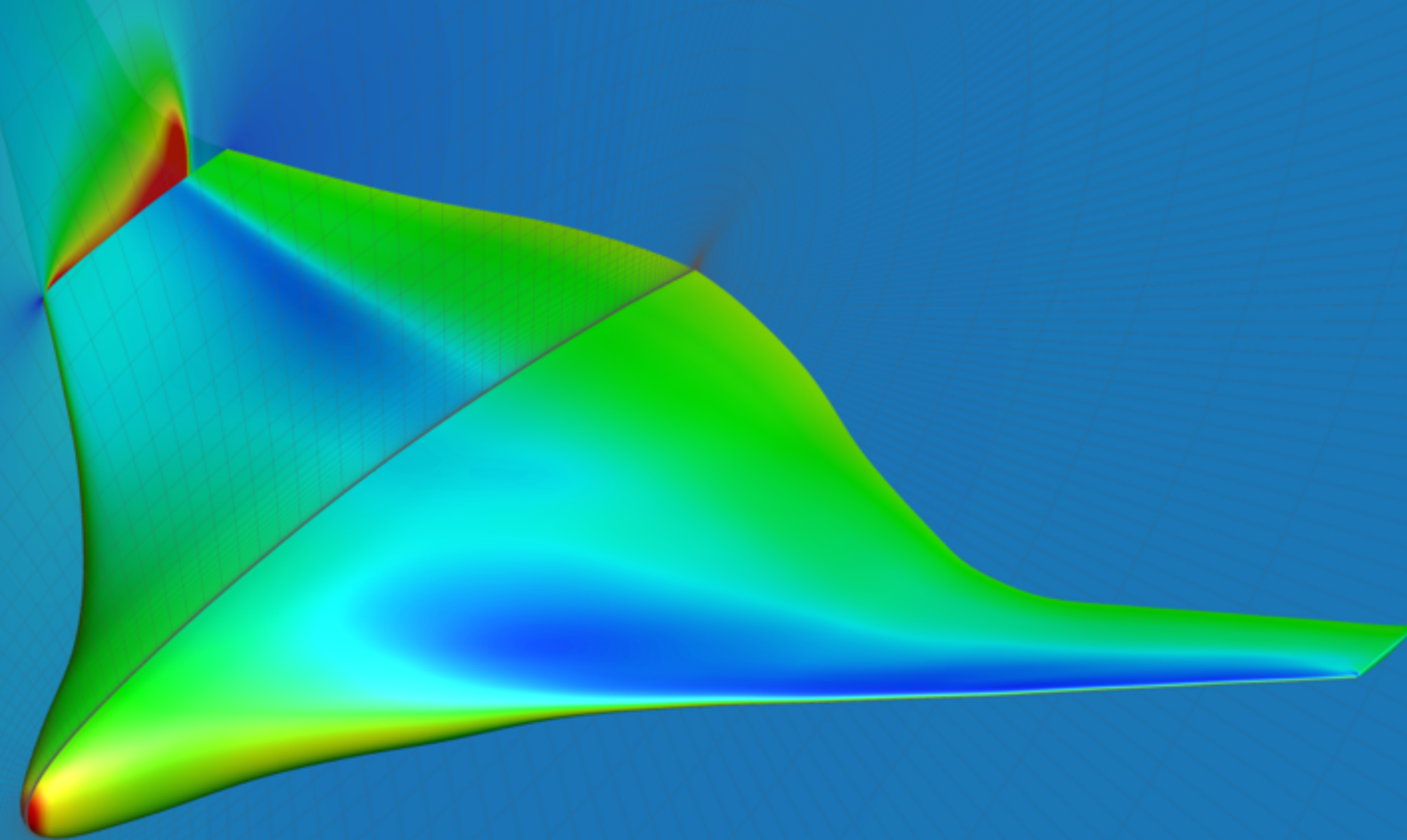
High-Fidelity Multidisciplinary Design Optimization for the Next Generation of Aircraft



Joaquim R. R. A. Martins

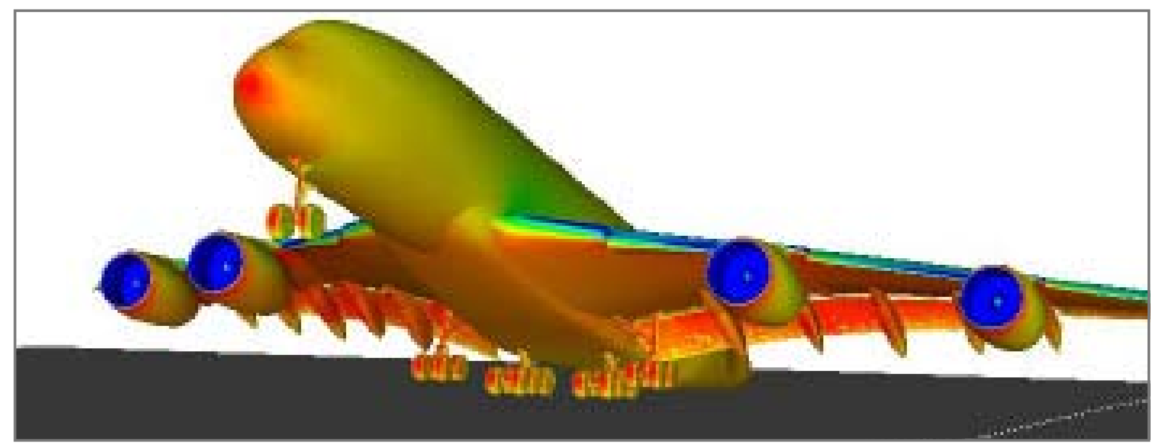
http://mdolab.engin.umich.edu

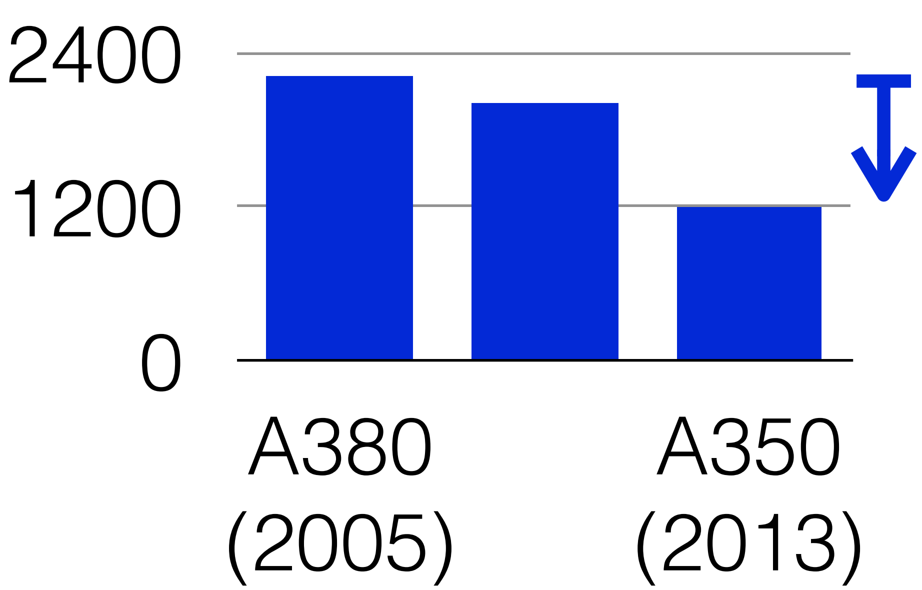
Congress on Numerical Methods in Engineering • Lisbon, Portugal • July 1st, 2015

Numerical methods have been playing an increasing role in engineering analysis

Experiments

Numerical simulations





40% fewer wind tunnel days

[Airbus A380 - RAe Hamburg & VDI January 2008]

Once numerical simulations are developed, they can be used for design optimization

Design optimization problem:

minimize	$f(x)$	objective
with respect to	x	design variables
subject to	$c(x) \leq 0$	constraints

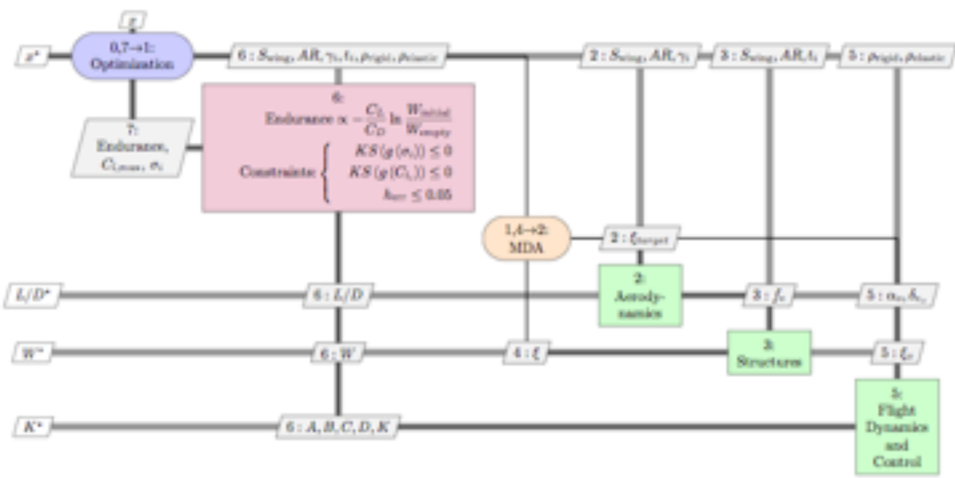
Complex systems require the consideration of multiple disciplines, hence MDO was born

Aerodynamics
Structures
Stability & control
Weights
Loads
Noise
Materials
Mission

JAL B787 climbing after takeoff from SAN • © J.R.R.A. Martins 2013

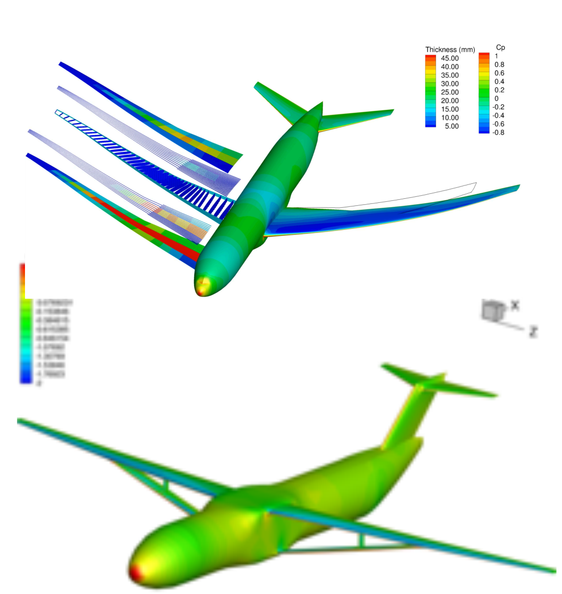
Research in the Multidisciplinary Design Optimization Laboratory is divided into two main thrusts

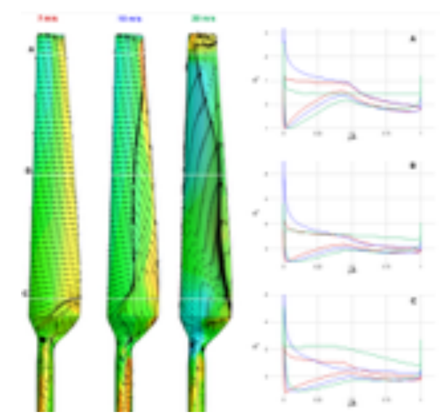
Fundamental MDO algorithms

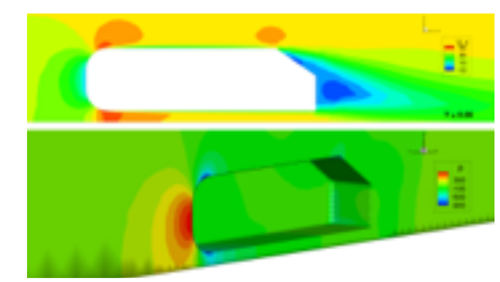


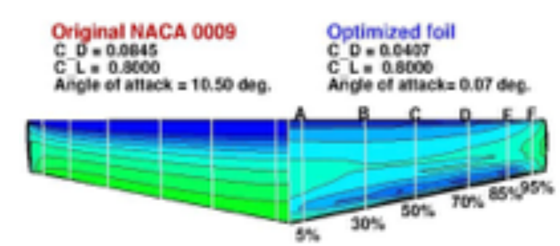
$$\frac{\partial R}{\partial u}\frac{du}{dr} = \mathcal{I} = \left[\frac{\partial R}{\partial u}\right]^T \left[\frac{du}{dr}\right]^T$$

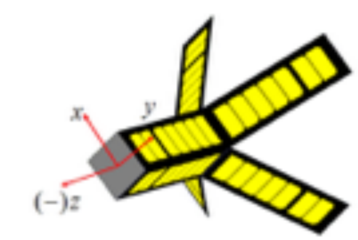
Applications of MDO

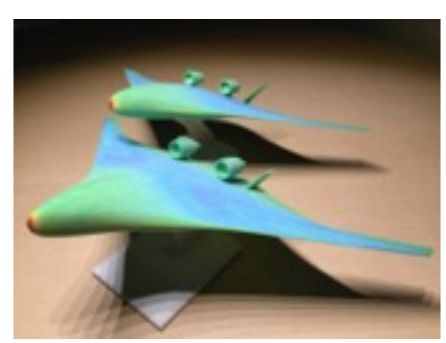


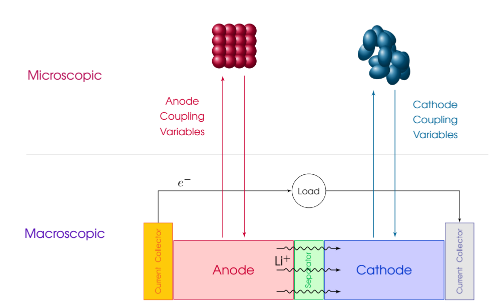






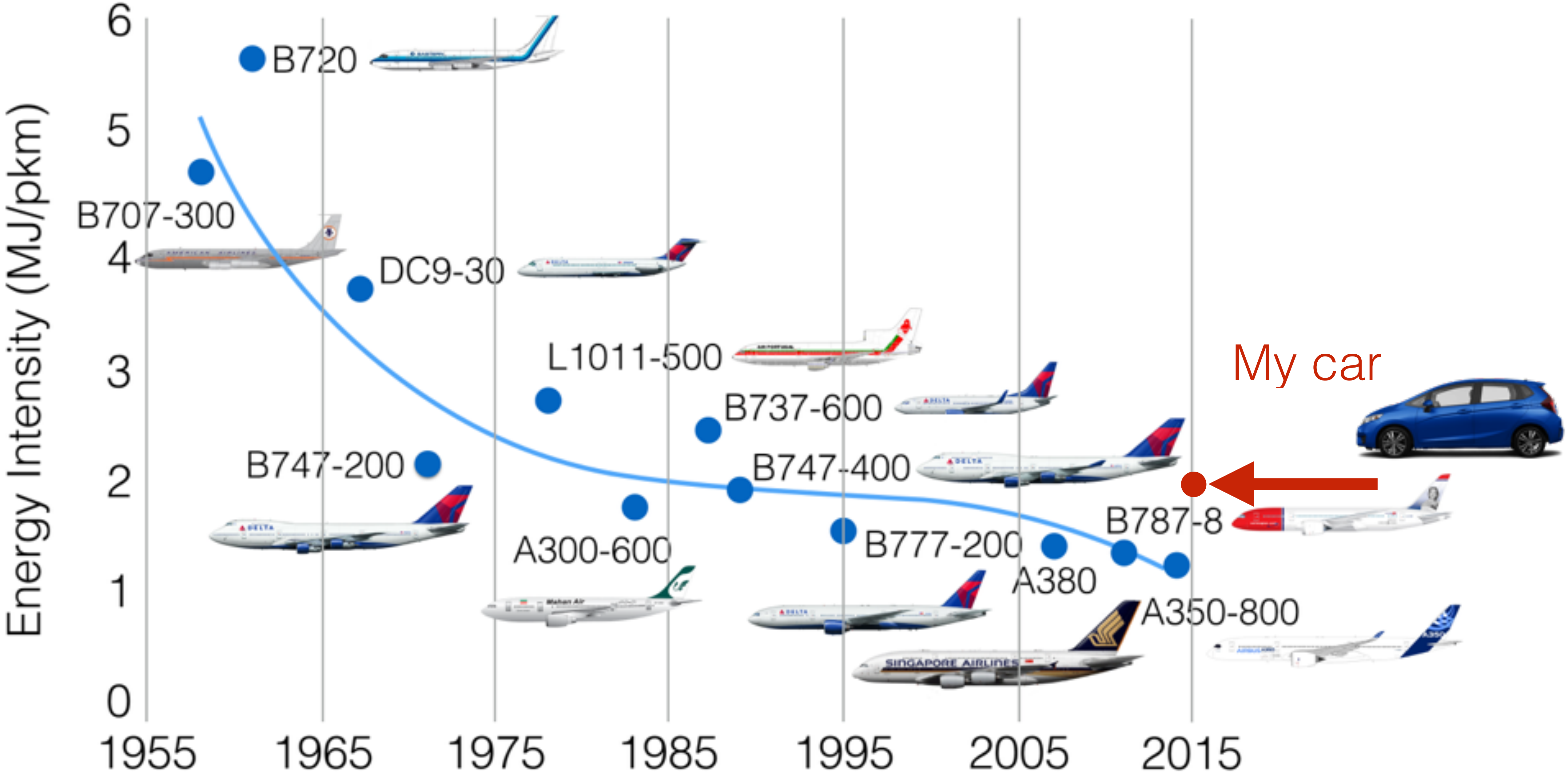




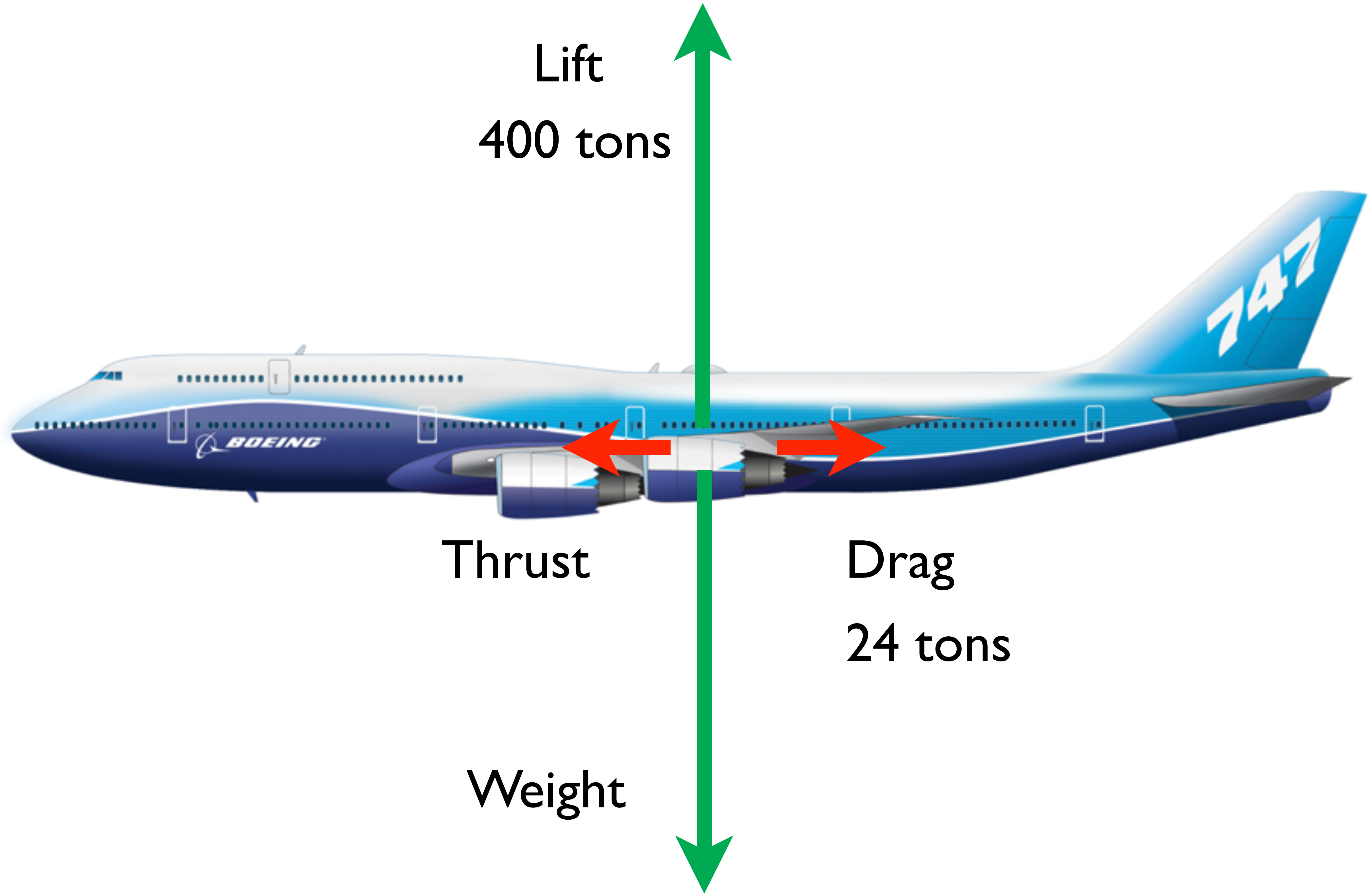


With 90,000 daily flights, improvements in aircraft performance has a huge impact

