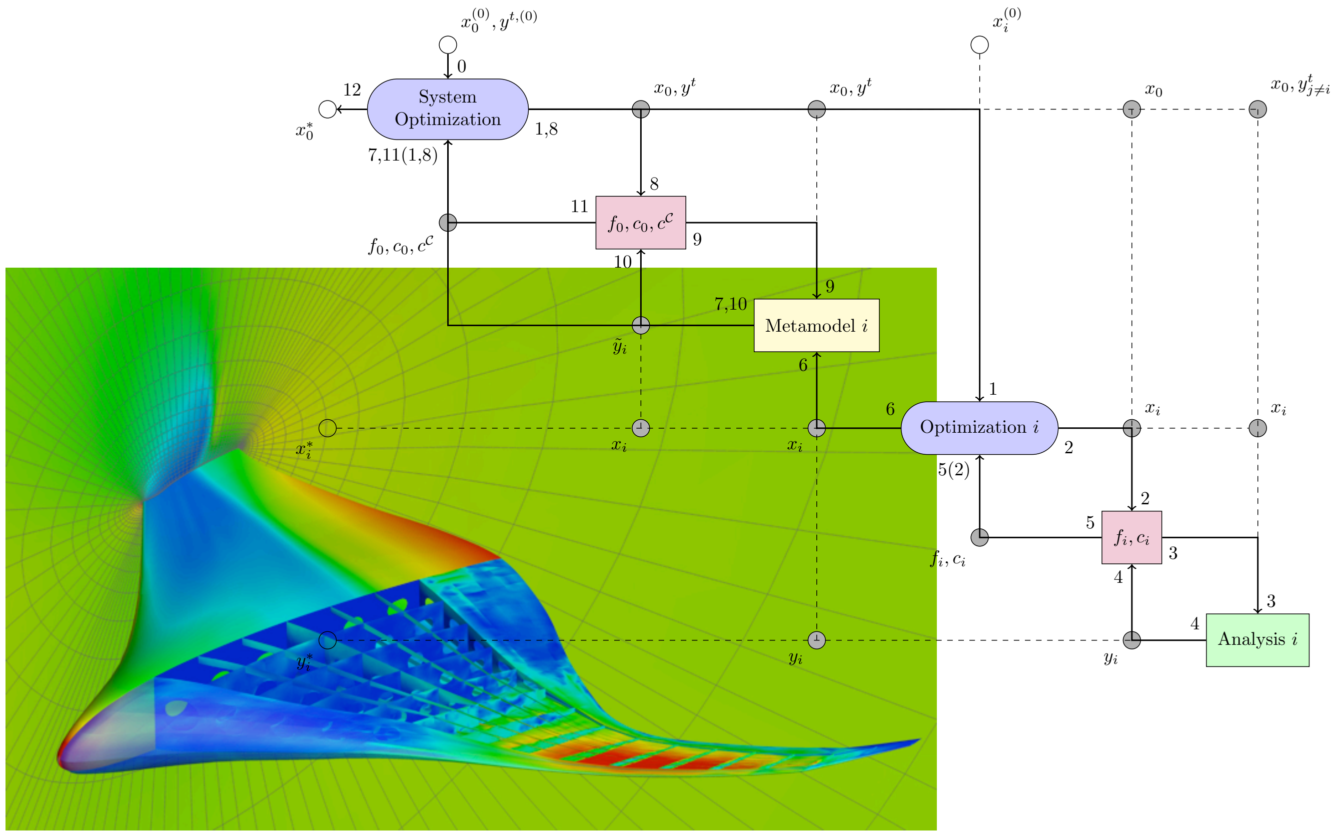
AA222: Introduction to Multidisciplinary Design Optimization



AA222

Lecture 1

April 2, 2012

Course Administrative Information

- Instructors: Dr. Jason E. Hicken and Prof. Juan J. Alonso
- Course Assistant: TBA
- Office Hours: J. Hicken: Fridays 2:00-3:30pm (Prof. Alonso: TBA)
- Schedule: Mon/Wed 2:15–3:30pm, McCullough 126
- Course Web Page: `http://adl.stanford.edu/aa222`
- Course Mailing List: `aa222-class`. Subscribe by going to `https://itservices.stanford.edu/service/mailinglists/tools` and entering `aa222-class` in the *Subscribe and unsubscribe to a list* box.
- Pre-requisites: multivariable calculus, basic linear algebra, familiarity with a programming language (C, C++, F90/95, Python, MATLAB).
- AA222 satisfies the MS and PhD Math Requirement. It is therefore going to deal with the mathematics of optimization and MDO.

- Homeworks & Projects: You can discuss ideas in groups but you MUST carry out and write up solutions on your own. Late policy is 10% of grade per day / fraction of day. Assignments will start from more mathematical and will shift towards more applied.

- Grading: 75% Homework, 25% Final Project.

Textbooks

No book is required. Detailed course notes will be handed out for every lecture. However, if you are interested in more details, the following books have been placed on reserve in the library and we would recommend that you get the first one (if you are likely to continue to work in optimization).

- Optimization Concepts and Applications in Engineering. Belegundu, A. and Tirupathi, R., Prentice Hall, 1999.
- Introduction to Engineering Design Optimization. Onwubiko, C., Prentice Hall, 2000.
- Applied Optimization with MATLAB programming. Venkataraman, P., Interscience, 2001.

Acknowledgements & Additional Courses

The first version of these notes was jointly put together by Prof. Joaquim R. R. A. Martins, from the University of Michigan, and Prof. Juan J. Alonso, from Stanford University. This is the fifth+ iteration of these notes which contains a tailoring for the subject matter covered in AA222, additional lectures in approximation theory, hierarchical decomposition, and setup of the MDO problem. In addition, a number of additional interactive optimization problems have been added, together with new homework problems and graphics for the explanation of concepts. Prof. Ilan Kroo and Dr. Dev Rajnarayan have contributed greatly to the current status of these notes.

