Promise and Challenges of MDO for the Next Generation of Aircraft

Joaquim R. R. A. Martins

with contributions from Timothy Brooks, Justin Gray, Ping He, John Hwang, John Jasa, Gaetan Kenway, Graeme Kennedy, Zhoujie Lyu, Charles Mader, Ney Secco, and Anil Yildirim

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By the inverse function theorem, if \( \frac{\partial}{\partial u} R \) is invertible at \( u^\ast \), there exists a local inverse \( R^1 \) defined on an open neighborhood of \( R(u^\ast) \) in the codomain. Moreover, \( \frac{\partial}{\partial u} R = \left( \frac{\partial (R^1)}{\partial r} \right)^T \). The Jacobian of the inverse turns out to be equal to the matrix of total derivatives we are after, so the result is \( \frac{\partial R}{\partial u} du \cdot dr = I = \left( \frac{\partial R}{\partial u} \right)^T \left( \frac{du}{dr} \right)^T \). This equation unifies all methods for computing the derivatives of a computational model.
Theoretical developments need to be implemented and applied in industry for impact and to inform research needs.
Airbus A350 first flight
Toulouse, June 14, 2013
Numerical methods have been playing an increasing role in engineering simulations

Experiments

Numerical simulations

40% fewer wind tunnel days

[Source: Airbus A380 - RAe Hamburg & VDI January 2008]
Numerical optimization provides a way to fully automate the design process.

Design optimization problem:

- minimize \( f(x) \) 
- subject to \( c(x) \leq 0 \)

- objective
- design variables
- constraints

Wing span
Airfoil shapes
Structural sizing

Fuel burn
Structural stresses

Design changes
The next generation of aircraft demands even more of the design process

- Highly-flexible high aspect ratio wings
- Unknown design space and interdisciplinary trade-offs
- High risk

[Source: NASA]
State of the art in aircraft MDO is many disciplines with low fidelity, or one/two with high fidelity.
Promise: A push-button solution?

Mach = 0.734
Minimize $C_d$
s.t. $C_l=0.824$, $C_m>-0.092$
Major Iteration: 0
In practice, there is another outer loop where the designer reformulates the optimization problem.
The challenges

- Geometry and meshing
- Robust and efficient solvers
- Large number of design variables
- New aircraft configurations and airframe technologies
- MDO architectures
Challenge:

Geometry and meshing

- Differentiable
- Robust
- Two-way compatibility with CAD
- Meshing is the bottleneck in the design cycle
We developed GeoMACH, an open source tool for rapidly generating aircraft geometries.

GeoMACH models aircraft geometries and structures using a differentiable parametrization.

[Hwang and Martins, AIAA 2012-5605]
GeoMACH can also generate structural geometries and meshes automatically

[Hwang and Martins, *Aerospace Science and Technology, 2016*]
Fast mesh deformation handles large design changes
Overset meshing and solver enables us to handle complex full configurations
Components are meshed independently using pyHyp, our in-house hyperbolic mesh generator.
We then assemble the overset mesh...
...and the collar meshes are generated automatically
This enables us to include the strut position as a design variable

[Secco et al., AIAA Journal 2018]
Wing-fuselage shape optimization study

[Secco et al., AIAA Journal, 2018]
Challenge: Geometry and meshing

- Challenges addressed:
  - Fast differentiable geometry engine
  - Automated structural mesh generation
  - Fast and robust mesh deformation
  - Semi-automated mesh generation
  - Movement of intersections

- Remaining challenges:
  - Two-way link with CAD
  - Fully automated mesh generation
Challenge:

Robust and efficient solvers

- Optimization demands additional robustness so the optimization cycle is not interrupted.
- Since optimization requires hundreds of iterations, even small increases in efficiency pay off.
Optimizing an airfoil starting from a circle is not a need...

