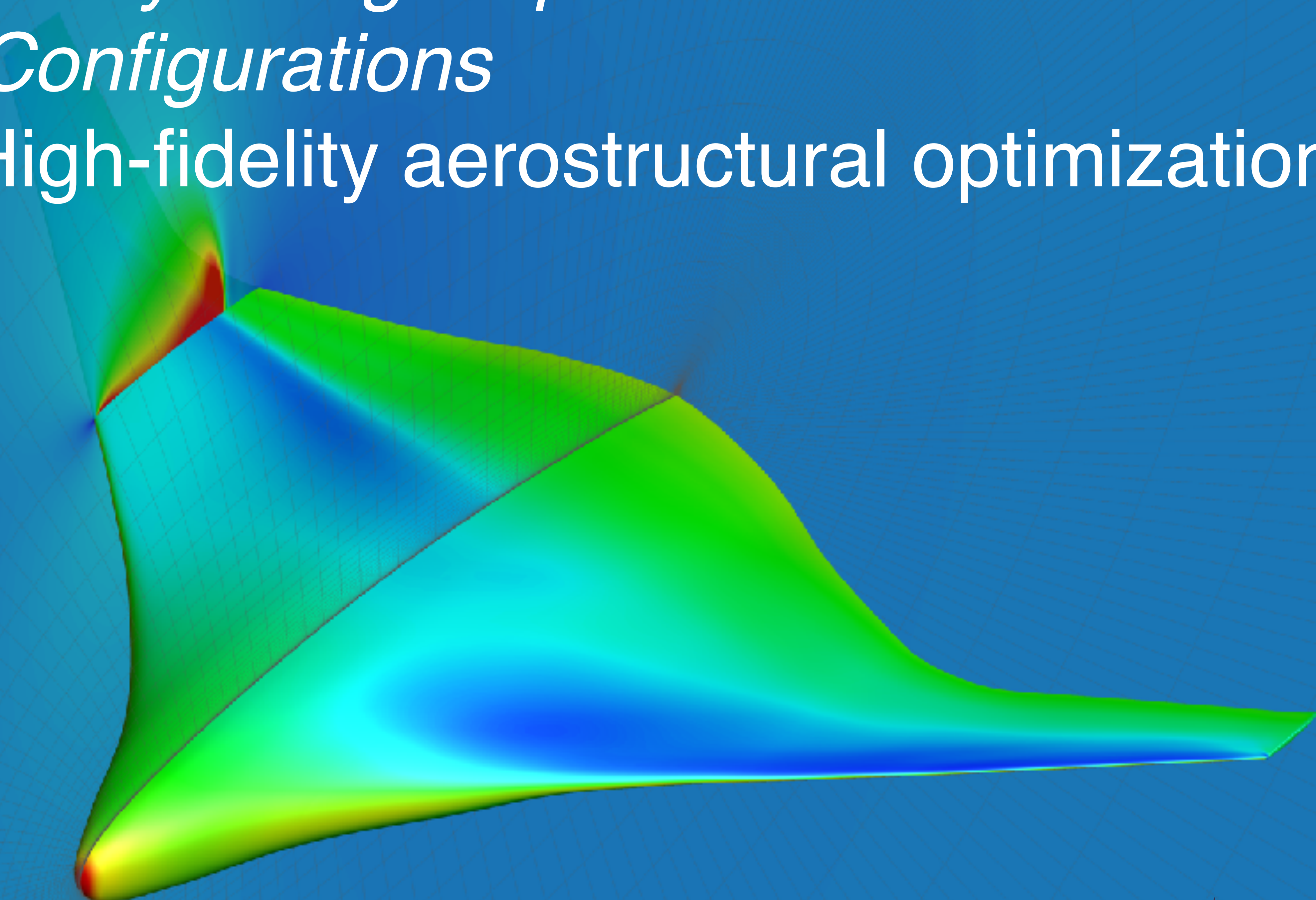
Multidisciplinary Design Optimization of Aircraft Configurations

Part 2: High-fidelity aerostructural optimization



Joaquim R. R. A. Martins

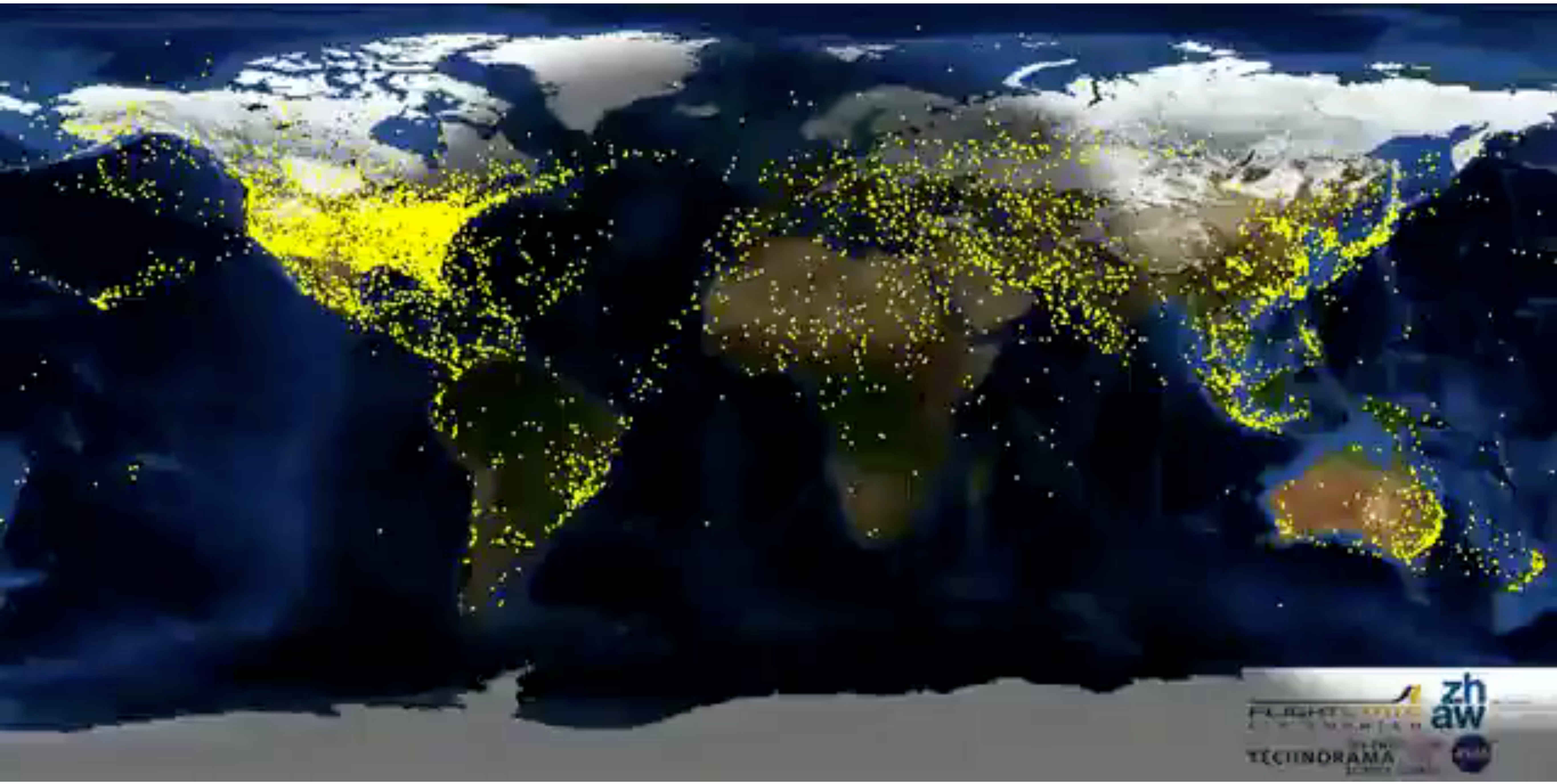
with contributions from Gaetan K. W. Kenway, Graeme J. Kennedy, Zhoujie Lyu, and Timothy Brooks

MARIE CURIE ACTIONS

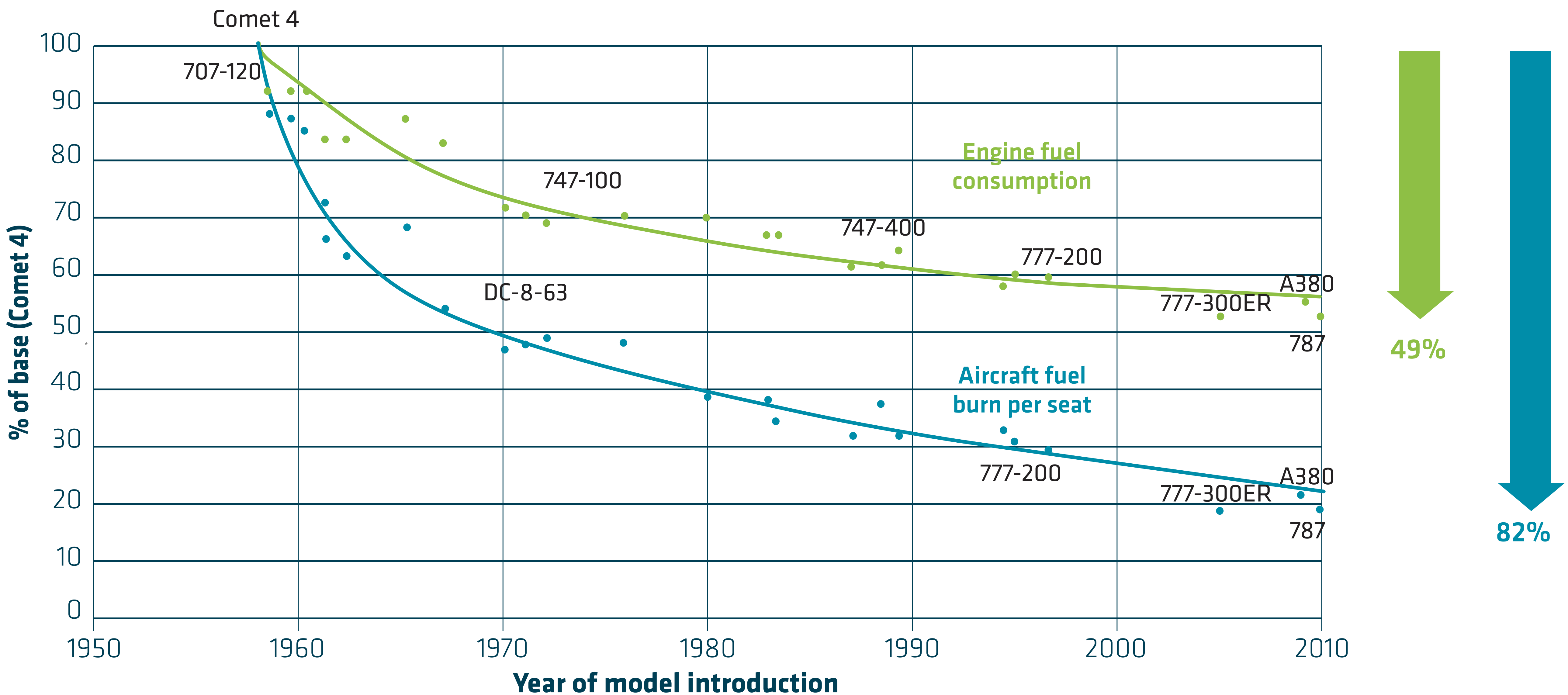
The von Karman Institute for Fluid Dynamics

VKI Lecture Series • Brussels, Belgium • May 24, 2016

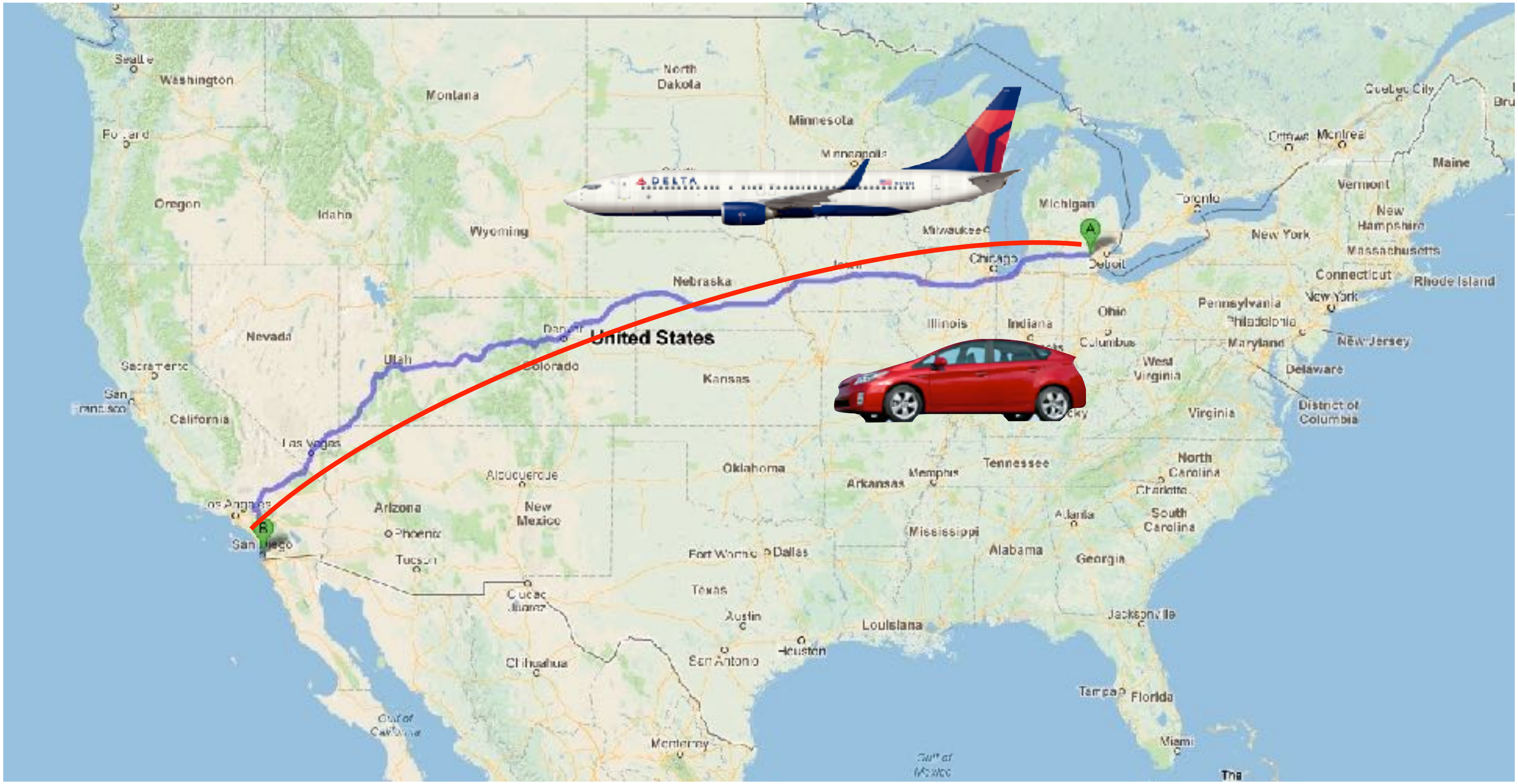
With 90,000 daily flights, improvements in aircraft performance has a huge impact



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



Boeing 737-800 vs. Toyota Prius

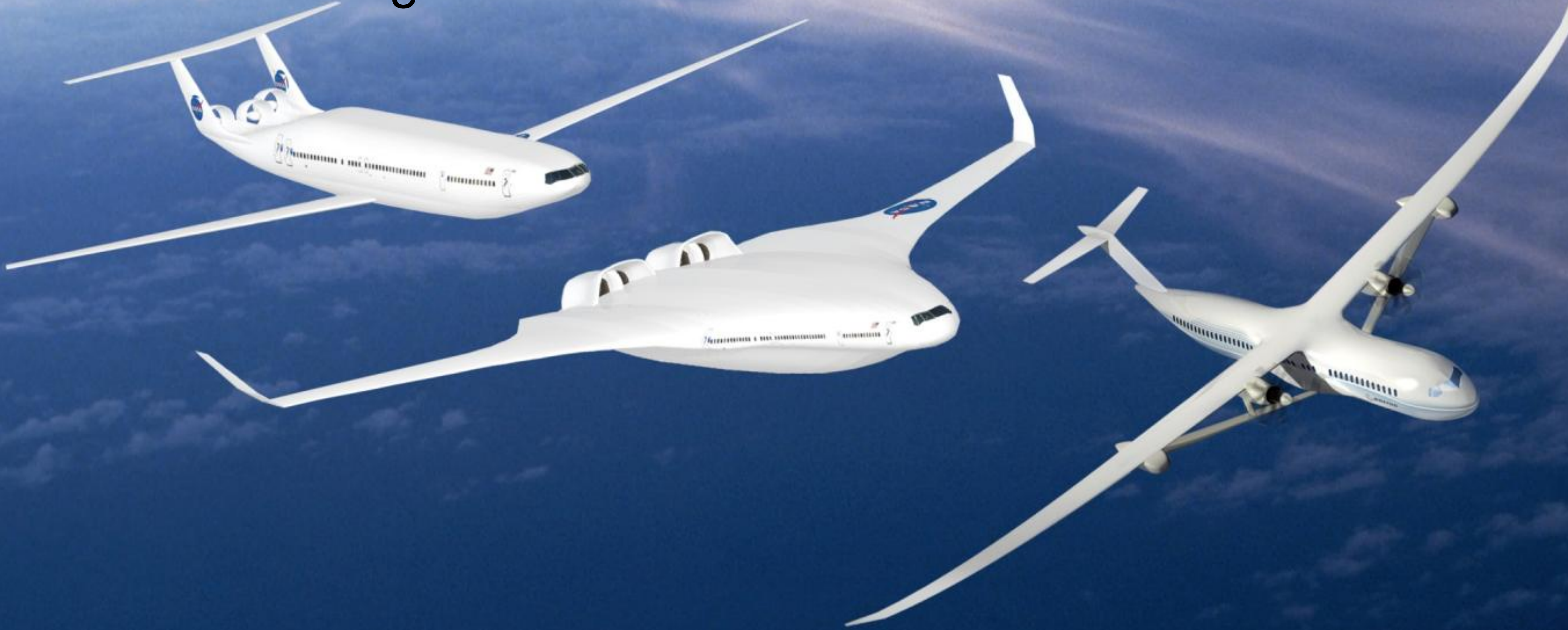


The 737 is equivalent to 2 people in a Prius

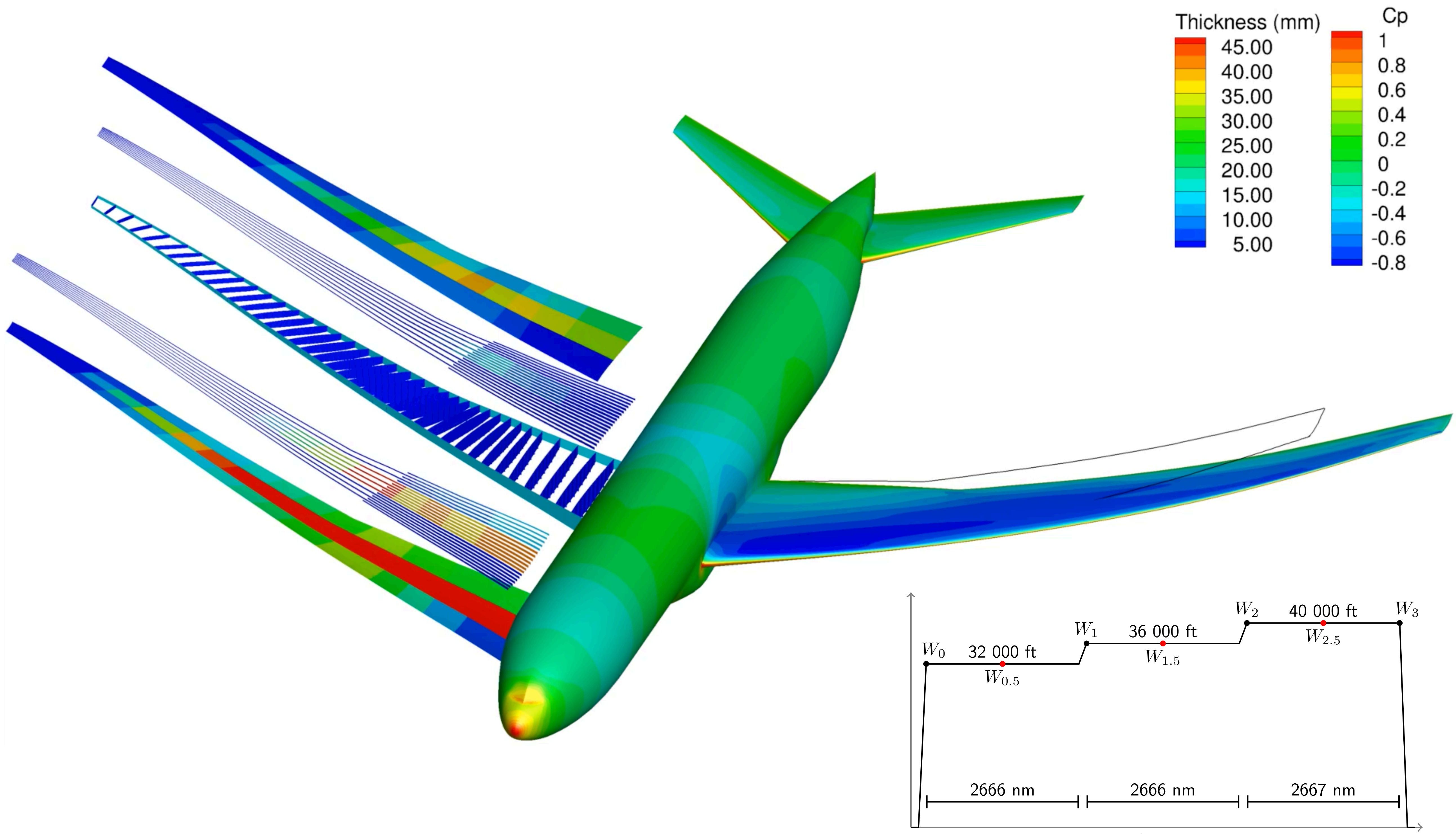
…but over 8x faster

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

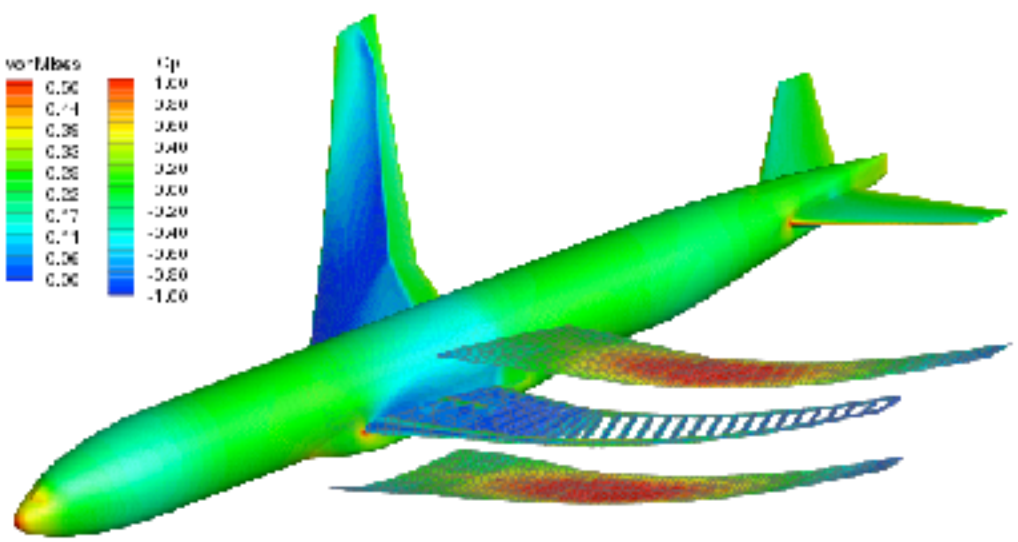
- Highly-flexible high aspect ratio wings
- Unknown design space and interdisciplinary trade-offs
- High risk

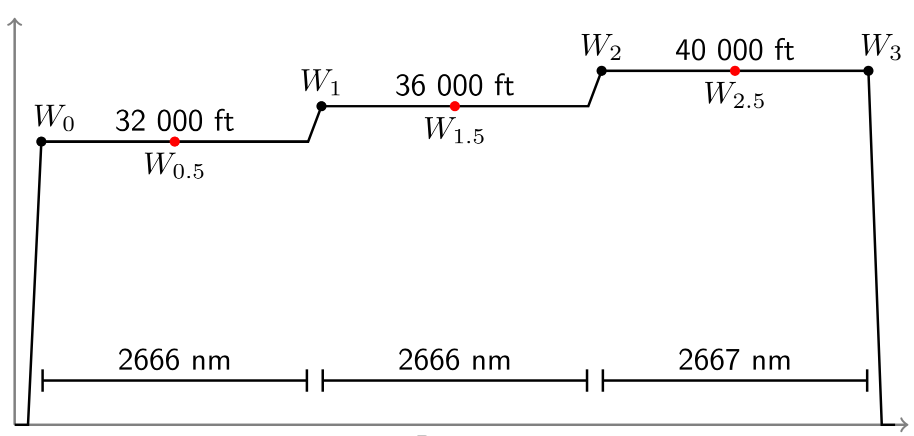


Want to optimize both aerodynamic shape and structural sizing, with high-fidelity



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

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Part 2: High-fidelity aerostructural optimization

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

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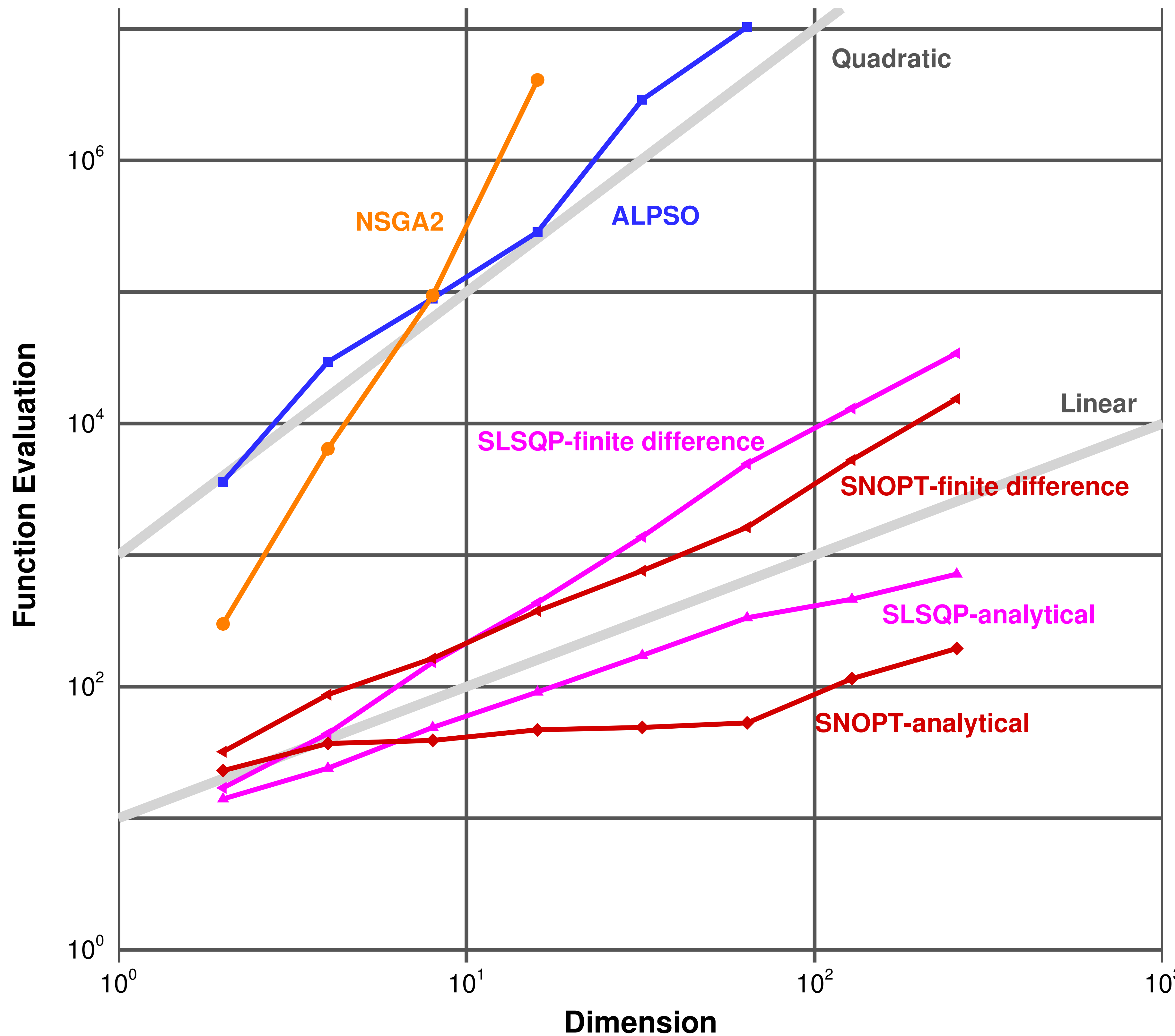
Gradient-based optimization is the only hope for large numbers of design variables



