Applied Mathematical Modelling 40 (2016) 7204–7215

Contents lists available at ScienceDirect

Applied Mathematical Modelling

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

Expedited constrained multi-objective aerodynamic shape optimization by means of physics-based surrogates

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ARTICLE INFO

Article history:
Received 4 August 2015
Revised 23 February 2016
Accepted 9 March 2016
Available online 24 March 2016

Keywords:
Aerodynamic shape optimization
Multi-objective design
Design space reduction
Physics-based surrogates
Kriging interpolation
Space mapping

ABSTRACT

In the paper, computationally efficient constrained multi-objective design optimization of transonic airfoil profiles is considered. Our methodology focuses on fixed-lift design aimed at finding the best possible trade-offs between the two objectives: minimization of the drag coefficient and maximization of the pitching moment. The algorithm presented here exploits the surrogate-based optimization principle, variable-fidelity computational fluid dynamics (CFD) models, as well as auxiliary data-driven surrogates (here, using Kriging). In order to permit computationally feasible construction of the Kriging models, initial design space reduction is also utilized. The design process has three major stages: (i) identification of the extreme points of the Pareto front through single-objective optimization (one objective at a time), (ii) construction of the Kriging model and initial Pareto front generation using multi-objective evolutionary algorithm (MOEA), and (iii) Pareto front refinement using response correction techniques and local response surface approximation (RSA) models. For the sake of computational efficiency, stages (i) and (ii) are realized at the level of coarse-discretization CFD model. The RSA models are also utilized to predict the angle of attack necessary to achieve the target lift coefficient, which considerably reduces the CFD simulation effort involved in the design process. Two design case studies are considered involving B-spline-parameterized airfoil shapes with 8 and 12 design variables. The 10-element Pareto front representations are obtained at the cost corresponding to just over two hundred of high-fidelity CFD model evaluations. This cost is not only considerably lower (up to two orders of magnitude) than the cost of direct high-fidelity model optimization using metaheuristics but, more importantly, renders multi-objective optimization of aerodynamic components computationally tractable even at the level of accurate CFD models.

1. Introduction

A critical aspect of contemporary aerodynamic design, especially regarding components such as aircraft wings and turbine blades is shape optimization [1,2]. The optimization process is normally executed—for the sake of reliability—at the level of high-fidelity computational fluid dynamic (CFD) simulations. Perhaps the most challenging bottleneck of automated

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http://dx.doi.org/10.1016/j.apm.2016.03.020

optimization of aerodynamic components is the high computational cost of accurate CFD simulations and the fact that conventional methods require large number of such simulations to yield a satisfactory design. Therefore, hands-on techniques (mostly based on parameter sweeps guided by engineering experience) are still widespread. These methods may allow for a design improvement in a reasonable timeframe; however, obtaining truly optimum designs is hardly possible. On the other hand, design automation using numerical optimization techniques is becoming more and more popular [3–6], which is partially due to the development of computationally efficient procedures, including gradient-based algorithms [7] exploiting adjoint sensitivities [8,9], as well as various types of surrogate-based optimization (SBO) techniques [10–15]. An important advantage of SBO over conventional algorithms is the possibility of efficient global optimization (for methods with data-driven surrogates), and a substantial reduction of the design cost compared to conventional methods (for algorithms exploiting physics-based surrogates) [12].

