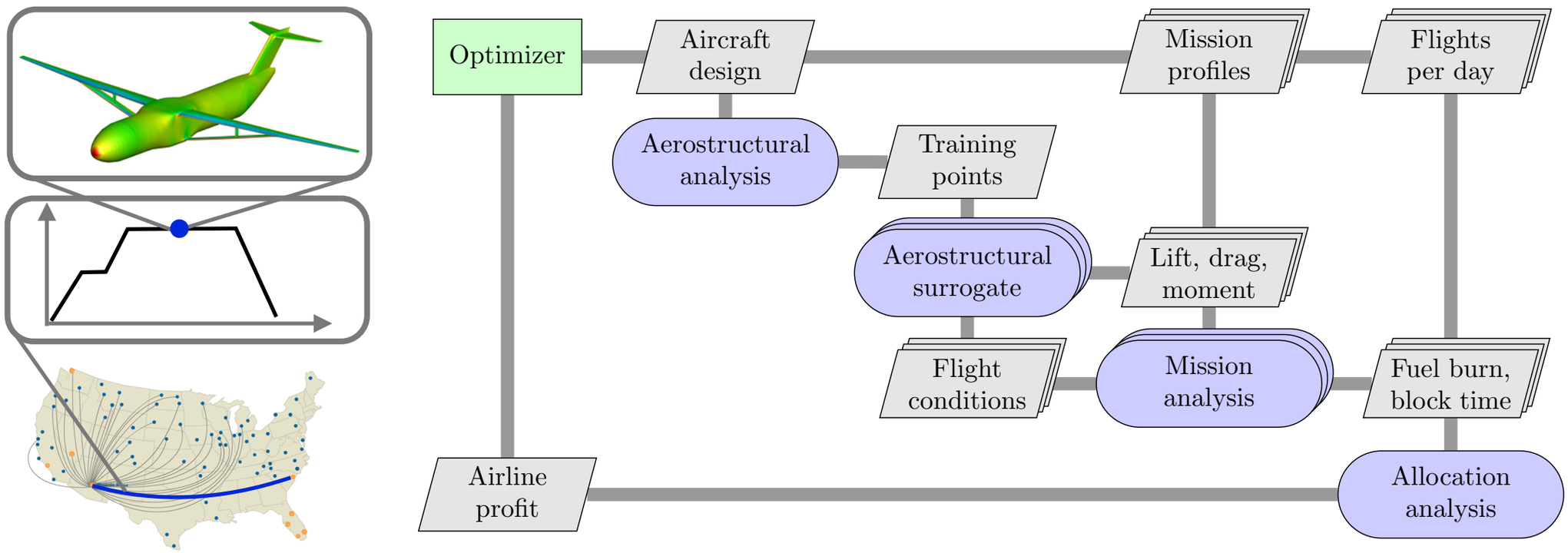
Scalable multifidelity design optimization: Next-generation aircraft and their impact on the air transportation system



Joaquim R. R. A. Martins (PI)
University of Michigan

Jason E. Hicken (co-I)
Rensselaer Polytechnic Institute

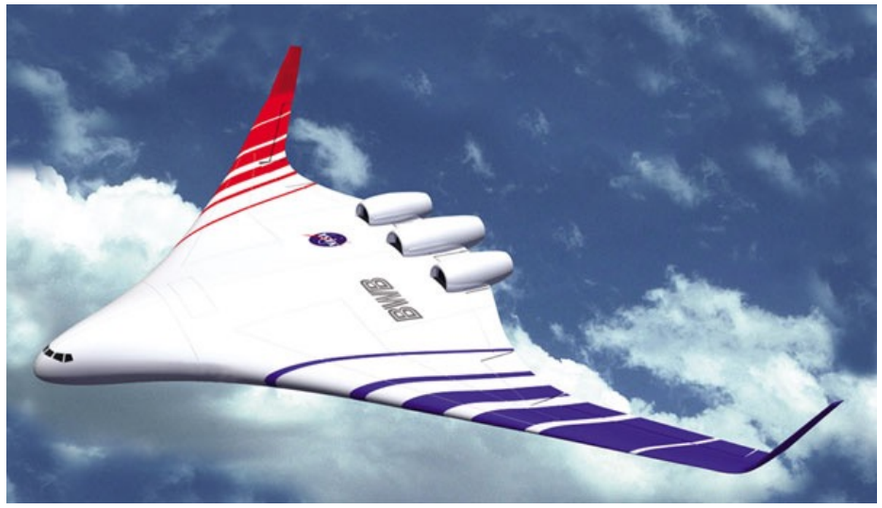
William A. Crossley (co-I)
Purdue University

Karen E. Willcox (co-I)
Massachusetts Institute of Technology

LEARN Seminar • September 6, 2017 • Virtual presentation

Breakthrough improvements require unconventional aircraft configurations

Truss-braced wing

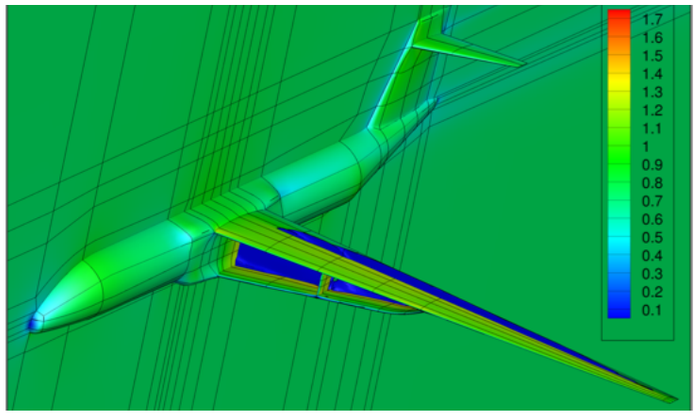


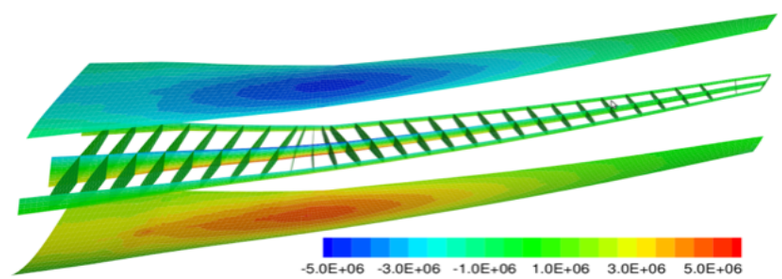
Blended wing body

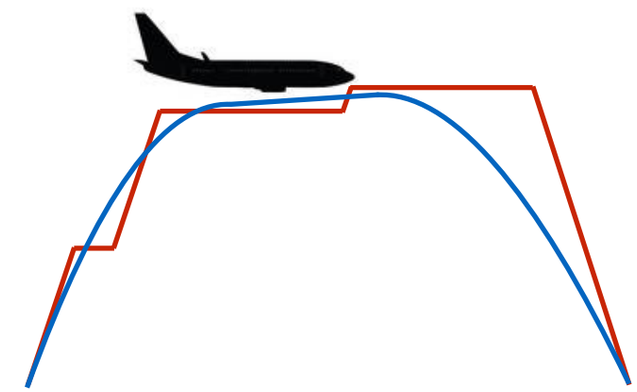
Joined wing

Double bubble

Low-fidelity and empirical design tools do not adequately model the tradeoffs





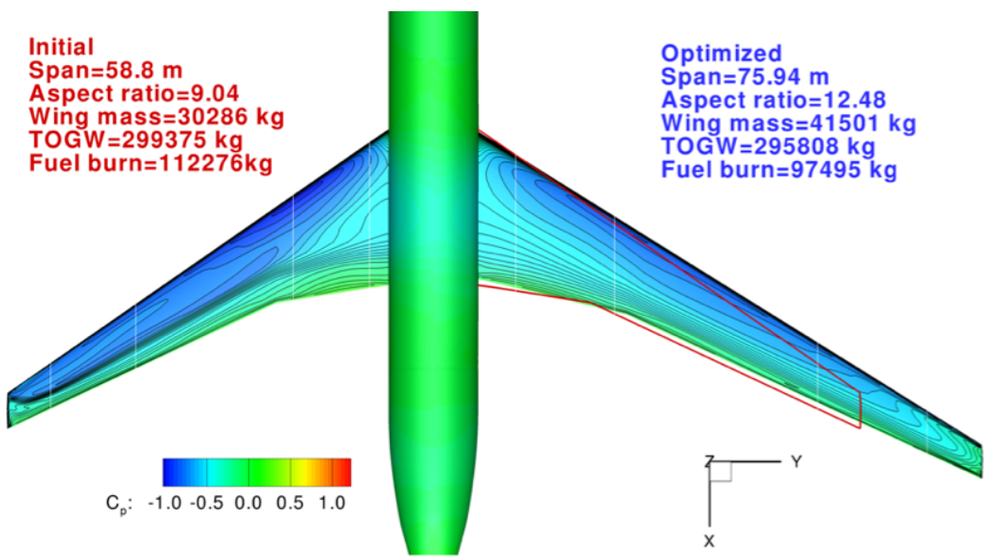


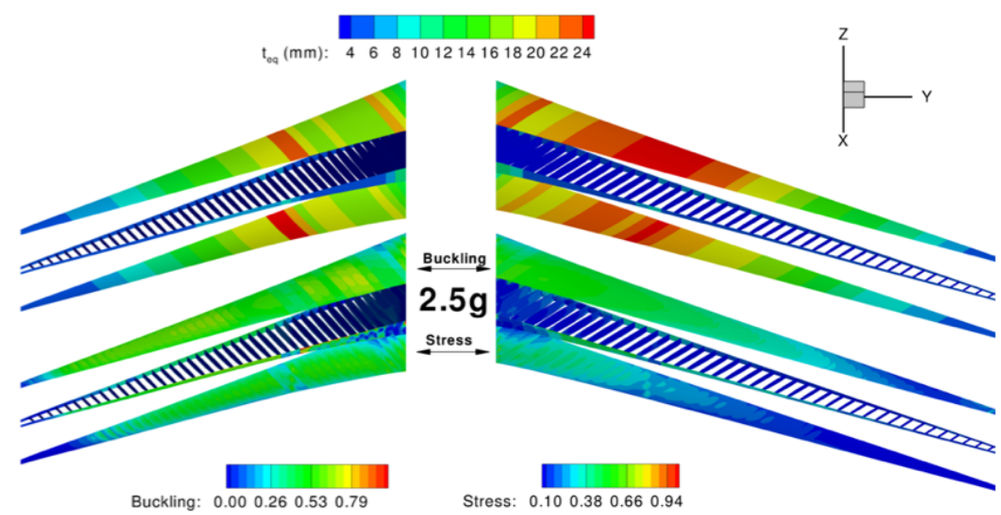
Additional wave and interference drag
↓
CFD analysis

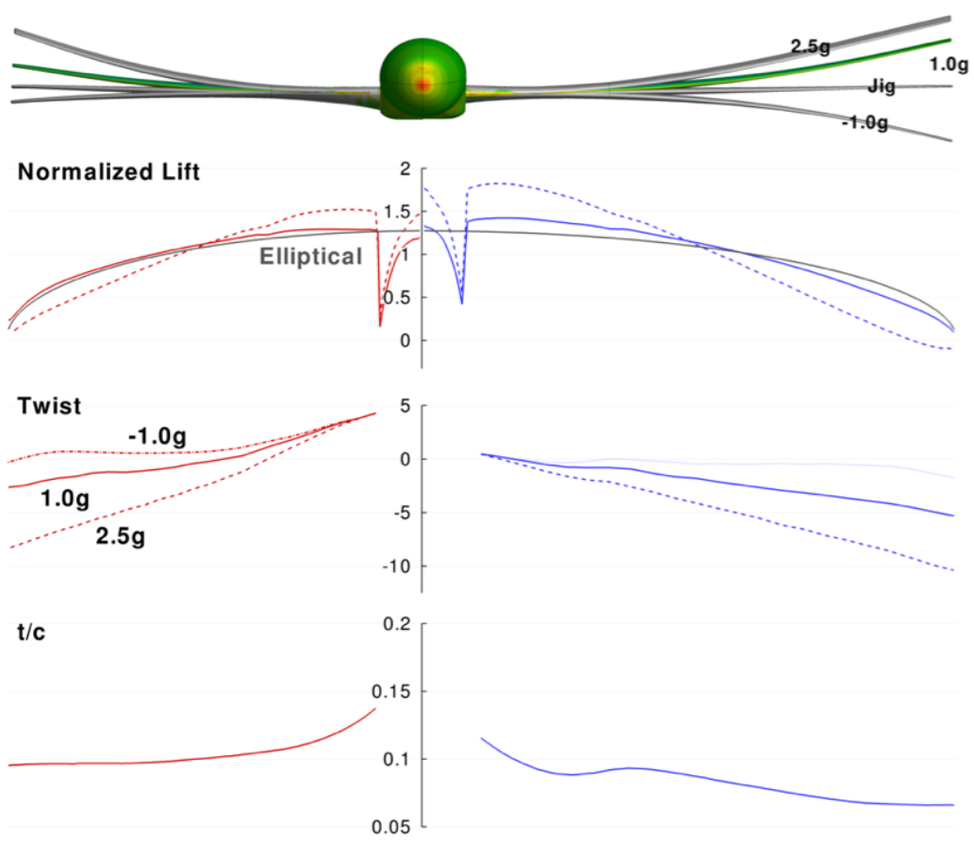
High aspect-ratio composite wings
↓
Aeroelastic tailoring

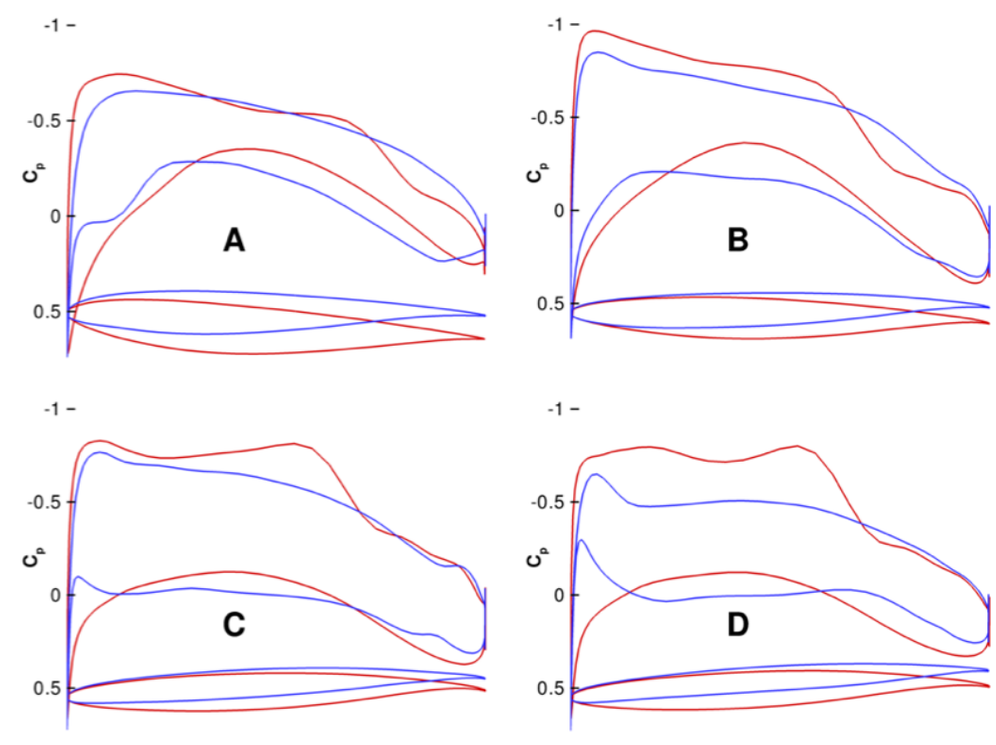
Continuous descent and low Mach number flight
↓
Mission analysis

Adjoint-based design optimization algorithms can accelerate the design process





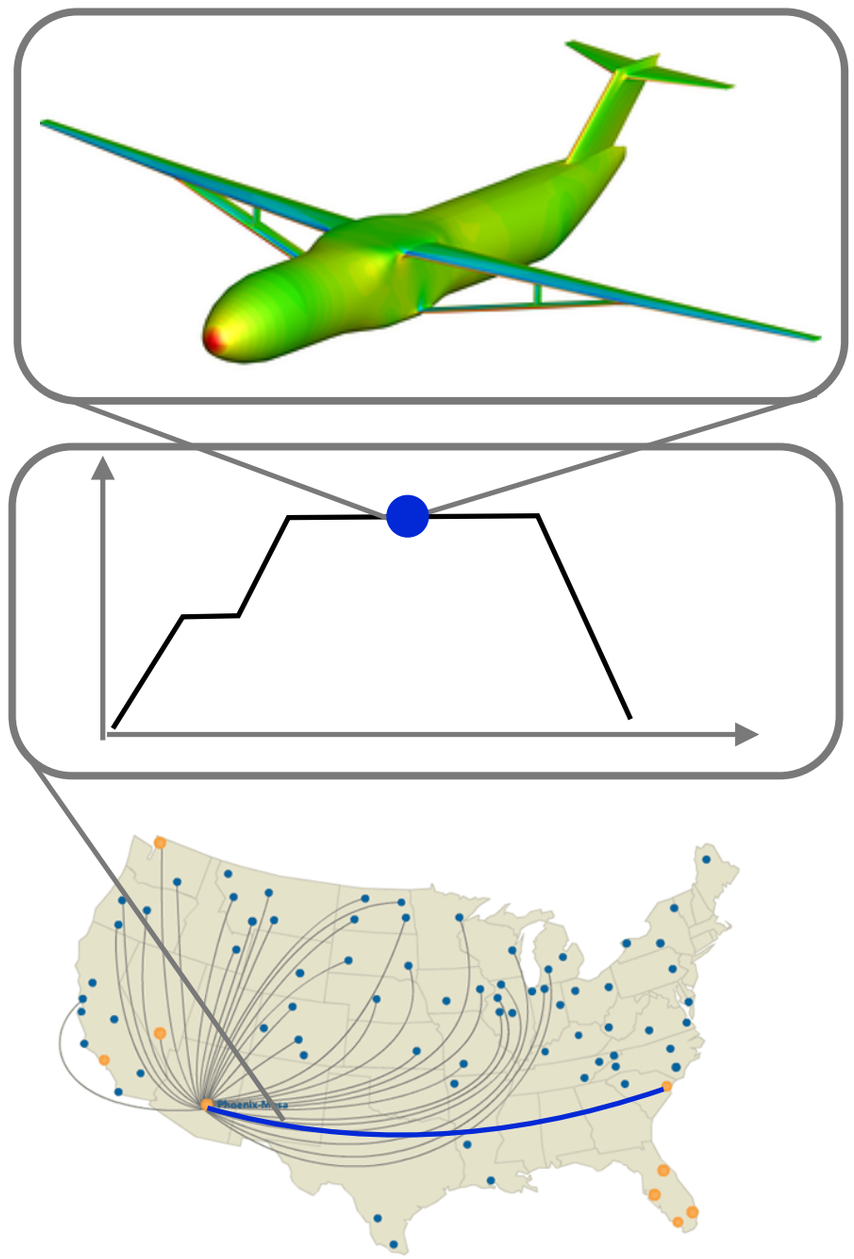




[Kenway, Kennedy, and Martins, AIAA 2014-3274]

The challenge problem:

How can we design a new configuration while considering the impact at the airline level?