AA222 is not meant to be a replacement for optimization courses offered elsewhere at Stanford. If you are interested in optimization you are strongly encouraged to get a depth of knowledge from some of the following courses: MS&E 111, 112, 120, 211, 212, 310, 311, 312, 318, Math 151 (or more advanced), EE 364A/B/S, and STATS 310 A,B,C, among others.

Course Outline

Introduction:

1. What is "MDO"?
2. Terminology and Problem Statement
3. Classification of Optimization Problems
4. Methods of Solution
5. Practical Applications

Single Variable Optimization:

1. Optimality Conditions
2. Line Search Methods

Gradient-Based Optimization:

1. Optimality Conditions
2. Steepest Descent and Conjugate Gradient Methods
3. Quasi-Newton Methods

Sensitivity Analysis:

1. Finite Differences
2. Complex-Step Derivative Approximation
3. Algorithmic Differentiation
4. Semi-Analytic Methods

Handling Constraints:

1. Karush–Kuhn–Tucker (KKT) Conditions
2. Penalty and Barrier Methods
3. Reduced Gradient and Gradient Projection Methods
4. Sequential Quadratic Programming (SQP)
5. Constraint Agglomeration

Gradient-Free Optimization:

1. Nelder–Mead Simplex
2. DIRECT Method
3. Genetic Algorithms and Pareto Optimality
4. Particle Swarm Algorithms

Function Fitting and Regression:

1. Polynomial approximations
2. Design of Experiments
3. Gaussian processes / Kriging
4. Multi-fidelity approximations
5. Other topics

MDO Architectures:

1. Collaborative Optimization (CO)
2. Concurrent Subspace Optimization (CSSO)
3. Bi-Level Integrated System Synthesis (BLISS)
4. Coupled-Sensitivity Analysis

1 Introduction

1.1 What is "MDO"?

Engineering Design Optimization

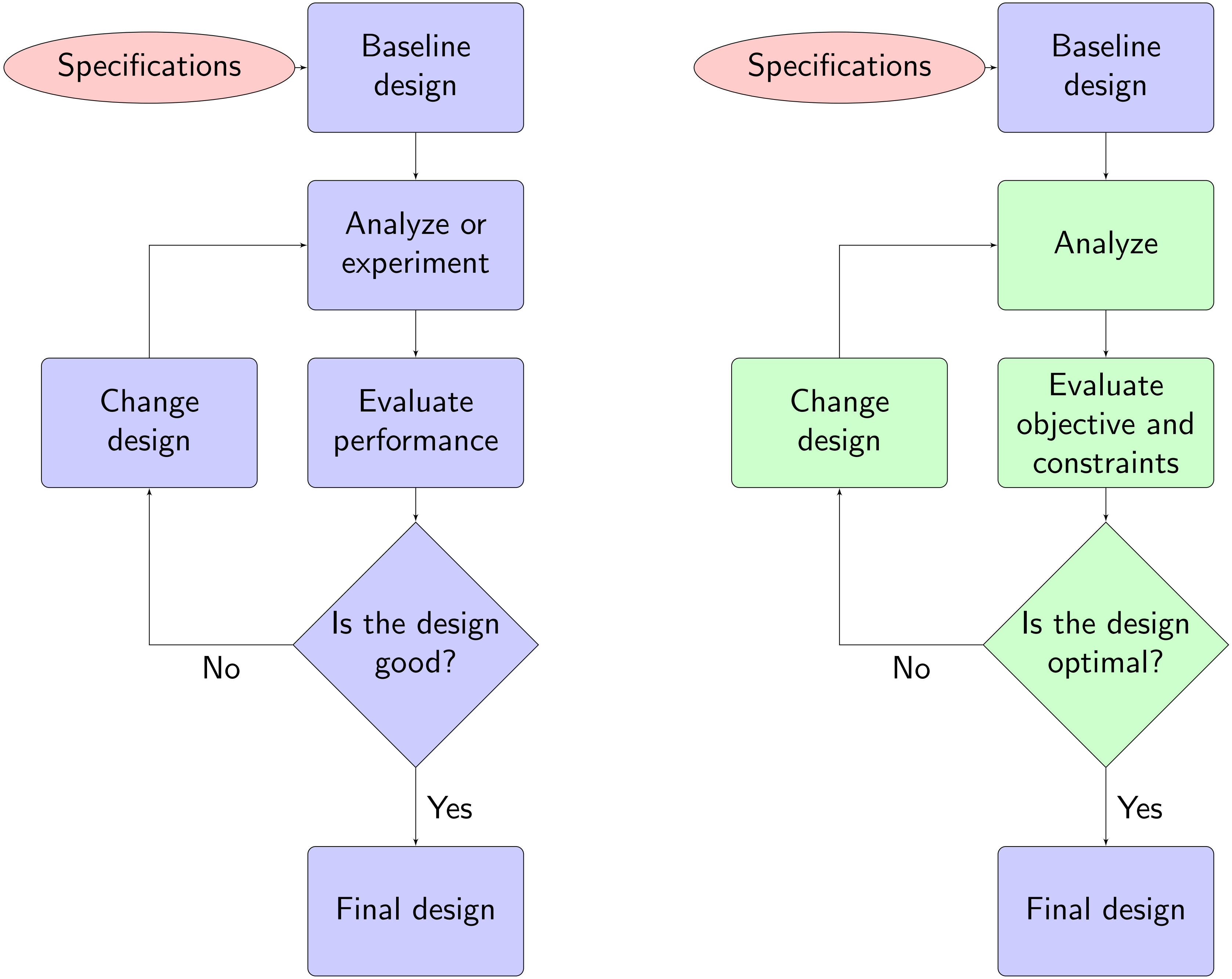
The "DO" in MDO.

In industry, problems routinely arise that require making the best possible design decision.

However, optimization is still underused in industry. . .

Aerospace is one of the leading applications of engineering design optimization. Why?