Mach = 0.734
Minimize $C_d$
$s.t. C_l=0.824, C_m>0.092$
Major Iteration: 0
...however, optimization does sometimes try crazy designs
ADflow is a RANS solver that includes an adjoint method for efficient derivative computation

- Based on SUmb RK solver of van der Weide et al. [AIAA 2006-0421]
- Parallel, finite-volume, cell-centered, overset, Newton–Krylov solver for RANS equations
- Spalart–Allmaras turbulence model
- Discrete adjoint developed using automatic differentiation (AD) to evaluate partial derivatives
- Full-turbulence adjoint
We implemented a robust approximate Newton–Krylov approach for the CFD

Nonlinear iteration loop

Adaptive CFL algorithm

Matrix-free approximate residual routines

\[ \frac{I}{\Delta t} + \frac{\partial R_1}{\partial Q} \]

Low bandwidth preconditioner

\[ \frac{I}{\Delta t} + \frac{\partial R_2}{\partial Q} \]

ILU preconditioned GMRES

\[ \left( \frac{I}{\Delta t} + \frac{\partial R_1}{\partial Q} \right) \Delta Q = -R_0(Q) \]

Physicality check and backtracking line search

\[ Q^{n+1} = Q^n + \omega \Delta Q^n \]

Sub-iterations for turbulence model
ANK is extremely robust: CRM at 90 deg and M=0.85
This 8 million cell M6 mesh converges in about 14 minutes with 120 processors.
Challenge: Robust and efficient solvers

- Challenges addressed:
  - Developed fast CFD solver
  - Extremely robust to changes in flow conditions and geometry
Challenge: Large number of design variables

- Aircraft design using high-fidelity MDO requires a large number of design variables
- All disciplines should be represented and optimized concurrently
- Computational cost of optimization should be scalable
Gradient-based optimization is the only hope for large numbers of design variables.

[Figure 3: Study 1: Dimension analysis for 2-D Rosenbrock function]

[Figure 4: Study 1: Local minimum of 8-D Rosenbrock function]

Methods reflect in their better ability to find global minimum. As the increasing of problem size, gradient methods tend toward the local minimum while non-gradient methods can still find the global minimum. However, consider their performance at high dimension, we cannot take fully use of this advantage.

[Lyu et al., ICCFD8-2014-0203]
Methods for computing derivatives

<table>
<thead>
<tr>
<th>Monolithic</th>
<th>Finite-differences</th>
<th>Complex-step</th>
</tr>
</thead>
</table>
| Black boxes                    | \[
\frac{df}{dx_j} = \frac{f(x_j + h) - f(x)}{h} + O(h)
\] | \[
\frac{df}{dx_j} = \frac{\text{Im} \left[f(x_j + ih]\right]}{h} + O(h^2)
\] |

<table>
<thead>
<tr>
<th>Analytic</th>
<th>Direct</th>
<th>Adjoint</th>
</tr>
</thead>
</table>
| Governing eqns                | \[
\frac{df}{dx} = \frac{\partial f}{\partial x} - \frac{\partial f}{\partial y} \left[\frac{\partial R}{\partial y}\right]^{-1} \frac{\partial R}{\partial x}
\] |         |

<table>
<thead>
<tr>
<th>Algorithmic differentiation</th>
<th>Forward</th>
<th>Reverse</th>
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<tbody>
<tr>
<td>Lines of code</td>
<td></td>
<td></td>
</tr>
<tr>
<td>code variables</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

We use a matrix-free hybrid adjoint approach to compute derivatives efficiently.

\[
\frac{df}{dx} = \frac{\partial f}{\partial x} - \frac{\partial f}{\partial y} \left[ \frac{\partial R}{\partial y} \right]^{-1} \frac{\partial R}{\partial x}
\]
Combine flow solver, adjoint solver, and gradient-based optimizer to enable design

Optimizor (SNOPT)

Geometry and mesh

Flow solver
\[ R(x, y(x)) = 0 \]

Adjoint solver
\[
\begin{bmatrix}
\frac{\partial R}{\partial y}
\end{bmatrix}^T \psi = -\frac{\partial f}{\partial y} \\
\frac{df}{dx} = \frac{\partial f}{\partial x} + \psi^T \frac{\partial R}{\partial x}
\]

For each \( x \), solve the equations governing physical systems to find \( y \):
\[ R(x, y(x)) = 0 \]
Wave drag is eliminated, and total drag is reduced by 8.5%.

