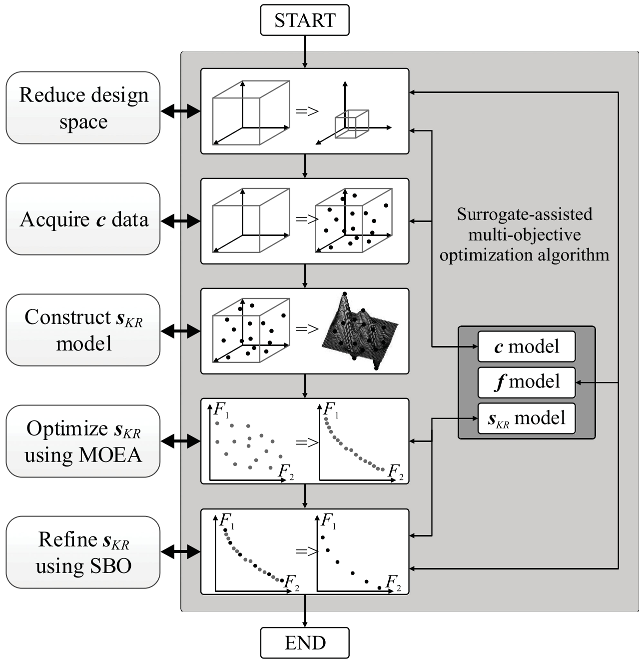


**FIGURE 5.** **Flowchart of the surrogate-assisted procedure for computationally efficient MO design [148]. The framework employs initial parameter space reduction, variable-fidelity simulation models, and design refinement scheme required to bring the Pareto-optimal designs to the high-fidelity level of accuracy.**

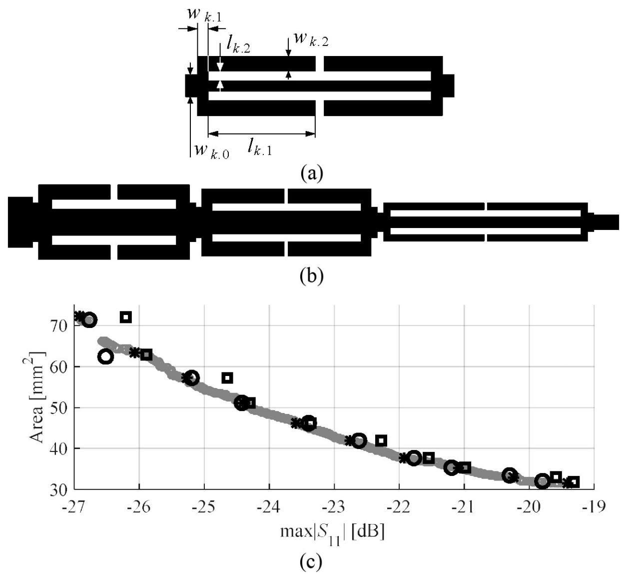


**FIGURE 6.** **Surrogate-assisted MO design of three-section impedance matching transformer: a) compact microstrip resonant cell (CMRC) cell; b) transformer geometry; c) Pareto-optimal solutions: (o) initial set obtained by optimizing the surrogate model, (∗) selected designs for refinement, (□) EM-simulated selected designs, (O) EM-simulated refined designs.**

**TABLE 2.** **Comparing Surrogate-Assisted MO Design Cost**

| Cost item | Surrogate model | |
|---|---|---|
| | Nested Kriging [153] | Kriging in hypercube [$l^*$,$u^*$] [148] |
| Extreme points | 515 × $\boldsymbol{R}$ | 515 × $\boldsymbol{R}$ |
| Data acquisition for surrogate | 200 × $\boldsymbol{R}$ | 1600 × $\boldsymbol{R}$ |
| Surrogate model optimization* | N/A | N/A |
| Refinement | 30 × $\boldsymbol{R}$ | 30 × $\boldsymbol{R}$ |
| Total cost# | 745 × $\boldsymbol{R}$ (31 h) | 2145 × $\boldsymbol{R}$ (89 h) |

∗. The cost of surrogate model optimization is negligible.
#. The total cost (equivalent number of EM simulations; CPU time shown in brackets); $N$×$\boldsymbol{R}$ stands for the number of EM simulations.

but it may not be practical for real-world problems featuring a dozen or more parameters.