We chose to focus on the truss-braced wing

Struts to brace the wing

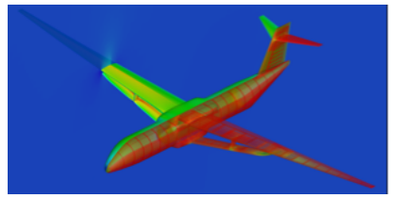
Lighter wing

High aspect-ratio wings

Lower drag

The approach is to find the best design that maximizes profit for the airline

Aircraft design



Aerostructural analysis

CL, CD, Cm at each point in the mission

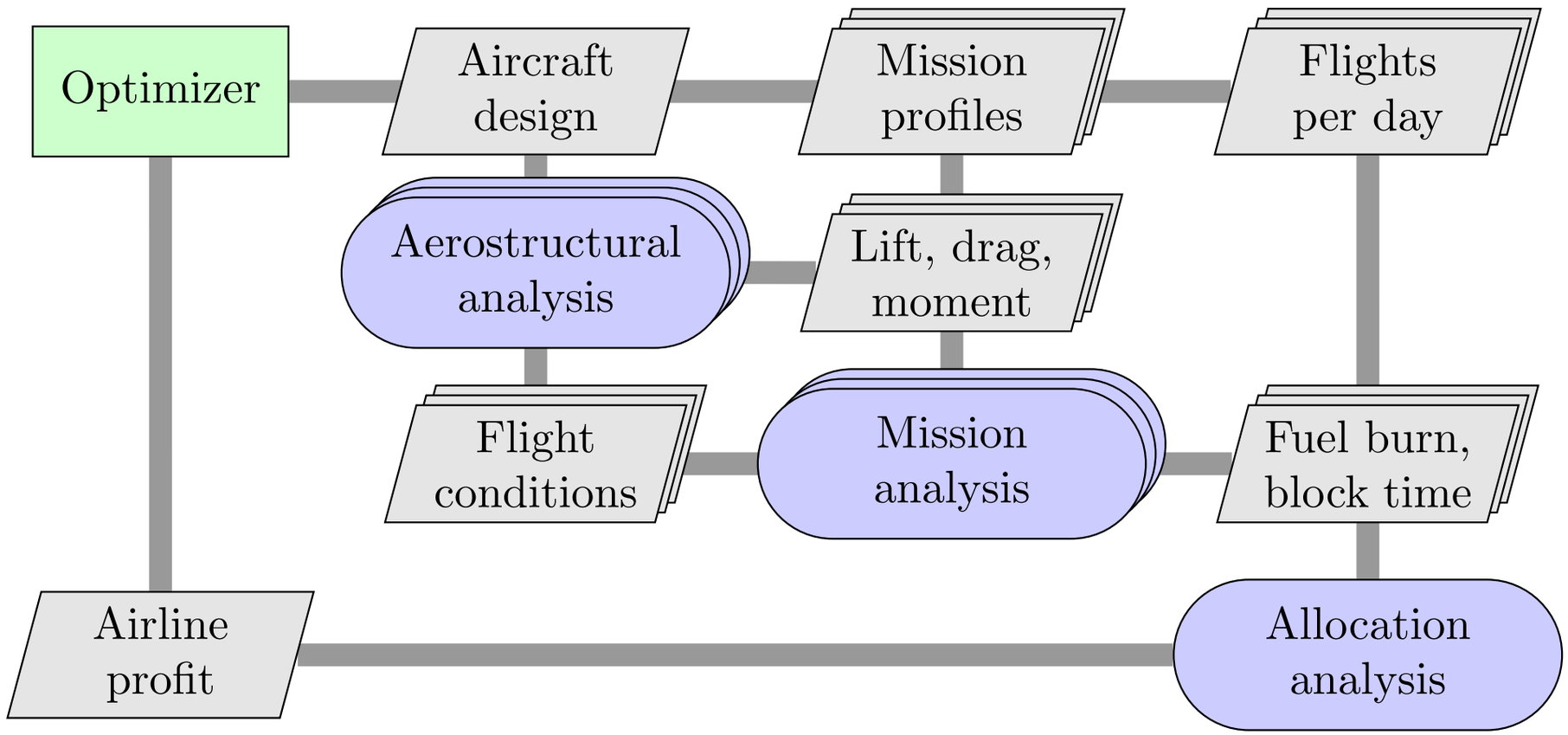
Mission analysis

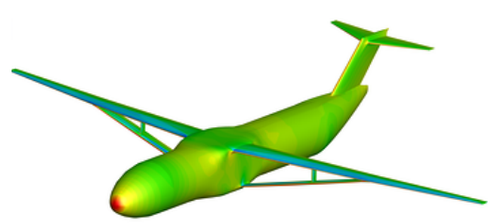
Fuel burn, block time on each route

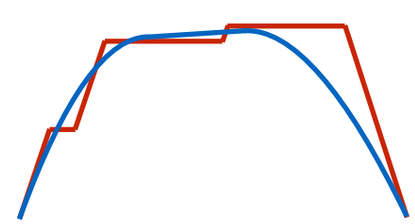
Allocation analysis

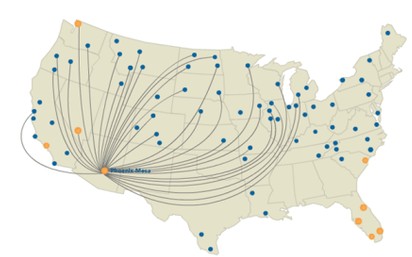
Profit

To do this, we perform simultaneous allocation-mission-design optimization



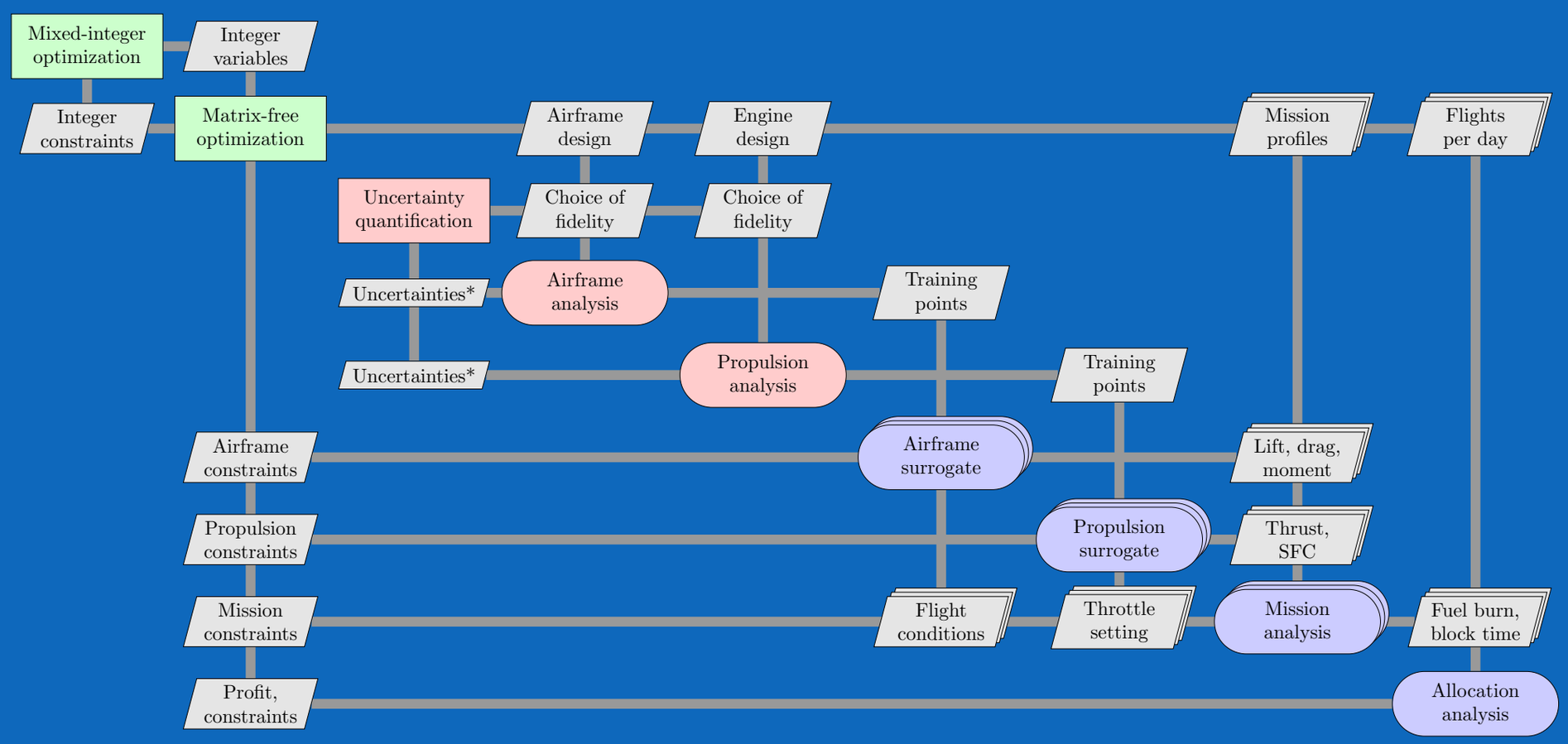




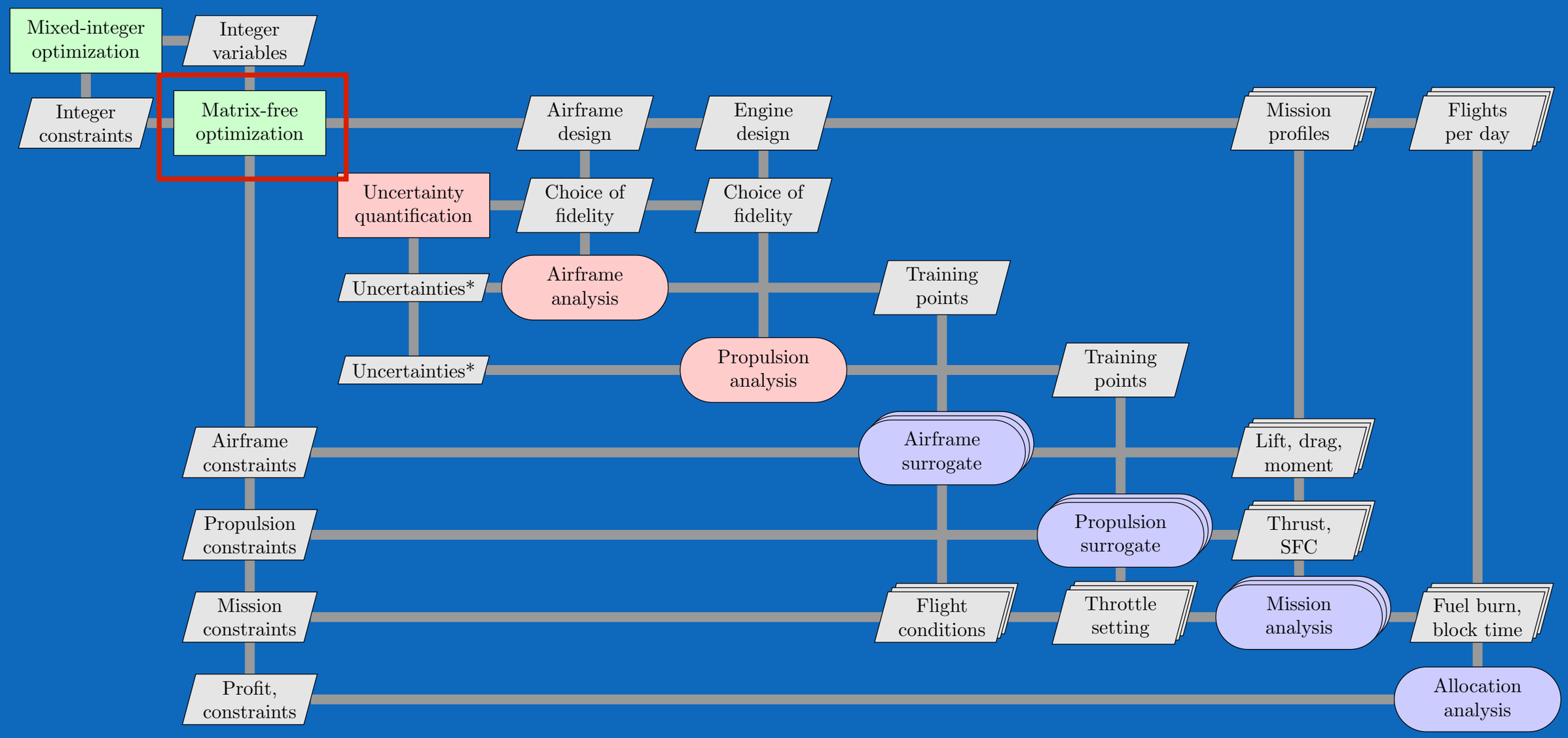


Subprojects for Phase 2

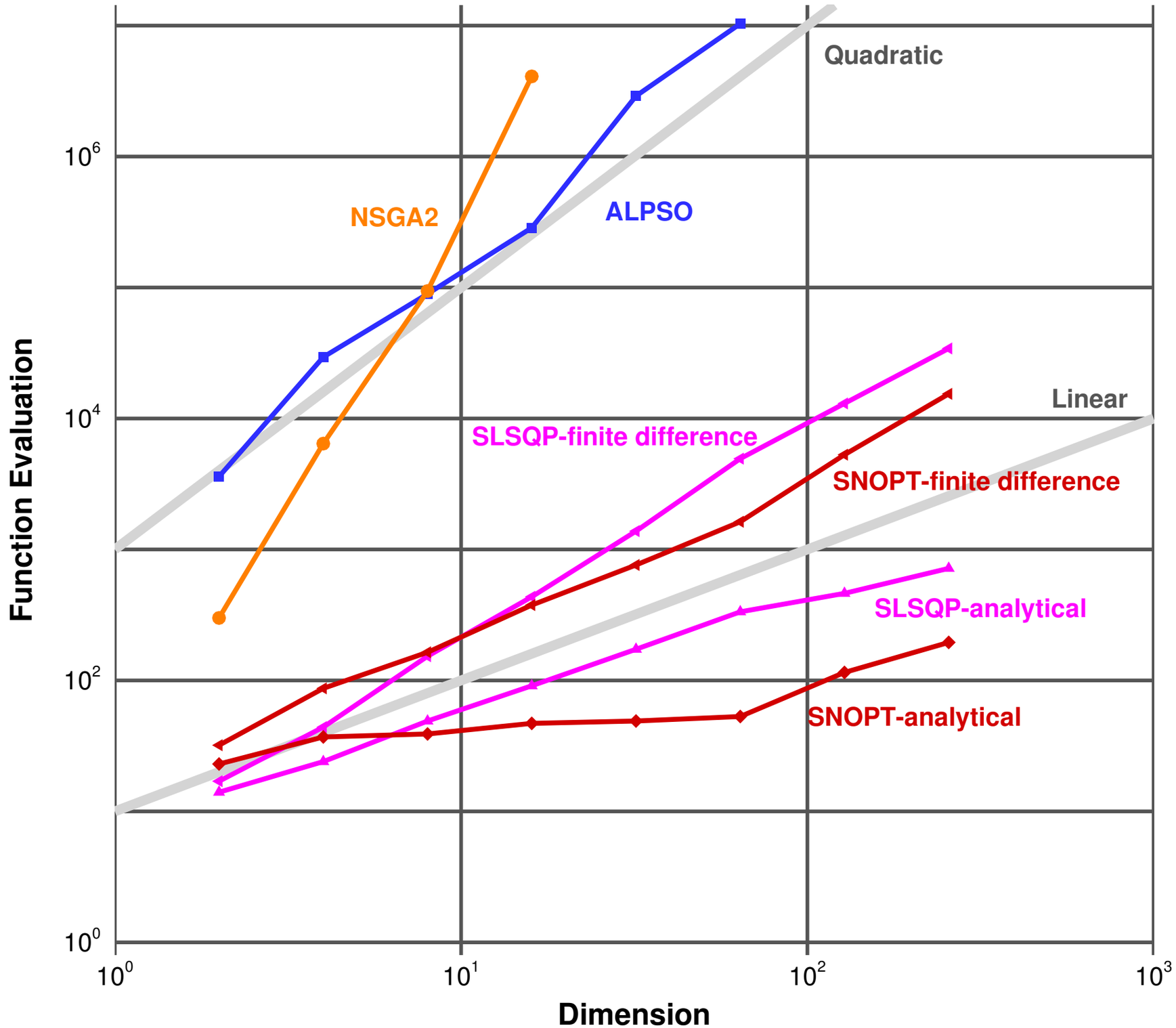
1. Parallel matrix-free optimizer
2. Scalable modular framework for MDO
3. Component-based aerodynamic shape optimization
4. Design, allocation and revenue optimization
5. Low-order model for transonic flutter prediction



Subproject 1
Parallel matrix-free optimizer



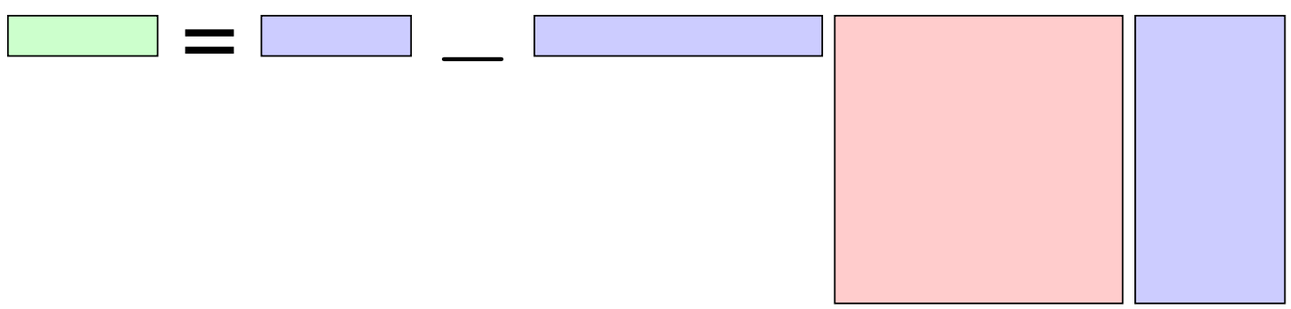
Gradient-based optimization is the only hope for large numbers of design variables



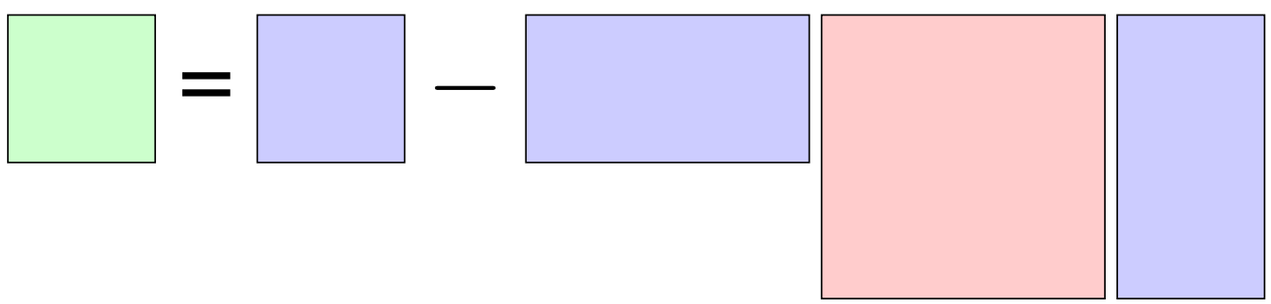
… but the adjoint method cannot handle large numbers of variables and constraints simultaneously

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

Large numbers of design variables



Large numbers of design variables and constraints



Current state-of-the-art optimizers do not scale well with problem size…

…they solve the optimality conditions using Newton's method

$$\begin{bmatrix} W_k & A_k^T \\ A_k & 0 \end{bmatrix} \begin{bmatrix} p \\ d \end{bmatrix} = - \begin{bmatrix} g_k \\ c_k \end{bmatrix}$$

This requires the matrices W and A explicitly, which are costly to compute for large problems

We developed an all new algorithm for numerical optimization that uses a matrix-free approach

Instead of requiring the matrices explicitly, our optimizer requires only matrix-vector products

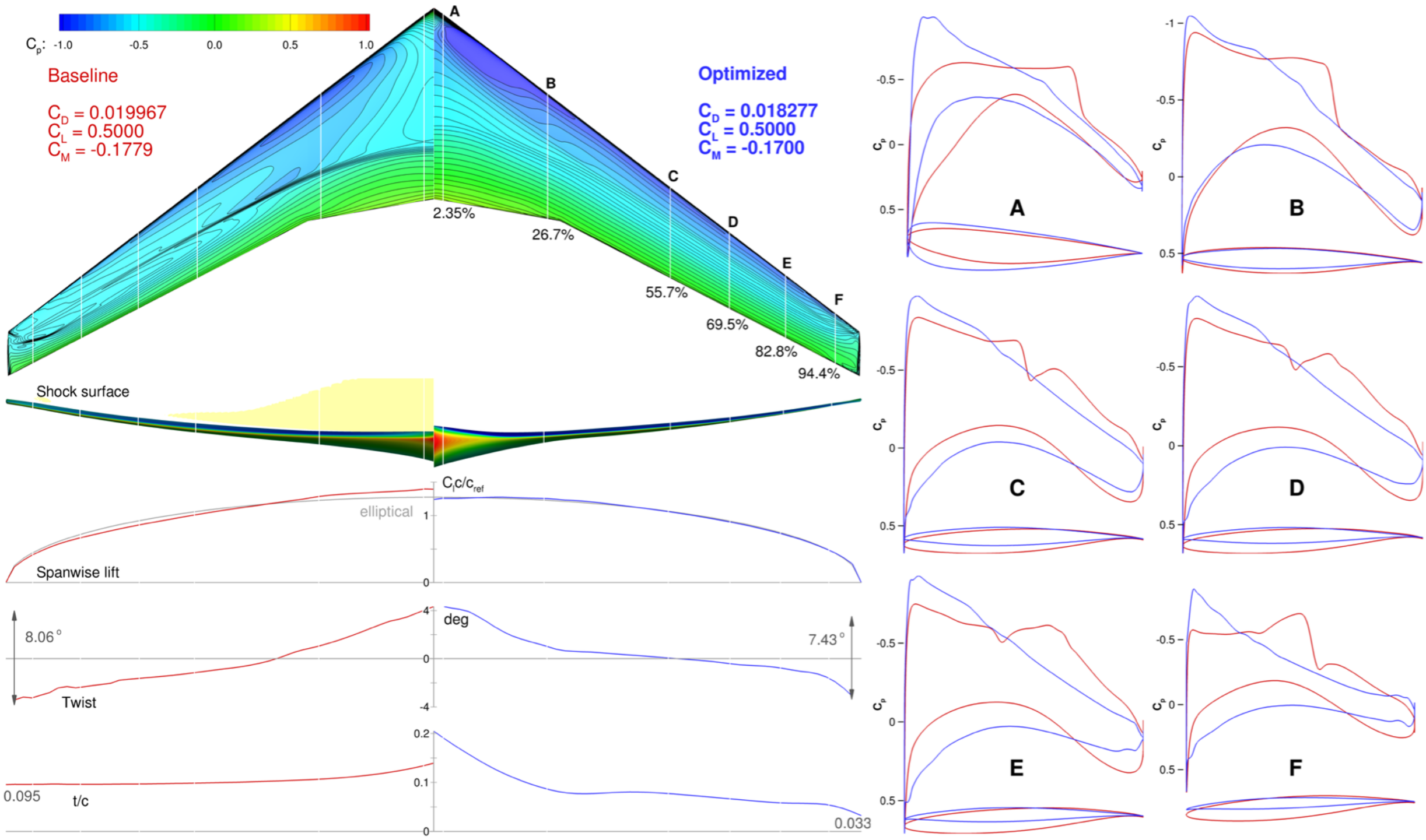
$$\begin{bmatrix} W_k & A_k^T \\ A_k & 0 \end{bmatrix} \begin{bmatrix} p \\ d \end{bmatrix} = - \begin{bmatrix} g_k \\ c_k \end{bmatrix}$$

This saves memory and computational time, enabling the solution of very large problems

RSNK: Reduced-space Newton—Krylov

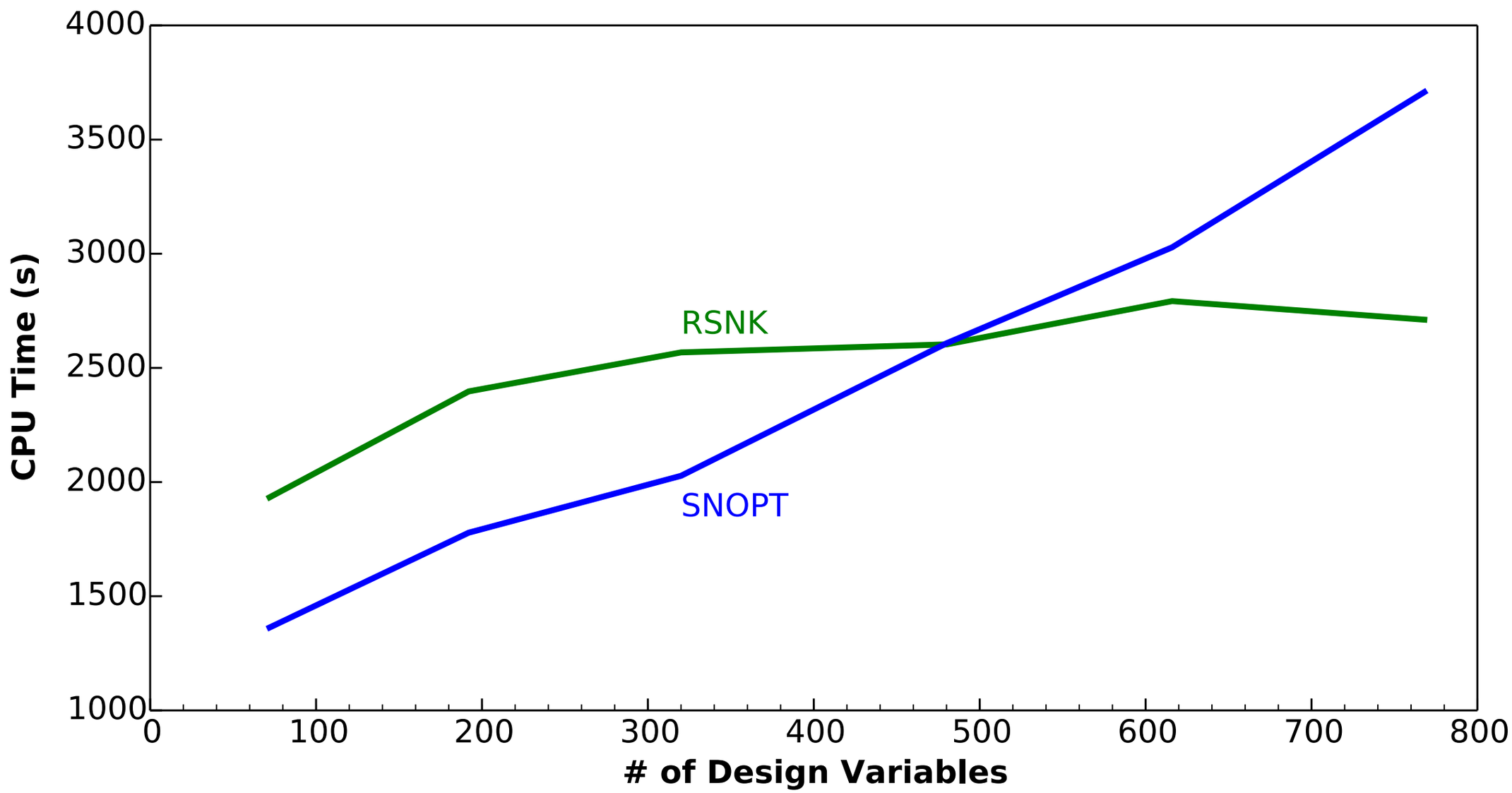
[Hicken and Dener, SIAM J.Opt., 2015]

Previous results with conventional optimizers show that this is a challenging problem



[Lyu, Kenway and Martins, 2015]

RSNK was shown to be more efficient than a state-of-the-art optimizer for large problems



[Dener, Hicken, Kenway, Lyu and Martins, AIAA 2015-1945]

Matrix-free optimization algorithms must address two challenges

In Phase 2, this subproject was focused on two challenges that face matrix-free optimization:

Challenge 1: handling nonconvexity

Challenge 2: matrix-free preconditioning

We implemented a continuation strategy to ensure convergence to local minimizers

easy problem:

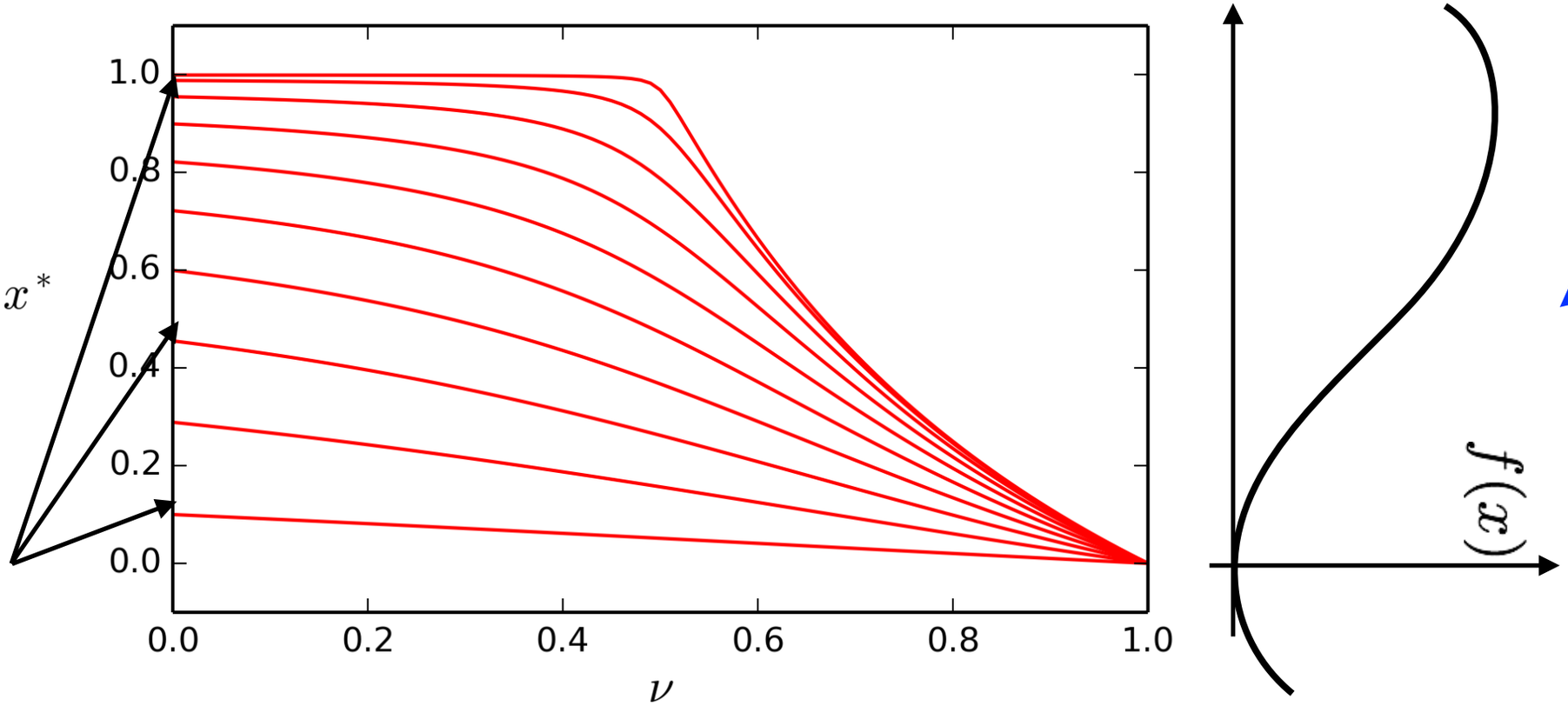
$$\min_x \frac{1}{2}(x - x_0)^2$$

follow path by solving sequence of problems

target problem:

$$\min_x f(x)$$

different x^* starting guesses x_0



We developed a matrix-free preconditioner that uses approximate adjoints

1) eliminate variables:

$$\begin{bmatrix} \mathsf{W} & 0 & \mathsf{A}^T \\ 0 & -\Lambda\mathsf{S} & -\mathsf{S} \\ \mathsf{A} & \mathsf{S} & 0 \end{bmatrix} \longrightarrow \left[\mathsf{W} - \mathsf{A}^T S^{-1} \Lambda \mathsf{A}\right]$$

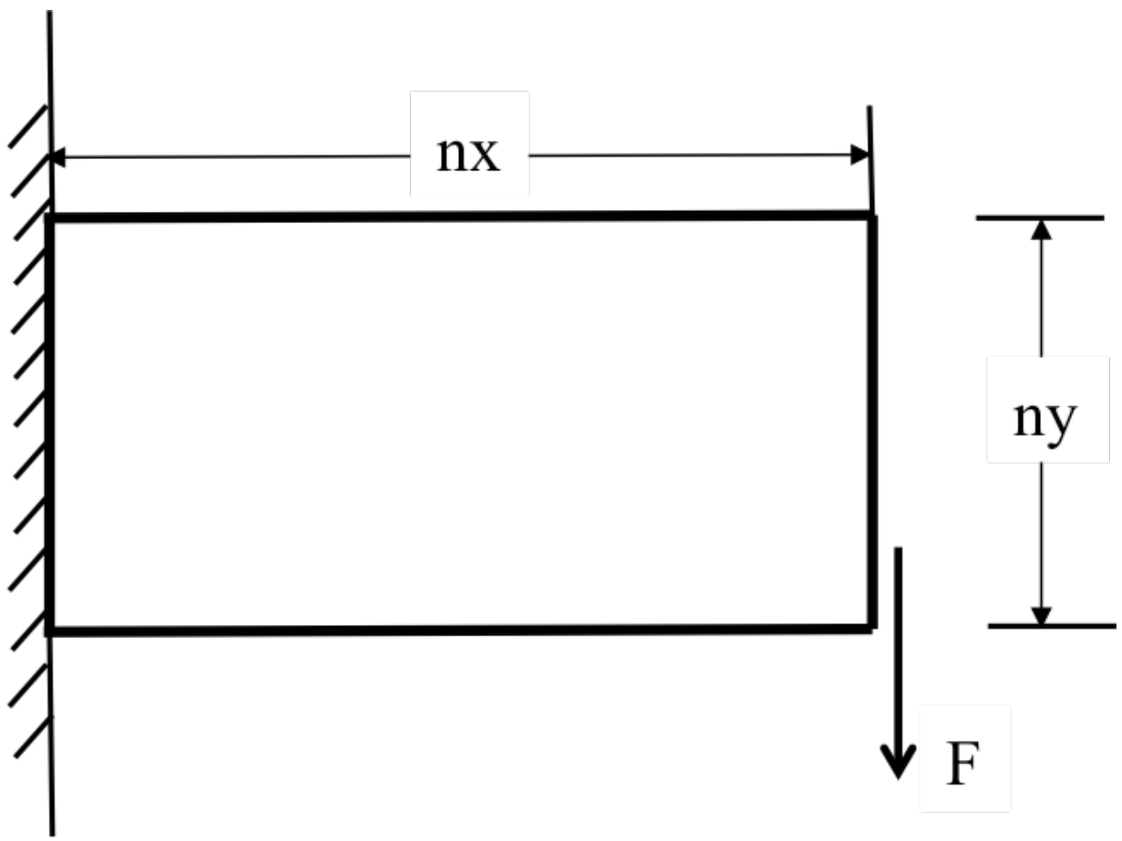
2) use approximate adjoints for matrix-vector products:

$$\left[\tilde{\mathsf{W}} - \tilde{\mathsf{A}}^T S^{-1} \Lambda \tilde{\mathsf{A}}\right] u = v$$

3) apply Lanczos to form low-rank SVD-based preconditioner:

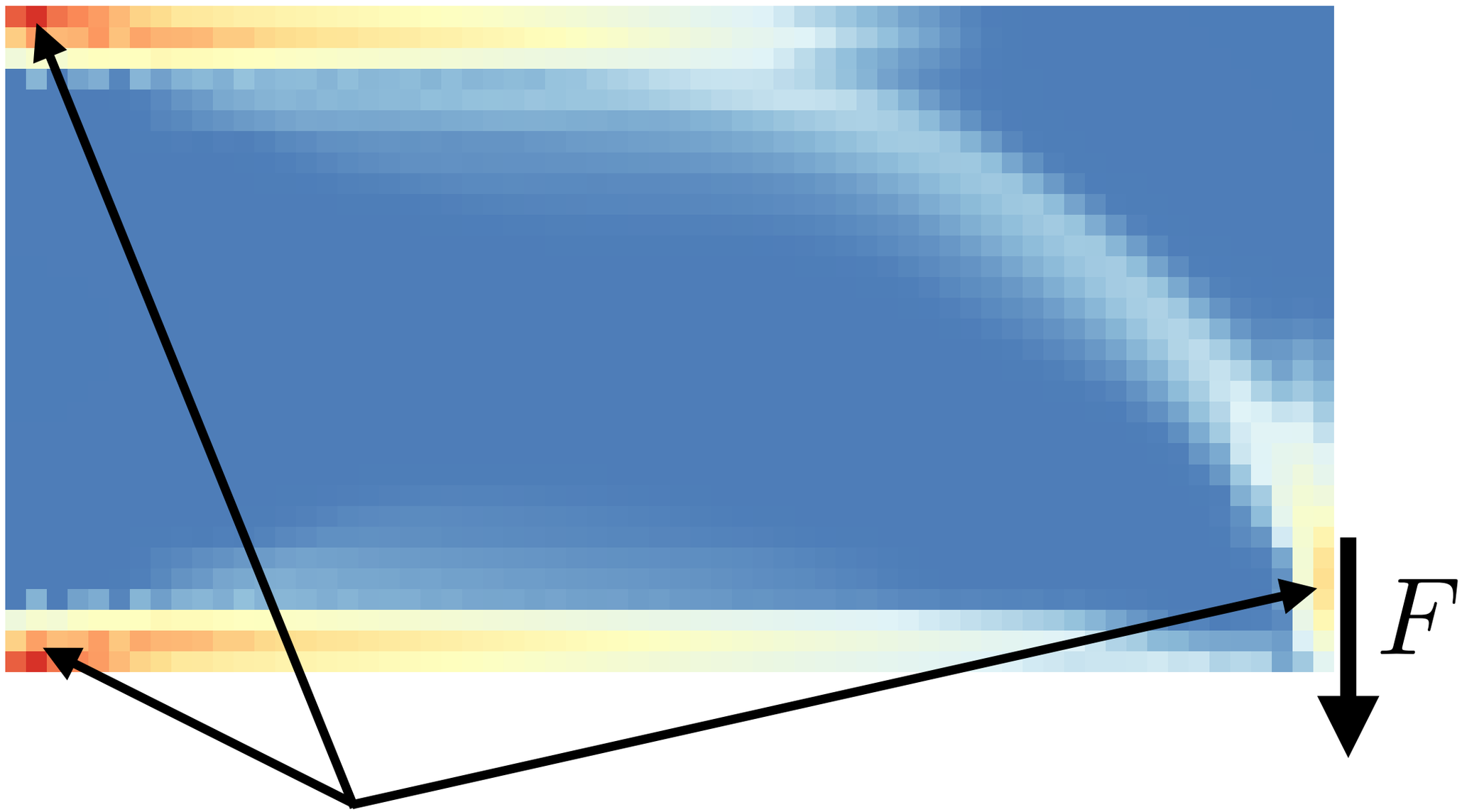
$$\left[\tilde{\mathsf{W}} - \tilde{\mathsf{A}}^T S^{-1} \Lambda \tilde{\mathsf{A}}\right]^{-1} \approx \mathsf{V} \Sigma^{-1} \mathsf{U}^T$$

