Progress in Aerodynamic Shape Optimization

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OUTLINE

- Turbulent flow solver
  - Summation-by-parts/simultaneous approximation terms
  - parallel Newton-Krylov-Schur algorithm
- Integrated geometry parameterization and mesh movement
- Adjoint-based gradient computation
- Turbulent flow solver
- Global optimization algorithms

FLOW SOLVER

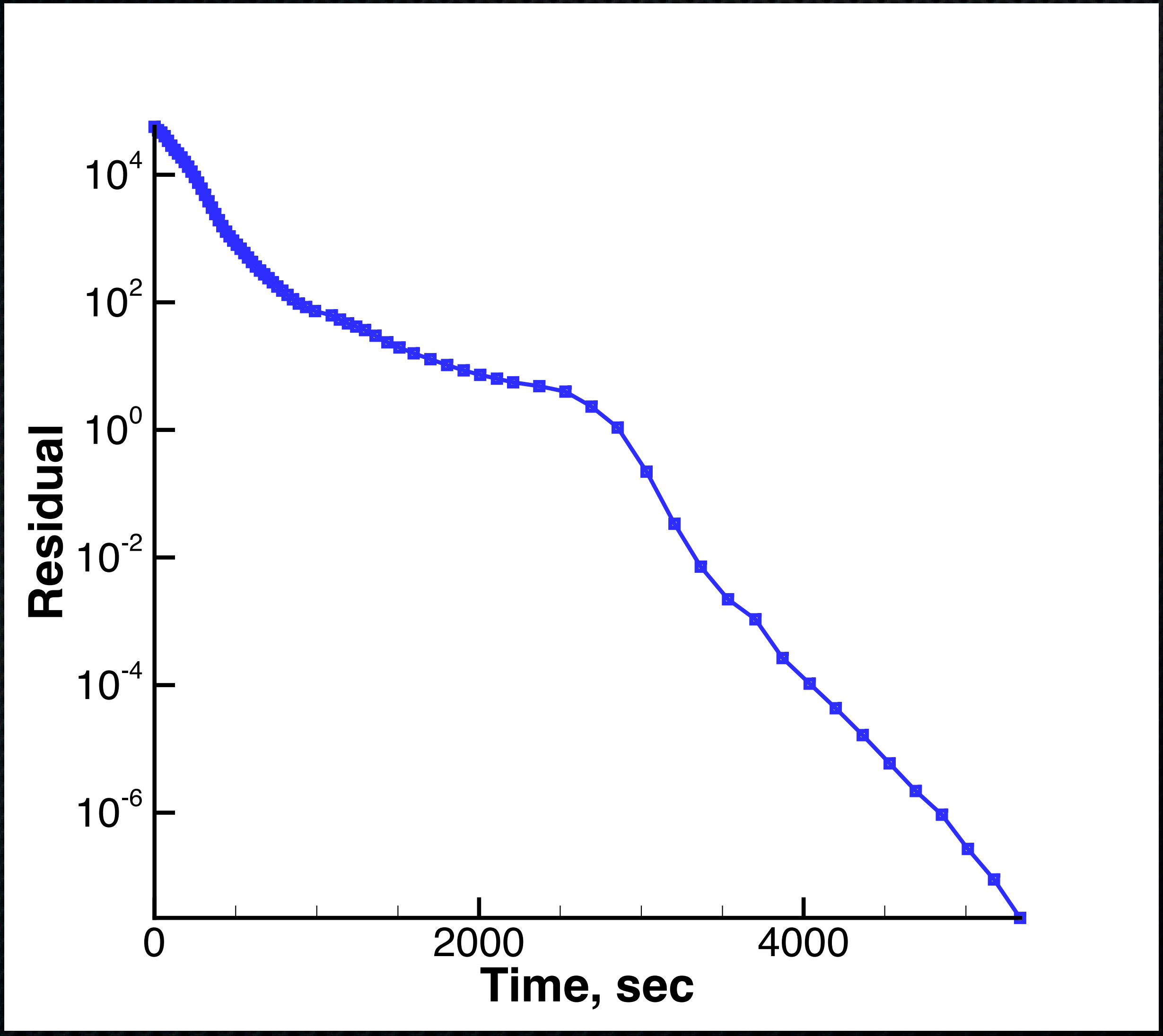
- Structured multi-block grids
- High-order finite-difference method with summation-by-parts operators and simultaneous approximation terms
- Parallel Newton-Krylov-Schur solver
- Jacobian-free Newton-Krylov algorithm with approximate Schur parallel preconditioning
- Promising dissipation-based continuation method for globalization

➡ Hicken, J.E., and Zingg, D.W., A parallel Newton-Krylov solver for the Euler equations discretized using simultaneous approximation terms, AIAA Journal, Vol. 46, No. 11, 2008

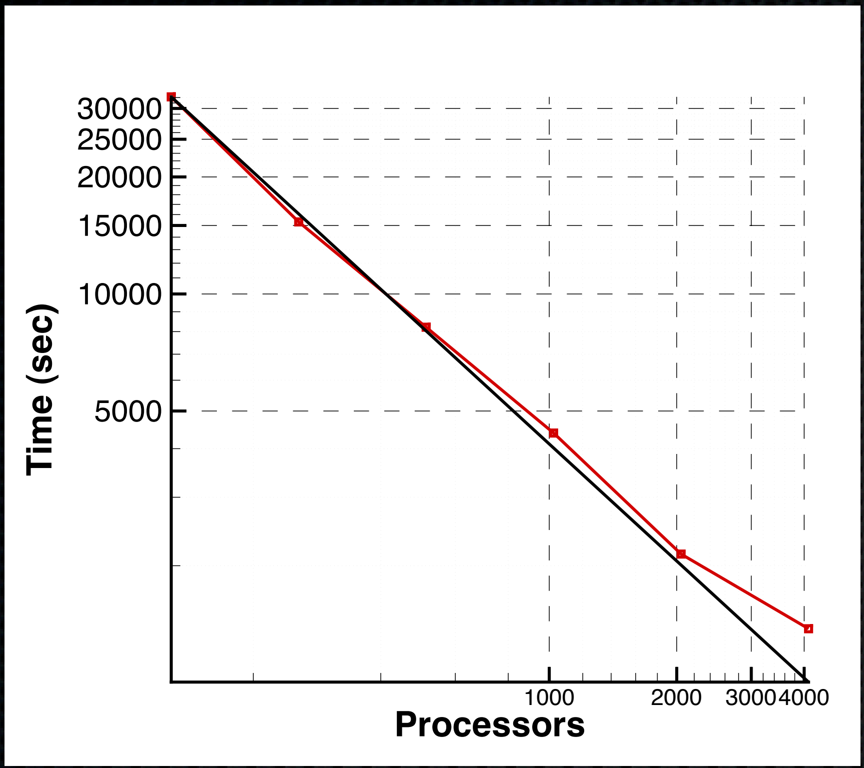
➡ Osusky, M., and Zingg, D.W., A parallel Newton-Krylov flow solver for the Reynolds-Averaged Navier-Stokes equations, AIAA ASM, Jan. 2012