The range of applicability of surrogate-assisted MO design can be extended by the employment of variable-fidelity models, where the surrogate is constructed at the level of low-fidelity representation (e.g., equivalent circuit or coarse-mesh EM analysis [129]). This requires subsequent refinement of the initial approximation of the Pareto set, which can be achieved using response correction methods, e.g., output space mapping [147]. However, the most important factor to improve the efficacy of the MO process is an initial reduction of the parameter space that aims at approximating the location of the Pareto front. This allows for a considerable reduction of the surrogate domain and for making the model construction computationally feasible. The simplest space reduction approach is to consider single-objective optima $\boldsymbol{x}_k^*$ obtained by considering one design objective at a time, $k = 1, \ldots, N_{obj}$. These "extreme" Pareto optimal design determine the front span and allow for defining the lower and upper bounds of the restricted domain as $\boldsymbol{l} = \min\{\boldsymbol{x}_1^*, \ldots, \boldsymbol{x}_{Nobj}^*\}$ and $\boldsymbol{u} = \max\{\boldsymbol{x}_1^*, \ldots, \boldsymbol{x}_{Nobj}^*\}$, respectively. The flowchart of the surrogate-assisted MO procedure capitalizing on the above mechanisms is shown in Fig. 5 [148]. The framework has been successfully applied to antenna and microwave structures [148], [149], also described by over twenty parameters [150].

To yield further improvements, a more precise allocation of the Pareto set is needed, which can be obtained using performance-driven modeling techniques [151], [152]. Although more information about the front geometry (e.g., its curvature) requires a certain computational effort necessary to produce additional reference designs, it is justified by the considerable savings in terms of training data acquisition when constructing the surrogate model. Fig. 6 shows the results of MO design of the 15-parameter impedance matching transformer optimized with respect to two objectives: reduction of the circuit footprint and improvement of the in-band matching. Table 2 makes a comparison of MO cost for the framework of [148] and the technique exploiting the nested-Kriging surrogate [153]. Over sixty-percent cost reduction is observed when the surrogate model constructed in the initially-reduced space is replaced by the nested-Kriging surrogate of [153], which gives a better account for the Pareto front geometry.

It seems that the employment of fast surrogate models is a prerequisite for computationally-efficient EM-driven MO design. Although the curse of dimensionality is the biggest bottleneck here, the incorporation of various mechanisms such as appropriate confinement of the surrogate model domain, the usage of variable-fidelity models, machine learning techniques, as well as dimensionality reduction methods may serve as effective workarounds. On the other hand, alternative methods that do not rely on quasi-global surrogates but rather on Pareto front exploration are also possible and may be useful for certain problems (e.g., point-by-point Pareto front exploration [154], sequential domain patching [155], or generalized bisection algorithm [156]).

## V. QUALITATIVE CHARACTERIZATION OF OUR DESIGN OPTIMIZATION PARADIGMS

This section provides a brief qualitative characterization of the main design optimization paradigms reviewed in this paper. In Table 3 , we outline their major advantages, potential issues, scope of applications (limited to high-frequency engineering), as well as practical challenges related to their usage for solving real-world problems. This characterization is by no means exhaustive, and its only purpose is to give the reader a rough idea of how our considered classes of techniques can be placed in the realm of microwave design methodologies. A more detailed characterization, apart from what was already contained in Sections II to IV, goes well beyond the scope of this work.