We have demonstrated the algorithm on a difficult structural optimization problem



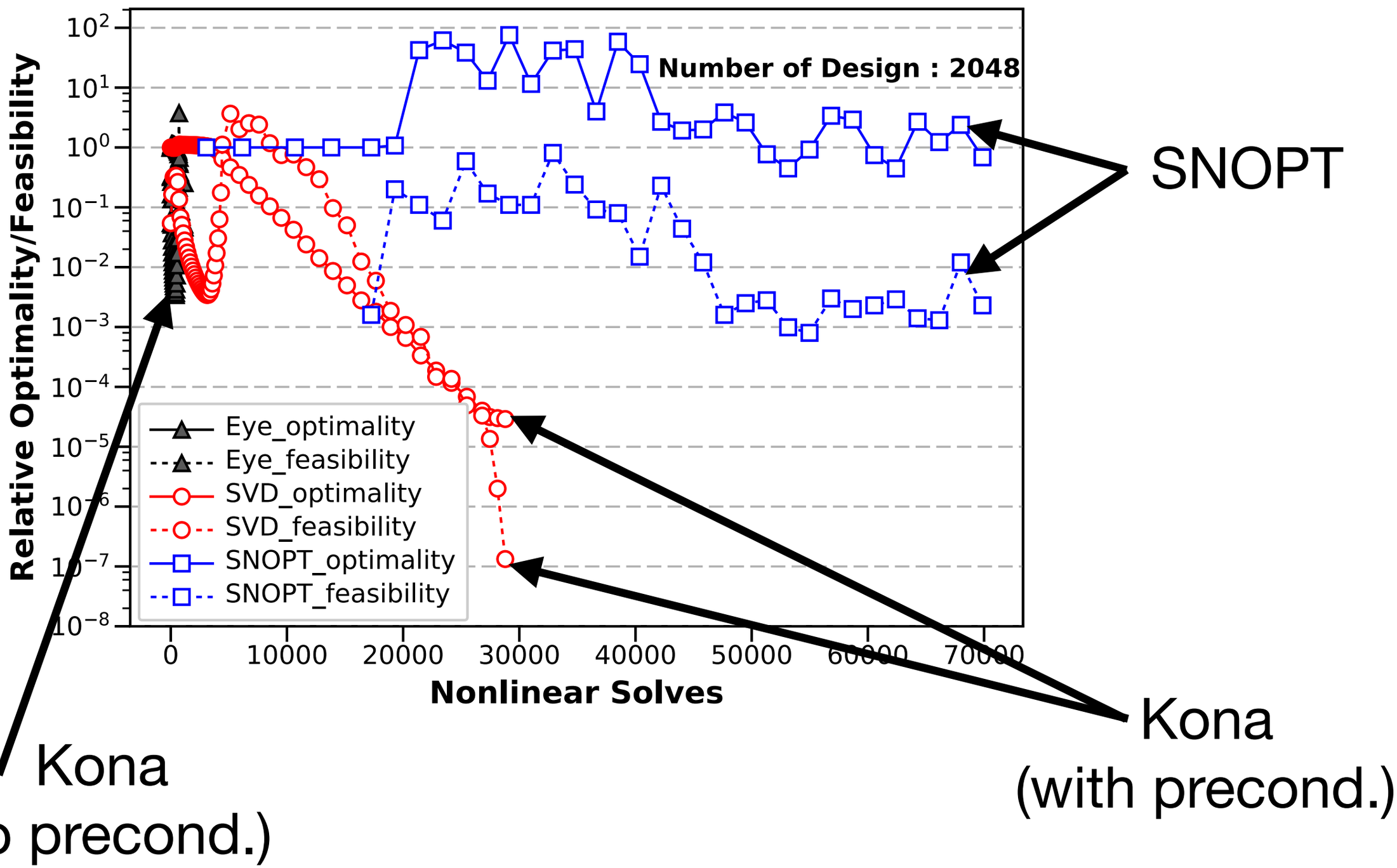
- minimize weight w.r.t. thickness distribution
- 2048 design variables
- 2048 stress constraints
- 4096 bound constraints

The algorithm successfully converges to the optimal thickness distribution

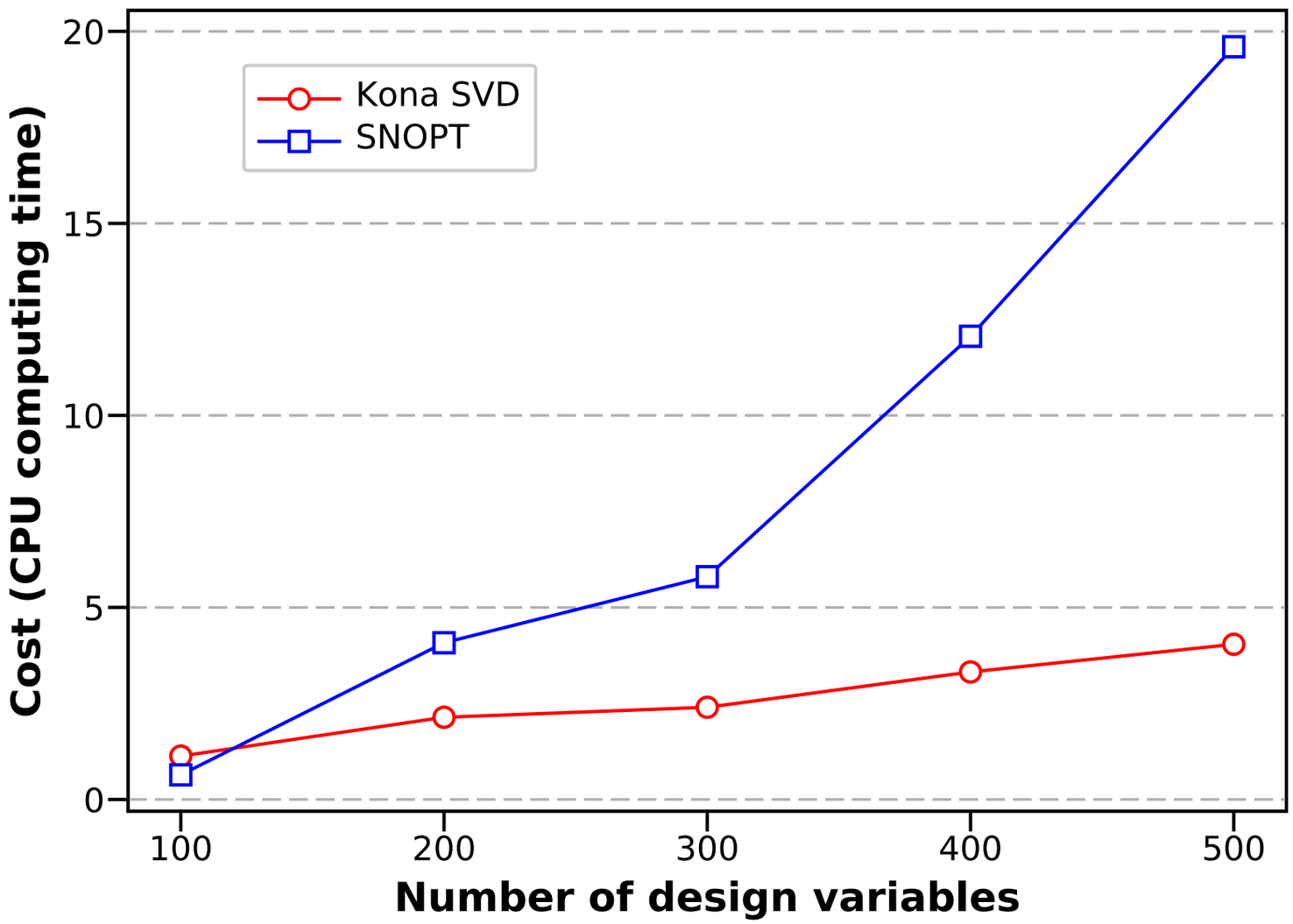


red indicates regions of increased thickness

The matrix-free algorithm outperforms a state-of-the-art optimization method

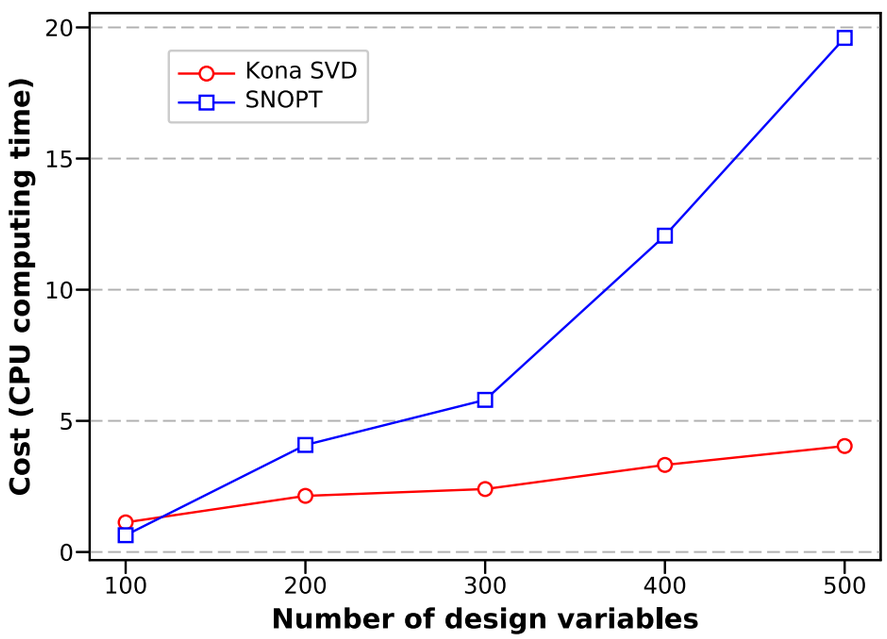


We observe excellent algorithmic scalability as the problem size increases



Comparison between Kona and SNOPT on a synthetic verification problem

Summary for Subproject 1



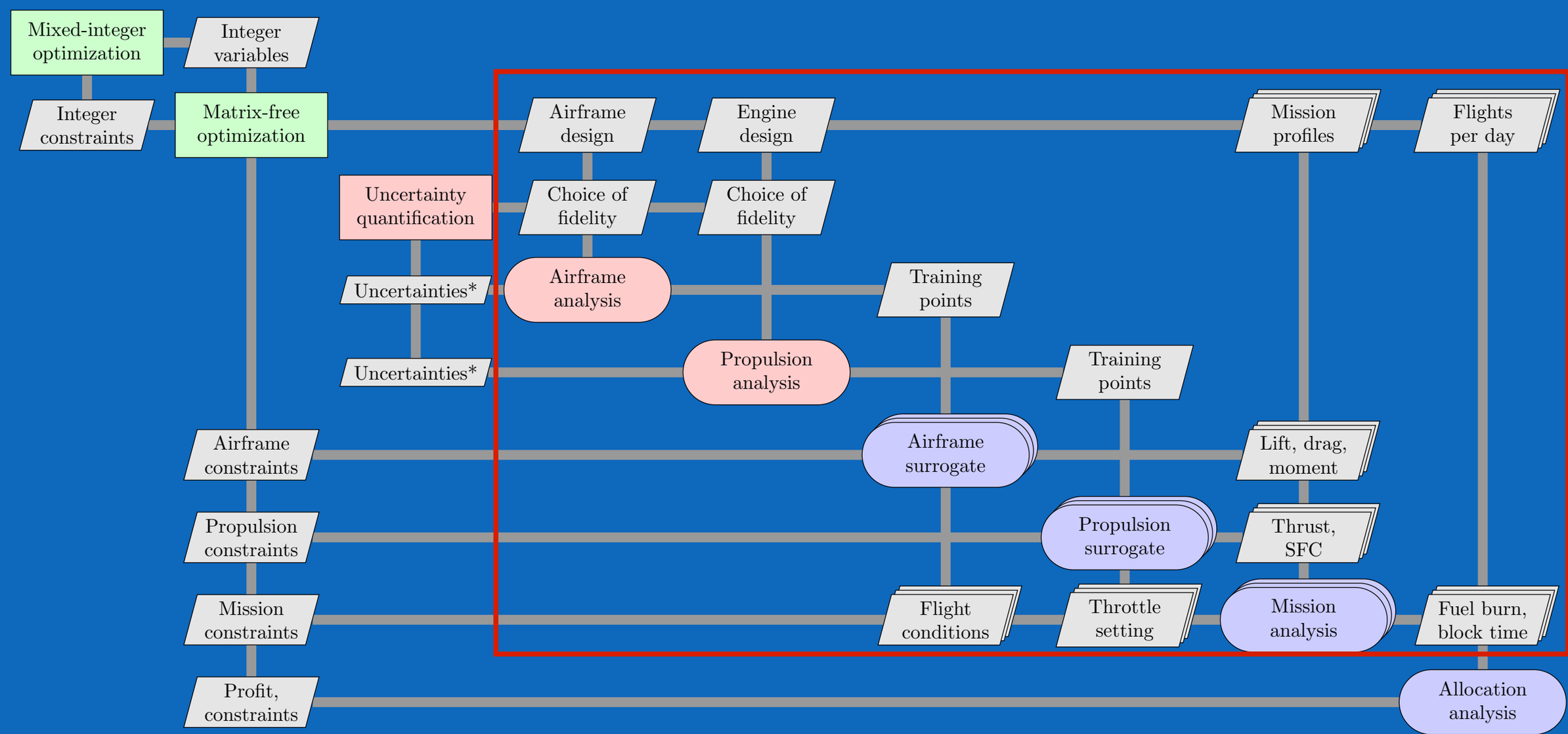
Phase 2 achievements:

- Developed a novel scalable matrix-free optimization algorithm
- Demonstrated algorithm on challenging large-scale structural optimization problem

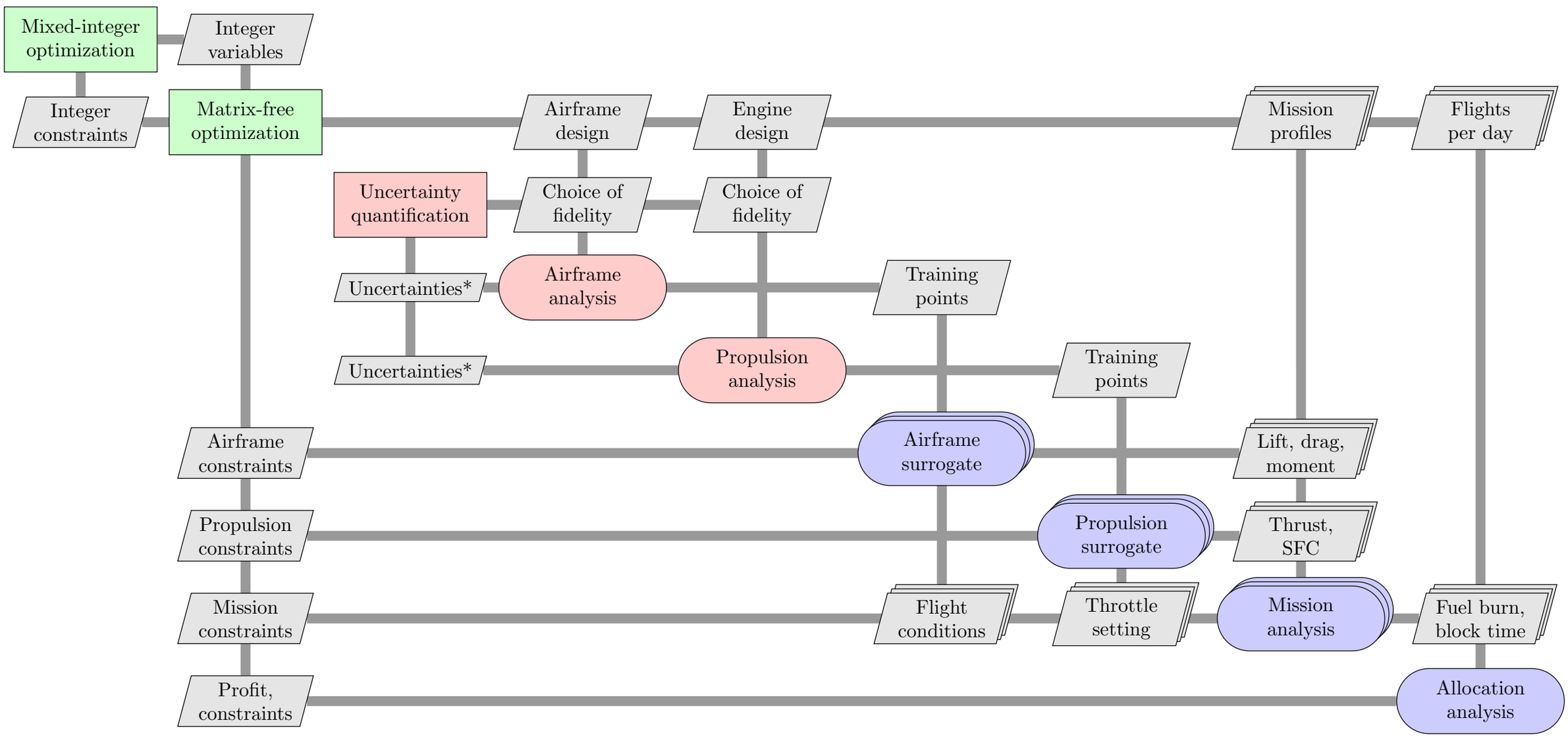
Next steps:

- Apply developed pre-conditioner to aerodynamic and aerostructural optimization

Subproject 2
Scalable modular framework for MDO



Combining many types of models and computing their gradients is challenging



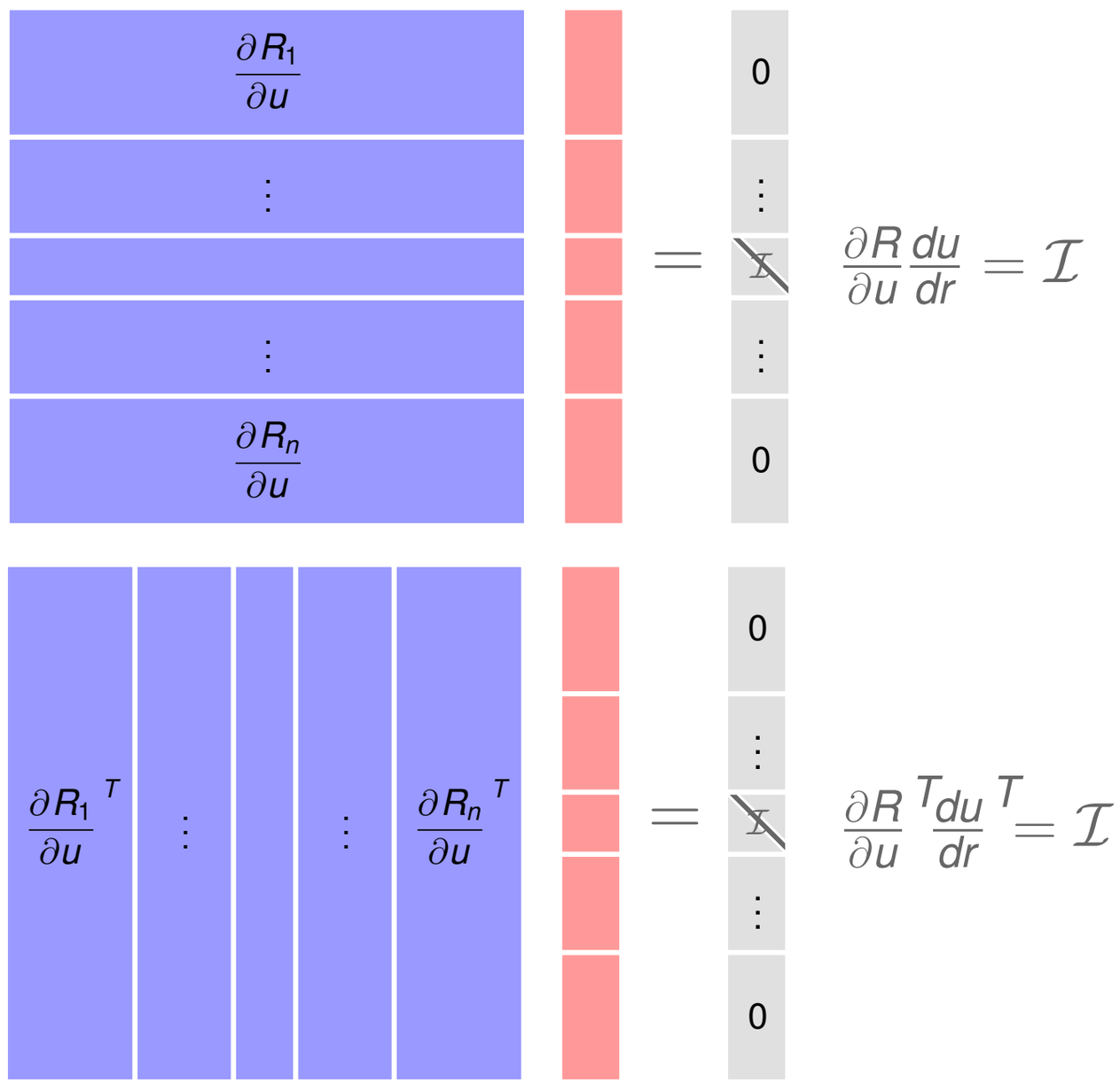
We recently developed an equation that unifies the methods for computing derivatives

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

- Finite differences $\frac{df}{dx} = \frac{\partial F}{\partial x}$
- Chain rule $\frac{df}{dx} = \frac{\partial F}{\partial x} + \frac{\partial F}{\partial y}\frac{dy}{dx}$
- Direct method/adjoint method $\frac{df}{dx} = \frac{\partial F}{\partial x} - \frac{\partial F}{\partial y}\frac{\partial R}{\partial y}^{-1}\frac{\partial R}{\partial x}$
- Algorithmic differentiation

[Hwang and Martins, AIAAJ, 2013]

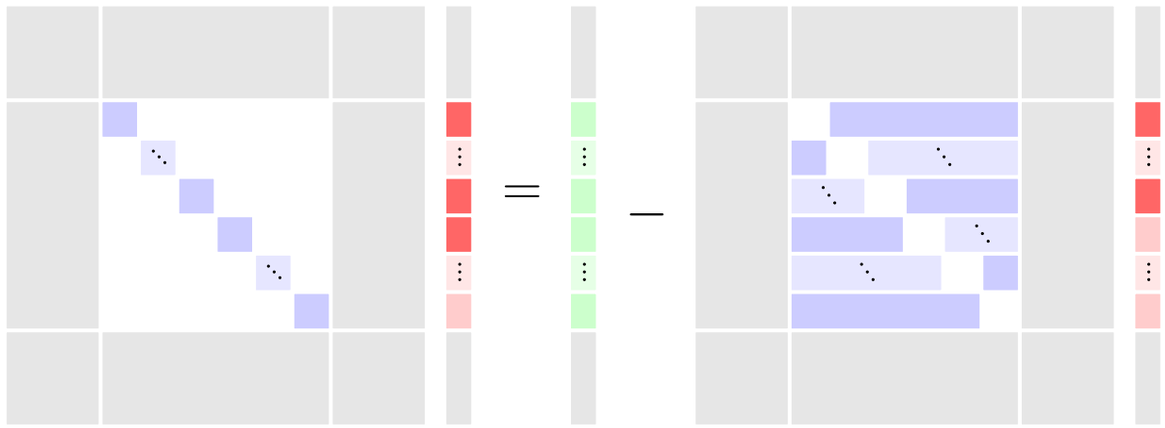
Using this theory, we developed a parallel framework that computes coupled gradients



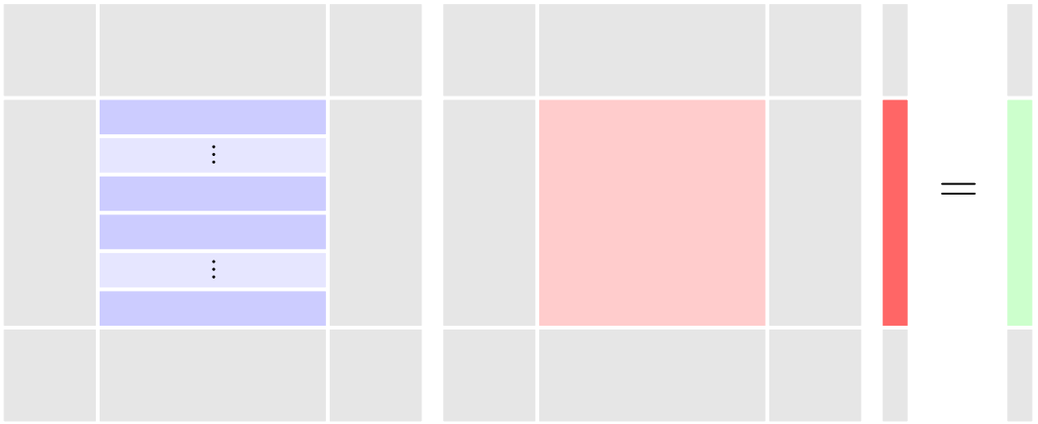
Each component computes its local derivatives;
the framework computes coupled gradients automatically

The framework uses efficient numerical linear algebra

Block Gauss-Seidel



Preconditioned
Krylov subspace methods



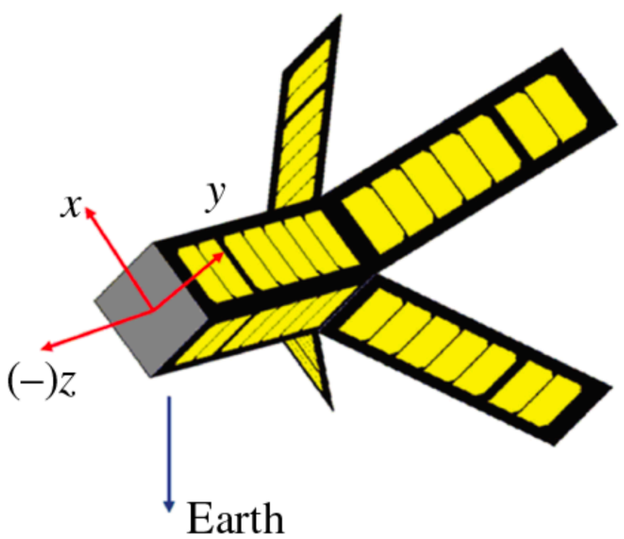
The built-in solvers are used extensively in the mission analysis component

[Hwang and Martins, ACM TOMS 2017]

This algorithmic framework has been implemented in NASA's OpenMDAO

Several other applications have been handled:

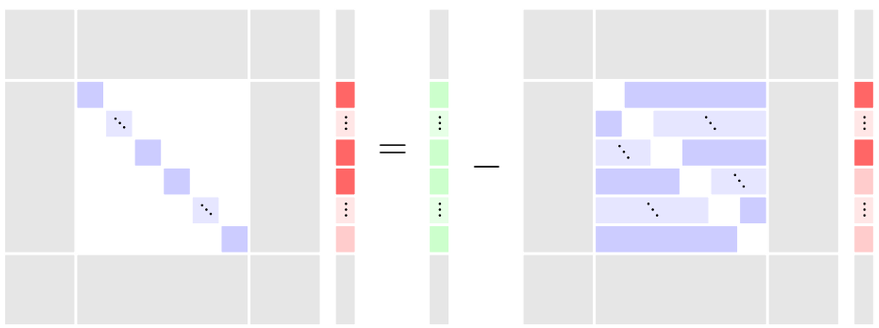
Satellite design and operation optimization

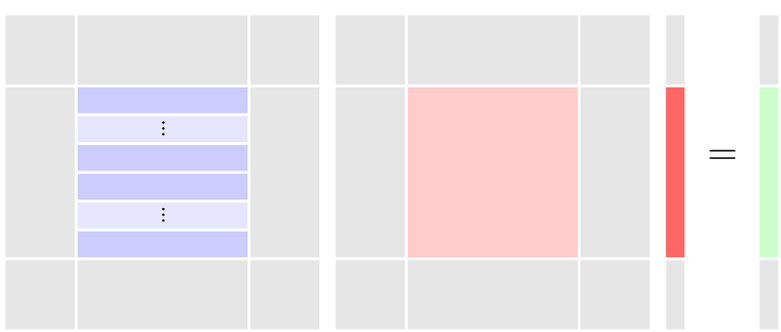


Wind turbine optimization

[Gray, Hearn, Moore, Hwang, Martins, and Ning, AIAA 2014-2042]

Summary for Subproject 2





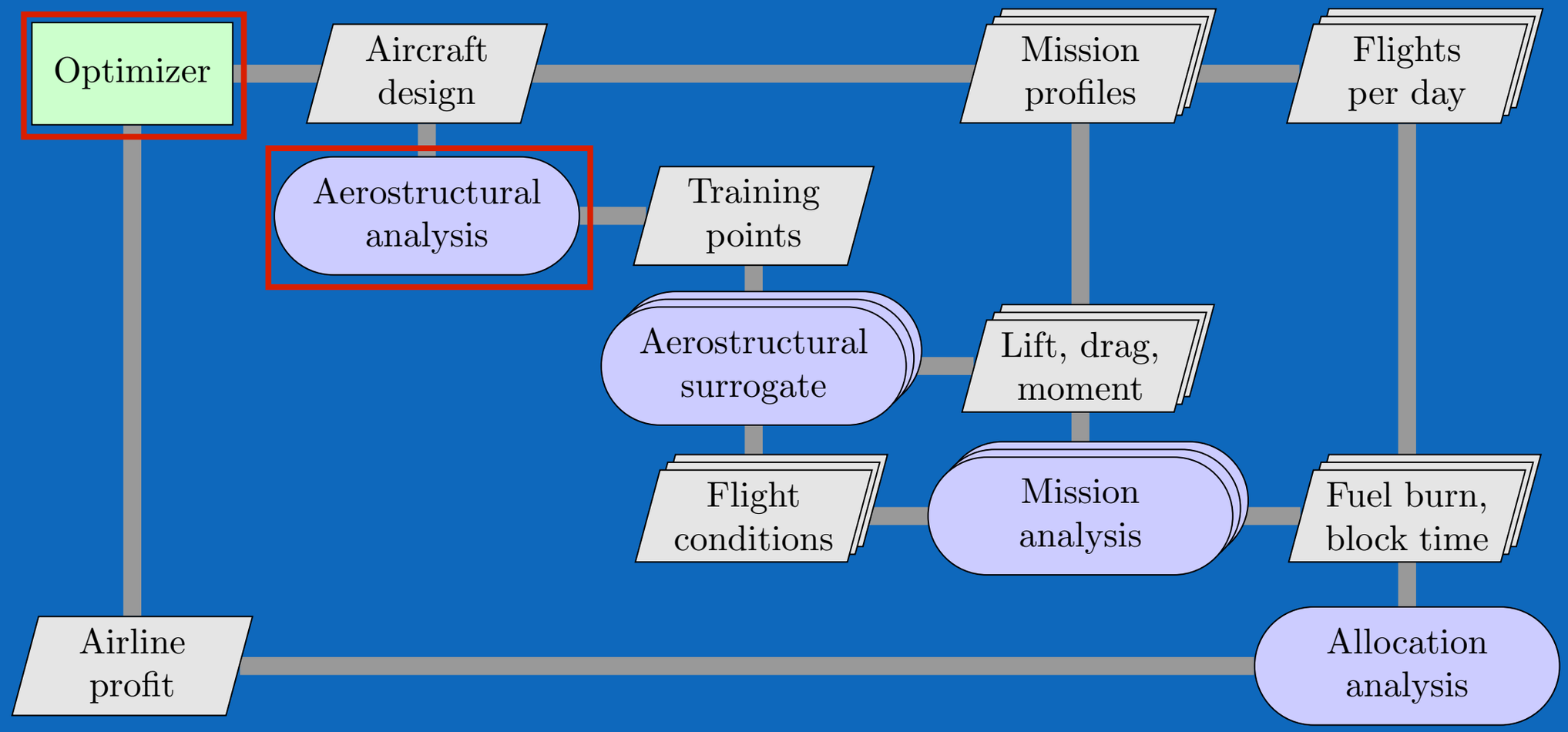
Phase 1 achievements:

- Developed a novel algorithmic framework for coupled analysis and gradient computation
- Implemented framework numerical methods in OpenMDAO
- Spin-off through OpenMDAO

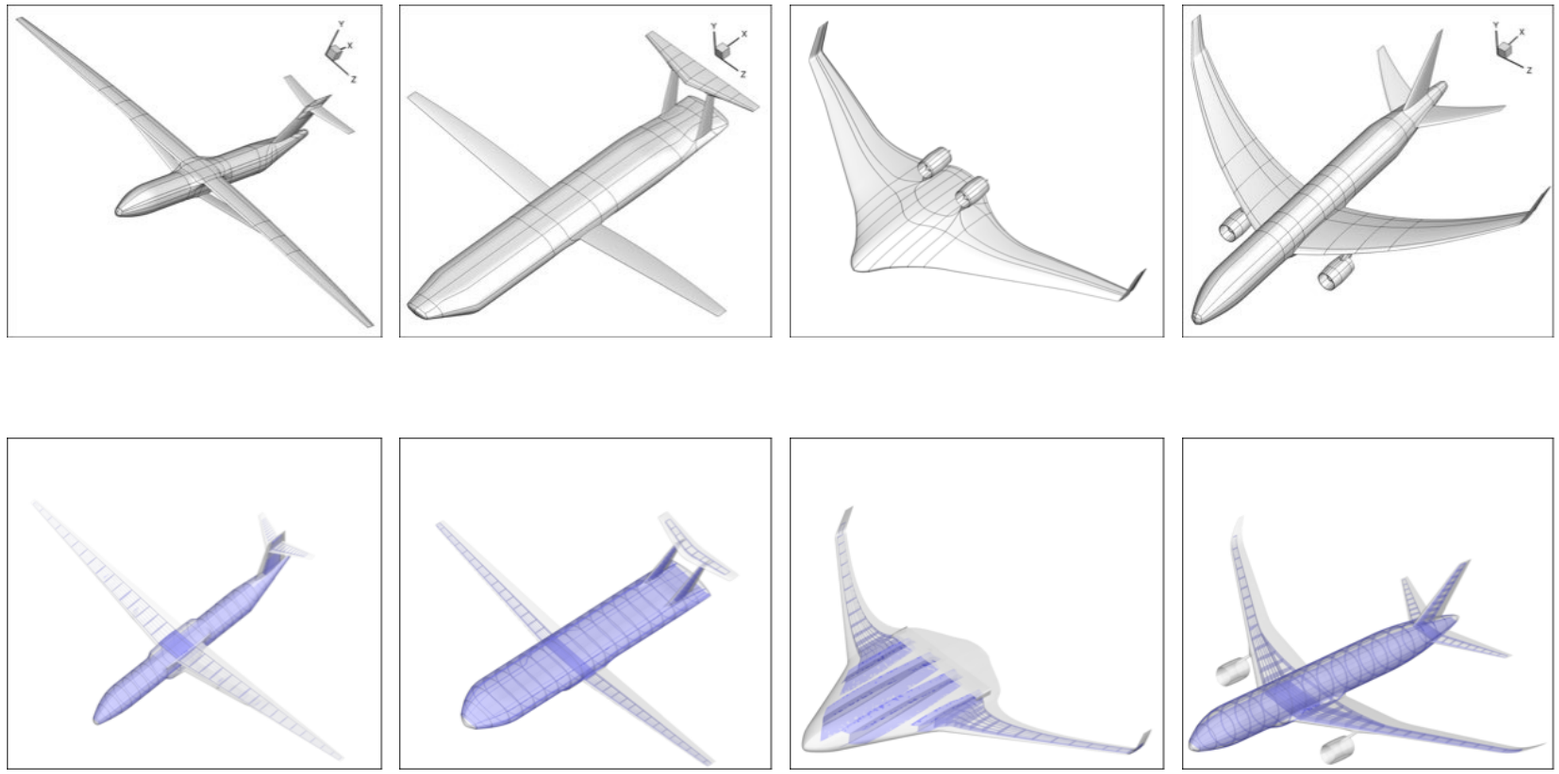
Phase 2 achievements:

- Benchmark framework in other problems
- Developed better parallel support
- Supported OpenMDAO team

Subproject 3
Component-based aerodynamic shape optimization

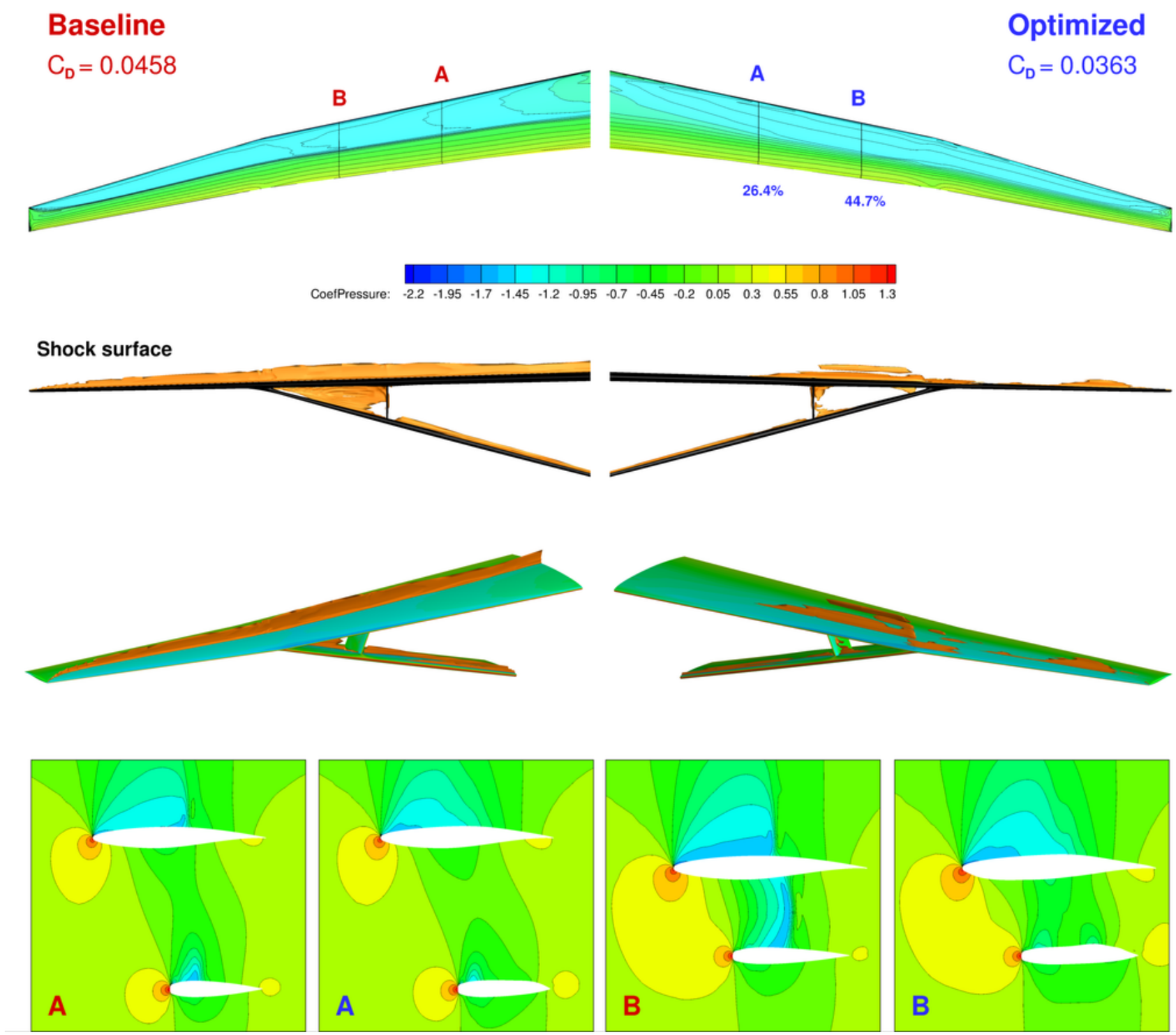


To model the TBW, we use GeoMACH, which was developed in an earlier NASA effort

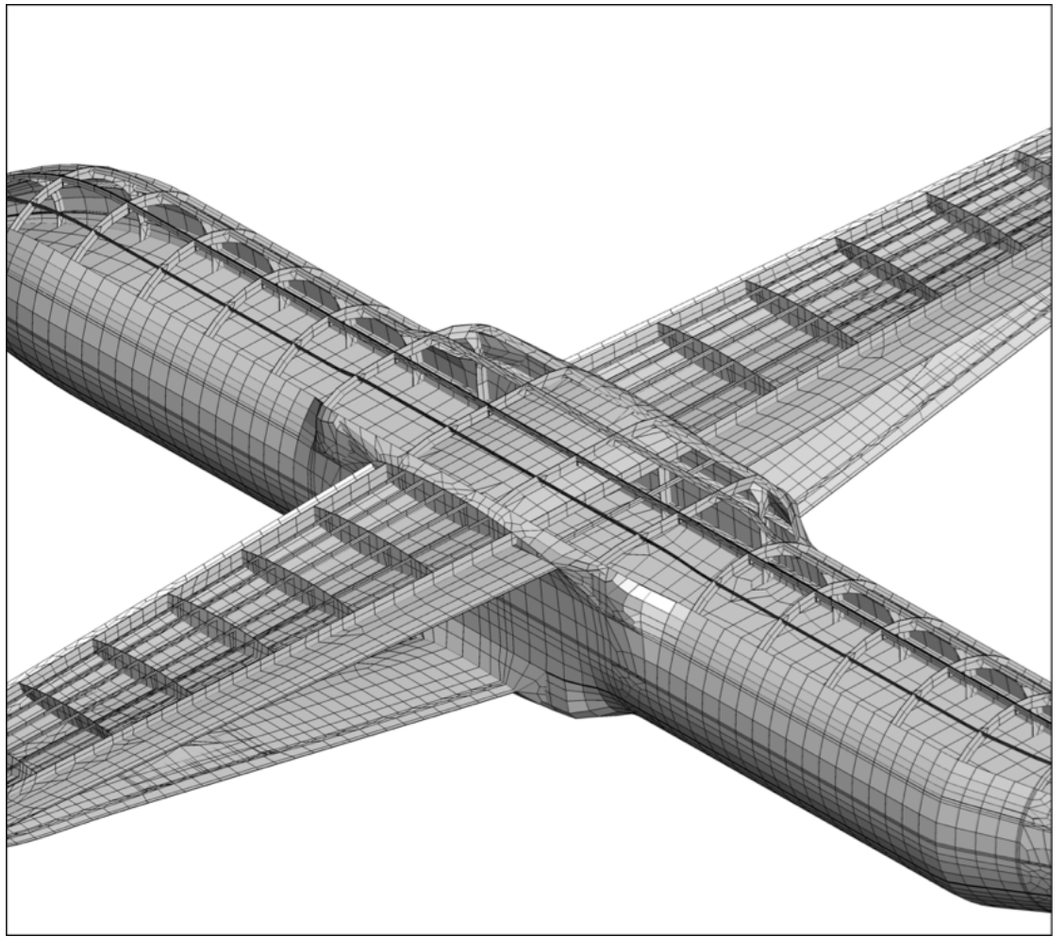


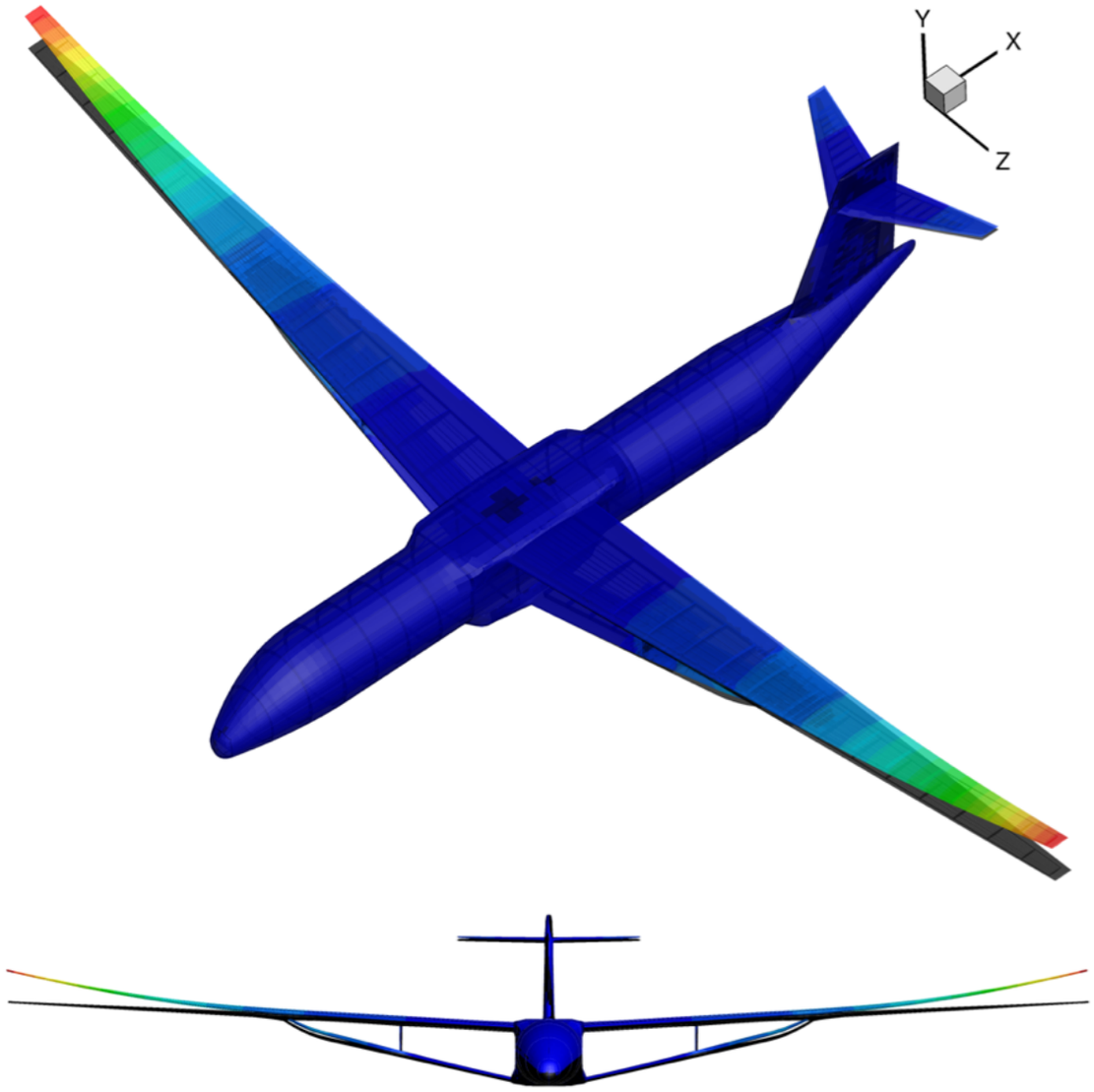
GeoMACH models aircraft geometries and structures using a differentiable parametrization

We obtained similar results with the RANS equations

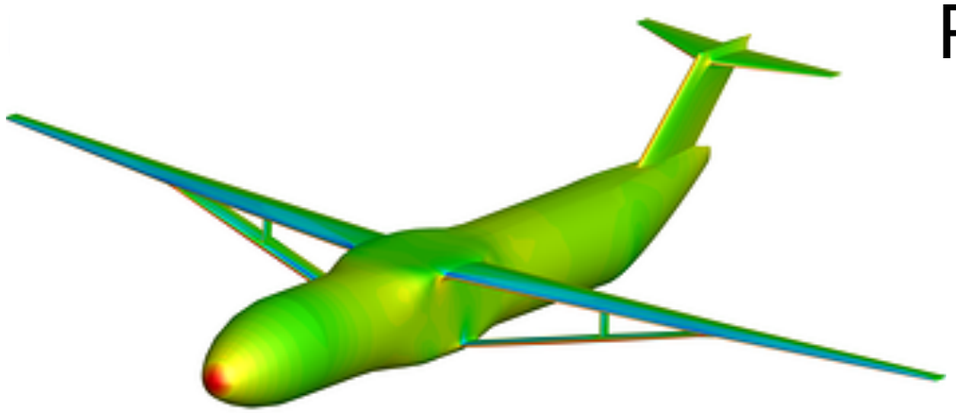


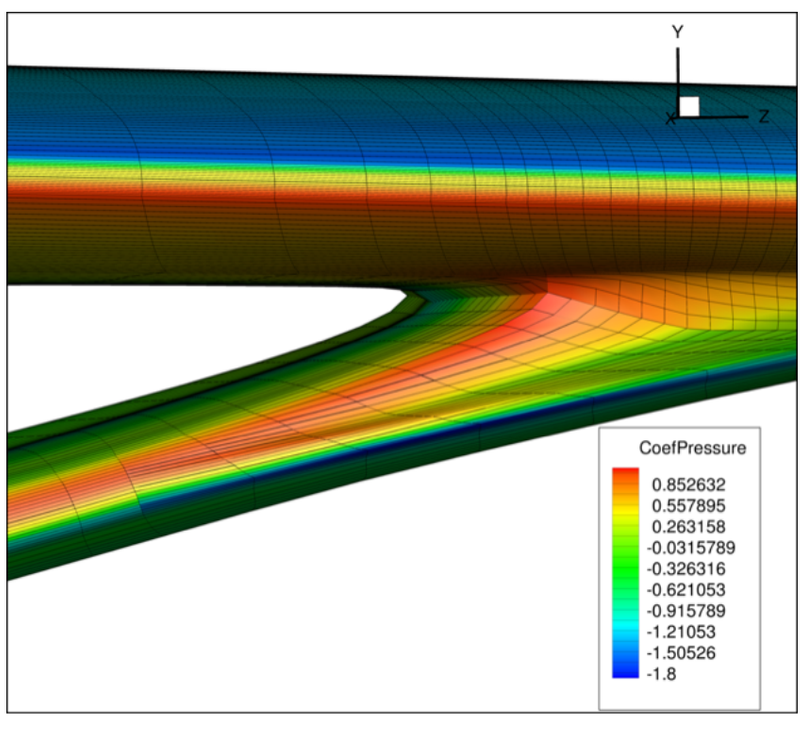
We also developed a structural model for the truss-braced wing using GeoMACH





Summary for Subproject 3





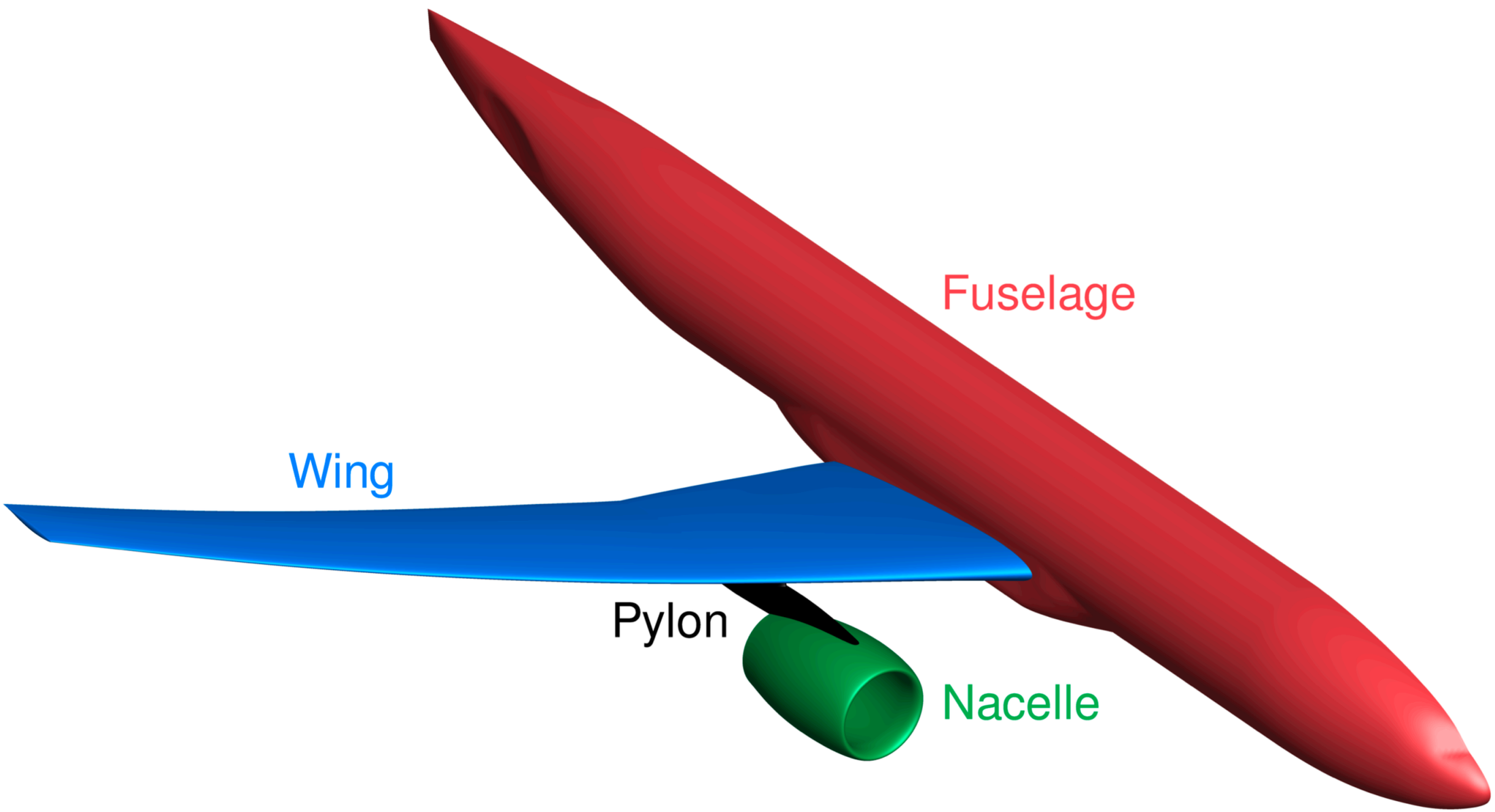
Phase 1 achievements:

- Developed geometries for the wing & struts and for the full TBW configuration
- Performed aerodynamic shape optimization to eliminate the shock
- Began development of a structural model for the TBW