- 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 takes 6 hours using 128 cores

- 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.

[Lyu et al., AIAA Journal, 2014]
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.

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
Want to optimize both aerodynamic shape and structural sizing, with high-fidelity
Coupled solution of aerodynamics and structures, and the corresponding coupled adjoint

Gradient-based Optimizer

Geometry and mesh

Aerostructural solver

\[ \begin{bmatrix} R_A(x, y_A, y_S) \\ R_S(x, y_A, y_S) \end{bmatrix} = 0 \]

Coupled adjoint solver

\[ \begin{bmatrix} \frac{\partial R_A}{\partial y_A} \\ \frac{\partial R_A}{\partial y_S} \\ \frac{\partial R_S}{\partial y_A} \\ \frac{\partial R_S}{\partial y_S} \end{bmatrix}^T \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} = 0 \]

\[ \frac{df}{dx} = \frac{\partial f}{\partial x} - \psi^T \frac{\partial R}{\partial x} \]

Analytic methods

\[ \frac{df}{dx} = \frac{\partial f}{\partial x} = \frac{\partial f}{\partial x} \frac{\partial x}{\partial y} \]
MDO for Aircraft Configurations with High-fidelity (MACH)

Python user script
Setup up the problem: objective function, constraints, design variables, optimizer and solver options

<table>
<thead>
<tr>
<th>Optimizer interface</th>
<th>Aerostructural solver</th>
<th>Geometry modeler</th>
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<tr>
<td>pyOptSparse</td>
<td>AeroStruct</td>
<td>DVGeometry/GeoMACH</td>
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<tr>
<td>Common interface to various optimization software</td>
<td>Coupled solution methods and coupled derivative evaluation</td>
<td>Defines and manipulates geometry, evaluates derivatives</td>
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<table>
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<th>SNOPT</th>
<th>Other optimizers</th>
<th>Flow solver</th>
<th>Structural solver</th>
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<td></td>
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<td>ADflow</td>
<td>TACS</td>
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<tr>
<td></td>
<td></td>
<td>Governing and adjoint equations</td>
<td>Governing and adjoint equations</td>
</tr>
</tbody>
</table>

- Underlying solvers are parallel and compiled
- Coupling done through memory only
- Emphasis on clean Python user interface
- Solver independent

[Kenway et al., AIAA Journal, 2014]
pyOptSparse and OptView are available as open source software [https://github.com/mdolab/pyoptsparspe]

[Perez et al., SMO, 2012]
Adjoint method efficiently computes gradients with respect to thousands of variables

![Graph showing comparison between finite differences and adjoint method](graph.png)

Kenway et al., *AIAA Journal*, 2014
Let's do aerostructural optimization!

NASA-Michigan undeformed Common Research Model (uCRM)

[Kenway et al., AIAA 2014-3274]
Optimize 973 “aerodynamic” and structural sizing design variables

Stiffener pitches
Stiffeners heights
Skin thicknesses
Tail rotation

[Kenway and Martins, AIAA 2015-2790]
Considering multiple flight conditions is required for a practical design

- 7 cruise conditions for performance
- 2 off design conditions
- 3 maneuver condition for structural constraints
- Aircraft trimmed at all conditions
We developed a new buffet onset constraint formulation based on a separation sensor

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

[Kenway et al., AIAA Journal, 2017]
The buffet constraint is essential to achieve a practical design.