Airplane fuel burn per seat has decreased by over 80% since the first jet

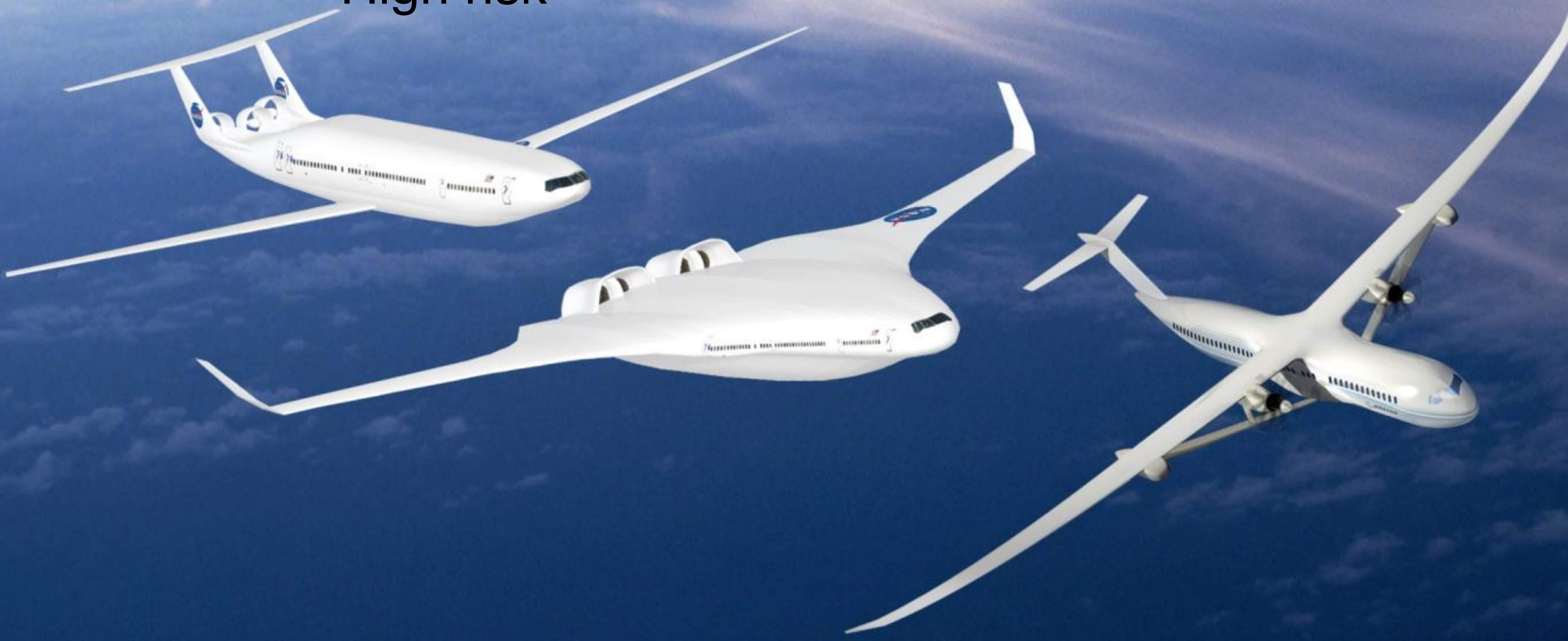


Drag and weight are the primary aircraft performance metrics

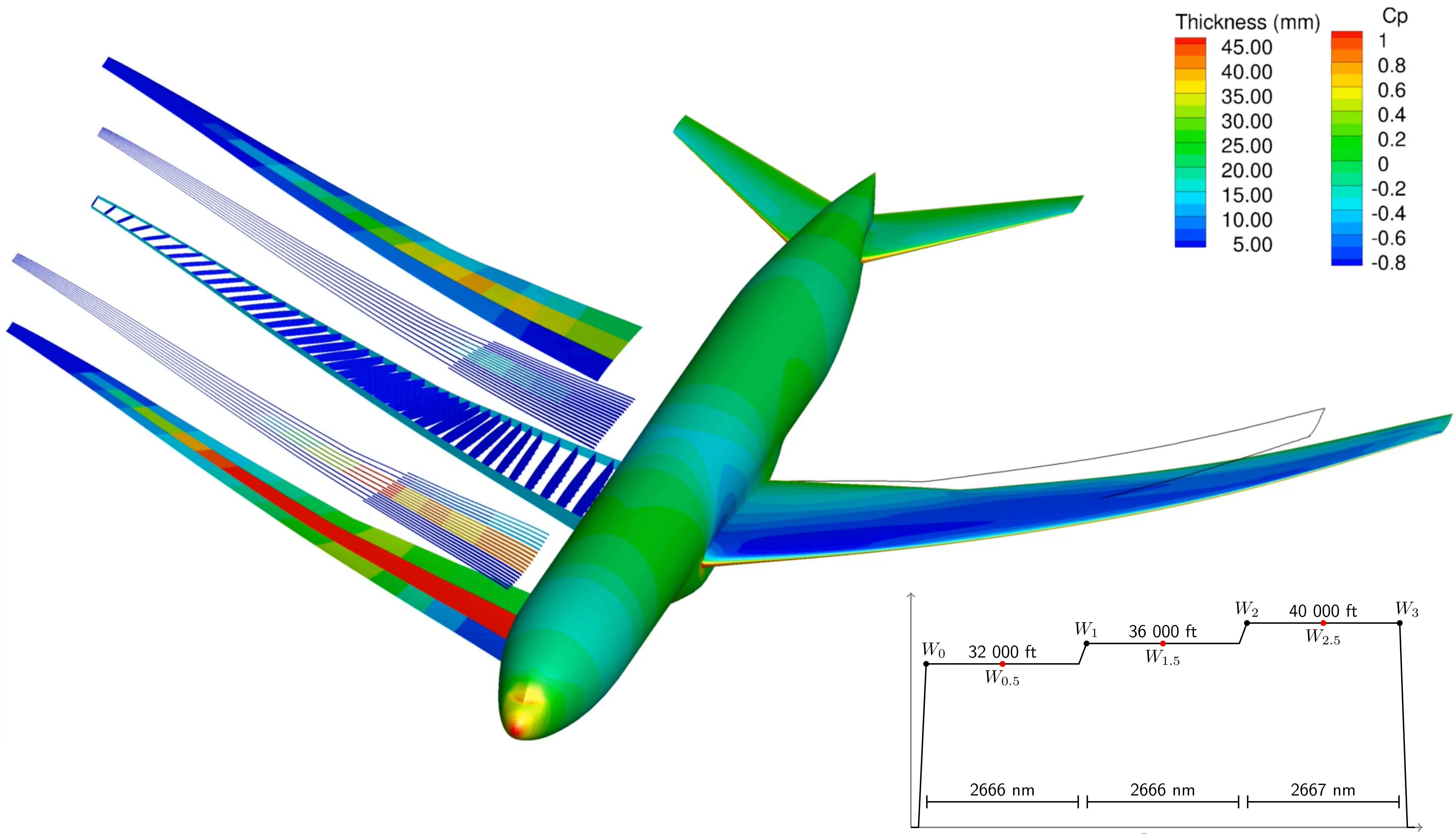


The next generation of aircraft demands even more of the design process

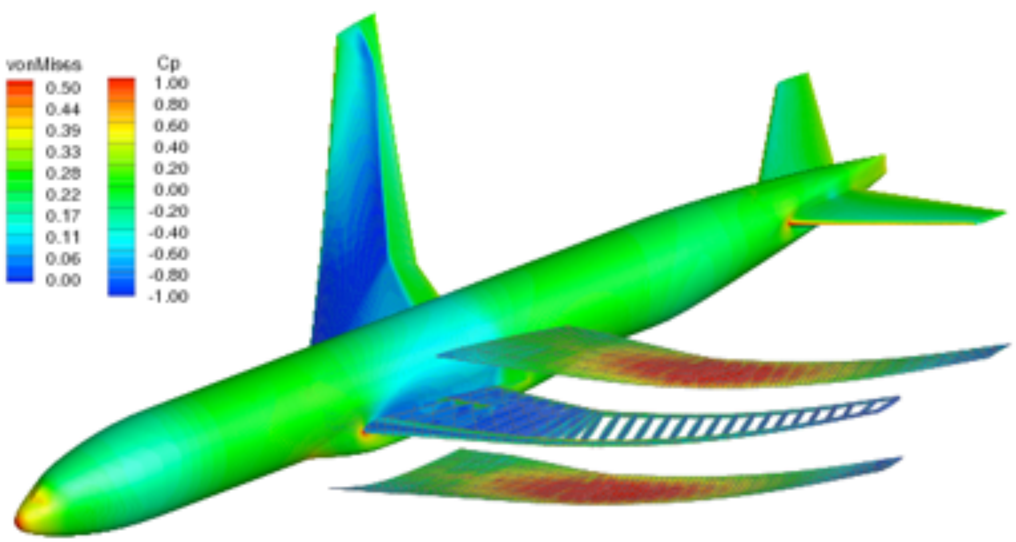
- Highly-flexible high aspect ratio wings
- Unknown design space and interdisciplinary trade-offs
- High risk

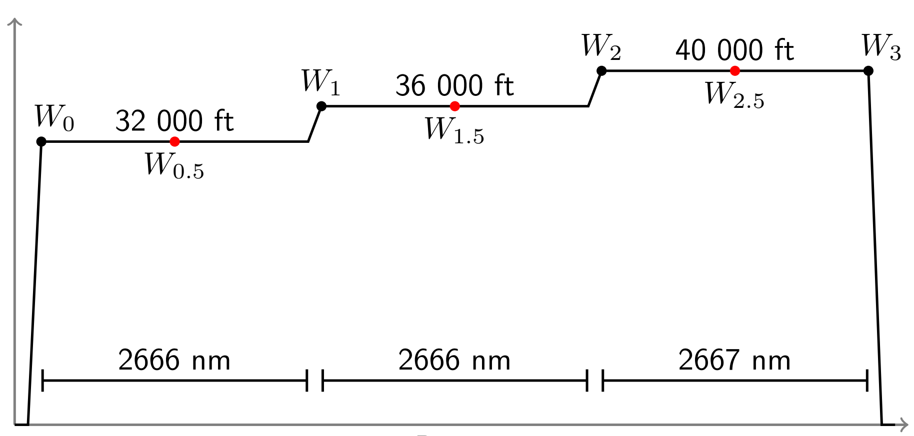


Want to optimize both aerodynamic shape and structural sizing, with high-fidelity



3 major challenges





1. Computational costly to evaluate objective and constraints
2. Multiple highly coupled systems
3. Large numbers of design variables, design points and constraints

High-Fidelity Multidisciplinary Design Optimization for the Next Generation of Aircraft

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- Computing derivatives efficiently
- Aerodynamic shape optimization
- Aerostructural design optimization
- Summary and ongoing work

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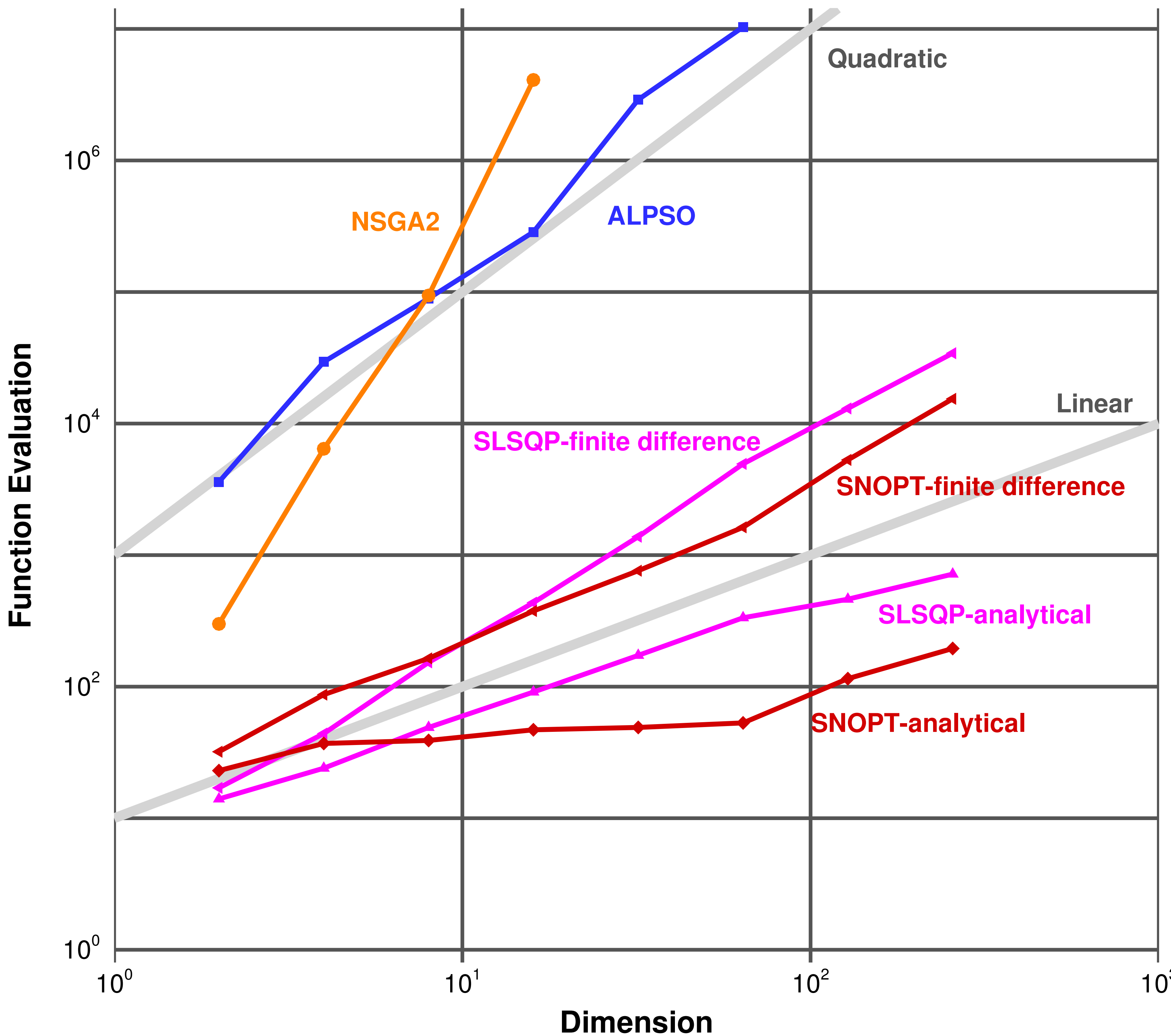
Gradient-based optimization is the only hope for large numbers of design variables



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Gradient-based optimization requires gradient of objective and Jacobian of constraints

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & f(x, y(x)) \\ \text{s.t.} \quad & h(x, y(x)) = 0 \\ & g(x, y(x)) \leq 0 \end{aligned}$$

x: design variables
y: state variables, determined implicitly by solving $R(x, y(x)) = 0$

Need $\mathrm{d}f / \mathrm{d}x$ (and also $\mathrm{d}h / \mathrm{d}x$, $\mathrm{d}g / \mathrm{d}x$)

Methods for computing derivatives

Monolithic ***Black boxes input and outputs***	Finite-differences	$\frac{\mathrm{d}f}{\mathrm{d}x_j} = \frac{f(x_j + h) - f(x)}{h} + \mathcal{O}(h)$
	Complex-step	$\frac{\mathrm{d}f}{\mathrm{d}x_j} = \frac{\mathrm{Im}\left[f(x_j + ih)\right]}{h} + \mathcal{O}(h^2)$
Analytic ***Governing eqns state variables***	Direct Adjoint	$\frac{\mathrm{d}f}{\mathrm{d}x} = \frac{\partial f}{\partial x} - \underbrace{\frac{\partial f}{\partial y}\left[\frac{\partial R}{\partial y}\right]^{-1}}_{\psi}\frac{\partial R}{\partial x}$
Algorithmic differentiation ***Lines of code code variables***	Forward Reverse	$\begin{bmatrix} 1 & 0 & \cdots & 0 \\ -\frac{\partial T_2}{\partial t_1} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ -\frac{\partial T_n}{\partial t_1} & \cdots & -\frac{\partial T_n}{\partial t_{n-1}} & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \frac{\mathrm{d}t_2}{\mathrm{d}t_1} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \frac{\mathrm{d}t_n}{\mathrm{d}t_1} & \cdots & \frac{\mathrm{d}t_n}{\mathrm{d}t_{n-1}} & 1 \end{bmatrix} = I = \begin{bmatrix} 1 & -\frac{\partial T_2}{\partial t_1} & \cdots & -\frac{\partial T_n}{\partial t_1} \\ 0 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & -\frac{\partial T_n}{\partial t_{n-1}} \\ 0 & \cdots & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & \frac{\mathrm{d}t_2}{\mathrm{d}t_1} & \cdots & \frac{\mathrm{d}t_n}{\mathrm{d}t_1} \\ 0 & 1 & \ddots & \vdots \\ \vdots & \ddots & 1 & \frac{\mathrm{d}t_n}{\mathrm{d}t_{n-1}} \\ 0 & \cdots & 0 & 1 \end{bmatrix}$