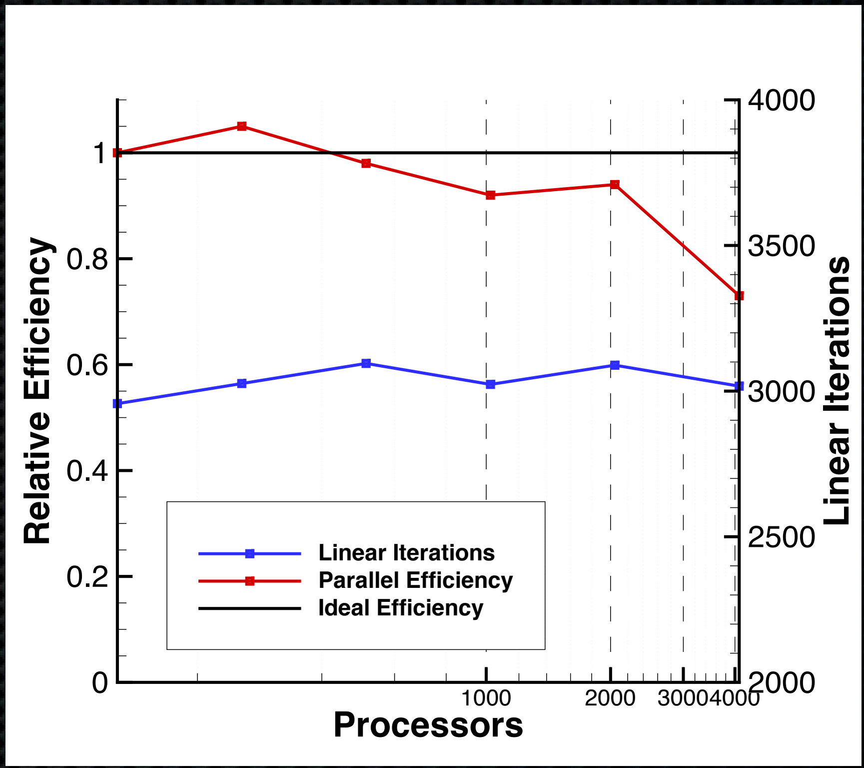
Turbulent Flow Solver

ONERA M6 wing: M=0.8395, alpha=3.06 degrees
Re=11.72 million, 15.1 million mesh nodes, 128 processors



Parallel Scalability (RANS)