No buffet constraint single point

Buffet constrained multipoint

[Kenway et al., AIAA Journal, 2017]
Challenge:
Large number of design variables

- Challenges addressed:
  - Efficient coupled derivative computation
  - Large number of constraints

- Remaining challenges:
  - More practical design constraints
  - Large number of loads cases
Challenge:
New aircraft configurations and airframe technologies

- High-fidelity MDO needed earlier in the design process
- More challenging geometries
Blended-wing body aerodynamic shape optimization including stability

Study 2
$C_D = 0.00972$
$C_L = 0.206$
$C_{Mz} = 0.000$
$K_n = 7.4\%$

Study 3
$C_D = 0.00955$
$C_L = 0.206$
$C_{Mz} = 0.000$
$K_n = 1.0\%$

Developed uCRM-13.5, a high-aspect ratio flexible version of the CRM

Initial uCRM 13.5
Fuel burn: 112161 kg
L/D: 18.01

Optimized uCRM 13.5
Fuel burn: 88783 kg
L/D: 21.81

[Brooks et al., *AIAA Journal*, 2018]
Morphing trailing edge assessment

No Morphing
Fuel Burn: 98627kg
Wing Mass: 30060 kg

Mach=0.88
Cp=0.55

-1 g

2.5 g

With Morphing
Fuel Burn: 93656 kg
Wing Mass: 22300 kg

Thickness [mm]:
0 5 1

Buckling
0 0.5 1

Stress
0 0.5 1

Normalized Lift

Twist
elliptical
cruise

2.5g maneuver

[Burdette et al., AIAA 2016-0159]
Tow-steered composite high AR wing

Conventional Composite Optimized
TOGW: 261707 kg
Fuel burn: 78703 kg
L/D: 22.42
Wing mass: 20004 kg

Tow-Steered Composite Optimized
TOGW: 257171 kg
Fuel burn: 77610 kg
L/D: 22.32
Wing mass: 16560 kg

Normalized Lift

Twist

[Brooks et al., AIAA 2017-1350]
Our design was built and is about to be tested

[Aurora Flight Sciences]

[NASA]

[Aviation Week & Space Technology, 2018]
We were able to tackle the aerodynamic design optimization of the strut-braced wing thanks to the overset capability.
Final design reduced interference drag and resulted in a strut with negative lift.

[Secco et al., Journal of Aircraft, 2018.]
D8 double-bubble configuration

[Mader et al., AIAA 2017-4436.]
### Initial:
- $C_L = 0.5459$
- $C_D = 0.0283$
- $L/D = 19.25$
- $M^2 C_L = 0.283$
- $C_L^2 S/\rho l b^2 = 0.0077$
- TOGW(lbs) = 120906
- Wing weight (lbs) = 12865
- Fuel Burn (lbs) = 20221
- Altitude (ft) = 34500

### Optimized:
- $C_L = 0.3357$
- $C_D = 0.0230$
- $L/D = 14.56$
- $M^2 C_L = 0.204$
- $C_L^2 S/\rho l b^2 = 0.0033$
- TOGW(lbs) = 128876
- Wing weight (lbs) = 13554
- Fuel Burn (lbs) = 26308
- Altitude (ft) = 30000

### Initial:
- $C_L = 0.5586$ (66%)
- $C_D = 0.0278$ (20%)
- $L/D = 20.06$ (38%)
- $M^2 C_L = 0.340$ (66%)
- $C_L^2 S/\rho l b^2 = 0.0091$ (178%)
- TOGW(lbs) = 122491 (-5%)
- Wing weight (lbs) = 13964 (3%)
- Fuel Burn (lbs) = 19471 (-27%)
- Altitude (ft) = 41000 (37%)
Tail cone thruster propulsion-airframe integration demands CFD-based MDO

[Gray et al., AIAA 2018-3976]
We are performing aero-thermal-propulsion-mission optimization.
We have developed the Surrogate Modeling Toolbox (SMT) because there was a need for surrogates with derivatives.

- International collaboration
- Python-based
- Open source
- Focus on using and providing derivatives
Using newly developed gradient-enhanced kriging surrogate modeling, we are able to optimize airfoils interactively.