Real-world aerodynamic shape optimization problems involve several design objectives that need to be handled simultaneously. Example design criteria include drag minimization, lift maximization, reduction of the aeroacoustic noise, control of the cross-sectional area (or the profile thickness) or a pitching moment. In many cases, it is possible to select the primary objective (e.g., drag minimization) and optimize it explicitly while handling other objectives using constraints. Another option is objective aggregation (using, e.g., weighted sum methods) [39]. In either case, the original problem can be turned into a single-objective task. On the other hand, gaining more comprehensive data about the component of interest is usually desirable, in particular, in terms of possible trade-offs between conflicting design objectives. In such cases, a genuine multi-objective optimization becomes a necessity. Multi-objective design is typically based on the concept of Pareto optimality [16]. According to a Pareto dominance relation [16] utilized for design assessment two different designs may not be comparable to each other (i.e., equally good in the multi-objective sense). Consequently, the outcome of the optimization process is sought as a set of designs representing a so-called Pareto front, i.e., the designs that are globally non-dominated in a Pareto sense [16]. Population-based metaheuristic algorithms belong to the most popular solution approaches to multi-objective optimization problems. These include multi-objective evolutionary algorithms (MOEAs) [17–19,35]. The fundamental advantage of population-based methods is their capability of generating the entire Pareto set in a single algorithm run. However, such algorithms are characterized by very high computational complexity, which is due to processing large sets (populations) of candidate solutions. Consequently, direct multi-objective optimization of high-fidelity CFD simulation models is normally impractical with these methods.

Acceleration of aerodynamic shape optimization can be achieved by means of surrogate-based optimization (SBO) [10–15]. The key concept behind reducing the computational effort in SBO is to replace the direct handling of expensive high-fidelity models by iterative construction and re-optimization of their cheap replacements, referred to as surrogates. There are two major approaches to surrogate model construction: data-driven (also called function-approximation) and physics-based modeling. According to the first approach, the surrogate is obtained by approximating the sampled high-fidelity model data (e.g., using response surface approximations, Kriging, radial basis function, and support vector machines) [10,11,15]. In the second approach, the surrogate is a suitably corrected physics-based low-fidelity model [12–14,25,26]; which is a less accurate but a computationally cheaper representation of the high-fidelity model. The physics-based low-fidelity model can be constructed based on (i) simplified physics, (ii) coarser discretization, (iii) reduced solver convergence criteria, or (iv) any combination of (i)–(iii) [12,13]. The main advantage of data-driven models is their low evaluation cost; another advantage is their good analytical properties (smoothness). A fundamental disadvantage is the high cost of training data acquisition, which might be prohibitive for high-dimensional design spaces (with over 40 design variables). In the context of design optimization, surrogate model construction and optimization is often carried out iteratively, with additional data points allocated using appropriate infill criteria that may be focused on design space exploration (for global optimization) or design space exploitation (for local modeling) [11].

The most important advantage of physics-based surrogates is their good generalization capabilities (normally, superior to that of the data-driven models). It comes from the knowledge about the system of interest embedded in the underlying low-fidelity model. Consequently, a rather limited amount of high-fidelity data is needed to ensure a good predictive power of the surrogate. In case of aerodynamic components, the low-fidelity models are usually obtained by means of coarse-discretization CFD analysis [13] often combined with simplified physics representation and/or relaxed convergence criteria. Various techniques for low-fidelity model enhancement are available, including bridge functions [27–29], calibration [25,26], space mapping [20,21,30], shape-preserving response prediction [31,32], adaptive response correction [33], and adaptive response prediction [34]. A downside of physics-based surrogates is that their evaluation cost is much higher than for data-driven models (because of the necessity to evaluate the underlying low-fidelity models). Therefore, applicability of physics-based SBO techniques is usually limited to low- and medium-dimensional design spaces where the cost of multiple low-fidelity model evaluations (while optimizing the surrogate) does not become a dominant contributor of the overall optimization cost. One of the most popular multi-fidelity SBO techniques is space mapping (SM) [20,21,30]. A SM surrogate is a composition of the low-fidelity model and simple, usually linear, transformations that re-shape the model domain (input-like SM) [21,30] to correct the model response (output-like SM) [20], or change the overall model properties (implicit-like SM) [21,30].

In this paper, we demonstrate surrogate-assisted multi-objective constrained optimization of aerodynamic components using a combination of data-driven and physics-based models. Our design approach exploits variable-fidelity CFD models, auxiliary data-driven and response surface approximation (RSA) models (both global and local), as well as multi-objective evolutionary algorithms (MOEAs). The data-driven model (here, Kriging) is constructed using sampled low-fidelity CFD