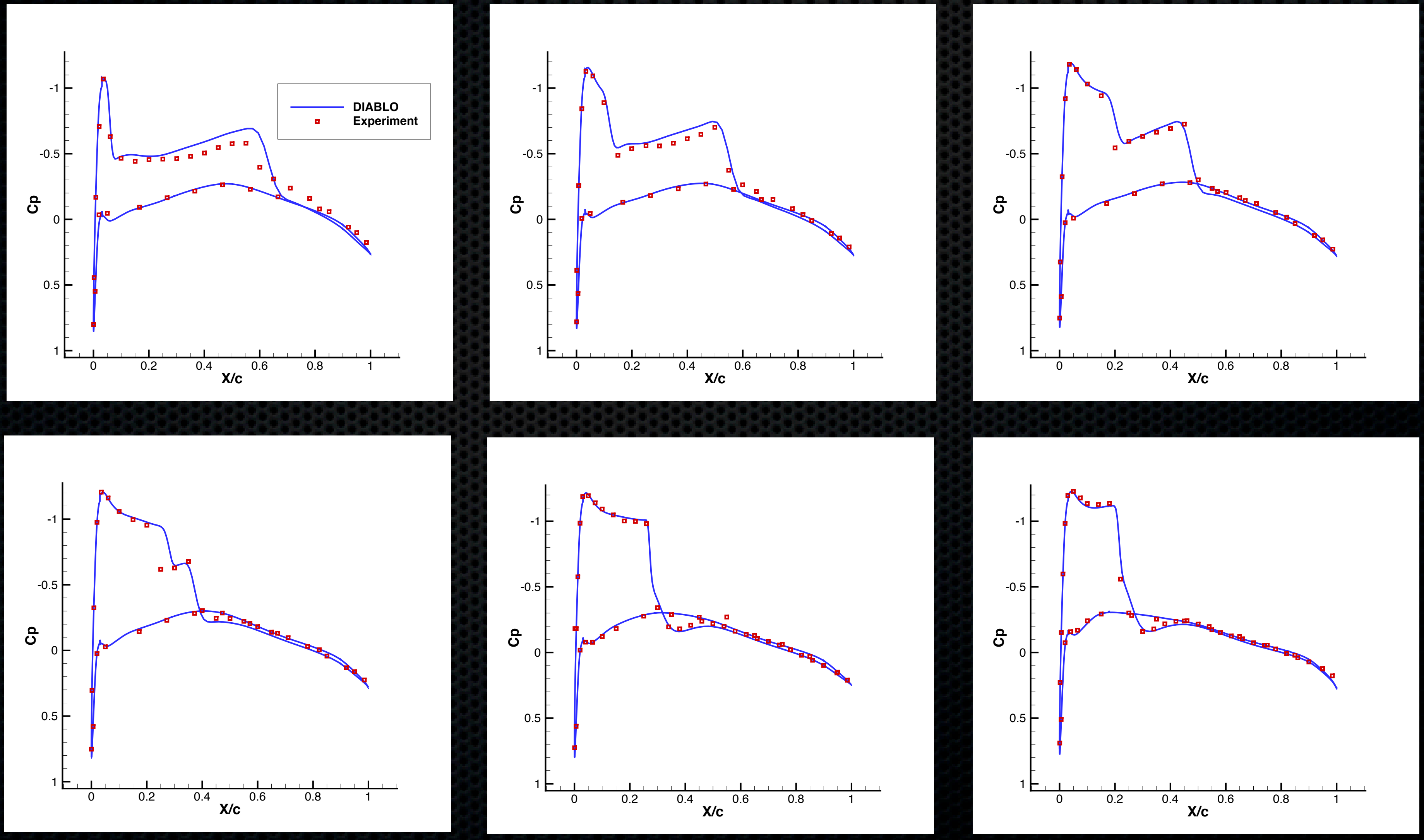




- 12 order residual reduction in 23 mins on 4096 processors (40 million mesh nodes)

Turbulent Flow Solver

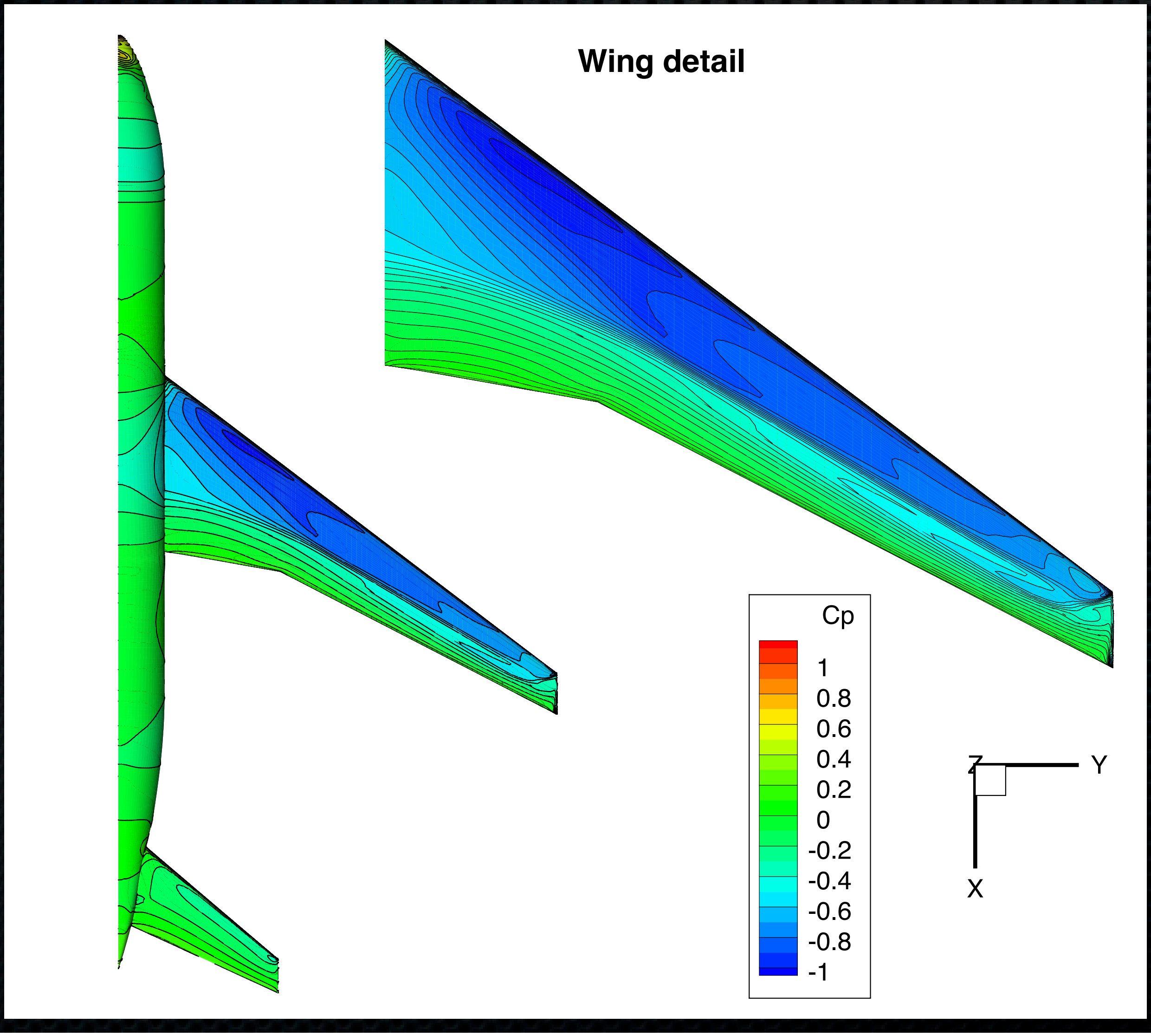
ONERA M6 wing: M=0.8395, alpha=3.06 degrees
Re=11.72 million, 15.1 million mesh nodes
20, 44, 65, 80, 90, 95 percent span