[Li et al., AIAA 2018-1383]
Challenge: New aircraft configurations and airframe technologies

- Challenges addressed:
  - Optimized aerodynamics with stability
  - Designed optimal tow steering wings
  - Optimized a strut-braced wing aircraft
  - Optimized propulsion-airframe integration
  - Considered thermal management and trajectory

- Remaining challenges:
  - Validation of the tools for the specific configurations
Challenge:

MDO architectures

- Computational efficiency
- Implementation effort
- Heterogeneous components
- Compatibility with the industrial setting
minimize \( f_o(x, y) + \sum_{i=1}^{N} f_i(x_0, x_i, y_i) \)

with respect to \( x, y, \hat{y}, \hat{\hat{y}} \)

subject to \( c_0(x, y) \geq 0 \)
\( c_i(x_0, x_i, y_i) \geq 0 \) for \( i = 1, \ldots, N \)
\( c_i^*(\hat{y}_i - y_i) = 0 \) for \( i = 1, \ldots, N \)
\( R_i(x_0, x_i, \hat{y}_{j\neq i}, \hat{y}_i) = 0 \) for \( i = 1, \ldots, N \)

### Distributed IDF

**CO:** Copies of the shared variables are created for each discipline, together with corresponding consistency constraints. Discipline subproblems minimize difference between the copies of shared and local variables subject to local constraints. System subproblem minimizes objective subject to shared constraints subject to consistency constraints.

**BLISS-2000:** Discipline subproblems minimize the objective with respect to local variables subject to local constraints. A surrogate model of the local optima with respect to the shared variables is maintained. Then, system subproblem minimizes objective with respect to shared design and coupling variables subject to shared design and consistency constraints, considering the disciplinary preferences.

**QSD:** Each discipline is assigned a “budget” for a local objective and the discipline problems maximize the margin in their local constraints and the budgeted objective. System subproblem minimizes a shared objective and the budgets of each discipline subject to shared design constraints and positivity of the margin in each discipline.

### Penalty

**ATC:** Copies of the shared variables are used in discipline subproblems together with the corresponding consistency constraints. These consistency constraints are relaxed using a penalty function. System and discipline subproblems solve their respective relaxed problem independently. Penalty weights are increased until the desired consistency is achieved.

**IPD/EPD:** Applicable to MDO problems with no shared objectives or constraints. Like ATC, copies of shared variables are used for every discipline subproblem and the consistency constraints are relaxed with a penalty function. Unlike ATC, the simple structure of the disciplinary subproblems is exploited to compute post-optimality sensitivities to guide the system subproblem.

**ECO:** As in CO, copies of the shared design variables are used. Disciplinary subproblems minimize quadratic approximations of the objective subject to local constraints and linear models of nonlocal constraints. Shared variables are determined by the system subproblem, which minimizes the total violation of all consistency constraints.

### Distributed MDF

**CSSO:** In system subproblem, disciplinary analyses are replaced by surrogate models. Discipline subproblems are solved using surrogates for the other disciplines, and the solutions from these discipline subproblems are used to update the surrogate models.

**BLISS:** Coupled derivatives of the multidisciplinary analysis are used to construct linear subproblems for each discipline with respect to local design variables. Post-optimality derivatives from the solutions of these subproblems are computed to form the system linear subproblem, which is solved with respect to shared design variables.

**MDOIS:** Applicable to MDO problems with no shared objectives, constraints, or design variables. Discipline subproblems are solved independently assuming fixed coupling variables, and then a multidisciplinary analysis is performed to update the coupling.

**ASO:** System subproblem is like that of MDF, but some disciplines solve a discipline optimization subproblem within the multidisciplinary analysis with respect to local variables subject to local constraints. Coupled post-optimality derivatives from the discipline subproblems are computed to guide the system subproblem.