**TABLE 3.** Qualitative Characterization of our Optimization Paradigms as Applied to RF and Microwave Engineering

| | |
|---|---|
| | **Space mapping** |
| Advantages | • Potential to dramatically expedite EM-driven optimization, especially in the context of local search<br>• Alleviates the problem of dimensionality<br>• Exploits problem-specific knowledge embedded in lower-fidelity models |
| Disadvantages | • Requires engineering insight into the problem<br>• Requires problem-specific low-fidelity models |
| Application Range | • Filters, couplers, multiplexers, and other structures with fast reliable physics-based models<br>• In principle, applicable to all EM-simulated structures with coarse-discretization low-fidelity model<br>• System level design with low-fidelity metamodels<br>• A potential cornerstone of multi-physics optimization |
| Challenges | • Low-fidelity model selection (type/resolution) may not be straightforward<br>• Convergence is not always guaranteed |
| | **Feature-based statistical design** |
| Advantages | • Flattens the functional landscape of the objective function, facilitating surrogate model construction<br>• Expedites statistical analysis and yield optimization |
| Disadvantages | • Requires well-structured system responses (consistent over the considered parameter space) |
| Application Range | • Filters, couplers, multiplexers<br>• Antennas (particularly, narrow- and multi-band structures) |
| Challenges | • Feature point definition may not be straightforward<br>• Implementation may be complex (e.g., response feature extraction) |
| | **Surrogate-assisted multi-objective design** |
| Advantages | • Permits rapid identification of the Pareto set<br>• Mitigates the curse of dimensionality (handling of up to 20-30 parameters is possible)<br>• Allows for exploration of variable-fidelity models |
| Disadvantages | • Typically requires the Pareto front to be a connected set<br>• Requires acquisition of extreme Pareto-optimal designs through single-objective optimization, which generates extra costs and may be challenging |
| Application Range | • Microwave components, including compact structures<br>• Antenna structures |
| Challenges | • Implementation may be complex and requires knowledge in both modelling and optimization methods<br>• May perform poorly for Pareto fronts of high level of irregularity (e.g., disconnected) |

## VI. COGNITION-DRIVEN DESIGN

In the previous sections, we briefly reviewed and projected advanced RF and microwave design optimization techniques, including space mapping, machine learning, and Bayesian approaches, as well as featured-based statistical design and surrogate-assisted multi-objective optimization. In this section, we speculate on future developments by going beyond current artificial intelligence, looking into direct analogies with human intelligence. We believe that design optimization will benefit from algorithms based on advanced neuroscience, leading to cognition-driven design approaches.

We interpret the term cognition-driven as a mentally inspired process that encompasses knowledge, comprehension, good judgement, expertise, and a thought-out evaluation of alternative solutions and decisions.

This interpretation already sounds like the basis for engineering design optimization. Cognition-driven in engineering design implies an optimization process that employs a strategy based on an underlying simplified model (surrogate)—perhaps mental—a model to iteratively drive the chosen design parameters of the accurately simulated engineering device under consideration—a model useful for a particular purpose—to a solution that meets certain design requirements. All this, preferably using all immediately prior knowledge gained during the iterative process.

The initial disbelief by engineers that such a simple technique as space mapping could cover such a wide range of design optimization problems evolved to the conviction that the idea had intuitively (cognitively) been in widespread use already. Indeed, those with "expert" (cognitive) knowledge, knowingly or unknowingly, harness the aggressive space mapping concept in activities ranging from everyday human experiences to expert tuning and design of complex engineering systems with electromagnetic accuracy.

Pattern search [2] followed by so-called "classical" Taylor-based optimization algorithms that exploit local linear and/or quadratic approximations with no underlying physics [2], [3], [5] are clear precursors to space mapping. But these algorithms depend on coarse models of a simplified mathematical nature, while space mapping enhances physics-based surrogates (physically based coarse models) of corresponding high-fidelity (fine) models. Design engineers came to see space

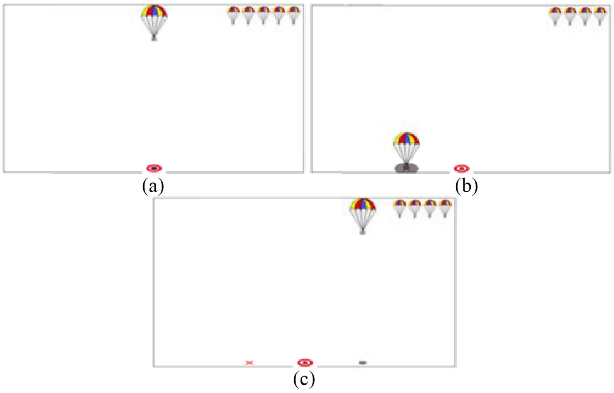


**FIGURE 7. [161] Parachute landing illustration of space mapping in action as originally devised by Cheng and Bandler [159], further developed by Bandler and Tajik [160]. (a) possible initial alignment vertically above the target (if there is no information about the expected trajectory); (b) the landing missing the target; (c) the next alignment for the next parachute taking the outcome of the first iteration into account. Iterations continue in this manner.**

mapping as a programmable manifestation of an experienced engineer's traditional "quasi-global" intuition or mysterious "feel" for a complex problem. Tuning space mapping, for example, embodies this synergy.

