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Response Feature Technology for High-Frequency Electronics. Optimization, Modeling, and Design Automation

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ISBN 978-3-031-43844-8 ISBN 978-3-031-43845-5 (eBook)
https://doi.org/10.1007/978-3-031-43845-5

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

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Preface

Contemporary high-frequency electronics, including design of antennas and microwave systems, is heavily reliant on computational tools, especially full-wave electromagnetic (EM) analysis. While offering evaluation reliability and versatility, EM-driven design entails considerable computational expenses, which manifest themselves whenever repetitive EM simulations are required. Examples include parametric optimization, multi-criterial design, or uncertainty quantification. More often than not, the employment of conventional numerical modeling or optimization techniques is impractical if not prohibitive. Needless to say, the literature offers a plethora of approaches developed to alleviate these difficulties. This book offers a yet another methodological perspective on simulation-driven design of high-frequency structures, which is the response feature technology as well as its applications to modeling, optimization, and computer-aided design of antenna and microwave components. The method capitalizes on the exploration of the specific structure of the system outputs, which facilitates simulation-driven design procedures, both in terms of improving computational efficiency and reliability. These advantages can be attributed to weakly nonlinear dependence between the feature point coordinates and designable parameters of the system at hand. In the context of optimization, another benefit is inherent regularization of the objective function leading to faster convergence and enabling quasi-global search capability while using formally local search techniques. The book overviews a definition and extraction of characteristic points, as well as feature-based design problem reformulation. It also outlines algorithms developed to handle local, global, and multi-criterial design, surrogate modeling, as well as uncertainty quantification. The discussed frameworks are extensively illustrated using examples of real-world microwave and antenna structures along with numerous design cases. Furthermore, the book provides an introductory material on simulation-driven design, numerical optimization, but also behavioral and physics-based surrogate modeling. Practical aspects of feature-based surrogate modeling and optimization are discussed along with recommendations concerning particular techniques. The book will be useful for the readers working in the area of high-frequency electronics, including microwave engineering, antenna design, and microwave photonics.

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July 2023

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Acknowledgments

We would like to acknowledge the efforts of all those students, researchers, and colleagues who have helped us during the research work presented in this book. We would also like to thank Dassault Systemes, France, for making CST Microwave Studio available for our research purposes, and Keysight Technologies for ADS.

Contents

Chapter 1
Introduction

The reliance of all branches of engineering on computational (or simulation) models has never been as strong as it is today. Their fundamental advantages over traditional methods of evaluating the system performance, e.g., analytical or semiempirical, include versatility and reliability. On the one hand, simulation environments allow for representing structures of almost arbitrary complexity, embed them in larger systems, and extract information about all sorts of characteristics, e.g., scattering parameters for microwave components (Pozar, 2012), or integral quantities such as gain or efficiency for antennas (Balanis, 2005). On the other hand, computer simulation permits quantification of physical phenomena affecting system operation, even those that are difficult or impossible to be obtained otherwise, e.g., mutual coupling in antenna arrays (Koziel & Ogurtsov, 2019a), or dielectric/radiation losses (Tang & Luo, 2021). The last two decades witnessed tremendous developments in simulation methods and computing hardware. Commercial simulation packages have evolved in all engineering disciplines, including mechanical and structural engineering (Fusion 360; Autodesk, 2022), aerospace engineering (Inventor; Autodesk, 2019), electrical engineering (Cadence, 2016; Microwave Office, 2019; National Instruments, 2019), or multi-physics and multidisciplinary simulations (Multiphysics Simulation; ANSYS, 2022; COMSOL Multiphysics, COMSOL Inc., 2022). Nowadays, it is possible to accurately simulate complex and large-scale systems such as allocation of antennas on military vehicles (Byun et al., 2013), full-scale aircraft (Liersch & Hepperle, 2011), laminar and turbulent flow through wind turbines (Rosenberg et al., 2014), weather and climate phenomena (hurricanes, concentration of pollutants in the atmosphere or the ocean; Smith & Fortin, 2022; Cebe & Balas, 2018), or chemical processes (Upreti, 2017). Practical limitations of simulation-based modeling capacity are mainly related to the reliability of available input data (e.g., boundary conditions, material parameters) and computational resources. Notwithstanding, simulation models have had major effects on engineer-

A. Pietrenko-Dabrowska, S. Koziel, *Response Feature Technology for High-Frequency Electronics. Optimization, Modeling, and Design Automation*,
https://doi.org/10.1007/978-3-031-43845-5_1

ing practice. Accurate system evaluation obtained therefrom allows us to replace costly prototyping, investigate larger numbers of alternative designs, and reduce time to market as well as the overall cost of design procedures.