Turbulent Flow Solver

Common Research Model: M=0.85, C_L=0.5

Re=5 million, 10.1 million mesh nodes



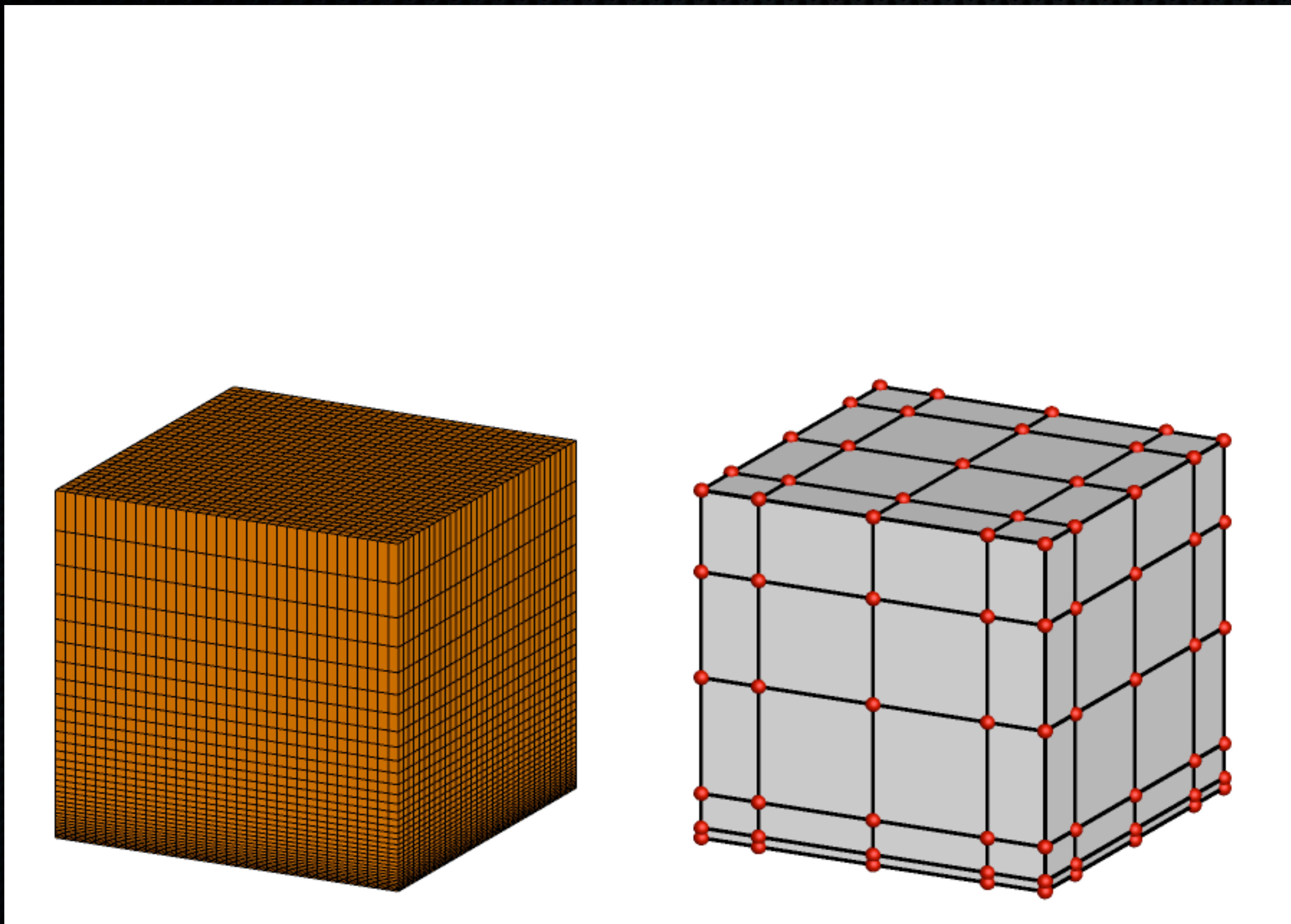
INTEGRATED GEOMETRY PARAMETERIZATION AND MESH MOVEMENT

- Must provide flexibility for large shape changes with a modest number of design variables
  - B-spline patches represent surfaces
  - B-spline control points are design variables

- Mesh movement must maintain quality through large shape changes
  - through tensor products, B-spline volumes map a cube to an arbitrary volume with the appropriate topology
  - can be arbitrarily discretized in the cube domain to create a mesh
  - B-spline volume control points can be manipulated to move the mesh in response to changes in the surface control points
  - efficiently generates a high quality mesh

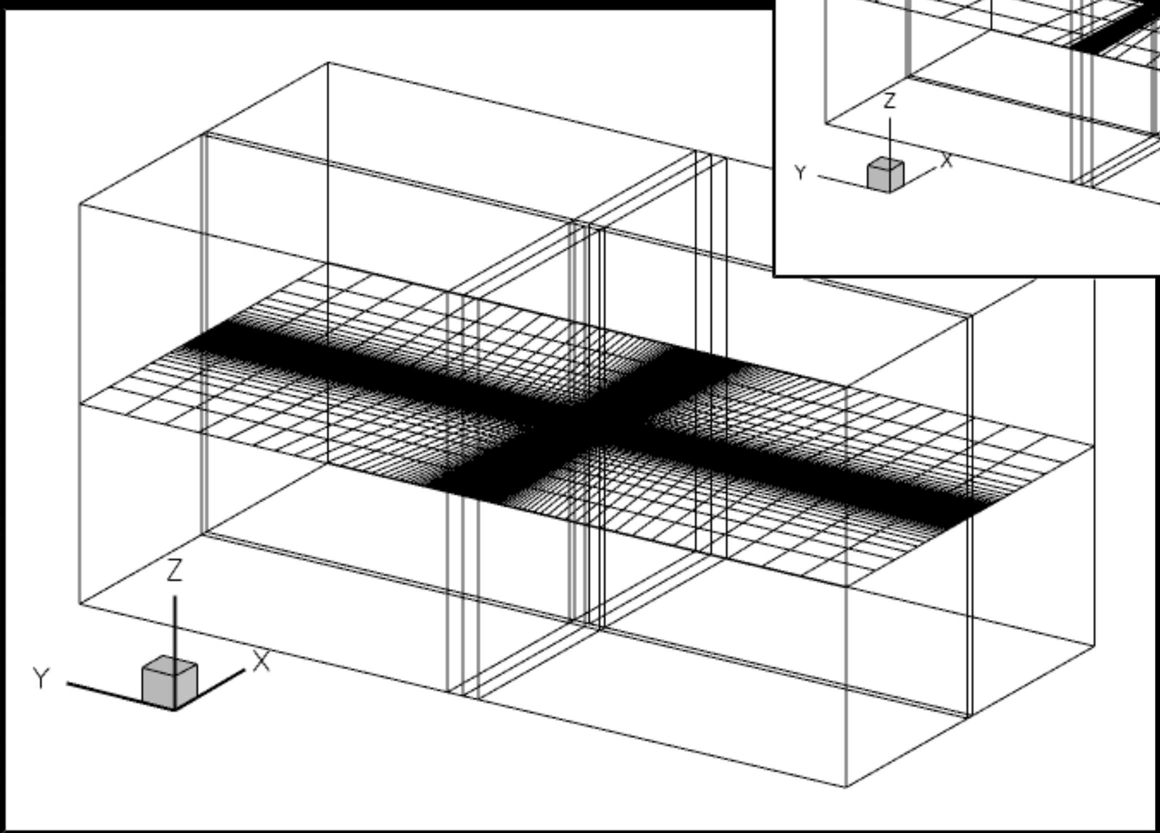
➡ Hicken, J.E., and Zingg, D.W., Aerodynamic Optimization Algorithm with Integrated Geometry Parameterization and Mesh Movement, AIAA Journal, Vol. 48, No. 2, 2010