Conventional Versus Optimum Design Process



Multidisciplinary Design Optimization (MDO)

Most modern engineering systems are *multidisciplinary* and their analysis is often very complex, involving hundreds computer programs, many people in different locations. This makes it difficult for companies to manage the design process.

In the early days, design teams tended to be small and were managed by a single chief designer who knew most about the design details and could make all the important decisions.

Modern design projects are more complex and the problem has to be decomposed and each part tackled by a different team. The way these teams should interact is still being debated by managers, engineers and researchers [2, 1, 12].

1.2 Terminology and Problem Statement

Objective Function

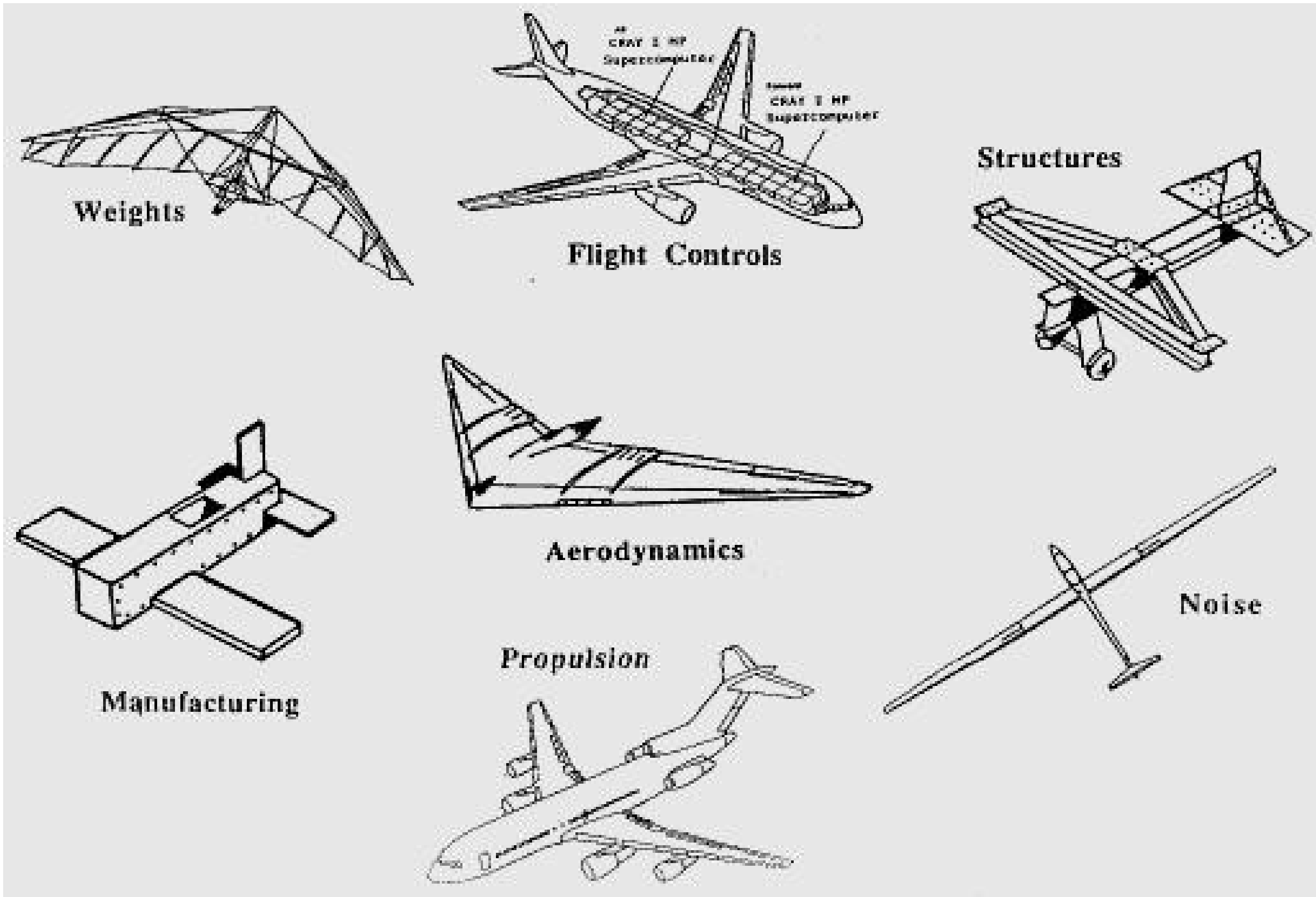
What do we mean by “best”?

Objective function is a “measure of goodness” that enables us to compare two designs quantitatively. Need to be able to estimate this measure numerically...

If we select the wrong goal, it doesn’t matter how good the analysis is, or how efficient the optimization method is. Therefore, it’s really important to select a good objective function. Underrated.

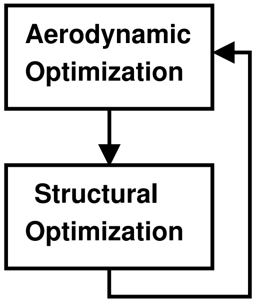
Objective function may be linear or nonlinear and may or not be given explicitly. We will represent it by the scalar f.

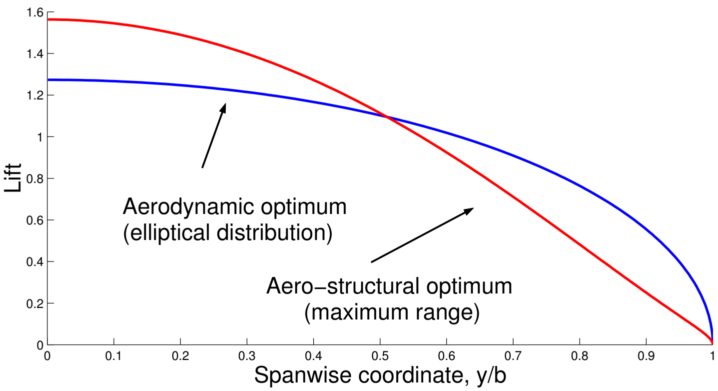
Is there *one* aircraft which is the fastest, most efficient, quietest, most inexpensive?