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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	$\frac{\mathrm{d}f}{\mathrm{d}x}=\frac{\partial f}{\partial x}-\frac{\partial f}{\partial y}\overbrace{\left[\frac{\partial R}{\partial y}\right]^{-1}\frac{\partial R}{\partial x}}^{-\mathrm{d}y/\mathrm{d}x}$
	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	$\begin{bmatrix} 1 & 0 & \dots & 0 \\ -\frac{\partial T_2}{\partial t_1} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ -\frac{\partial T_n}{\partial t_1} & \dots & -\frac{\partial T_n}{\partial t_{n-1}} & 1 \end{bmatrix}\begin{bmatrix} 1 & 0 & \dots & 0 \\ \frac{\mathrm{d}t_2}{\mathrm{d}t_1} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \frac{\mathrm{d}t_n}{\mathrm{d}t_1} & \dots & \frac{\mathrm{d}t_n}{\mathrm{d}t_{n-1}} & 1 \end{bmatrix}=\boldsymbol{I}=\begin{bmatrix} 1 & -\frac{\partial T_2}{\partial t_1} & \dots & -\frac{\partial T_n}{\partial t_1} \\ 0 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & -\frac{\partial T_n}{\partial t_{n-1}} \\ 0 & \dots & 0 & 1 \end{bmatrix}\begin{bmatrix} 1 & \frac{\mathrm{d}t_2}{\mathrm{d}t_1} & \dots & \frac{\mathrm{d}t_n}{\mathrm{d}t_1} \\ 0 & 1 & \ddots & \vdots \\ \vdots & \ddots & 1 & \frac{\mathrm{d}t_n}{\mathrm{d}t_{n-1}} \\ 0 & \dots & 0 & 1 \end{bmatrix}$
	Reverse	

[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

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

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

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]

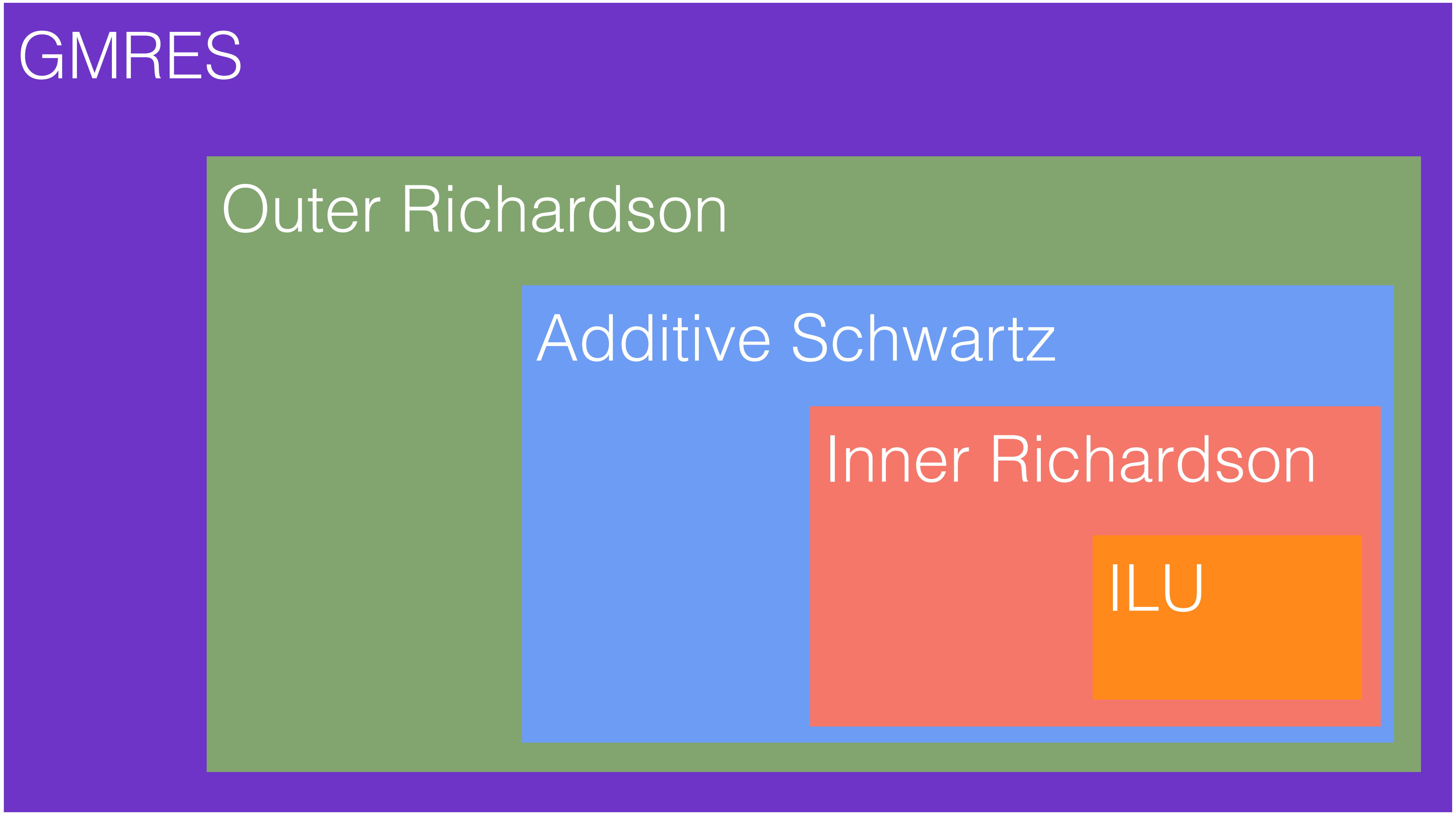
Our requirements are that the approach should:

- Yield derivatives **consistent** with the flow solution and be verifiable (e.g., with complex step).
- Require **no modification** of original code.
- Require **no duplication** of original code.
- Result in **efficient adjoint** derivative computation.
- Have an **automatic implementation**.
- Incur **no penalty to the CFD solution** code.
- **Low memory** usage.

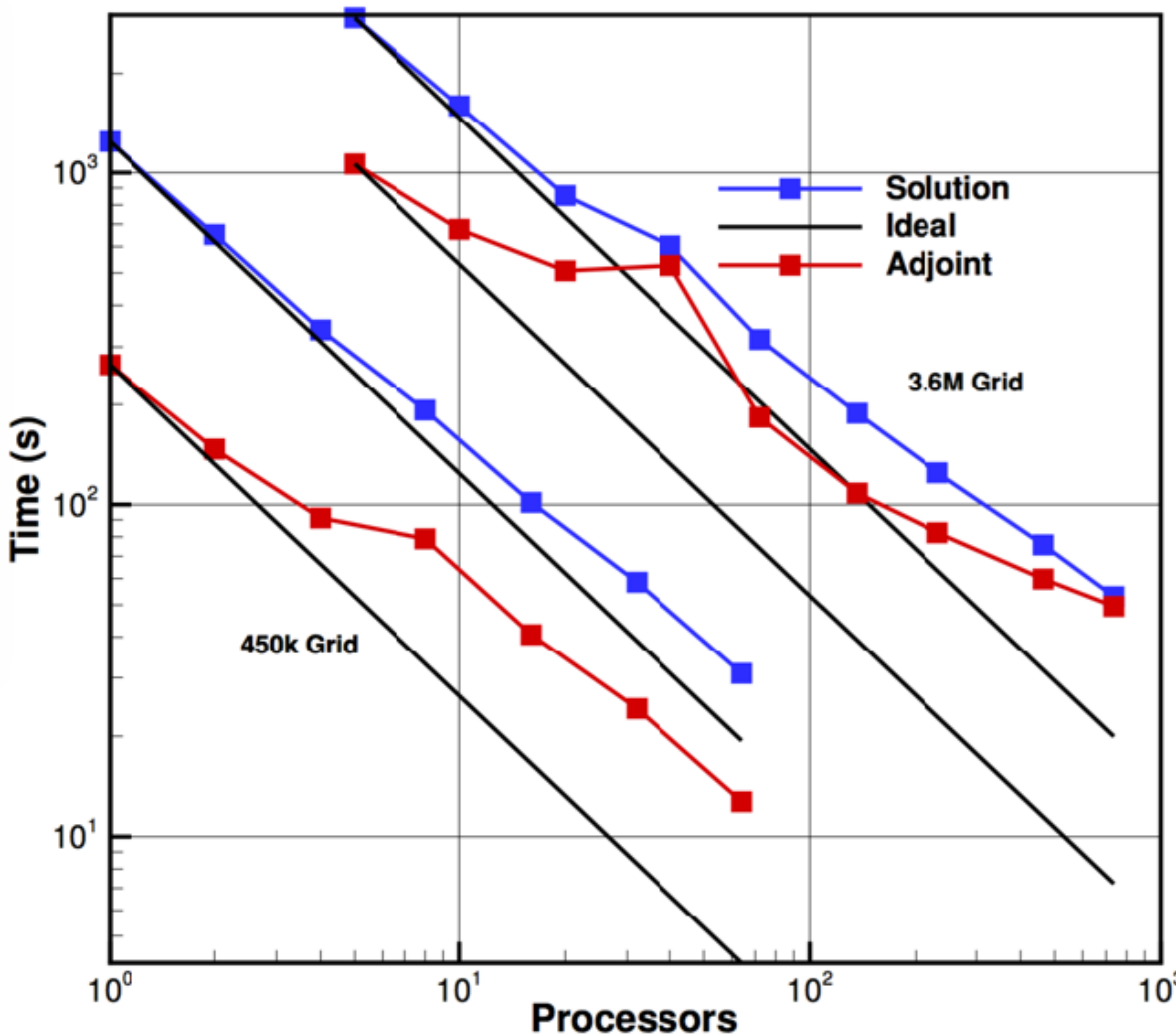
Our ADjoint has evolved over four distinct approaches

1. **Single cell**: AD cell residual routine, loop over cells to assemble full Jacobian [2005].
2. **Forward mode coloring**: AD original residual routine using coloring for efficiency and store full Jacobian [2011].
3. **Full reverse mode**: AD master ghost routine that yields the desired Jacobian-vector products and derivatives, matrix free [2014].
4. **Hybrid reverse mode**: AD individual subroutines in master ghost routine and assemble Jacobian-vector products manually [2015].

Flow adjoint solved with PETSc, using a hierarchy of pre-conditioners



Both the flow and adjoint solution scale well with the number of processors



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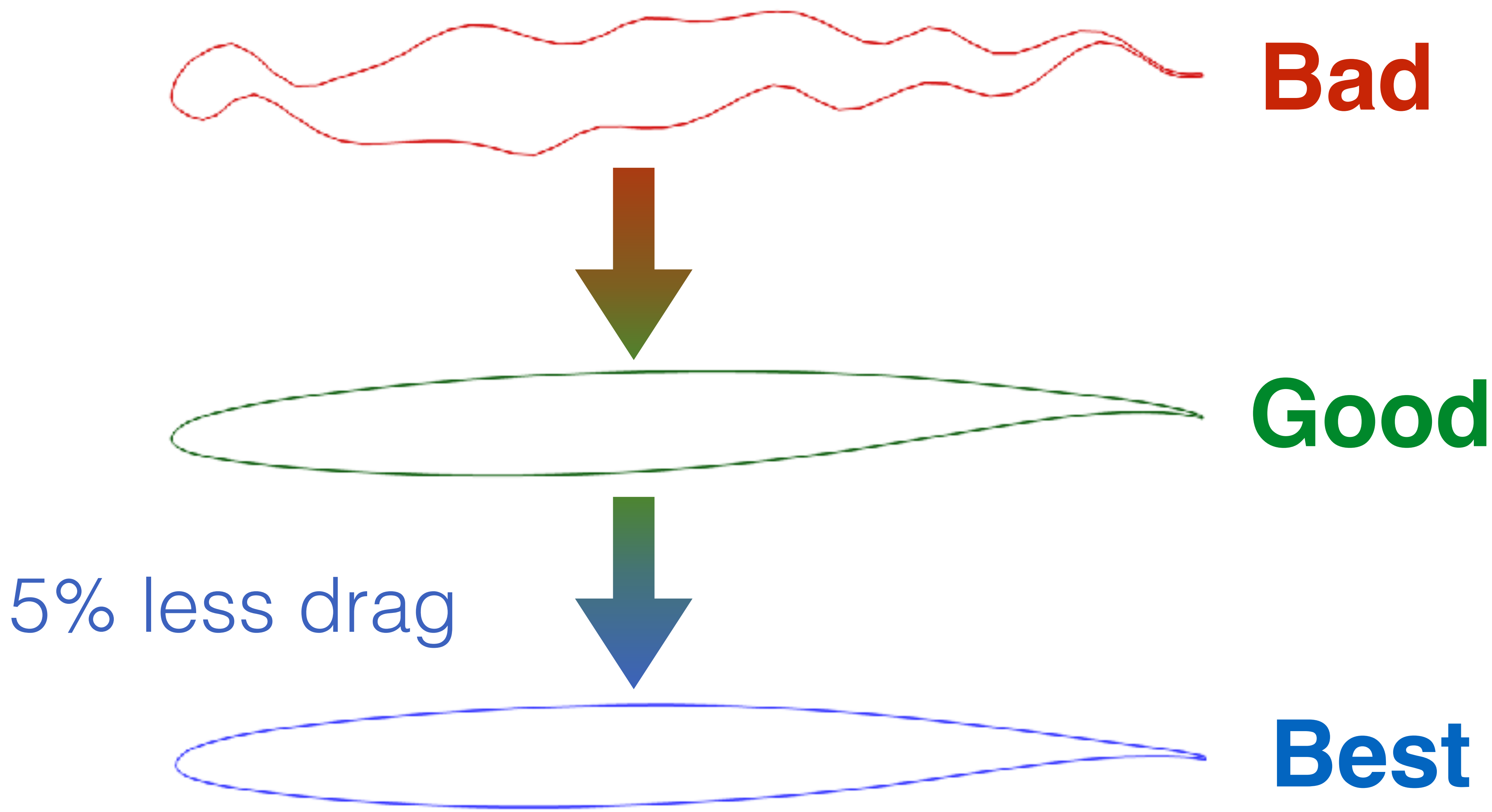
Small differences in shape make a big difference in performance



Wing aerodynamic shape optimization requires a high-fidelity model

Navier–Stokes equations

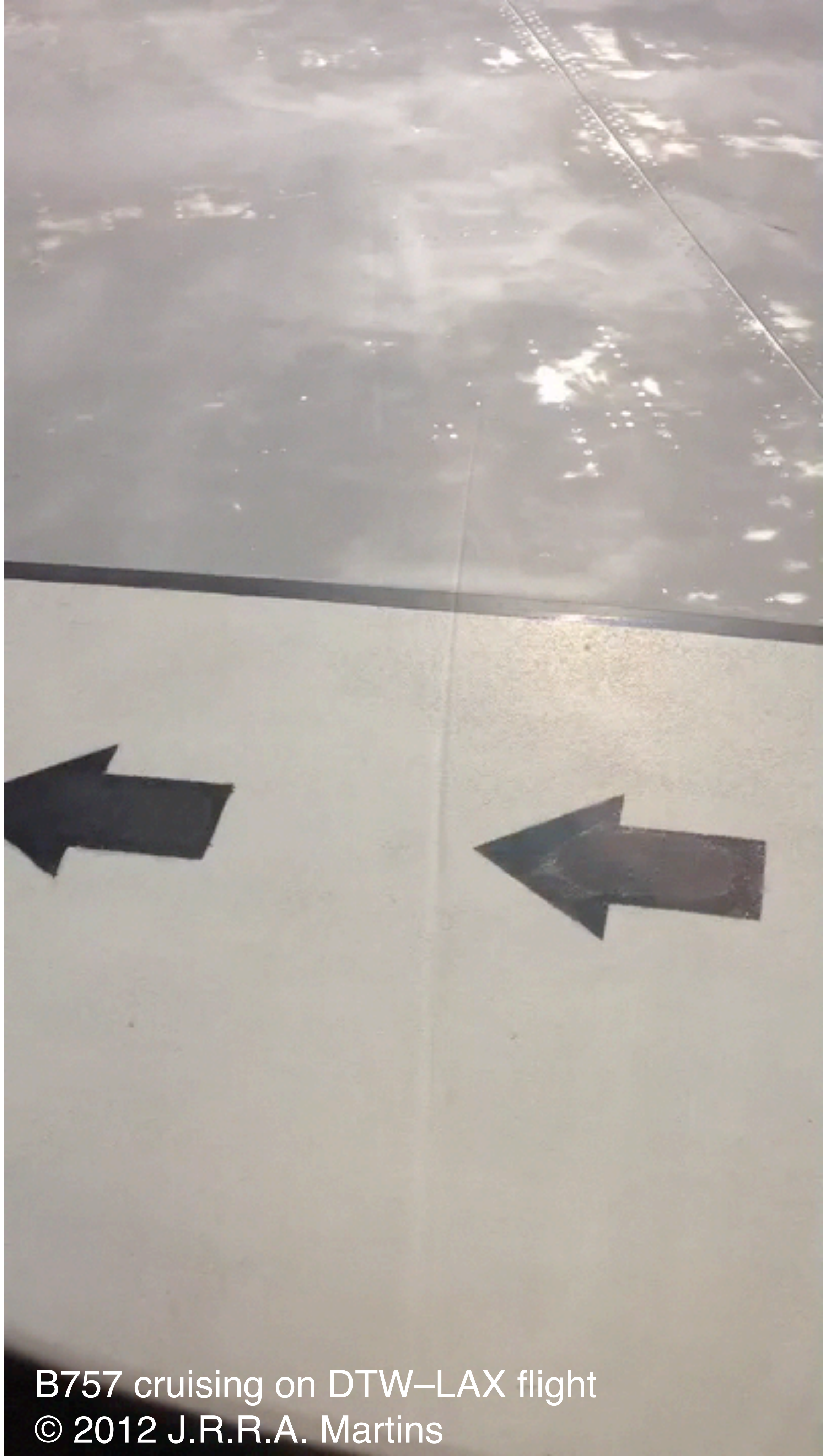
$$\frac{\partial w}{\partial t} + \frac{1}{A}\oint F_i \cdot \hat{n} dl - \frac{1}{A}\oint F_v \cdot \hat{n} dl = 0$$

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

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

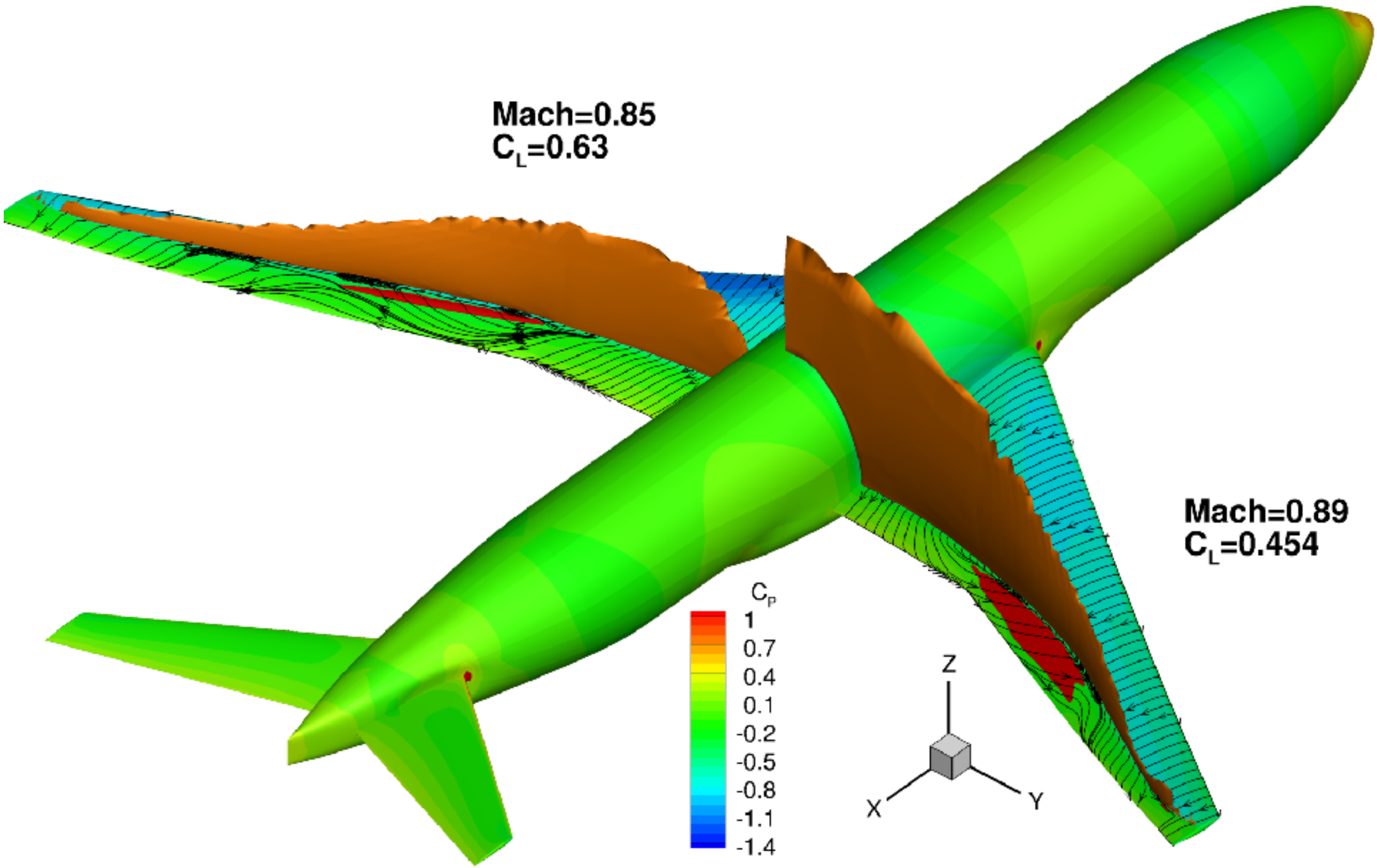
$$q_1 = -\frac{M_\infty}{Re(\gamma - 1)}\left(\frac{\mu}{Pr} + \frac{\mu_t}{Pr_t}\right)\frac{\partial a^2}{\partial x_1}$$

[Shockwaves on wings]

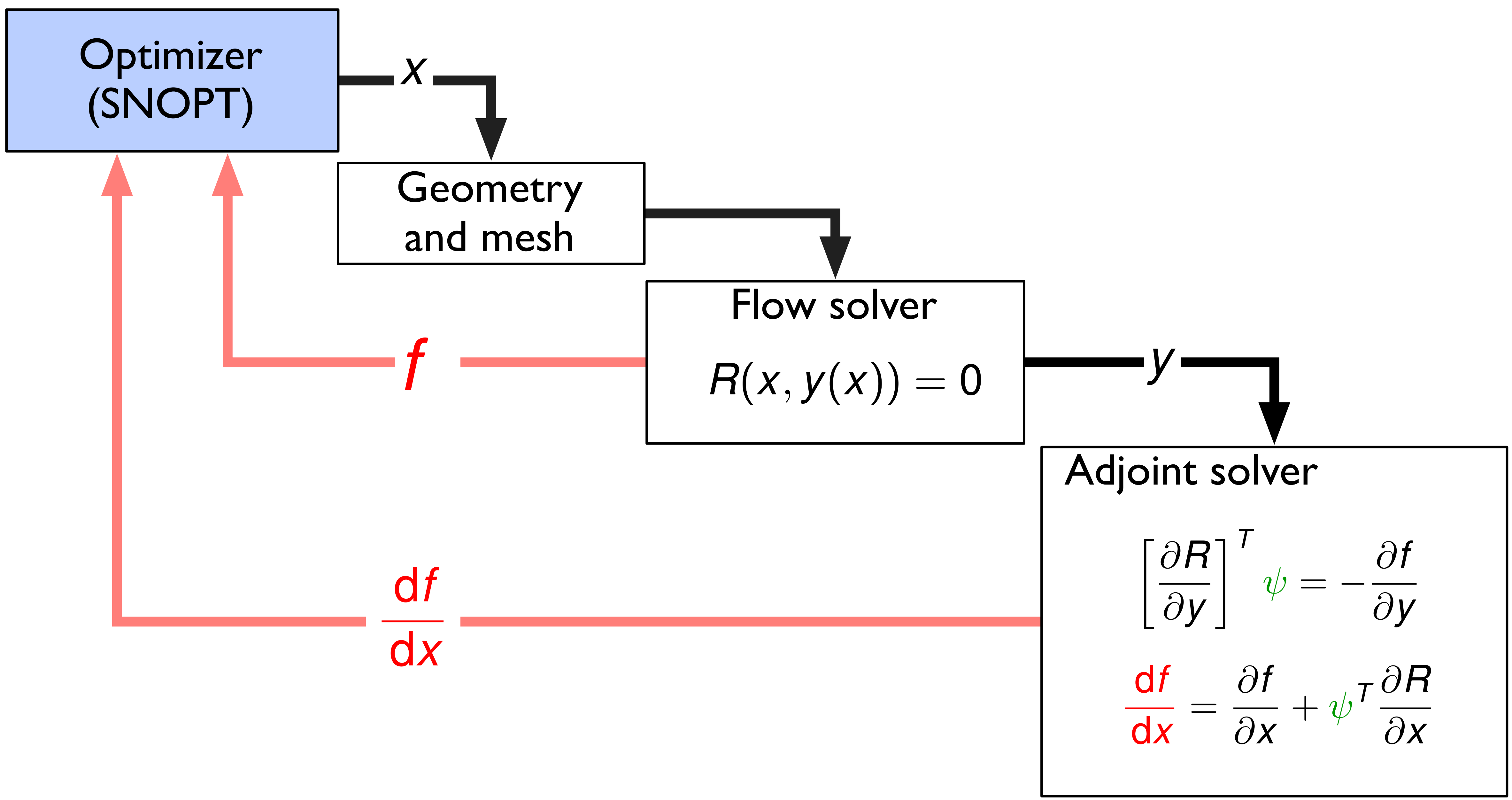


B757 cruising on DTW–LAX flight

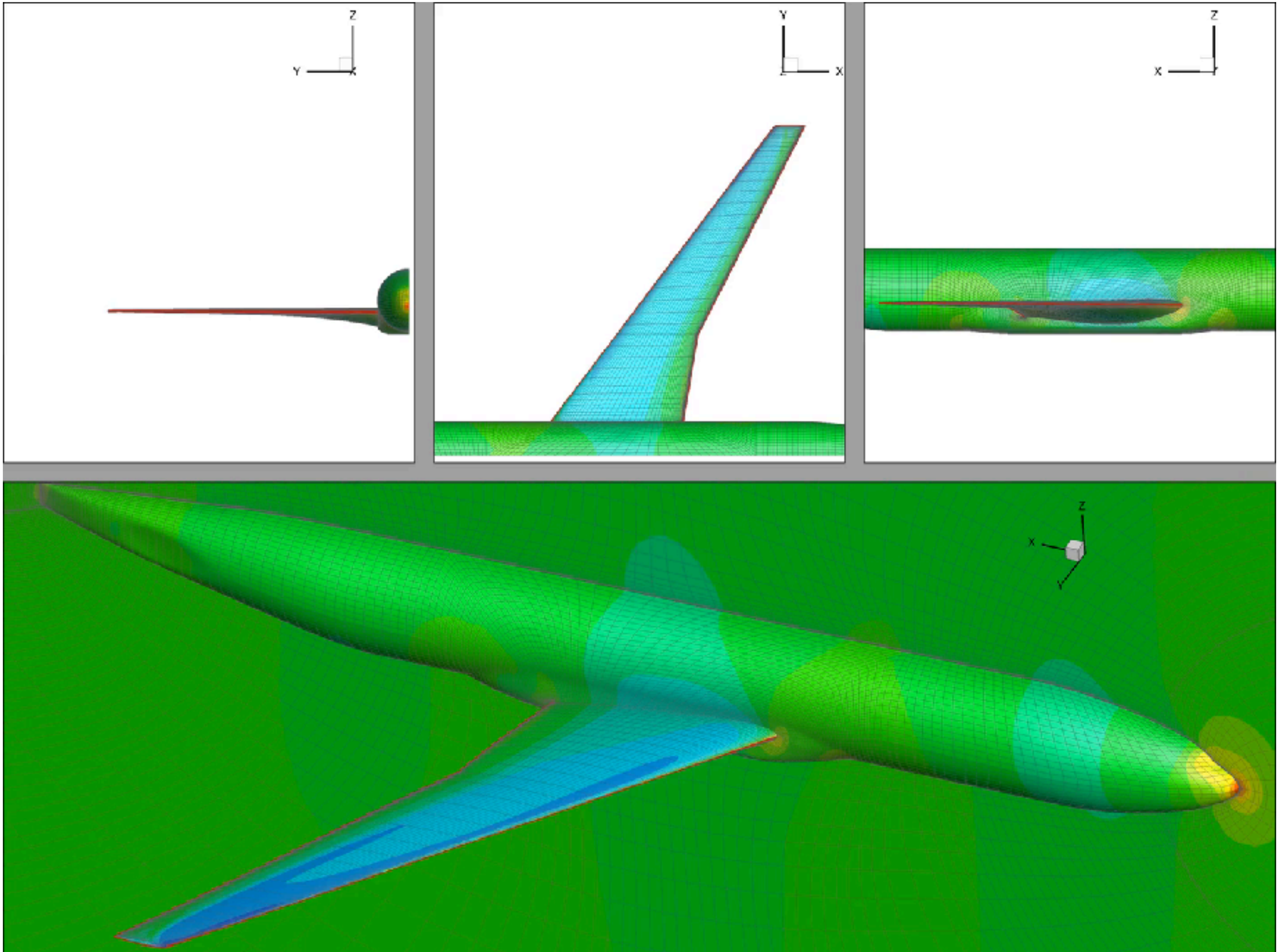
Reynolds-averaged Navier–Stokes equations are solved in a 3D domain