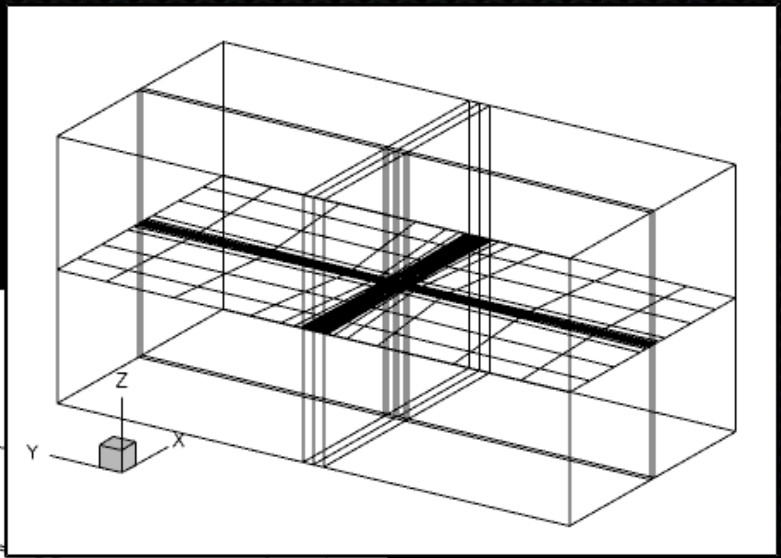
B-spline Volumes



Mesh Movement Example

flat plate to blended-wing body: ≈ 1 million nodes





DISCRETE-ADJOINT GRADIENT COMPUTATION

- Cost independent of the number of design variables
- Efficient if the number of design variables exceeds the number of constraints
- Hand linearization complemented by judicious use of the complex step method for difficult terms
- Adjoint equation solved by parallel Schur-preconditioned modified Krylov method GCROT(m,k)

➡ Hicken, J.E., and Zingg, D.W., A Simplified and Flexible Variant of GCROT for Solving Nonsymmetric Linear Systems, SIAM Journal on Scientific Computing, Vol. 32, No. 3, March 2010

Discrete Adjoint Gradient

Define a Lagrangian function using objective, flow equations, and mesh movement equations

$$\mathcal{L}(\mathbf{v}, \mathbf{q}, \mathbf{b}, \psi, \boldsymbol{\lambda}) = \mathcal{J} + \psi^T \mathcal{R} + \boldsymbol{\lambda}^T \mathcal{M}$$

- ψ and $\boldsymbol{\lambda}$ are the flow and mesh adjoint variables

At local optima, all derivatives of $\mathcal{L}$ vanish:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{q}} = \frac{\partial \mathcal{J}}{\partial \mathbf{q}} + \psi^T \left(\frac{\partial \mathcal{R}}{\partial \mathbf{q}} \right) = 0$$

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\lambda}} = \mathcal{M} = 0$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{v}} = \frac{\partial \mathcal{J}}{\partial \mathbf{v}} + \psi^T \left(\frac{\partial \mathbf{R}}{\partial \mathbf{v}} \right) + \boldsymbol{\lambda}^T \left(\frac{\partial \mathcal{M}}{\partial \mathbf{v}} \right)$$

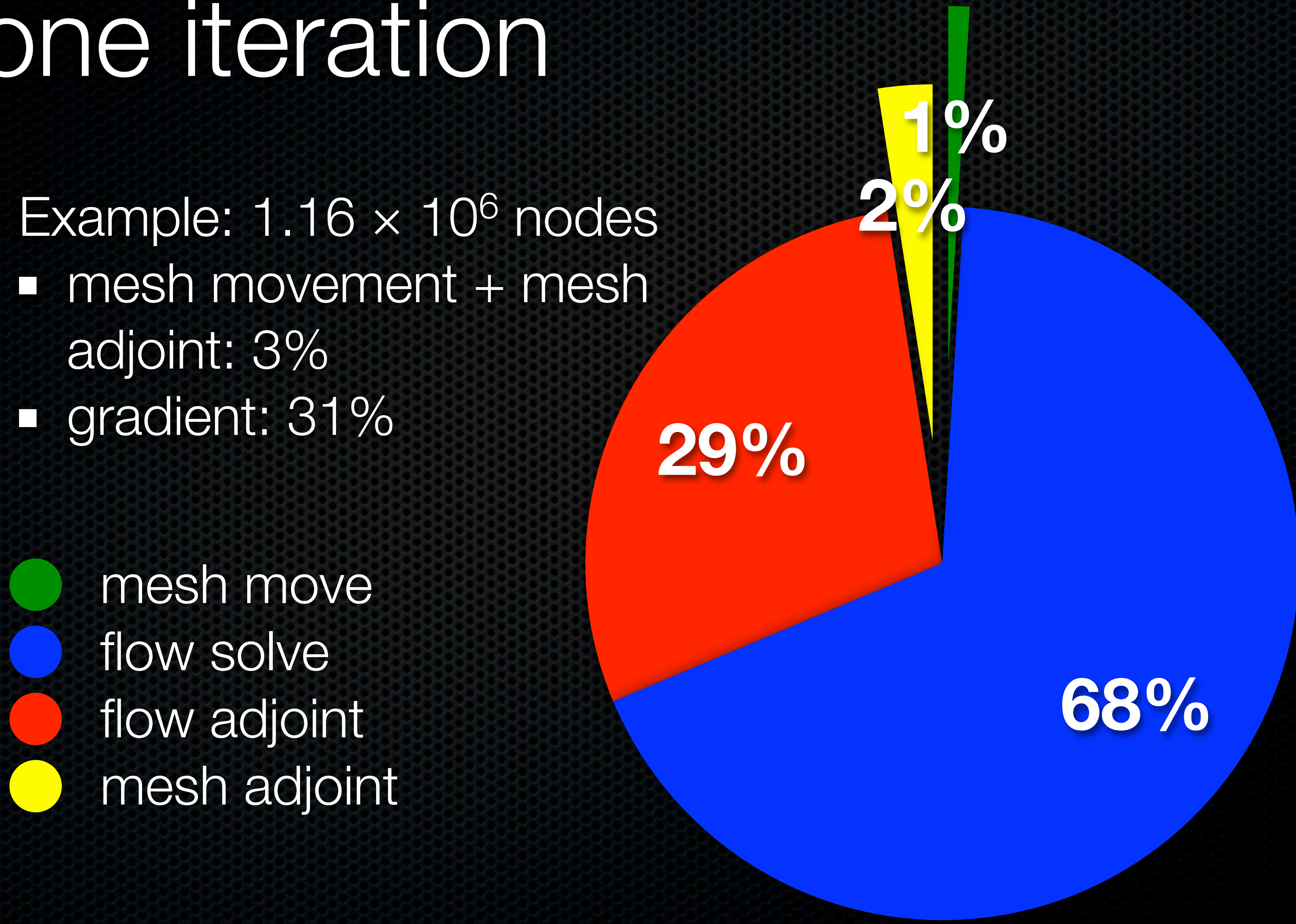
$$\frac{\partial \mathcal{L}}{\partial \psi} = \mathcal{R} = 0$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{b}} = \frac{\partial \mathcal{J}}{\partial \mathbf{b}} + \psi^T \left(\frac{\partial \mathcal{R}}{\partial \mathbf{b}} \right) + \boldsymbol{\lambda}^T \frac{\partial \mathcal{M}}{\partial \mathbf{b}} = 0$$