[Martins and Hwang, AIAA Journal, 2013] [Martins et al., ACM TOMS, 2003]

Analytic methods evaluate derivatives by linearizing the governing equations

Need $\mathrm{d}f/\mathrm{d}x$ (and also $\mathrm{d}h/\mathrm{d}x$, $\mathrm{d}g/\mathrm{d}x$), $\quad f(x, y(x))$

$$\frac{\mathrm{d}f}{\mathrm{d}x} = \frac{\partial f}{\partial x} + \frac{\partial f}{\partial y}\frac{\mathrm{d}y}{\mathrm{d}x}$$

Derivative of the governing equations: $R(x, y(x)) = 0$

$$\frac{\mathrm{d}R}{\mathrm{d}x} = \frac{\partial R}{\partial x} + \frac{\partial R}{\partial y}\frac{\mathrm{d}y}{\mathrm{d}x} = 0 \quad \Rightarrow \quad \frac{\partial R}{\partial y}\frac{\mathrm{d}y}{\mathrm{d}x} = -\frac{\partial R}{\partial x}$$

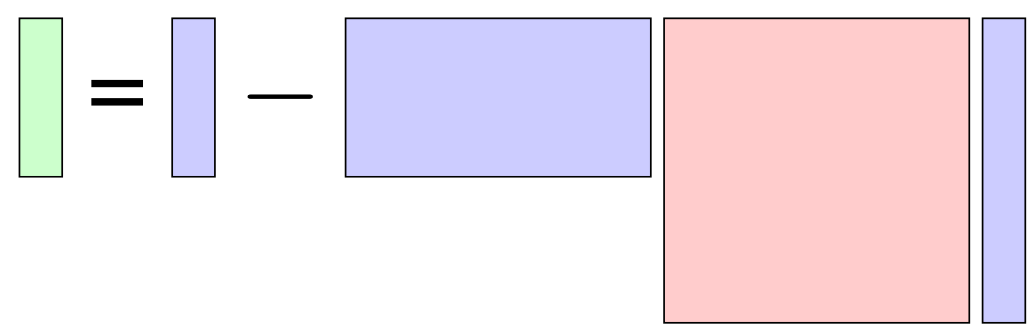
Substitute result into the derivative equation

$$\frac{\mathrm{d}f}{\mathrm{d}x} = \frac{\partial f}{\partial x} \underbrace{- \frac{\partial f}{\partial y}\overbrace{\left[\frac{\partial R}{\partial y}\right]^{-1}\frac{\partial R}{\partial x}}^{-\mathrm{d}y/\mathrm{d}x}}_{\psi}$$

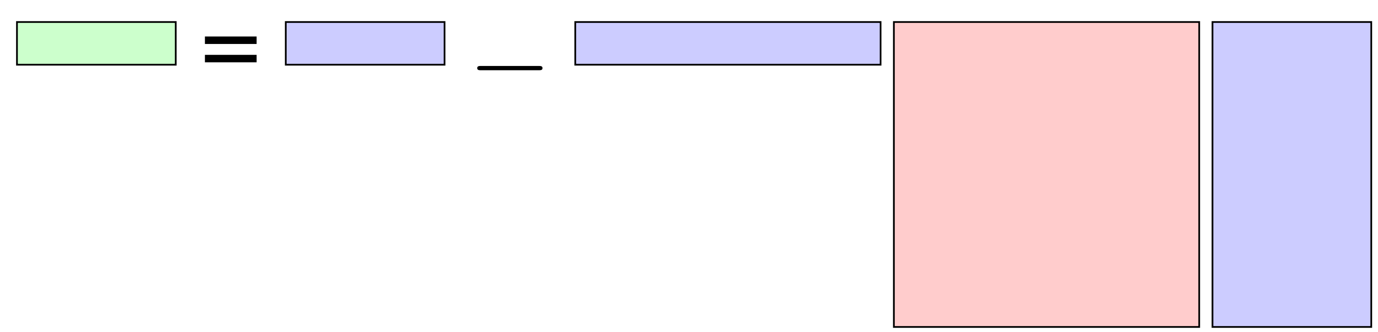
Cost of adjoint evaluation is independent of the number of design variables

$$\frac{\mathrm{d}f}{\mathrm{d}x} = \frac{\partial f}{\partial x} - \rlap{\underbrace{\phantom{\frac{\partial f}{\partial y}\left[\frac{\partial R}{\partial y}\right]^{-1}}}_{\psi}}\frac{\partial f}{\partial y}\overbrace{\left[\frac{\partial R}{\partial y}\right]^{-1}\frac{\partial R}{\partial x}}^{-\,\mathrm{d}y/\,\mathrm{d}x}$$

$n_x < n_f$



$n_x > n_f$



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Wing aerodynamic shape optimization requires a high-fidelity model

Navier–Stokes equations

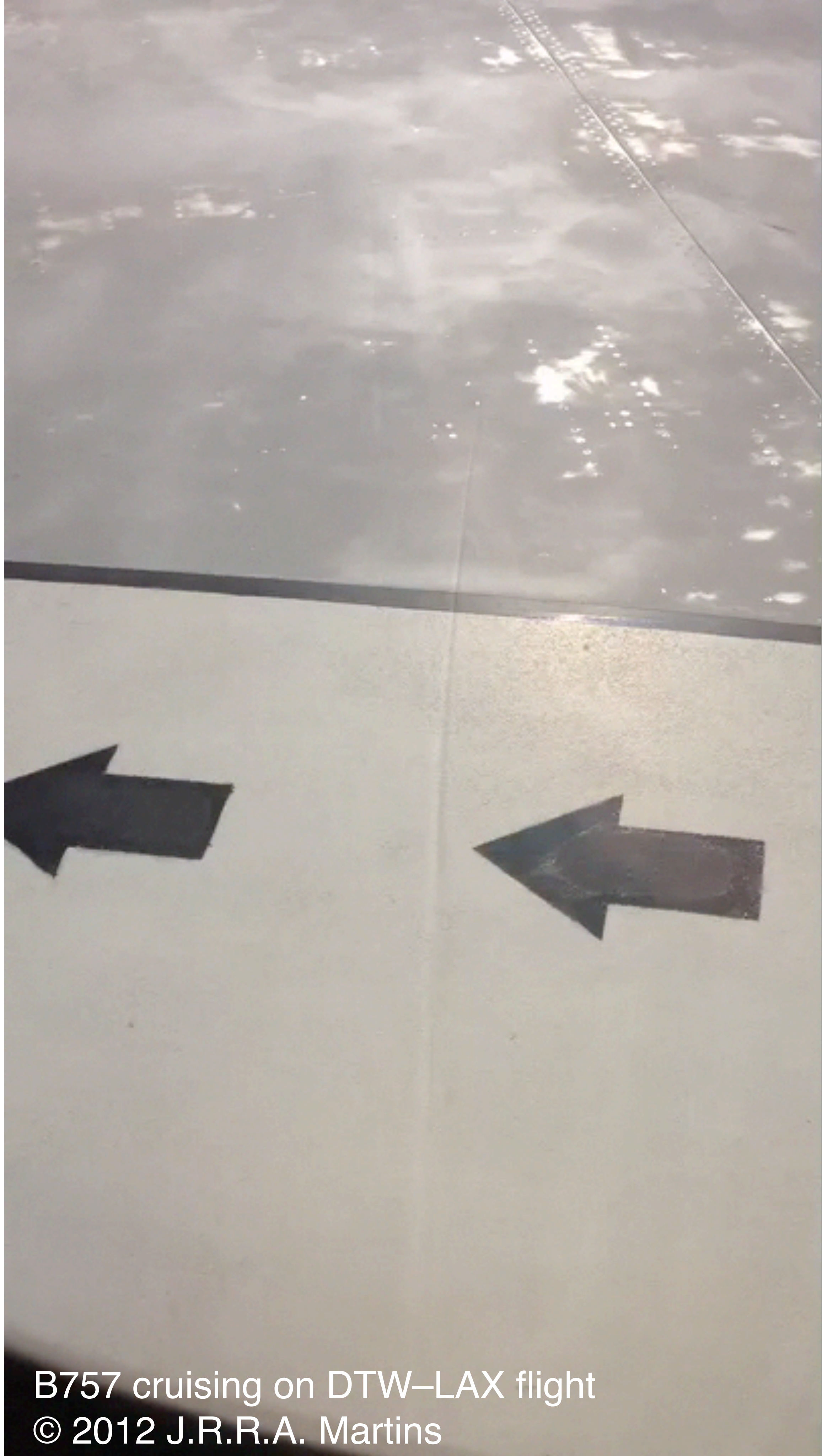
$$\frac{\partial w}{\partial t} + \frac{1}{A}\oint F_i \cdot \hat{n} dl - \frac{1}{A}\oint F_v \cdot \hat{n} dl = 0$$

$$w = \begin{bmatrix} \rho \\ \rho u_1 \\ \rho u_2 \\ \rho E \end{bmatrix} \quad F_{i_1} = \begin{bmatrix} \rho u_1 \\ \rho u_1^2 + p \\ \rho u_1 u_2 \\ (E+p)u_1 \end{bmatrix} \quad F_{v_1} = \begin{bmatrix} 0 \\ \tau_{11} \\ \tau_{12} \\ u_1\tau_{11} + u_2\tau_{12} - q_1 \end{bmatrix}$$

$$\tau_{11} = (\mu + \mu_t)\frac{M_\infty}{Re}\frac{2}{3}(2u_1 - u_2)$$

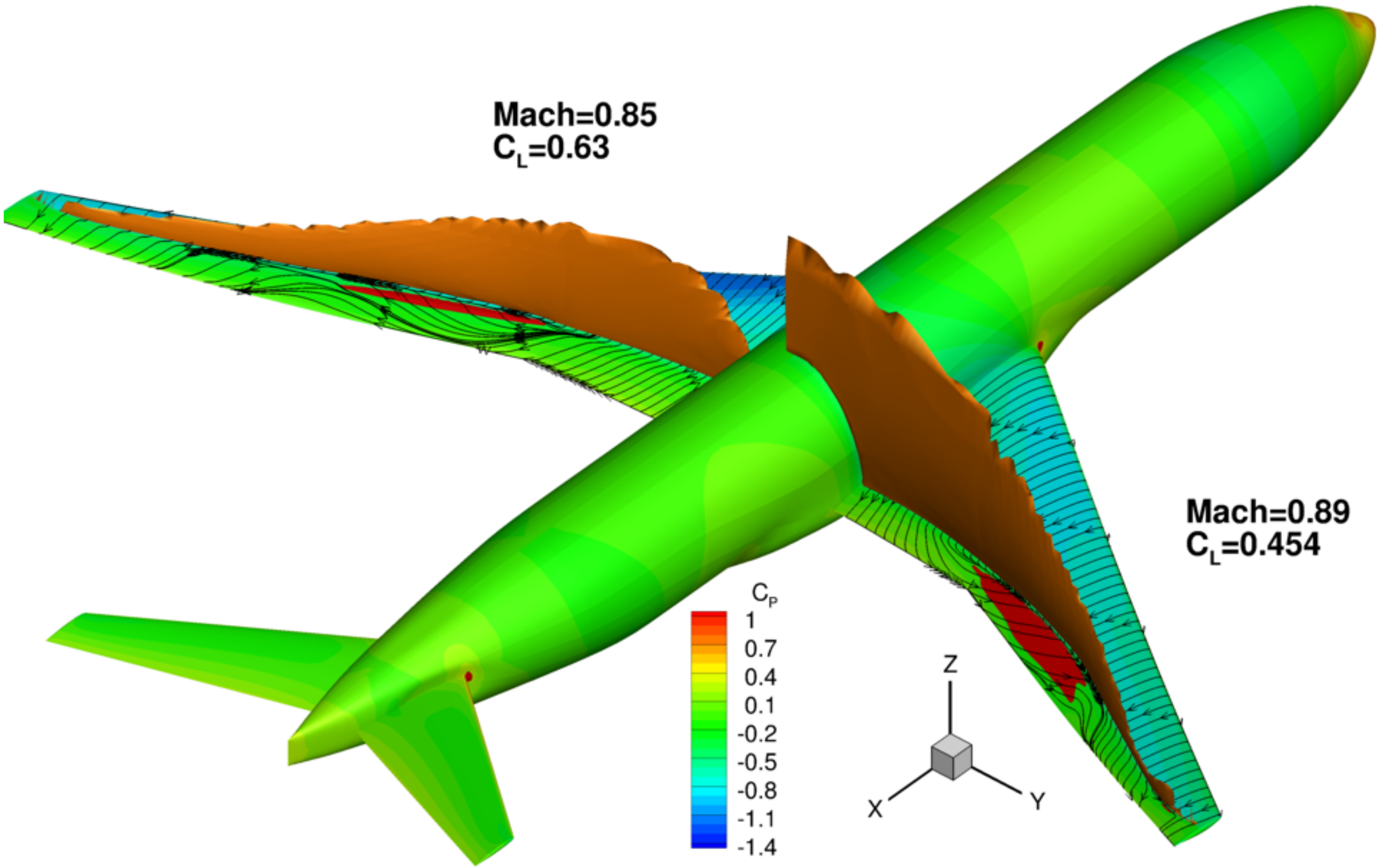
$$q_1 = -\frac{M_\infty}{Re(\gamma - 1)}\left(\frac{\mu}{Pr} + \frac{\mu_t}{Pr_t}\right)\frac{\partial a^2}{\partial x_1}$$

[Shockwaves on wings]

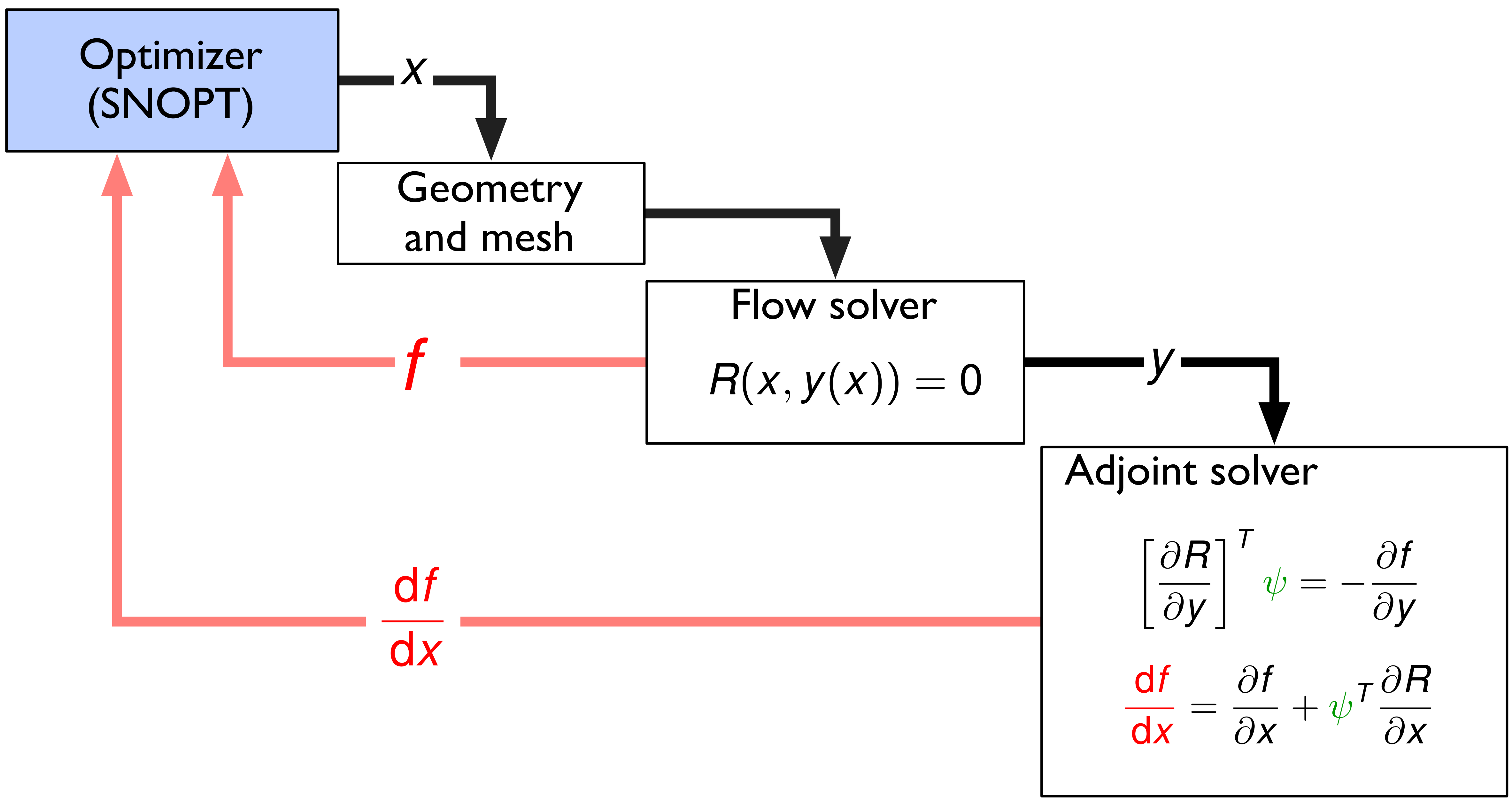


B757 cruising on DTW–LAX flight

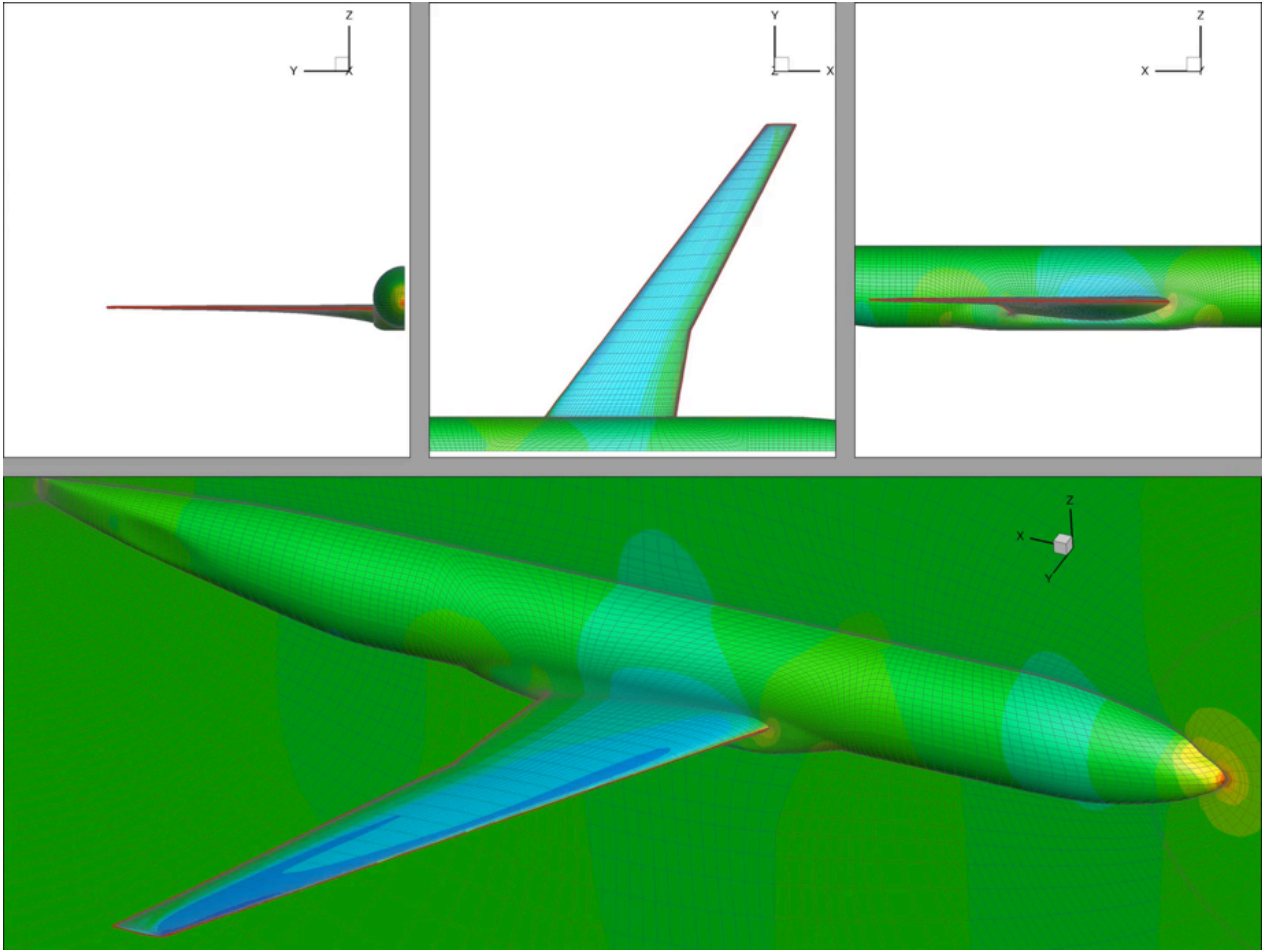
Reynolds-averaged Navier–Stokes equations are solved in a 3D domain