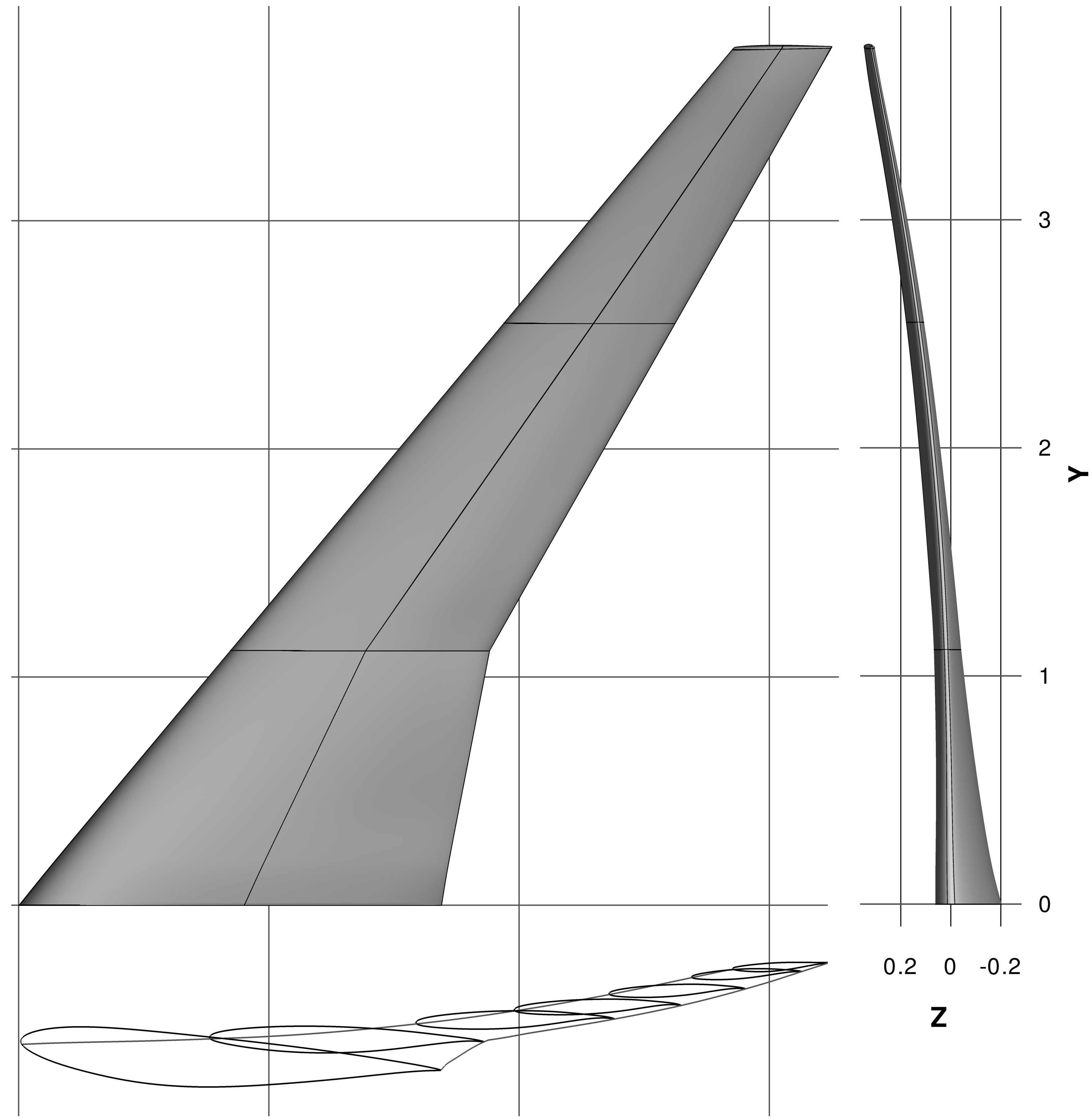
Combine flow solver, adjoint solver, and gradient-based optimizer to enable design



Fast mesh deformation handles large design changes

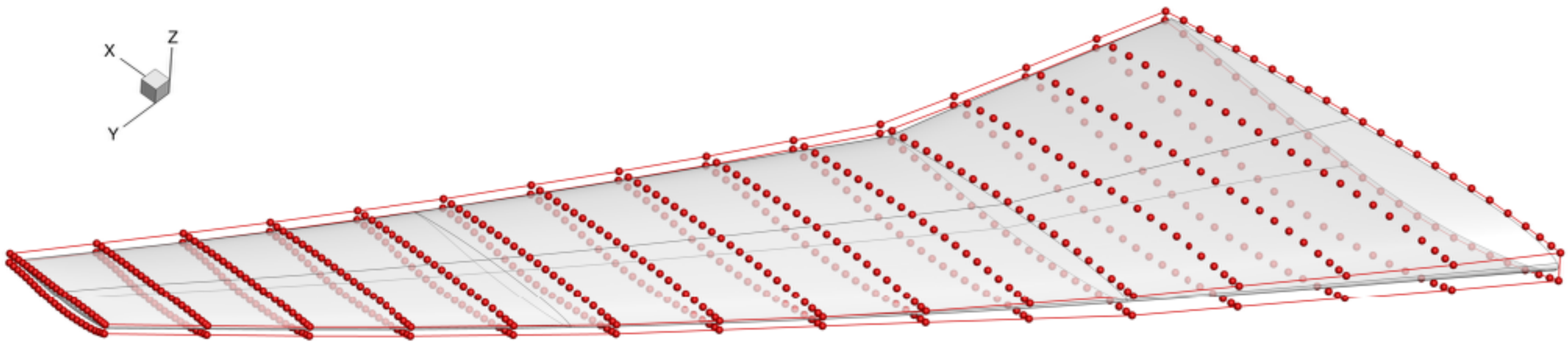


Common Research Model (CRM) wing is a new aerodynamic shape optimization benchmark



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

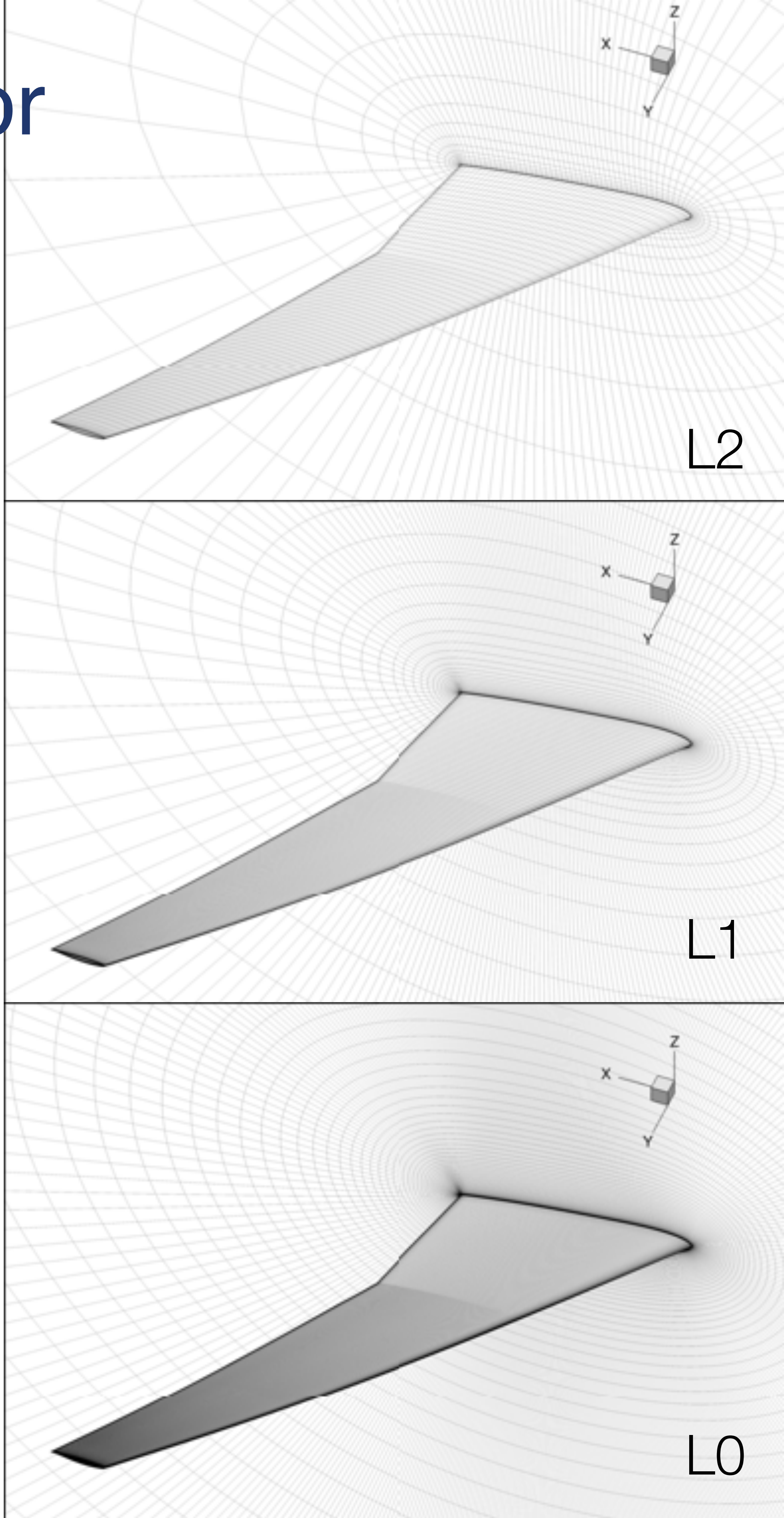
	Function/variable	Description	Quantity
minimize	C_D	Drag coefficient	
with respect to	α	Angle of attack	1
	z	FFD control point z-coordinates	720
		Total design variables	721
subject to	$C_L = 0.5$	Lift coefficient constraint	1
	$C_{M_y} \geq -0.17$	Moment coefficient constraint	1
	$t \geq 0.25 t_{\text{base}}$	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]

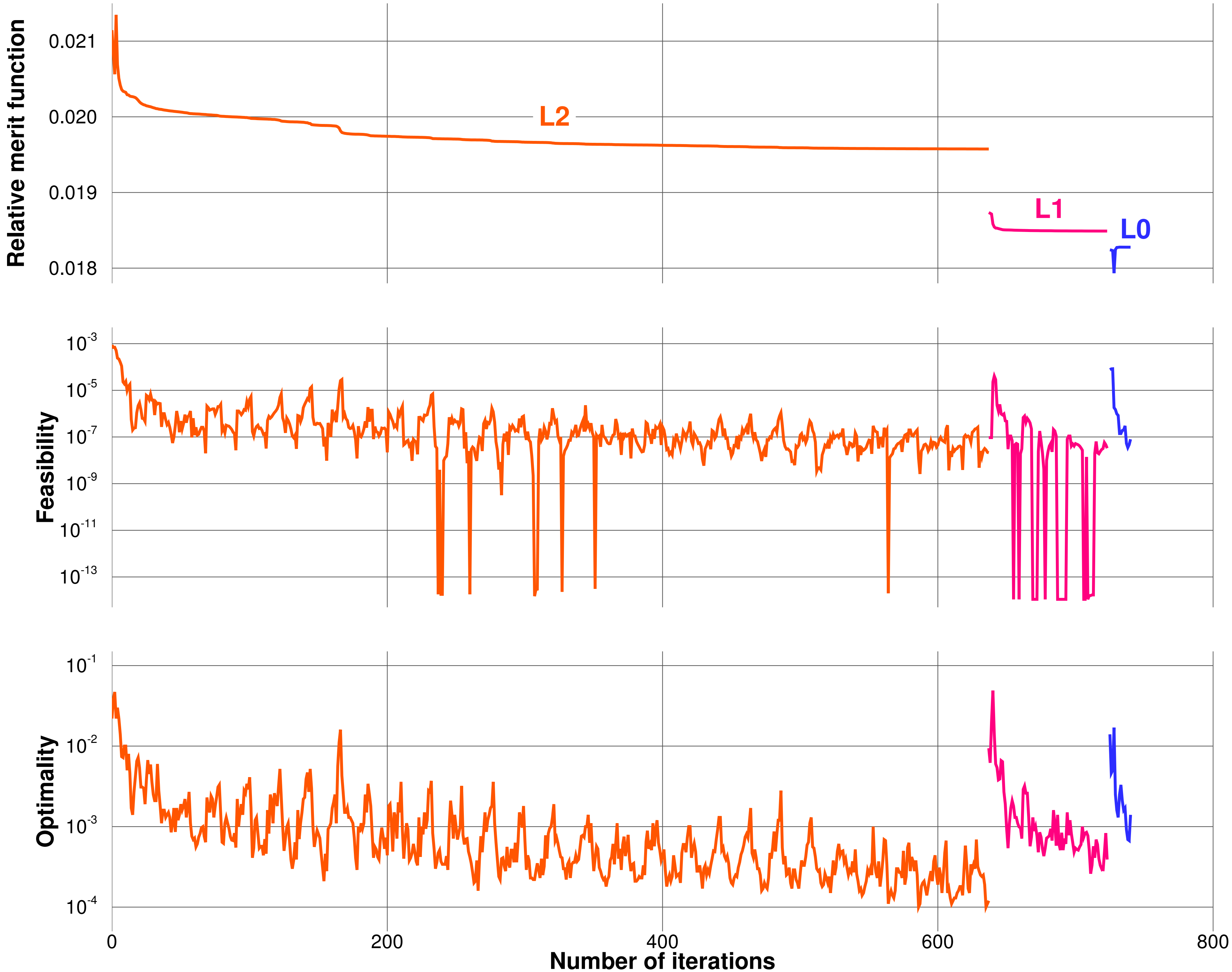
28 million-cell mesh is used for optimization

- Wing of the CRM configuration [Vassberg AIAA 2008-6919]
- Wing optimization problem developed by AIAA Aerodynamic Design Optimization DG.
- Hyperbolically-generated meshes are used.
- The meshes have O-grid topology to a farfield located at a distance of 25 times span.
- Mesh sizes range from 450k to 230M.

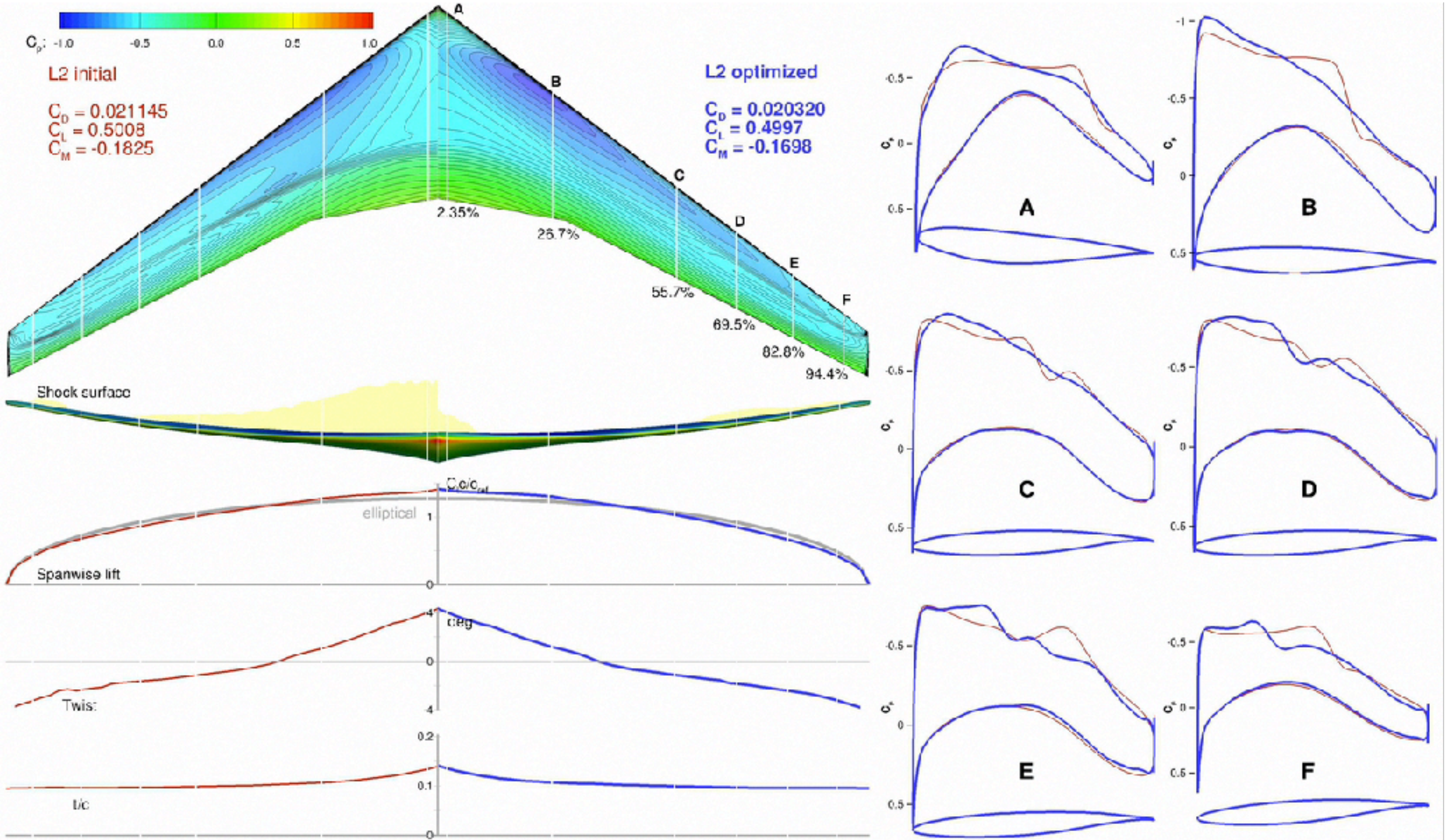
Grid level	Grid size	y^+
L00	$230,686,720$	0.233
L0	$28,835,840$	0.493
L1	$3,604,480$	0.945
L2	$450,560$	2.213



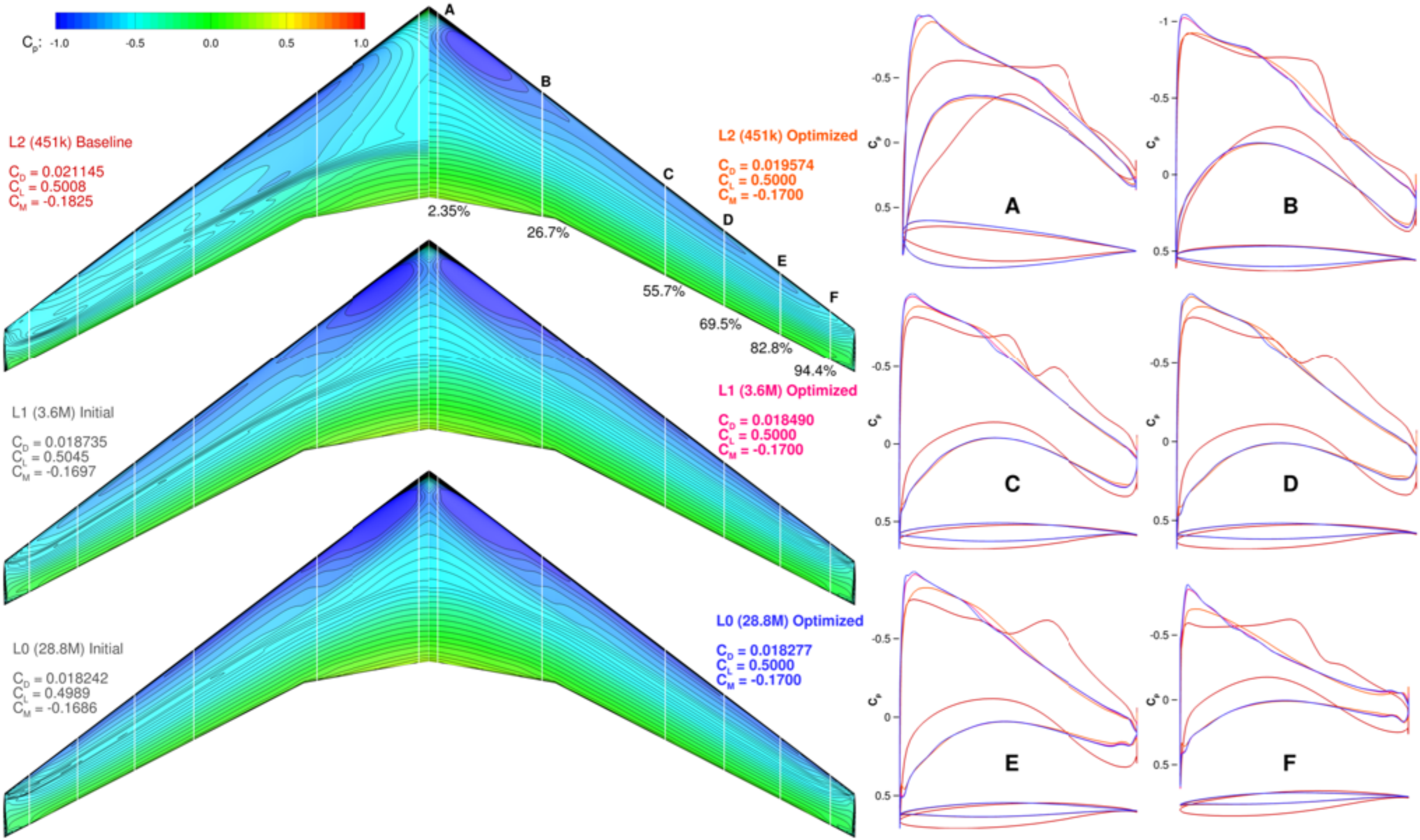
We use a multilevel approach to refine the optimum



A multilevel approach to design optimization

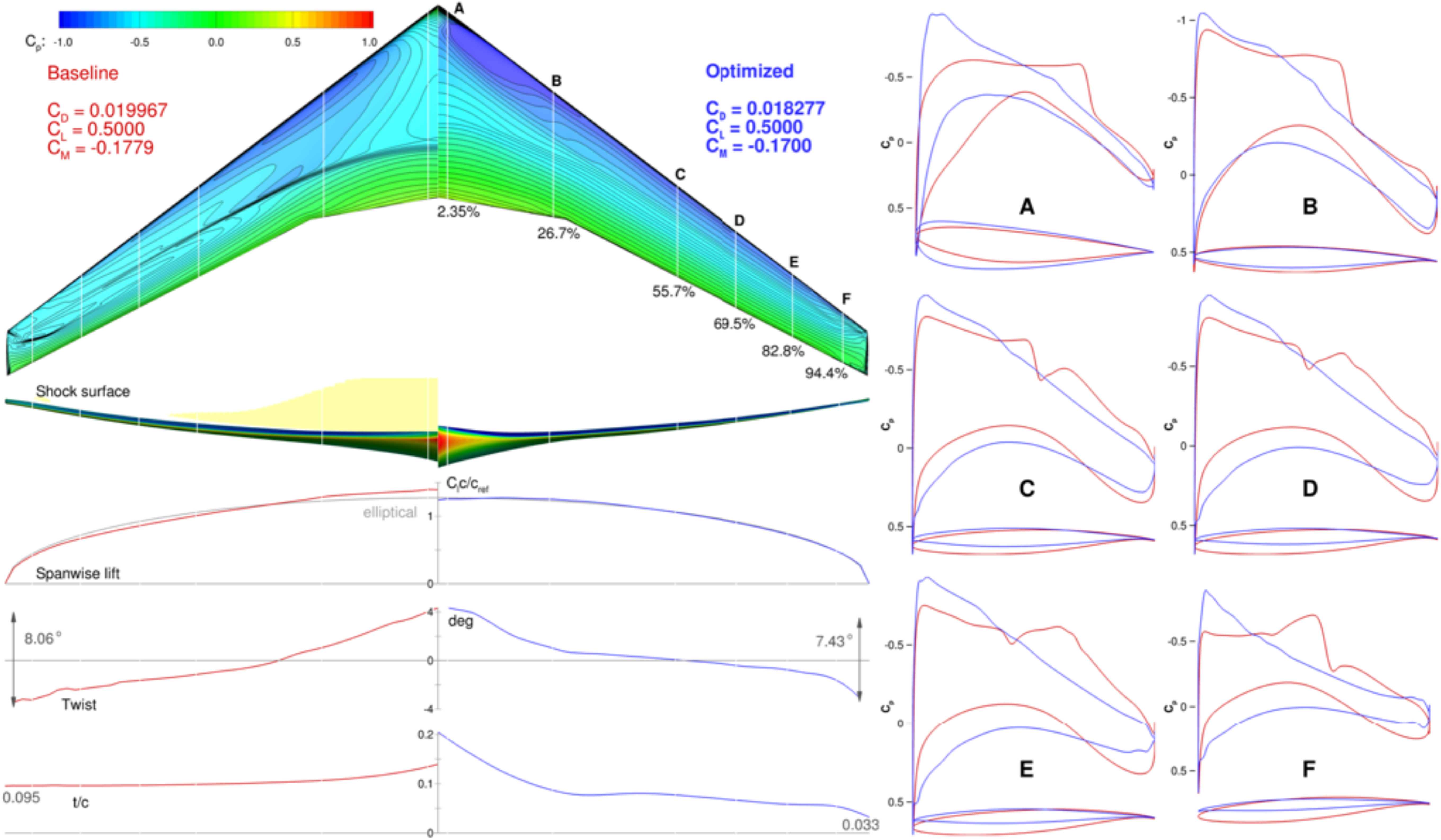


Multilevel optimization approach is 23 times faster

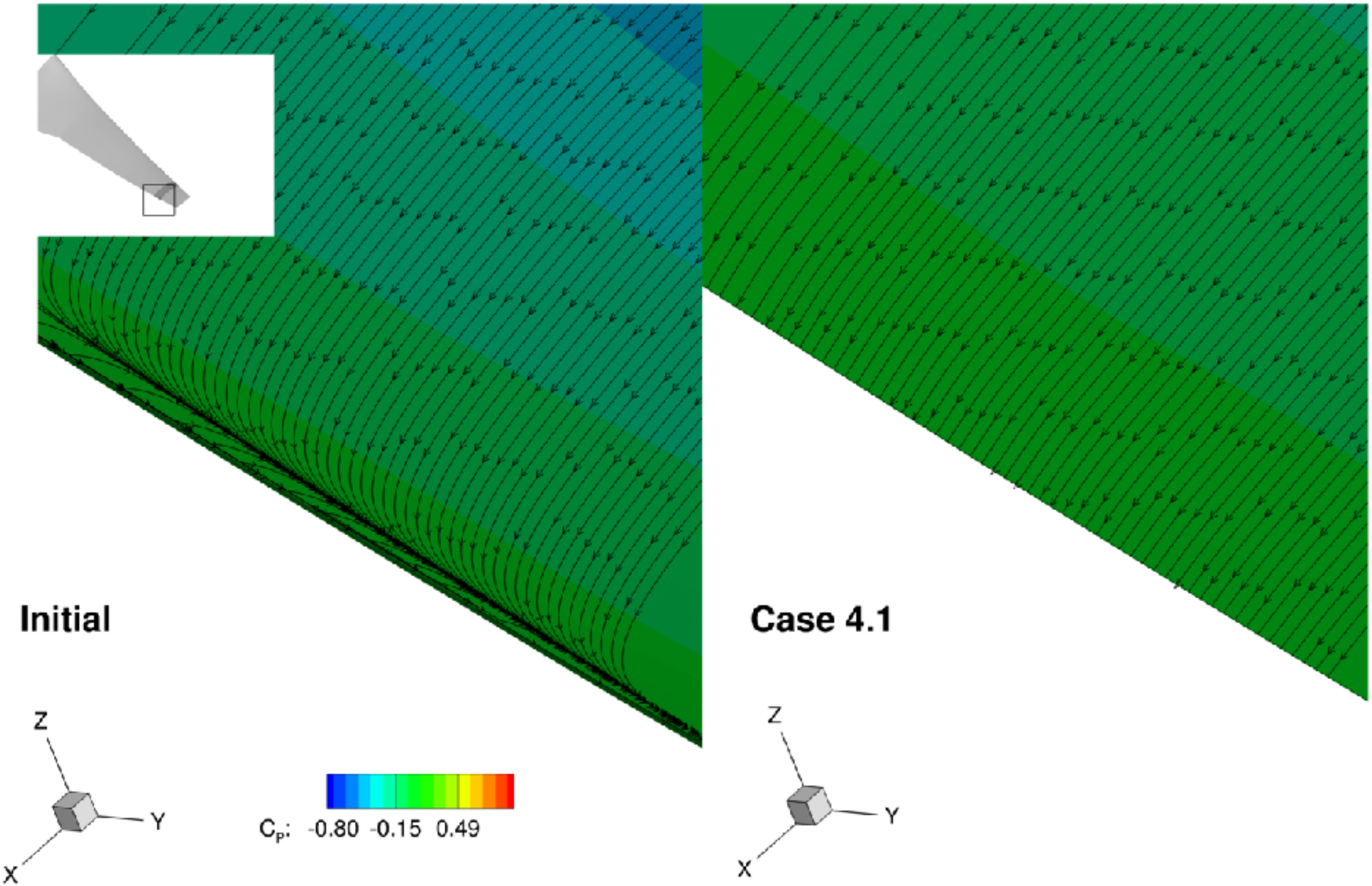


Started with a good design and made it 8.5% better

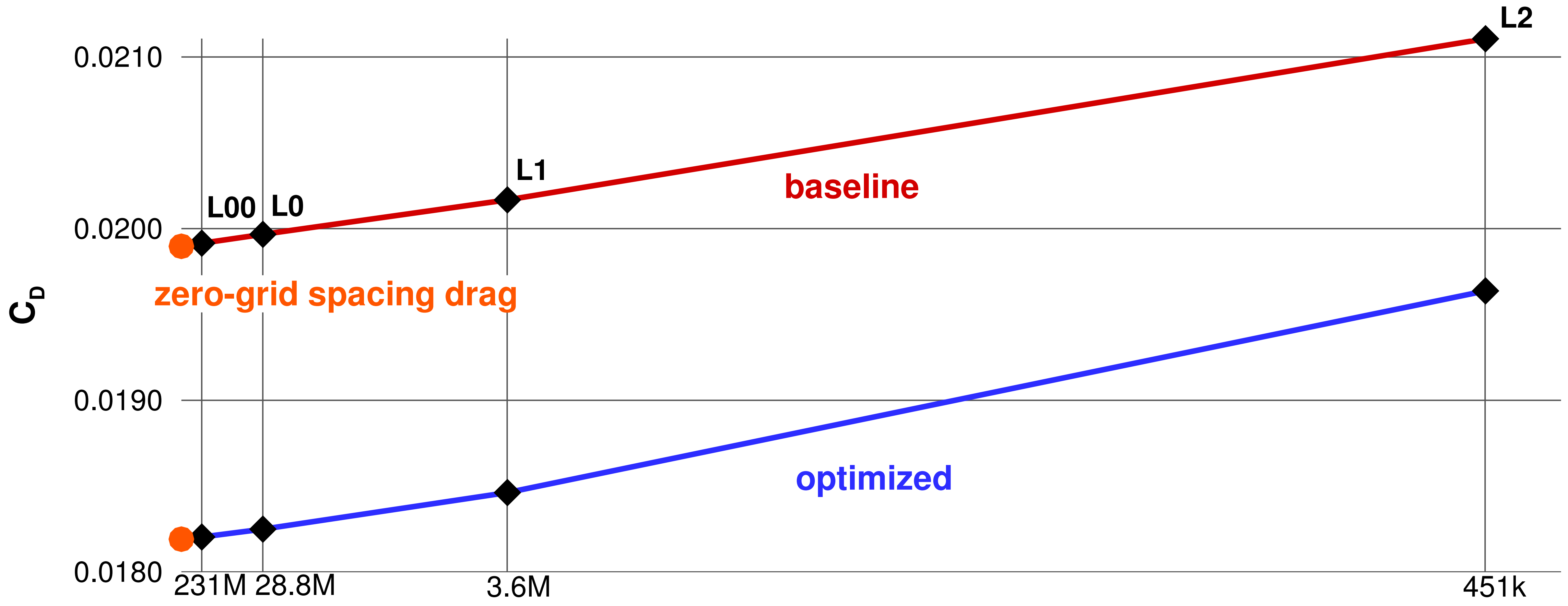
[Lyu et al., *AIAA Journal*, 2014]