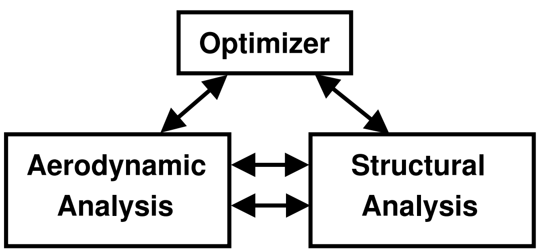


"You can only make one thing best at a time."

Example: Trade-off Between Aerodynamics and Strutures







Sequential optimization does not lead to the true optimum.

Aero-structural optimization requires coupled sensitivities.

Add structural element sizes to the design variables.

Including structures in the high-fidelity wing optimization will allow larger changes in the design.

Design Variables

Design variables are also known as design parameters and will be represented by the vector x. They are the variables in the problem that we allow to vary in the design process.

Optimization is the process of choosing the design variables that yield an optimum design.

Design variables should be as independent of each other as possible.

Design variables can be *continuous* or *discrete*. Discrete variables are sometimes *integer variables*.

Constraints

Few practical engineering optimizations problems are unconstrained.

Constraints on the design variables are called *bounds* and are easy to enforce.

Like the objective function, constraints can be linear or nonlinear and may or not be given in an explicitly form. They may be *equality* or *inequality* constraints.

At a given design point, constraints may be *active* of *inactive*. This distinction is particularly important at the optimum.

Optimization Problem Statement

$$
\boxed{\begin{array}{ll}
\text{minimize} & f(x) \\
\text{by varying} & x \in \mathbb{R}^n \\
\text{subject to} & h_p(x) = 0, \quad p = 1, 2, \ldots, N_h \\
& g_m(x) \geq 0, \quad m = 1, 2, \ldots, N_g
\end{array}}
$$

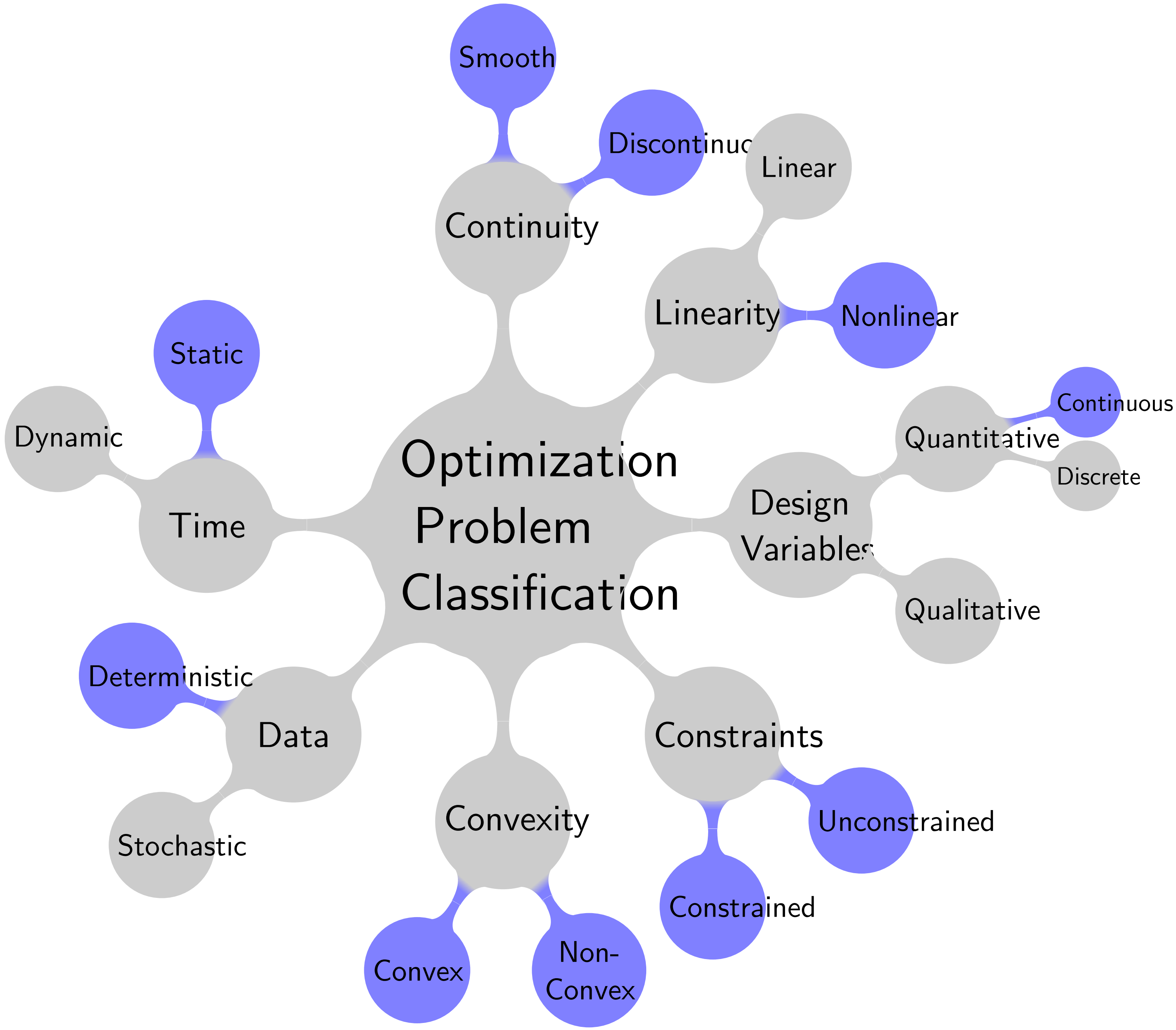
f : objective function, output (e.g. structural weight).

x : vector of design variables, inputs (e.g. aerodynamic shape); bounds can be set on these variables.

h : vector of equality constraints (e.g. lift); in general these are nonlinear functions of the design variables.