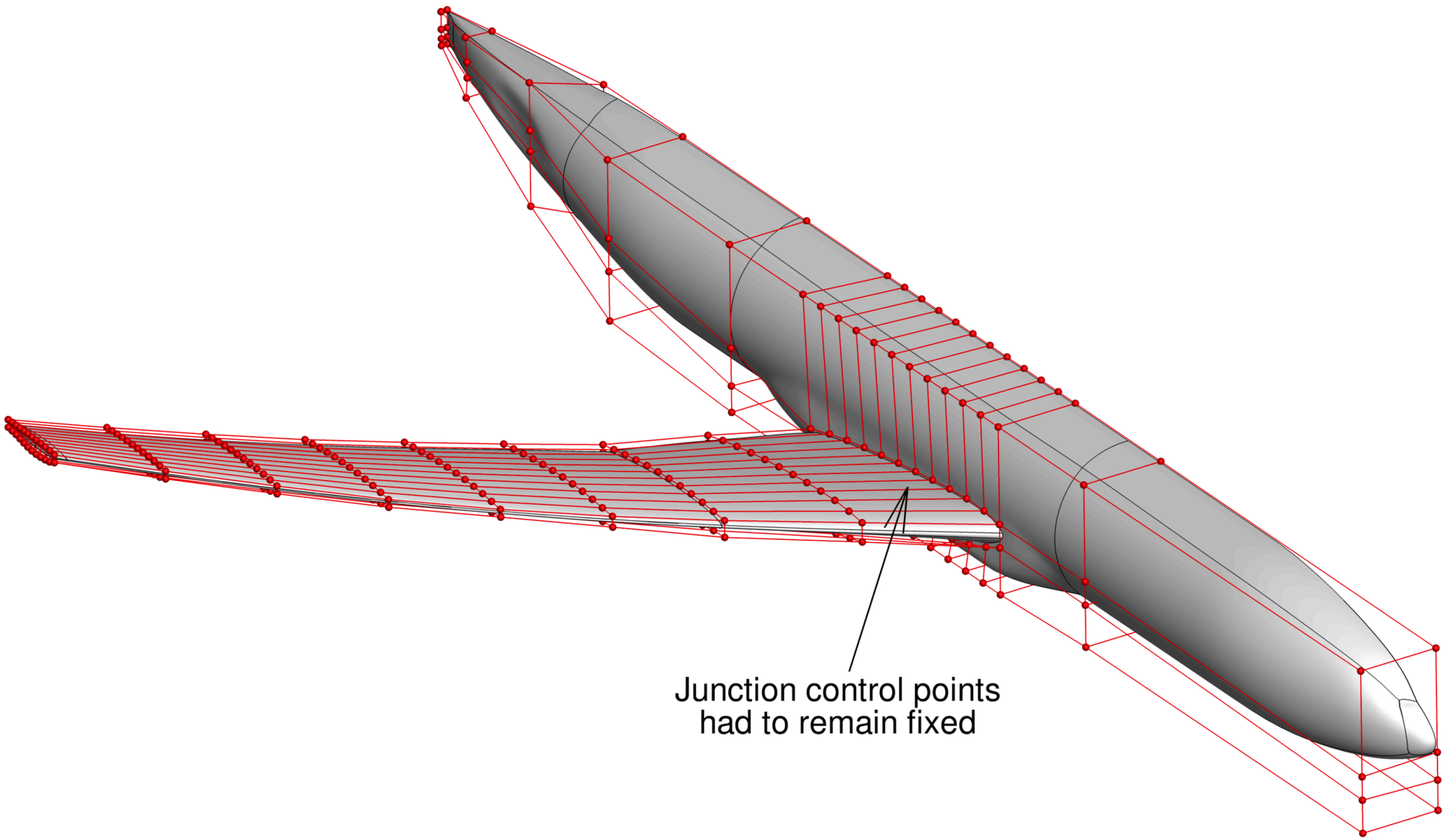
Phase 2:

- Perform detailed shape optimization
- Develop new shape optimization approach to address identified issues

When we think about an airplane design, we think about components

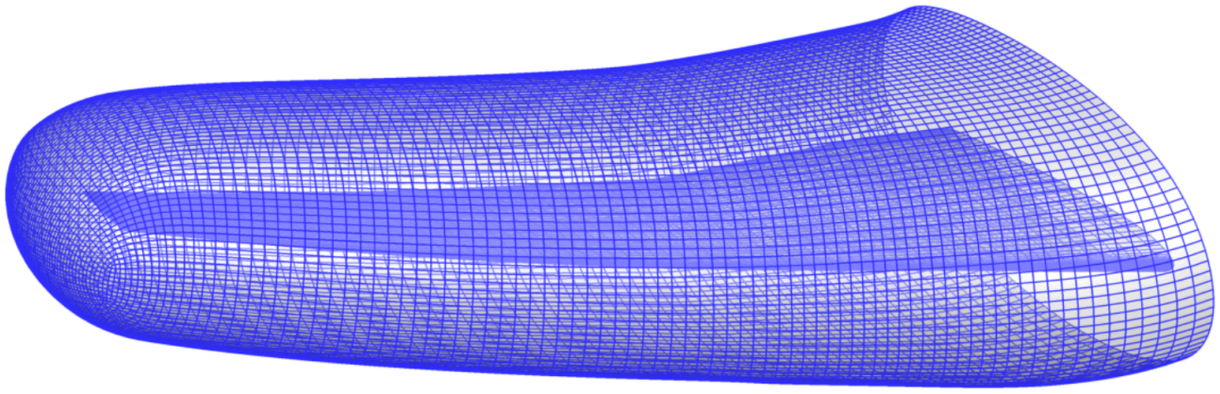


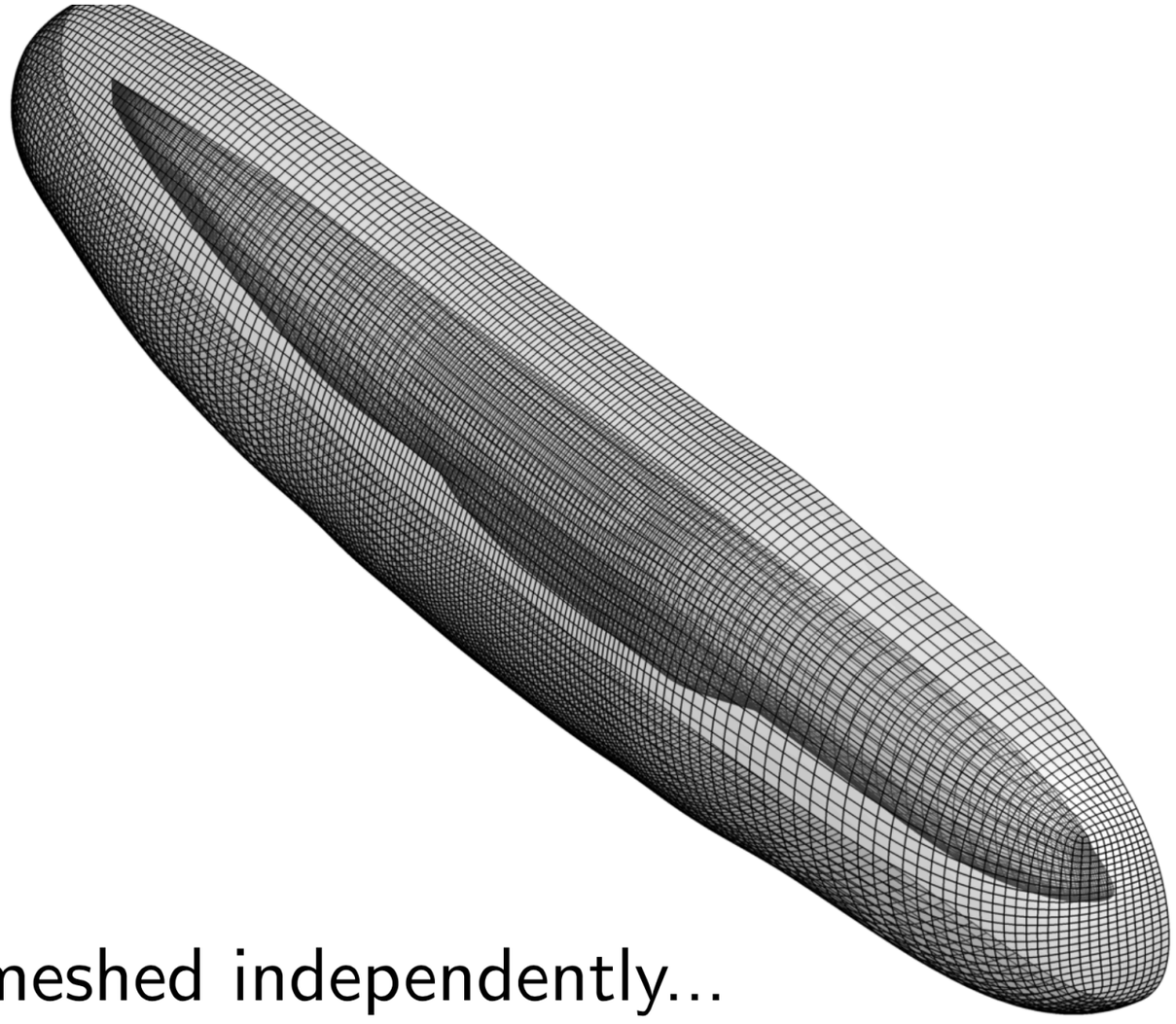
However, we have been operating on the complete configuration, which has limitations



Free-form deformation boxes (FFDs)

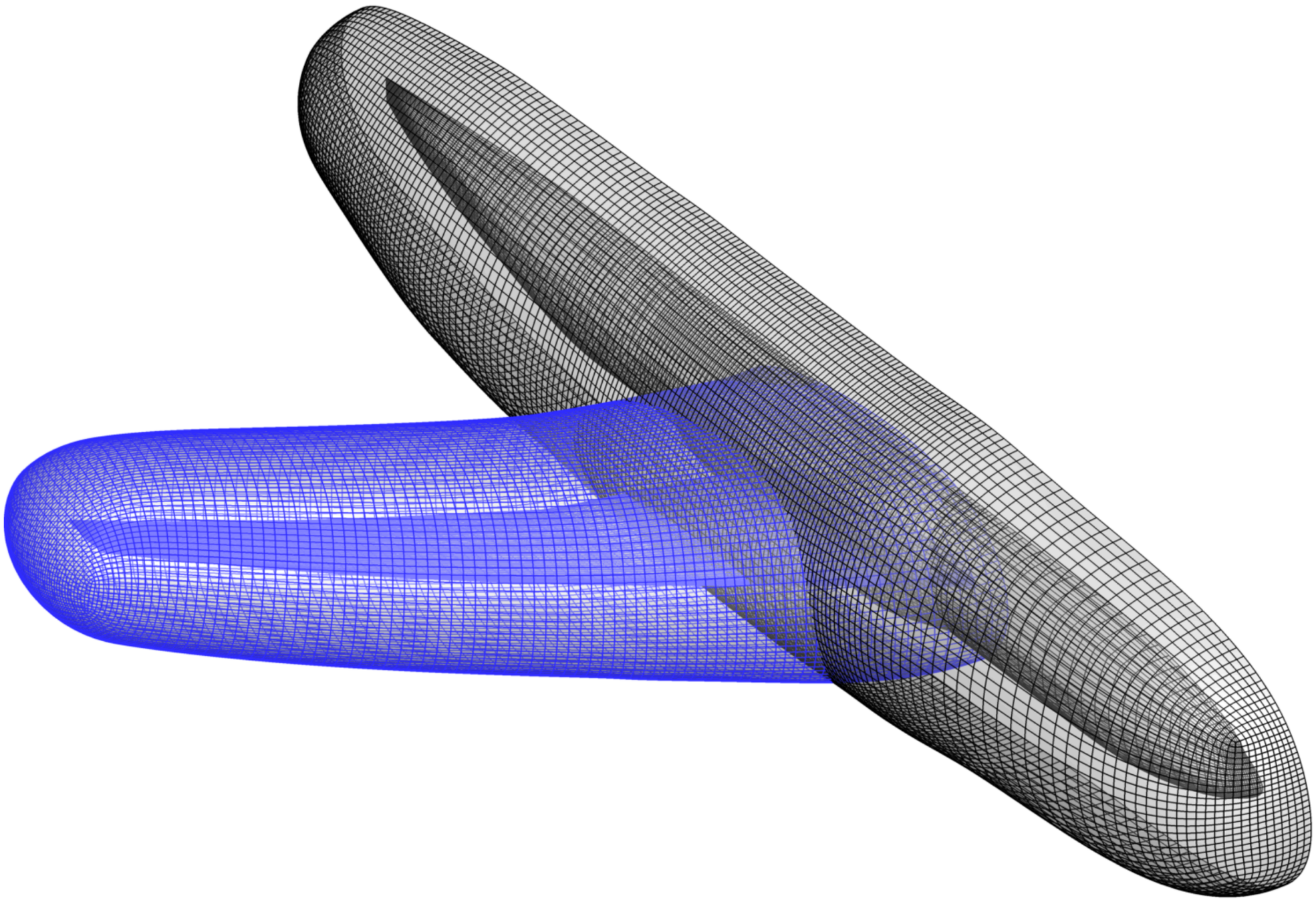
Overset meshes allow component-based mesh generation for CFD analysis





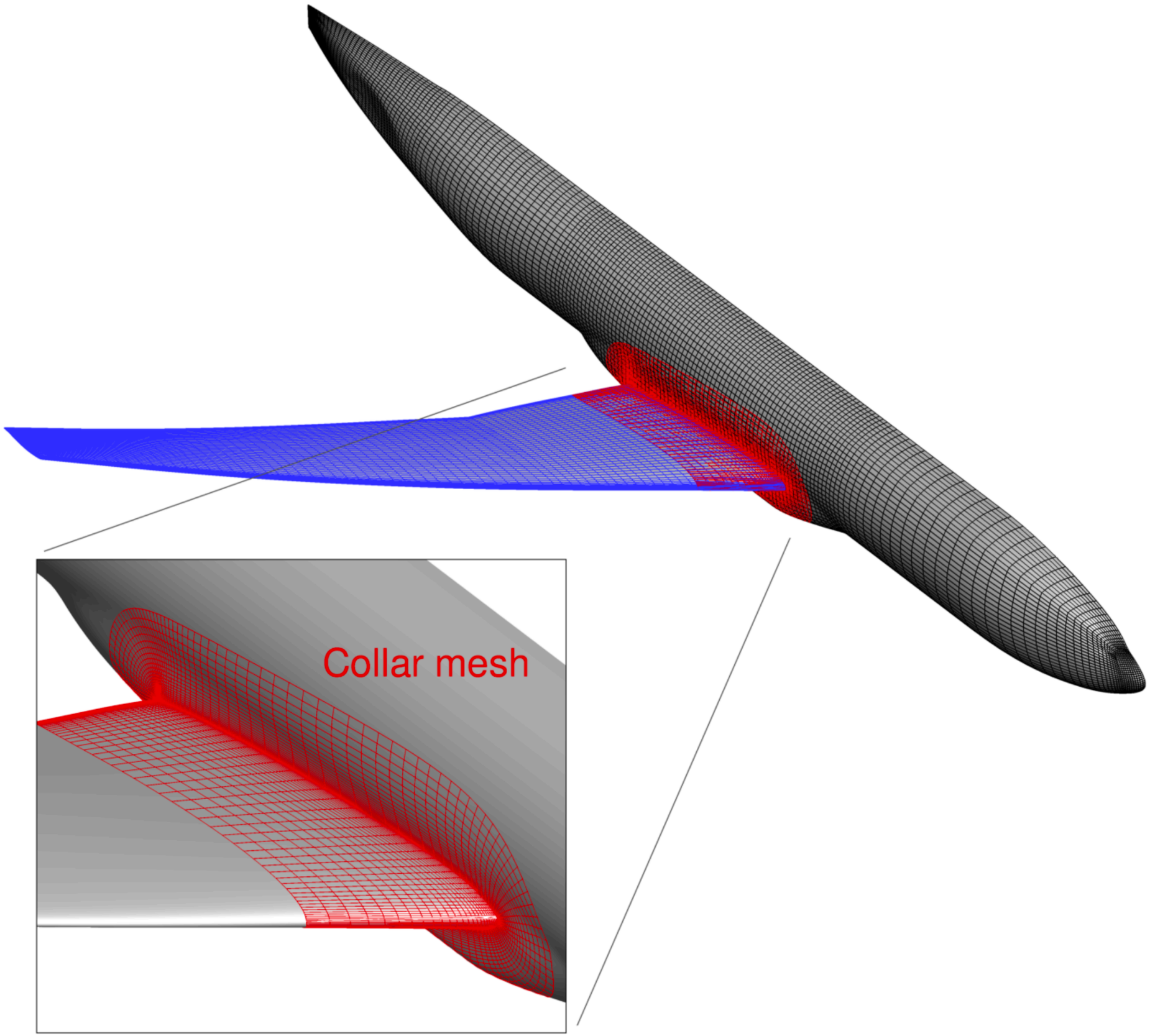
Each component can be meshed independently...

Overset meshes allow component-based mesh generation for CFD analysis



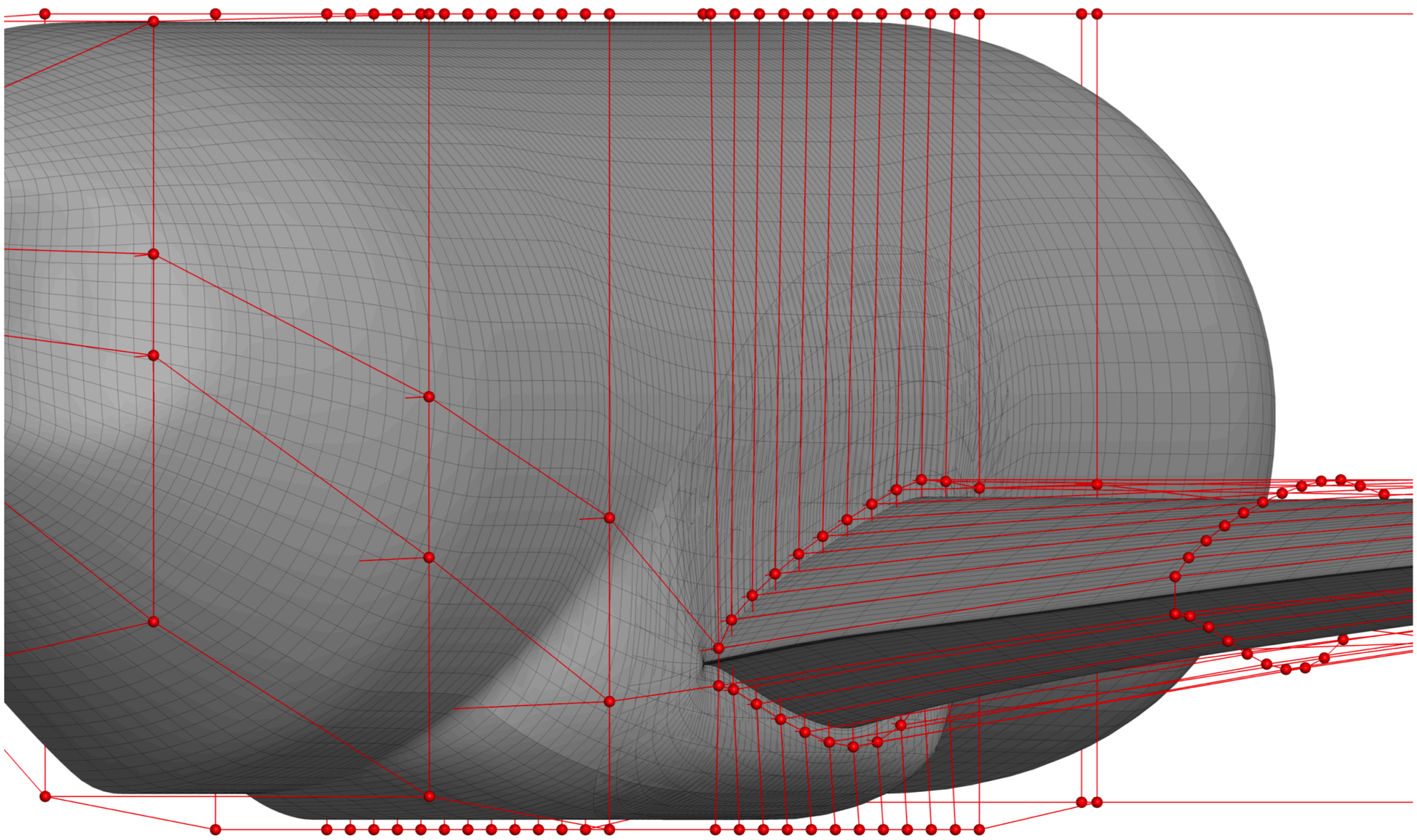
... and then combined to build the full geometry.

We need collar meshes to represent intersections



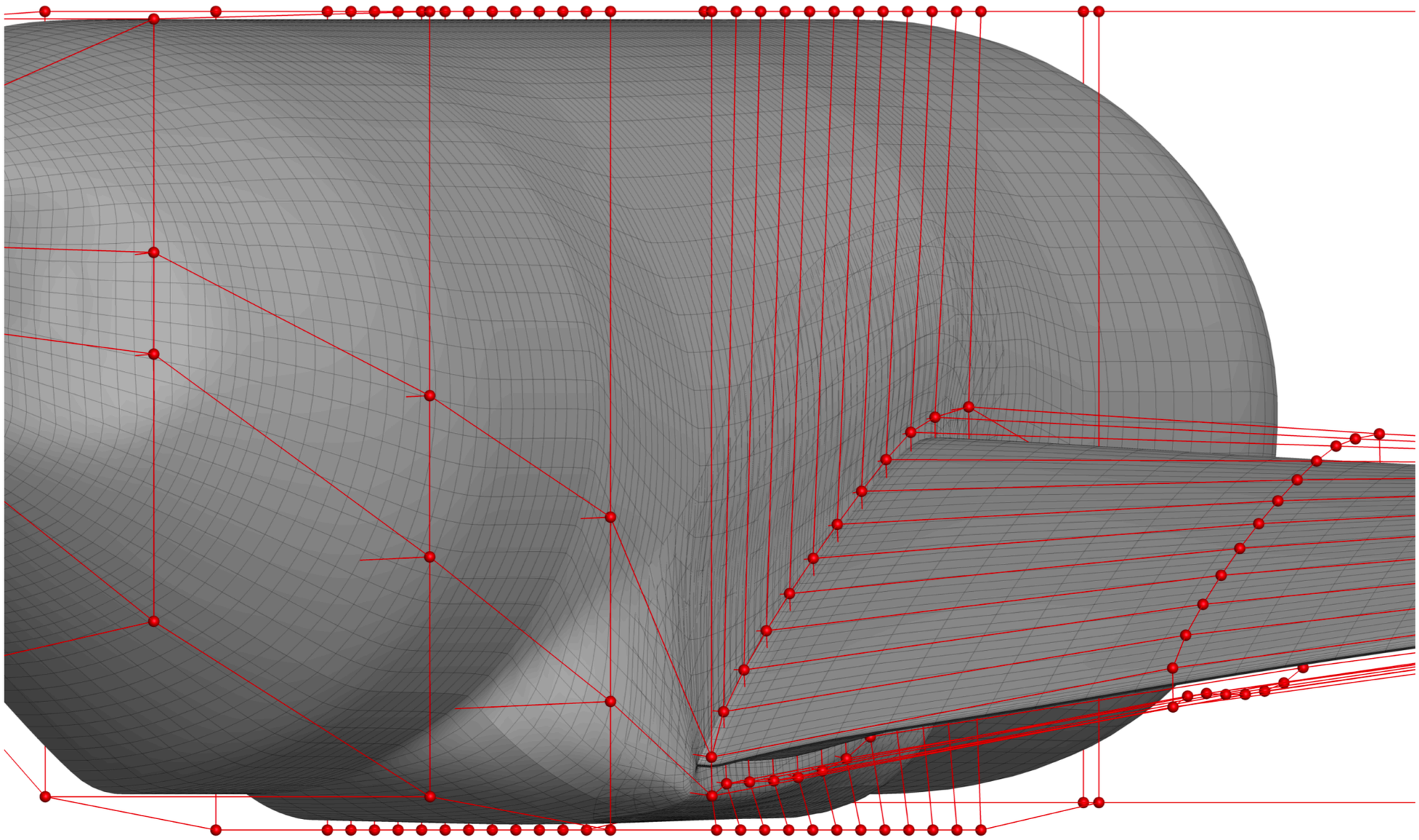
Overset maybe hampered if geometry manipulation is not compatible

If we rotate the wing...



Overset maybe hampered if geometry manipulation is not compatible

... the fuselage also changes

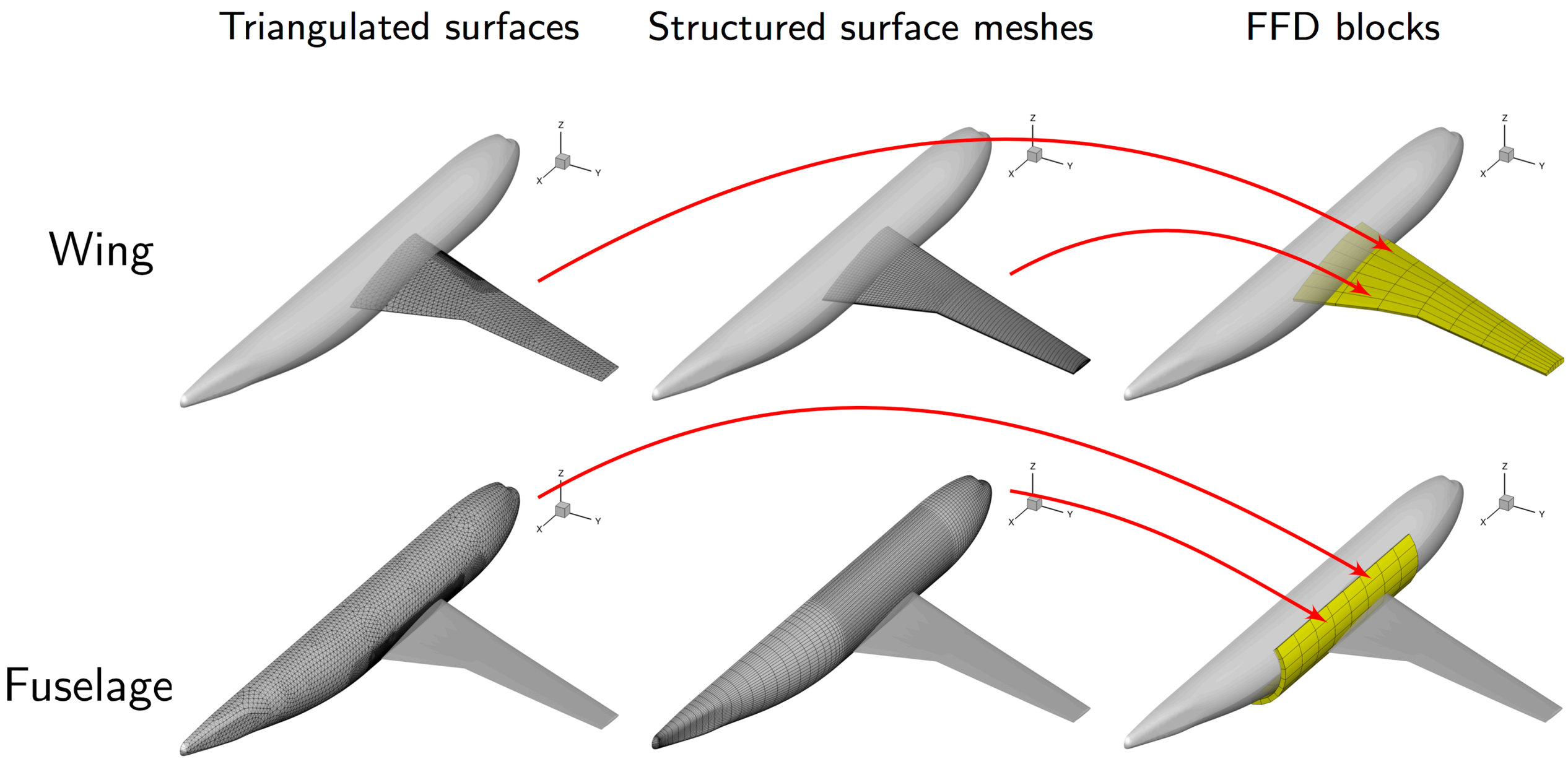


We implement a component-based geometry manipulator for aerodynamic shape optimization

pySurf is developed with the following points in mind:

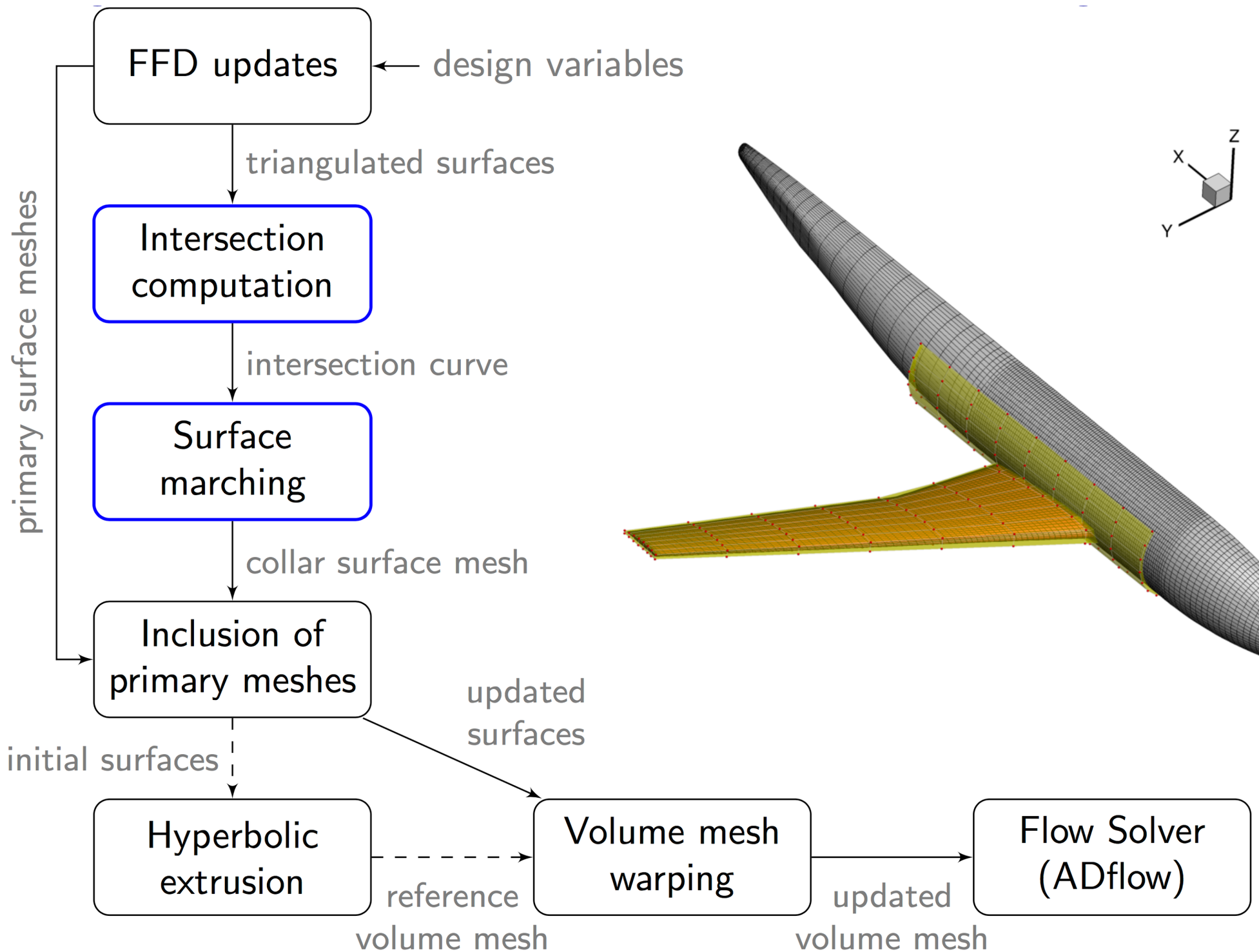
- Independent parametrization and manipulation of primary components
- Efficient computation of intersections between primary components
- Automatic collar mesh generation
- Differentiated code for gradient-based optimization

Each primary component requires three inputs

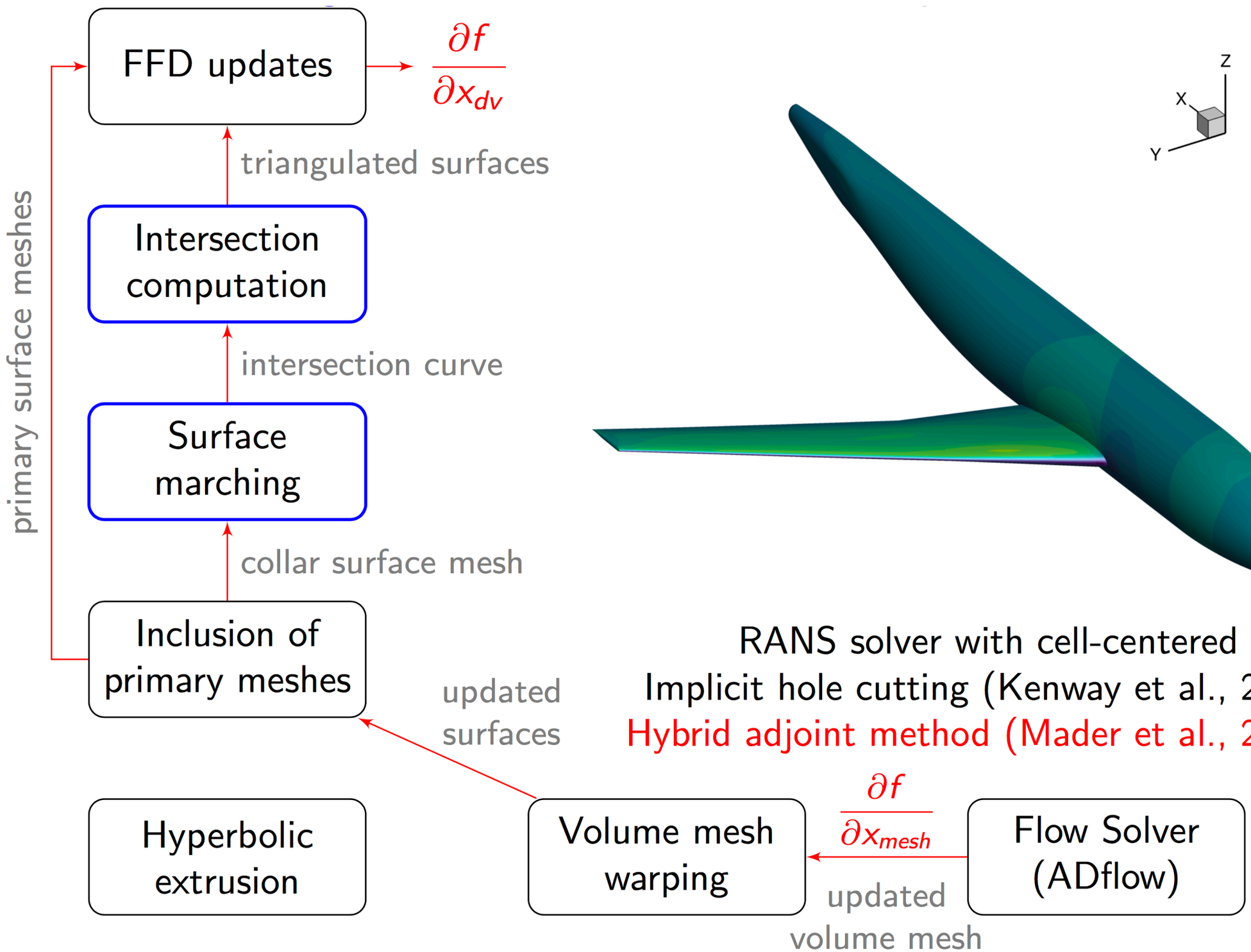


Both representations are embedded in the same FFD to ensure consistent displacements

Triangulated surfaces are used for automatic collar mesh generation

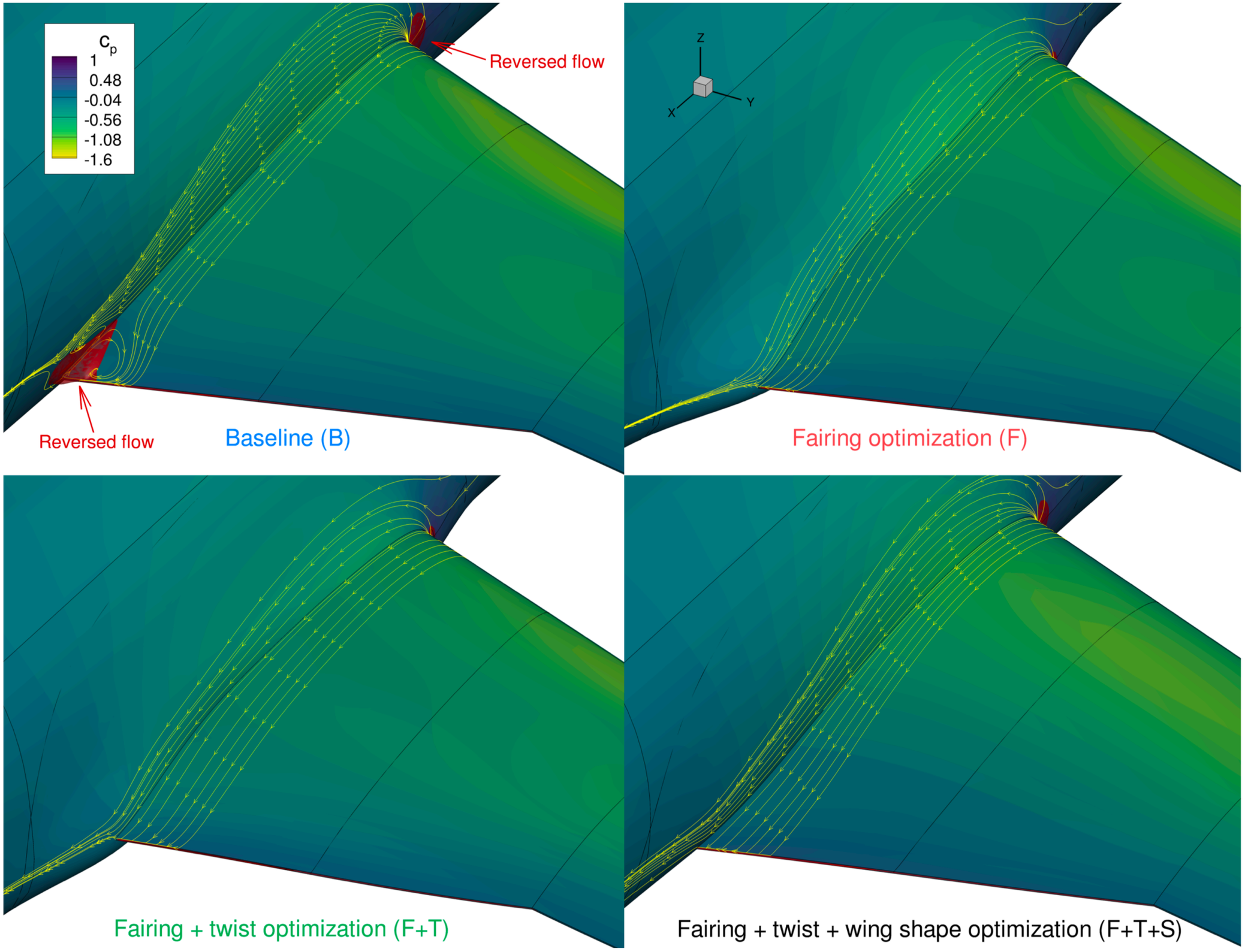


We use reverse algorithmic differentiation to compute derivatives

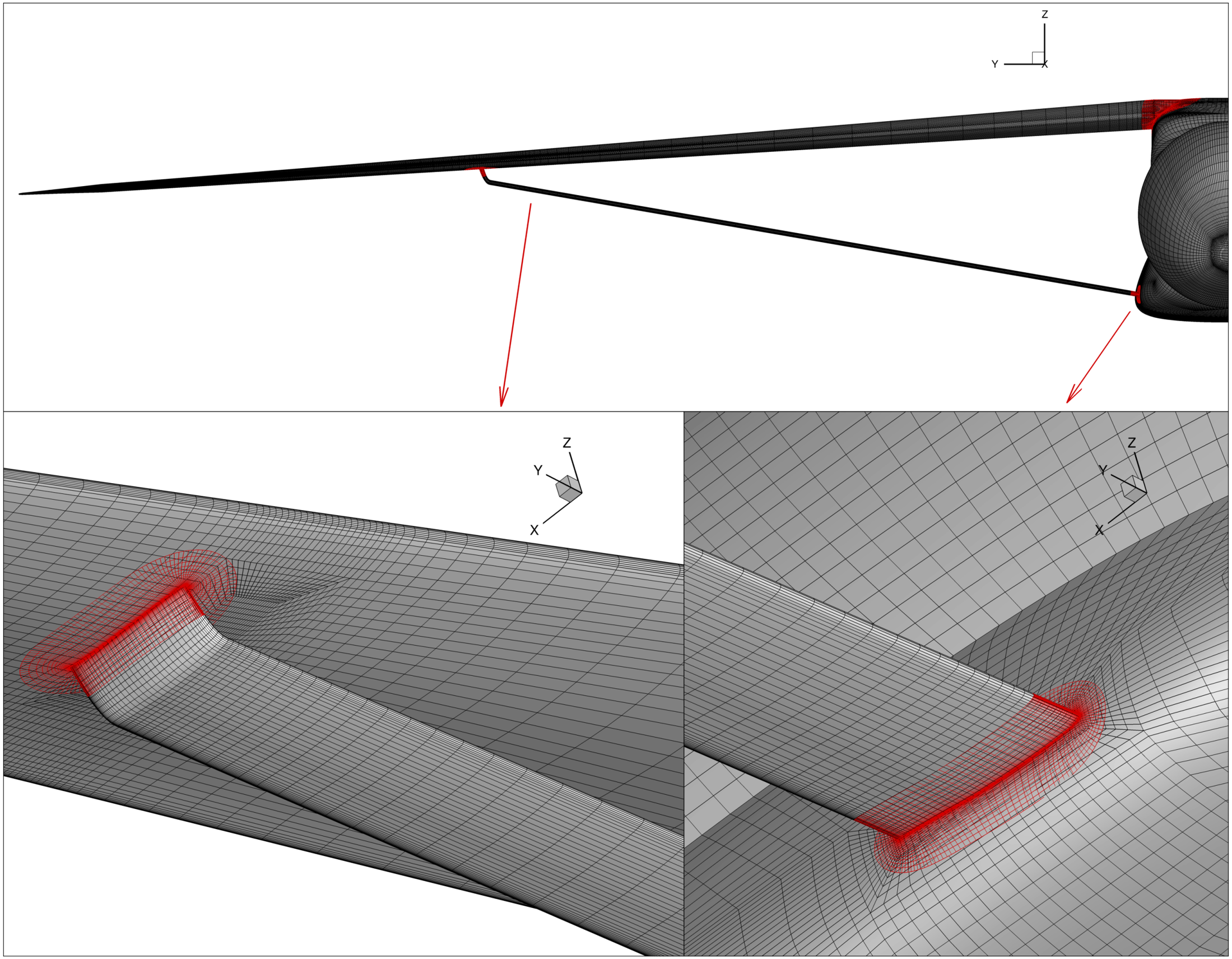


RANS solver with cell-centered FVM
Implicit hole cutting (Kenway et al., 2017)
Hybrid adjoint method (Mader et al., 2008)

We tested the capability by doing a wing-fuselage shape optimization study



We are applying this approach to the TBW



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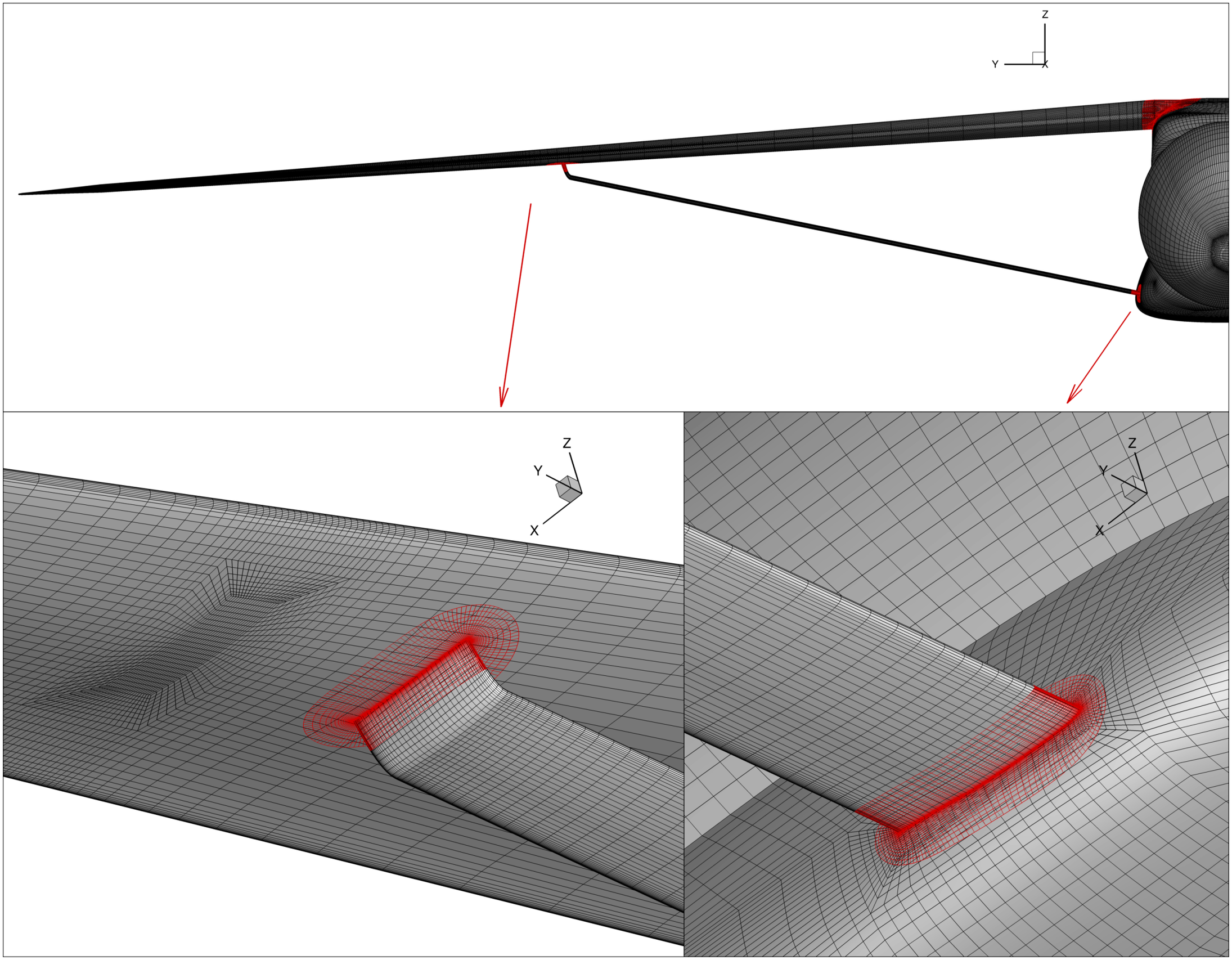
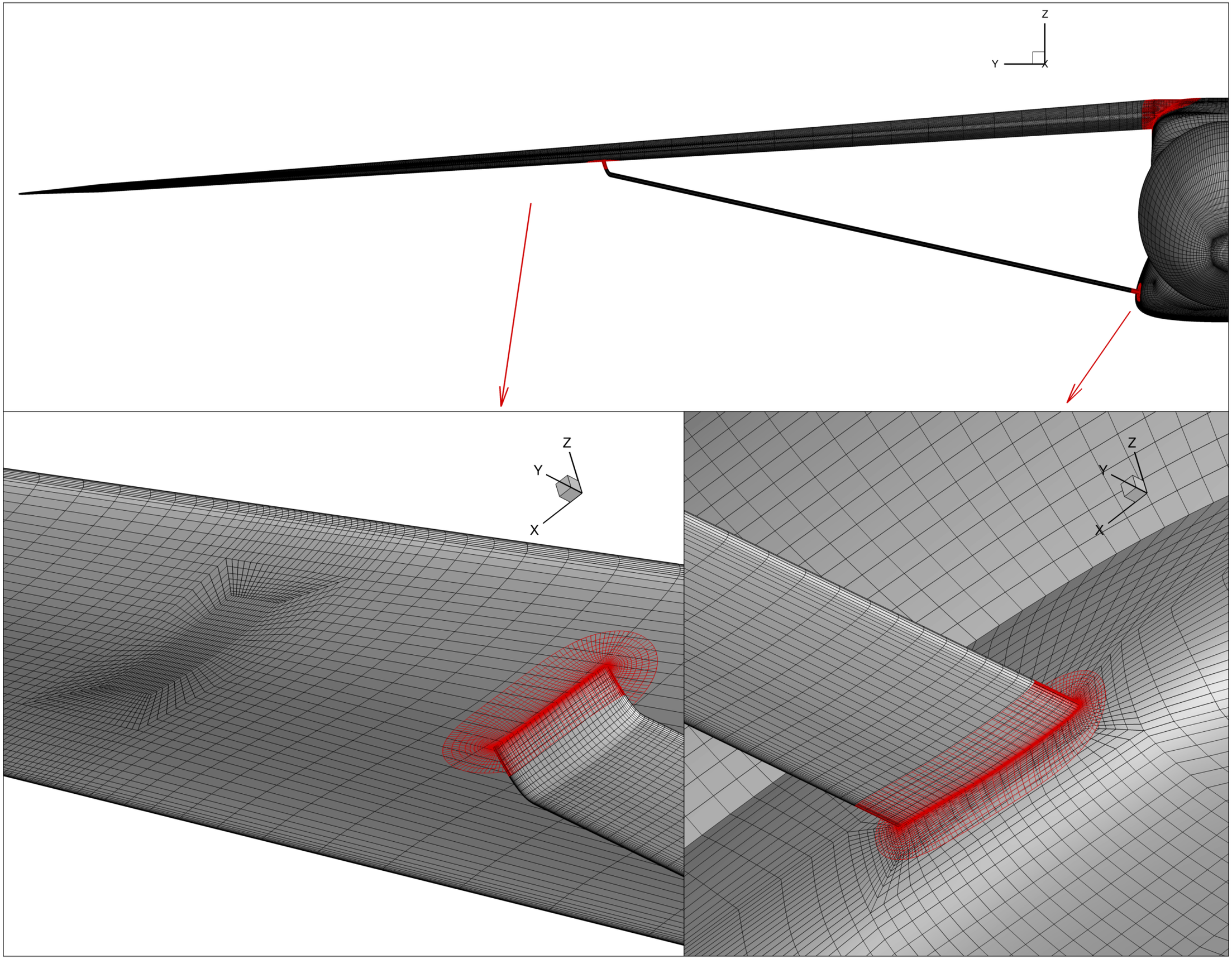
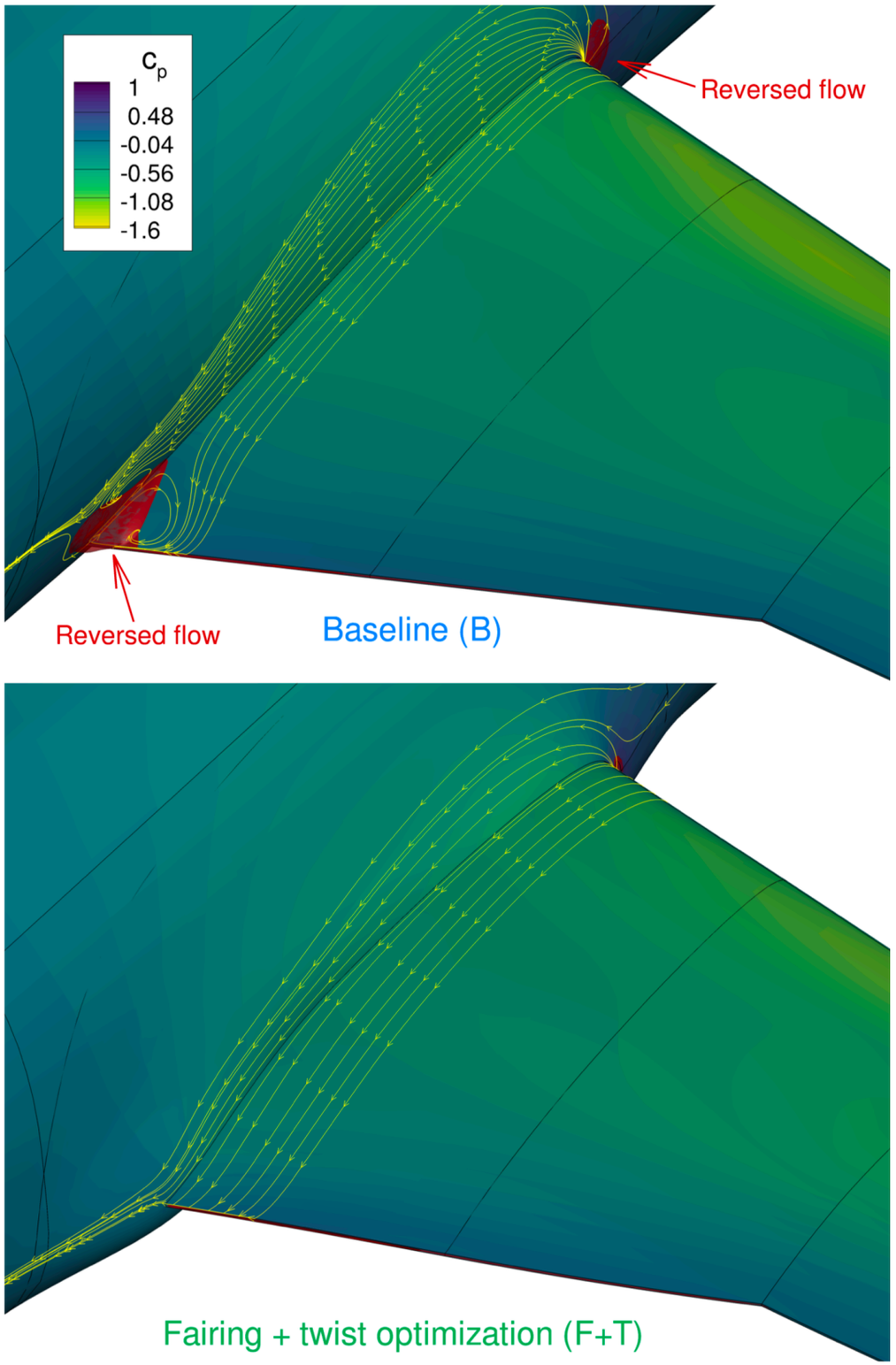


We are applying this approach to the TBW



Summary for Subproject 3



Phase 2 achievements:

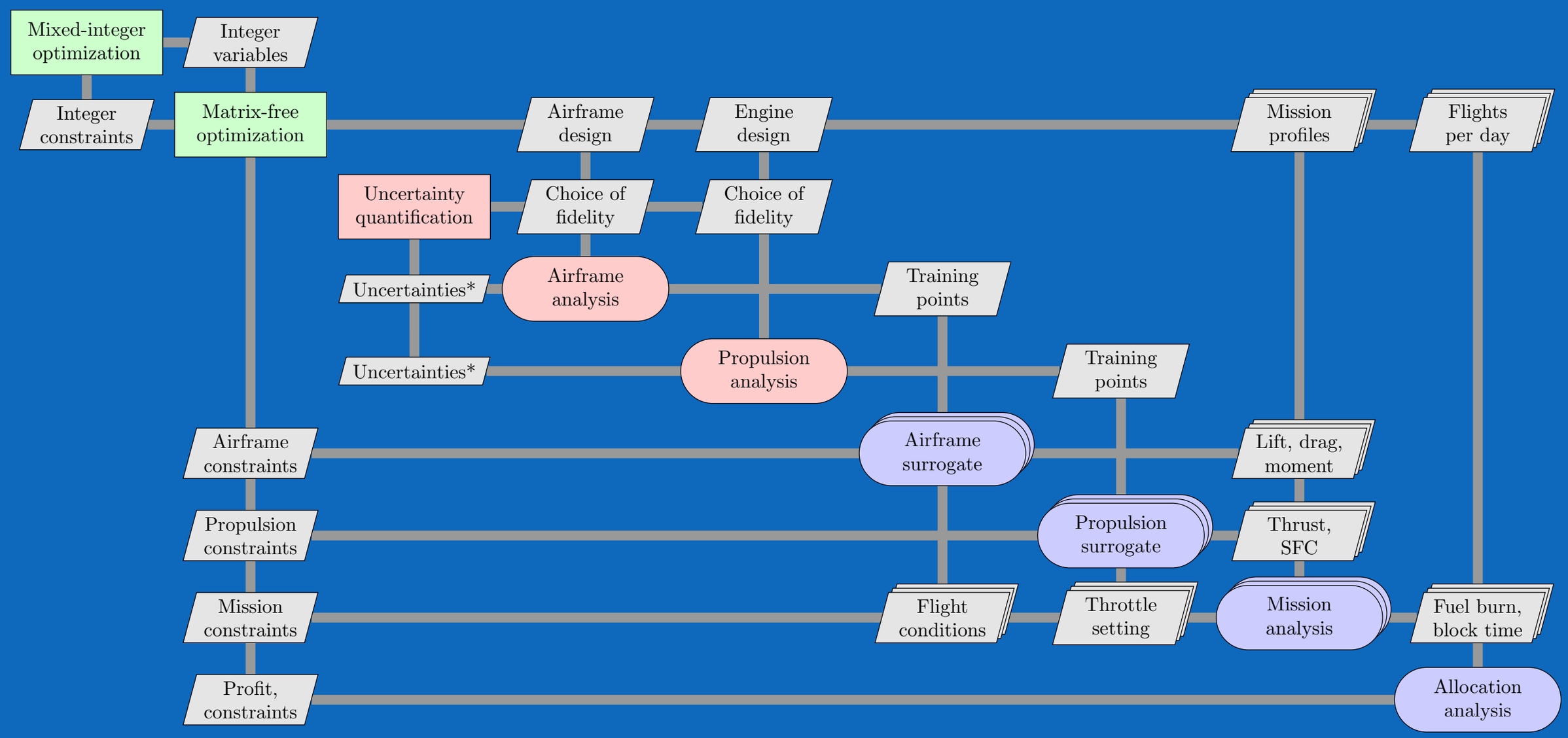
- Developed the capability to optimize components and intersections
- Discovered aerodynamic shape optimization trends in wing-fuselage design