Optimization eliminated outboard trailing edge separation

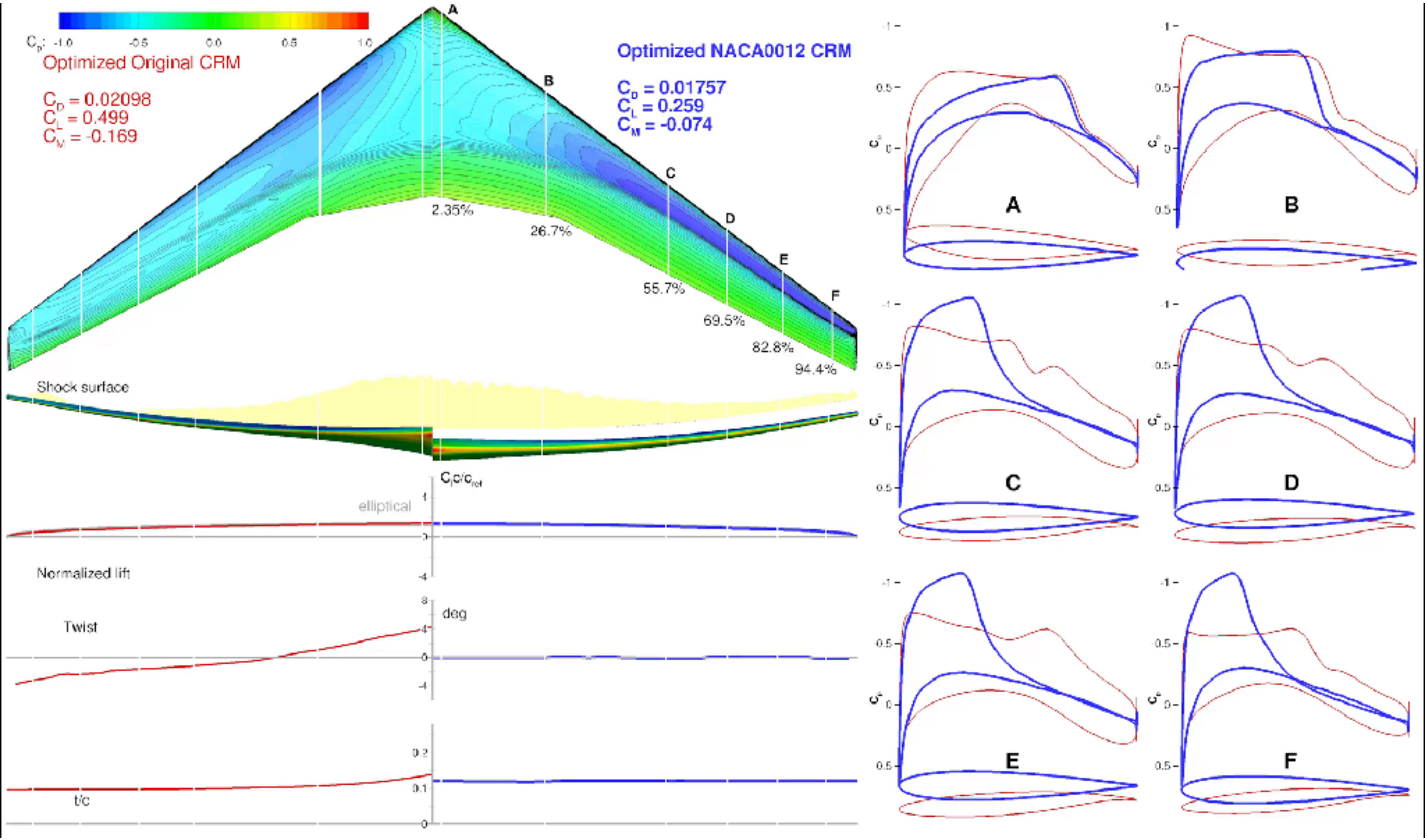


Grid convergence verifies the accuracy

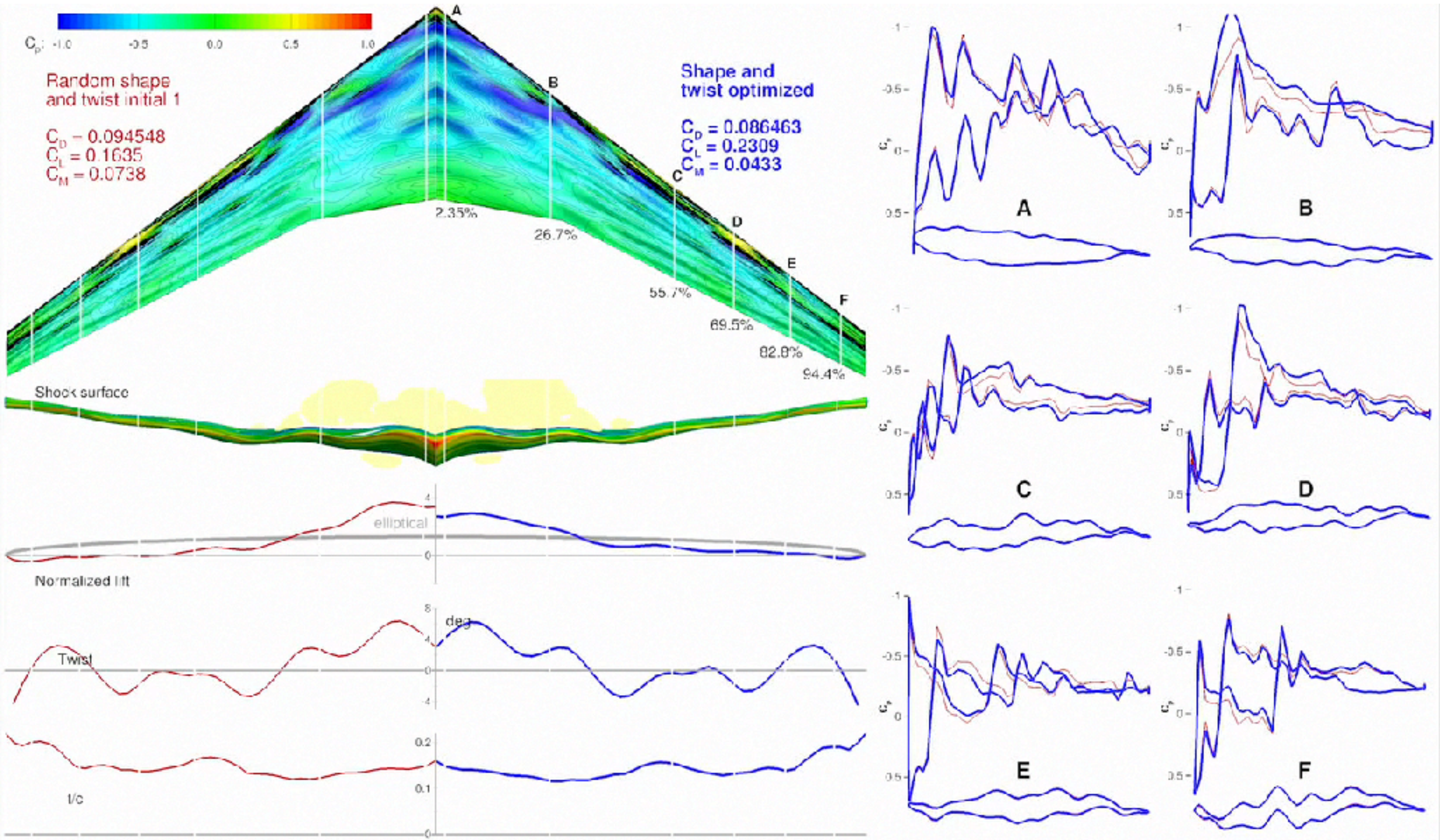


[Lyu et al., *AIAA Journal*, 2014]

Now, let's start with a bad design!

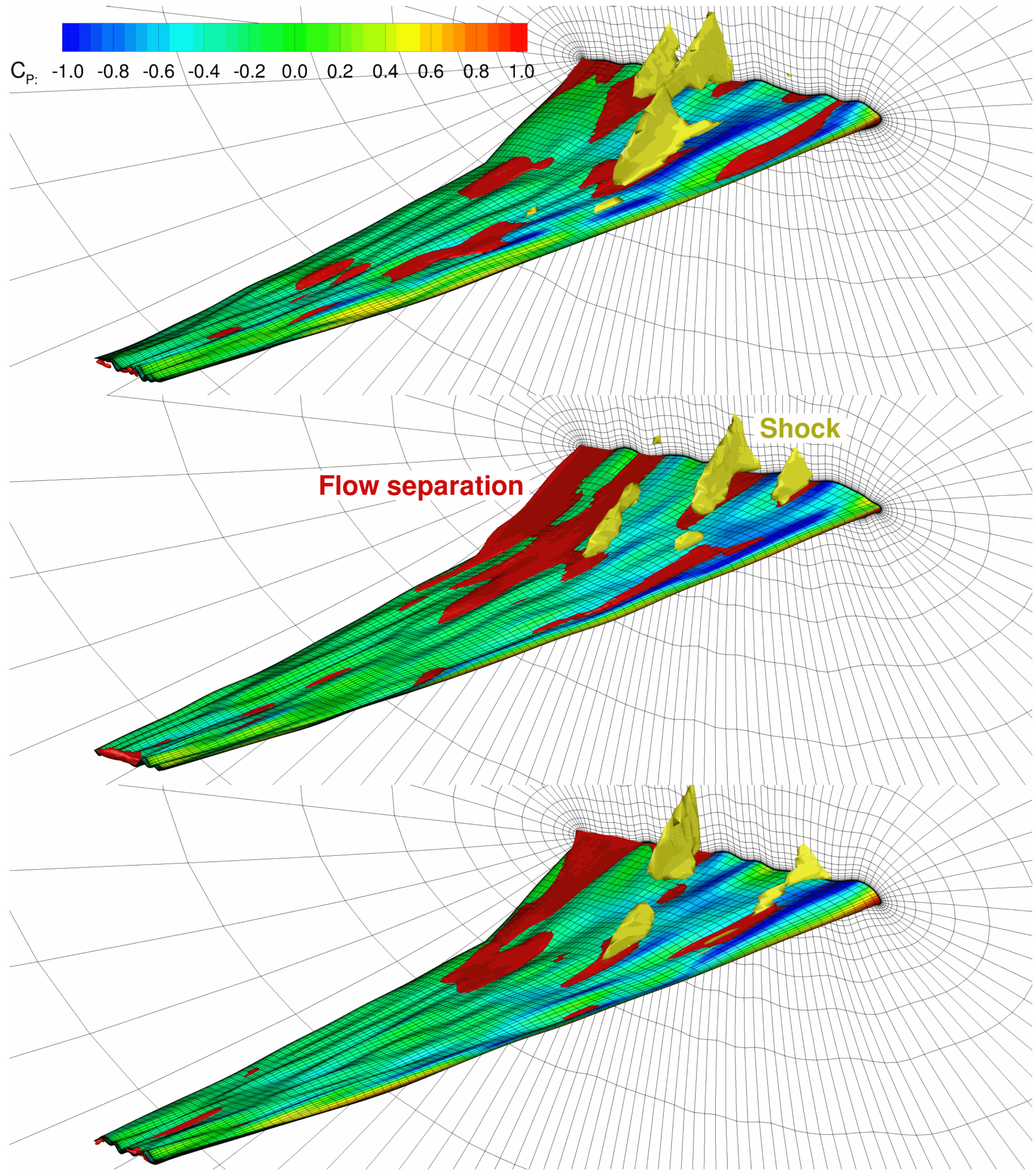


Now, let's start with a really bad design!

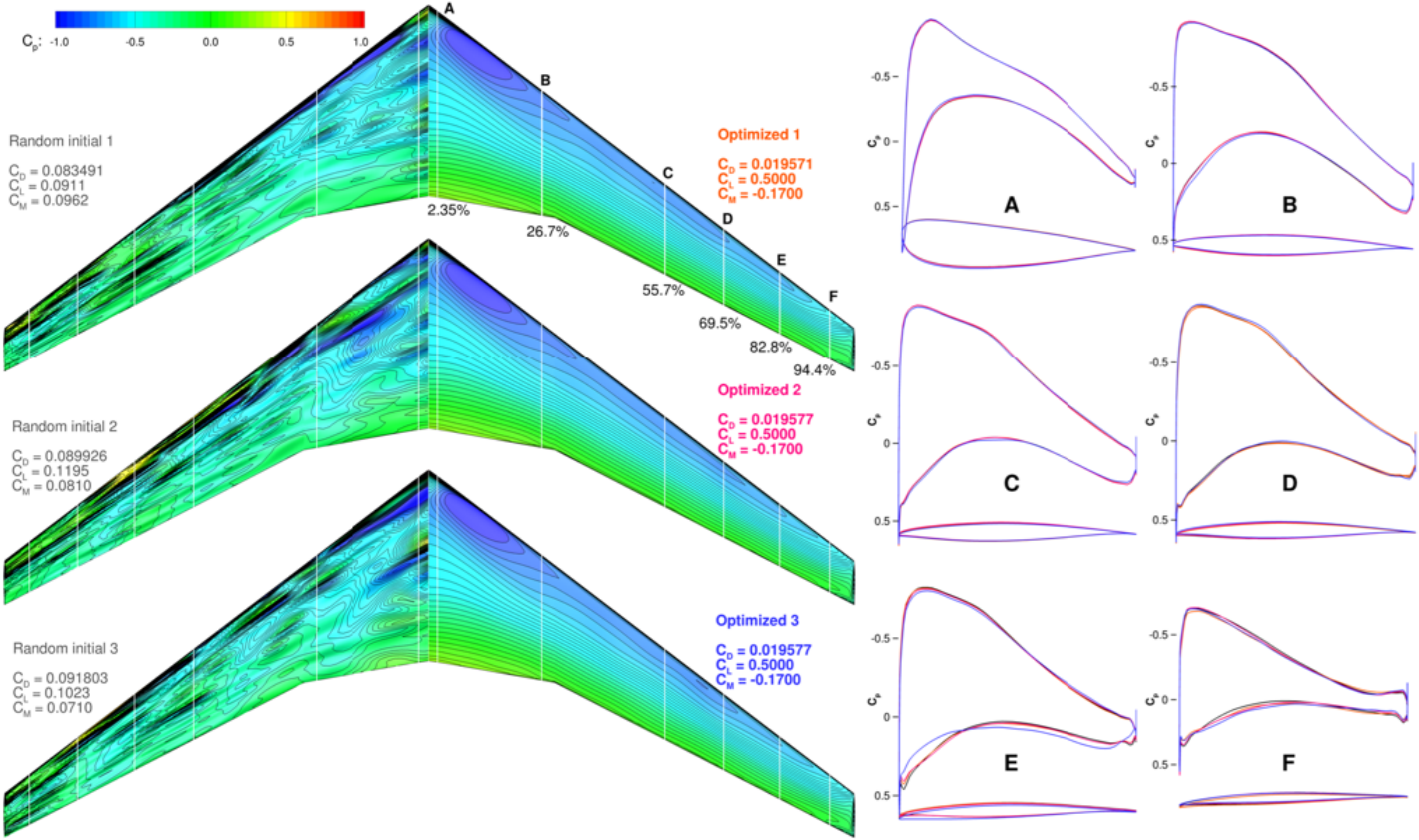


Are there multiple local minima?

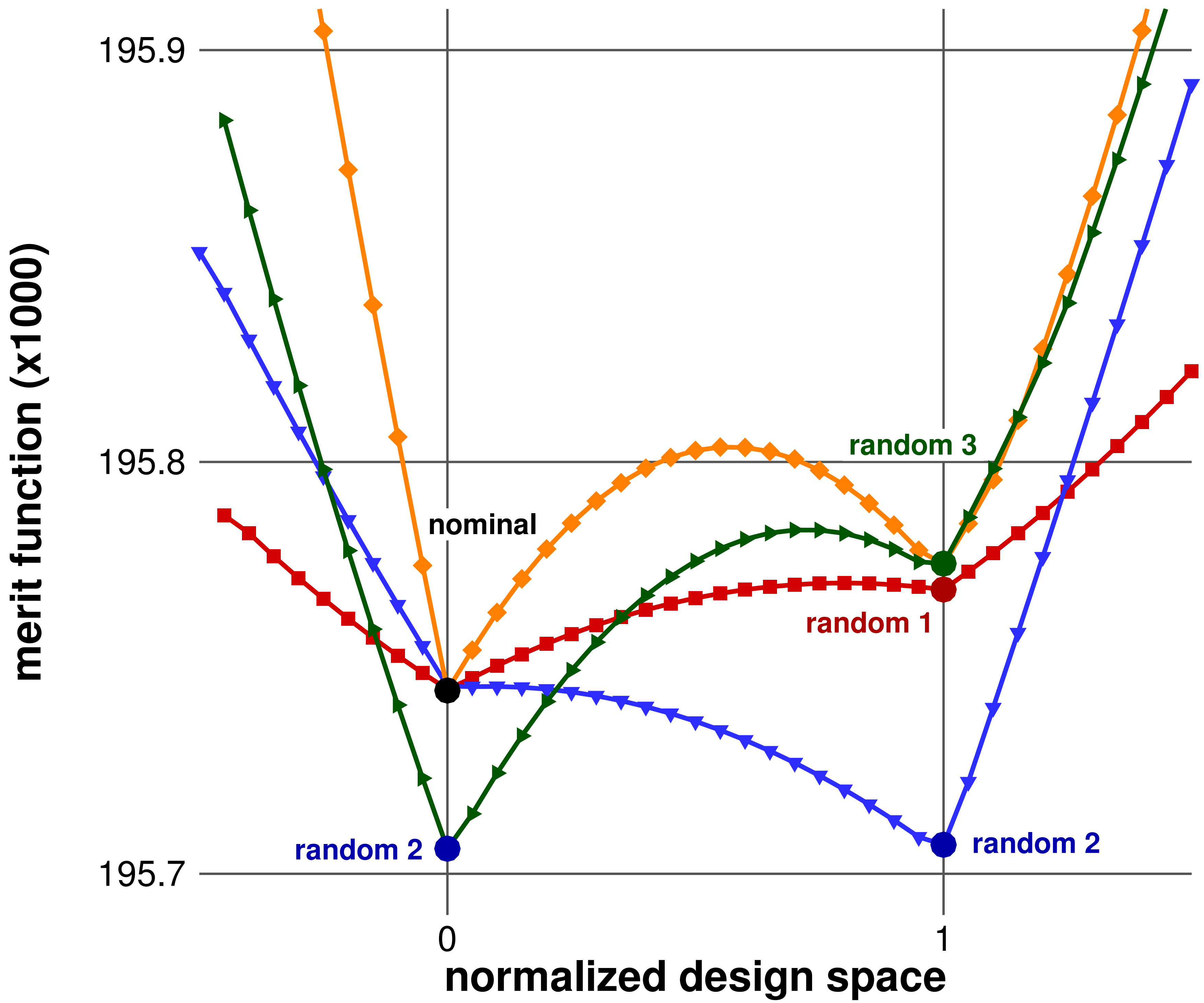
- Wings with randomly generated surface used as the starting point of the optimization
- The geometries are generated by putting random surface perturbations on the CRM wing
- A total of 3 cases



Three random geometries converged to similar designs

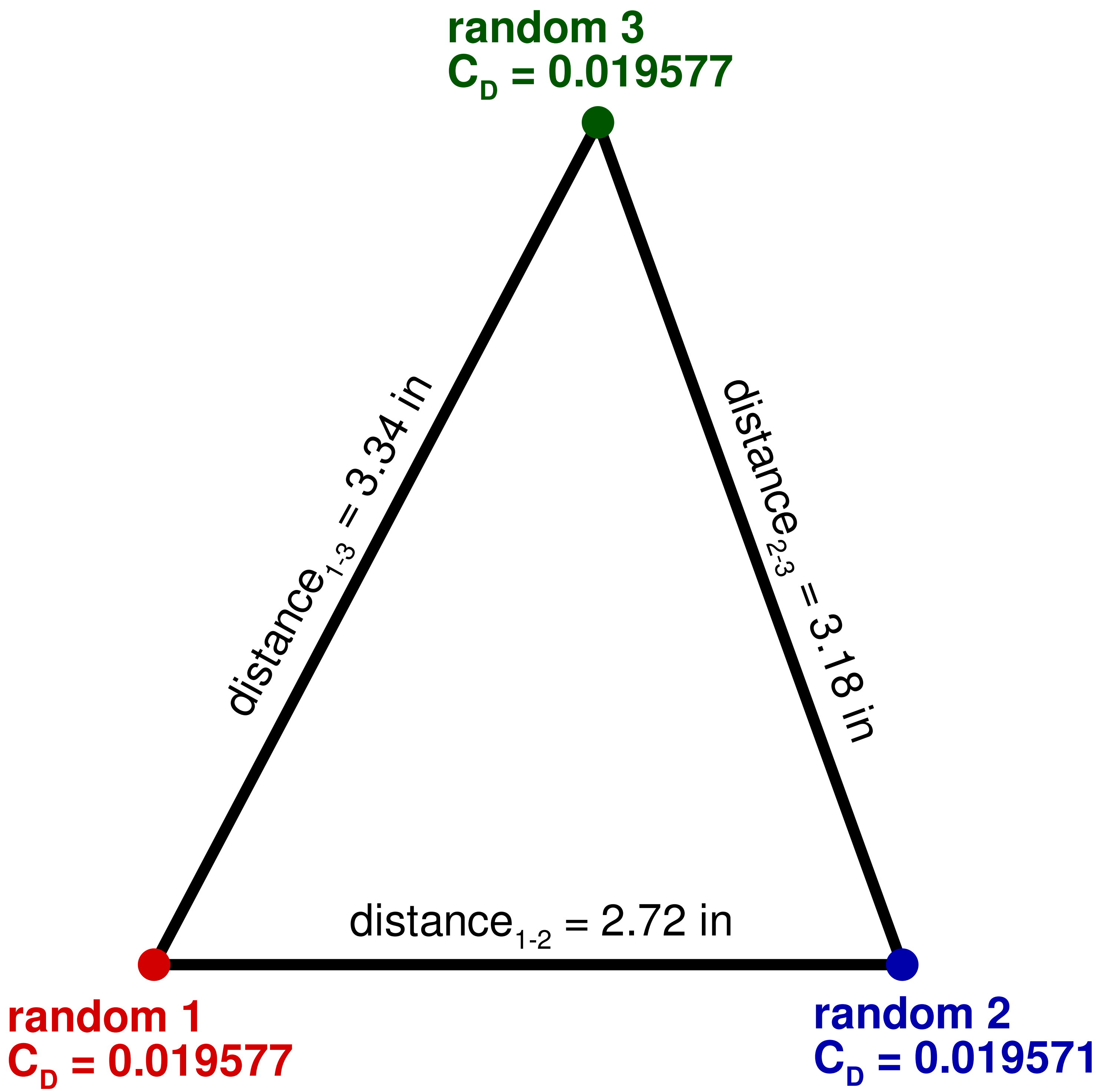


1D slices connecting optimal point show multiple local minima



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

Variation in objective function is 0.05%, while the variation in geometry is 1% of MAC



Conclusion:
The design space is very flat,
and yes, numerically there are local minima…
but who cares?

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

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

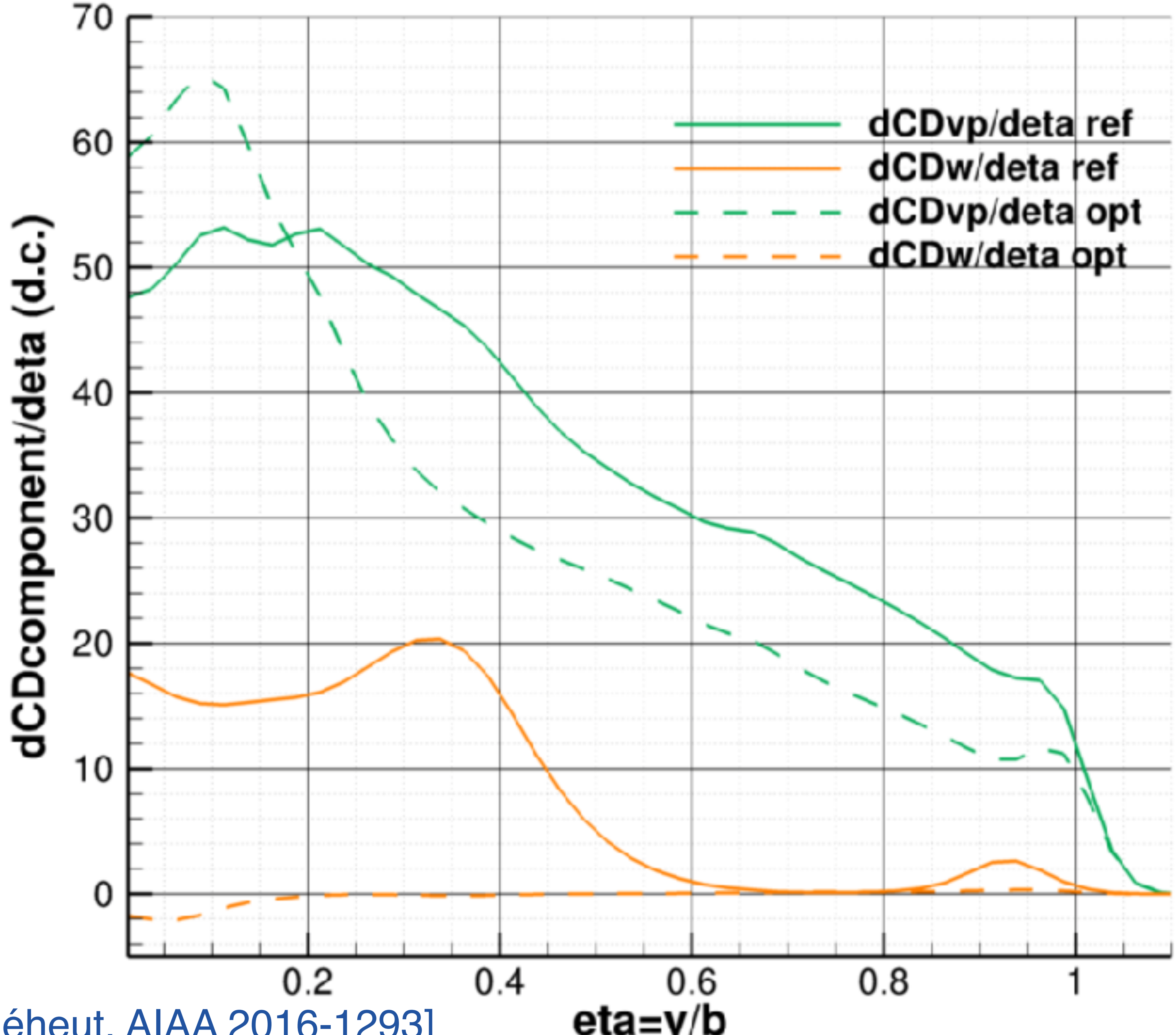
Despite considerable research on aerodynamic shape optimization, there is no standard benchmark problem allowing researchers to compare results. This work addresses this issue by solving a series of aerodynamic shape optimization problems based on the Common Research Model wing benchmark case defined 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

Drag decomposition of this result by ONERA shows low spurious drag

CD components (d.c.)	Ref. CRM (CL=0,503)	Opt. CRM (CL=0,505)
CDw	8,47	-0,18
CDvp	36,49	30,80
CDi	97,45	96,35
CDfriction	59,32	58,58
CDfardfield	201,73	185,55
CDnearfield	202,26	187,13
CDspurious	0,53	1,58

[Dumont and Méheut, AIAA 2016-1293]