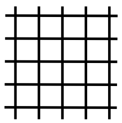
g : vector of inequality constraints (e.g. structural stresses), may also be nonlinear and implicit.

Classification of Optimization Problems

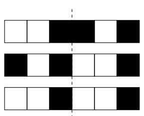


1.3 Optimization Methods

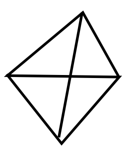
Intuition: decreases with increasing dimensionality.



Grid or random search: the cost of searching the design space increases rapidly with the number of design variables.

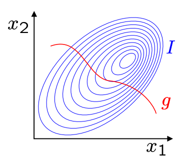


Genetic algorithms: good for discrete design variables and very robust; but infeasible when using a large number of design variables. Multi-objective optimization.



Nelder–Mead algorithm: simple and robust but inefficient for more than a few design variables.

Response surfaces: good for noisy functions, still requires a large number of evaluations to create fit.

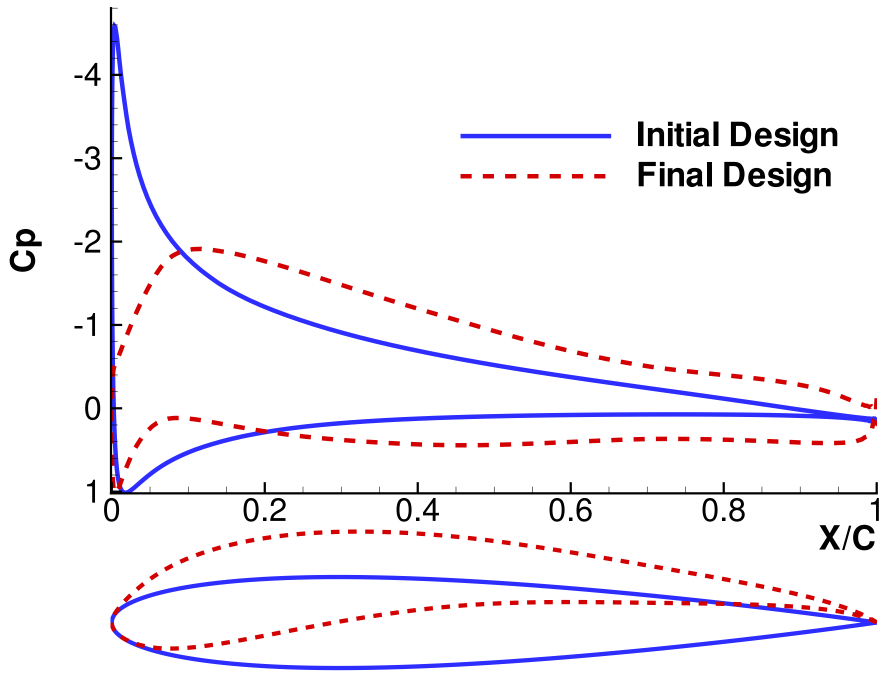


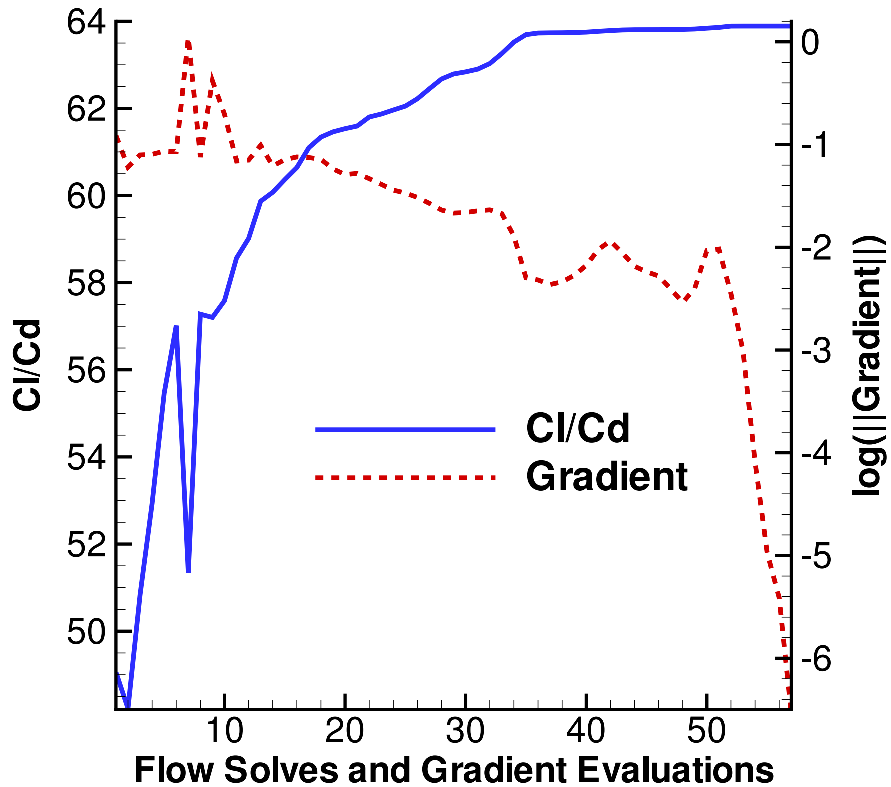
Gradient-based: the most efficient for a large number of design variables; assumes the objective and constraints are smooth functions.