Bandler first recognized the parallels between space mapping and cognition in 2002 [157].

Many common-sense examples soon emerged, prominent among them the cheese-cutting problem [14], [15] and the shoe selection problem [14]. Space mapping seems like a natural mechanism for the brain to relate objects, images and patterns with other objects, images, reality, or experience.

The mental processes of System 1, fast and intuitive, and System 2, slow and effortful, proposed by Kahneman [158], adds a new dimension to the ideas of low-fidelity and high-fidelity models. "Expert intuition strikes us as magical, but it is not. Indeed each of us performs feats of intuitive expertise many times each day," Kahneman says [158] (p. 22). He continues, "Our everyday intuitive abilities are no less marvelous than the striking insights of an experienced firefighter or physician—only more common." Indeed, this is how common sense (cognition) works.

Aggressive space mapping [14], [15], [18], [19] is a clear manifestation of a cognitive underpinning. In the words of Bandler [14], "Aggressive space mapping efficiently invokes inner loops of conventional optimization—common sense at work—often yielding excellent results in an acceptable two or three iterations." "The aggressive space mapping update/execution process ... uncannily mimics both common sense and the expert's 'feel'."

One of many simple examples is a certain interactive illustration [159], [160]: "to iteratively position parachutes to land on the target in the fewest number of trials." See Fig. 7 [161]. Initially, the player positions the parachute above the target. When the player notes that the parachute drifts and lands away from the target, the player repositions the next parachute to correct for this drift. When the player again sees the parachute missing the target, hopefully by a smaller margin, the player tries again, assuming common sense, repositioning the third parachute, taking into account (mentally) *trends observed in all previous iterations*. How subsequent parachutes quickly converge to the target is what forms the game or challenge.

More examples of the coarse/fine duality as it relates to cognition are easily found in Wikipedia, examples such as spatial cognition, mental model, mental rotation, and so on: "Mental rotation is the ability to rotate mental representations of two-dimensional and three-dimensional objects as it is related to the visual representation of such rotation within the human mind." In terms of object recognition and categorization: "People can quickly and accurately categorize objects ... and recognize them as familiar, despite changing viewing conditions ..." [162], and dual process concepts: C-system: reflective (fine), X-system reflexive (coarse) [163]. From Wikipedia: "In psychology, a dual process theory provides an account of how a phenomenon can occur in two different ways, or as a result of two different processes. Often, the two processes consist of an implicit (automatic), unconscious process and an explicit (controlled), conscious process." For more on dual process concepts, see [164]–[166].

We see clear parallels between space mapping and human behavior and decision-making. Humans are cognition-driven. Good algorithms are cognition-driven. Their effectiveness depends on the degree of relevant expertise harnessed in matching process to goal [67], [167]. Key developments in our cognition point of view: many simple, intuitive examples of space mapping like the cheese-cutting problem [15]; the popularity of aggressive space mapping [18]; the parallels with space mapping found in Kahneman [158] and others; and continual advances in space-mapping-based design exploiting cognition-style markers such as response features [62], [64], [123].

Space mapping and surrogate-based optimization continue to evolve into cognition-driven design, a cornerstone in the push towards multiphysics-based modeling and design. Crucial, physics-based surrogates and feature-based and cognition-driven paradigms will lead to solution-based commercial offerings. Eventually, we will automate the once mysterious engineer's "feel" for accurate predictions of successes rather than explanations of failures, facilitating important diverse applications in medical imaging, detection, diagnostics, inverse problems, and more.

## VII. CONCLUSION

We foresee a number of imminent and future challenges in RF and microwave design optimization. They include the reliable and computationally efficient optimization of highly accurate system-level complex models, especially when those system-level representations are subject to statistical uncertainty and varying operating or environmental conditions. They also include the computationally-efficient EM-driven multi-objective design optimization in high-dimensional design spaces including categorical, conditional, or combinatorial variables. Another prominent challenge consists of the manufacturability assessment, statistical design, and yield optimization of high-frequency structures considering high-fidelity multi-physical performance.

The future will testify to the development of sophisticated algorithmic optimization approaches to address these major challenges, including confined and dimensionally reduced surrogate vehicles, automated feature-engineering-based optimization, and formal cognition-driven space mapping approaches, supported by Bayesian and machine learning techniques.

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