---

Unfortunately, no distributed architecture has been shown to converge as well as the monolithic ones.
The unified derivatives equation can be used to derive all derivative computation methods:

**Direct method**

\[
\frac{\partial R}{\partial y} \frac{dy}{dx} = - \frac{\partial R}{\partial y}
\]

\[
\frac{df}{dx} = \frac{\partial F}{\partial x} + \frac{\partial F}{\partial y} \frac{dy}{dx}
\]

**Coupled direct**

\[
\begin{bmatrix}
I & -\frac{\partial y_1}{\partial y_2} \\
-\frac{\partial y_2}{\partial y_1} & I
\end{bmatrix}
\begin{bmatrix}
\frac{dy_1}{dx} \\
\frac{dy_2}{dx}
\end{bmatrix}
= \begin{bmatrix}
\frac{\partial y_1}{\partial x} \\
\frac{\partial y_2}{\partial x}
\end{bmatrix}
\]

\[
\frac{df}{dx} = \frac{\partial F}{\partial x} + \frac{\partial F}{\partial y_1} \frac{dy_1}{dx} + \frac{\partial F}{\partial y_2} \frac{dy_2}{dx}
\]

**Chain rule**

\[
\frac{\partial R}{\partial y} \frac{du}{dr} = \mathcal{I} = \frac{\partial R}{\partial u} \frac{du}{dr}
\]

**Adjoint method**

\[
\frac{\partial R}{\partial y} \frac{df}{dr} = - \frac{\partial R}{\partial y}
\]

\[
\frac{df}{dx} = \frac{\partial F}{\partial x} + \frac{df}{dr} \frac{\partial R}{\partial x}
\]

**Coupled adjoint**

\[
\begin{bmatrix}
I & -\frac{\partial y_1}{\partial y_2} \\
-\frac{\partial y_2}{\partial y_1} & I
\end{bmatrix}
\begin{bmatrix}
\frac{df}{dy_1} \\
\frac{df}{dy_2}
\end{bmatrix}
= \begin{bmatrix}
\frac{\partial F}{\partial y_1} \\
\frac{\partial F}{\partial y_2}
\end{bmatrix}
\]

\[
\frac{df}{dx} = \frac{\partial F}{\partial x} + \frac{df}{dy_1} \frac{\partial y_1}{dx} + \frac{df}{dy_2} \frac{\partial y_2}{dx}
\]

The unified derivatives equation lead to a new monolithic approach: Modular Analysis and Unified Derivatives (MAUD)

1. Nonlinear coupled system
\[ R(u) = 0 \]

2. Newton solver for coupled system
\[ \frac{\partial R}{\partial u} \Delta u = -r \]

3. Coupled analytic derivatives in forward (direct) mode
\[ \frac{\partial R}{\partial u} \frac{du}{dr} = \mathcal{I} \]

4. Coupled analytic derivatives in reverse (adjoint) mode
\[ \frac{\partial R^T}{\partial u} \frac{du^T}{dr} = \mathcal{I} \]

[Hwang and Martins, ACM TOMS 2018]
MAUD was implemented in an open-source framework.

- Developed at NASA Glenn
- Python-based
- Open source framework
- Facilitates the coupling multiple models and optimization
- Efficient coupled solution
- Efficient coupled derivative computation

[Gray et al., AIAA 2014-2042]
OpenAeroStruct is a good place to get started with OpenMDAO

[https://github.com/mdolab/OpenAeroStruct]

fuel burn: 205172.6 kg
structural mass: 20677.3 kg
span: 58.85 m

[Jasa et al., SMO 2018]  [Chauhan et al., EngOpt, 2018]
Problem structure can be visualized using an interactive design structure matrix diagram
Simultaneous optimization of design, trajectory, and allocation

Objective
Profit

Design variables
(shape)
Shape
192
Twist
7
Area
1
Sweep
1

(mission)
Altitude
2560
Cruise Mach
128

(allocation)
Pax / flight
640
Flight / day
640

Constraints
/design
LE / TE
16
Thickness
750
Volume
1

(mission)
Climb angle
12800
Thrust limits
256

(allocation)
Demand
128
Aircraft fleet
5

4169 design variables
13956 constraints

[Hwang et al., AIAA 2016-1662]
The optimization was performed in roughly 2 hours on 140 processors
OpenMDAO can handle heterogenous models and mix methods for derivative computation.

