Perspectives on Aerodynamic Design Optimization

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with contributions from Nicolas Bons, Benjamin Brelje, Ping He, Gaetan Kenway, Zhoujie Lyu, Charles Mader, Ney Secco, Anil Yildirim, and Yin Yu

http://mdolab.engin.umich.edu

Link to full paper AIAA 2020-0043
State of the art in aircraft MDO is many disciplines with low fidelity, or one or two with high fidelity.
Before doing high-fidelity aerostructural optimization well, we need to understand aerodynamic shape optimization.
MACH-Aero is an open-source framework with all the tools required for aerodynamic design optimization.

All modules have a Python interface, which is used to couple them.
CFD Solvers: ADflow and OpenFOAM

Both of these CFD solvers are open source

https://github.com/mdolab/adflow
ADflow is a RANS solver that includes an adjoint method for efficient derivative computation

- Parallel, finite-volume, cell-centered, overset, solver for RANS equations
- Approximate Newton–Krylov method for speed and robustness
- Spalart–Allmaras turbulence model
- Discrete adjoint developed using automatic differentiation (AD) to evaluate partial derivatives
- Full-turbulence adjoint

ANK is extremely robust

CRM at 90 deg and M=0.85
Optimizing an airfoil starting from a circle

Mach = 0.734
Minimize $C_d$
\[ s.t. \ C_l=0.824, \ C_m>-0.092 \]
Major Iteration: 0
Optimizations often try intermediate crazy designs

He, Li, Mader, Yildirim, Martins. Robust aerodynamic shape optimization—from a circle to an airfoil. Aerospace Science and Technology, 2019
OpenFOAM can be used interchangeably in MACH-Aero using the same interface

- Pressure based solver better suited for low speed applications
- Can handle unstructured meshes
- Slower than ADflow, but still fast enough for optimization
Geometry Parametrization: pyGeo or OpenVSP

1: Pre-processing
2: Baseline design
3: Updated FFD displacement
4: Updated design surface coordinates
5: Updated mesh
6: State variables
7: Values of objectives and constraints
8: Optimized design

https://github.com/mdolab/pygeo
pyGeo parametrizes geometries using free-form deformation volumes
Mesh Deformation: IDWarp

1: Pre-processing
2: Baseline design
3: FFD points
4: Updated design surface coordinates
5: Updated mesh
6: State variables
7: Values of objectives and constraints
8: Optimized design

https://github.com/mdolab/idwarp
IDWarp deforms the volume mesh based on new surface mesh.
Optimization Algorithms

1: Pre-processing
2: Baseline design
3: FFD points
4: Volume mesh
5: CFD solver
6: State variables
7: Values of objectives and constraints
8: Optimized design
3: Updated FFD deformation
4: Volume mesh deformation
5: Updated mesh
6: Adjoint solver

https://github.com/mdolab/pyoptsparse
PyOptSparse and OptView facilitate the use of optimization algorithms

- Python wrapper for various optimizers
- Supports both gradient-based and gradient-free optimizers
- Facilitates comparisons
- Includes OptView for history visualization
- Open source

Derivative Computation

1: Pre-processing

2: Baseline design

2, 7→3: Optimizer

3: FFD points

3: Updated FFD displacement

4: Volume mesh

4: Updated design surface coordinates

4: Volume mesh deformation

5: Updated mesh

5: CFD solver

6: State variables

6: Adjoint solver

7: Values of objectives and constraints

7: Derivatives of objectives and constraints

7: Geometric constraints and derivatives
We divide the adjoint implementation into solver-agnostic and solver-specific parts.

\[
\frac{df}{dx} = \frac{\partial f}{\partial x} - \frac{\partial f}{\partial y} \left[ \frac{\partial R}{\partial y} \right]^{-1} \frac{\partial R}{\partial x}
\]

- **Solver-agnostic implementation**
  - Partial derivative computation
  - Adjoint equation solution

- **Solver-specific implementation**
  - Elements in \( R \) and \( y \)
  - Sparsity pattern for \( \frac{\partial R}{\partial y} \)
  - Specific form for \( R(y, x) \)

Kenway, Mader, He, and Martins. *Effective adjoint approaches for computational fluid dynamics.* Progress in Aerospace Sciences, 2019
DAFoam framework can implement the adjoint approach for any OpenFOAM solver.
## ADODG benchmark cases

