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Expected drag minimization for aerodynamic design optimization based on aircraft operational data

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A B S T R A C T

Aerodynamic shape optimization must consider multiple flight conditions to obtain designs that perform well in a range of situations. However, multipoint studies have relied on heuristic choices for the flight conditions and associated weights. To eliminate the heuristics, we propose a new approach where the conditions and weights are based on actual flight data. The proposed approach minimizes the expected drag value given by a probability density function in the space of the flight conditions, which can be estimated based on data from aircraft operations. To demonstrate our approach, we perform drag minimizations of the Aerodynamic Design Optimization Discussion Group Common Research Model wing, for both single-point and multipoint cases. The multipoint cases include five- and nine-point formulations, some of which approximate the expected drag value over the specified flight-condition probability distribution. We conclude that if we focus on the resulting design, a five-point optimization with points based on the flight-condition distribution and equal weights is sufficient to obtain an optimal shape with respect to the expected drag value. However, if it is important to retain the accuracy of the expected drag integration at each optimization iteration, we recommend the proposed approach.

1. Introduction

Prior to 1960, the aircraft design process relied mainly on flow visualization techniques and wind-tunnel experiments using pressure and force measurements [18]. Computational aerodynamics was brought about by radical improvements in numerical algorithms coupled with advances in computing technologies. Early investigations of aerodynamic shape optimization include those by Hicks et al. [15], Hicks and Henne [14], and Constentino and Holst [5] in the late 1970s and early 1980s. In these early efforts, full potential flow solvers were coupled with conjugate gradient optimization algorithms to enable the automated design of airfoils and wing shapes. Major advances in aerodynamic shape optimization occurred in the late 1980s and early 1990s, when adjoint methods made it possible to efficiently compute shape gradients [18,16,39,40]. With adjoint methods, the cost of computing the gradients became independent of the number of design variables, which enabled detailed optimization based on high-fidelity models.

The first adjoint-based investigations focused on drag minimization at a single flight condition [2,32,36,38]. Single-point optimized designs suffer performance degradations at off-design conditions [18,4]. The drag polar for single-point designs features a cusp because the optimization eliminates the shock at the nominal flight condition, while making the shock much stronger at off-design conditions. This cusp tends to become more prominent as the number of design variables increases [9].

Because of the limitations of single-point optimizations, it is necessary to consider multiple flight conditions in aerodynamic shape optimization. Jameson [18] pioneered this effort, seeking a compromise design by taking the sum of the cost functions for several design points. The design problem was formulated as a control problem, where the cost function measured the wave drag and the deviation from a desired pressure distribution. The wave drag was added to the cost function with a multiplier, which could be varied to alter the trade-off between drag reduction and deviation from the desired distribution.

The most common approach in multipoint formulations has been a composite objective function, typically expressed as a weighted sum of the drag coefficient over several flight conditions [33]. To emulate the different flight conditions, Reuther et al. [37] varied the lift coefficient in an unconstrained transonic optimization, and Drela [9] varied lift coefficient for a low Reynolds number airfoil optimization. In some airfoil optimization problems, the Mach numbers in the multipoint formulation were varied [9,33]. Other authors went a step further and varied both Mach num-

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ber and lift coefficient [18,11,4]. Multipoint optimization results have been shown to be more robust and thus more practical than those of single-point optimizations [9,18,37,4,30,21]. Furthermore, the optimizer typically increases the drag-divergence Mach numbers [9,21].

Motivated by the desire to compare the various aerodynamic design optimization methods, researchers formed the Aerodynamic Design Optimization Discussion Group (ADODG),[1] which is sponsored by the American Institute of Aeronautics and Astronautics (AIAA). The ADODG cases range from a 2D airfoil inviscid drag minimization to a full-configuration multipoint drag minimization based on the solution of the Reynolds-averaged Navier–Stokes equations (RANS). For the inviscid airfoil optimization problem, Méheut et al. [31] performed gradient-based single-point and multipoint aerodynamic optimizations. They performed cross-validation to compare six different optimized shapes that were produced using different grid types, solvers, and postprocessing procedures. For the Common Research Model (CRM) wing drag minimization using RANS, Méheut et al. [31] showed that the two three-point optimization problems yielded a consistent performance improvement, and Lee et al. [23] showed similar trends. Lyu et al. [30] and Kenway and Martins [21] compared the single-point and multipoint optimizations of the CRM wing with five to nine points; they quantified the robustness of the various cases by plotting contours of the performance over the flight-condition space.

