Applied Soft Computing 47 (2016) 332–342

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Multi-objective optimization of expensive electromagnetic simulation models

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ARTICLE INFO

Article history:
Received 30 June 2015
Received in revised form 30 March 2016
Accepted 24 May 2016
Available online 18 June 2016

Keywords:
Computer-aided design (CAD)
Computational electromagnetics
Electromagnetic (EM)-simulation models
Simulation-driven design
Multi-objective optimization
Surrogate modeling
Evolutionary algorithms
Space mapping

ABSTRACT

Vast majority of practical engineering design problems require simultaneous handling of several criteria. For the sake of simplicity and through a priori preference articulation one can turn many design tasks into single-objective problems that can be handled using conventional numerical optimization routines. However, in some situations, acquiring comprehensive knowledge about the system at hand, in particular, about possible trade-offs between conflicting objectives may be necessary. This calls for multi-objective optimization that aims at identifying a set of alternative, Pareto-optimal designs. The most popular solution approaches include population-based metaheuristics. Unfortunately, such methods are not practical for problems involving expensive computational models. This is particularly the case for microwave and antenna engineering where design reliability requires utilization of CPU-intensive electromagnetic (EM) analysis. In this work, we discuss methodologies for expedited multi-objective design optimization of expensive EM simulation models. The solution approaches that we present here rely on surrogate-based optimization (SBO) paradigm, where the design speedup is obtained by shifting the optimization burden into a cheap replacement model (the surrogate). The latter is utilized for generating the initial approximation of the Pareto front representation as well as further front refinement (to elevate it to the high-fidelity EM simulation model level). We demonstrate several application case studies, including a wideband matching transformer, a dielectric resonator antenna and an ultra-wideband monopole antenna. Dimensionality of the design spaces in the considered examples vary from six to fifteen, and the design optimization cost is about one hundred of high-fidelity EM simulations of the respective structure, which is extremely low given the problem complexity.

1. Introduction

Electromagnetic (EM)-simulation models are nowadays ubiquitous in various fields such as RF and microwave engineering [1], antenna design [2], photonics [3], design of wireless power transfer systems [4], microwave imaging [5], non-destructive testing [6], to name just a few. High-fidelity EM analysis permits accurate evaluation of the system performance, however, it might be computationally expensive, particularly for complex structures. In many situations, computational models have to account not just for the structure under design but also its environment that the system is electromagnetically coupled with, and which affects its operation [7,8]. As a matter of fact, EM simulation might be the only reliable way of estimating the system performance with the simplified (e.g., analytical) models either not available or being very inaccurate.

High cost of high-fidelity EM analysis becomes a fundamental bottleneck from the simulation-driven design point of view, especially design automation through numerical optimization. While relatively simple EM models of individual components (filters, antennas, couplers, etc.) simulate in a few minutes per design, more complex structures (antenna arrays, electrically large structures, components simulated with their environment such as on-vehicle antennas, integrated photonic devices) require a few hours up to many days for simulation. Conventional optimization algorithms (both gradient-based [9] and derivative-free [10], particularly population-based metaheuristics such as evolutionary algorithms [11], particle swarm optimizers [12] or differential evolution [13]) require large number of objective function evaluations to converge, which is often computationally prohibitive. Consequently, the most popular approaches to simulation-driven design

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http://dx.doi.org/10.1016/j.asoc.2016.05.033
1568-4946/

are hand-on procedures involving heavy interactions with the designer [14,15]. A notable example is design through parameter sweeps (usually, one parameter at a time), guided by engineering experience. Such methods, although laborious, typically lead to acceptable (yet not optimum) results in reasonable timeframe when executed by skilled engineers with sufficient background and experience in solving a particular class of design tasks.

Clearly, automated design optimization is highly desirable. Adjoint sensitivity [16,17] is one of technologies that allow speeding up EM-driven optimization process [18,19] by providing information about the system response and its gradients at little extra computational cost. Unfortunately, this technology is not yet widely used in computational electromagnetic community and commercially only available through a few EM solvers [20,21]. One of the most promising approaches to computationally efficient simulation-driven design is surrogate-based optimization (SBO) [22,23]. In SBO, direct optimization of the expensive simulation model is replaced by iterative construction and re-optimization of its cheap representation, referred to as a surrogate [22]. Various SBO techniques mostly differ in the way the surrogate model is constructed. A comprehensive review of surrogate-based techniques for solving expensive real-world problems can be found in [24]. In [25] a survey of surrogate-assisted optimization from the perspective of evolutionary computation is presented.