Combine flow solver, adjoint solver, and gradient-based optimizer to enable design



Fast mesh deformation handles large design changes



Derivatives are obtained using the algorithmic differentiation adjoint (ADjoint)

Solve the governing equations

$$R(x, y(x)) = 0$$

form and solve the adjoint equations

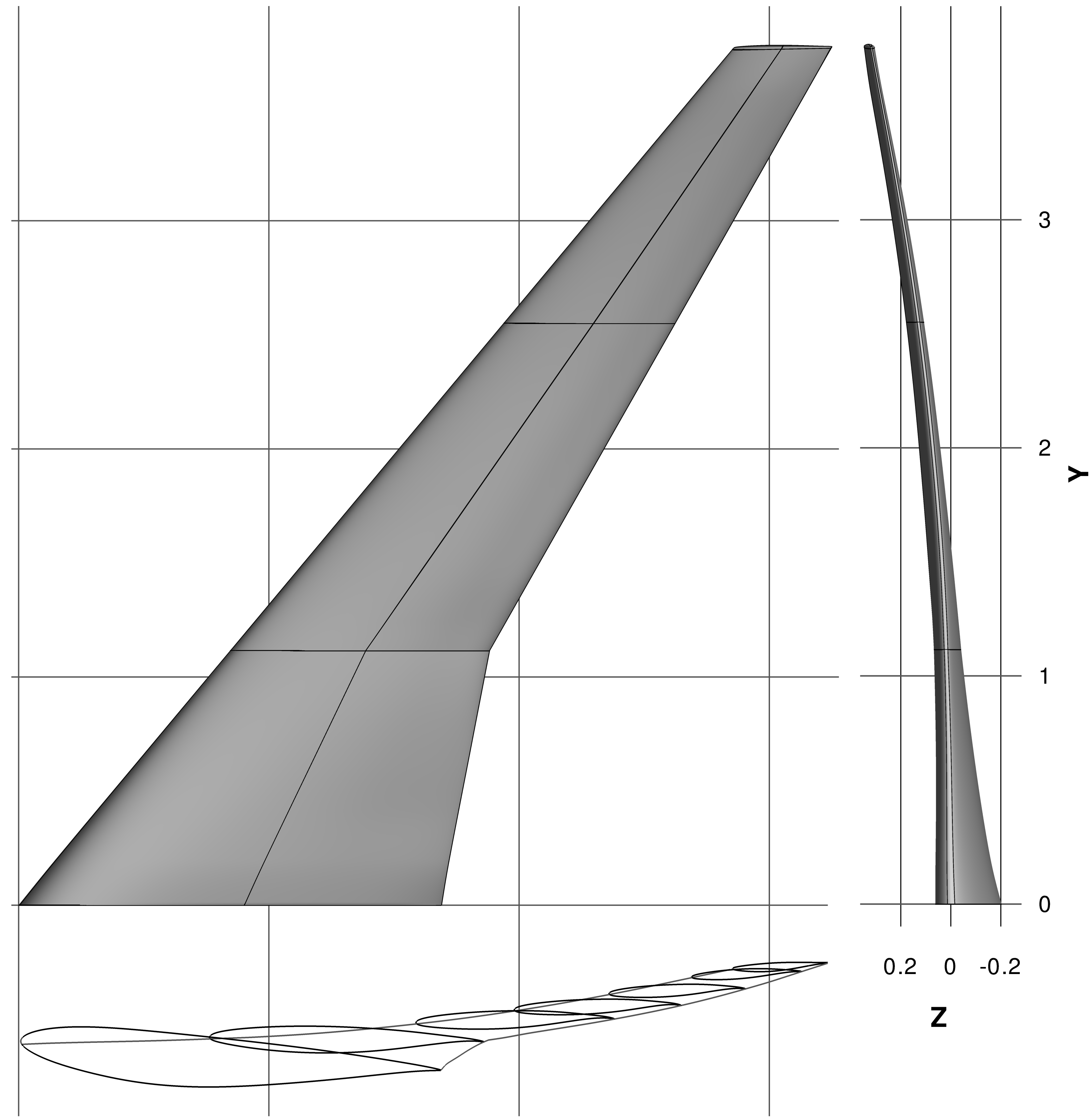
$$\left[\frac{\partial R}{\partial y}\right]^T \psi = -\frac{\partial f}{\partial y}$$

and compute the derivatives

$$\frac{\mathrm{d}f}{\mathrm{d}x} = \frac{\partial f}{\partial x} + \psi^T \frac{\partial R}{\partial x}$$

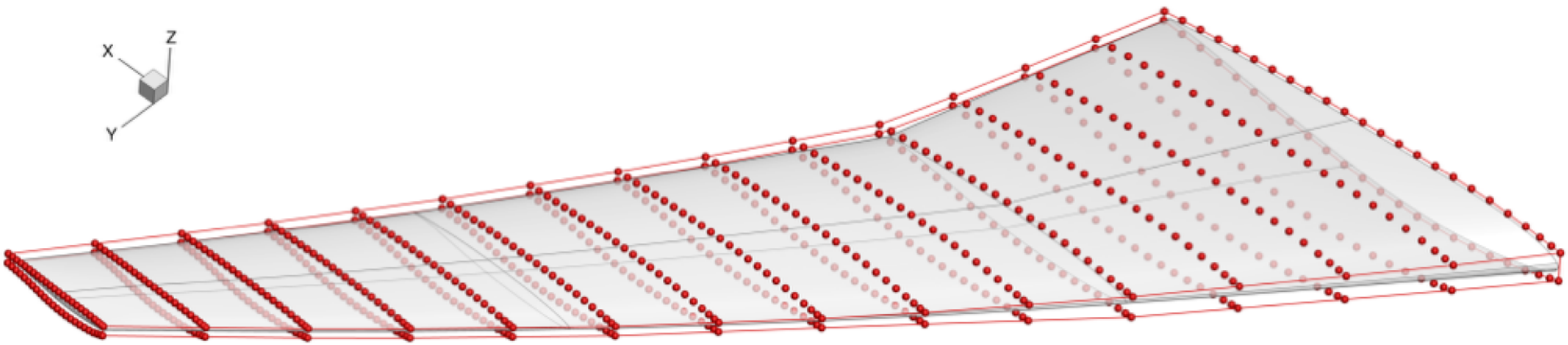
[Mader et al., *AIAA Journal*, 2008]

Common Research Model (CRM) wing is a new aerodynamic shape optimization benchmark



AIAA
Aerodynamic Design Optimization
Discussion Group (ADODG)

Wing aerodynamic shape optimization requires hundreds of design variables



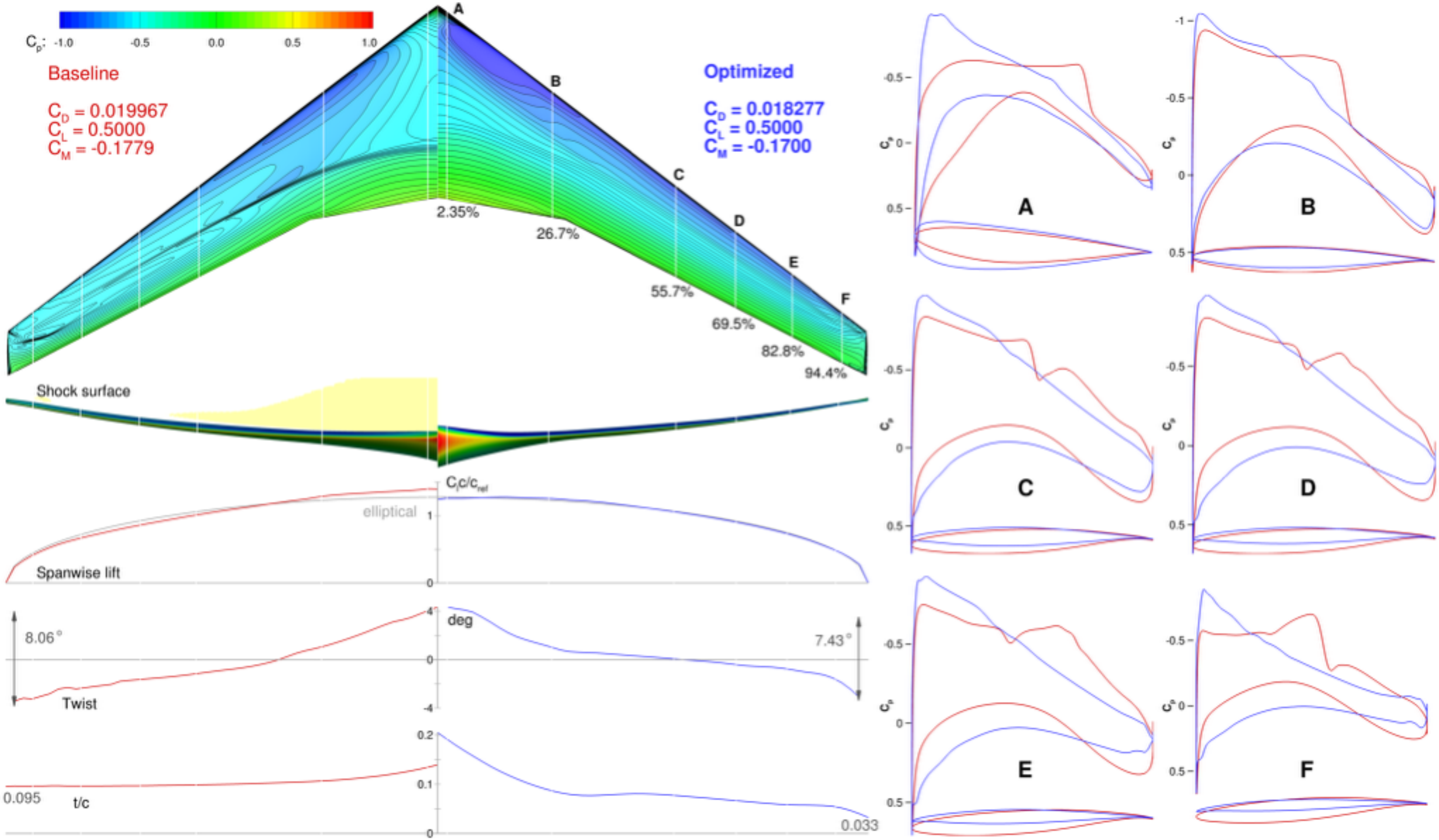
Want to minimize drag by varying shape, subject to lift and geometric constraints

	Function/variable	Description	Quantity
minimize	C_D	Drag coefficient	
with respect to	α	Angle of attack	1
	z	FFD control point z-coordinates	720
		Total design variables	721
subject to	$C_L = 0.5$	Lift coefficient constraint	1
	$C_{M_y} \geq -0.17$	Moment coefficient constraint	1
	$t \geq 0.25 t_{\text{base}}$	Minimum thickness constraints	750
	$V \geq V_{\text{base}}$	Minimum volume constraint	1
	$\Delta z_{\text{TE,upper}} = -\Delta z_{\text{TE,lower}}$	Fixed trailing edge constraints	15
	$\Delta z_{\text{LE,upper,root}} = -\Delta z_{\text{LE,lower,root}}$	Fixed wing root incidence constraint	1
		Total constraints	769

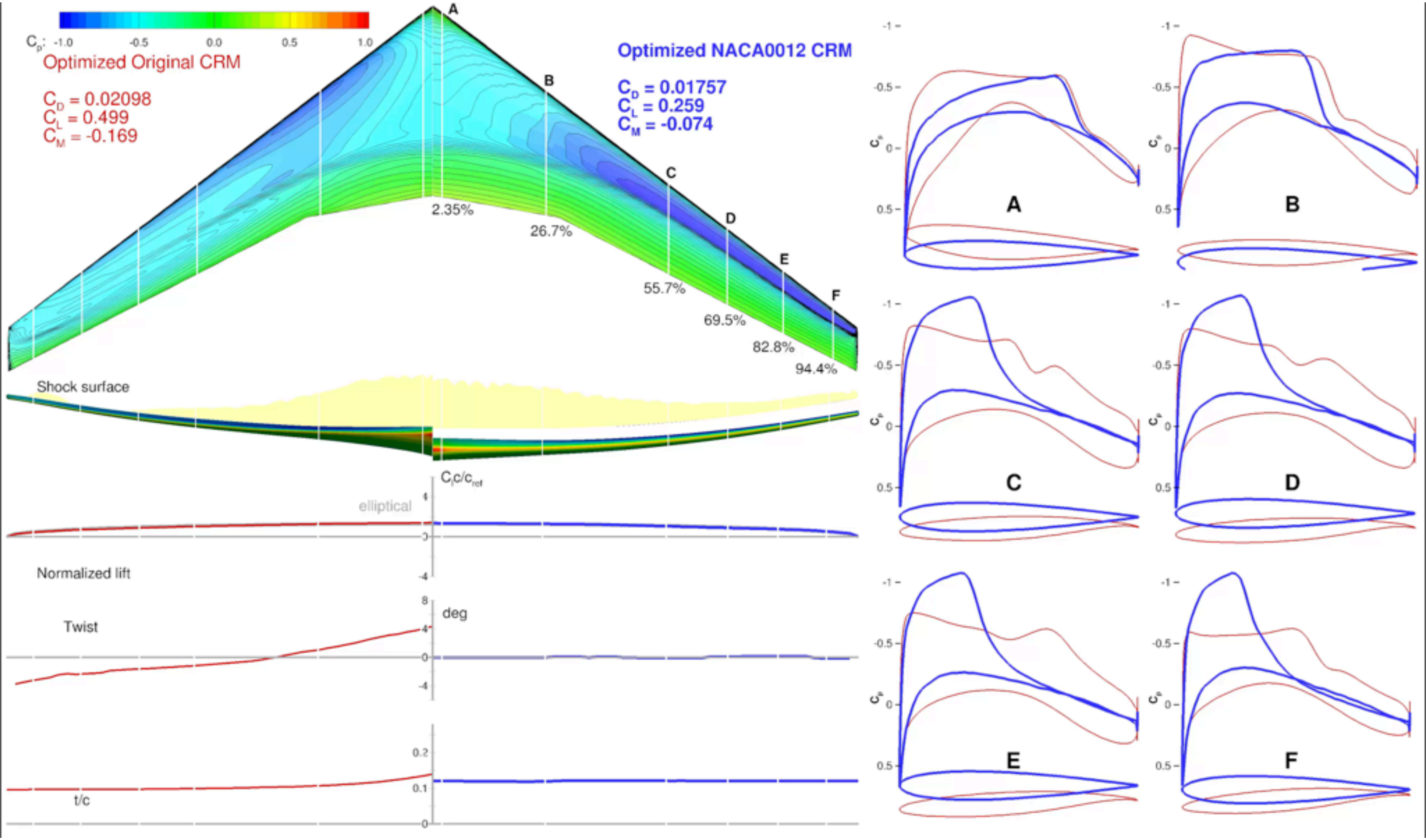
[Lyu et al., *AIAA Journal*, 2014]

Started with a good design and made it 8.5% better

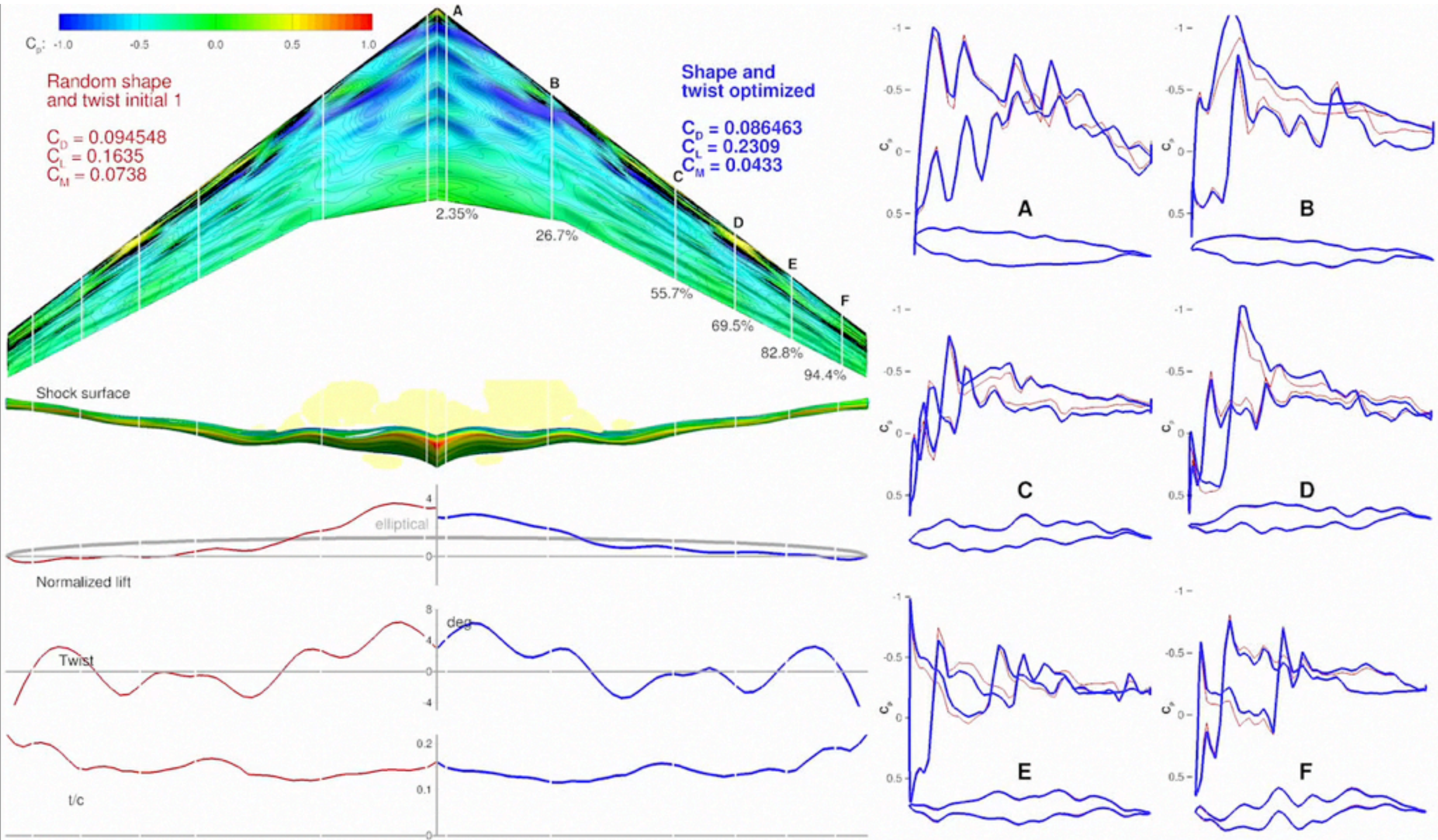
[Lyu et al., *AIAA Journal*, 2014]



Now, let's start with a bad design!