CPU Time Breakdown: one iteration

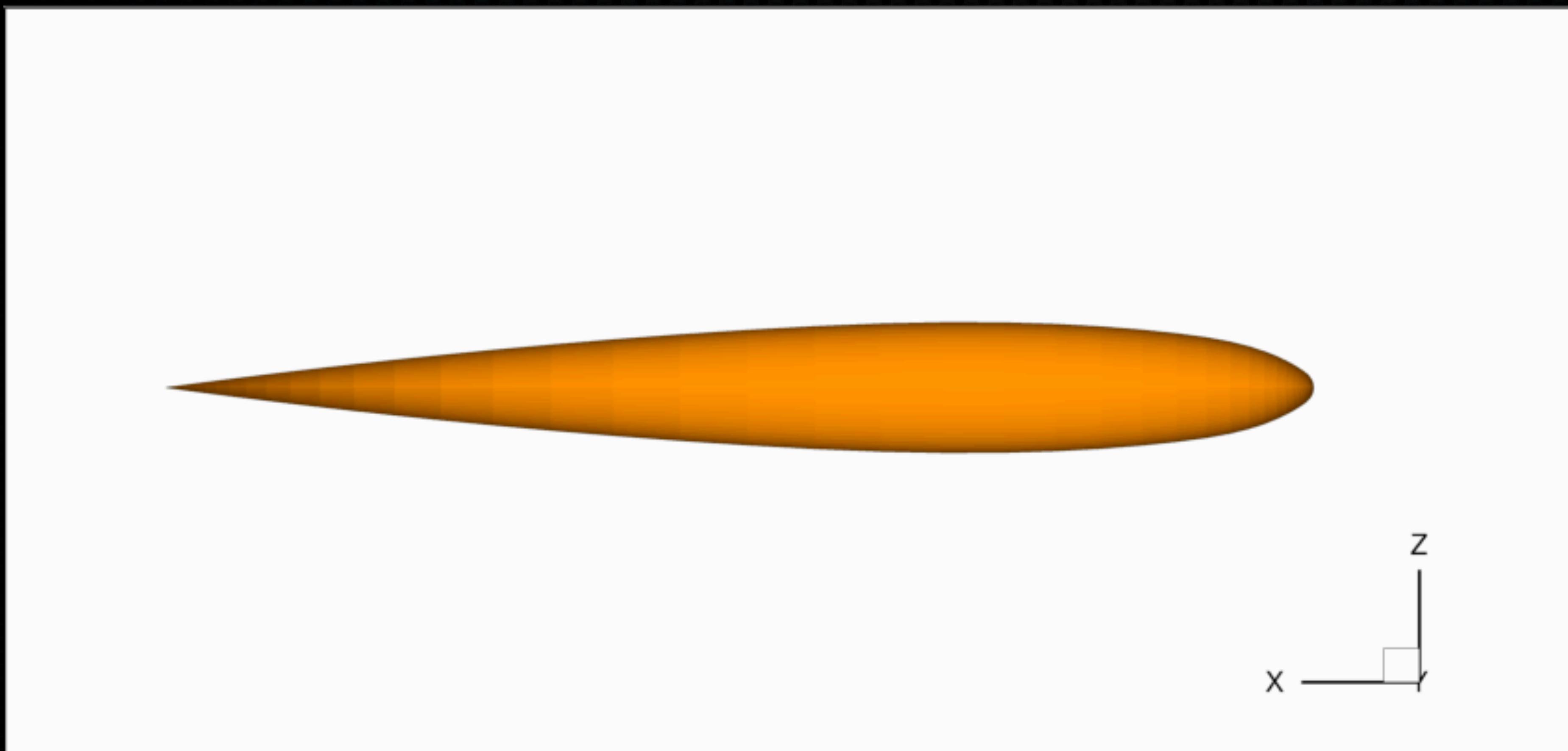
Example: 1.16×10^6 nodes

- mesh movement + mesh adjoint: 3%
- gradient: 31%



Application to Wing Design

Lift-constrained induced-drag minimization

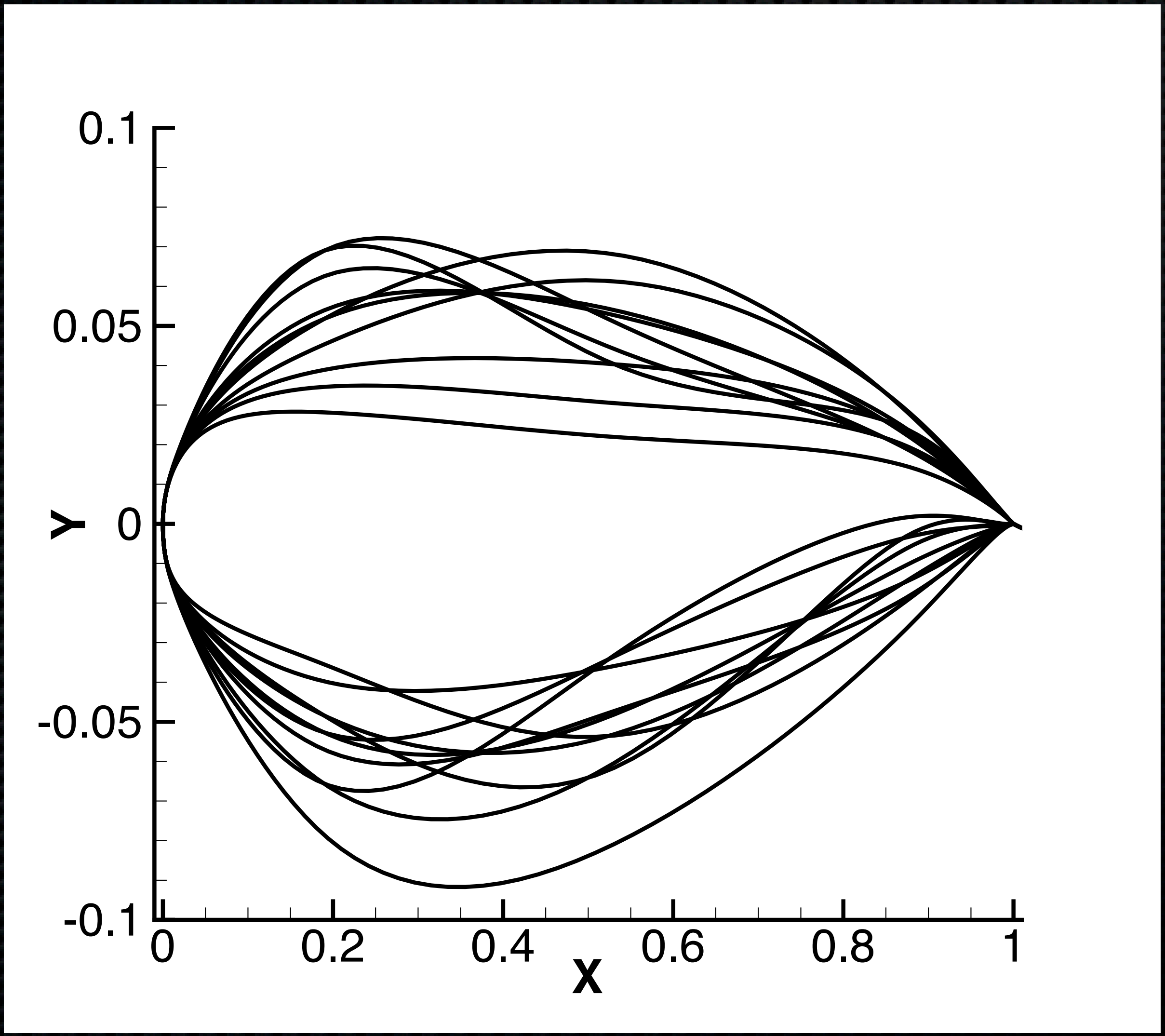


Global Optimization Algorithms

- Gradient-based algorithm (GB) - converges to a local minimum
- Multi-start Sobol (GB-MS): initial guesses based on Sobol sequences cover the design space in a deterministic manner (sampling in linear feasible region)
- Hybrid method (HM): combination of genetic algorithm, Sobol sampling, and gradient-based algorithm (SNOPT is run on each chromosome)
- Genetic algorithm (GA)