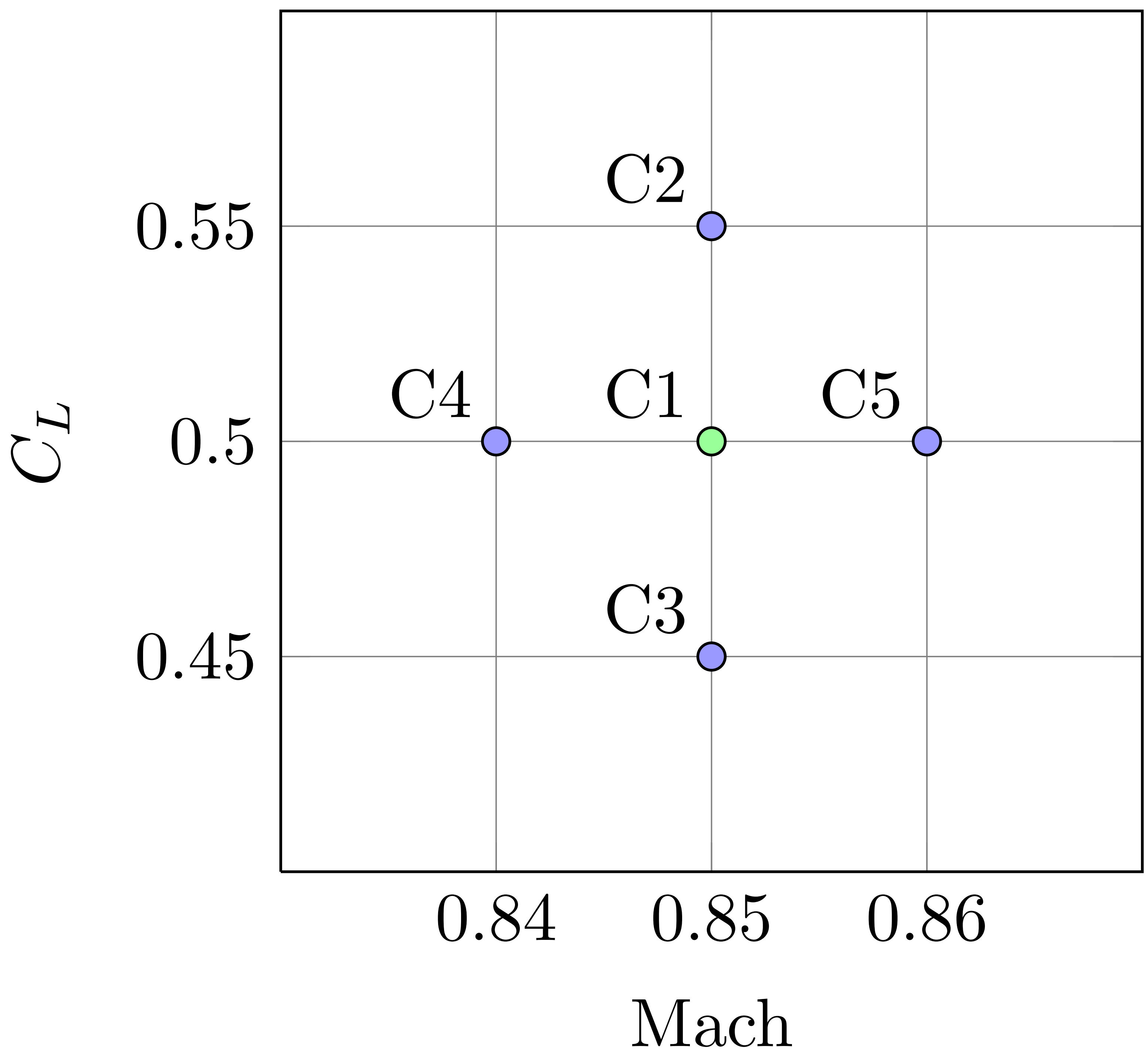
Drag decomposition by ONERA shows the optimization trade-offs



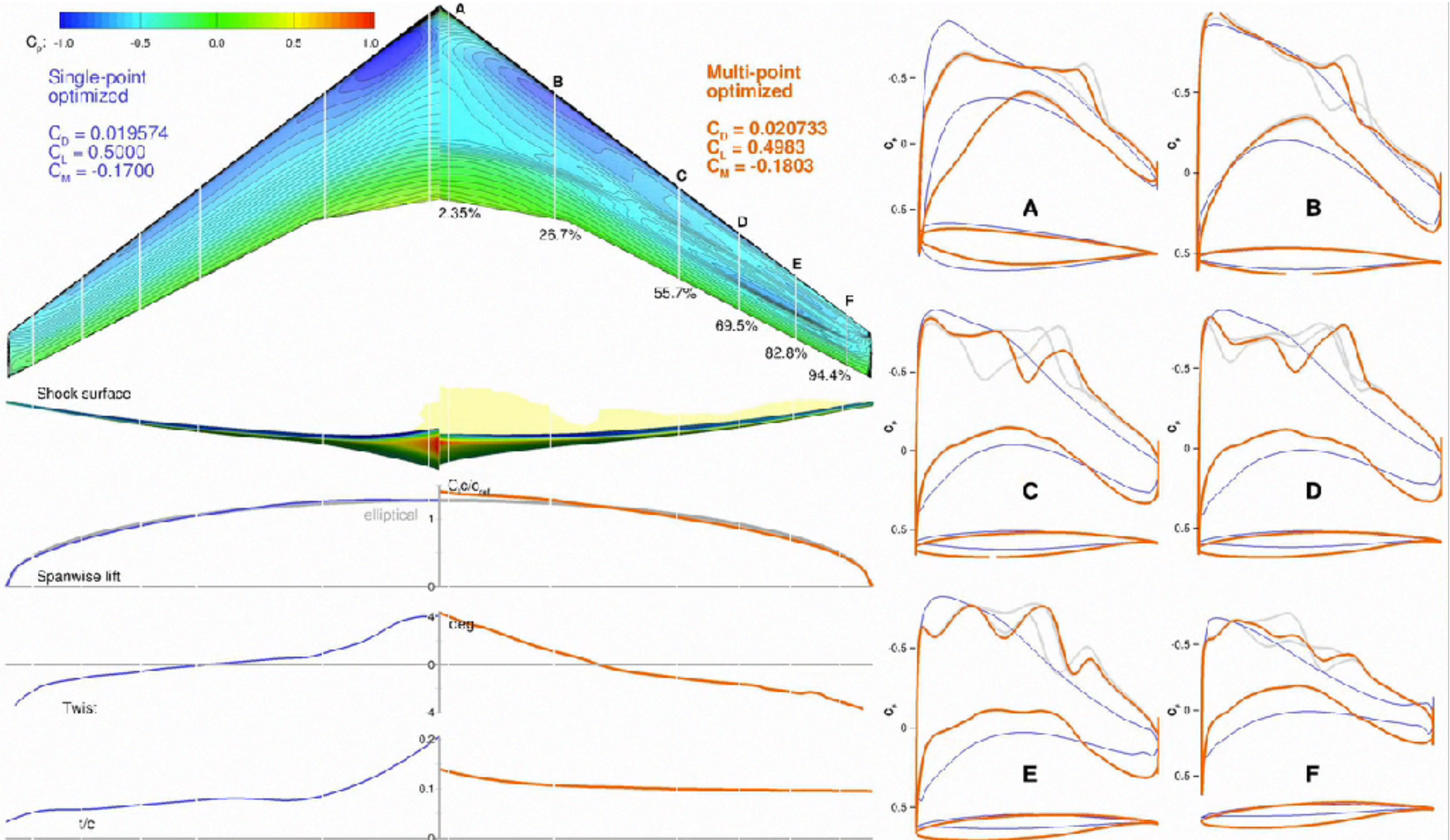
[Dumont and Méheut, AIAA 2016-1293]

Consider 5 flight conditions for a more robust design

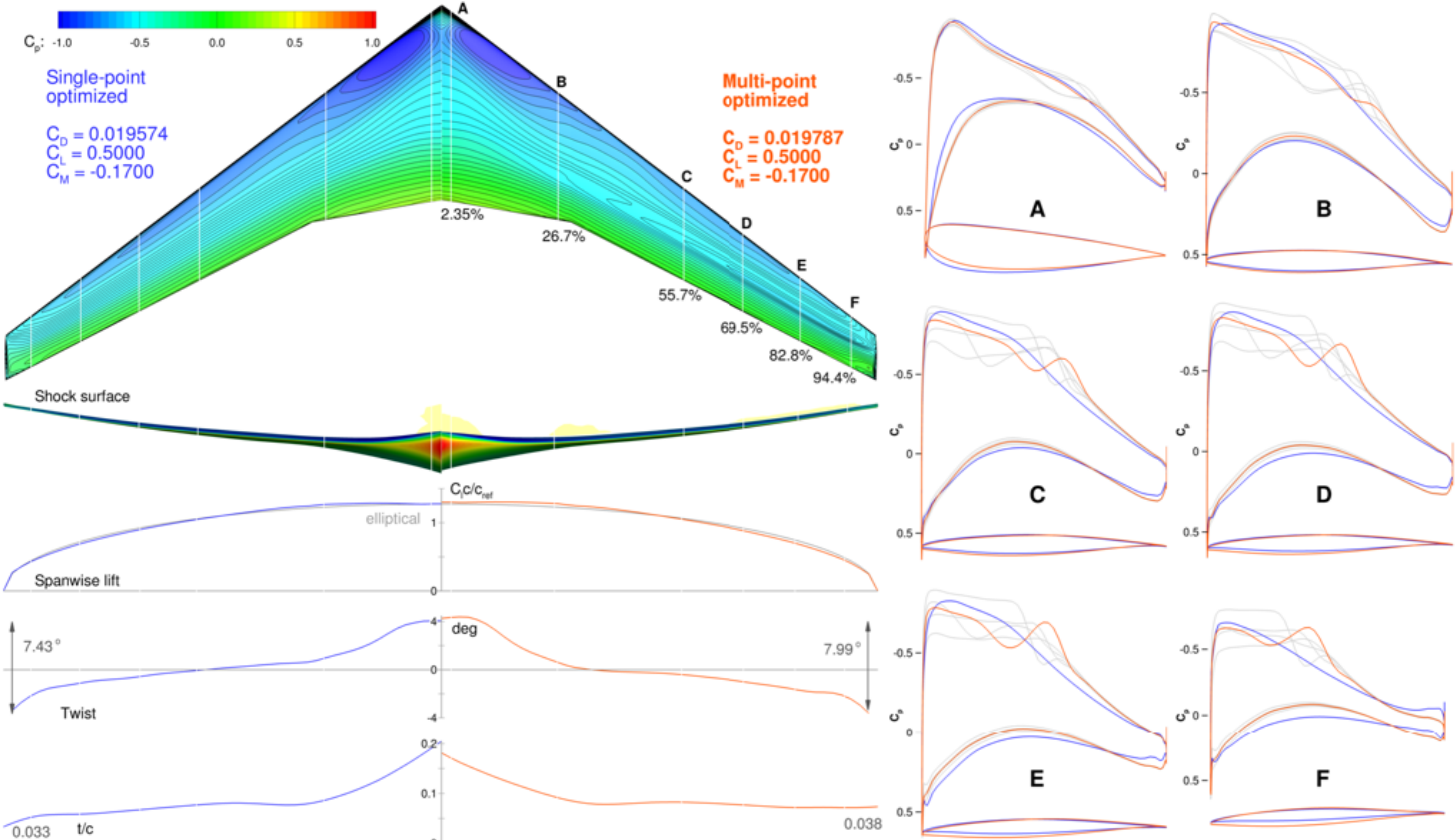
- 5 point cross in Mach-CL space
- Equally weighted sum of the drag coefficients



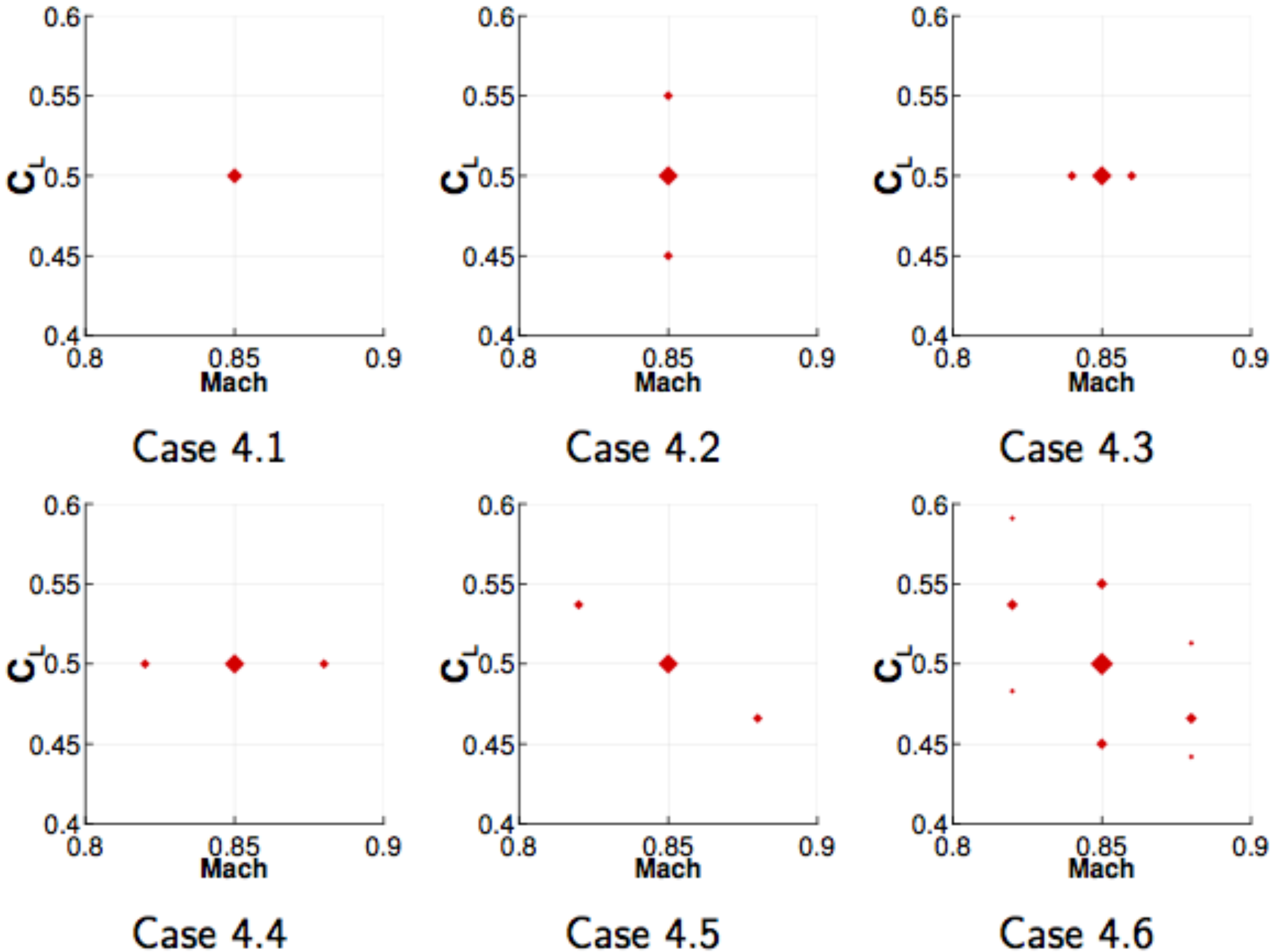
Resulting wing design compromises optimally between flight conditions



Drag coefficient is 2 counts higher at nominal condition

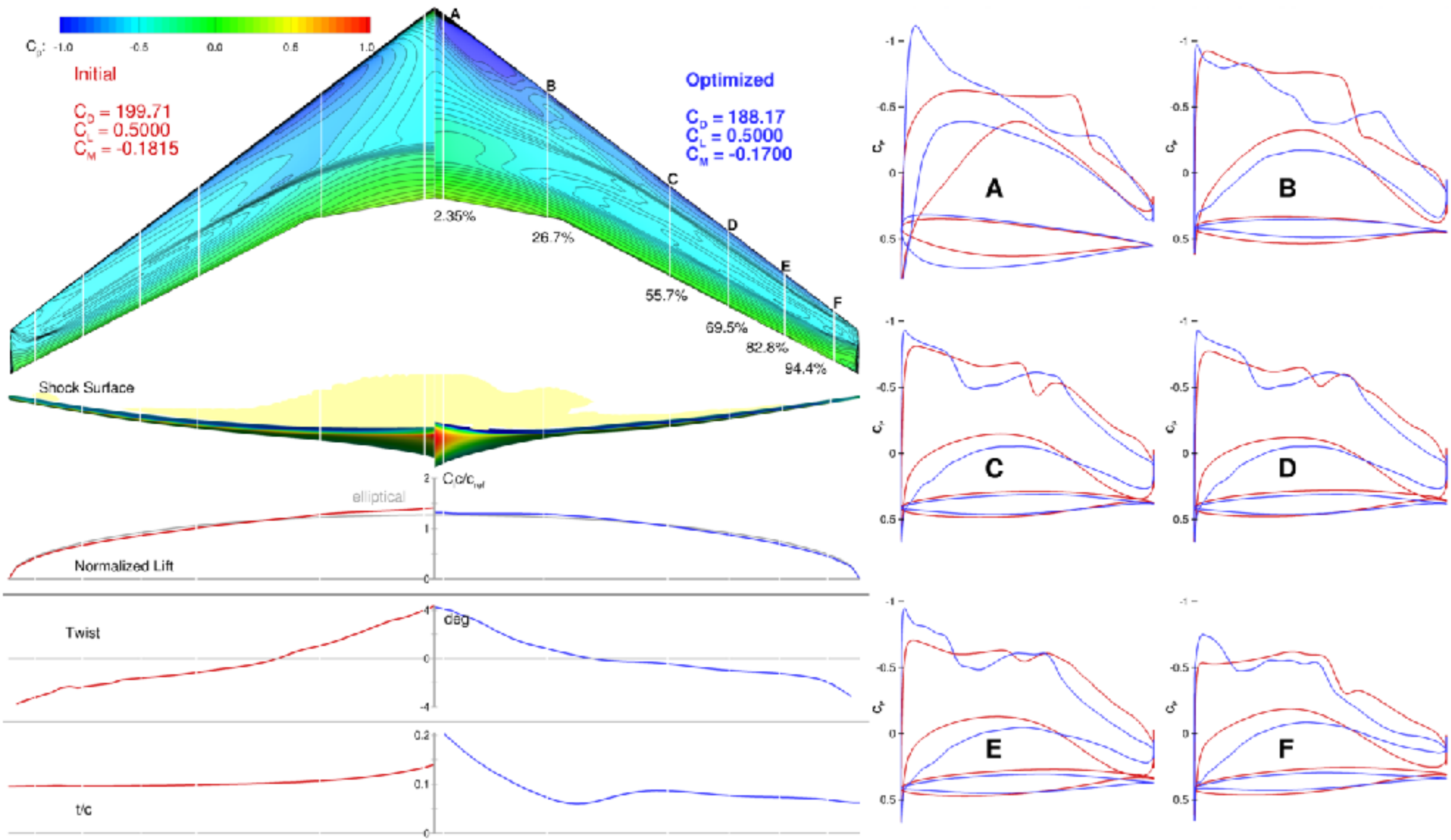


The ADODG introduced new multipoint benchmark cases

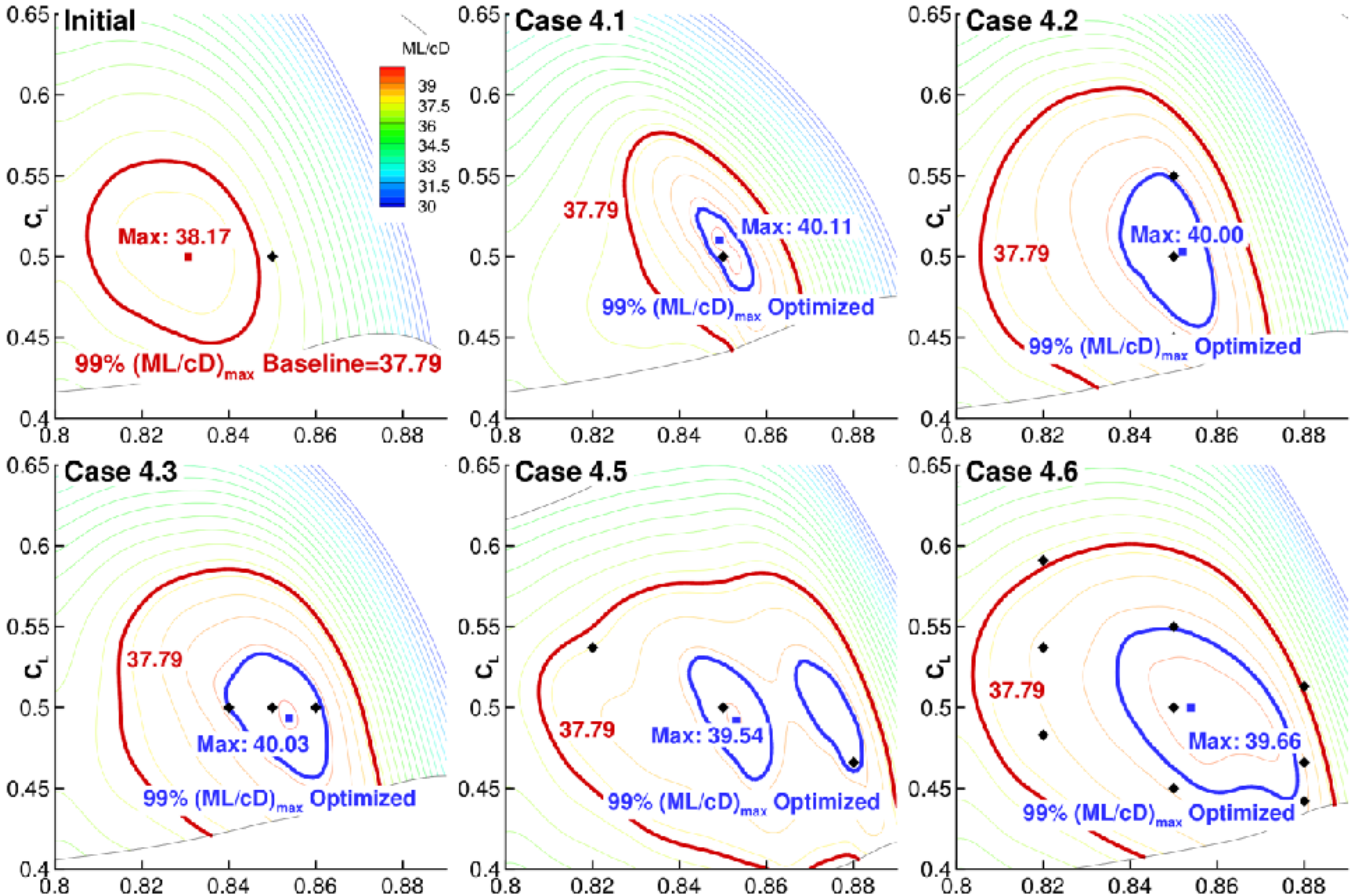


[Kenway and Martins, *AIAA Journal*, 2015]

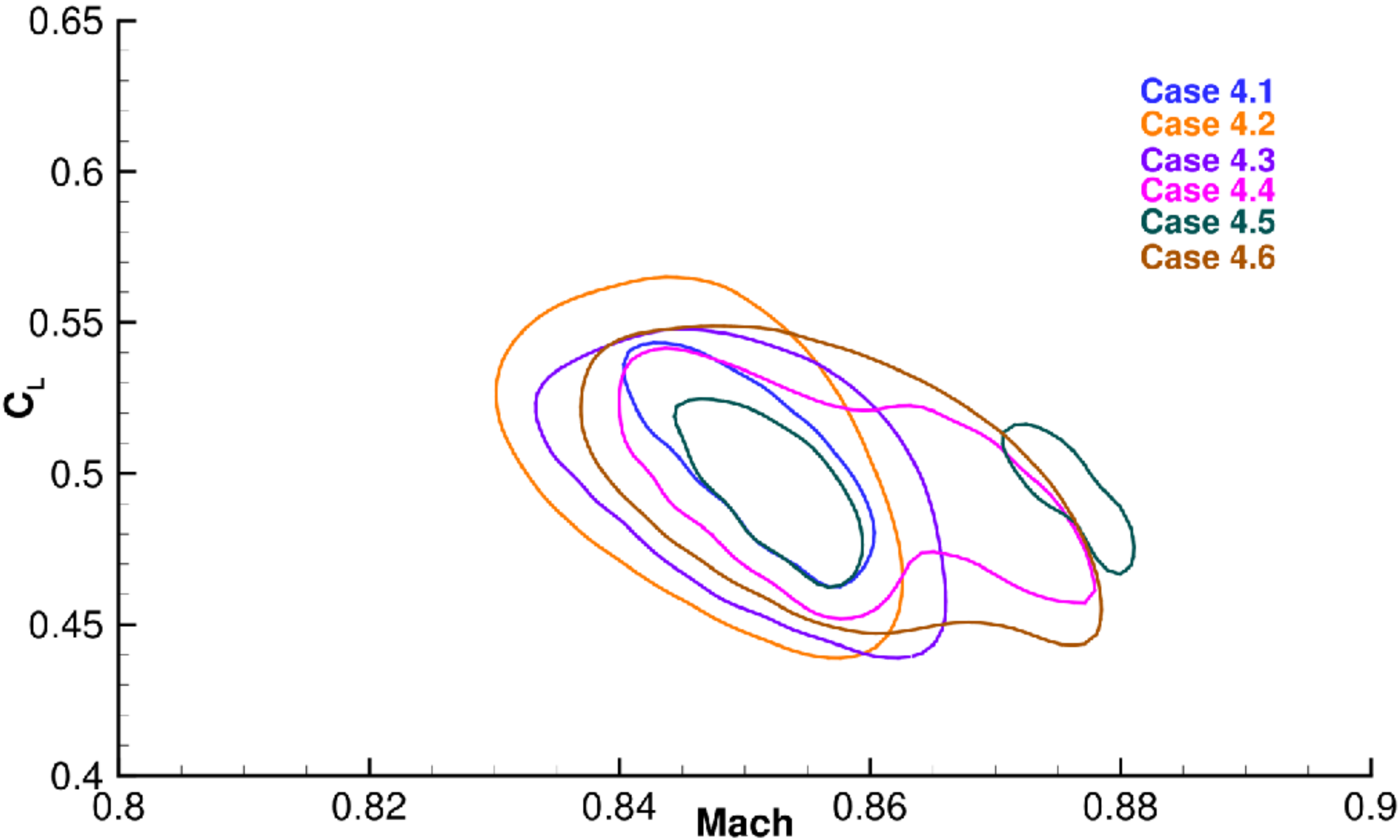
The optimum wing for the 9-point case has a more reasonable airfoil thickness and leading edge curvature



ML/cD contours show the off-design performance of the optimized wings



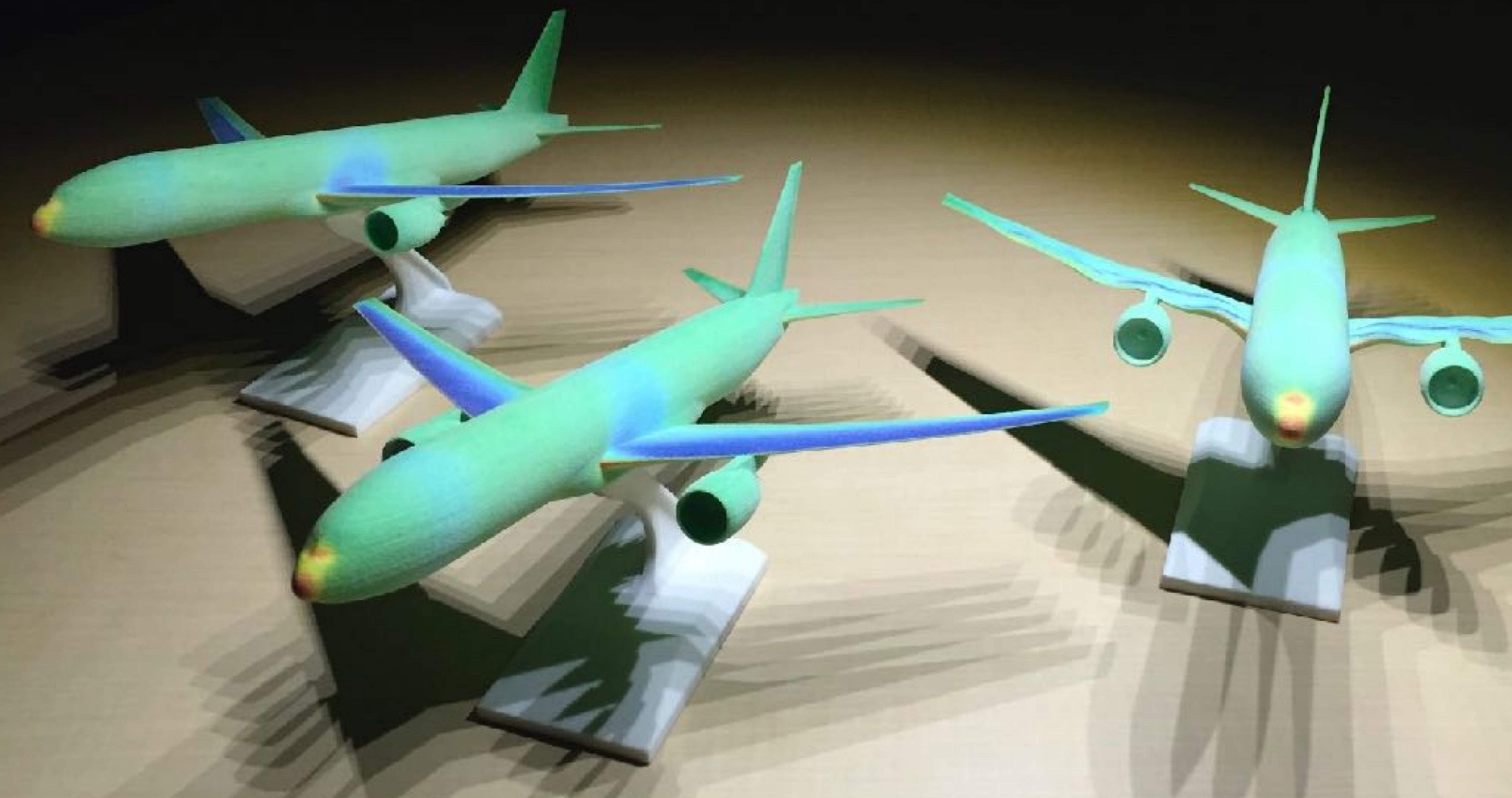
The contours of 99% max ML/cD for the 9-point case (4.6) highlight the off-design performance differences



Computational cost (in CPU-hours)

Case	L2 Opt	L1 Opt	α-Mach sweep	Contour	Total
Initial	–	–	820	3 234	4 054
4.1	344	1 088	580	2 629	4 641
4.2	935	3 023	638	3 308	7 904
4.3	825	3 266	624	2 700	7 414
4.4	820	3 441	597	3 247	8 105
4.5	809	3 508	676	3 236	8 229
4.6	2 631	10 053	1 850	2 777	17 311
Total	6 363	24 380	5 768	21 131	**57 659**