The methods exploiting data-driven (approximation) surrogates are usually used for global optimization (EGO-type methods [26,27], artificial neural networks [42], or SAEA algorithms [28,29]), where a surrogate model is constructed from sampled simulation data and subsequently used as a prediction tool for identifying the most promising designs. The surrogate is updated using suitably defined infill points aiming either at improvement of the global accuracy of the model [22] or in exploitation of the promising regions of the design space [22]. Physics-based surrogate models are constructed by suitable correction of the underlying low-fidelity models (such as equivalent circuits [30] or coarse-mesh EM simulation models [7]). The most popular physics-based SBO techniques in computational electromagnetics include space mapping (SM) [31,32], various response correction methods [33–35], feature-based optimization [36], as well as adaptively adjusted design specifications [37]. Because of embedding knowledge about the system at hand, physics-based models normally exhibit better generalization capability than approximation surrogates. On the other hand, due to being relatively expensive, they are better suited for local optimization [7].

Majority of real-world design problems in computational electromagnetics require handling multiple criteria. A typical example that applies particularly to wireless communication systems (especially portable, battery-operated, and wearable devices [38,39]) is design of miniaturized components that still satisfy stringent requirement concerning their electrical performance [7,14,18]. In many cases the design task can be converted into a single-objective optimization problem by appropriate goal prioritization [7]. However, finding possible trade-offs between conflicting objectives may be necessary in certain situations, e.g., to obtain comprehensive information about the capabilities of a given structure/system. This can only be achieved through genuine multi-objective optimization yielding a set of alternative solutions that are Pareto-optimal with respect to given design criteria. Obviously, it leads to additional challenges from the simulation-driven design standpoint.

The most popular multi-objective optimization methods are population-based metaheuristics such as genetic algorithms (GAs) [11,40], or particle swarm optimizers (PSO) [12,41]. Their most important advantage is a capability of finding the entire Pareto set in a single algorithm run. A disadvantage is huge computational cost (normally hundreds, thousands or tens of thousands of objective evaluations) which is computationally prohibitive if the high-fidelity EM simulations are utilized for system evaluation.

Recently, it has been demonstrated that surrogate-based optimization techniques may be extended to handle multi-objective optimization problems in engineering [7,35]. Particular examples of using approximation surrogates for solving real-world problems can be found in [42,43]. In [42], an artificial neural network has been utilized in a combination with a Monte Carlo procedure to accelerate multi-objective design of optical networks by 88% with respect to direct optimization driven by network simulator. Surrogate-based optimization has been also successfully applied for solving multi-objective problems in antenna engineering [43]. Because of relatively high cost of low-fidelity antenna simulations, auxiliary kriging interpolation models have been exploited in [43] to permit feasible Pareto front identification using evolutionary methods.

In this paper, we review the approach introduced in [43] and demonstrate its application—in conjunction with the initial design space reduction—to the design of various types of microwave and antenna components. In particular, we consider examples of miniaturized impedance matching transformer, a dielectric resonator antenna (with three design objectives), and a compact ultra-wideband monopole antenna. Our results indicate that utilization of variable-fidelity EM simulations, approximation modeling, and response correction techniques, allows for identifying Pareto front representations at the cost corresponding to less than a hundred high-fidelity EM simulations of the structures under design. The critical components of the design optimization process, which is an enhancement compared to [43], is utilization of the initial design space reduction. Also, the refinement procedure has been generalized for arbitrary number of objectives. Moreover, we demonstrate that possible imperfections and statistical variability of multi-objective evolutionary optimization of the approximation surrogate (an intermediate step of the design process leading to the initial approximation of the Pareto front) has minor influence on the final Pareto set quality, which is mostly a result of the overall optimization flow arrangement (specifically, operating within a confined region of the design space containing the Pareto front, and surrogate-assisted front refinement procedures).

2. Multi-objective optimization of expensive electromagnetic simulation models

In this section, we briefly outline the procedure for expedited multi-objective optimization of expensive electromagnetic (EM) simulation models. We start by formulating the multi-objective design problem, discuss variable-fidelity EM modeling, describe a simple design space reduction procedure as well as surrogate model construction using kriging interpolation. We also formulate the procedure for generating the initial Pareto-optimal set approximation and its refinement strategy.

2.1. Multi-objective design. Problem formulation

We denote by $\boldsymbol{R}_f(\boldsymbol{x})$ a high-fidelity electromagnetic simulation of the system/structure under design. The response vector $\boldsymbol{R}_f(\boldsymbol{x})$ represent relevant figures of interest, which normally are so-called scattering parameters evaluated over a frequency band of interest [43]. Designable parameters (i.e., structure dimensions) are represented by a vector $\boldsymbol{x}$.

Let $F_k(\boldsymbol{x})$, $k = 1, \ldots, N_{obj}$, be a k-th design objective. A typical situation would be to satisfy minimax-type of specifications such as minimize the reflection coefficient (in particular, to ensure $|S_{11}| \leq -10$ dB in a predefined frequency band, in case of antenna structures [44]). However, other objectives, related to minimiza-