1.4 Practical Applications

Airfoil Design (D. Zingg, UTIAS / M.Nemec, NASA) [10]

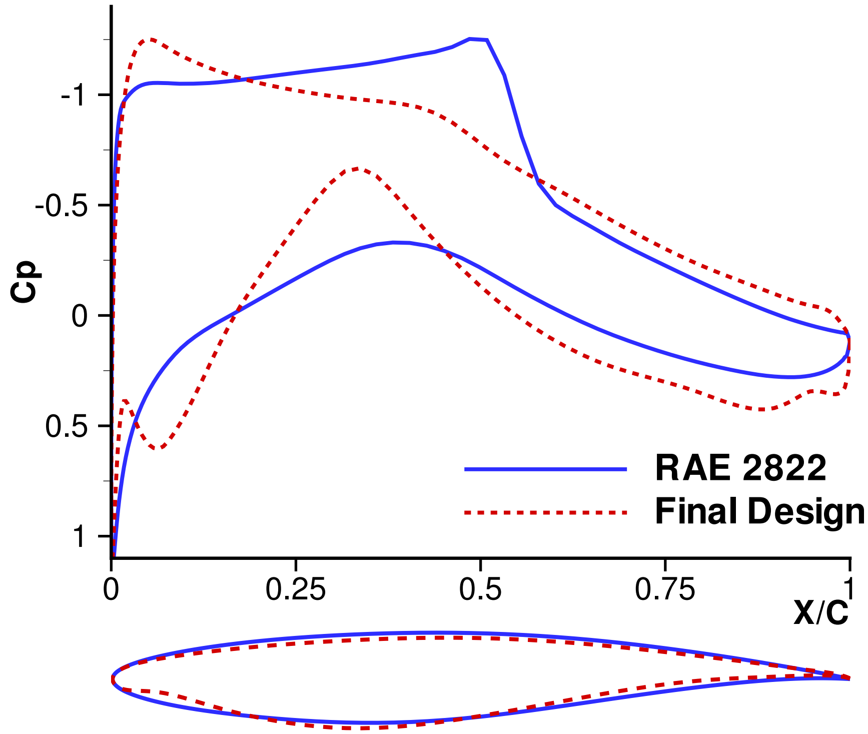
Lift-to-drag ratio maximization

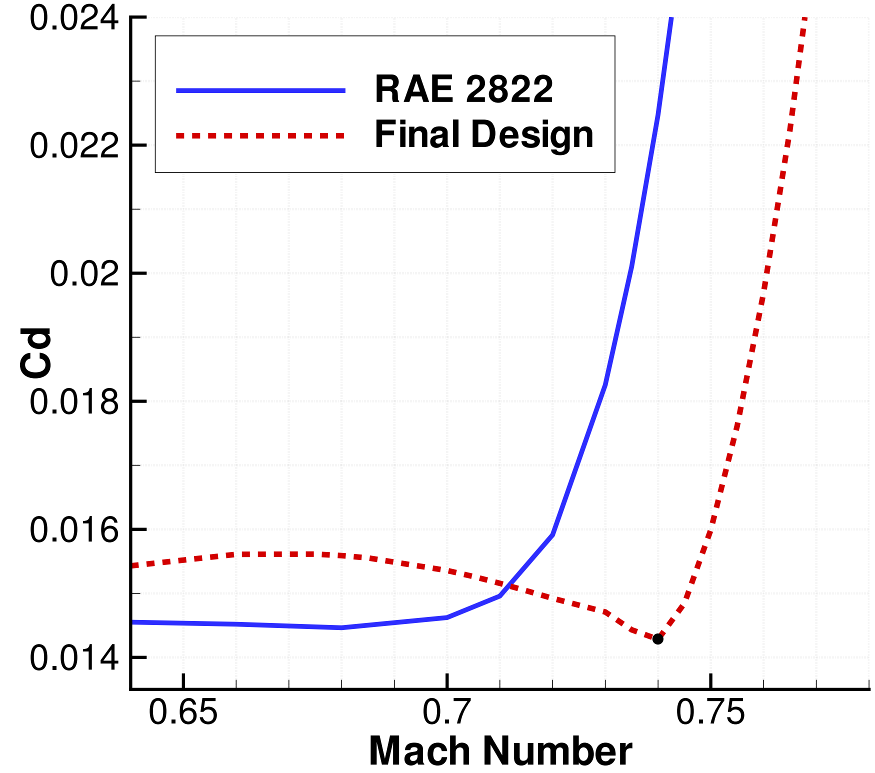




$M = 0.25,\ Re = 2.88 \times 10^6$

Drag minimization with fixed lift

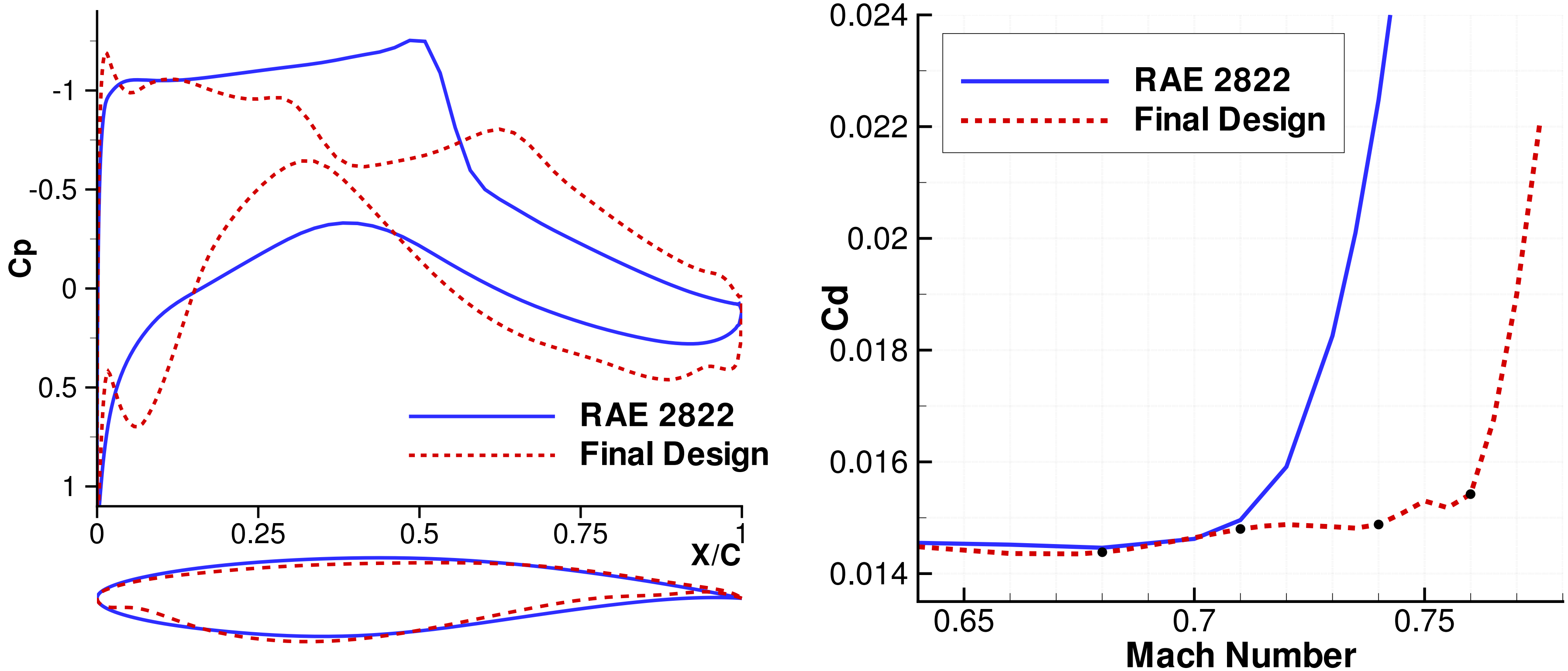




Single flight condition, $M = 0.74$.