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Drag minimization of the RAE 2822 in transonic viscous flow</td>
<td>He et al. [2019c] Carrier et al. [2014], Telidetzki et al. [2014], Bisson and Nadarajah [2015], Poole et al. [2015], Gariepy et al. [2015], Lee et al. [2015], Zhang et al. [2016], Ren et al. [2016], Masters et al. [2017], Amrit, Du, Thelen, Leifsson, and Koziel [2017a]</td>
</tr>
<tr>
<td>3</td>
<td>Lift-constrained drag minimization of a rectangular wing in inviscid subsonic flow</td>
<td>Telidetzki et al. [2014], Bisson and Nadarajah [2015], Lee et al. [2015]</td>
</tr>
<tr>
<td>4</td>
<td>Lift-constrained drag minimization of the CRM wing in viscous flow</td>
<td>Lyu, Xu, and Martins [2014], Lyu, Kenway, and Martins [2015], Yu, Lyu, Xu, and Martins [2018], Telidetzki et al. [2014], Lee et al. [2015], Bisson and Nadarajah [2015], Méheut, Dumont, Carrier, and Peter [2016], Amrit et al. [2017b]</td>
</tr>
<tr>
<td>5</td>
<td>Lift-constrained drag minimization of the CRM wing-body-tail configuration at flight Reynolds number</td>
<td>Chen, Lyu, Kenway, and Martins [2016], Méheut et al. [2016]</td>
</tr>
<tr>
<td>6</td>
<td>Multimodal subsonic inviscid lift-constrained drag minimization</td>
<td>Bons, He, Mader, and Martins [2019], Streuber and Zingg [2017]</td>
</tr>
</tbody>
</table>
Optimization of transonic wings requires at least RANS models.

ADODG benchmark Case 4 is based on the Common Research Model (CRM) wing.
Wave drag is eliminated, and while achieving an elliptical lift distribution

Optimization takes 6 hours using 128 cores

- Fuselage and tail are deleted from original CRM.
- A series of ASO results of the CRM wings for Aerodynamic Design Optimization Workshop are presented.
- RANS optimized results are significantly different from Euler results.
- Efficient RANS adjoint implementation allows reasonable computational time.
Optimization eliminated outboard trailing edge separation
Grid convergence verifies the accuracy we capture the correct design trends.

Table 3. The drag differences between the baseline and optimized meshes are nearly constant for each grid level.

Two very different starting points: CRM baseline vs. NACA0012 airfoil with no twist

- Optimized Original CRM
  - \( C_D = 0.02098 \)
  - \( C_L = 0.499 \)
  - \( C_M = -0.169 \)

- Optimized NACA0012 CRM
  - \( C_D = 0.01757 \)
  - \( C_L = 0.259 \)
  - \( C_M = -0.074 \)
Now, let’s start with an even worse design!

‣ Fuselage and tail are deleted from original CRM.

‣ A series of ASO results of the CRM wings for Aerodynamic Design Optimization Workshop are presented.

‣ RANS optimized results are significantly different from Euler results.

‣ Efficient RANS adjoint implementation allows reasonable computational time.
Three random geometries converged to similar designs

- Fuselage and tail are deleted from original CRM.
- Root is

A series of ASO results of the CRM wings for Aerodynamic Design Optimization Workshop are presented.

- RANS optimized results are significantly different from Euler results.
- Efficient RANS adjoint implementation allows reasonable computational time.
Multiple random starting points in Case 2 converge to the same airfoil shape, so the design space is most likely unimodal.
“How do you know that you found the global minimum?”

1. It is impossible to prove that we have found the global optimum.

2. We only need to find a second local minimum to disprove it.

Therefore:

An optimum should be assumed to be the global one until proven otherwise
“Have you considered using a *global* optimizer like a genetic algorithm?”
All geometries and grids are available with the AIAA Journal paper as supplemental data.


Aerodynamic Shape Optimization Investigations of the Common Research Model Wing Benchmark

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ABSTRACT

Despite considerable research on aerodynamic shape optimization, there is no standard benchmark problem allowing researchers to compare results. This work addresses this issue by solving a series of aerodynamic shape optimization problems based on the Common Research Model wing benchmark case defined by the Aerodynamic Design Optimization Discussion Group. The aerodynamic model solves the Reynolds-averaged Navier-Stokes equations with a Spalart-Allmaras turbulence model. A gradient-based optimization algorithm...
Drag decomposition of this result by ONERA shows low spurious drag