The focus of this book is high-frequency electronics. Therein, the two fundamental types of computational models are circuit simulators (ADS, Keysight Technologies, 2021) and full-wave electromagnetic (EM) analysis (Davidson, 2010; Sullivan, 2013; Sevgi, 2014; Swanson & Hoefer, 2003; White, 2004). The former allows for fast (circuit theory-based) evaluation of electrical characteristics; however, it becomes grossly inaccurate at the presence of strong cross-coupling effects (Kurgan & Koziel, 2019), dielectric/radiation losses (Rajab et al., 2005), or when the geometry of the structure at hand is of high level of complexity. On the other hand, EM analysis is conducted by numerical solving of Maxwell equations established over a selected computational domain. It enables identification of the distribution of the electric and magnetic fields, and, through appropriate post-processing, acquisition of the relevant system characteristics such as scattering parameters (Nikolova et al., 2006) or radiation patterns (Paulotto et al., 2008). Over the years, a large variety of general-purpose and specialized analysis techniques have been developed that are suitable for various purposes (e.g., finite-element analysis; Jin, 2002; finite-difference time domain analysis; Webb, 2004; methods of moments; Gibson, 2007, etc.). EM-driven design including design closure (in particular, adjustment of geometry and/or material parameters to fine-tune the system performance) has become an academic and industry standard. Nowadays, it is possible to conduct the entire design process within the simulation environment. Many commercial simulation software packages are available, including the general-purpose EM solvers such as HFSS (2021), Altair FEKO (2021), CST Microwave Studio (2022), XFDTD (2021), Momentum (Keysight, 2020), SEMCAD (2022), or Sonnet *em* (Sonnet, 2020), but also specific design tools, e.g., ADS (Advanced Design System, Keysight 2021) and Antenna Magus (2023), for antenna design.

The times when computational models were mainly used for design verification are long gone. Their larger-scale employment was fundamentally hindered by available computers and inefficiency of early simulation software. Rapid advancements in simulation technologies but also the developments of hardware, along with dramatically increased computational throughput (that including parallelization and hardware acceleration), have changed this picture entirely. In many cases, it is possible to carry out the entire design cycle with the aid of simulation tools. In fact, this is a practical necessity for a growing number of components and systems. In particular, traditional approaches, largely based on design-ready theoretical models are no longer adequate. One of the reasons is the increasing level of complexity of engineering systems; another is various system- and component-level interactions that have to be taken into account in the design process (Fang & Lin, 2016; Cheung & Long, 2006; Ittipiboon et al., 1998; Taflove & Hagness, 2005; Kuo et al., 1997). Simulation-driven design tasks can be formulated in various ways, depending on the type (geometry, material ones, etc.) and the number of adjustable parameters that have to be handled, the number of objectives, as well as possible constraints. Undoubtedly, the most common design task is parametric optimization, where the values of selected variables are adjusted in order to improve the system performance (Bubnicki, 2005; Zaslavski, 2010; Pistikopoulos et al., 2007; Koziel & Bandler, 2015a; Koziel et al., 2016; Cao et al., 2011; Chakravorty & Mandal, 2016; Sadrossadat et al., 2013). The latter is quantified by means of appropriately defined objective function, which is typically scalar-valued (Koziel et al., 2013; Sobester & Forrester, 2015). In some cases, simultaneous handling of multiple goals is required, leading to multi-criterial problems (Mirjalili & Dong, 2019; Mandal et al., 2018), where the objective function is vector-valued (Koziel & Pietrenko-Dabrowska, 2021a; Taran et al., 2018). Multi-criterial design typically seeks for a family of designs (a so-called Pareto set, Toktas et al., 2019), representing the best possible trade-offs between conflicting goals (Lv et al., 2019; Bramerdorfer & Zavoianu, 2017). Here, a representative example is a reduction of the physical dimensions of a microwave or antenna component, which is normally detrimental to electrical performance figures (Mahrokh & Koziel, 2021; Koziel & Pietrenko-Dabrowska, 2022). Other tasks include statistical design (e.g., Monte Carlo analysis; Styblinski & Opalski, 1986) or, in more general terms, uncertainty quantification (Hosder, 2012; Allaire & Willcox, 2014). One of the frequently considered problems in this field is maximization of the fabrication yield under the assumed manufacturing tolerances (Pietrenko-Dabrowska et al., 2020; Kouassi et al., 2016). A wide range of specialized algorithms have been developed to perform each of these tasks (Nocedal & Wright, 2000; Conn et al., 2000; Gorissen et al., 2010; Yang, 2010). Some of the methods are generic, i.e., applicable to a number of problems in different areas (Nocedal & Wright, 2000); others are problem-specific (e.g., Koziel et al., 2013; Koziel & Leifsson, 2013a).