Now, let's start with a really bad design!



The initial and optimized geometries and grids are available with the AIAA Journal paper as supplemental data

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doi: 10.2514/1.J053318

Aerodynamic Shape Optimization Investigations of the Common Research Model Wing Benchmark

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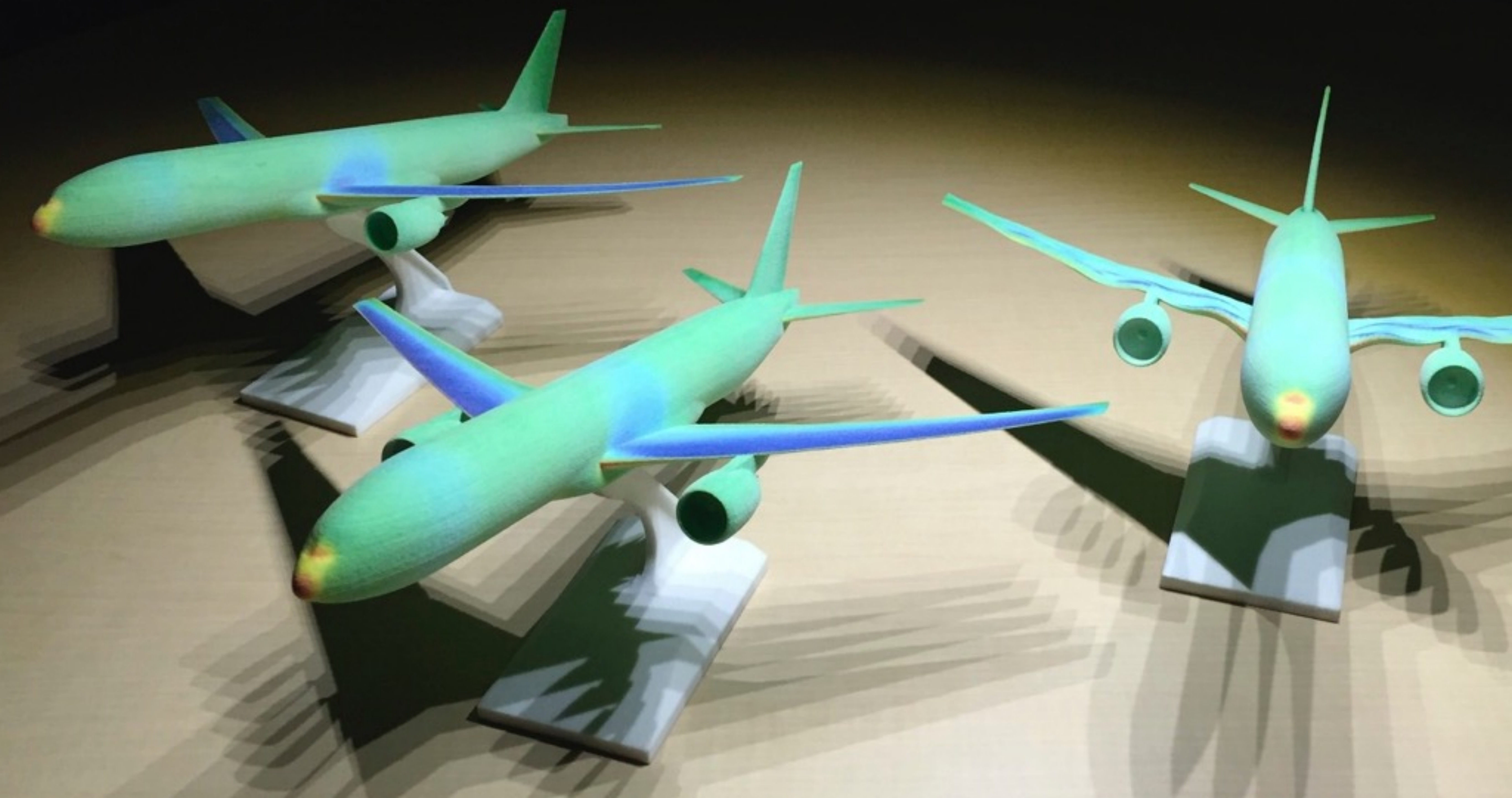
Sections: Choose

ABSTRACT Choose

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

3D-printed models colored with C_p distributions



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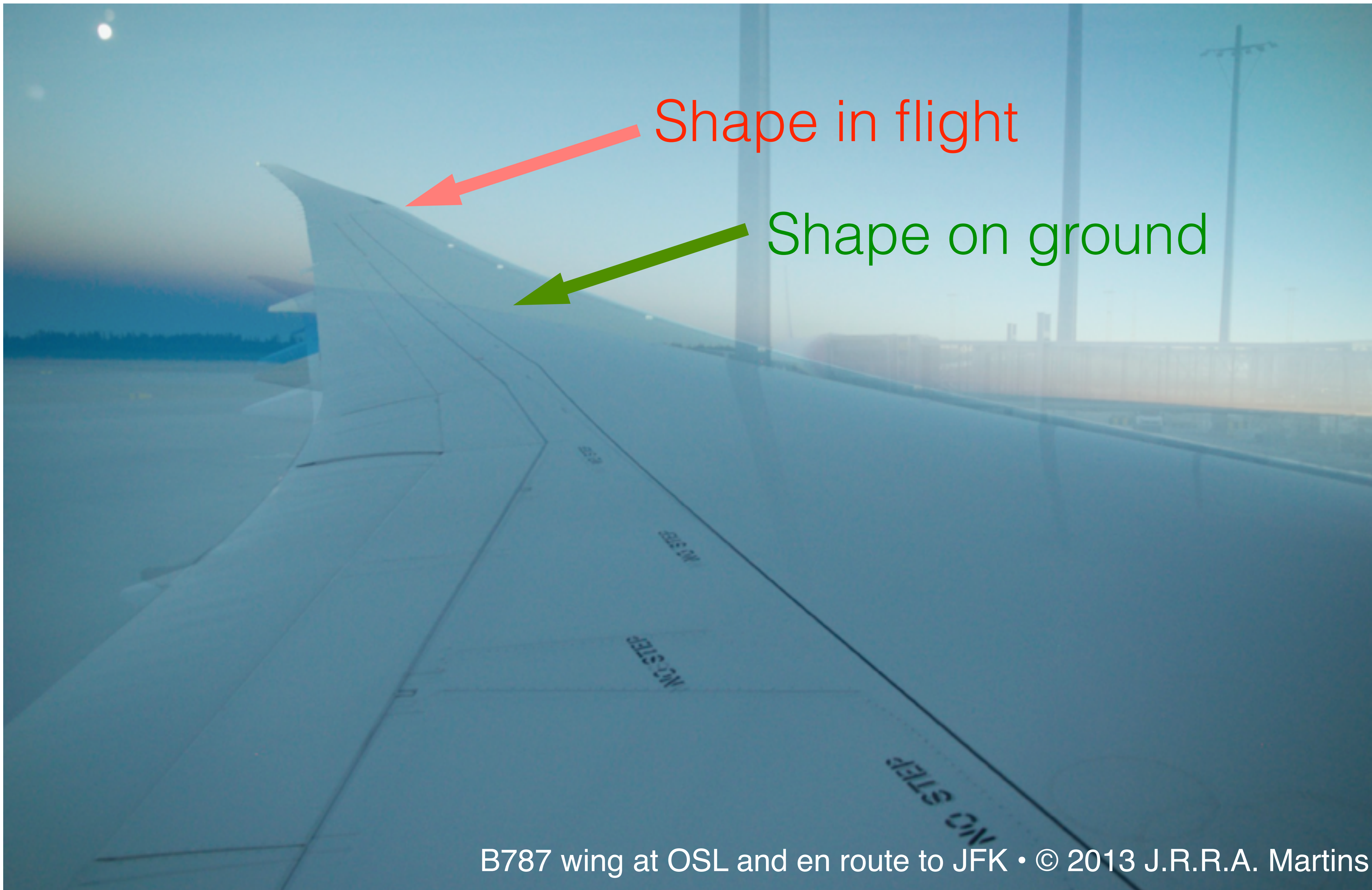
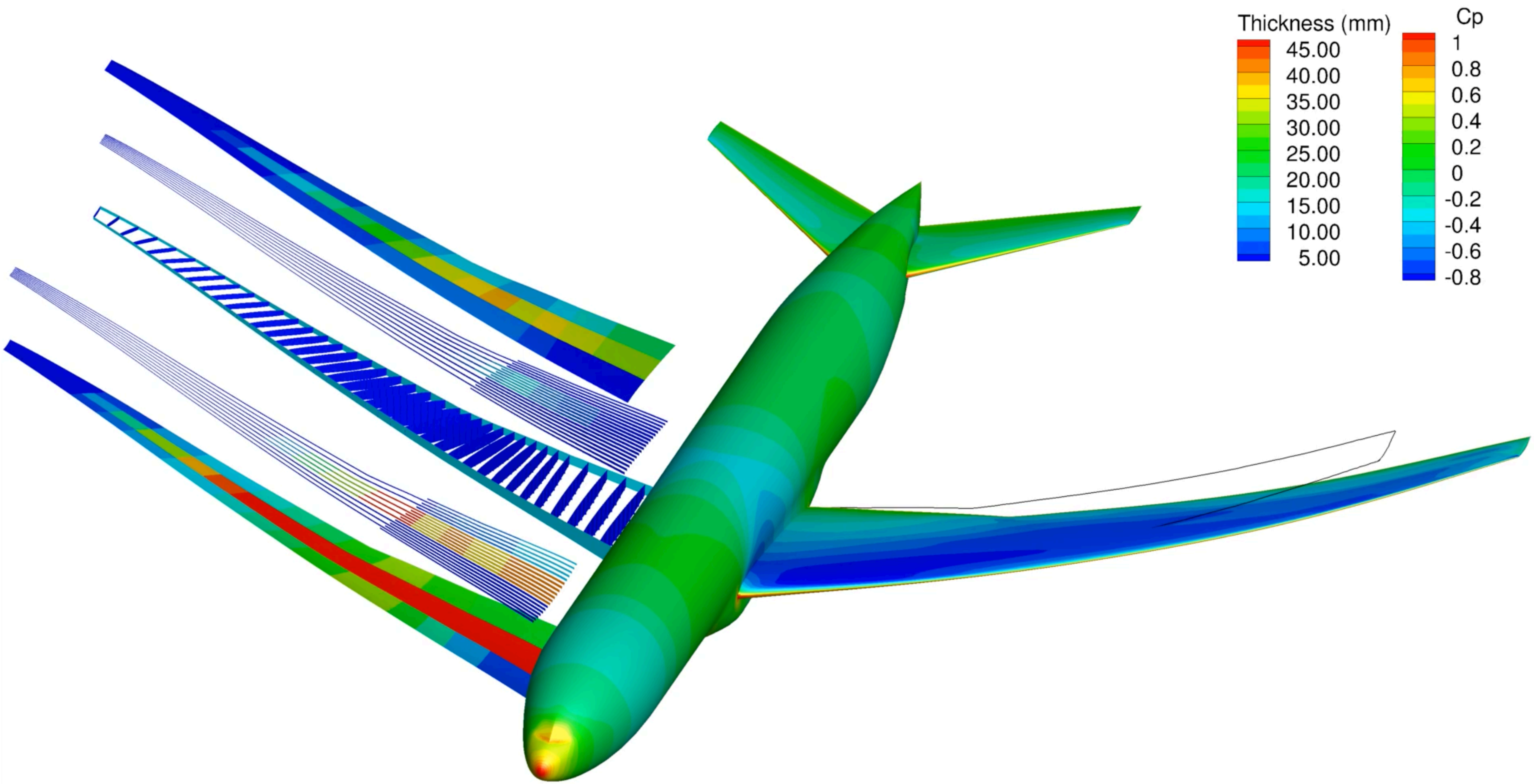
Wing design demands more than just aerodynamics



B787 wing at OSL and en route to JFK • © 2013 J.R.R.A. Martins

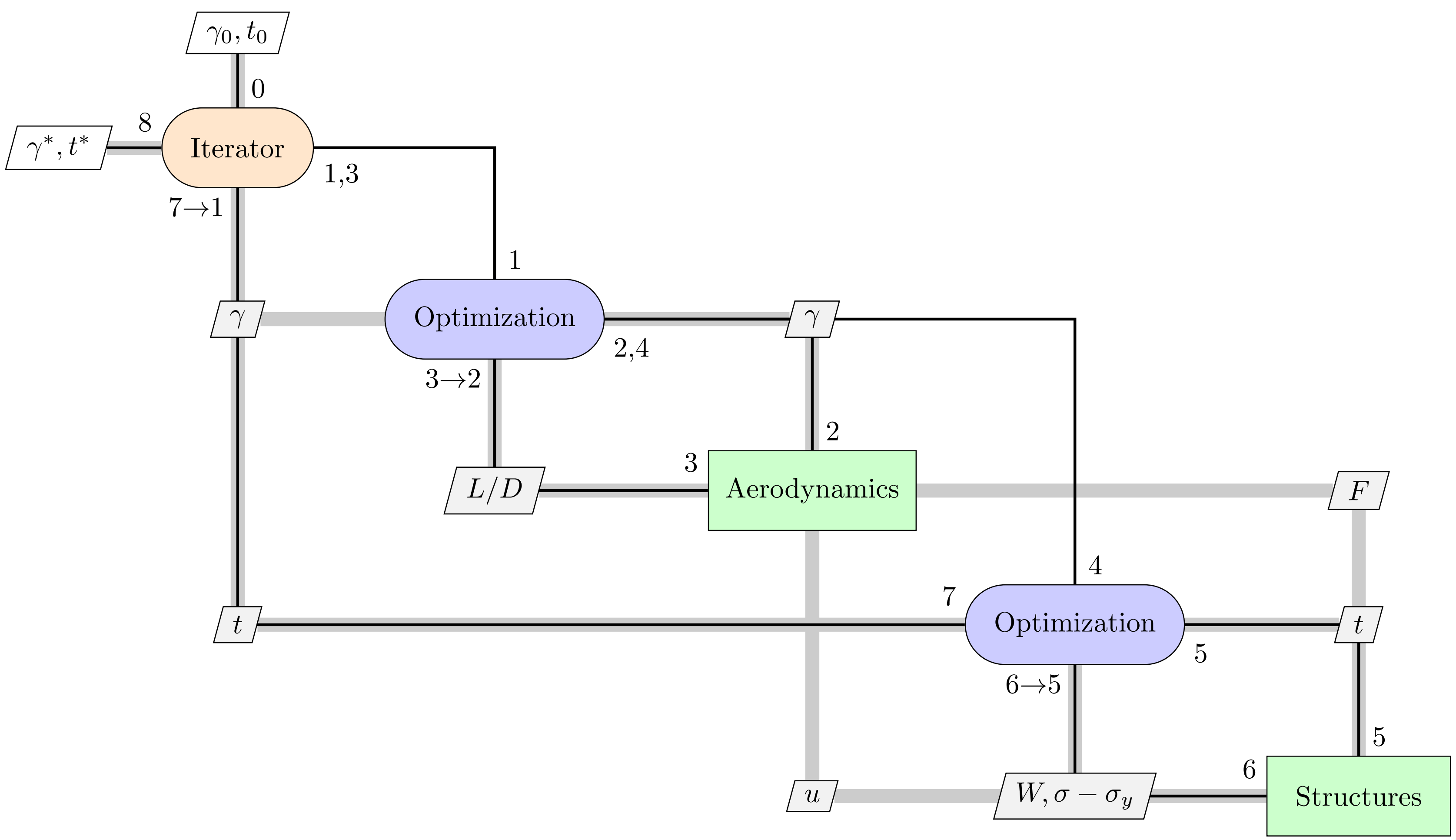
Want to optimize both aerodynamic shape and structural sizing, with high-fidelity

