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On the influence of optimization algorithm and initial design on wing aerodynamic shape optimization

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ABSTRACT

Aerodynamic shape optimization is a useful tool in wing design, but the impact of the choice of optimization algorithm and the multimodality of the design space in wing design optimization is still poorly understood. To address this, we benchmark both gradient-based and gradient-free optimization algorithms for computational fluid dynamics based aerodynamic shape optimization problems based on the Common Research Model wing geometry. The aerodynamic model solves the Reynolds-averaged Navier–Stokes equations with a Spalart–Allmaras turbulence model. The drag coefficient is minimized subject to lift, pitching moment, and geometry constraints, with up to 720 shape variables and 11 twist variables for two mesh sizes. We benchmark six gradient-based and three gradient-free algorithms by comparing both the accuracy of the optima and the computational cost. Most of the optimizers reach similar optima, but the gradient-based methods converge to more accurate solutions at a much lower computational cost. Since multimodality and nonsmoothness of the design space are common arguments for the use of gradient-free methods, we investigate these issues by solving the same optimization problem starting from a series of randomly generated initial geometries, as well as a wing based on the NACA 0012 airfoil with zero twist and constant thickness-to-chord ratio. All the optimizations consistently converge to practically identical results, where the differences in drag are within 0.05%, and the shapes and pressure distributions are very similar. Our overall conclusion is that the design space for wing design optimization with a fixed planform is largely convex, with a very small flat region that is multimodal because of numerical errors. However, this region is so small, and the differences in drag so minor, that the design space can be considered unimodal for all practical purposes.

1. Introduction

The aerodynamic shape optimization of transonic aircraft wings has long been a difficult and expensive task. Small changes in shape can have a large impact on aerodynamic performance, and therefore the optimization requires hundreds of design variables [1]. Thus, aerodynamic shape optimization based on computational fluid dynamics (CFD) can be costly.

Aerodynamic shape optimization problems can be solved with gradient-based or gradient-free methods. Gradient-based methods are preferable when an efficient gradient evaluation is available [2]. The application of gradient-based optimization to this problem was pioneered in the 1970s, with gradients computed using finite-difference approximations [3]. As the number of design variables increases, the cost of this computation becomes prohibitive. Adjoint methods were developed to address this issue; they provide a way to evaluate the gradients with a cost that is independent of the number of design variables. Peter and Dwight [4] reviewed these and other methods for computing aerodynamic shape derivatives. Martins and Hwang [5] generalized the adjoint method and discussed its connection to other derivative evaluation methods.

Pironneau pioneered the use of adjoint-based gradient calculation in airfoil profile optimization by deriving the adjoint for the Stokes equations [6] and for the incompressible Euler equations [7]. Jameson [8] then made the adjoint method useful in the design of transonic airfoils by developing an adjoint for inviscid compressible flow. The aerodynamic design of transonic wings requires a model that can represent the shock-wave boundary layer interaction, since there is a strong nonlinear coupling between airfoil shape, wave drag, and viscous effects. Therefore, transonic wing optimization based on the Euler equation performs poorly when analyzed in turbulent flow [9,10].

The adjoint method was later extended to the compressible Navier–Stokes equations with turbulence models, making it possible to solve practical aerodynamic design problems. Jameson et al. [11] optimized a wing-body configuration modeled with the

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compressible Navier–Stokes equations using a continuous adjoint approach. They used a 590k-cell mesh and achieved a shock-free solution at Mach 0.86. Anderson and Venkatakrishnan [12] optimized airfoil shapes using a discrete adjoint that included the linearization of the Spalart–Allmaras turbulence model. Nielsen and Anderson [13] further extended the approach to the three-dimensional Reynolds-averaged Navier–Stokes (RANS) equations. They achieved an 8% drag reduction for the ONERA M6 wing with thickness and camber design variables at two chordwise locations. Dwight and Brezillon [14] and [15] optimized the DLR-F6 wing-body configuration using a RANS solver and a discrete adjoint, achieving a 10-count drag reduction by varying 96 design variables.

Lyu et al. [9] developed a discrete adjoint for the RANS equations and Spalart–Allmaras turbulence model using automatic differentiation to construct the required derivative terms. They used this adjoint implementation to perform aerodynamic shape optimizations of the ONERA M6 wing with 192 design variables for both the Euler and RANS models. They observed significant differences between the optimal shapes obtained with Euler and RANS, which emphasized the importance of including the viscous compressible effects in transonic aerodynamic shape design. The framework developed by Lyu et al. [9] has since been used in a variety of applications and studies [16–20]. Telidetzki et al. [21] performed a series of high-fidelity aerodynamic shape optimizations using a parallel Newton–Krylov–Schur method based on the Euler or RANS equations. They demonstrated the effectiveness of the gradient-based aerodynamic shape optimization methodology, obtaining significant drag reductions in all their cases. Chen et al. [18] performed RANS-based aerodynamic shape optimization on a common research model (CRM) wing-body-tail configuration. Elham [22] presented a quasi-three-dimensional method for wing aerodynamic analysis and drag prediction. They used a combination of the adjoint method, the chain rule for differentiation, and automatic differentiation to compute the gradients. Drela [23,24] performed a constrained shape optimization on two-dimensional airfoils, using the Newton-based direct method to generate sensitivity information from inviscid Euler equations.