Despite the mentioned advancements in computing hardware and software, simulation-driven design poses considerable challenges for a majority of real-world situations. The fundamental issue is the high cost of evaluating the computational models. The CPU cost of simulation highly depends on the model complexity. It may be just a few seconds per frequency for simple electromagnetic (EM) analysis of two-dimensional models (e.g., planar microwave filters; Hazdra et al., 2005), a few minutes for computational fluid dynamics (CFD) analysis of two-dimensional airfoil profiles (Siegler et al., 2016) or EM analysis of compact planar antennas (Koziel & Pietrenko-Dabrowska, 2021b), and up to several hours (e.g., CFD analysis of three-dimensional structures such as aircraft wings, or EM analysis of integrated photonic components; Krause & Jäger, 2005; Fakhfakh et al., 2015). Particularly involved structures (a full aircraft, a ship, climate models) may require many hours or even days of the analysis time (Wehner et al., 2010; Dennis et al., 2012; Yondo et al., 2018). At the same time, availability of better computational resources does not alleviate the cost-related difficulties to a large extent because it is counterbalanced by a growing complexity of the systems considered in all fields of engineering and science. Simulation-driven design procedures require repetitive and sometimes massive evaluations of the system at hand, which entail computational costs that might be impractical or even prohibitive. The problem is more pronounced for high-dimensional parameter spaces but also when global or multi-objective optimization is necessary. Nowadays, the most popular global search procedures involve nature-inspired population-based algorithms (Li et al., 2019; Jia & Lu, 2019), known for poor computational efficiency: the typical number of objective function evaluations ranges from a few thousands to many thousands per algorithm run. Multi-criterial problems are also routinely handled using population-based methods that allow generation of the entire Pareto set representation in a single run (Tang et al., 2018; Yang & Kiang, 2015). Uncertainty quantification problems are even more expensive due to the necessity of numerical integration of the underlying probability density functions describing parameter deviations (e.g., Monte Carlo analysis; Ma et al., 2018), which has to be carried out repetitively when optimizing statistical figures of merit (yield, Zhang et al., 2021; tolerance hypervolume, Wu et al., 2021). Another issue pertinent to computational models is the numerical noise, which may be a result of terminating the simulation process before full convergence, or it may be related to adaptive meshing employed by modern solvers. The latter manifests itself through noticeable changes of the simulated system responses due to even very small changes of the structure geometry (these leading to considerable changes of the mesh topology). The noise may affect the operation of gradient-based optimization routines that normally require the objective function to be smooth. Yet another problem is reliability of simulation-based design procedures. For example, the most widely used procedure is local parameter tuning, the performance of which is highly dependent on availability of a sufficiently good starting point. In many cases, this is problematic, e.g., in size reduction of compact microwave or antenna components, where miniaturization techniques employing slow-wave phenomenon (Qin & Xue, 2013) or geometrical modifications (stubs, Wei et al., 2015; slots, Zhang et al., 2019; defected ground structures, Sen & Moyra, 2019) increase the number of variables and result in nonintuitive relations between geometry parameters and the system outputs (Pietrenko-Dabrowska & Koziel, 2020a). Also, many problems are of multimodal nature (i.e., feature multiple local optima), and the employment of local algorithms typically leads to inferior results, whereas resorting to global methods generates excessive computational costs.

From the perspective of practical design applications of the simulation tools, the challenges outlined in the previous paragraphs are combined with inefficiency of conventional optimization/modeling algorithms, which are normally incorporated into commercial simulation software packages (e.g., CST, 2022; HFSS, 2021; Altair FEKO, 2021). This resulted in the development of a variety of informal and interactive ways of utilizing simulation models for design purposes, which are still ubiquitous in many engineering fields, including high-frequency design. The key factor is the engineering insight, which allows for making reasonable predictions about the promising changes of the system parameters. Practical workflows involve parameter sweeping (usually, one parameter at a time). Experienced designers are often capable of identifying satisfactory parameter setups using an acceptable number of simulations even though the interactive procedures are rather laborious and do not guarantee optimum results. However, the adequacy of parameter sweeping-based and similar methods has become questionable with the increasing complexity of the engineering systems, the need of simultaneous tuning of many variables, as well as the presence of multiple objectives and constraints.