3D-printed models colored with C_p distributions

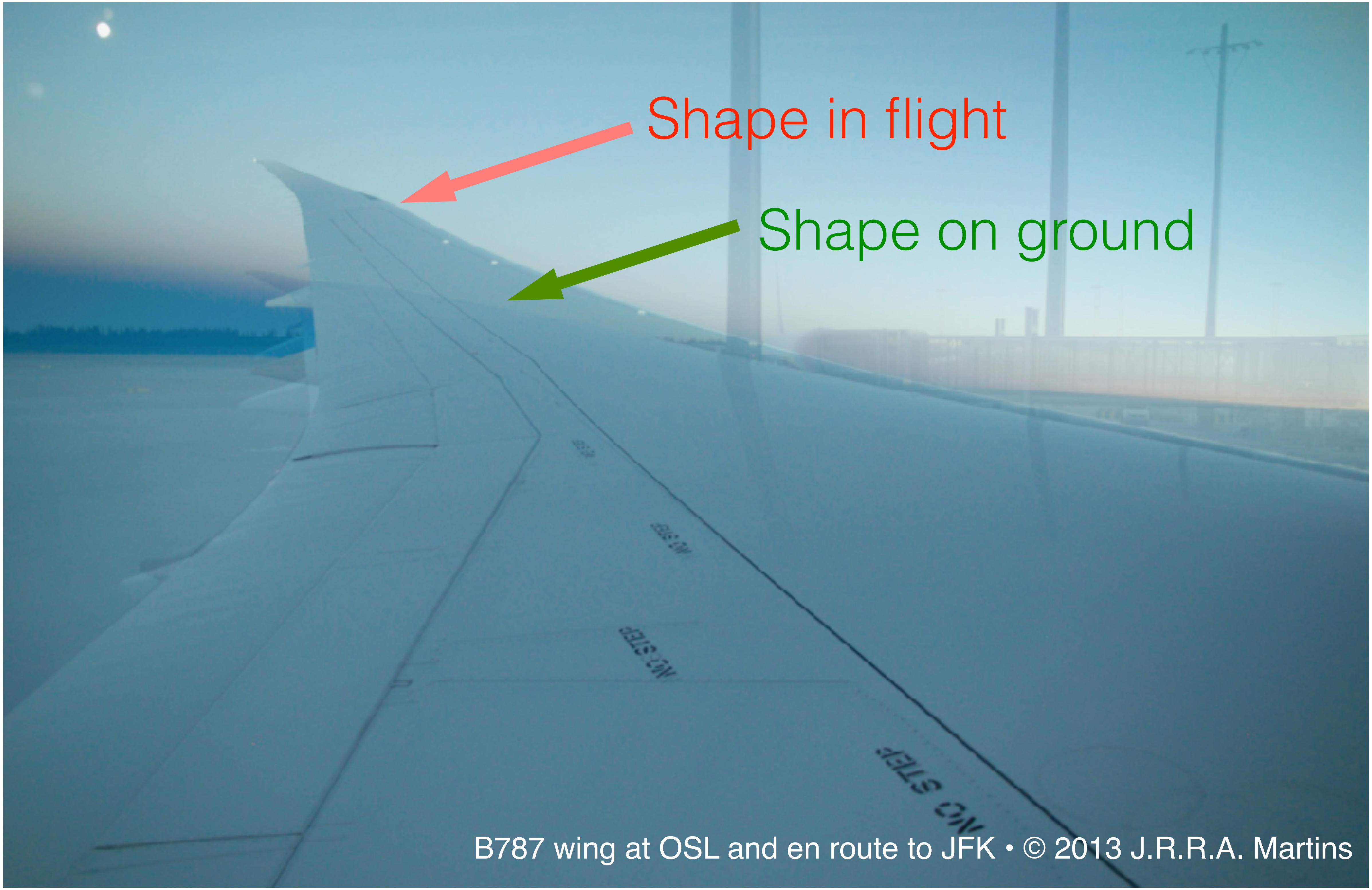


Multidisciplinary Design Optimization of Aircraft Configurations

Part 2: High-fidelity aerostructural optimization

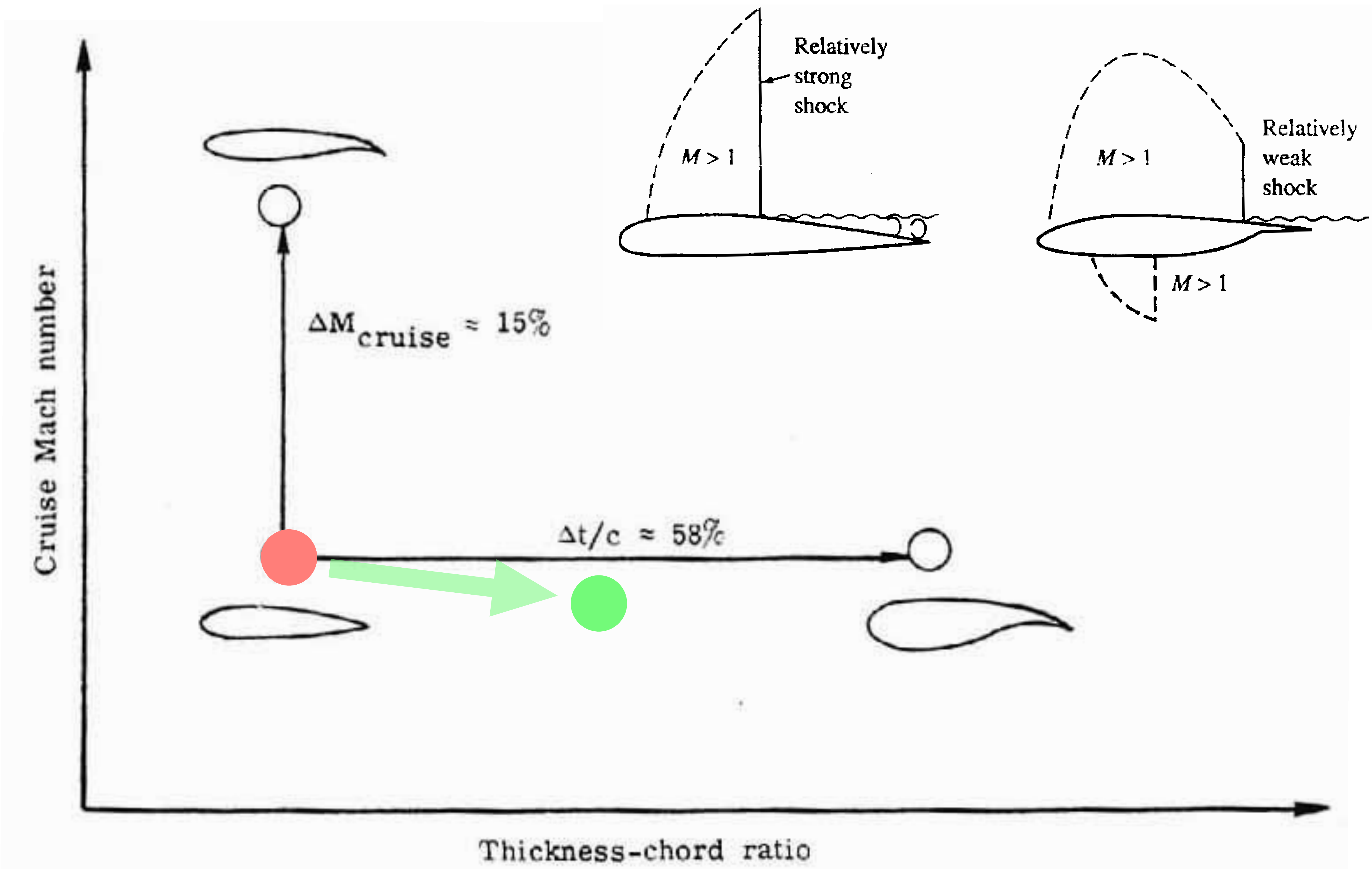
- Choice of optimization algorithm
- Computing derivatives efficiently
- Aerodynamic shape optimization
- Aerostructural design optimization
- Summary

Wing design demands more than just aerodynamics



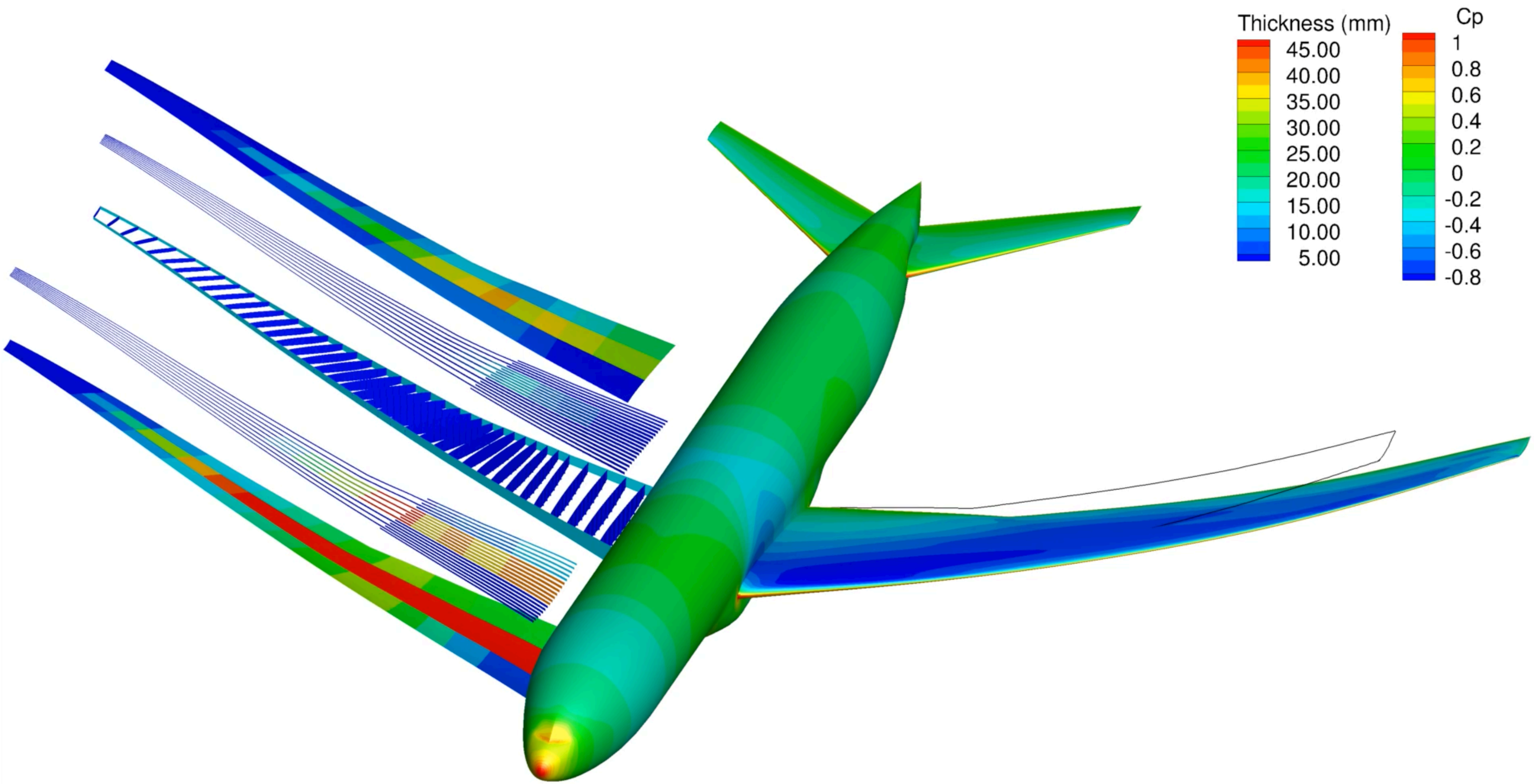
B787 wing at OSL and en route to JFK • © 2013 J.R.R.A. Martins

Why you should not trust an aerodynamicist (even a brilliant one) to make design decisions



[NASA]

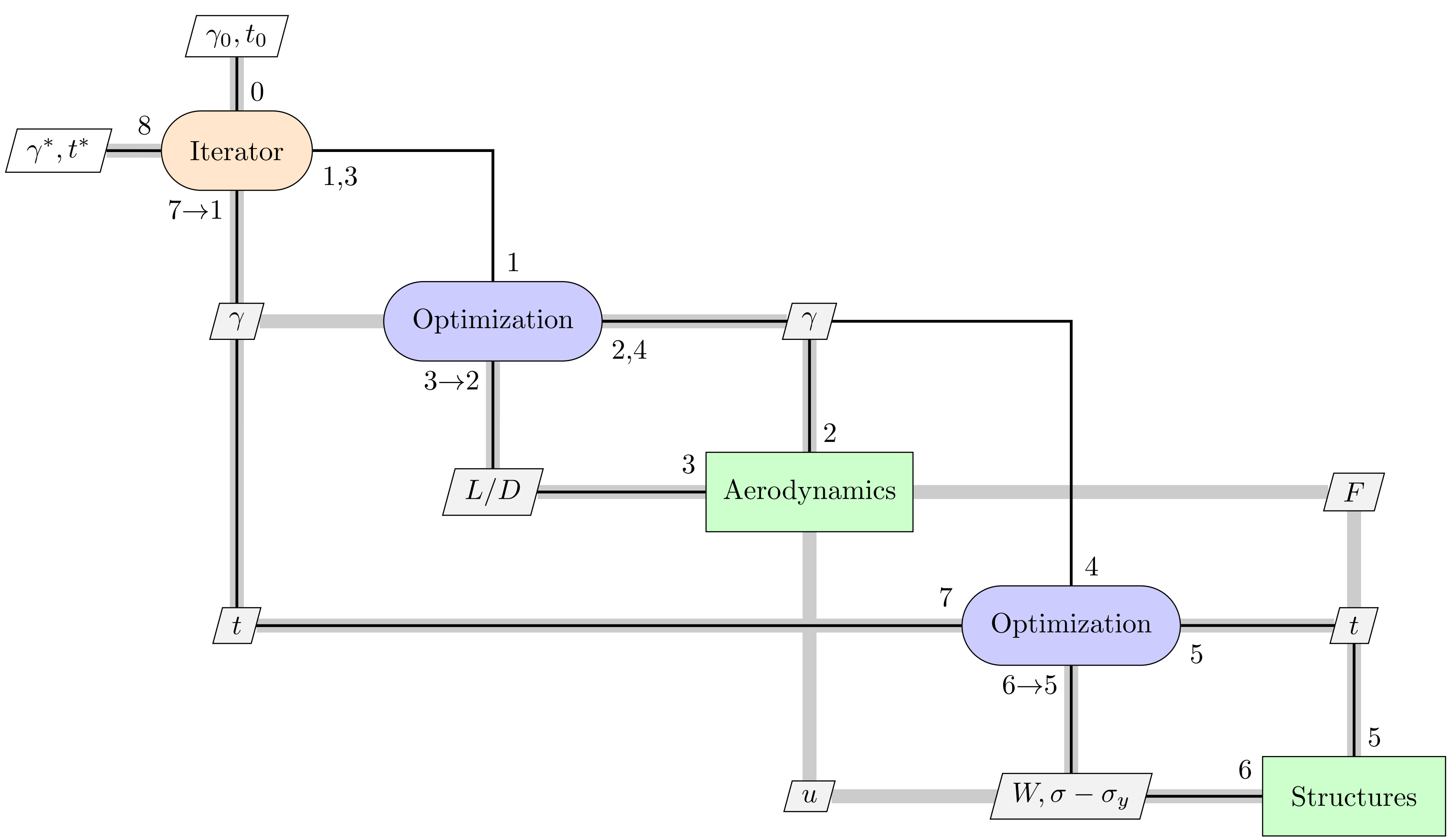
Want to optimize both aerodynamic shape and structural sizing, with high-fidelity

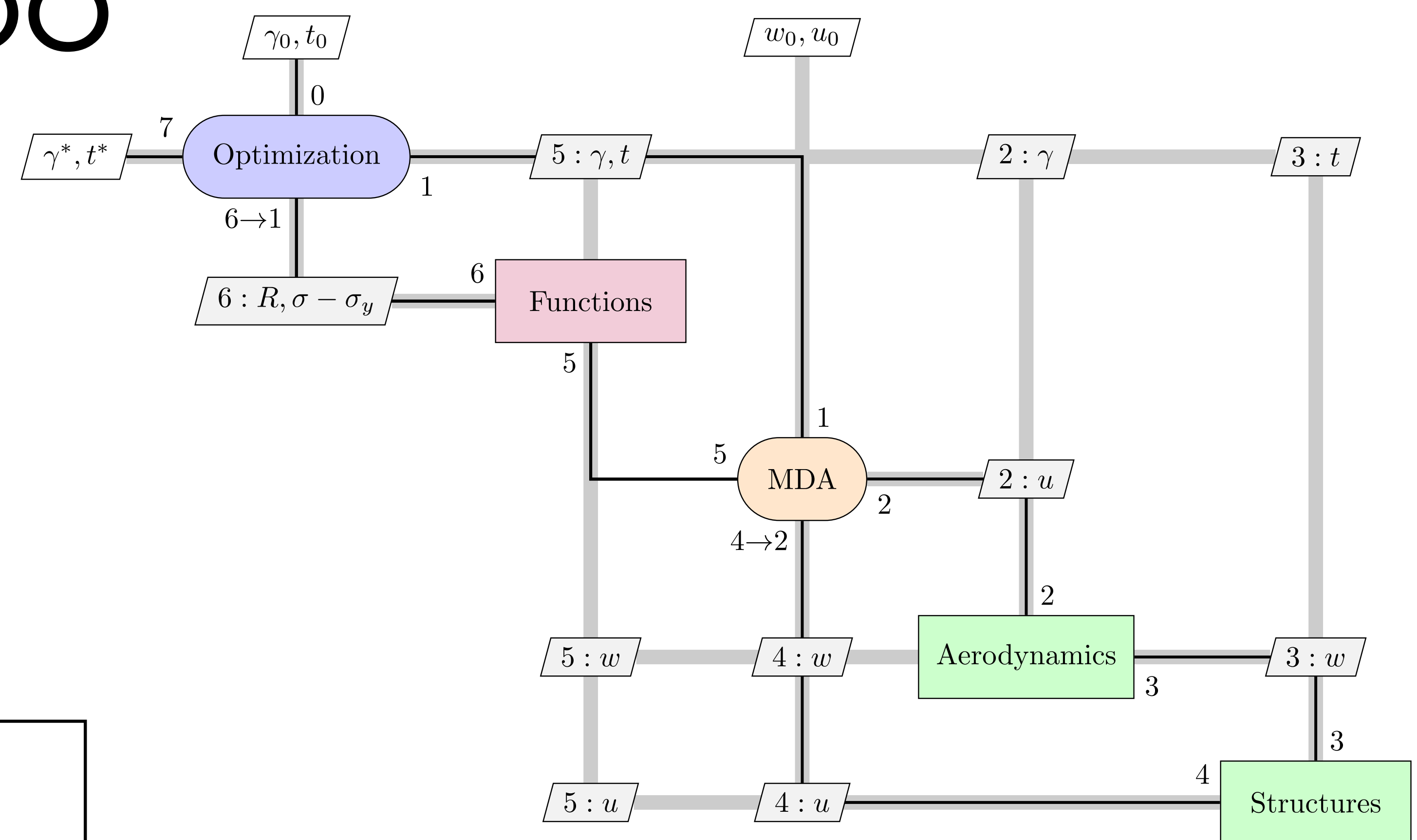


Sequential optimization is equivalent to coordinate descent

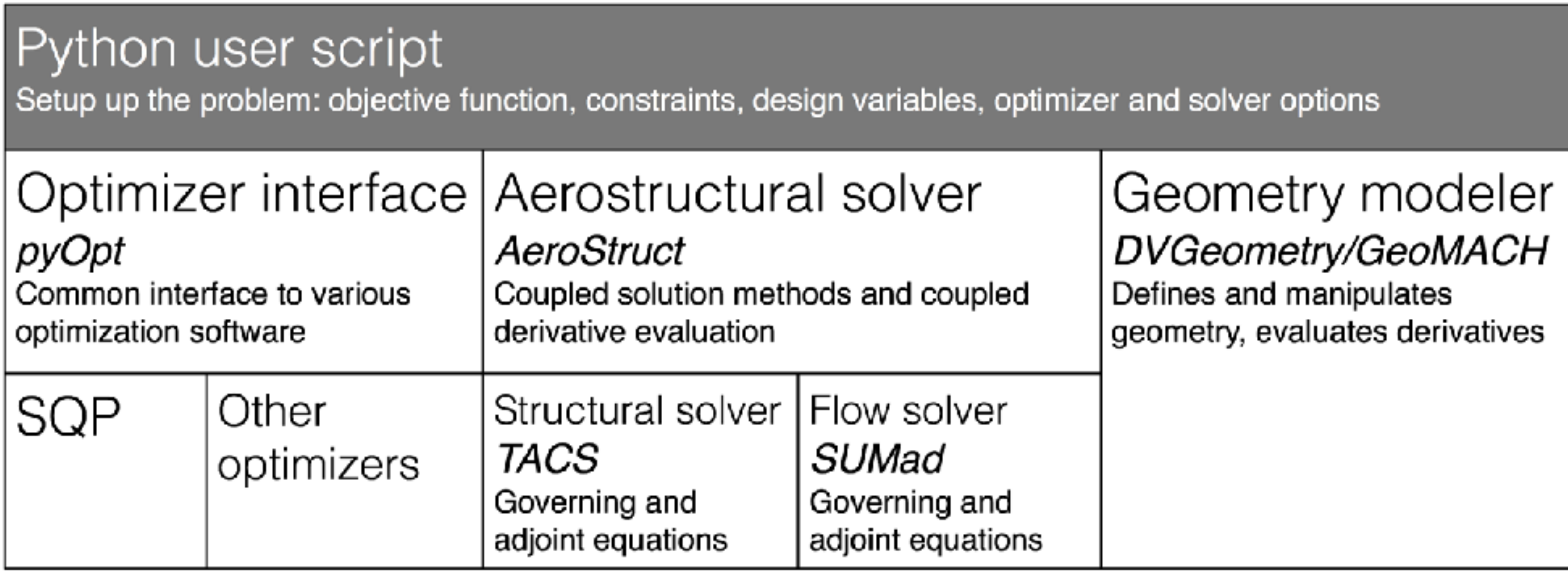
MDO

Sequential optimization





MDO for Aircraft Configurations with High-fidelity (MACH)



- 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]

pyOptSparse is available as open source software

https://bitbucket.org/mdolab/pyoptsparse

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Source

default pyOptSparse / doc / tutorial.rst Source Diff History

d8545f0 2015-09-14 Full commit Blame Embed Raw Edit

Tutorial

The following shows how to get started with pyOptSparse by solving Schittkowski's TP37 constrained problem. First, we show the complete program listing and then go through each statement line by line:

```
import pyoptsparse
def objfunc(xdict):
    x = xdict['xvars']
    funcs = {}
    funcs['obj'] = -x[0]*x[1]*x[2]
    conval = [0]*2
    conval[0] = x[0] + 2.*x[1] + 2.*x[2] - 72.0
    conval[1] = -x[0] - 2.*x[1] - 2.*x[2]
    funcs['con'] = conval
    fail = False

    return funcs, fail

optProb = pyoptsparse.Optimization('TP037', objfunc)
optProb.addVarGroup('xvars',3, 'c',lower=[0,0,0], upper=[42,42,42], value=10)
optProb.addConGroup('con',2, lower=None, upper=0.0)
optProb.addObj('obj')
print optProb
opt = pyoptsparse.SLSQP()
sol = opt(optProb, sens='FD')
print sol
```

Coupled solution of aerodynamics and structures, and the corresponding coupled adjoint

Solve the coupled governing equations

$$R(x,y) = \left[\begin{array}{c} R_A(x, y_A, y_S) \\ R_S(x, y_A, y_S) \end{array} \right] = 0$$

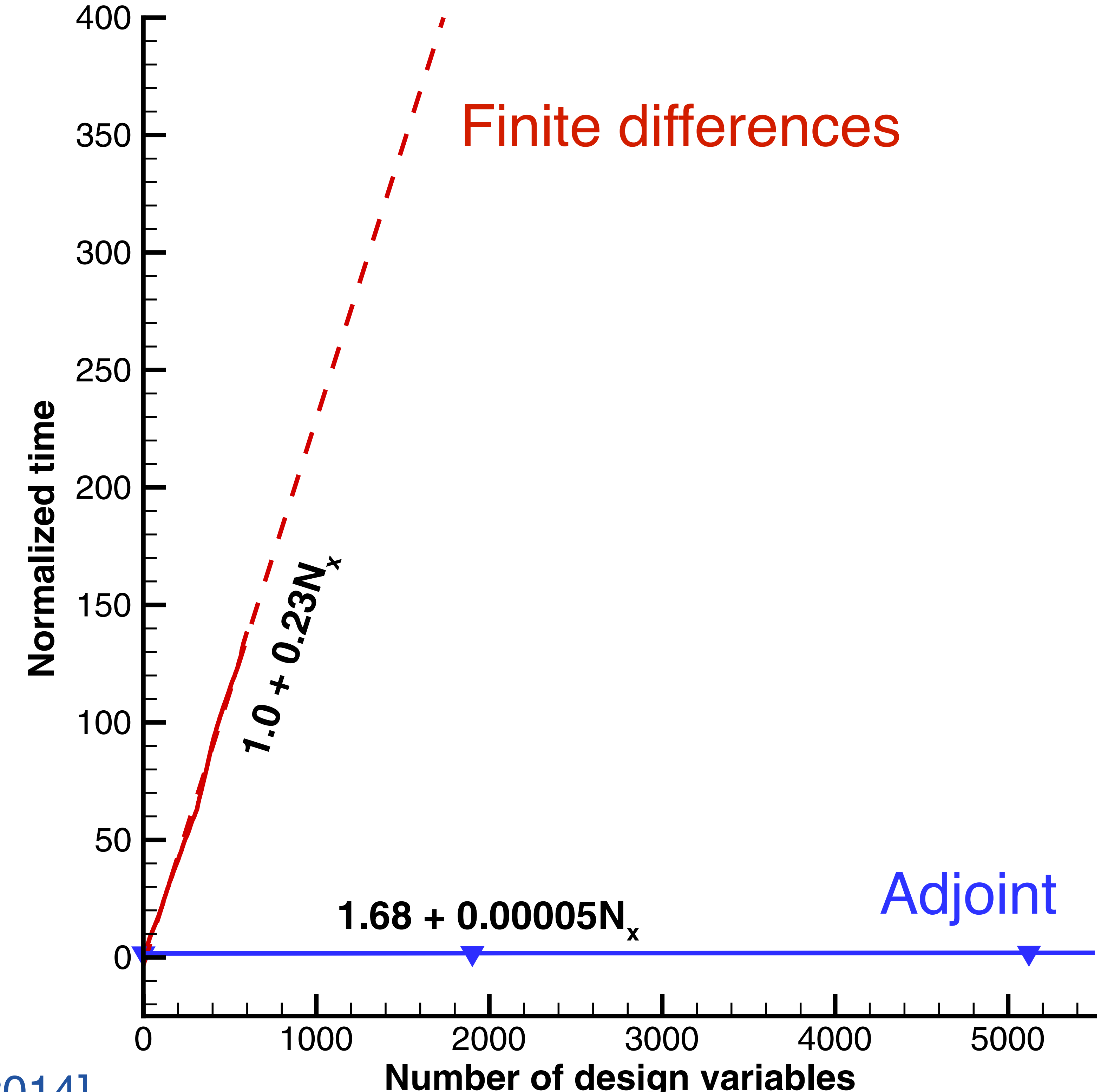
form and solve the adjoint equations

$$\frac{\partial R}{\partial y}^T \psi = \frac{\partial f}{\partial y}^T \quad \text{where} \quad \frac{\partial R}{\partial y}^T = \begin{bmatrix} \frac{\partial R_A}{\partial y_A}^T & \frac{\partial R_S}{\partial y_A}^T \\ \frac{\partial R_A}{\partial y_S}^T & \frac{\partial R_S}{\partial y_S}^T \end{bmatrix}$$

and compute the gradient

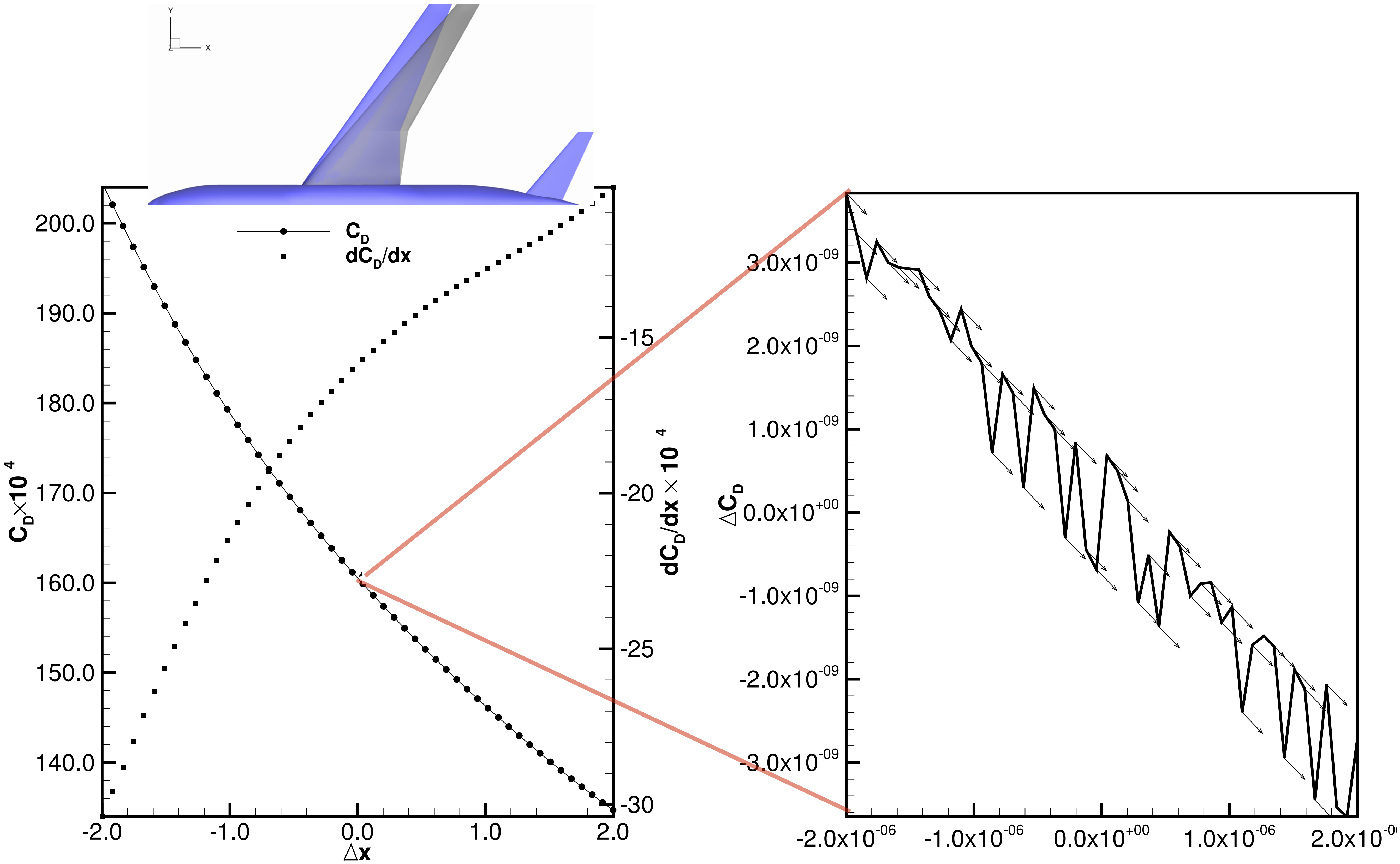
$$\frac{\mathrm{d}f}{\mathrm{d}x} = \frac{\partial f}{\partial x} - \psi^T \frac{\partial R}{\partial x}$$