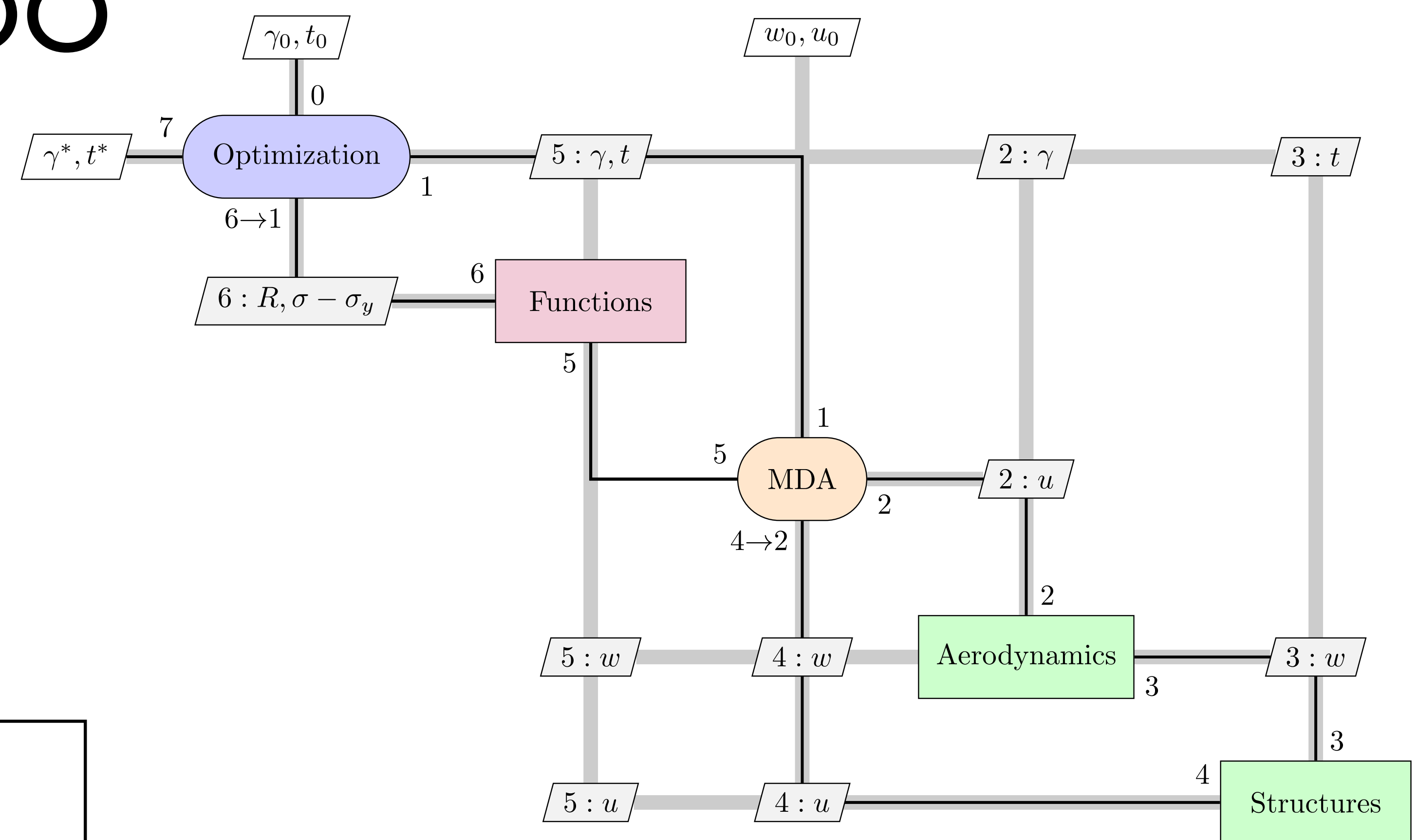


Sequential optimization is equivalent to coordinate descent

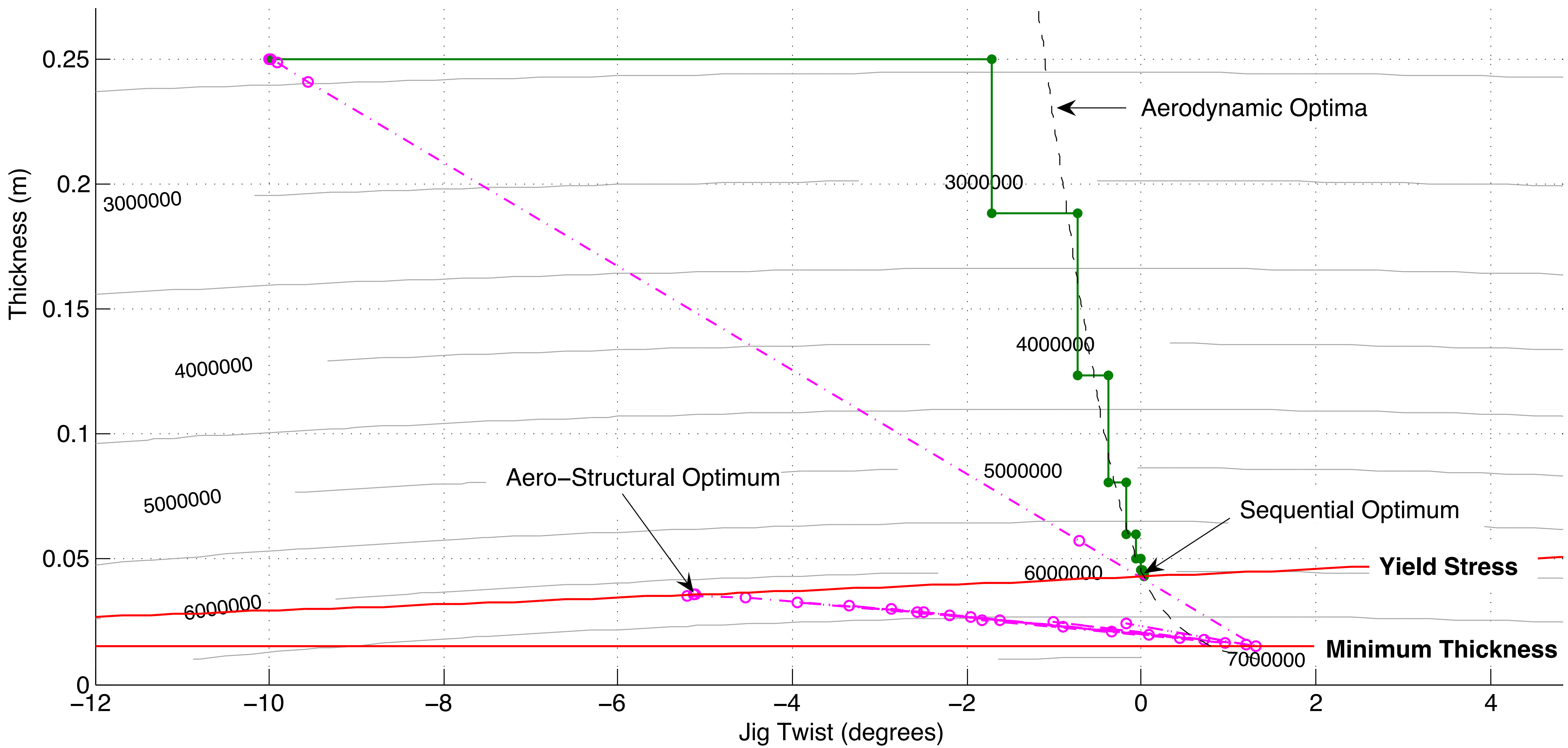
MDO

Sequential optimization





Sequential optimization fails to find the multidisciplinary optimum



[Chittick and Martins, *Struct. Multidiscip. O.*, 2008]

MDO for Aircraft Configurations with High-fidelity (MACH)

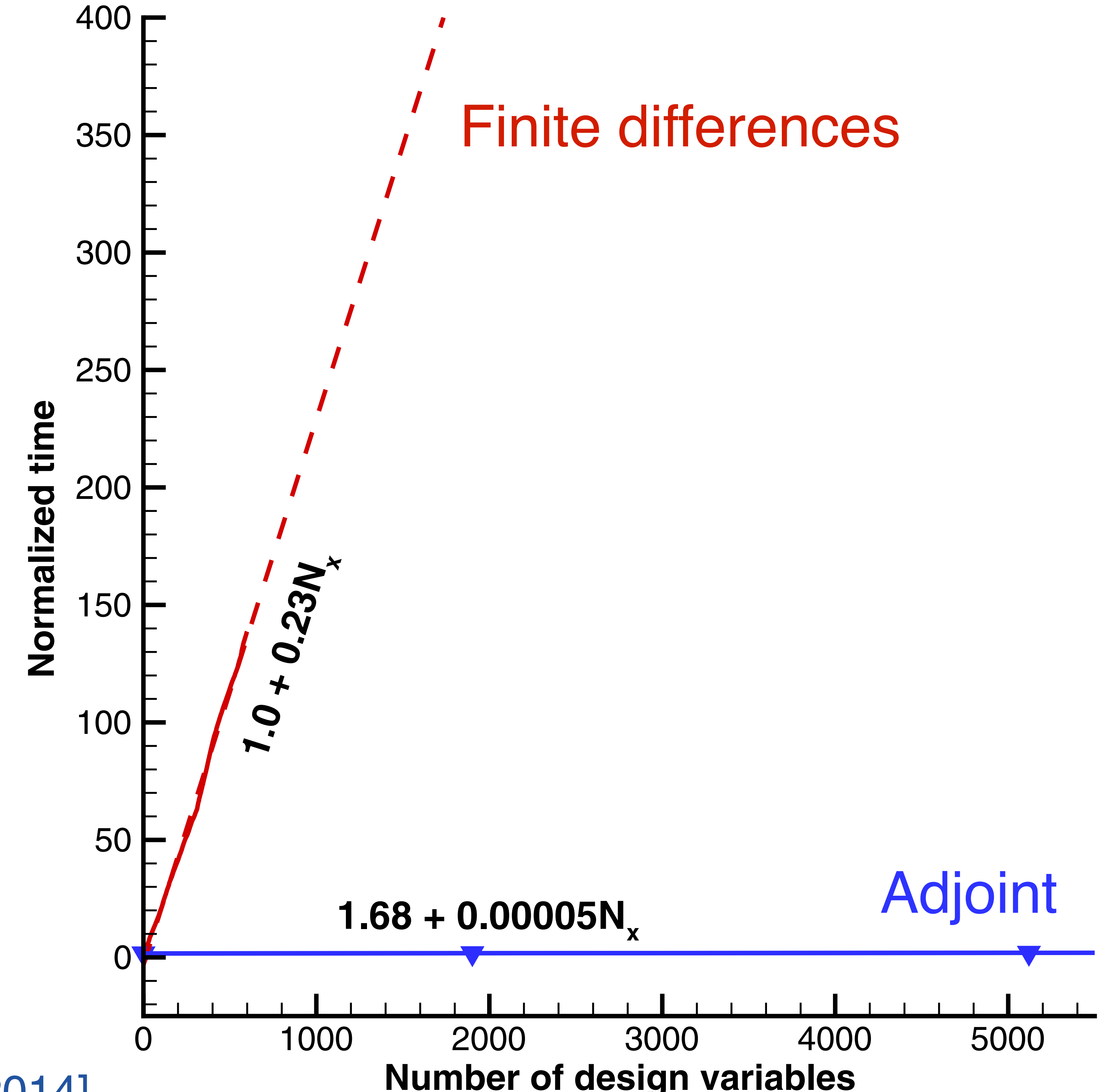
Python user script
Setup up the problem: objective function, constraints, design variables, optimizer and solver options

Optimizer interface		Aerostructural solver		Geometry modeler
pyOpt Common interface to various optimization software		*AeroStruct* Coupled solution methods and coupled derivative evaluation		*DVGeometry/GeoMACH* Defines and manipulates geometry, evaluates derivatives
SQP	Other optimizers	Structural solver *TACS* Governing and adjoint equations	Flow solver *SUMad* Governing and adjoint equations	

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

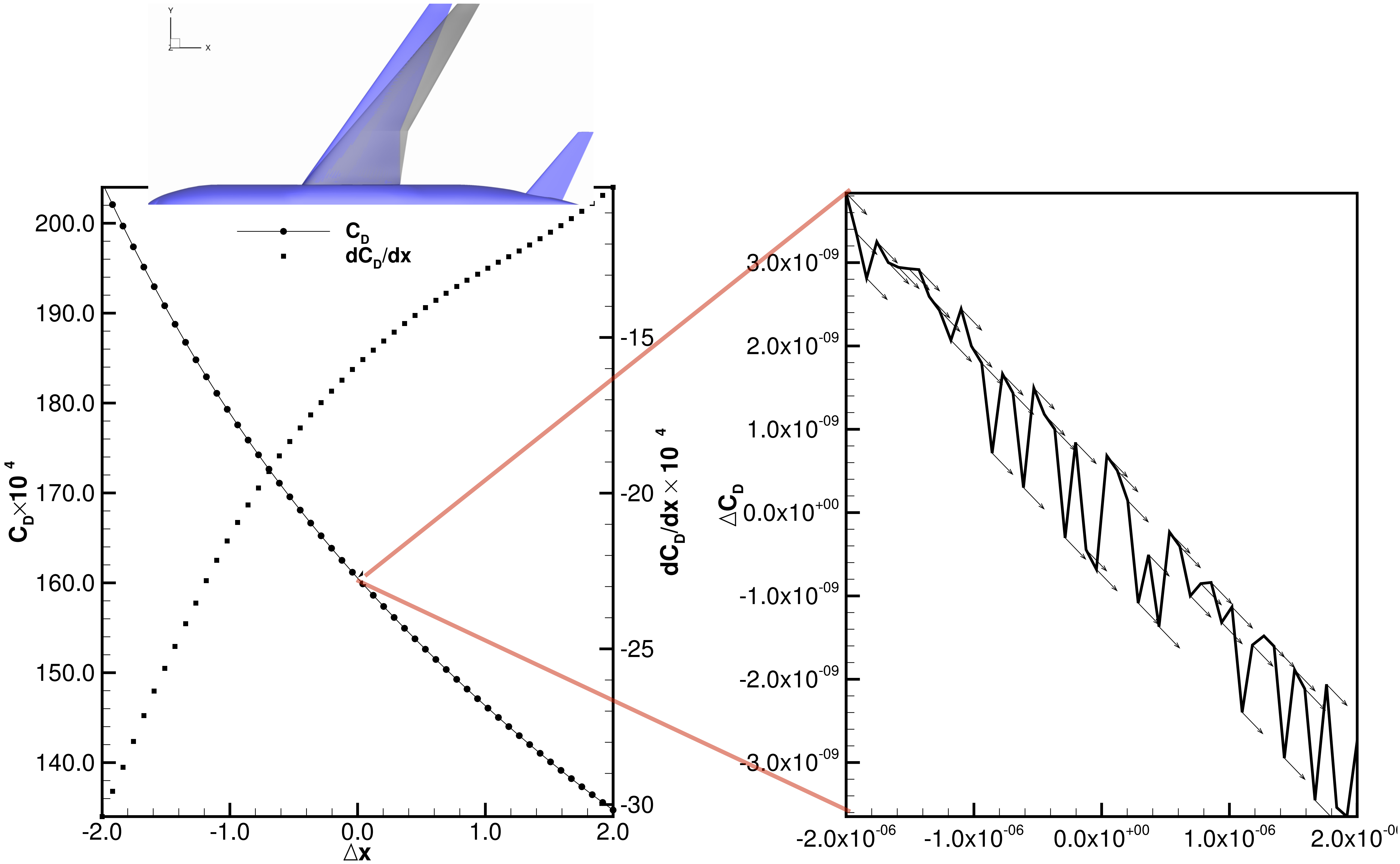
[Kenway et al., *AIAA J.*, 2014]
[Kennedy and Martins, *Finite Elem. Des.*, 2014]

Adjoint method efficiently computes gradients with respect to thousands of variables

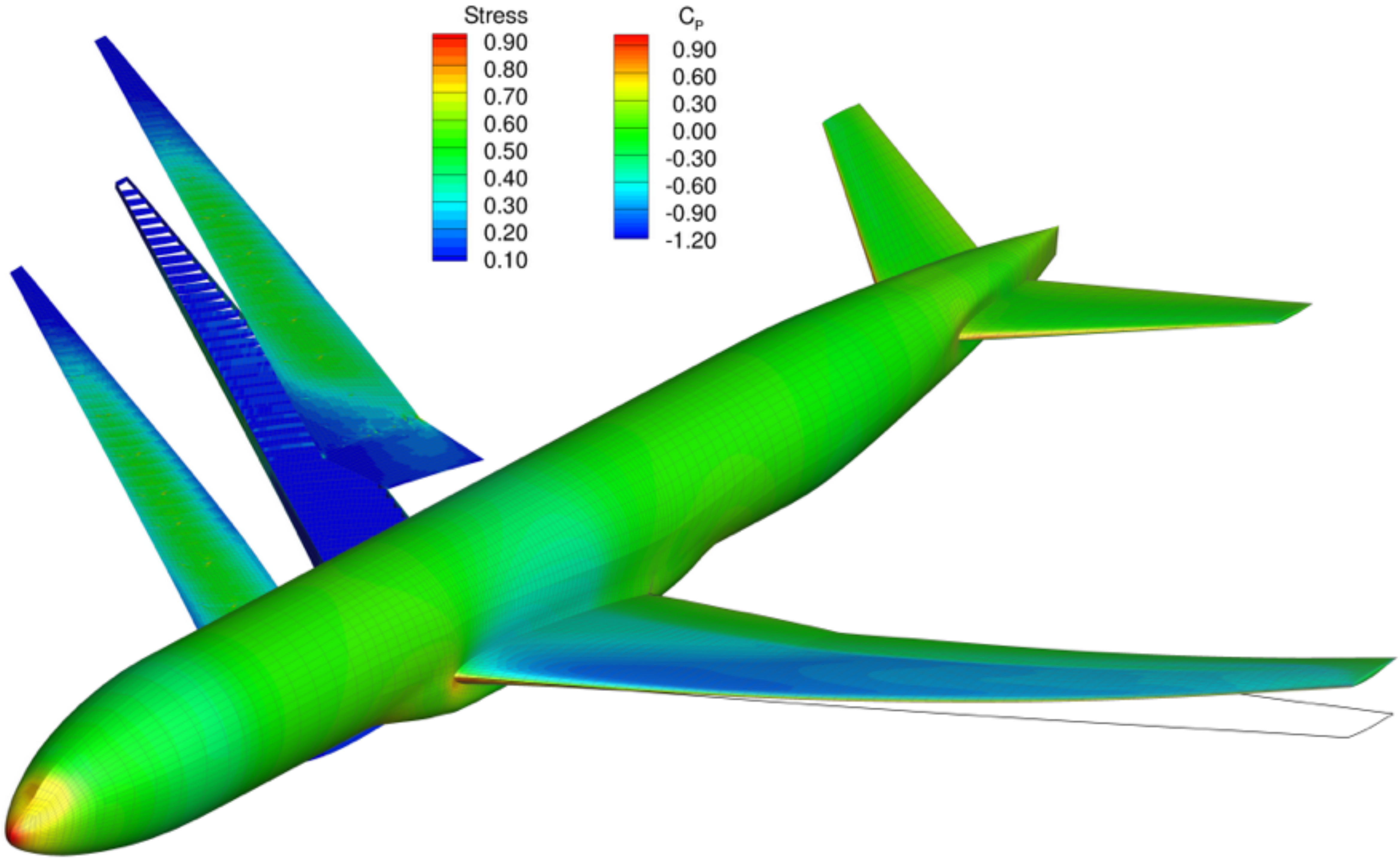


[Kenway et al., *AIAA J.*, 2014]

A smooth function and accurate gradients keep the optimizer happy

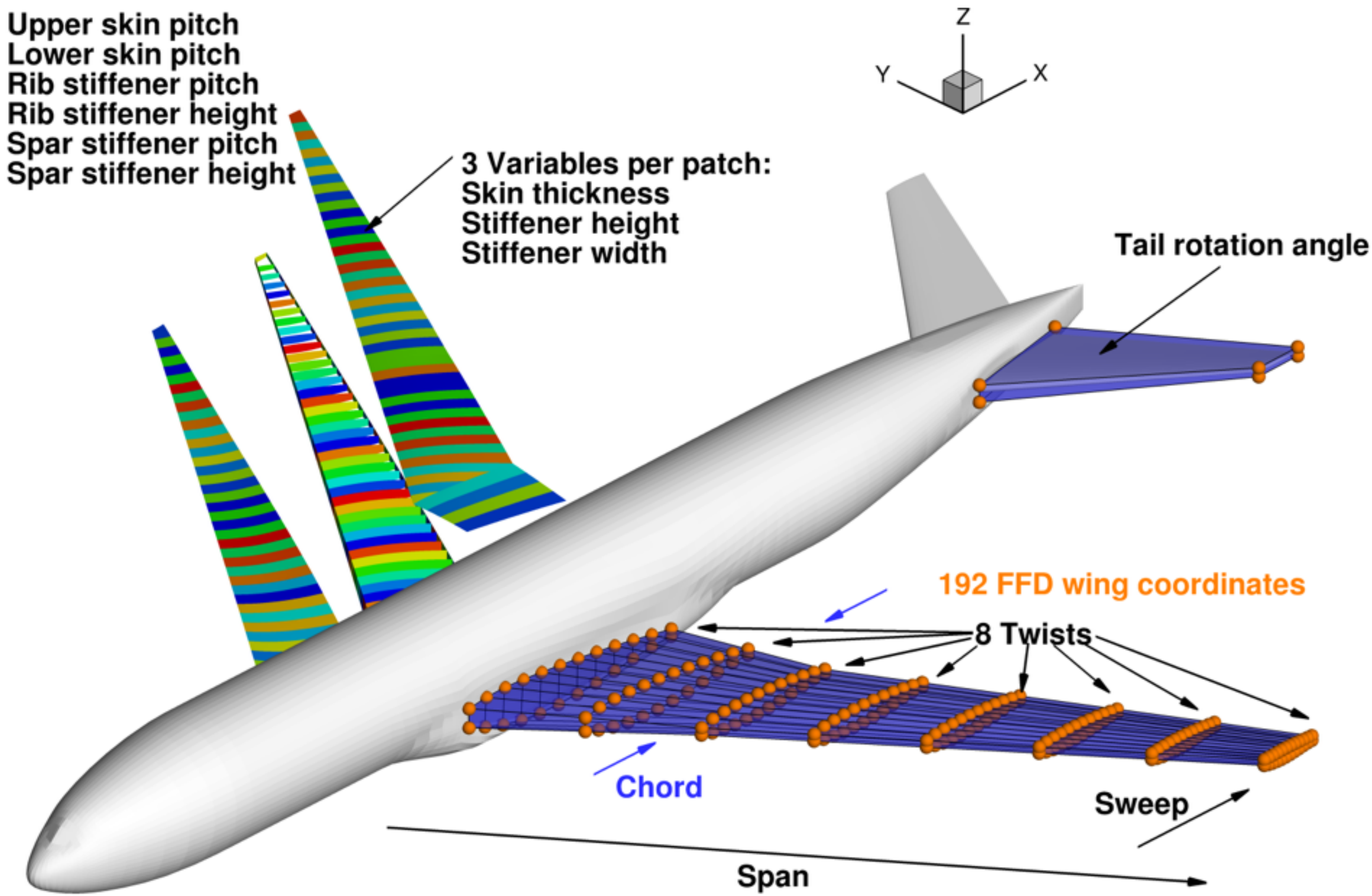


Let's do aerostructural optimization!