Needless to say, the last two decades or so witnessed considerable research efforts directed toward mitigating the common issues of simulation-driven design, particularly, its high cost. In the realm of local optimization, perhaps the most serious bottleneck is evaluation of the system response gradients, which—when carried out using finite differentiation (Levy & Lessman, 1992)—generates considerable computational overhead proportional to the dimensionality of the parameter space. This can be alleviated using adjoint sensitivities (Director & Rohrer, 1969; Pironneau, 1984; Jameson, 1988; El Sabbagh et al., 2006; Papadimitriou & Giannakoglou, 2008; Toivanen et al., 2009), or automated differentiation (Griewank, 2000; Bischof et al., 2008)). These methods allow for a fast evaluation of gradients of the figures of interest at small extra computational effort (often only one additional simulation), regardless of the number of designable parameters. Consequently, the benefits of adjoints are particularly evident for higher-dimensional problems. Adjoint sensitivities are currently available in some commercial simulation packages in various areas (e.g., computational fluid dynamics solvers: ANSYS Fluent, 2015; Star-CCM+, 2015), as well as some noncommercial codes (e.g., Stanford University Unstructured; Palacios et al., 2013). In the context of high-frequency modeling, they are supported by CST Microwave Studio (CST, 2022) and ANSYS HFSS (HFSS, 2021). Other available techniques include sparse sensitivity updating schemes, where finite differentiation-based gradient estimation is limited to selected parameters based on various metrics (e.g., Koziel & Pietrenko-Dabrowska, 2019a, b; Pietrenko-Dabrowska & Koziel, 2019, 2020a). Local search procedures can also be expedited using parallelization (Zhang et al., 2020b), utilization of fast dedicated solvers (Arndt, 2012), or techniques exploiting specific shapes of the system responses (e.g., cognition-driven design, Zhang et al., 2015; feature-based optimization, Koziel, 2015).

One of the most promising approaches to alleviating the challenges of simulation-driven design is utilization of fast replacement models, referred to as surrogates (Simpson et al., 2001; Queipo et al., 2005; Bandler et al., 2008; Forrester & Keane, 2009; Koziel & Pietrenko-Dabrowska, 2020b; Yondo et al., 2019). The underlying idea is to shift most of the computational burden into a cheap surrogate while only making occasional references to the original (high-fidelity) simulation model. Although a construction of the surrogate is also associated with certain computational expenses, the benefits often outweigh those costs for well-working procedures (Koziel & Ogurtsov, 2019b; Van Nechel et al., 2018). This is particularly the case for design tasks incurring massive system evaluations (uncertainty quantification, Koziel & Ogurtsov, 2019b; global search, Easum et al., 2018) but may be advantageous also for local optimization (e.g., space mapping, Li et al., 2020). For the surrogate to be effectively used instead of the original simulation model, it needs to be fast, sufficiently accurate, and, preferably, analytically tractable (e.g., smooth) (Alexandrov & Lewis, 2001; Bandler et al., 2008; Jin, 2011; Koziel & Leifsson, 2013a). The surrogates can be constructed locally (e.g., in the vicinity of the optimization path for the purpose of local optimization (Koziel & Unnsteinsson, 2018) in the neighborhood of the nominal design for the purpose of statistical analysis (Rayas-Sanchez et al., 2021)), or over the entire parameter space pertinent to a given problem (e.g., for the purpose of global optimization (Koziel & Abdullah, 2021)). Although surrogate models have been around for several decades, their importance has been steadily growing over the last two decades or so because of the increasing role of computational models themselves. The literature on surrogate models, also referred to as replacement models or metamodels, is replete (Simpson et al., 2001; Muller & Shoemaker, 2014; Bilicz, 2016; Declercq et al., 2013; Leary et al., 2003; Mendes et al., 2013; Du & Roblin, 2018; Wang et al., 2018; Yang et al., 2019). On the other hand, the surrogates entered the field of high-frequency engineering relatively recently, i.e., in the late 1990s and early 2000s (Rayas-Sanchez, 2016; Koziel et al., 2008), whereas their widespread use originated about a decade ago (Liu et al., 2014; Zhang et al., 2021; Koziel & Ogurtsov, 2019a).