Adjoint method efficiently computes gradients with respect to thousands of variables

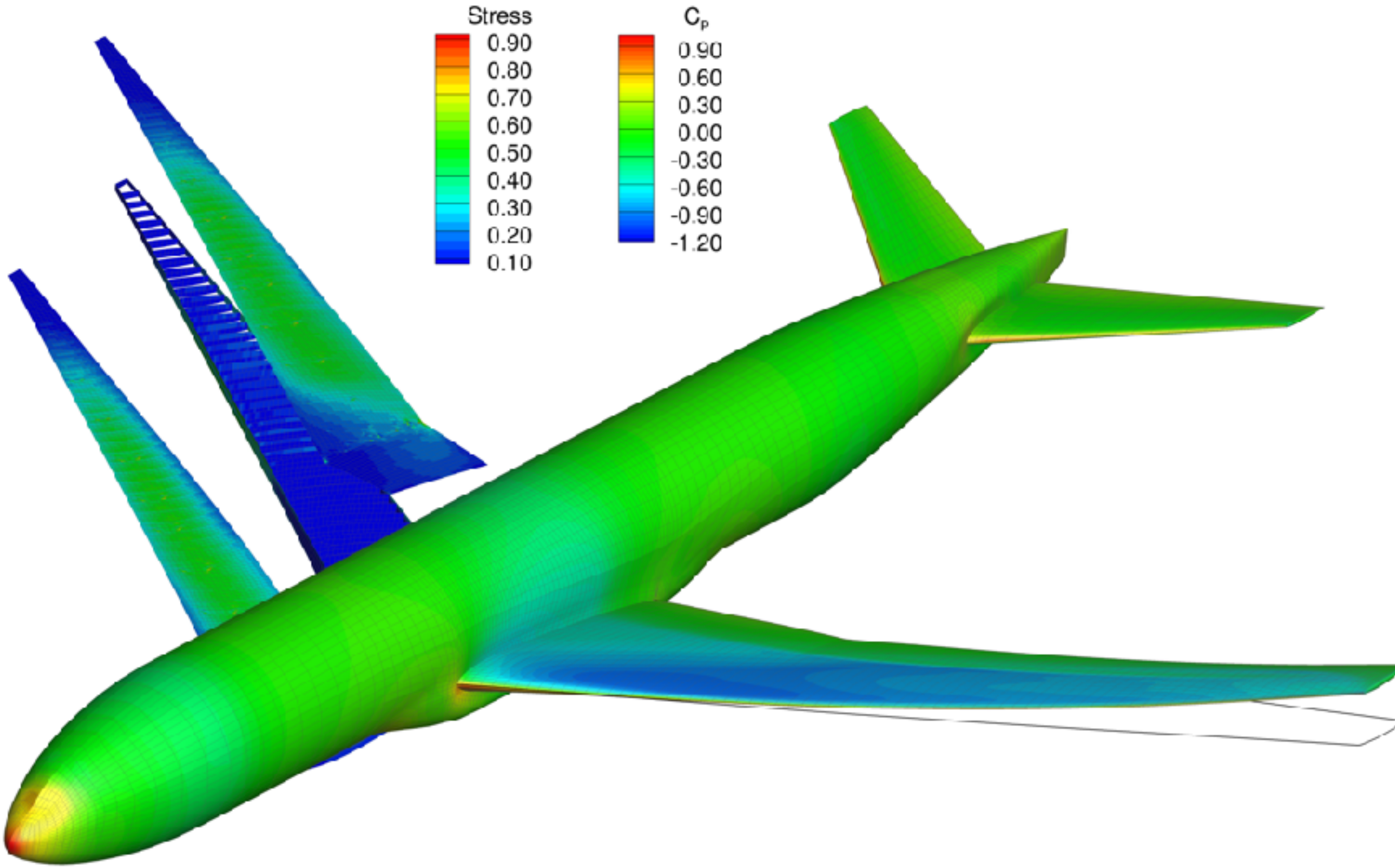


[Kenway et al., *AIAA J.*, 2014]

A smooth function and accurate gradients keep the optimizer happy

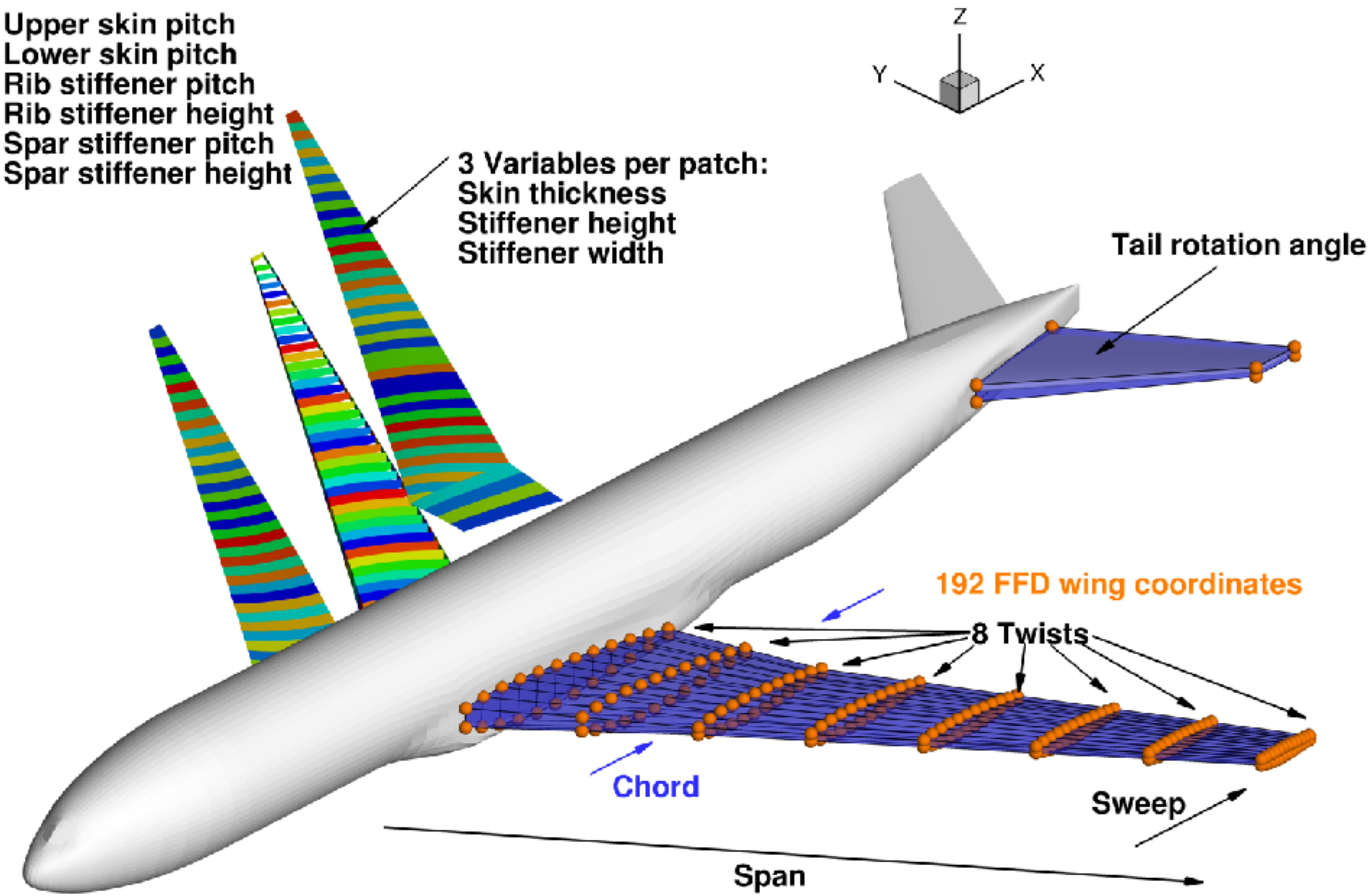


Let’s do aerostructural optimization!



NASA-Michigan undeformed Common Research Model (uCRM)

Optimize 973 “aerodynamic” and structural sizing design variables



Objective and design variables

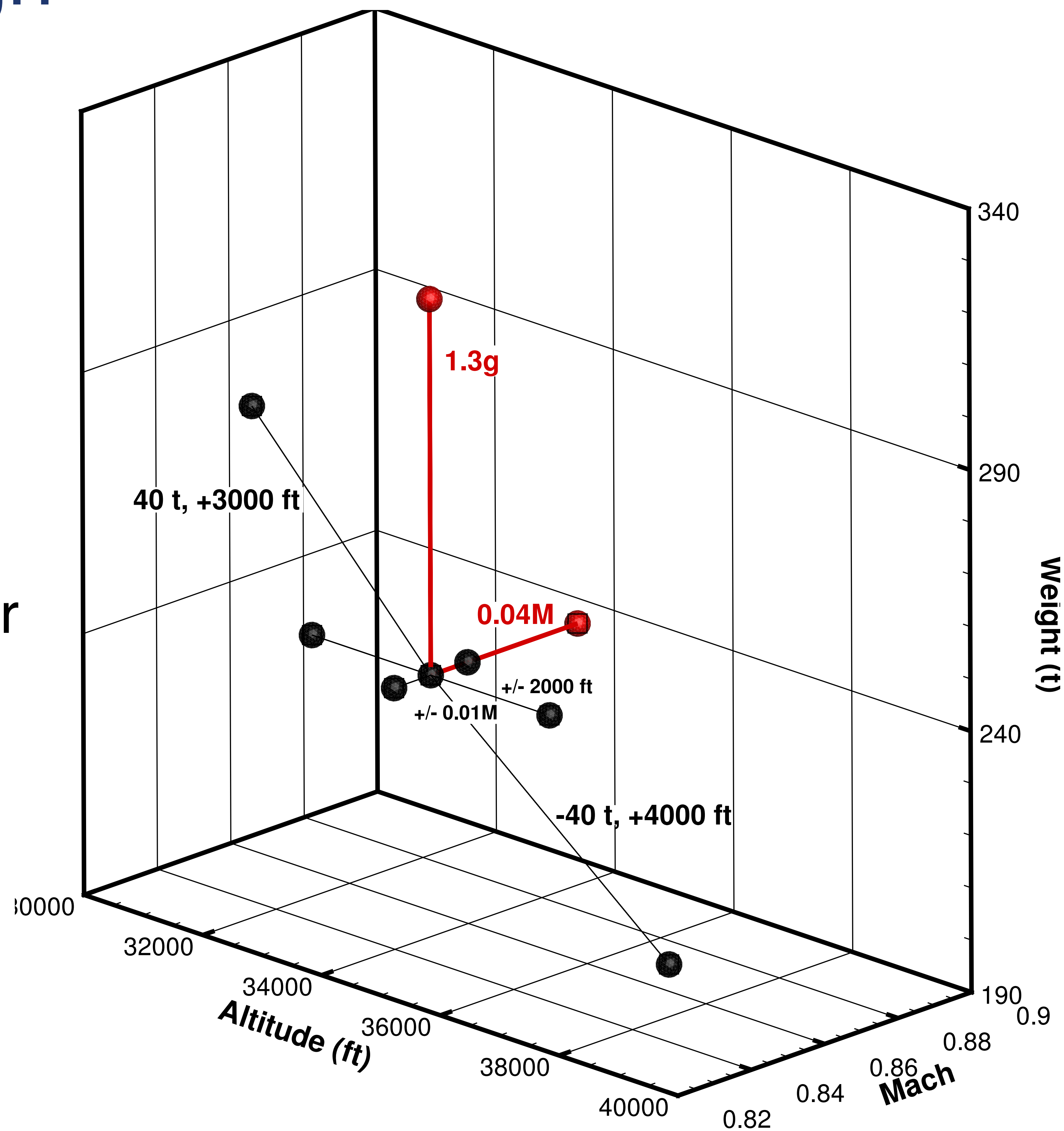
	Function/variable	Description	Quantity
minimize	βFuel burn + $(1-\beta)$TOGW		
with respect to	x_{span}	Wing span	1
	x_{sweep}	Wing sweep	1
	x_{chord}	Wing chord	1
	x_{twist}	Wing twist	8
	x_{airfoil}	FFD control points	192
	x_{alpha_i}	Angle of attack at each flight condition	12
	x_{η_i}	Tail rotation 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
	$t_{\mathrm{LE}}/t_{\mathrm{LE}_{\mathrm{Init}}} \geq 1.0$	Leading edge radius	20
	$t_{\mathrm{TE}}/t_{\mathrm{TE}_{\mathrm{Init}}} \geq 1.0$	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
	$L_{\mathrm{panel}} - x_{\text{panel length}} = 0$	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
	$\left\lvert x_{\text{panel thick}_i} - x_{\text{panel thick}_{i+1}} \right\rvert \leq 0.0025$	Skin thickness adjacency	168
	$\left\lvert x_{\text{stiff thick}_i} - x_{\text{stiff thick}_{i+1}} \right\rvert \leq 0.0025$	Stiffener thickness adjacency	168
	$\left\lvert x_{\text{stiff height}_i} - x_{\text{stiff height}_{i+1}} \right\rvert$	Stiffener height adjacency	168
	$x_{\text{stiff thick}} - x_{\text{panel thick}} < 0.005$	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

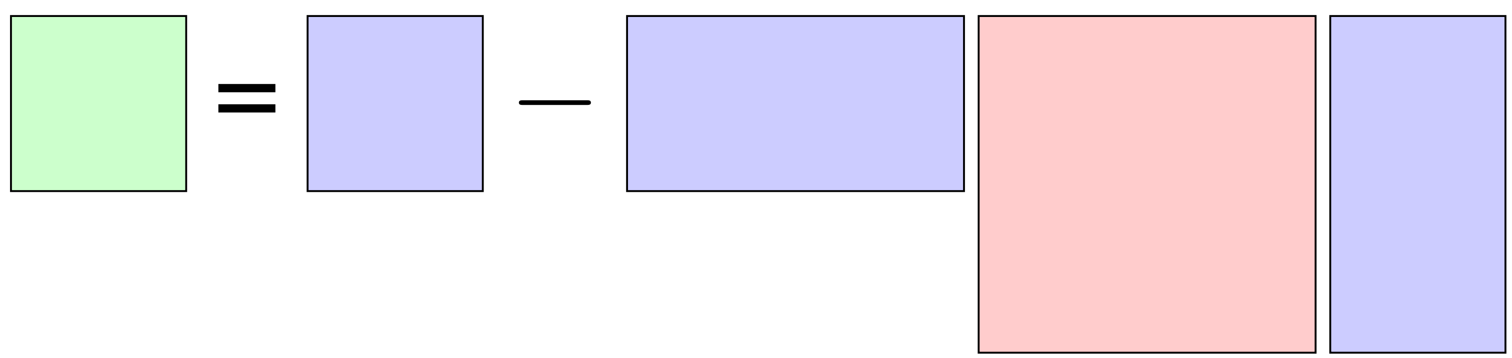
- 7 cruise conditions for performance
- 2 off design conditions
- 3 maneuver condition for structural constraints
- Aircraft trimmed at all conditions



There is no efficient way of evaluating a large square Jacobian…

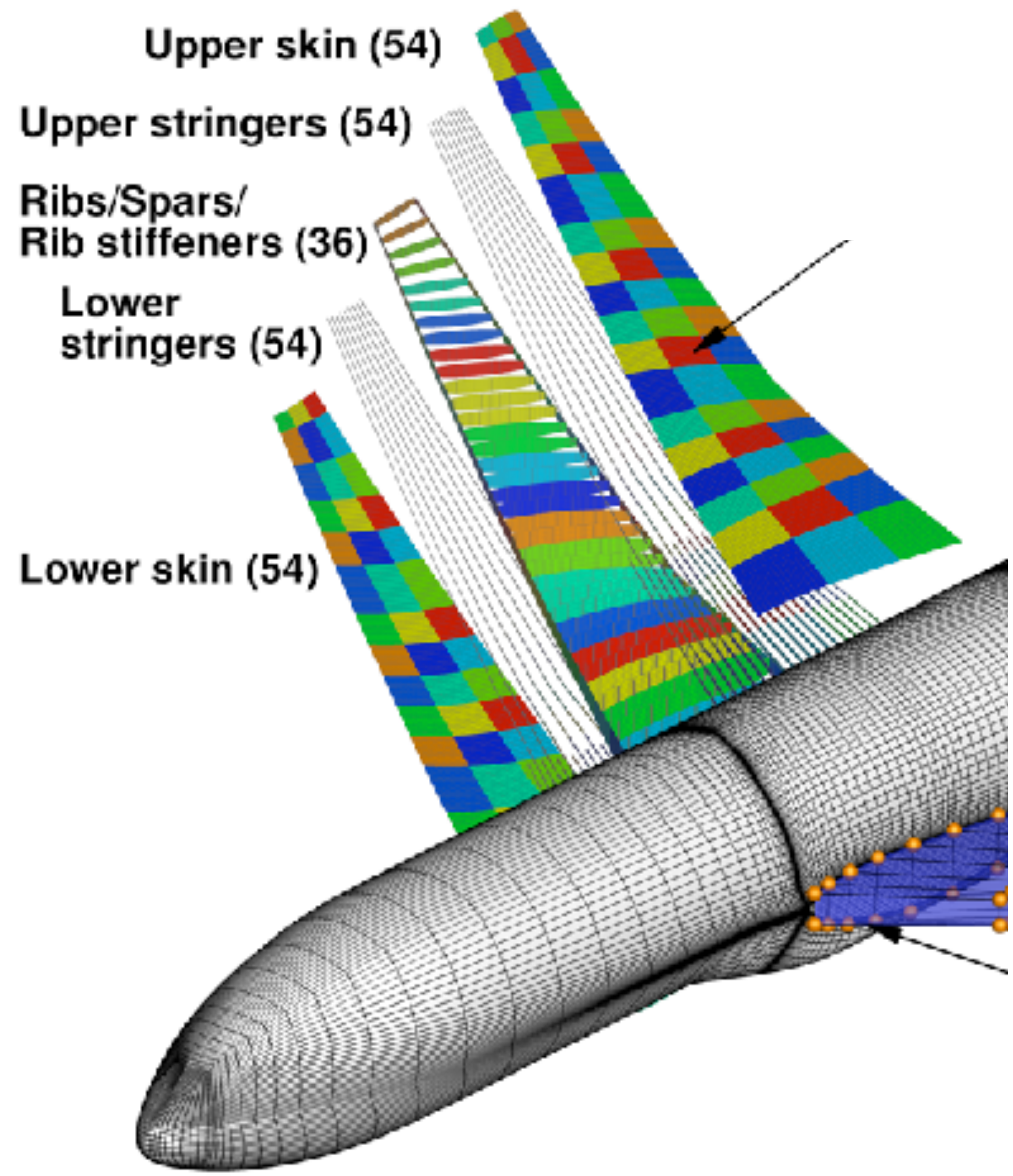
$$\frac{\mathrm{d}f}{\mathrm{d}x} = \frac{\partial f}{\partial x} - \underbrace{\frac{\partial f}{\partial y}\mathrlap{\overbrace{\phantom{\left[\frac{\partial R}{\partial y}\right]^{-1}\frac{\partial R}{\partial x}}}^{-\,\mathrm{d}y/\mathrm{d}x}}\left[\frac{\partial R}{\partial y}\right]^{-1}}_{\psi}\frac{\partial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

$n_x \approx n_f$



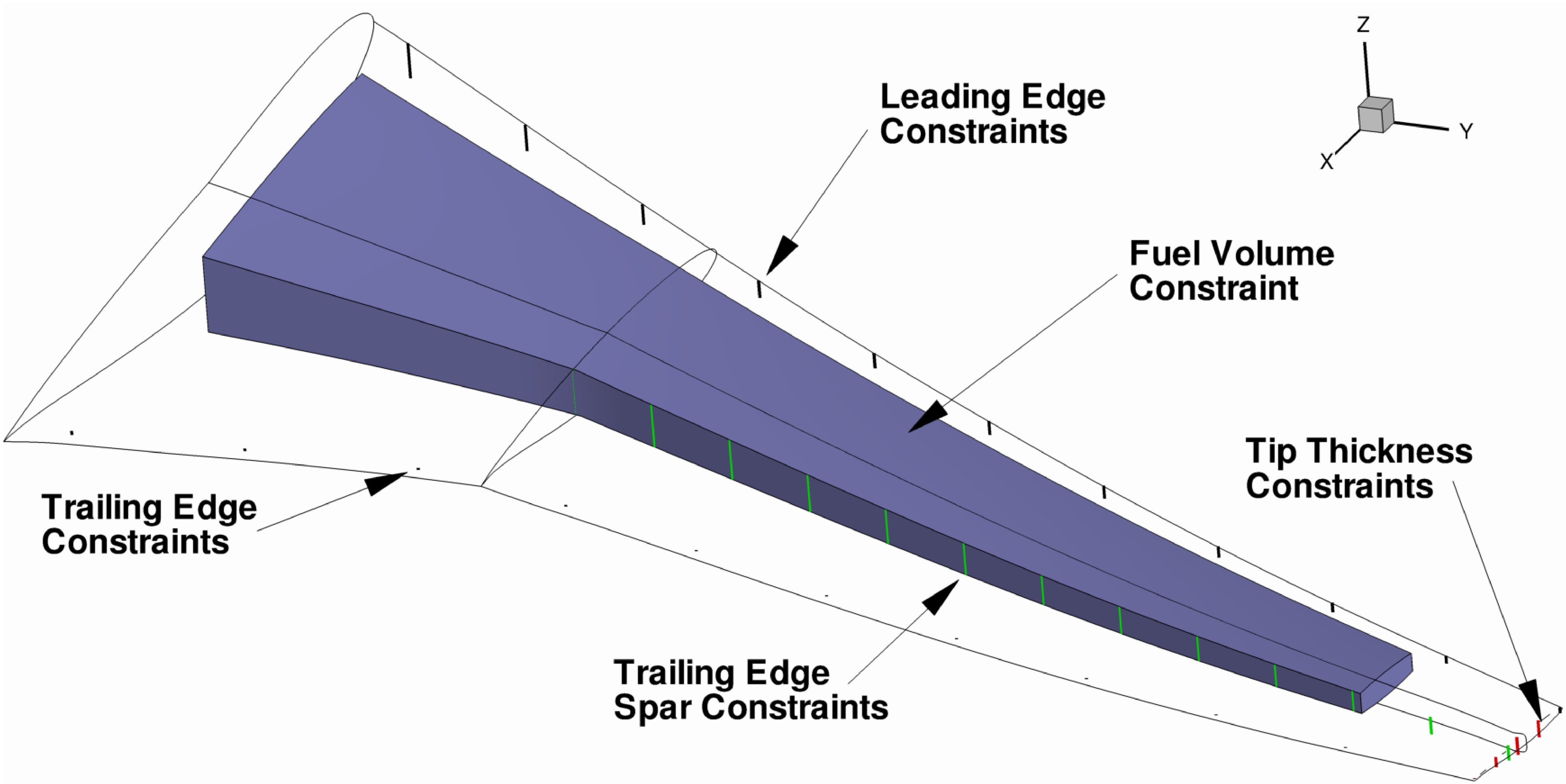
…so we aggregate the constraints to avoid large square Jacobians

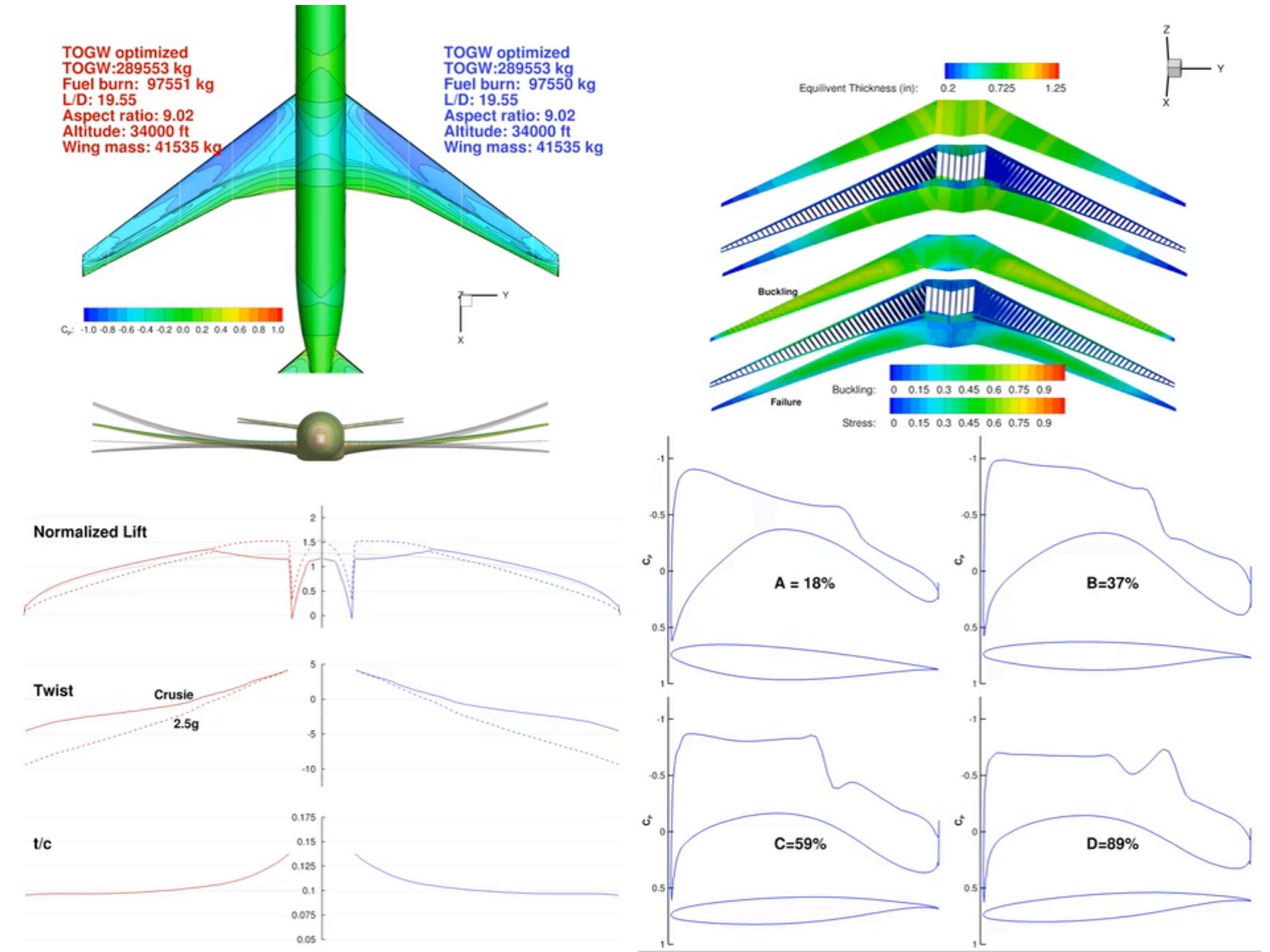
$$\mathrm{KS}(x, y(x)) = \frac{1}{\rho} \ln \left[\sum_{i=1}^{m} e^{\rho g_i(x, y(x))} \right]$$