NASA-Michigan undeformed Common Research Model (uCRM)

Optimize 973 “aerodynamic” and structural sizing design variables



Objective and design variables

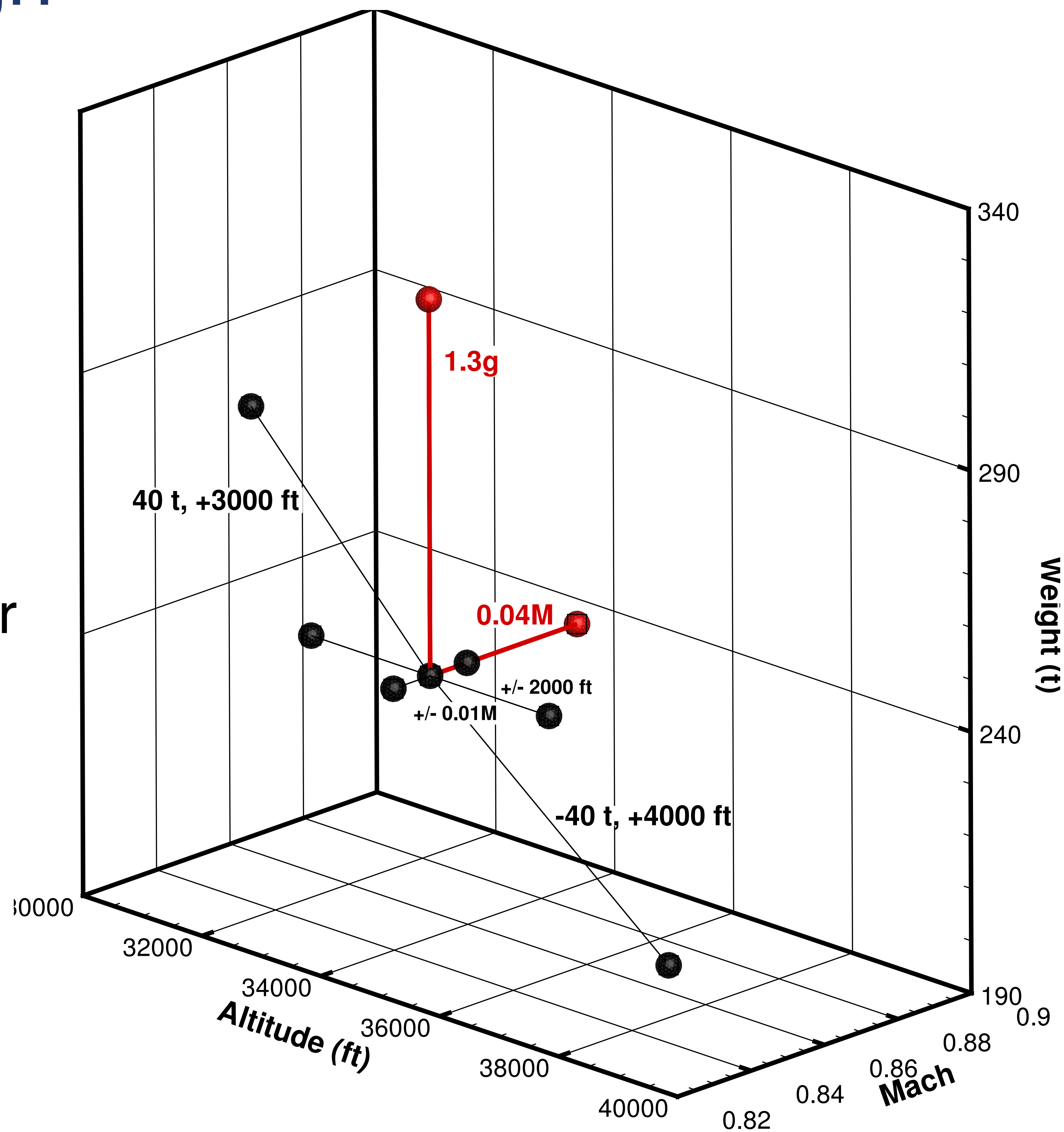
	Function/variable	Description	Quantity
minimize	βFuel burn $+ (1-\beta)$TOGW		
with respect to	x_{span}	Wing span	1
	x_{sweep}	Wing sweep	1
	x_{chord}	Wing chord	1
	x_{twist}	Wing twist	8
	x_{airfoil}	FFD control points	192
	x_{alpha_i}	Angle of attack at each flight condition	12
	x_{η_i}	Tail rotation angle at each flight condition	12
	x_{throttle_i}	Throttle setting for each cruise flight condition	7
	x_{altitude}	Cruise altitude	1
	X_{CG}	CG position	1
	$x_{\text{skin pitch}}$	Upper/lower stiffener pitch	2
	$x_{\text{spar pitch}}$	Le/Te Spar stiffener pitch	2
	x_{ribs}	Rib thickness	45
	$x_{\text{panel thick}}$	Panel thickness Skins/Spars	172
	$x_{\text{stiff thick}}$	Panel stiffener thickness Skins/Spars	172
	$x_{\text{stiff height}}$	Panel stiffener height Skins/Spars	172
	$x_{\text{panel length}}$	Panel length Skin/Spars	172
		Total design variables	**973**

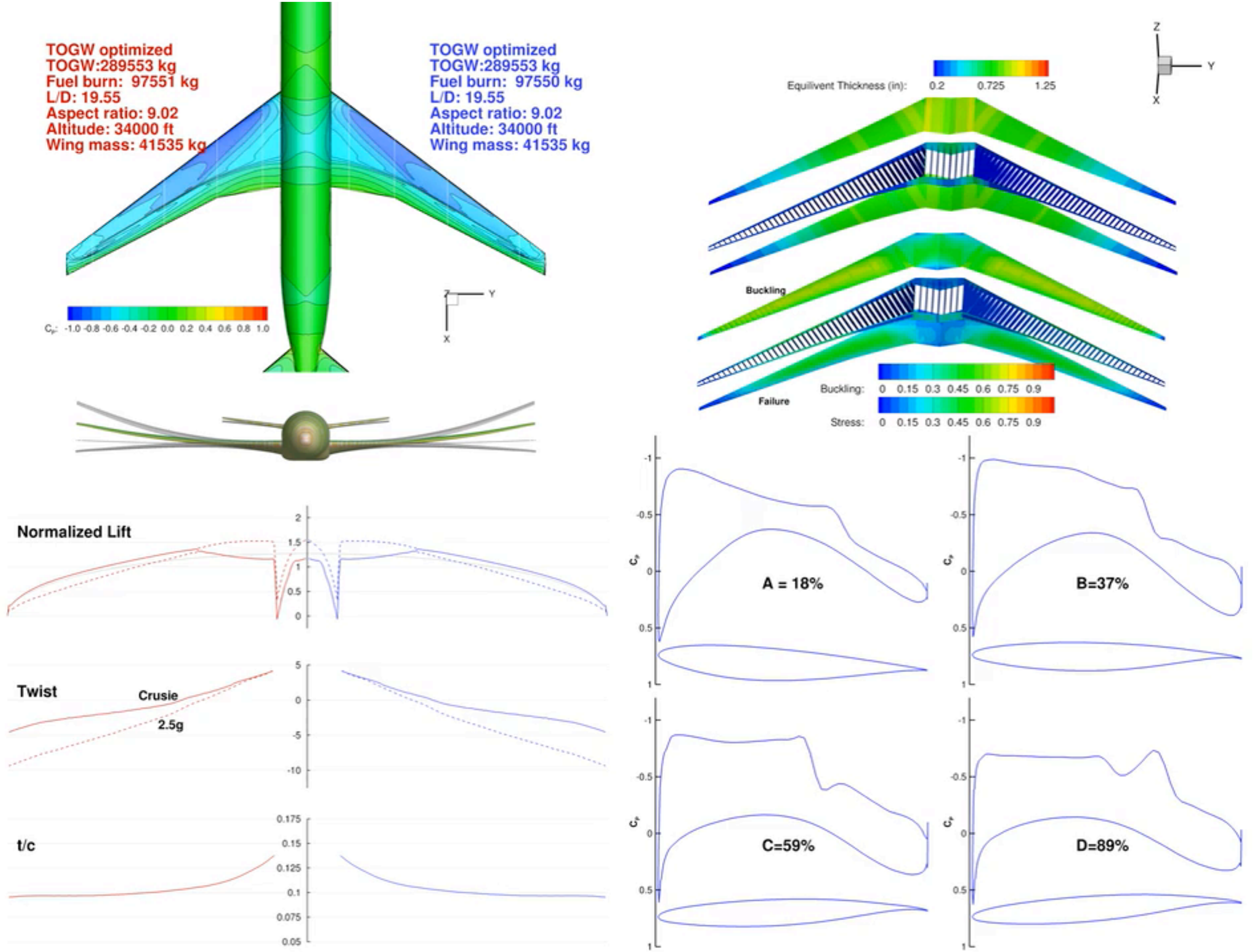
Constraints

subject to	$L = n_i W$	Lift constraint	12
	$C_{M_{y_i}} = 0.0$	Trim constraint	12
	$T = D$	Thrust constraint	7
	$1.08D - T_{\max} < 0$	Excess thrust constraint	7
	$t_{\mathrm{LE}}/t_{\mathrm{LE_{Init}}} \geq 1.0$	Leading edge radius	20
	$t_{\mathrm{TE}}/t_{\mathrm{TE_{Init}}} \geq 1.0$	Trailing edge thickness	20
	$\mathcal{V}_{\mathrm{wing}} > \mathcal{V}_{\mathrm{fuel}}$	Minimum fuel volume	1
	$x_{\mathrm{CG}} - 1/4MAC = 0$	CG location at 1/4 chord MAC	1
	$L_{\mathrm{panel}} - x_{\mathrm{panel\ length}} = 0$	Target panel length	172
	$\mathrm{KS}_{\mathrm{stress}} \leq 1$	2.5 g Yield stress	4
	$\mathrm{KS}_{\mathrm{buckling}} \leq 1$	2.5 g Buckling	3
	$\mathrm{KS}_{\mathrm{buckling}} \leq 1$	-1.0 g Buckling	3
	$\mathrm{KS}_{\mathrm{buckling}} \leq 1$	1.78 g Yield stress	3
	$\mathrm{KS}_{\mathrm{buckling}} \leq 1$	1.78 g Buckling	4
	$\left\lvert x_{\mathrm{panel\ thick}_i} - x_{\mathrm{panel\ thick}_{i+1}} \right\rvert \leq 0.0025$	Skin thickness adjacency	168
	$\left\lvert x_{\mathrm{stiff\ thick}_i} - x_{\mathrm{stiff\ thick}_{i+1}} \right\rvert \leq 0.0025$	Stiffener thickness adjacency	168
	$\left\lvert x_{\mathrm{stiff\ height}_i} - x_{\mathrm{stiff\ height}_{i+1}} \right\rvert$	Stiffener height adjacency	168
	$x_{\mathrm{stiff\ thick}} - x_{\mathrm{panel\ thick}} < 0.005$	Maximum stiffener-skin difference	172
	$\Delta z_{\mathrm{TE,upper}} = -\Delta z_{\mathrm{TE,lower}}$	Fixed trailing edge	8
	$\Delta z_{\mathrm{LE,upper}} = -\Delta z_{\mathrm{LE,lower}}$	Fixed leading edge	8
		Total constraints	**961**

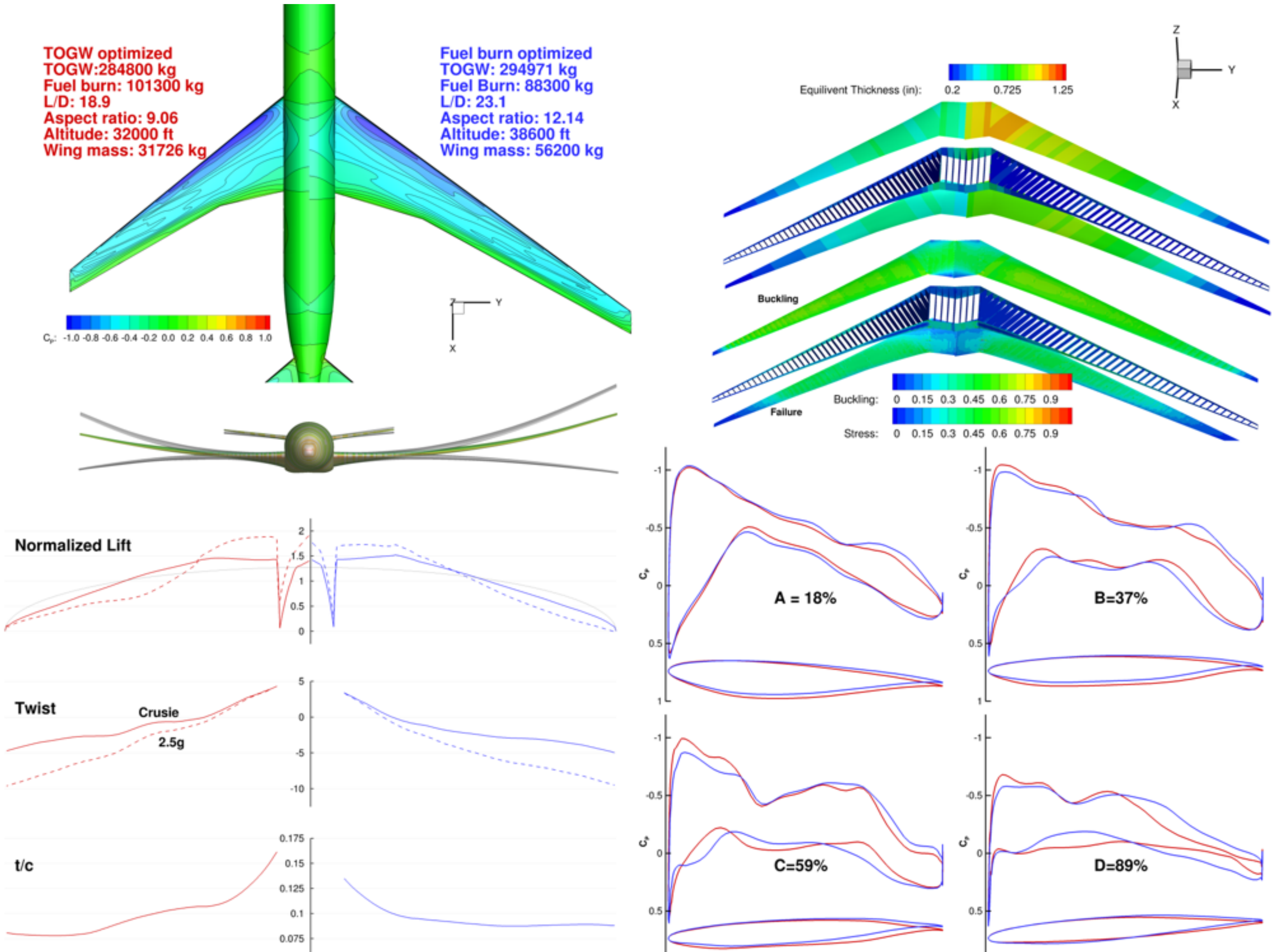
Considering multiple flight conditions is required for a practical design

- 7 cruise conditions for performance
- 2 off design conditions
- 3 maneuver condition for structural constraints
- Aircraft trimmed at all conditions