<table>
<thead>
<tr>
<th>CD components (d.c.)</th>
<th>Ref. CRM (CL=0.503)</th>
<th>Opt. CRM (CL=0.505)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDw</td>
<td>8.47</td>
<td>-0.18</td>
</tr>
<tr>
<td>CDvp</td>
<td>36.49</td>
<td>30.80</td>
</tr>
<tr>
<td>CDi</td>
<td>97.45</td>
<td>96.35</td>
</tr>
<tr>
<td>CDfriction</td>
<td>59.32</td>
<td>58.58</td>
</tr>
<tr>
<td>CDfarfield</td>
<td>201.73</td>
<td>185.55</td>
</tr>
<tr>
<td>CDnearfield</td>
<td>202.26</td>
<td>187.13</td>
</tr>
<tr>
<td>CDspurious</td>
<td>0.53</td>
<td>1.58</td>
</tr>
</tbody>
</table>
Drag decomposition by ONERA shows the optimization trade-offs
The ADODG introduced new multipoint benchmark cases

Resulting wing design compromises optimally between flight conditions.
Drag coefficient is 2 counts higher at nominal condition

Single-point optimized

\[ C_D = 0.019574 \]
\[ C_L = 0.5000 \]
\[ C_M = -0.1700 \]

Multi-point optimized

\[ C_D = 0.019787 \]
\[ C_L = 0.5000 \]
\[ C_M = -0.1700 \]
The optimum wing for the 9-point case has a more reasonable airfoil thickness and leading edge curvature.
ML/cD contours show the off-design performance of the optimized wings.
3D-printed models colored with $C_p$ distributions
Case 5 is the full CRM configuration with rotating tail to trim at all flight conditions.

With Case 5, we studied the effect of tail trim on optimizations.

### Case Comparisons

<table>
<thead>
<tr>
<th>Case</th>
<th>$C_D$</th>
<th>$C_{MY}$</th>
<th>Tail shape</th>
<th>Tail rotation</th>
<th>$C_{MY} = 0$ constraint</th>
<th>Configuration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.02907</td>
<td>-0.0410</td>
<td></td>
<td></td>
<td></td>
<td>Wing-body–tail</td>
</tr>
<tr>
<td>Trimmed baseline</td>
<td>0.02947</td>
<td>0.0</td>
<td></td>
<td></td>
<td></td>
<td>Wing-body–tail</td>
</tr>
<tr>
<td>1</td>
<td>0.02804</td>
<td>-0.0780</td>
<td></td>
<td></td>
<td></td>
<td>Wing-body–tail</td>
</tr>
<tr>
<td>2</td>
<td>0.02826</td>
<td>0.0</td>
<td></td>
<td></td>
<td></td>
<td>Wing-body–tail</td>
</tr>
<tr>
<td>3</td>
<td>0.02838</td>
<td>0.0</td>
<td></td>
<td></td>
<td></td>
<td>Wing-body–tail</td>
</tr>
<tr>
<td>4</td>
<td>0.02840</td>
<td>0.0</td>
<td></td>
<td></td>
<td></td>
<td>Wing-body–tail</td>
</tr>
<tr>
<td>5</td>
<td>0.02796</td>
<td>-0.1326</td>
<td></td>
<td></td>
<td></td>
<td>Wing-body–tail</td>
</tr>
<tr>
<td>6</td>
<td>0.02823</td>
<td>0.0</td>
<td></td>
<td></td>
<td></td>
<td>Wing-body–tail</td>
</tr>
</tbody>
</table>
For Case 5, we developed a new buffet onset constraint based on a separation sensor.

\[
\cos \theta = \frac{\vec{V} \cdot \vec{V}_\infty}{|\vec{V}| |\vec{V}_\infty|} < 0 \\
\bar{\chi} = \frac{1.0}{1.0 + e^{2k(\cos \theta + \lambda)}} \\
S_{\text{sep}} = \frac{1}{S_{\text{ref}}} \int_S \bar{\chi} \, dS
\]

The approach correlates well with both another numerical method and experimental data.
The buffet constraint is essential to achieve a practical design.

No buffet constraint single point

Buffet constrained multipoint

Case 6 was developed to explore the possibility of multimodality in wing design optimization

- With Euler alone, there are an infinite number of combinations of chord and twist distributions for the same minimum drag
- What about with RANS?
Skin friction on its own is multimodal, but this multimodality decreases with lift

Bons, He, Mader, and Martins. Multimodality in aerodynamic wing design optimization. AIAA Journal, 2019
We verified this using the panel code with skin friction estimate from OpenAeroStruct.