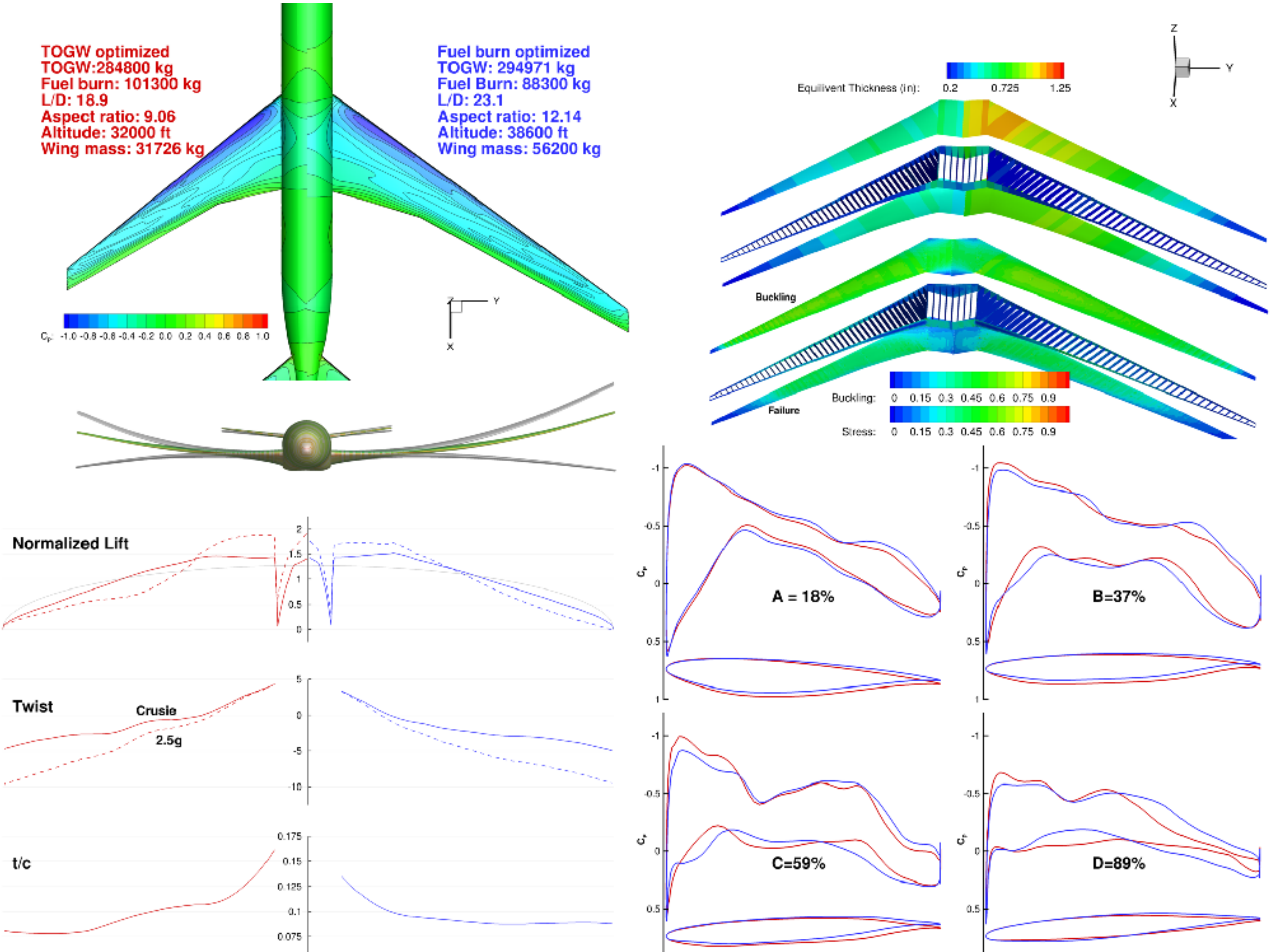


[Poon and Martins, *Struct. Multidiscip. O.*, 2005]

The fuel volume is not allowed to decrease



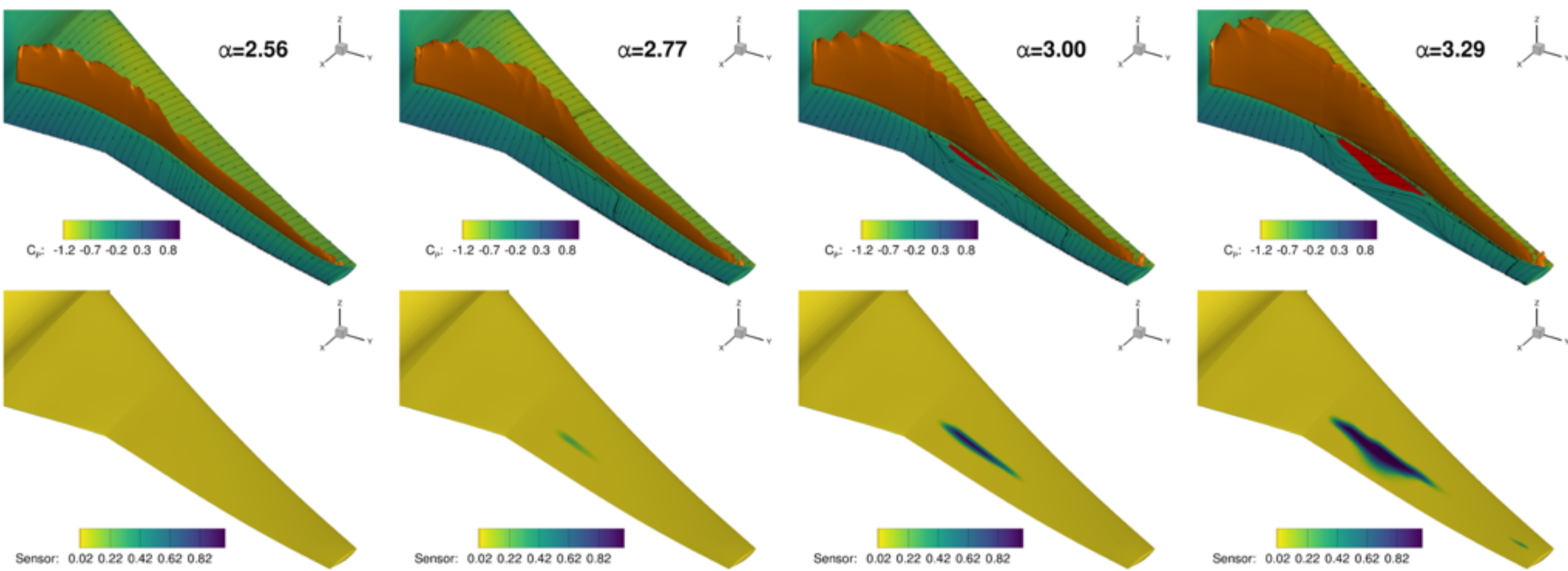

TOGW optimized
TOGW:289553 kg
Fuel burn: 97551 kg
L/D: 19.55
Aspect ratio: 9.02
Altitude: 34000 ft
Wing mass: 41535 kg
TOGW optimized
TOGW:289553 kg
Fuel burn: 97550 kg
L/D: 19.55
Aspect ratio: 9.02
Altitude: 34000 ft
Wing mass: 41535 kg
Cp: -1.0 -0.8 -0.6 -0.4 -0.2 0.0 0.2 0.4 0.6 0.8 1.0
Equilivent 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%



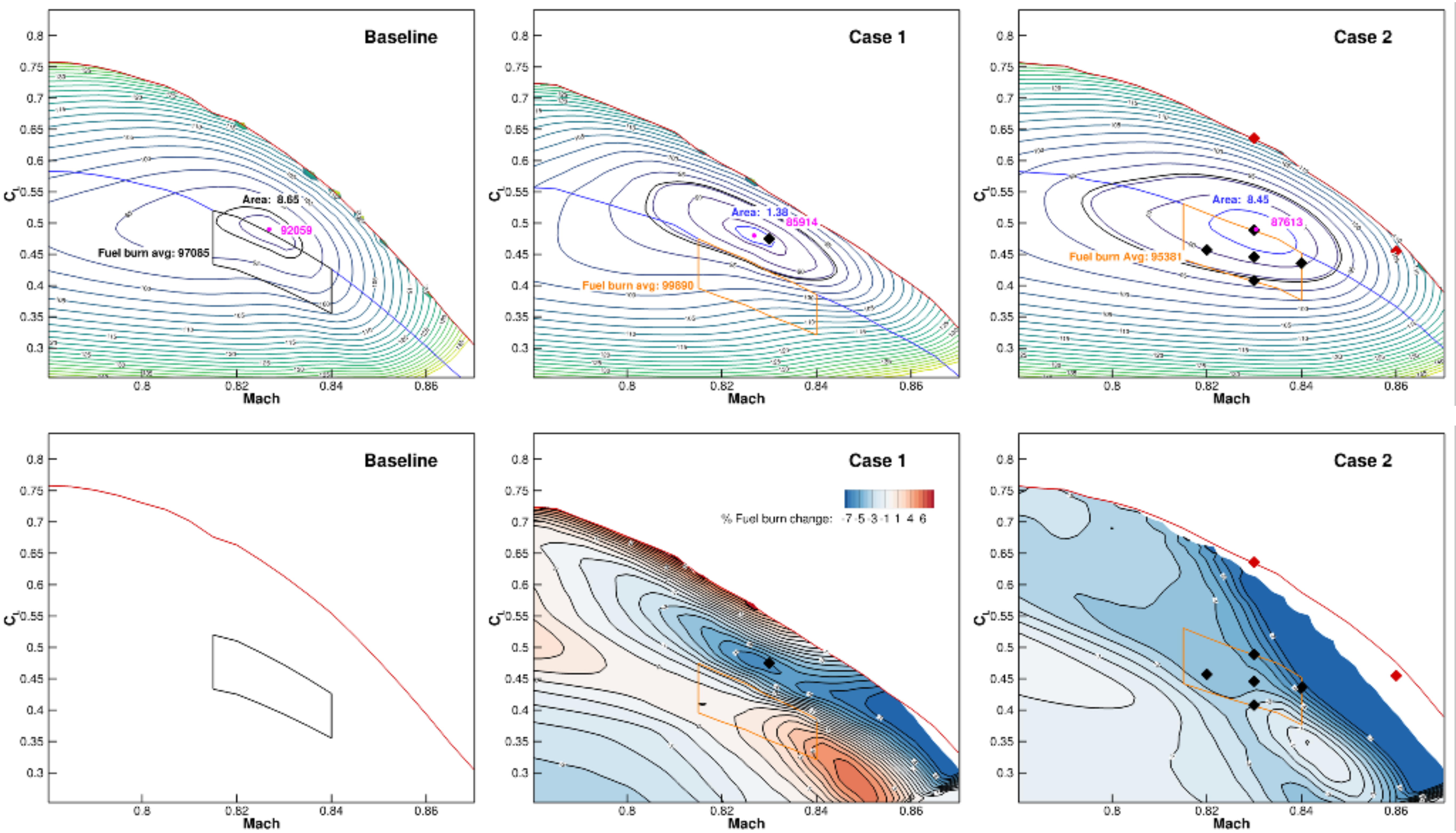
TOGW optimized
TOGW:284800 kg
Fuel burn: 101300 kg
L/D: 18.9
Aspect ratio: 9.06
Altitude: 32000 ft
Wing mass: 31726 kg
Fuel burn optimized
TOGW: 294971 kg
Fuel Burn: 88300 kg
L/D: 23.1
Aspect ratio: 12.14
Altitude: 38600 ft
Wing mass: 56200 kg
Equilivent Thickness (in): 0.2 0.725 1.25
Buckling
Failure
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%

We developed a new buffet onset constraint formulation based on a separation sensor

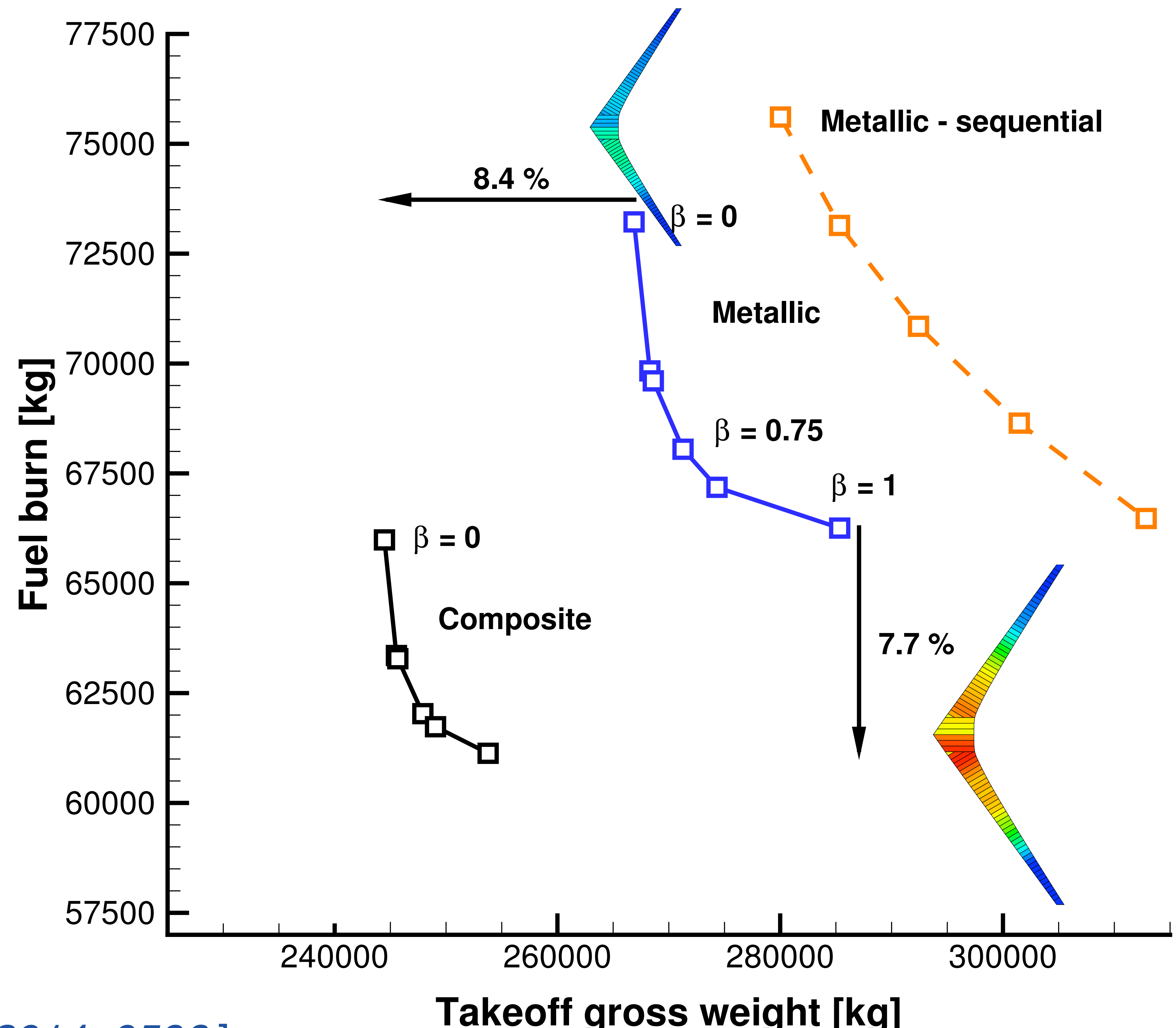
$$\cos\theta = \frac{\vec{V}\cdot\vec{V}_\infty}{|\vec{V}||\vec{V}_\infty|} < 0 \qquad \bar{\chi} = \frac{1.0}{1.0 + e^{2k(\cos\theta+\lambda)}} \qquad S_{\text{sep}} = \frac{1}{S_{\text{ref}}}\int_S \bar{\chi}\,\mathrm{d}S$$



Fuel burn contours show the need for multipoint optimization and buffet constraints

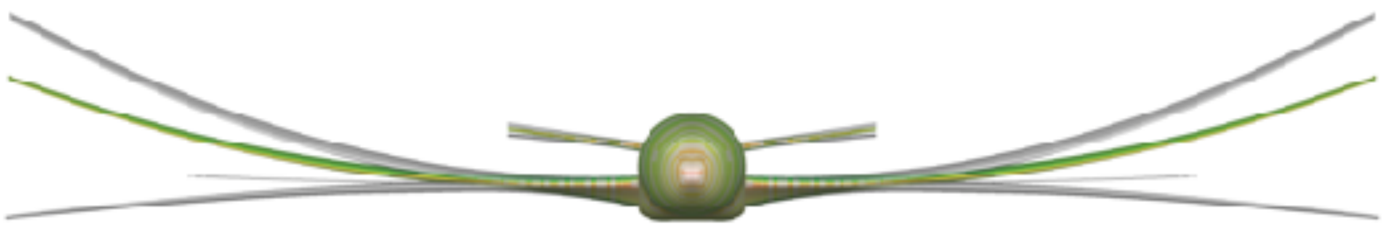


This framework enables designers to perform optimal objective and technology tradeoffs

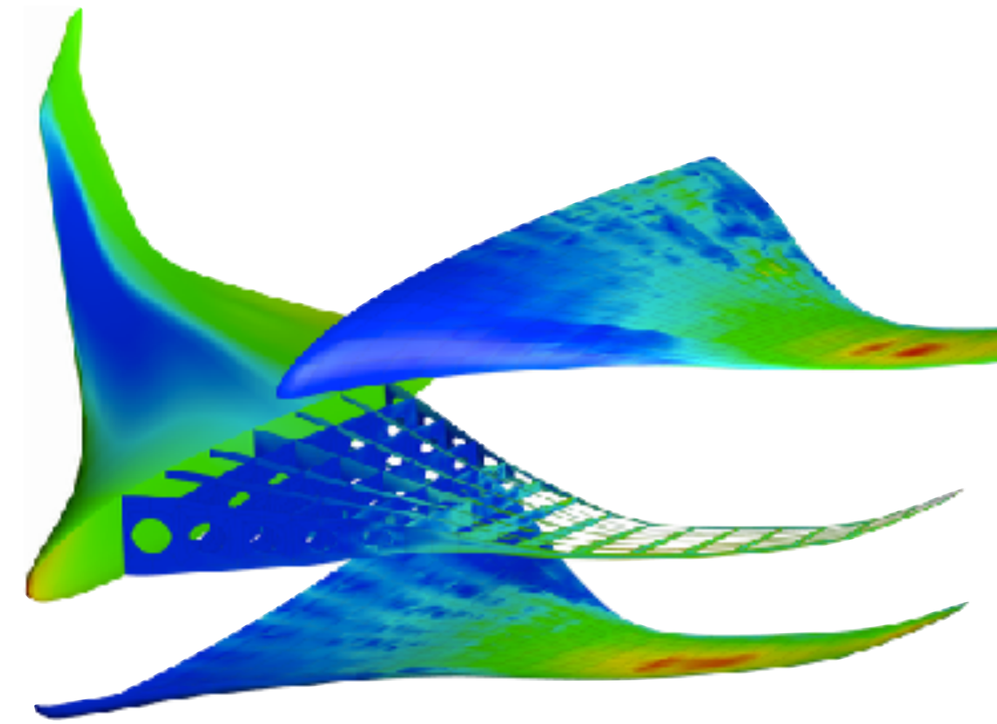


[Kennedy et al., *AIAA 2014–0596*]

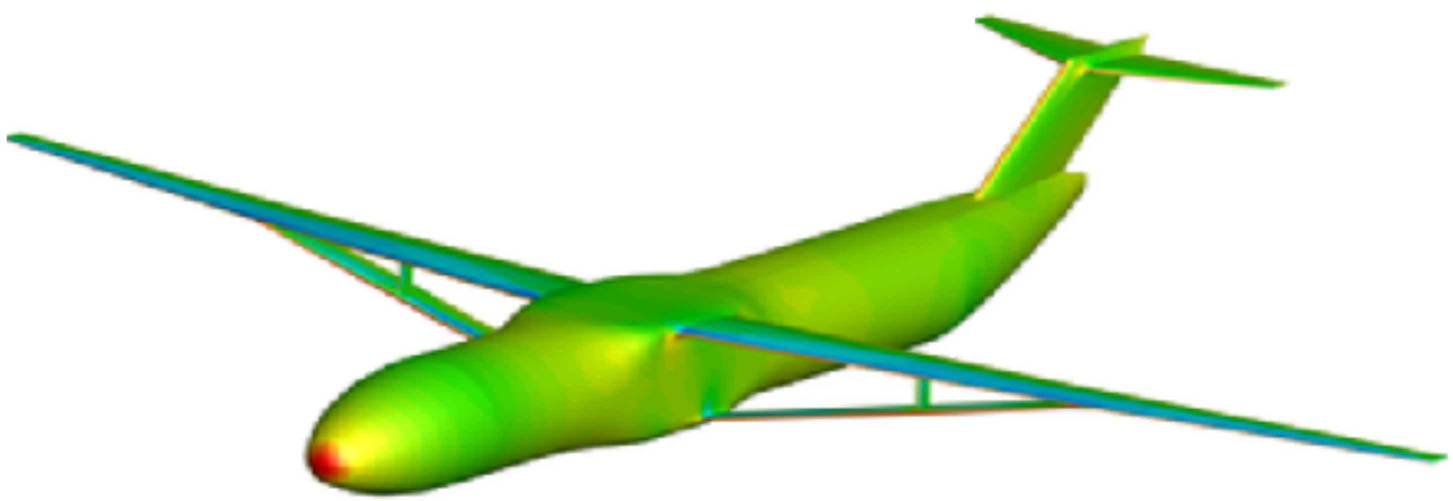
Currently using these tools to refine the next generation of aircraft



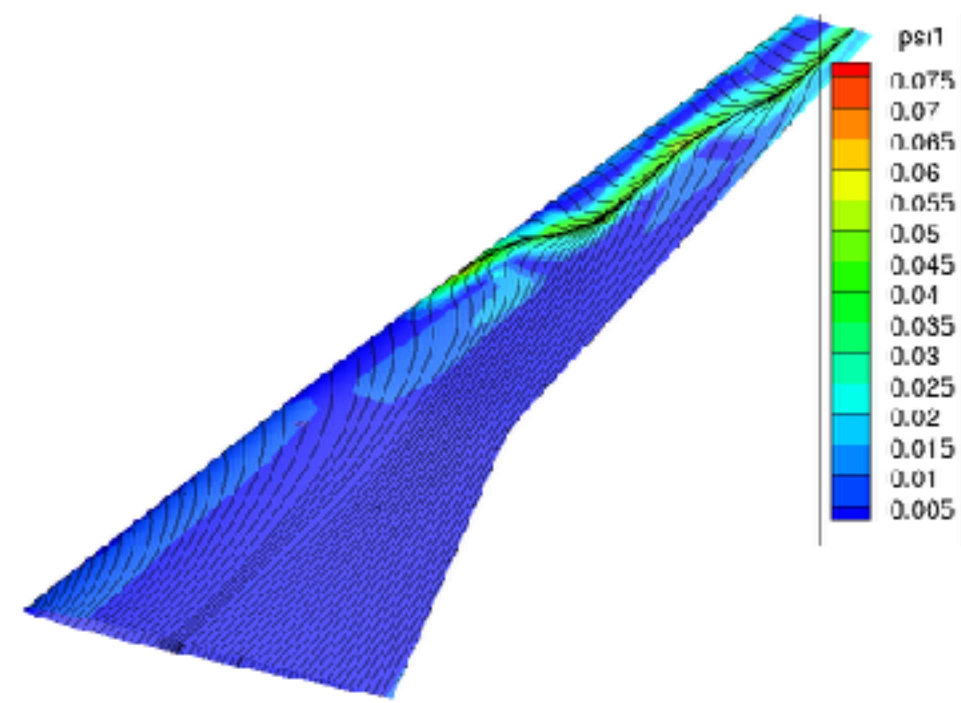
Flexible high-aspect ratio wings
[Kenway and Martins, AIAA 2015-2790]



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]

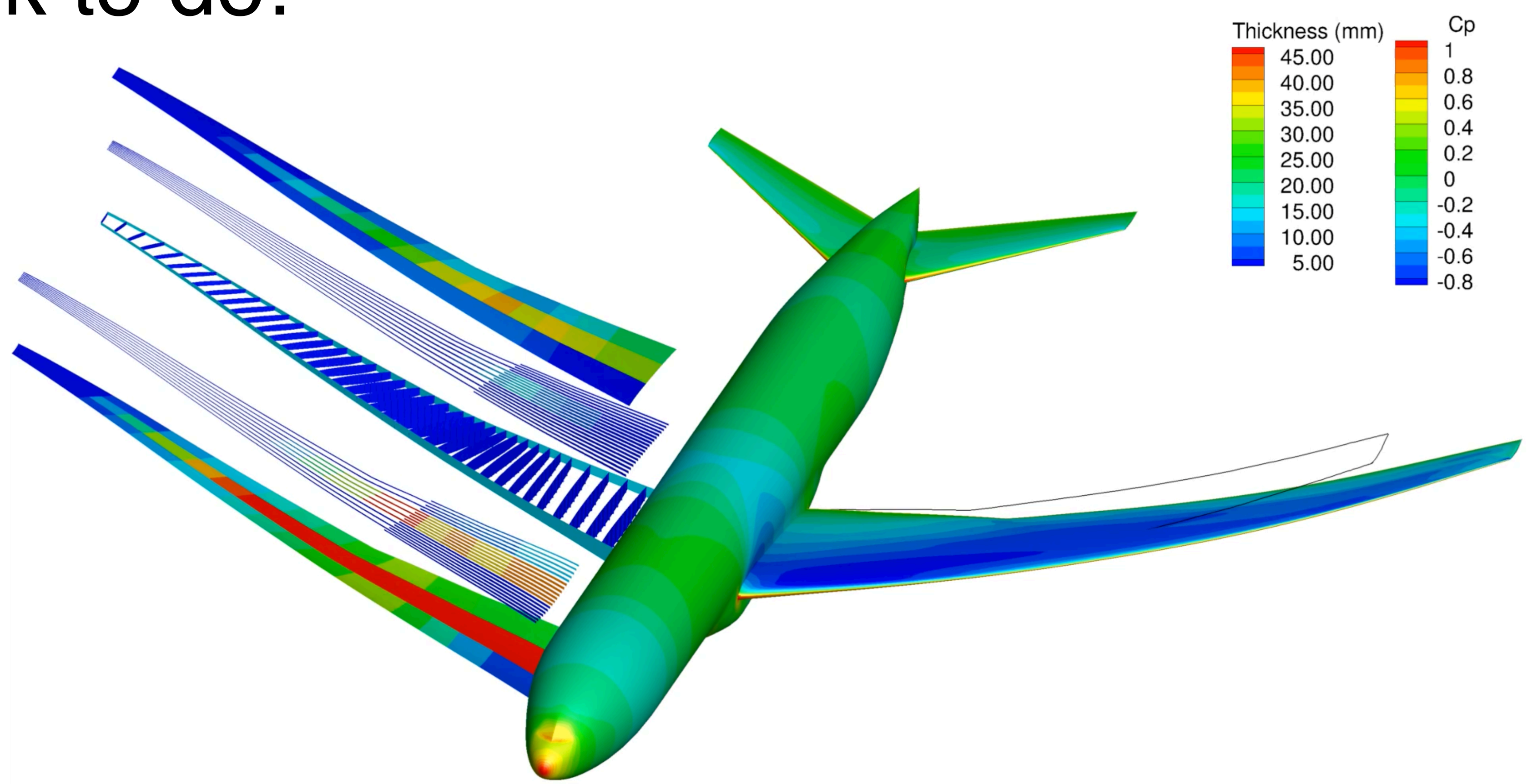
Multidisciplinary Design Optimization of Aircraft Configurations

Part 2: High-fidelity aerostructural optimization

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

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
- Still a lot of work to do!



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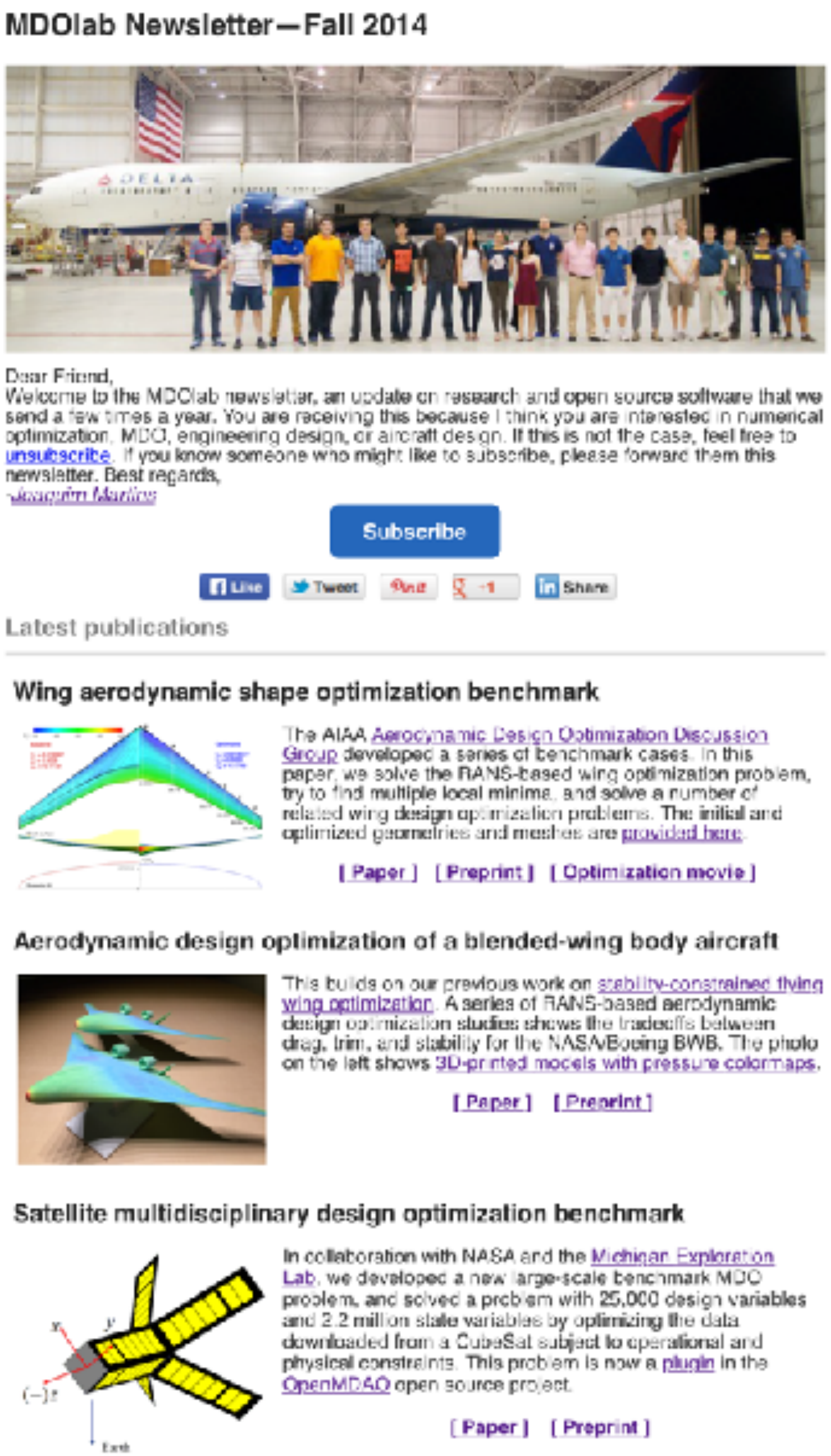
MDOlab Newsletter—Fall 2014

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 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.