Baseline: RAE2822, $\alpha = 2.9°$. Final: $\alpha = 1.9°$. Drag reduced by 36.4%.

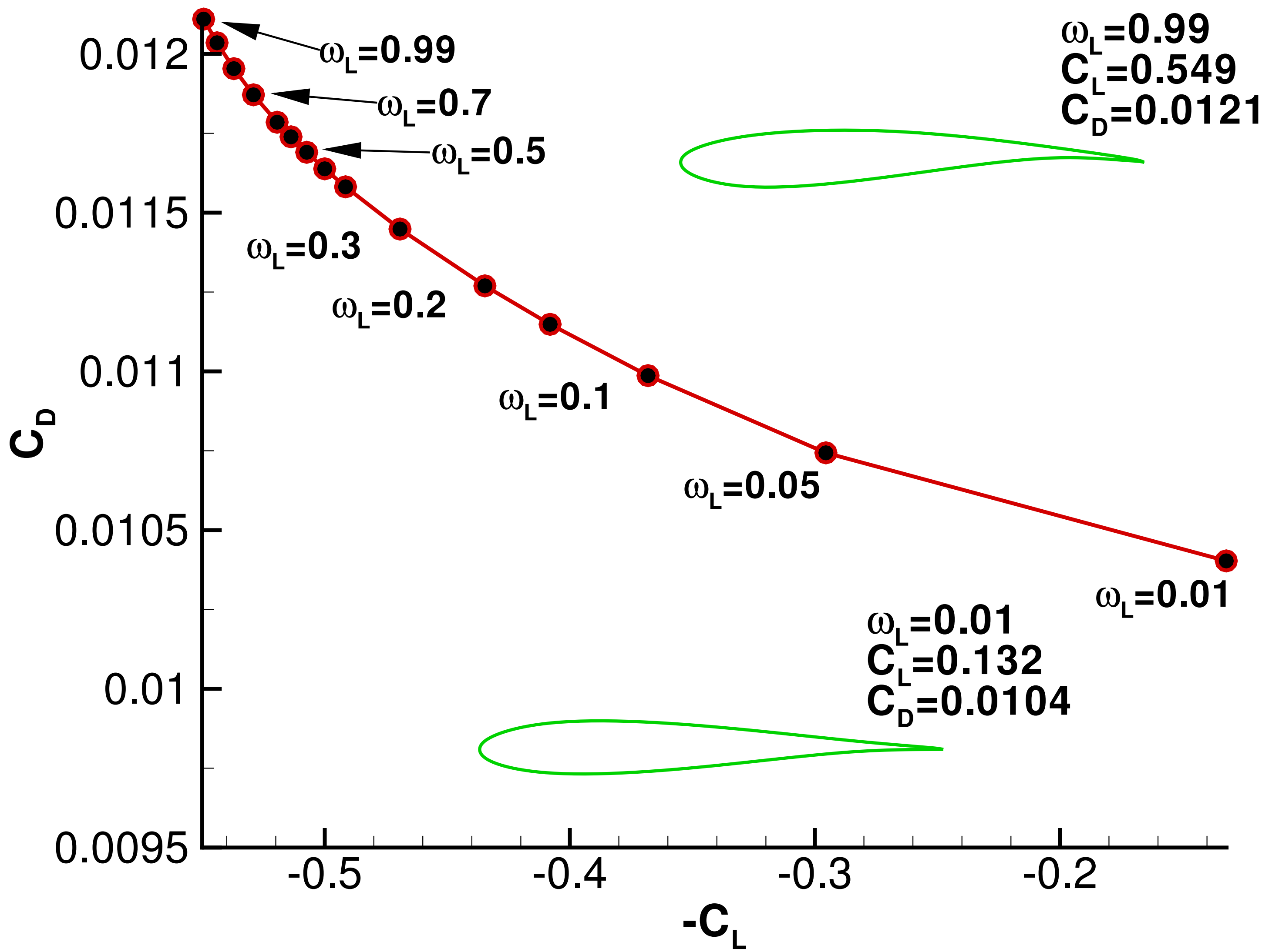
Drag minimization for fixed lift with multiple flight conditions



Four flight conditions: $M_1 = 0.68$, $M_2 = 0.71$, $M_3 = 0.74$, $M_4 = 0.76$.

For $M = 0.74$, $\alpha = 1.65°$, drag was reduced by 33.8%.

