CFD-based Aircraft Design Optimization

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ABSTRACT
CFD-based aircraft design optimization has matured significantly in the last few years thanks to the refinement of CFD solvers, mesh deformation, sensitivity computation, and optimization tools. We review recent developments for each of these components, and present open-source tools recently made available for aerodynamic shape optimization. A variety of applications is presented, including the optimization of a supercritical airfoil starting from a circle, a web application that optimizes airfoils within a few seconds, aircraft aerodynamic and aerostructural optimization, and aeropropulsive optimization.

1. Introduction

While CFD-based aircraft design optimization was introduced decades ago, several challenges have prevented its widespread use in industry: (1) CFD solver robustness, (2) scalability with number of design variables, (3) efficient and accurate gradient computation, (4) robust mesh deformation, (5) practical industrial constraints, and (6) inclusion of aircraft design disciplines other than aerodynamics. This paper and associated keynote presentation reviews the efforts at the University of Michigan MDO Lab to address these challenges. Challenges 1 through 5 pertain more specifically to aerodynamic shape optimization, while Challenge 6 broadens the scope to aircraft design optimization.

2. Review of Developments

2.1. CFD Solver Robustness

Integrating CFD in a numerical optimization cycle demands additional requirements on the robustness of the CFD solver. The reason is that if the CFD solver fails to converge during an optimization iteration, it interrupts the optimization process, which must then be restarted. In addition, the CFD solver is more likely to fail during optimization because the optimizer does not share the intuition of a designer, and will provide bad design shapes to the CFD solver. Therefore, it is crucial that the CFD solver be able to solve for designs that might not make much sense.

To this end, we developed an approximate Newton–Krylov approach for robustly solving the Reynolds-averaged Navier–Stokes (RANS) equations for a wide range of geometries [1]. We implemented this approach in the ADflow CFD solver. [1] This solver has been demonstrated on a number of applications [2, 3, 4], including an airfoil shape optimization problem that started from a circular shape and converged to a supercritical airfoil [5].

2.2. Scaling with Number of Design Variables

Aerodynamic shape optimization requires a large number of shape design variables to achieve the best possible performance (about 200 variables for wing design [6]). Only gradient-based optimization algorithms can handle this number of variables efficiently. Therefore, we use SNOPT, a gradient-based algorithm that implements sequential quadratic programming and can handle nonlinear constraints [7], through the pyOptSparse wrapper [8].

2.3. Gradient Computation

A good gradient-based algorithm is not sufficient; it is also necessary for the gradients to be computed accurately and efficiently. Adjoint methods compute gradients with respect to large numbers of design variables efficiently, but require a long development time. To address these issues, we have developed a general recipe for adjoint method implementation [9], which we have applied to both ADflow and OpenFOAM [10].

Even though gradient-based optimization with the adjoint method enables efficient aerodynamic shape optimization, it still requires hours in a parallel computer to perform the full optimization. To make aerodynamic shape optimization more accessible, we have developed a web-based data-driven approach to airfoil design that takes just a few seconds for optimization [11]. [2]

2.4. Robust Mesh Deformation

When the optimizer decides on a new set of design variables, we must perturb the original CFD mesh to conform to the new shape. For the same reasons mentioned in Sec. 2.1., this process must be robust. To address this need, we developed an efficient analytic inverse-distance method for volume mesh deformation [3], which was also crucial in the airfoil optimization starting from a circle [5].

2.5. Practical Industrial Constraints

From working closely with industry, we identified several constraints that had to be enforced that required new formulations. Geometric constraints, such as variable fuel volume, wing thickness, leading edge radius, and trailing edge angle constraints are linear and were relatively easy to implement [6]. To consider these constraints implicitly, it is also possible to use a data-driven approach [12].

Other constraints are highly nonlinear and require much more development effort, such as buffet and flutter. We developed a constraint formulation for buffet

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[1] `https://github.com/mdolab/adflow`

[2] `http://webfoil.engin.umich.edu`

[3] `https://github.com/mdolab/idwarp`

based on a separator sensor function [13] and made developments towards constraining flutter [14, 15, 16].

2.6. Multidisciplinary Design Optimization

Aerodynamics is not enough to achieve high aircraft performance. One of the most important other disciplines is structures, which couples with aerodynamics to determine the wing performance. We have developed a coupled-adjoint approach [17] to perform the simultaneous design optimization of aerodynamic shape including wing planform variables and structural sizing [18, 19, 20, 21, 22]. This coupled-adjoint approach has also been generalized to an arbitrary number and type of disciplines [23].

Other multidisciplinary design optimization (MDO) capabilities include the simultaneous optimization of aerodynamic shape and propulsion system [24], and optimization of wing, mission, and allocation [25, 26].

3. Concluding Remarks

This paper is only an outline of the methods developed in the MDO Lab to enable CFD-based aircraft design optimization. The cited references provide many more details on the methods themselves and the applications.

Gradient-based optimization combined with efficient gradient computation via adjoint methods have been one of the keys that made this work possible. Working closely with industry has been invaluable in identifying the challenges that needed to be solved for practical applications.

Given the contributions above and the fact that much of the code that we developed is available under open-source licenses, we expect that the use CFD-based optimization will continue to increase and become more widespread than ever.

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