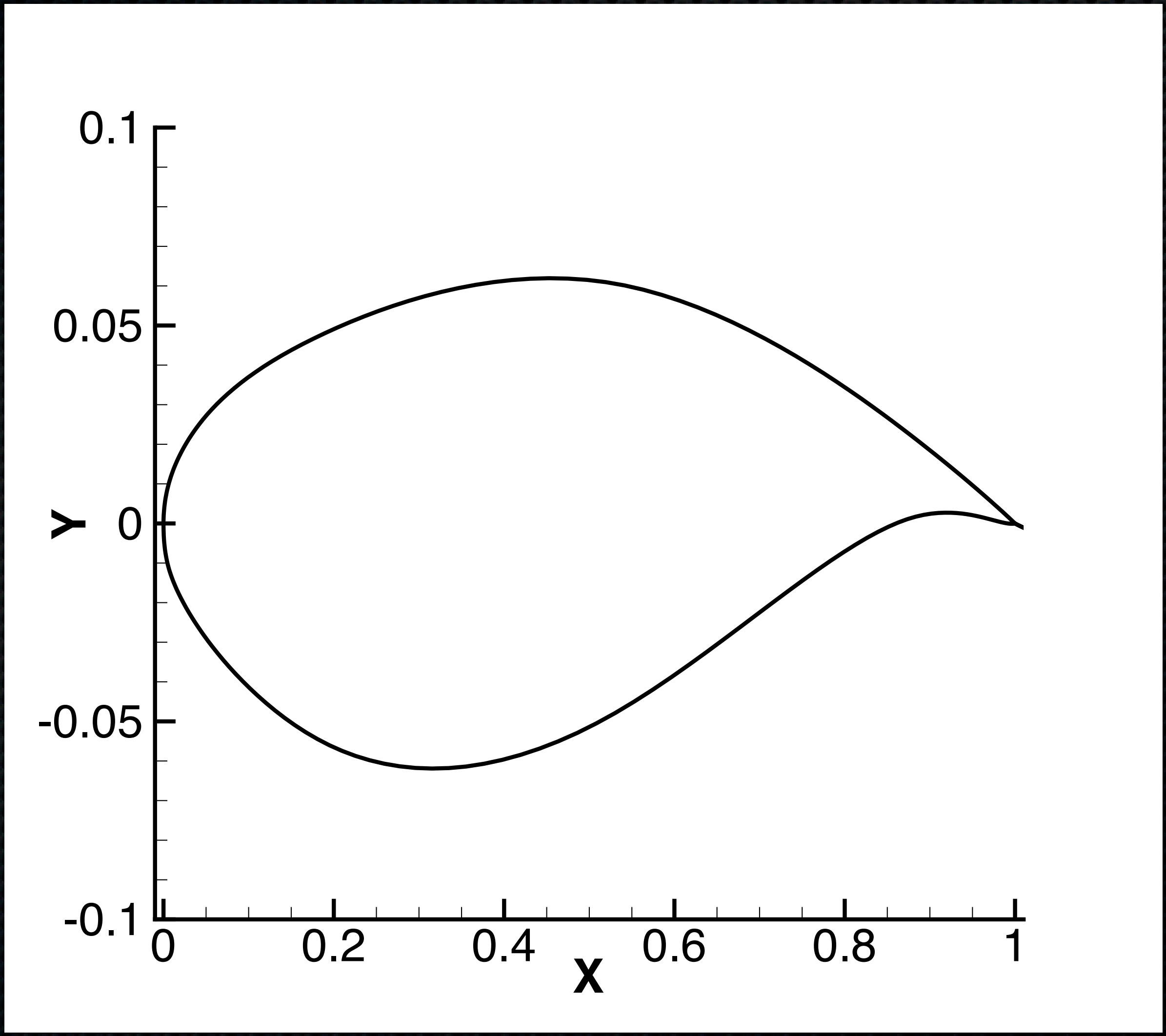
Multimodality

Multistart procedure for 2D airfoil optimization
(transonic lift-constrained drag minimization, 6 DVs)



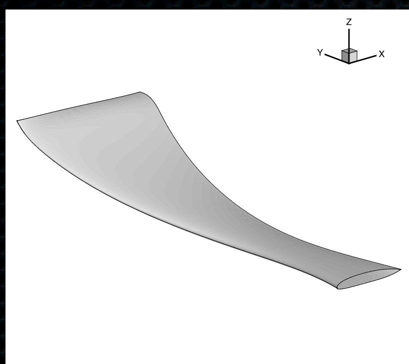
Multimodality

A unique global optimum in 2D - no local optima!



Multimodality

- 3D: subsonic lift-constrained drag minimization, 129 DVs
- 7 local minima found - somewhat multimodal
- GB-MS most efficient



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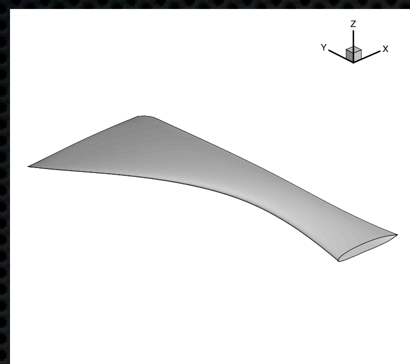

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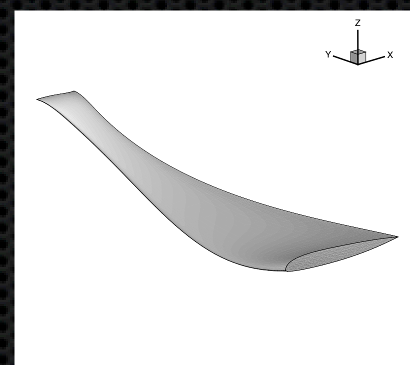

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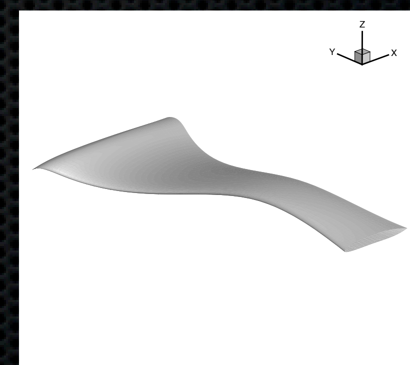

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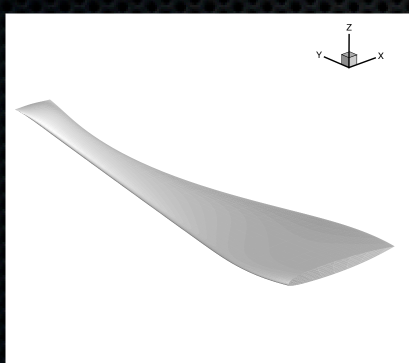

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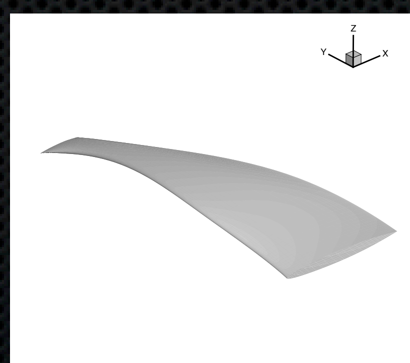

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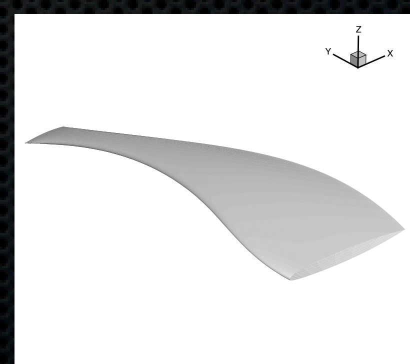

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Multimodality

- BWB optimization: 8 local minima from 34 initial geometries using GB-MS

Future Work

- improve speed and reliability of turbulent flow solver
- address issues in optimization based on turbulent flow
- address geometry, mesh, and optimization issues
- extend transition prediction to 3D
- incorporate into MDO framework