The goal of this paper is to address two major questions in multipoint aerodynamic design optimization: (1) Which flight conditions should be considered, and (2) how much weight should be attributed to each of these conditions? Although designers generally know the nominal flight condition based on the particular aircraft mission, as well as the likely range of the flight conditions, it is not clear how to translate this information into a multipoint drag minimization formulation. In previous work, the multipoint formulation has been based on common sense or prior design experience, which is somewhat arbitrary [4,9]. Lyu et al. [30] and Kenway and Martins [20] assigned equal weights in a multipoint drag minimization with five flight conditions, which has been a popular approach in multipoint optimization. Buckley and Zingg [3] employed an integration rule to formulate a weighted-integral objective function in their multipoint airfoil optimization. Each flight condition was assigned a weighting function based on design experience. For high-fidelity aerostructural design optimization, Liem et al. [24] chose the flight conditions to be considered and the associated weights based on a histogram of the aircraft missions. Gallard et al. [12] analyzed the linear dependencies between the shape gradients and computed a minimal set of flight conditions.

We propose a new formulation that selects the flight conditions based on a flight-condition probability density function (PDF). When this PDF is used, the expected performance provides a first-moment measure of the real-world performance. The exact PDF, however, is typically unknown. Therefore, we replace the PDF with a distribution generated based on publicly available flight mission data. To demonstrate the proposed approach, we perform our drag minimizations for the ADODG CRM wing geometry, for the ADODG single-point and multipoint cases. We also perform a series of studies to compare the various multipoint approaches and to analyze the effect of the number of flight conditions considered. In the proposed formulation, we minimize the expected performance over all flight conditions, accounting for the time that is spent at each condition.

We describe the basic optimization problem and the numerical tools used in Section 2. Then, in Section 3 we explain the optimization formulations to be compared, including the proposed expected drag minimization approach. We then discuss our numerical results and findings in Section 4, and Section 5 provides concluding remarks.

2. Aerodynamic design optimization approach

This section describes the aerodynamic design optimization approach, including the numerical tools, the overall optimization problem formulation (objective function, design variables, and constraints), and the baseline geometry that is optimized. The overall approach and geometry have been previously presented by Lyu et al. [30] and Kenway and Martins [21], but we add the new formulation for the expected drag minimization. The baseline wing geometry and specifications follow those given by the ADODG, consisting solely of the wing from the CRM full configuration. The single-point optimization benchmark has been previously solved by various groups [30,31,42], and the baseline and optimized geometries and meshes are provided by Lyu et al. [30].[2] Multipoint optimization results for this case are presented by Kenway and Martins [21].

2.1. Multilevel optimization acceleration

To reduce the computational cost of the high-fidelity multipoint optimization, we first perform the optimization on a coarse grid and then find the final solution on a fine grid, following the work of Lyu et al. [30] and Kenway and Martins [21]. The coarse result is used as the starting point for the optimization on the fine grid. This multilevel approach accelerates the optimization process because iterations on the coarse grid are faster and cheaper. However, it is important to ensure that the coarse grid captures the main characteristics of the flow, e.g., the shock strength and location. The geometries for the coarse and fine meshes used in this optimization are briefly described next.

2.2. Computational meshes

We use two different meshes in the optimization: a coarse mesh with 450 k cells (L2) and a fine mesh with 3.5 M cells (L1), as shown in Fig. 1. The multiblock meshes are generated using a hyperbolic mesh generator and exhibit an O-type topology. Kenway and Martins [21] presented a convergence study for these meshes as well as a finer mesh with over 28 M grid cells (L0) and an extrapolated zero-mesh spacing. The L0 mesh is not considered in this work because the optimization is too expensive [30]. The convergence study showed that the drag-count difference between the L1 mesh and the zero-mesh spacing is $\mathcal{O}(1)$, an error of 1.5%. The difference in drag (when comparing the baseline and optimized designs) is $\mathcal{O}\left(10^{-2}\right)$ drag counts, corresponding to a relative error of 0.4%. Thus, the L1 mesh was considered a good compromise between computational cost and accuracy.

2.3. Optimization problem formulation

The optimization problem is formulated as a drag minimization, subject to aerodynamic and geometric constraints. The formulation is similar to the ADODG CRM wing single-point and multipoint benchmarks [30,21], and it is summarized in Table 1. It differs from the ADODG benchmarks only in the formulation of the objective function.

[1] AIAA Aerodynamic Design Optimization Discussion Group, https://info.aiaa.org/tac/ASG/APATC/AeroDesignOpt-DG/default.aspx (accessed 11 July 2016).

[2] http://mdolab.engin.umich.edu/content/aerodynamic-design-optimization-workshop (Accessed January 14, 2017).