Surrogate models can be categorized into two major groups, data-driven (Simpson et al., 2001) and physics-based ones (Koziel & Ogurtsov, 2014). Data-driven or approximation models are constructed from sampled high-fidelity simulation data (Queipo et al., 2005). Some of the popular methods include polynomial regression (Jin et al., 2001), radial basis functions, RBF (Wild et al., 2008), kriging (Jones, 2001; Forrester & Keane, 2009; Kleijnen, 2009), Gaussian process regression, GPR (Angiulli et al., 2007; Jacobs, 2012), support vector regression, SVR (Smola & Schölkopf, 2004), rational approximation (Shaker et al., 2009), polynomial chaos expansion, PCE (Zhang et al., 2018a), as well as artificial neural networks, ANN (Haykin, 1998). The latter come in many variations, including convolutional neural networks (Liang et al., 2020), recurrent neural networks (Shen & Wang, 2008) and deep neural networks (DNN) (Koziel et al., 2021b), and found many applications in high-frequency electronics (Zhang et al., 2020a; Belen et al., 2021; Zhao & Wu, 2020). Approximation models are constructed exclusively using data acquired from the system of interest (no engineering insight is required), which makes them versatile and easily transferrable between the problem domains. At the same time, they are cheap to evaluate because their underlying structure is based on analytical equations (e.g., linear combinations of appropriate basis functions; Rozhenko, 2018). For the purpose of design optimization but also general-purpose modeling, data-driven surrogates are often incorporated into machine learning frameworks (Xiao et al., 2018; Wu et al., 2020), where the model is iteratively updated using sequential sampling methods (Couckuyt et al., 2012). Various ways of incorporating new training points into the model (so-called infill criteria) have been developed, including exploitative models (i.e., models oriented toward improving the design in the vicinity of the current one), explorative models (i.e., models aiming at improving global accuracy), as well as models with balanced exploration and exploitation (Forrester & Keane, 2009; Couckuyt et al., 2010). Generally, these techniques are often referred to as efficient global optimization (EGO) methods (Jones et al., 1998) or surrogate-assisted evolutionary algorithms (SAEAs) (Gorissen et al., 2009; Lim et al., 2010; Jin, 2011; Yang et al., 2019).

Physics-based models constitute the second major class of surrogates. The name refers to the fundamental structure of these surrogates which exploit, to a certain extent, the system-specific knowledge (Cervantes-González et al., 2016; Koziel &

Leifsson, 2016). This, in turn, is most often a simplified physical description of the system in the form of an underlying low-fidelity model (Robinson et al., 2008; Koziel & Leifsson, 2013b; Sarkar et al., 2019). The low-fidelity model is subsequently corrected using a limited amount of high-fidelity simulation data, typically through linear or nonlinear regression (Bandler et al., 2004). A representative example of a low-fidelity model in the area of microwave engineering is an equivalent network of the structure (e.g., a filter), with the high-fidelity model being evaluated through a full-wave electromagnetic analysis (Zhu, 2002). The fundamental benefit of this type of arrangement is that sharing the same physics by the low- and high-fidelity models normally results in a better generalization capability of the surrogate, its validity over wider ranges of parameters, and limited vulnerability to dimensionality-related issues. Consequently, the number of high-fidelity training samples required to construct physics-based models is lower than for the data-driven ones. Thus, physics-based modeling solves some of the issues of data-driven surrogates, which contribute to their growing popularity (Pantoja et al., 2007; Salleh et al., 2008; Crevecoeur et al., 2010; Koziel & Leifsson, 2013a; Cervantes-González et al., 2016; Baratta et al., 2018; Zhang et al., 2018b). Unfortunately, the same factors that contribute to the attractiveness of the physics-based surrogates also imply their limitations. The first issue is the low-fidelity model itself. It is normally problem-specific (Bandler et al., 2004; Koziel & Leifsson, 2013a); therefore, physics-based surrogates lack the versatility of data-driven models. In high-frequency engineering, low-fidelity models are typically obtained by simulating the system at a different level of physical description (e.g., equivalent network representation evaluated using circuit theory rules; Bandler et al., 2004), or lower resolution (e.g., simulation with coarser discretization of the structure and/or relaxed convergence criteria; Koziel & Ogurtsov, 2014). Because the low-fidelity models typically involve computer simulation, their evaluation time cannot be neglected. The aggregated cost of the low-fidelity model simulations may be significant in certain applications, e.g., parametric optimization (Zhou et al., 2007; Koziel & Leifsson, 2016). Another issue is a trade-off between the low-fidelity model speed and accuracy. While this can be easily adjusted in many situations, e.g., by changing the discretization density in coarse-mesh simulation models, selection of a particular model setup might not be a trivial task (Koziel & Ogurtsov, 2012).