Decreasing multimodality

\[
\begin{align*}
C_L = 0.0 & \quad C_L = 0.1 & \quad C_L = 0.2 & \quad C_L = 0.5 & \quad C_L = 0.8 \\
\text{Planform} & \quad \text{Planform} & \quad \text{Planform} & \quad \text{Planform} & \quad \text{Planform} \\
\text{Normalized Lift Distribution} & \quad \text{Normalized Lift Distribution} & \quad \text{Normalized Lift Distribution} & \quad \text{Normalized Lift Distribution} & \quad \text{Normalized Lift Distribution} \\
C_{D,i} & \quad C_{D,i} & \quad C_{D,i} & \quad C_{D,i} & \quad C_{D,i} \\
0.0 & \quad 5.3 & \quad 20.8 & \quad 128.8 & \quad 330.0 \\
C_{D,v} & \quad C_{D,v} & \quad C_{D,v} & \quad C_{D,v} & \quad C_{D,v} \\
91.5 & \quad 91.5 & \quad 91.5 & \quad 91.5 & \quad 91.5
\end{align*}
\]
Also used OpenAeroStruct to quickly explore the twist-dihedral design space

One optimal design found when chord and sweep distributions are constrained to be linear.

Bons, He, Mader, and Martins. Multimodality in aerodynamic wing design optimization. AIAA Journal, 2019
Webfoil is an online airfoil database that will also optimize airfoils in a few seconds.

http://webfoil.engin.umich.edu
Can we optimize from a sphere to a wing?

## Applications of MACH beyond ADODG

<table>
<thead>
<tr>
<th>Application</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerodynamic shape optimization</td>
<td>• 2-D transonic aerodynamic shape optimization: Li, Bouhlel, and Martins [2018], He et al. [2019c]</td>
</tr>
<tr>
<td></td>
<td>• 3-D transonic aerodynamic shape optimization: Lyu et al. [2015], Lyu and Martins [2015], Kenway and Martins [2016], Chen et al. [2016]</td>
</tr>
<tr>
<td></td>
<td>• Optimization of novel configurations: Mader and Martins [2013], Lyu and Martins [2014], Secco and Martins [2019]</td>
</tr>
<tr>
<td></td>
<td>• Formulation of buffet constraint for wing design optimization: Kenway and Martins [2017]</td>
</tr>
<tr>
<td></td>
<td>• 2-D and 3-D supersonic aerodynamic shape optimization: Mangano and Martins [2019]</td>
</tr>
<tr>
<td></td>
<td>• Optimization with spatial integration constraints: Breije and Martins [2019], Breije, Anibal, Yildirim, Mader, and Martins [2019]</td>
</tr>
<tr>
<td></td>
<td>• Simultaneous design optimization of shape, trajectory, and aircraft allocation: Hwang, Jasa, and Martins [2019]</td>
</tr>
<tr>
<td>Aerostructural design optimization</td>
<td>• Optimization of a transport configuration: Kenway and Martins [2014], Liem, Kenway, and Martins [2015], Brooks, Kenway, and Martins [2018]</td>
</tr>
<tr>
<td></td>
<td>• Optimization with tow-steered composite structures: Brooks and Martins [2018], Brooks, Martins, and Kennedy [2019]</td>
</tr>
<tr>
<td></td>
<td>• Optimization of morphing trailing edge device: Burdette and Martins [2018, 2019]</td>
</tr>
<tr>
<td></td>
<td>• Optimization with flutter constraints: He, Jonsson, Mader, and Martins [2019b,a, 2018]</td>
</tr>
<tr>
<td>Aeropropulsive design optimization</td>
<td>• Boundary layer ingestion modeling: Gray, Mader, Kenway, and Martins [2018b]</td>
</tr>
<tr>
<td></td>
<td>• Design optimization of a boundary layer ingestion system: Yildirim, Gray, Mader, and Martins [2019], Gray and Martins [2019],</td>
</tr>
<tr>
<td></td>
<td>Gray, Kenway, Mader, and Martins [2018a], Kenway and Kiris [2018]</td>
</tr>
<tr>
<td>Optimization of hydrofoils</td>
<td>• Hydrodynamic hydrofoil shape optimization: Garg, Kenway, Lyu, Martins, and Young [2015]</td>
</tr>
<tr>
<td></td>
<td>• Hydrostructural optimization of metallic and composite hydrofoils: Garg, Pearce, Brandner, Phillips, Martins, and Young [2019],</td>
</tr>
<tr>
<td></td>
<td>Garg, Kenway, Martins, and Young [2017], Liao, Garg, Martins, and Young [2019]</td>
</tr>
</tbody>
</table>
The ADODG benchmarks have been a success story

- For the first time, we have aerodynamic shape optimization benchmarks (what took us so long?).
- We should not solve problems that do not exist.
- Gradient-based optimization with adjoint gradients is the way to go.
- People worry more about multimodality than they should.
- Some researchers still have not embraced these benchmarks…why not?
- Open source tools are now available that can solve all these benchmarks.
Go forth and optimize!

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