[Gray et al., AIAA 2018-3976]
### Other OpenMDAO applications

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<th>Model structure</th>
<th>Design variables</th>
<th>Objective</th>
<th>Constraints</th>
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<td>Cantilever beam thickness opt.</td>
<td>![Diagram]</td>
<td>thickness</td>
<td>compliance</td>
<td>weight</td>
</tr>
<tr>
<td>Low-fidelity wing aerostructural opt.</td>
<td>![Diagram]</td>
<td>thickness &amp; twist dist.</td>
<td>fuel burn</td>
<td>trim stress</td>
</tr>
<tr>
<td>Structural topology optimization</td>
<td>![Diagram]</td>
<td>element densities</td>
<td>compliance</td>
<td>mass fraction</td>
</tr>
<tr>
<td>RANS-based wing optimization</td>
<td>![Diagram]</td>
<td>shape variables</td>
<td>drag coefficient</td>
<td>lift coefficient</td>
</tr>
<tr>
<td>Allocation-design optimization</td>
<td>![Diagram]</td>
<td>wing variables; altitude profiles; cruise Mach; allocation vars.</td>
<td>profit</td>
<td>wing geometry; thrust limits; demand &amp; fleet limits</td>
</tr>
<tr>
<td>Aero-propulsive optimization</td>
<td>![Diagram]</td>
<td>inlet shape variables</td>
<td>fuel burn</td>
<td>trim</td>
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<tr>
<td>CubeSat MDO</td>
<td>![Diagram]</td>
<td>solar panel angle; antenna angle; num. radiators; power distribution; attitude profile; solar panel controls</td>
<td>data downloaded</td>
<td>bat. charge rate; bat. charge level</td>
</tr>
<tr>
<td>CTOL electric aircraft MDO</td>
<td>![Diagram]</td>
<td>altitude prof.; velocity prof.; prop RPM profs.; prop chord; prop twist; prop diam.; wing twist; beam thickness</td>
<td>range</td>
<td>average speed; eqs. of motion; max. power; min. torque; ground clear.; tip speed; wing failure</td>
</tr>
</tbody>
</table>
Challenge: MDO Architectures

- Challenges addressed:
  - Facilitated the computation of coupled derivatives
  - Handled thousands of variables and constraints

- Remaining challenges:
  - An architecture more compatible with the current industrial environment
Theoretical developments need to be implemented and applied in industry for impact and to inform research needs.

\[
\begin{bmatrix}
\frac{\partial R_A}{\partial y_A} & \frac{\partial R_S}{\partial y_A} \\
\frac{\partial R_A}{\partial y_S} & \frac{\partial R_S}{\partial y_S}
\end{bmatrix}
\psi = \frac{\partial f}{\partial y}
\]

\[
\frac{df}{dx} = \frac{\partial f}{\partial x} - \psi^T \frac{\partial R}{\partial x}
\]
Go forth and optimize!

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Research Summaries

Summary: Aerodynamic Shape Optimization Research

On this page, we introduce aerodynamic shape optimization and summarize our research on this area, putting some of our journal articles into context. We include a video of an optimization that reinvents the supercritical airfoil starting from a circle.

[ Webpage ]  [ Optimization movie ]

Presentation: Aircraft Design via Numerical Optimization Are We There Yet?

These slides summarize our research on aircraft design optimization. Click on the figures to see the videos and on the references to get the papers. A video of an earlier version of this presentation is also available here.

[ Slides ]  [ Video ]

Notes: VKI Lecture Series on MDO

These lecture notes are from the Von Karman Institute of Fluid Dynamics lecture series "Introduction to optimization and multidisciplinary design". Part 1 introduces general MDO approaches, and Part 2 focuses on high-fidelity aerostructural optimization of aircraft configurations.

[ Part 1 ]  [ Part 2 ]

Recent Journal Articles

Constraining buffet in wing design optimization

We have found that aerodynamic and aerostructural optimizations for transonic aircraft tend to make the wings buffet critical. To address this, we developed a buffet constraint formulation that can be used with gradient-based optimization. The buffet prediction is validated against experimental data and a series of optimizations illustrate the consequences of constraining buffet.

[ Paper ]  [ Preprint ]