Physics-based surrogates are typically used for local optimization. One of the most popular physics-based SBO methods in high-frequency electronics is space mapping (SM) (Bandler et al., 2004; Koziel et al., 2008; Rayas-Sanchez, 2016) which comes in many variations (aggressive SM, Bandler et al., 1995; implicit SM, Koziel et al., 2011; manifold-mapping, Echeverria et al., 2006; neural SM, Gutiérrez-Ayala & Rayas-Sánchez, 2010; output SM, Ayed et al., 2012; input SM, Khalatpour et al., 2011). Because the most straightforward way of constructing the surrogate model from the underlying low-fidelity model is correcting its response, many physics-based SBO algorithms employ such mechanisms. Some of the techniques include approximation model management optimization (AMMO; Alexandrov & Lewis, 2001), multipoint correction (Toropov, 1989), manifold mapping (Echeverria & Hemker, 2005), adaptive response correction (Koziel et al., 2009), shape-preserving response prediction (Koziel, 2010), or adaptive response scaling (Koziel & Unnsteinsson, 2018). Apart from design optimization, surrogate models are used for many other purposes as well. An important area is uncertainty quantification (e.g., yield estimation; Bandler et al., 2002; Biernacki et al., 2012) and tolerance-aware (or robust) design (Ko et al., 2011; Koziel & Bandler, 2015a; Kouassi et al., 2016; Aubry et al., 2016). Statistical analysis is typically performed in order to find the effects of manufacturing tolerances or uncertainties concerning operating conditions on the system performance. Traditional methods such as Monte Carlo (MC) simulation (Hu et al., 2016; Liu, 2017) are computationally heavy, and fast surrogates seem to be an ideal way of accelerating the process. Certain types of models, such as polynomial chaos expansion (PCE), are particularly suitable in this context due to their capability of directly assessing the statistical moments of the output probability distributions without the necessity of running MC (Sudret, 2008; Xiu, 2009; Du & Roblin, 2017; Manfredi et al., 2017). Another important application of surrogates is inverse modeling, which allows for directly yielding the optimum values of design variables corresponding to the required values of performance figures (Akkaram et al., 2007; Kabir et al., 2008; Liu et al., 2016; Zhang et al., 2018b).