Next steps:

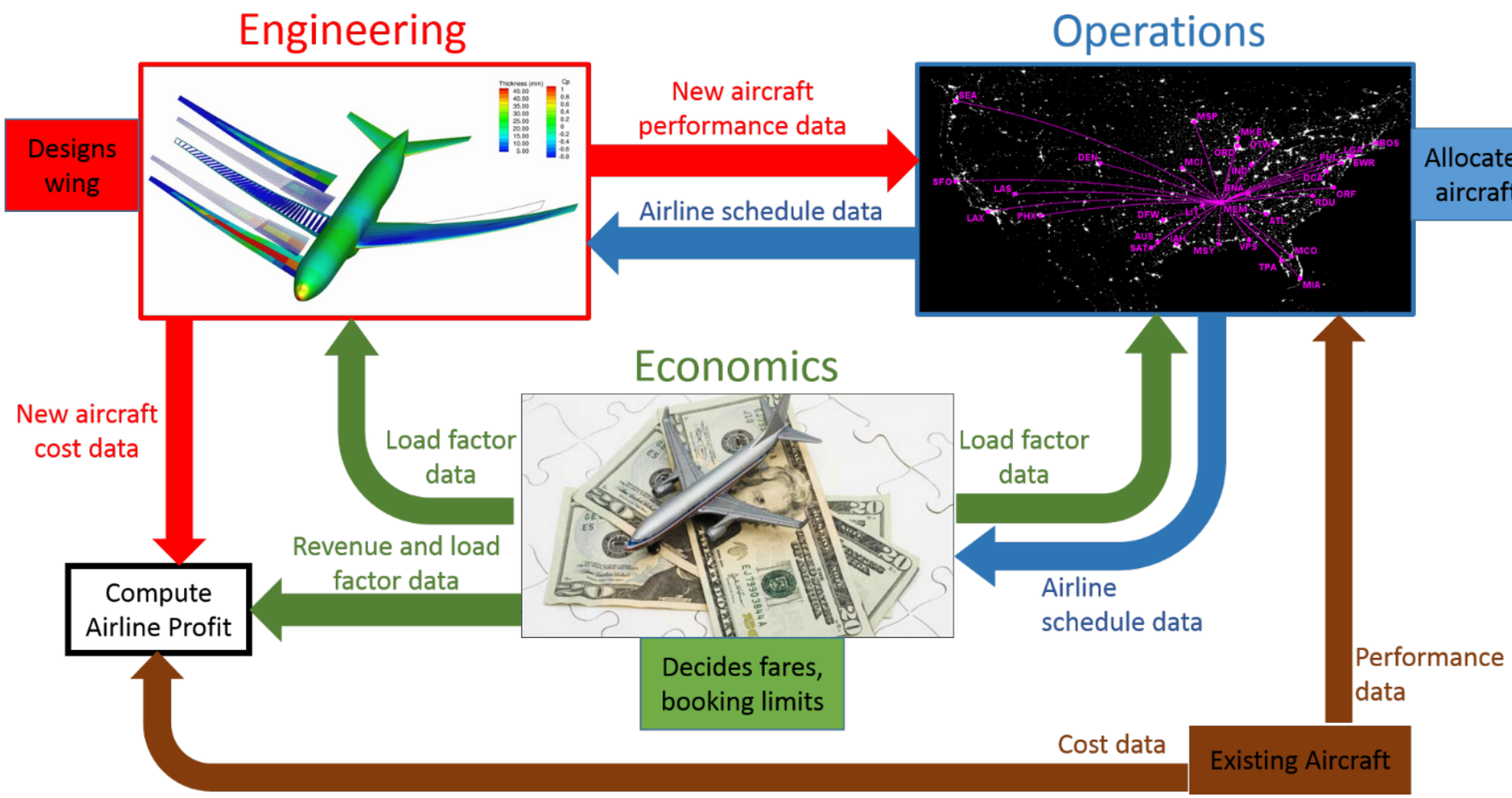
- Perform aerodynamic and aerostructural design optimization of TBW configuration

Subproject 4

Design, allocation and revenue management modeling and optimization



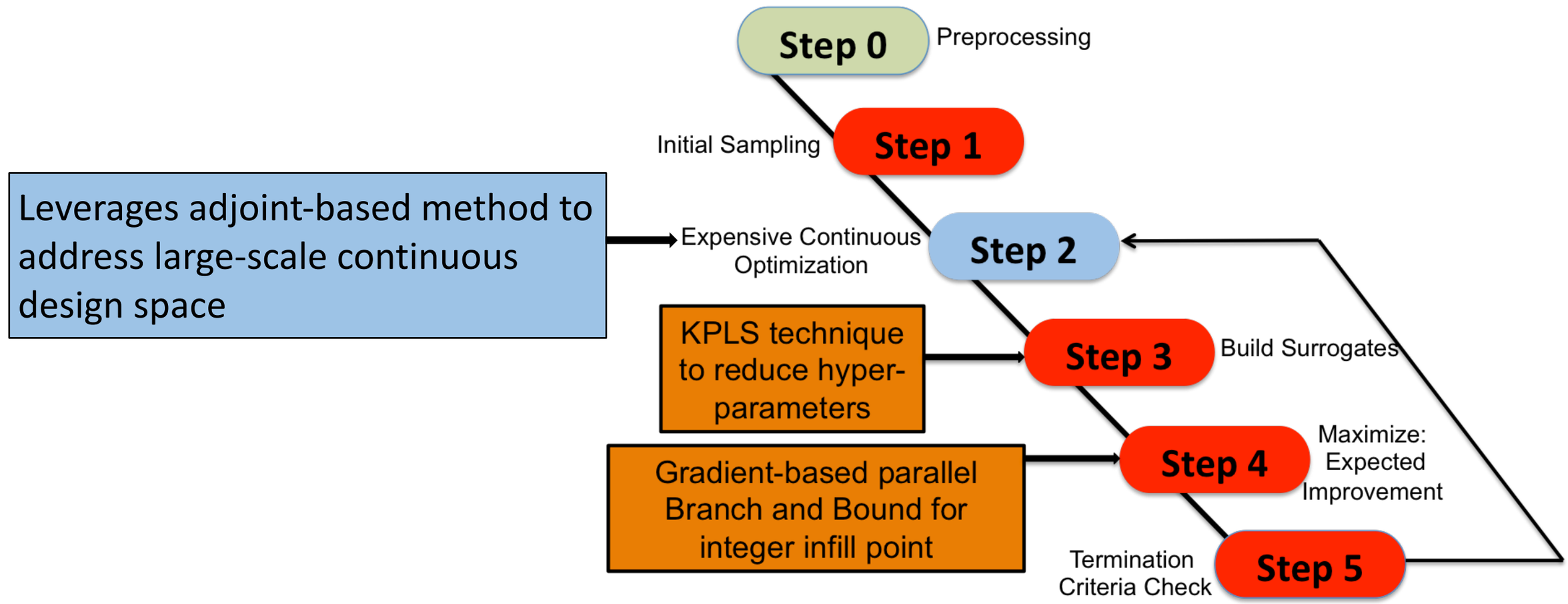
We demonstrated the ability to pose and solve design, allocation and revenue management as a monolithic optimization problem



Different subspaces and their interactions

Newly introduced “Economic” subspace to better calculate the fleet-level profit

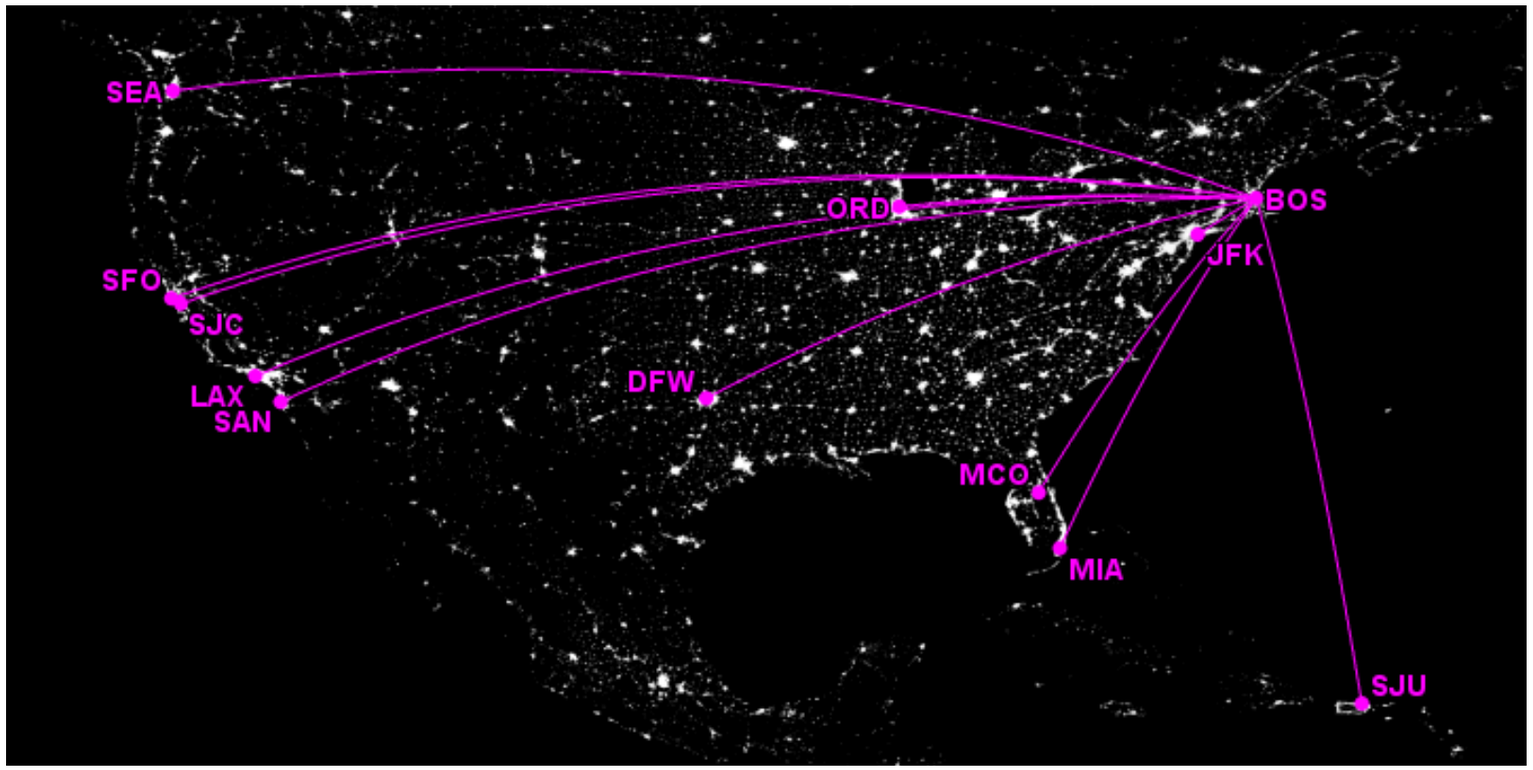
To address the monolithic problem, we developed a new optimization framework - A Mixed Integer Efficient Global Optimization (AMIEGO)

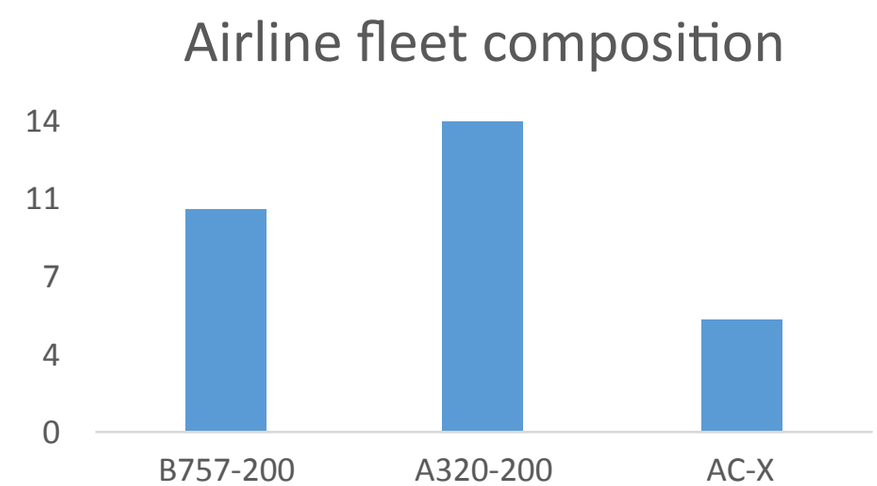


Can handle fully coupled expensive design-allocation-revenue management subspaces, moderate-scale integer design space and large-scale continuous design space

[Roy and Crossley, AIAA, 2016-1659]
[Roy, Moore, Hwang, Gray, Crossley, and, Martins, AIAA, 2017-1305]

We tested the design, allocation and revenue management problem on a 11 route problem using FLOPS

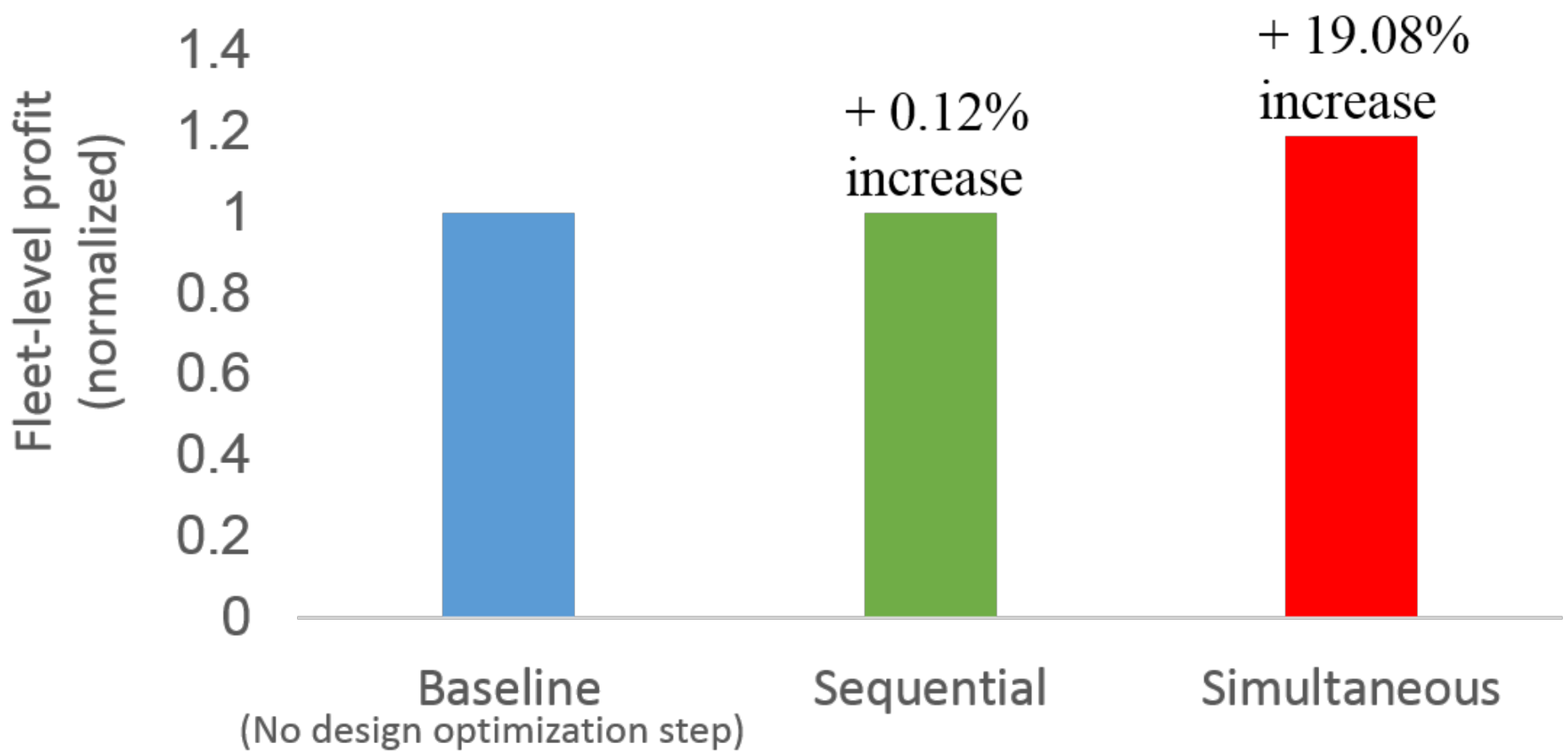




Goal is to design a 162 seat, 2940nmi passenger aircraft, ‘yet-to-be-acquired’ by the airline (based on Boeing 737-800 aircraft)

This problem has 33 integer variables of the allocation problem and 61 continuous variables of the design and revenue management problems

Design-allocation-revenue management optimization yielded large profit increases with the simultaneous approach



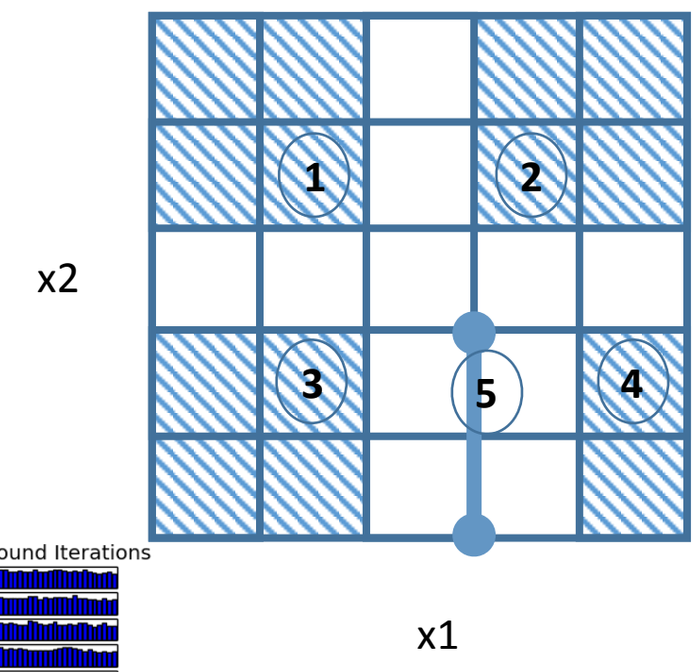
Demonstrates the need to capture the synergism that exists among the interacting group of subspaces

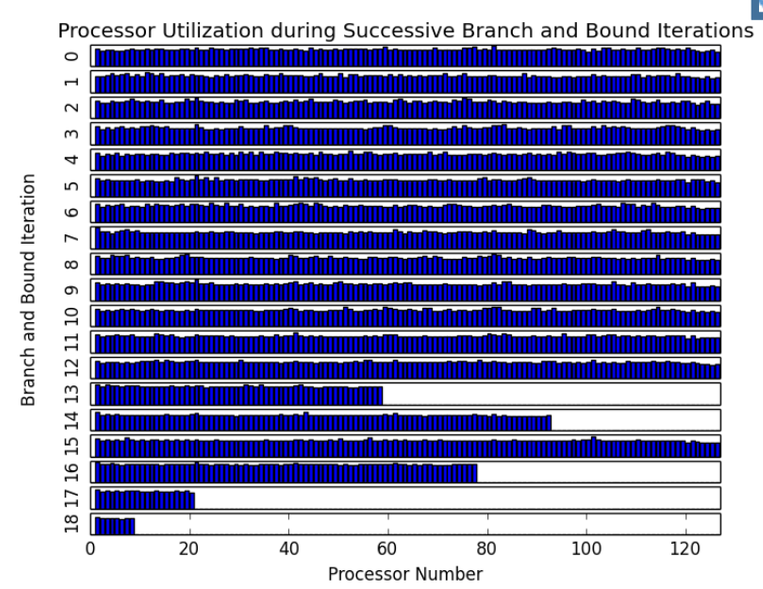
[Roy, S., Ph.D. Thesis, Purdue University, 2017]

We have ported AMIEGO to OpenMDAO

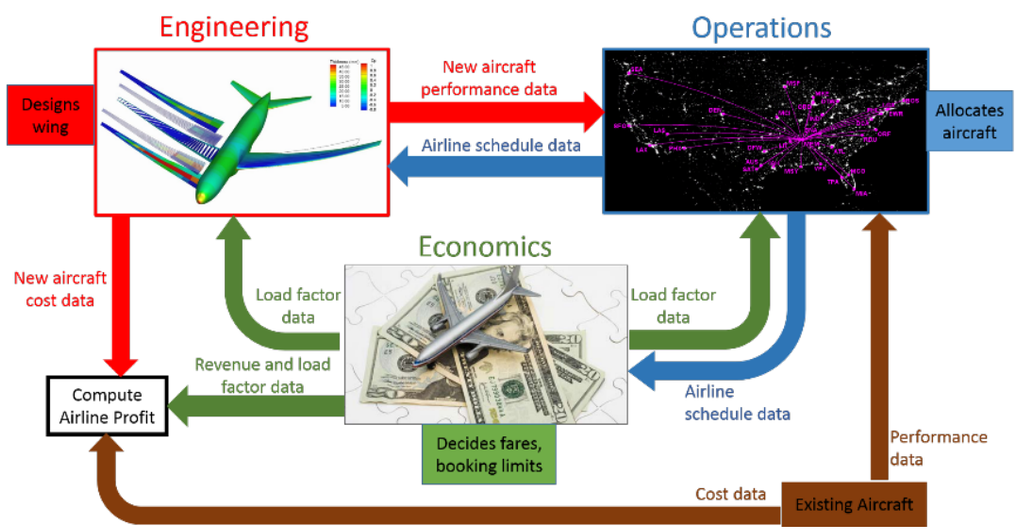
Available as an MINLP driver

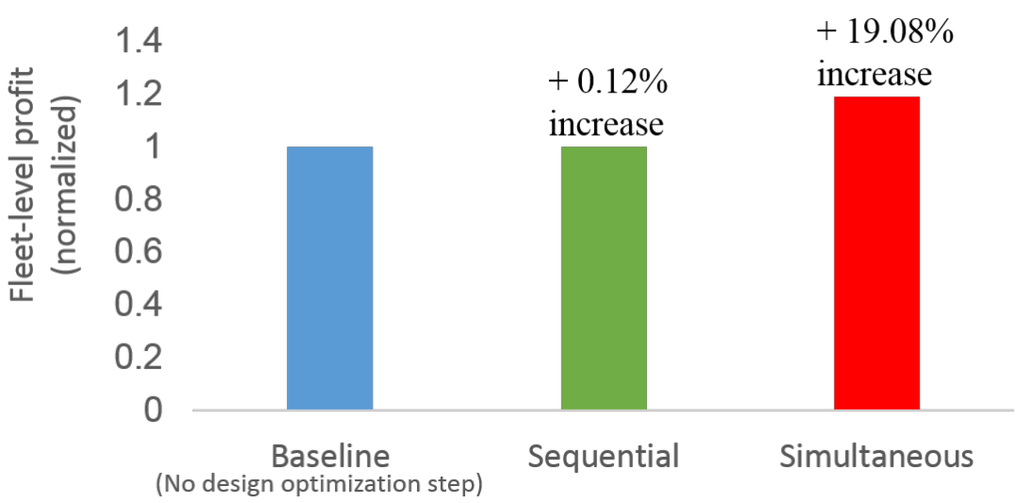
Initial aggressive splitting feature (step 4 of AMIEGO) makes efficient use of parallel computing resources – helps get rid of vast majority of design space





Summary for Subproject 4





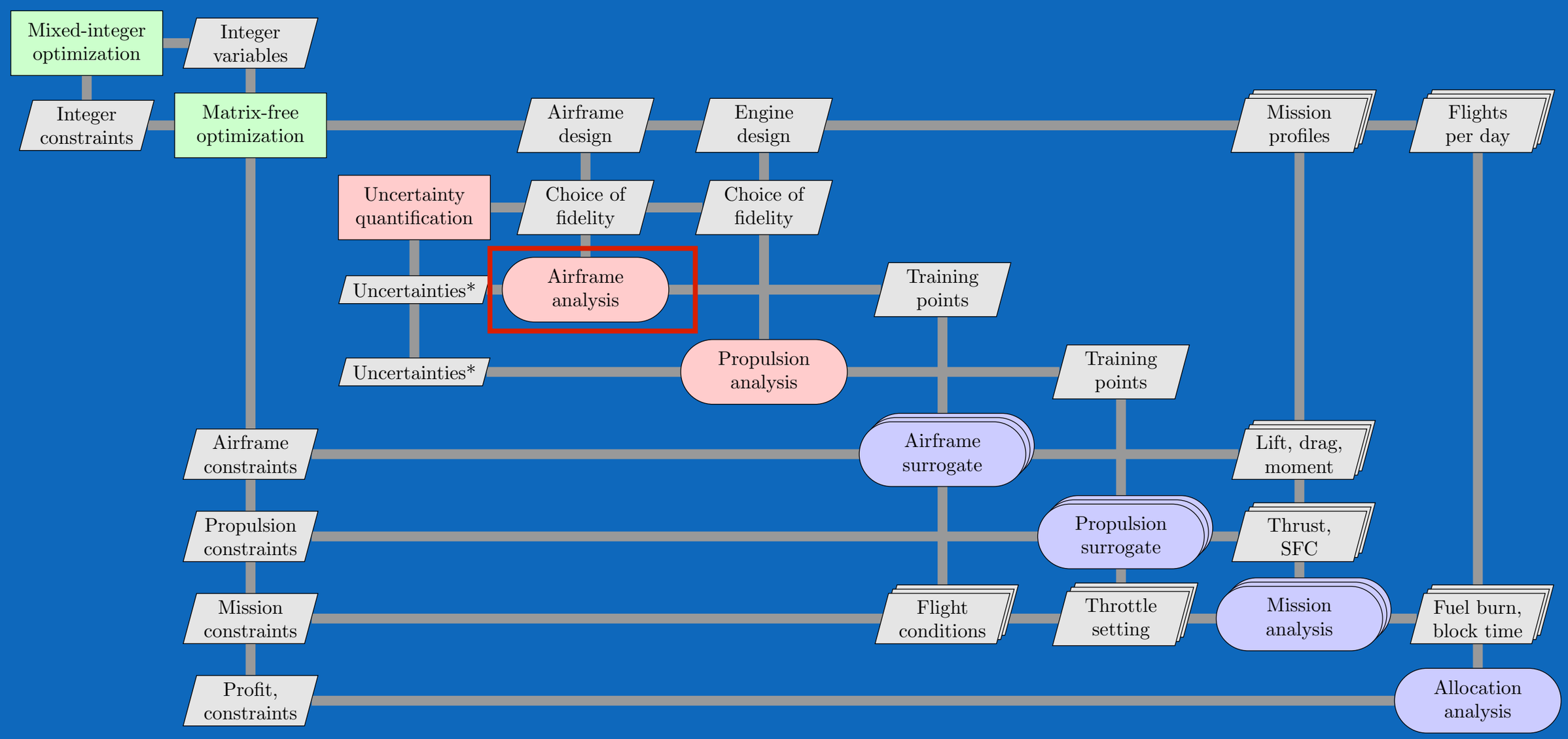
Phase 2 achievements:

- Developed the ability to pose and solve design and allocation as a monolithic optimization problem
- Introduced revenue management subspace
- Developed a new optimization framework (AMIEGO) to address expensive MINLP problems

Next steps:

- Replace FLOPS with the high fidelity analysis tools

Subproject 5:
A low-order model for transonic flutter prediction



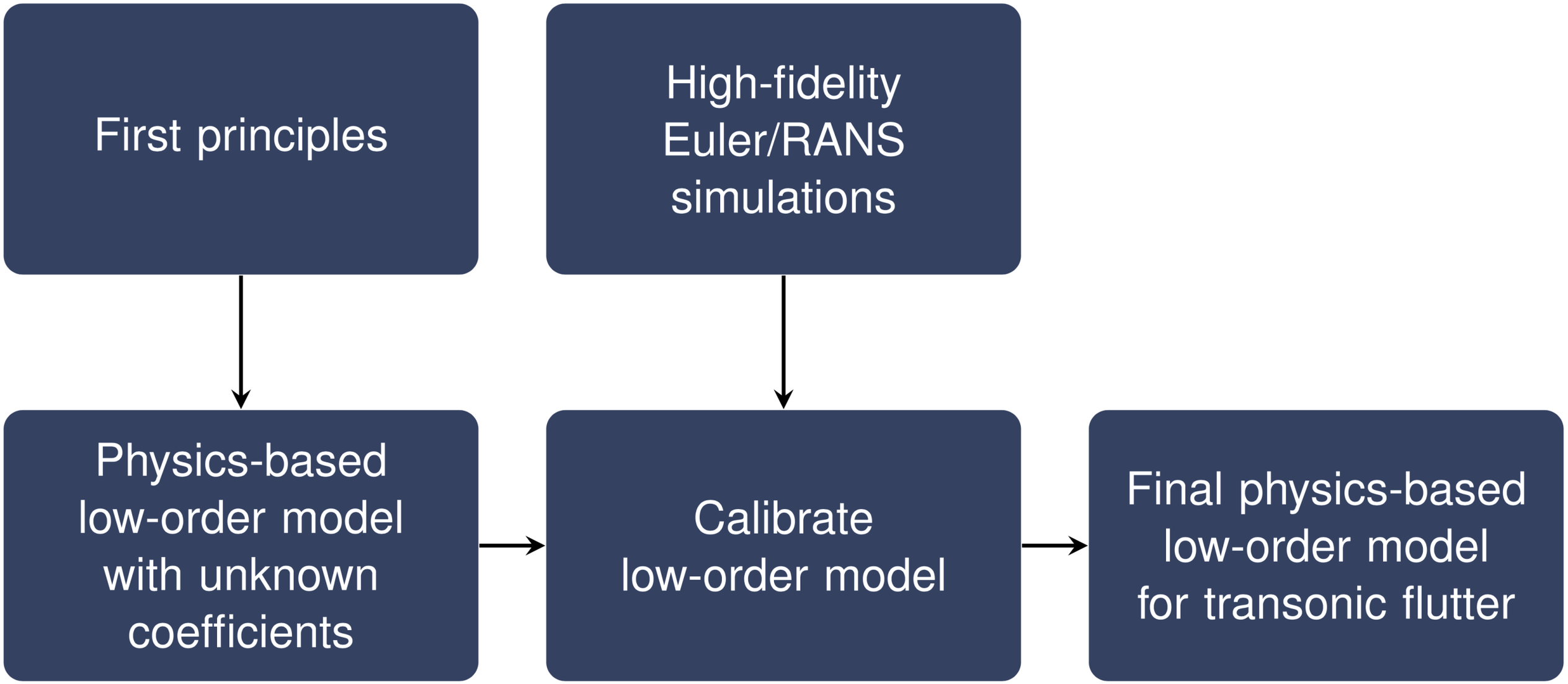
Research problem

- Commercial transport aircraft fly in transonic flow regime
- Need accurate transonic flutter models for conceptual aircraft design
- Models need to be cheap to allow for thousands of design iterations

Goals

- Develop physics-based low-order model for transonic flutter over airfoils
- Train coefficients of low-order model using high-fidelity Euler/RANS simulations

Our approach

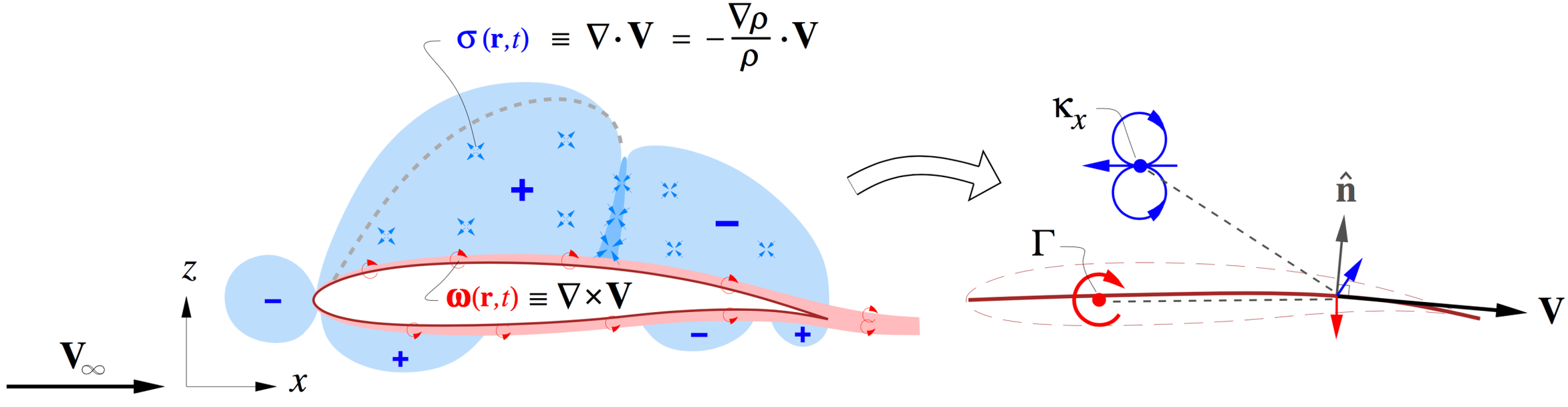


Helmholtz decomposition

Any external velocity field is uniquely defined by its divergence and curl (volume-source and vorticity) fields

Basic idea: Represent $\sigma\left(\mathbf{r},t\right)$ and $\boldsymbol{\omega}\left(\mathbf{r},t\right)$ fields by only their lowest spatial moments

$$\mathbf{V}(\mathbf{r},t) \;=\; \frac{1}{2\pi}\iint \sigma(\mathbf{r}',t)\frac{\mathbf{r}-\mathbf{r}'}{|\mathbf{r}-\mathbf{r}'|^2}\,\mathrm{d}\mathcal{A}' \;+\; \frac{1}{2\pi}\iint \boldsymbol{\omega}(\mathbf{r}',t)\times\frac{\mathbf{r}-\mathbf{r}'}{|\mathbf{r}-\mathbf{r}'|^2}\,\mathrm{d}\mathcal{A}' \;+\; \mathbf{V}_\infty$$



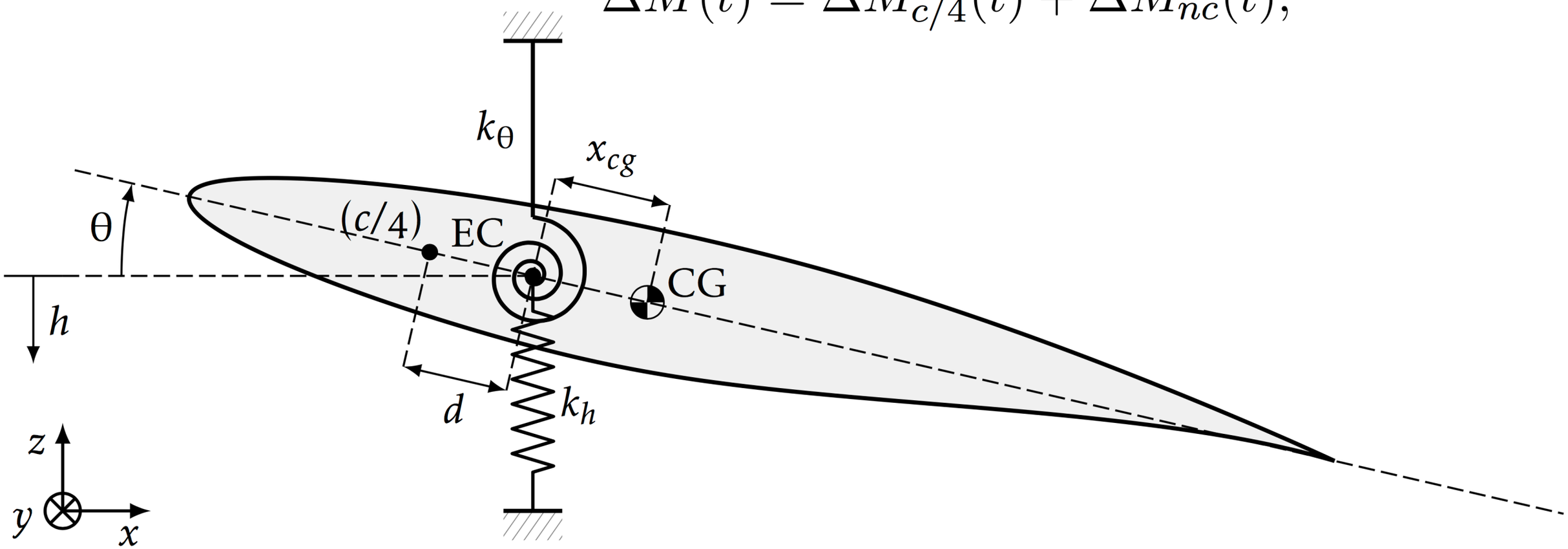
Typical section structural model

$$
\begin{aligned}
m\Delta\ddot{h} + k_h\Delta h + S_\theta\Delta\ddot{\theta} &= -\Delta L \\
S_\theta\Delta\ddot{h} + k_\theta\Delta\theta + I_\theta\Delta\ddot{\theta} &= \Delta M + \Delta L\, d
\end{aligned}
$$

(Bisplinghoff et al. 1996)

$$\Delta L(t) = \rho_\infty V_\infty \Delta\Gamma + \rho_\infty c\Delta\dot{\Gamma} + \Delta L_{nc}(t)$$

$$\Delta M(t) = \Delta M_{c/4}(t) + \Delta M_{nc}(t),$$



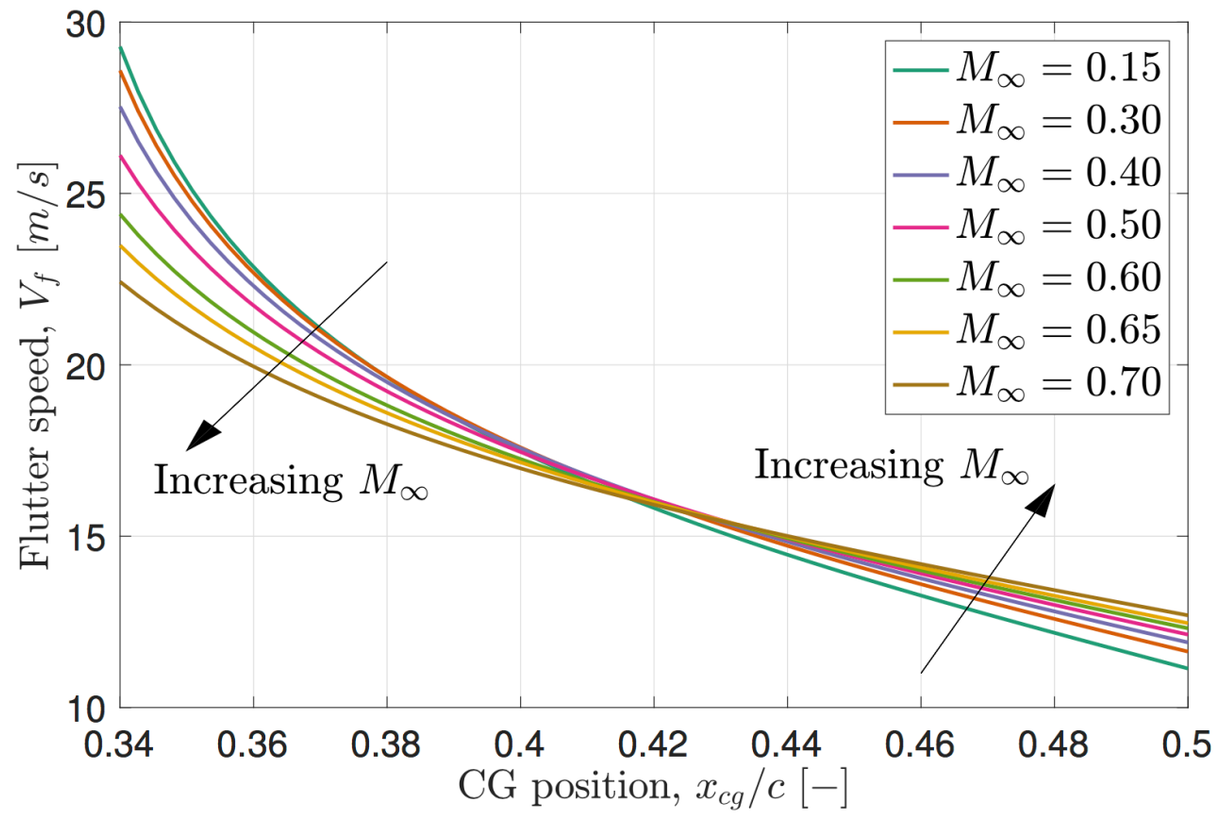
Fitting the aerodynamic model

$$\frac{\mathrm{d}}{\mathrm{d}t}\begin{bmatrix}\Delta\Gamma(t)\\ \Delta\kappa_x(t)\\ \Delta\dot{\kappa}_x(t)\end{bmatrix} = \underbrace{\begin{bmatrix}-\frac{A_\Gamma}{A_{\dot{\Gamma}}} & -\frac{A_\kappa}{A_{\dot{\Gamma}}} & 0\\ 0 & 0 & 1\\ B_\Gamma & B_\kappa & B_{\dot{\kappa}}\end{bmatrix}}_{\mathbf{A}_a}\underbrace{\begin{bmatrix}\Delta\Gamma(t)\\ \Delta\kappa_x(t)\\ \Delta\dot{\kappa}_x(t)\end{bmatrix}}_{\mathbf{x}_a} + \underbrace{\begin{bmatrix}\frac{-V_\infty}{A_{\dot{\Gamma}}} & \frac{-c/4}{A_{\dot{\Gamma}}} & -\frac{1}{A_{\dot{\Gamma}}}\\ 0 & 0 & 0\\ 0 & 0 & 0\end{bmatrix}}_{\mathbf{B}_a}\underbrace{\begin{bmatrix}\Delta\theta(t)\\ \Delta\omega(t)\\ \Delta w(t)\end{bmatrix}}_{\mathbf{u}_a}$$

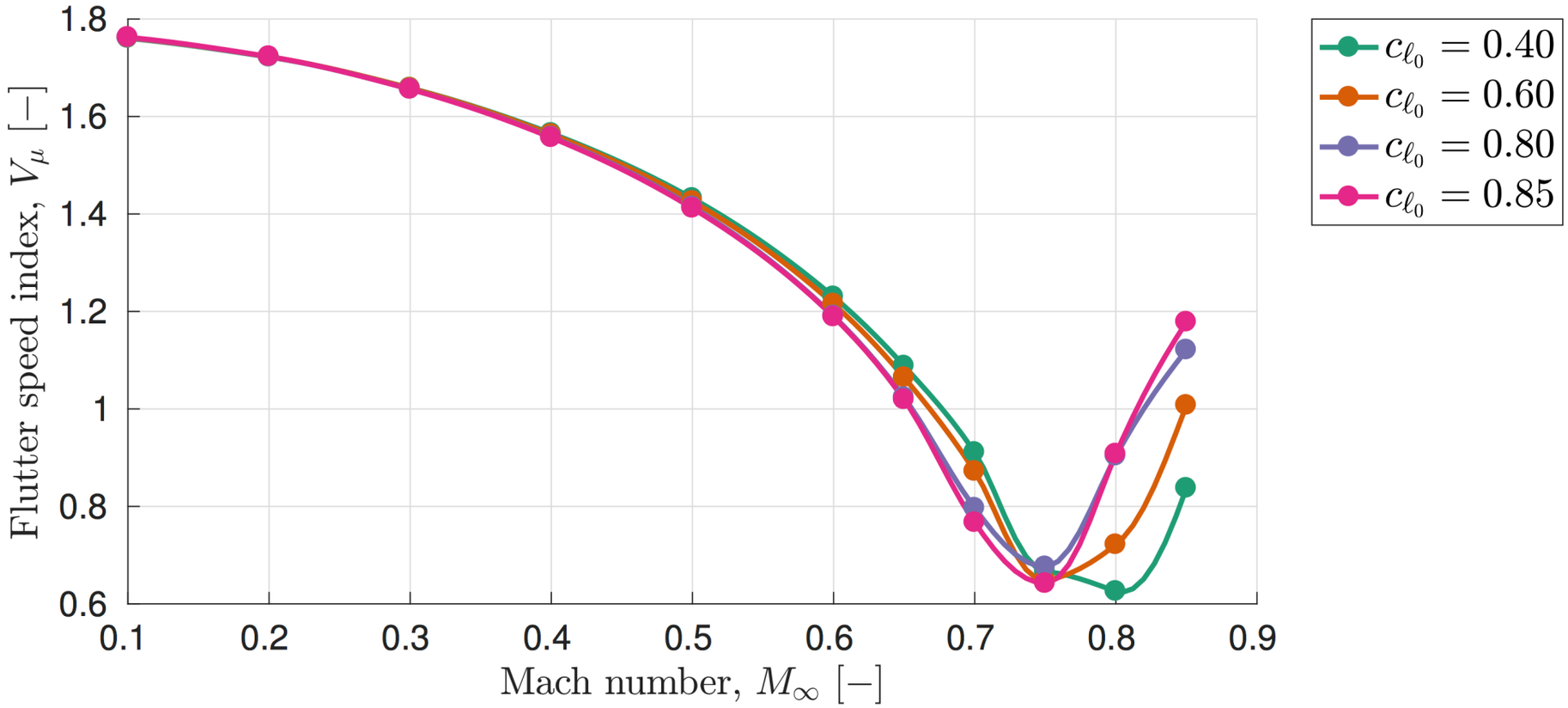
Use **Dynamic Mode Decomposition (DMD)** (Schmid 2010, Proctor et al. 2016) to find A_a and B_a

Flutter boundary as a function of CG using LOM

Airfoil parameters (Drela 1999)		
Apparent-mass ratio	$\pi\rho_\infty c^2/4m$	0.2405
Inertia/mass ratio	$4I_\theta/mc^2$	1.60
Elastic axis position	x_{ea}/c	0.50
In-vacuo heave natural frequency	$\sqrt{k_h/m}$	$\sqrt{50.0}$
In-vacuo pitch natural frequency	$\sqrt{k_\theta/I_\theta}$	$\sqrt{400}$



Influence of lift coefficient on flutter boundary

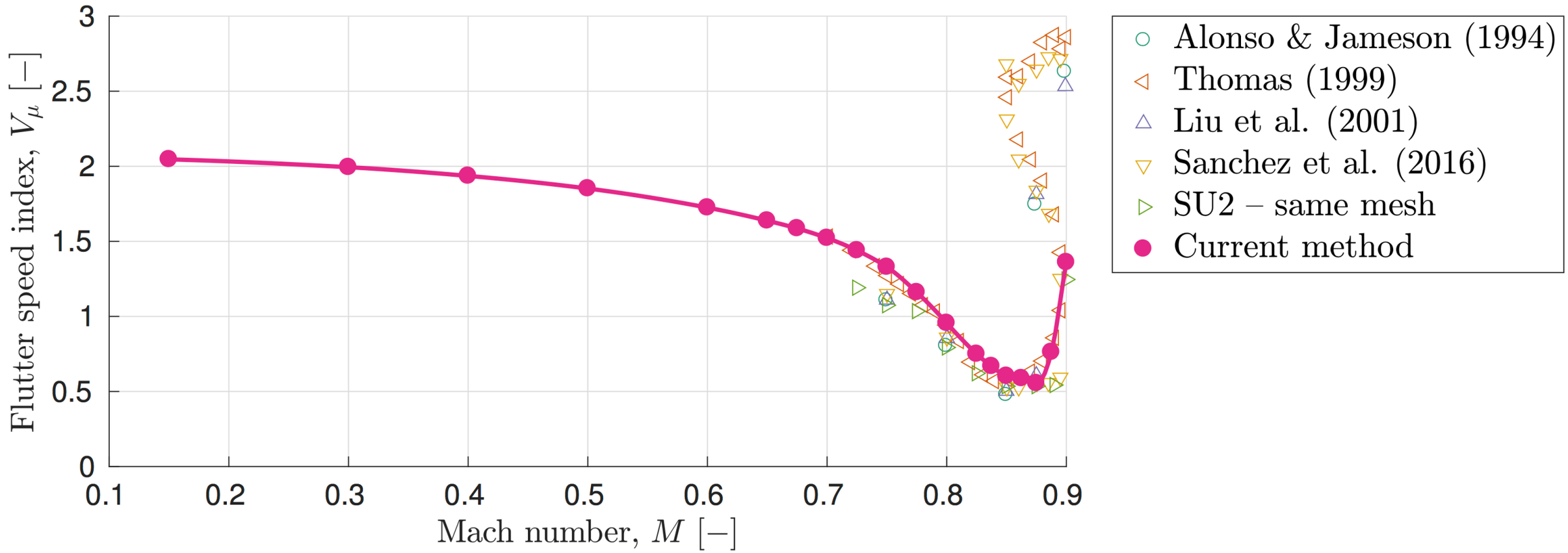


For this case $\mu = 40$, $\omega_\theta/\omega_h = 0.9$, $r_\theta^2 = 2.5$, $x_{ea}/c = -0.35$, $x_{cg}/c = 0.35$ for 11% thick transonic airfoil.

For low freestream Mach numbers there is barely any dependency on the baseline lift coefficient, but for transonic Mach numbers this dependency becomes substantial.

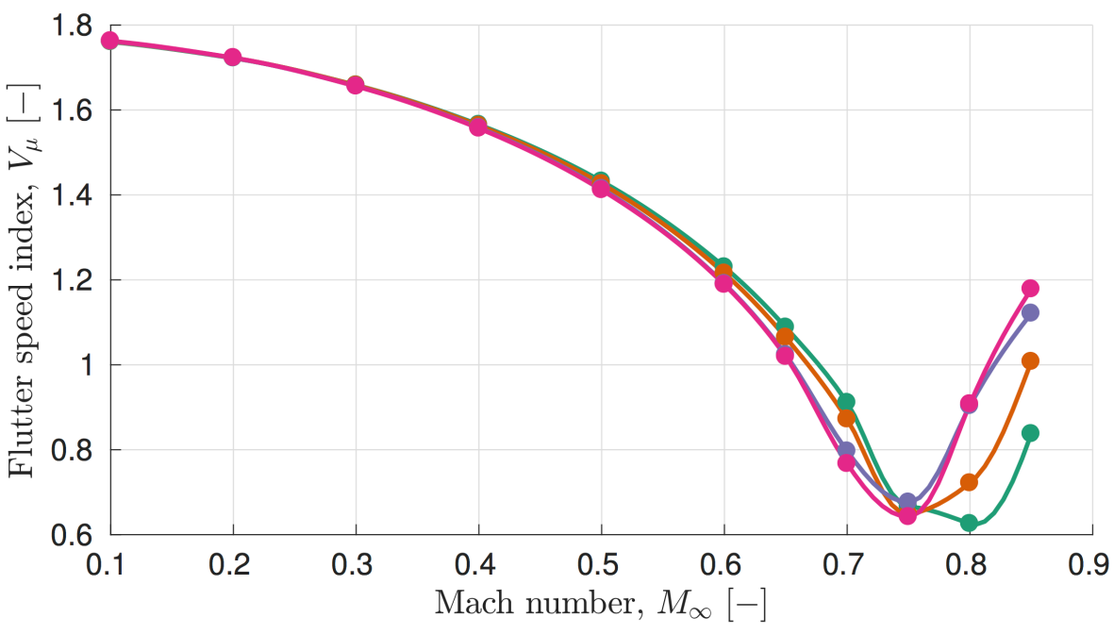
The dots indicate where we calibrate the model, the lines in between are computed using splines for the entries in the aerodynamic state space matrix.

Validation



Good agreement with other methods. S-shape of flutter boundary is not recovered. However, this is not a problem since we intend to use the model in a design setting. An optimal design should never operate in the upper stability region.

Summary for Subproject 3



Phase 2 achievements:

- Developed accurate fast method to include transonic flutter constraints in conceptual aircraft design
- Demonstrated approach on 2D problem

Next steps:

- Extend approach to 3D
- Implement a flutter constraint computation for the TWB

Summary of novel contributions

1. A new modular, scalable, and general numerical optimization algorithm that handles parallel problems
2. A parallel, scalable framework for MDO and gradient computation (now implemented in OpenMDAO)
3. A matrix-free CFD adjoint
4. A component-based geometry manipulation for aerostructural optimization of full unconventional configurations
5. An adjoint-based mission analysis and trajectory optimization code
6. A method for simultaneously optimizing aircraft trajectory and allocation
7. A framework for performing aircraft design optimization under uncertainty
8. A new technique for low-order modeling with application to flutter

Products

- 22 papers
- 2 PhD thesis
- 1 Masters thesis
- 1 researcher hired by NASA
- 1 researcher hired by AFRL
- 4 software package contributions:
  - OpenMDAO
  - Kona
  - pyMission
  - AMIEGO

Publications

1. S. Roy, W. A. Crossley, , J. T. Hwang, K. T. Moore, J. S. Gray, and J. R. R. A. Martins. Next Generation Aircraft Design Considering the Operations and Economics of Multiple Airlines. In Proceedings of the 59th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, Kissimmee, FL, 2018. (Abstract accepted)

2. J. T. Hwang and J. R. R. A. Martins. A computational architecture for coupling heterogeneous numerical models and computing coupled derivatives. ACM Transactions on Mathematical Software, 2017. (Accepted subject to revisions).

3. J. T. Hwang and J. R. R. A. Martins. Parallel allocation-mission optimization of a 128-route network. In Proceedings of the 16th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Dallas, TX, June 2015.

4. D. Ivaldi, N. R. Secco, S. Chen, J. T. Hwang, and J. R. R. A. Martins. Aerodynamic shape optimization of a truss-braced-wing aircraft. In Proceedings of the 16th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Dallas, TX, June 2015. doi: 10.2514/6.2015-3436.

5. 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.

6. 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.

7. J. T. Hwang, G. K. W. Kenway, and J. R. R. A. Martins. Geometry and structural modeling for high-fidelity aircraft conceptual design optimization. In Proceedings of the 15th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Atlanta, GA, June 2014. AIAA 2014-2041.

8. J. Gray, J. Chin, T. Hearn, E. Hendricks, T. Lavelle, and J. R. R. A. Martins. Chemical equilibrium analysis with adjoint derivatives for propulsion cycle analysis. Journal of Propulsion and Power, 33(5):1041–1052, September 2017. doi:10.2514/1.B36215.

9. J. T. Hwang and J. R. R. A. Martins. Allocation-mission-design optimization of next-generation aircraft using a parallel computational framework. In 57th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference. American Institute of Aeronautics and Astronautics, January 2016. doi:10.2514/6.2016-1662.

10. J. S. Gray, J. Chin, T. Hearn, E. S. Hendricks, T. M. Lavelle, and J. R. R. A. Martins. Thermodynamics for gas turbine cycles with analytic derivatives in OpenMDAO. In 57th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference. American Institute of Aeronautics and Astronautics, January 2016. doi:10.2514/6.2016-0669.

11. J. Gray, T. Hearn, K. Moore, J. T. Hwang, J. R. R. A. Martins, and A. Ning. Automatic evaluation of multidisciplinary derivatives using a graph-based problem formulation in OpenMDAO. In Proceedings of the 15th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Atlanta, GA, June 2014. doi:10.2514/6.2014-2042.

12. S. Roy, K. Moore, J. T. Hwang, J. S. Gray, W. A. Crossley, and J. R. R. A. Martins. A mixed integer efficient global optimization algorithm for the simultaneous aircraft allocation-mission-design problem. In Proceeding of the 58th AIAA Structures, Structural Dynamics, and Materials Conference, Grapevine, TX, January 2017. doi:10.2514/6.2017-1305.

13. S. Roy and W. A. Crossley. An EGO-like Optimization Framework for Simultaneous Aircraft Design and Airline Allocation. In Proceedings of the 57th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, San Diego, CA, 2016. AIAA 2016-1659.

14. J. T. Hwang, S. Roy, J. 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, 2015. AIAA 2016-0900.

15. Hicken and Dener, A Flexible Iterative Solver for Nonconvex, Equality-Constrained Quadratic Subproblems, SIAM Journal on Scientific Computing (Submitted)

16. Opgenoord, M., Drela, M. and Willcox, K. "Towards a Low-Order Model for Transonic Flutter Prediction", 8th AIAA Theoretical Fluid Mechanics Conference, 2017 AIAA AVIATION Forum (AIAA 2017-4340)

17. Opgenoord, M. and Willcox, K. "Sensitivity Analysis Methods for Uncertainty Budgeting in System Design", AIAA Journal, Volume 54, Issue 10, pp. 3134-3148, 2016

18. Opgenoord, M., Allaire, D. and Willcox, K. "Variance-Based Sensitivity Analysis to Support Simulation-based Design under Uncertainty", Journal of Mechanical Design, Vol. 138, No. 11, pp. 111410-111410-12, 2016.

19. Opgenoord, M., Drela, M. and Willcox, K. "Influence of Transonic Flutter on the Conceptual Design of Next-Generation Transport Aircraft", to be presented at 2018 AIAA SciTech Forum.

20. Jason E. Hicken and Alp Dener. A Flexible Iterative Solver for Nonconvex, Equality-Constrained Quadratic Subproblems. SIAM J. Sci. Comput., 37(4), A1801–A1824. . doi:10.1137/140994496

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