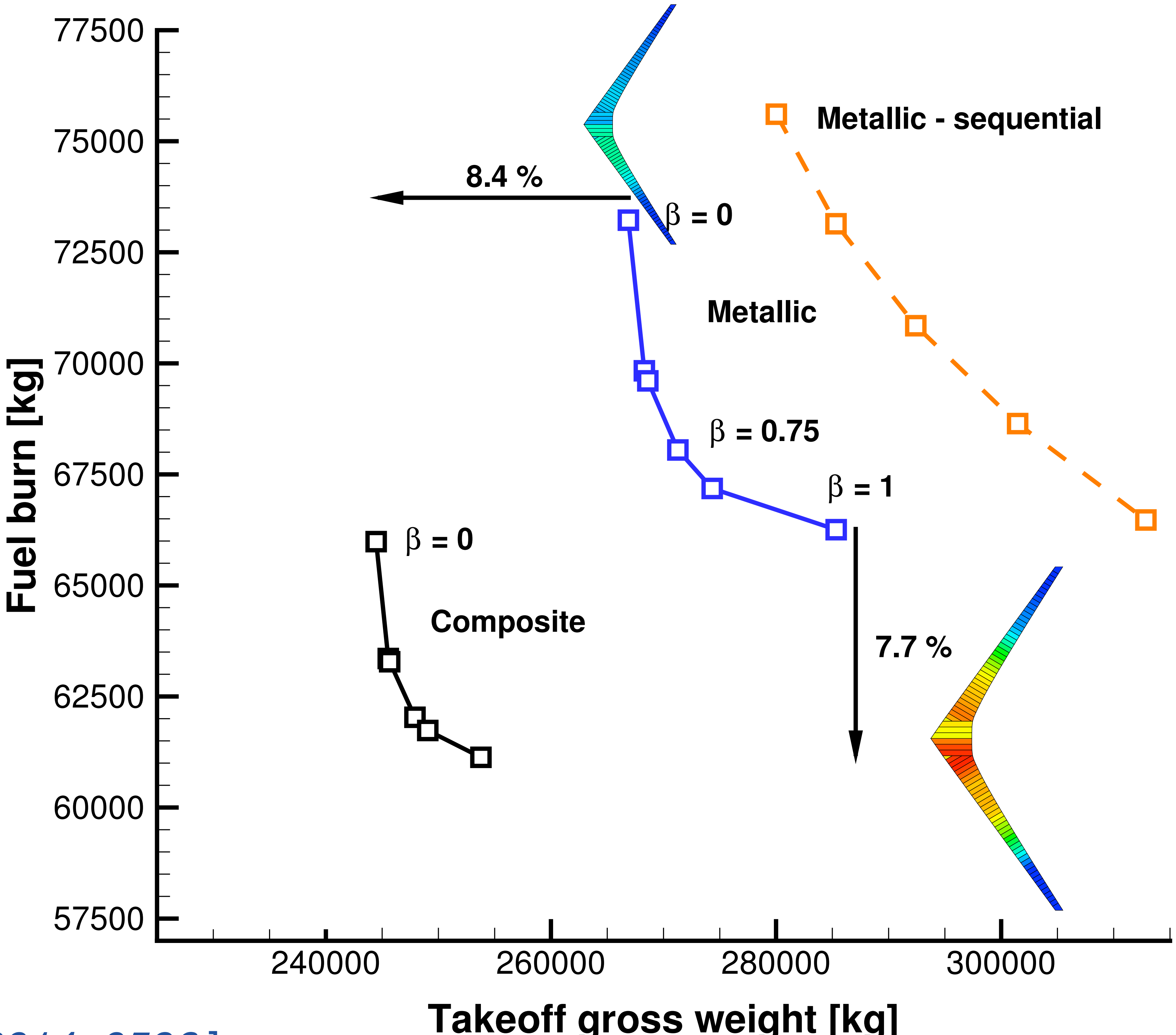




TOGW optimized
TOGW:289553 kg
Fuel burn: 97551 kg
L/D: 19.55
Aspect ratio: 9.02
Altitude: 34000 ft
Wing mass: 41535 kg
TOGW optimized
TOGW:289553 kg
Fuel burn: 97550 kg
L/D: 19.55
Aspect ratio: 9.02
Altitude: 34000 ft
Wing mass: 41535 kg
Cp: -1.0 -0.8 -0.6 -0.4 -0.2 0.0 0.2 0.4 0.6 0.8 1.0
Equilivent Thickness (in): 0.2 0.725 1.25
Buckling
Failure
Buckling: 0 0.15 0.3 0.45 0.6 0.75 0.9
Stress: 0 0.15 0.3 0.45 0.6 0.75 0.9
Normalized Lift
Twist
Crusie
2.5g
t/c
A = 18%
B=37%
C=59%
D=89%


TOGW optimized
TOGW:284800 kg
Fuel burn: 101300 kg
L/D: 18.9
Aspect ratio: 9.06
Altitude: 32000 ft
Wing mass: 31726 kg
Fuel burn optimized
TOGW: 294971 kg
Fuel Burn: 88300 kg
L/D: 23.1
Aspect ratio: 12.14
Altitude: 38600 ft
Wing mass: 56200 kg
Cp: -1.0 -0.8 -0.6 -0.4 -0.2 0.0 0.2 0.4 0.6 0.8 1.0
Equilivent Thickness (in): 0.2 0.725 1.25
Buckling
Failure
Buckling: 0 0.15 0.3 0.45 0.6 0.75 0.9
Stress: 0 0.15 0.3 0.45 0.6 0.75 0.9
Normalized Lift
Twist
Crusie
2.5g
t/c
A = 18%
B=37%
C=59%
D=89%

This framework enables designers to perform optimal objective and technology tradeoffs



[Kennedy et al., *AIAA 2014–0596*]

Boeing 777x will use folding wing tips to fit in current airport gates

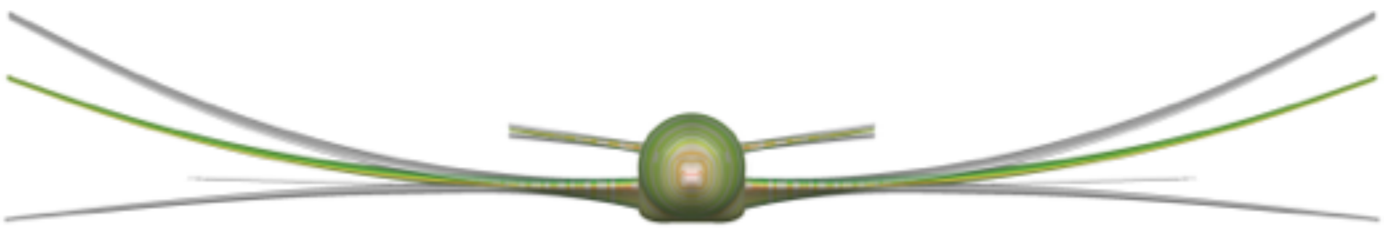
High-Fidelity Multidisciplinary Design Optimization for the Next Generation of Aircraft

- Choice of optimization algorithm
- Computing derivatives efficiently
- Aerodynamic shape optimization
- Aerostructural design optimization
- Summary and ongoing work

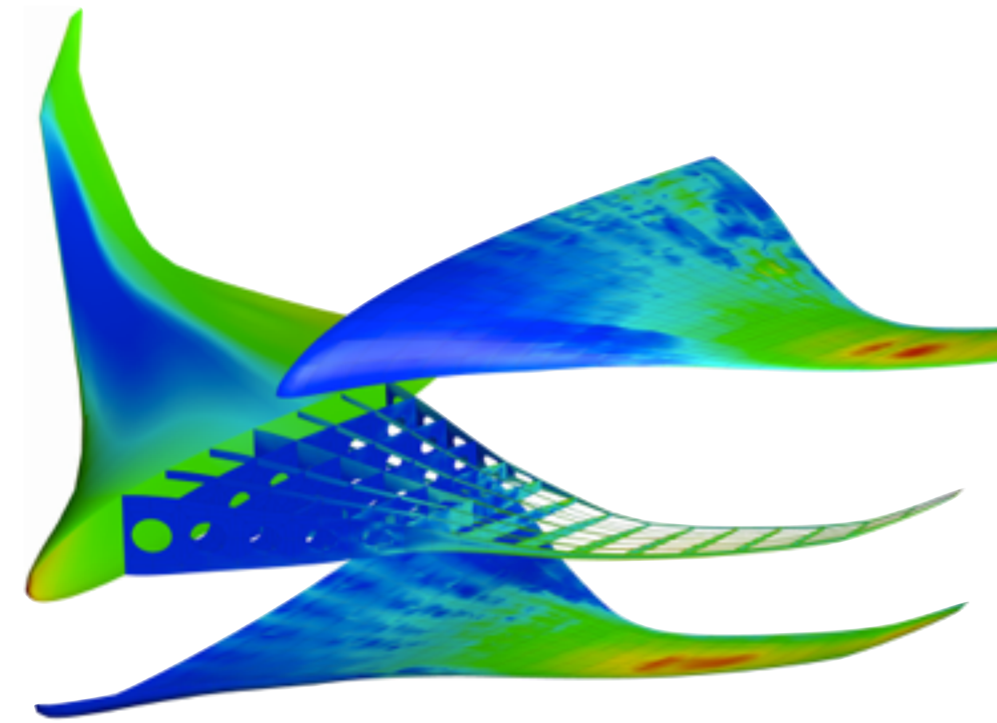
Summary

- Efficient and accurate gradient computation via adjoints methods
- Robust aerodynamic shape optimization
- Extended adjoint method to multiple disciplines
- Aerostructural design optimization with respect to 1000 design variables
- Muito mais a fazer!

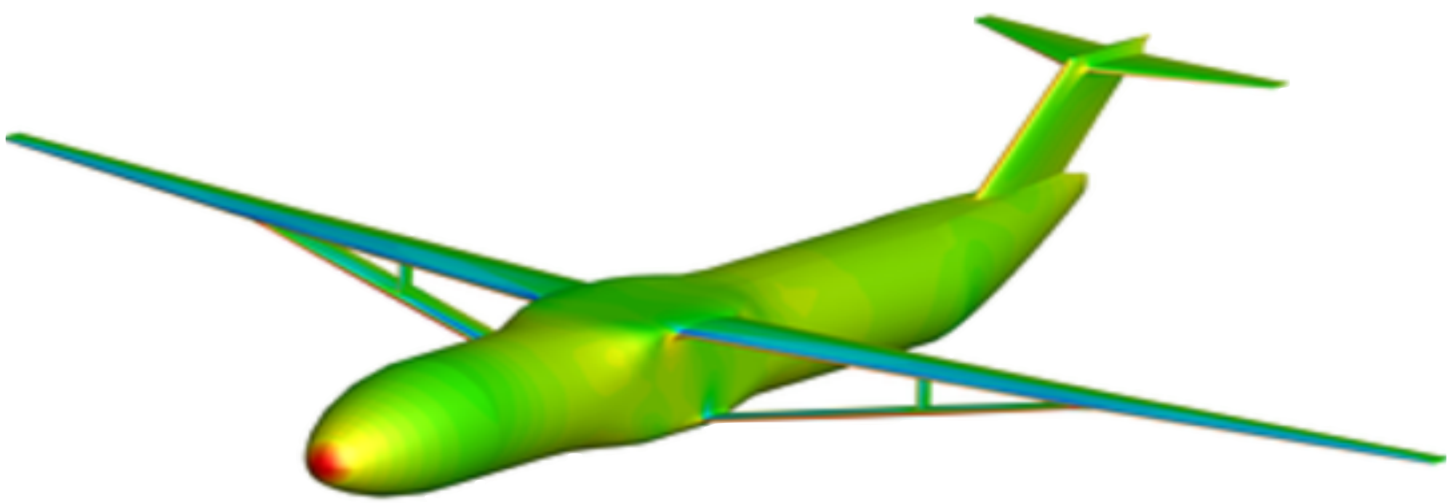
Currently using these tools to refine the next generation of aircraft



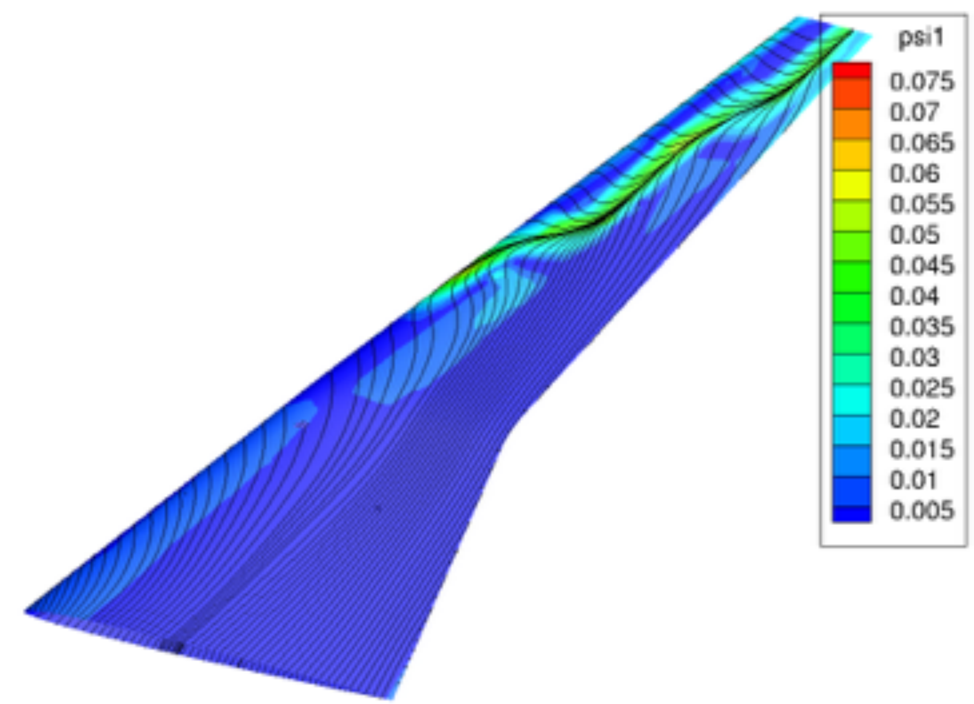
Flexible high-aspect ratio wings
[Kenway and Martins, AIAA 2015-2790]



Blended-wing body
[Lyu and Martins, *Journal of Aircraft*, 2014]



Truss-braced wing
[Ivaldi, et al., AIAA 2015-3436]



Tow-steered composite
[Brooks et al., 2015]

We are now extending the coupled-adjoint approach and developing a general framework for MDO

$$R(u) = 0 \quad , \quad u = [\overbrace{x_1, \ldots, x_n}^{\text{Inputs}}, \overbrace{y_1, \ldots, y_m}^{\text{States}}, \overbrace{f_1, \ldots, f_p}^{\text{Outputs}}]^T$$

$$\boxed{\frac{\partial R}{\partial u}\frac{\mathrm{d}u}{\mathrm{d}r} = \mathcal{I} = \frac{\partial R}{\partial u}^T \frac{\mathrm{d}u}{\mathrm{d}r}^T}$$

$$\begin{bmatrix} \mathcal{I} & 0 & 0 \\ -\frac{\partial R}{\partial x} & -\frac{\partial R}{\partial y} & 0 \\ -\frac{\partial F}{\partial x} & -\frac{\partial F}{\partial y} & \mathcal{I} \end{bmatrix} \begin{bmatrix} \mathcal{I} & 0 & 0 \\ \frac{\mathrm{d}y}{\mathrm{d}x} & \frac{\mathrm{d}y}{\mathrm{d}r} & 0 \\ \frac{\mathrm{d}f}{\mathrm{d}x} & \frac{\mathrm{d}f}{\mathrm{d}r} & \mathcal{I} \end{bmatrix} = \begin{bmatrix} \mathcal{I} & 0 & 0 \\ 0 & \mathcal{I} & 0 \\ 0 & 0 & \mathcal{I} \end{bmatrix}$$

openMDAO

[Martins and Hwang, *AIAA Journal*, 2013]

Vamos a optimizar!

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More information:

MDOlab Newsletter—Fall 2014

Dear Friend,
Welcome to the MDOlab newsletter, an update on research and open source software that we send a few times a year. You are receiving this because I think you are interested in numerical optimization, MDO, engineering design, or aircraft design. If this is not the case, feel free to unsubscribe. If you know someone who might like to subscribe, please forward them this newsletter. Best regards,
-Joaquim Martins

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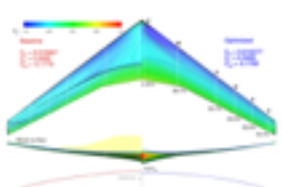
Latest publications

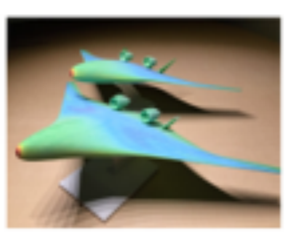
Wing aerodynamic shape optimization benchmark



The AIAA Aerodynamic Design Optimization Discussion Group developed a series of benchmark cases. In this paper, we solve the RANS-based wing optimization problem, try to find multiple local minima, and solve a number of related wing design optimization problems. The initial and optimized geometries and meshes are provided here.

[Paper] [Preprint] [Optimization movie]

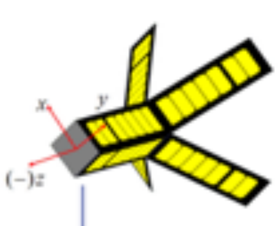
Aerodynamic design optimization of a blended-wing body aircraft



This builds on our previous work on stability-constrained flying wing optimization. A series of RANS-based aerodynamic design optimization studies shows the tradeoffs between drag, trim, and stability for the NASA/Boeing BWB. The photo on the left shows 3D-printed models with pressure colormaps.

[Paper] [Preprint]

Satellite multidisciplinary design optimization benchmark



In collaboration with NASA and the Michigan Exploration Lab, we developed a new large-scale benchmark MDO problem, and solved a problem with 25,000 design variables and 2.2 million state variables by optimizing the data downloaded from a CubeSat subject to operational and physical constraints. This problem is now a plugin in the the OpenMDAO open source project.

[Paper] [Preprint]

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Relevant publications

1. J. R. R. A. Martins and J. T. Hwang. Review and unification of methods for computing derivatives of multidisciplinary computational models. AIAA Journal, 51(11):2582–2599, November 2013. doi: 10.2514/1.J052184.
2. J. R. R. A. Martins and A. B. Lambe. Multidisciplinary design optimization: A survey of architectures. AIAA Journal, 51(9):2049–2075, September 2013. doi:10.2514/1.J051895.
3. J. T. Hwang, D. Y. Lee, J. W. Cutler, and J. R. R. A. Martins. Large-scale multidisciplinary optimization of a small satellite's design and operation. Journal of Spacecraft and Rockets, 51(5):1648–1663, September 2014. doi: 10.2514/1.A32751.
4. G. K. W. Kenway and J. R. R. A. Martins. Multipoint high-fidelity aerostructural optimization of a transport aircraft configuration. Journal of Aircraft, 51(1):144–160, January 2014. doi:10.2514/1.C032150.
5. G. K. W. Kenway, G. J. Kennedy, and J. R. R. A. Martins. Scalable parallel approach for high-fidelity steady-state aeroelastic analysis and derivative computations. AIAA Journal, 52(5):935–951, May 2014. doi: 10.2514/1.J052255.
6. R. E. Perez, P. W. Jansen, and J. R. R. A. Martins. pyOpt: a Python-based object-oriented framework for nonlinear constrained optimization. Structural and Multidisciplinary Optimization, 45(1):101–118, January 2012. doi:10.1007/s00158-011-0666-3.
7. J. T. Hwang, S. Roy, J. Y. Kao, J. R. R. A. Martins, and W. A. Crossley. Simultaneous aircraft allocation and mission optimization using a modular adjoint approach. In Proceedings of the 56th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference, Kissimmee, FL, Jan. 2015. AIAA 2015-0900.
8. J. Y. Kao, J. T. Hwang, J. R. R. A. Martins, J. S. Gray, and K. T. Moore. A modular adjoint approach to aircraft mission analysis and optimization. In Proceedings of the AIAA Science and Technology Forum and Exposition (SciTech), Kissimmee, FL, January 2015. AIAA 2015-0136.