Despite their potential efficacy, surrogate-assisted methods are affected by a number of issues. The major bottleneck is the curse of dimensionality (Wu et al., 2019), which is commonly referred to as a rapid growth of the number of training data samples necessary to render a reliable model. As a matter of fact, a construction of the surrogates within highly dimensional spaces (say, 20 or more dimensions) is only possible if the system responses are weakly nonlinear. In the case of high-frequency electronics, practical data-driven modeling of components, such as multi-band antennas (characterized by sharp, resonant-like responses), filters (featuring multiple poles and transmission zeros), or compact microwave components (e.g., couplers), is limited to a few parameters. Meanwhile, in the case of the mentioned structures, modeling within wide ranges of parameters is even more important for the surrogates to be of any utility for design purposes (Feng et al., 2019; Yelten et al., 2012; Koziel et al., 2013, 2016). This poses even more challenges than the dimensionality issue because characteristic features of the responses (e.g., the resonances) relocate considerably along the frequency spectrum (Ullah & Koziel, 2018; Rossi et al., 2014). In practice, globally accurate approximation modeling is usually justified in the case of multiple-use library models of components described by a limited number of parameters. There have been many attempts and techniques developed to mitigate these problems. One is sequential sampling (Xiong et al., 2009; Mukhopadhyay, 2011; Wei et al., 2012, Mackman et al., 2013; Xu et al., 2014), nowadays commonly used as a design of experiments approach for data-driven surrogates. The idea is to replace a one-shot (typically uniform) sample allocation by an iterative process in which additional (or infill) samples are distributed based on the feedback obtained from the current sample distribution and/or the current surrogate. In the case of explorative design of experiments schemes (Mandal et al., 2012), the infill samples are added without referring to the system output but merely based on the data points allocated so far, with the purpose of improving uniformity of the set. In general, especially for the exploitative sampling schemes (Koziel & Ogurtsov, 2019a), a suitable infill criterion may be maximization of the mean square error, i.e., identifying locations where the error (as predicted by the surrogate, typically, kriging) is the highest (Jiang et al., 2018). In these cases, finding the infill points requires global optimization, typically realized using population-based metaheuristics (Beheshti & Shamsuddin, 2013; Mehmani et al., 2015; Park et al., 2018; Liu et al., 2018a), which makes the procedure slow. The advantage is that more samples may be allocated in the regions corresponding to higher nonlinearity of the system responses, which improves the model accuracy. Unfortunately, this sort of approach rarely pays off for many high-frequency structures where "nonlinear" regions are almost everywhere within the model domain (San et al., 2004; Hajjaj et al., 2017; Shitvov et al., 2014). Co-kriging (Forrester et al., 2007) and gradient kriging (Han et al., 2013) are other ways of reducing the computational cost of the training data acquisition. Co-kriging uses densely sampled low-fidelity model data blended together with a limited number of high-fidelity points which allows for constructing the surrogate of the accuracy similar to that obtained solely from (densely sampled) high-fidelity simulations. This is of course under the assumption that the low- and high-fidelity models are sufficiently well correlated. Gradient kriging, on the other hand, incorporates sensitivity data into the surrogate, which also potentially reduces the number of necessary training points; however, this approach is only practical if the gradient information can be obtained in a computationally efficient matter (e.g., through adjoints; Giles & Pierce, 2000; Allaire, 2015). A different approach to handle dimensionality issues is high-dimensional model representation (HDMR) (Foo & Karniadakis, 2010; Ma & Zabaras, 2010; Shan & Wang, 2011; Cai et al., 2017; Liu et al., 2018b; Wu et al., 2019), where the system responses are represented as a linear combination of functions that account for lower order effects, specifically, cooperative effects of individual variables, pairs of variables, etc. Model order reduction (MOR) is another class of methods that generally refers to various ways of reducing the complexity of large-scale dynamical systems, while preserving (as much as possible) their input-output behavior (Baur et al., 2014; Henneron & Clénet, 2014). The reduced models mimic (from the point of view of the input and output) the behavior of the large-scale system so that they can be efficiently used for design automation, parametric optimization, or sensitivity analysis. Particular numerical techniques utilized by MOR include, among others, Krylov subspace methods (Lin et al., 2007), proper orthogonal decomposition (POD; Willcox & Peraire, 2002), principal component analysis (PCA; Dray, 2008), solution space projection (SSP; Lee & Jin, 2007), or rational approximation (Deschrijver et al., 2007). Examples of MOR in high-frequency engineering include parameterized MOR models of complex electromagnetic systems (Burgard et al., 2013; Sato et al., 2015), reduced order macromodels of high-speed microstrip structures (Zhu & Cangellaris, 2001), or accelerated frequency sweeps in FEM analysis (de la Rubia et al., 2009). Several methods have also been developed to handle situations when the regression problem (e.g., in the construction of response surface approximation models; Khuri & Mukhopadhyay,

2010) is heavily underdetermined. This essentially means that the system at hand is characterized by a large number of internal degrees of freedom (e.g., analog or mixed-signal circuits, analog-to-digital converters, or RF front ends), whereas the regression model has to be built using a relatively small number of samples due to the computational budget issues or simply numerical problems pertinent to handling large data sets. Orthogonal matching pursuit (Tropp, 2004; Tao et al., 2016; Li, 2010; Bishop, 2006) is a technique that identifies a small set of basis functions that approximate the model (or function) of interest. In order to ensure fast convergence, a set of basis functions that are normalized and orthogonal is normally adopted (Needell & Tropp, 2009). Another method, Bayesian model fusion (Wang et al., 2013, 2016) can be classified as a physics-based surrogate technique because it uses the so-called early-stage data (e.g., schematic-level simulation data) in order to fit the late-stage model (e.g., a post-layout one with extracted parasitic components) (Li et al., 2012). By blending these two-level data, realized using Bayesian inference, the overall cost of model construction can be greatly reduced because very few late-stage samples are typically used (Tao et al., 2019).