The gradient-free methods are generally easier to implement and use, and several of them are geared toward finding global optima. However, they incur a higher computational cost compared with gradient-based methods, especially when costly high-fidelity simulations are involved. Genetic algorithms (GA) and their derivatives are among the most widely used gradient-free methods today [25,26]. GAs are particularly suitable for problems with discontinuous objective functions, discrete design variables, or multiple local optima, i.e., multimodal functions. He and Agarwal [27] performed aerodynamic shape optimization of a wind turbine blade airfoil using a multiobjective GA.

There have been a few studies of the performance of different optimizers for aerodynamic shape optimization. Zingg et al. [28] compared gradient-based methods and a GA in aerodynamic airfoil optimization. They found that the GA used 5 to 200 times more function evaluations than the gradient-based method to find the optimum design. They suggested that GAs are better suited for low-fidelity preliminary design, while gradient-based methods are preferable for high-fidelity detailed design. Obayashi and Tsukahara [29] compared a gradient-based method with simulated annealing and a GA on an airfoil lift maximization problem. The GA required the highest number of function evaluations but achieved the best design.

Gradient-based methods can converge to a local minimum when the objective or constraint functions involved are multimodal. Holst and Pulliam [30] and Sasaki et al. [31] both used GAs for airfoil and wing optimization cases, and they found no evidence of multimodality. Chernukhin and Zingg [32] compared the performance of a gradient-based method, a GA, and a hybrid approach on a two-dimensional airfoil shape optimization and three-dimensional wing optimizations based on the Euler equations. While they concluded that the airfoil design problem was unimodal, they found multiple local optima for the wing case. In addition to twist and airfoil shape variables, the wing optimization cases included planform variables (chord variation, sweep, and dihedral). The physical significance of these multiple local optima is compromised by the fact that no viscous effects were considered. Therefore, variations in surface area and local chord do not affect drag as they would in the real design problem, leading to a design space that is completely different from the true physical one. Furthermore, dihedral has a weak influence on the aerodynamic forces, and letting dihedral vary without a penalty on the viscous drag leads to designs that are not realistic. A more recent study by Bons et al. [33] has started to address multimodality with respect to planform variables as well.

Lyu et al. [10] solved the AIAA Aerodynamic Design Optimization Discussion Group (ADODG) CRM wing using a gradient-based RANS solver.[1] This problem involves a lift-constrained drag minimization, where the design variables are the spanwise twist distribution and airfoil shapes. They achieved a 8.5% drag reduction using a multilevel optimization approach, and they addressed multimodality concerns by starting the same optimization problem from randomly generated initial geometries. They observed multiple local optima around a small region, but these were close together and exhibited similar drag values. Other researchers have also tackled this problem. Dumont and Méheut [34] analyzed the optimal geometries obtained by Lyu et al. [10] with their solver and independently verified the performance of this design, adding further insight using their drag decomposition tool. Lee et al. [35] obtained similar results and did not report multiple local minima for this problem. Shi-Dong et al. [36] also solved the ADODG CRM wing and concluded that all the results point to a unimodal design space for the CRM wing. Finally, Koo and Zingg [37] performed another study of the ADODG CRM case, and they concluded that it does not have multiple local optima.

Motivated by the work cited above, our goals are twofold: we compare various gradient-based and gradient-free optimizers, and we examine the issue of multiple local minima more closely. We focus on the ADODG CRM design optimization mentioned above, which does not include planform design variables [10]. Once the planform is allowed to vary, many other issues arise, and it is difficult to obtain a meaningful design optimization problem without considering other aircraft design aspects, such as structural weight and stability. We benchmark several optimization algorithms using a wing twist optimization problem and a wing shape problem. Six of the optimizers are gradient-based and three are gradient-free.

To examine the issue of multiple local minima, we perform various optimizations starting from several random initial points. We also use an initial geometry that has the planform of a CRM wing but with zero initial twist and a NACA 0012 airfoil. We go beyond the study of Lyu et al. [10] by trying different variations in the design variable set. We also look more closely at the cluster of close local minima by using even smaller convergence tolerances and by performing a grid refinement.

2. Numerical tools

We now describe the numerical methods and tools that are used for this study. These tools are a subset of the multidisciplinary design optimization (MDO) framework of aircraft configurations with high fidelity (MACH) [38]. MACH can perform the si-

[1] https://info.aiaa.org/tac/ASG/APATC/AeroDesignOpt-DG.