The last few paragraphs outlined the methodologies developed to mitigate the common issues of simulation-driven design, especially those related to excessive costs of the optimization or modeling procedures. While keeping the formulation of the underlying design problem intact, they focused on reducing the number of evaluation of the high-fidelity model (e.g., by reducing the sensitivity updating schemes in the gradient-based algorithms) or incorporating cheaper representations (surrogate models), delegated to absorb most of the computational burden incurred by a given algorithm. Many of these methods exhibit excellent efficiency when implemented properly, although generality and automation are often questionable. Also, acceleration techniques do not address reliability of the design procedures. For example, the performance of local (e.g., gradient- or stencil-based algorithms; Nocedal & Wright, 2000; Kolda et al., 2003), whether conventional or expedited, is still reliant on the availability of a sufficiently good initial design. In the recent years, a conceptually distinct approach has been proposed, which is referred to as the response feature technology (Koziel, 2015). In the context of design optimization, it is often termed feature-based optimization (FBO) (Koziel & Pietrenko-Dabrowska, 2020b). Its major purpose is to improve both the computational efficiency and the reliability of the modeling and optimization procedures in high-frequency engineering. The response feature approach operates by reformulating the underlying design tasks in terms of the appropriately defined characteristic (feature) points of the system at hand. The characteristic points are problem-dependent and assigned to account for the relevant features of the system outputs, e.g., frequency and level coordinates of antenna resonances (Koziel & Pietrenko-Dabrowska, 2021b), frequencies corresponding to specific levels of reflection or transmission characteristics (Koziel and Bandler, 2015b), local maxima of the in-band return loss response of a filter (Koziel & Bandler, 2015a), etc. The type and the number of response features are decided upon so that the information carried therein is sufficient to quantify the design objectives.

The major advantage of the response feature approach is that the dependence between the characteristic point coordinates and the system parameters (both geometry and material) is normally weakly nonlinear, as opposed to a similar relationship for the complete response. Consequently, problem reformulation leads to "flattening" of the functional landscape to be handled, which has several advantages: (i) accelerating convergence of the optimization procedures (Koziel, 2015); (ii) enabling quasi-global search capabilities (Pietrenko-Dabrowska et al., 2021); (iii) reducing the number of training data sets required for surrogate model construction (Pietrenko-Dabrowska et al., 2022); (iv) improving reliability of EM-driven design processes, in particular, reducing sensitivity of local tuning algorithms to the quality of the initial design (Koziel & Pietrenko-Dabrowska, 2021b); and (v) facilitating inverse modeling procedures (Koziel & Pietrenko-Dabrowska, 2020c), which also carries over to forward modeling (Koziel et al., 2021a). Response features can be incorporated into the majority of existing optimization and modeling procedures because the employment is related to reformulating the design task rather than modifying the procedure itself. However, feature-based algorithms can also be developed from ground up, particularly in relation to modeling methods (both inverse and forward, Koziel & Pietrenko-Dabrowska, 2021c) but also optimization (Koziel & Pietrenko-Dabrowska, 2021d) and uncertainty quantification (Pietrenko-Dabrowska & Koziel, 2021).

The primary purpose of this book is an exposition of the response feature technology and its application for modeling, optimization, and design automation of high-frequency structures, including antennas and microwave devices. In order to be self-contained, in Chap. 2, we formulate common simulation-driven tasks, including local and global optimization, multi-objective design, statistical analysis, as well as tolerance-aware optimization, whereas, Chaps. 3 and 4 overview local and global optimization methods and provide the fundamentals of surrogate modeling and surrogate-assisted optimization. Chapter 5 introduces the response feature technology, discusses the definition of characteristic points and their fundamental properties, as well as illustrates their employment for optimization of antenna and microwave components. Chapter 6 provides an overview of local feature-based optimization. The main purpose is to discuss the various ways of defining the characteristic points, depending on a particular design scenario, as well as the underlying type (shape) of the system characteristics. Chapters 7 and 8 discuss accelerated feature-based optimization strategies, whereas Chap. 9 outlines feature-inspired methods for reliability improvement of local tuning algorithms. The two representative techniques discussed therein are frequency-based regularization and adaptively adjusted design specification approach. Chapter 10 overviews utilization of response features for global optimization of antenna and microwave components. Feature-based methodologies for warm-start optimization and rapid redesign of high-frequency components are discussed in Chap. 11. The next two chapters cover feature-based surrogate modeling, both in conventional (Chap. 12) and confined domains (using a so-called performance-driven paradigm; Chap. 13). Chapter 14 elaborates on utilization of response features for rapid statistical analysis and tolerance optimization of high-frequency devices. The concept of generalized features is discussed in Chap. 15, whereas Chap. 16 concludes the work. The book is illustrated with a large number of practical design cases from various areas of high-frequency electronics, especially microwave and antenna engineering. Despite this particular focus, some of the optimization and modeling methods discussed here are of a generic nature and can be adopted for solving problems in other engineering disciplines. The authors believe that the presented material may be helpful for engineers and researchers interested in methods for improving computational efficiency and reliability of simulation-driven procedures, especially in the context of design optimization, constructing fast replacement models, or other projects that require massive evaluations of expensive computer simulation models as well as handling highly nonlinear system outputs.

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