Trade-off between Lift and Drag Coefficients



Induced-drag Minimization (J. Hicken and D. Zingg, UTIAS) [4, 5]

Induced drag represents approximately 40% of the total drag on a conventional aircraft in cruise flight. In this example, the induced drag is minimized while the lift is held fixed. The initial wing has a span of $b = 3$.

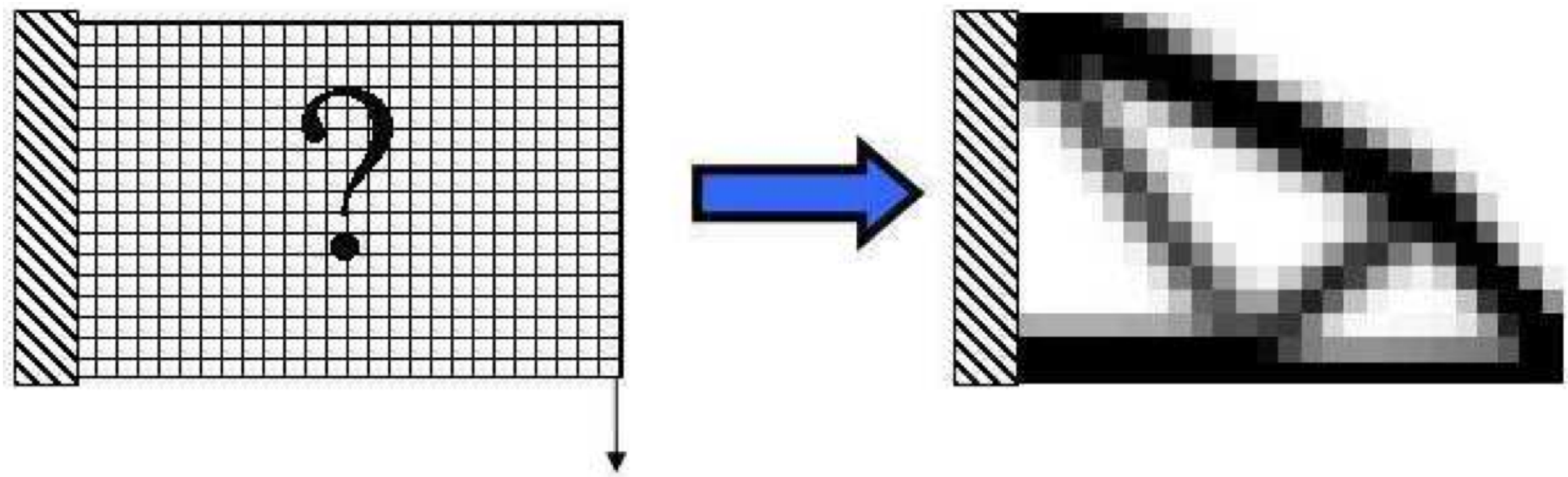
Variables: Wing sections at six spanwise stations control the shape of the wing. These sections are allowed to twist and scale about the quarter chord, and the sections can translate vertically. The wing span is also allowed to change as is the angle of attack.

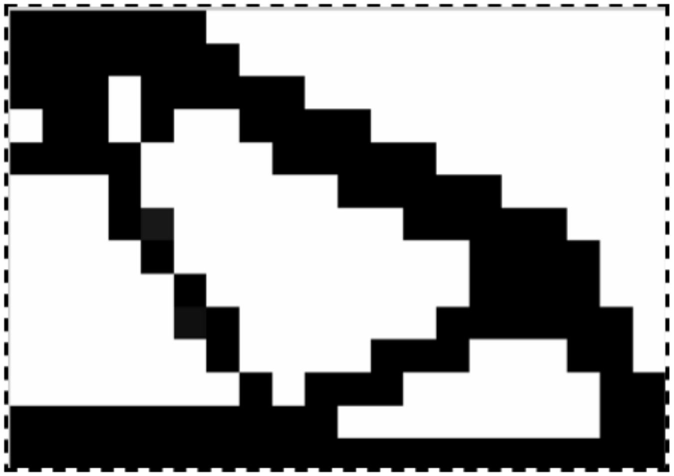
Constraints: C_L and surface area are constrained to their initial values. The entire geometry is constrained to remain inside the box defined by $|y| \leq 2.5$ and $|z| \leq 0.25$

What do you think will happen?

Structural Topology Optimization (K. James and J. Martins, UTIAS)

This example is from recent work by James and Martins [6]. The objective of structural topology optimization is to find the shape and *topology* of a structure that has the minimum compliance (maximum stiffness) for a given loading condition.

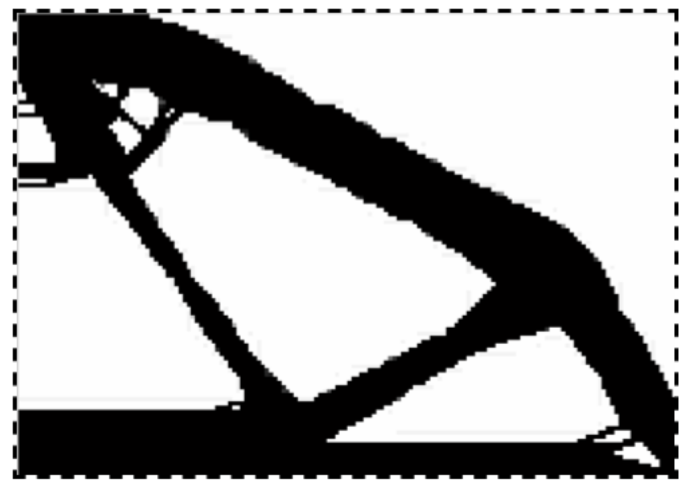




(a) unrefined solution

(b) solution after one refinement

(c) solution after two refinements



(d) solution after three refinements

Aircraft Design with Minimum Environmental Impact

The environmental impact of aircraft has been a popular topic in the last few years. In this example, Antoine and Kroo [3] show the trade-offs between cost, noise, and greenhouse gas emissions, by solving a number of multiobjective problems.

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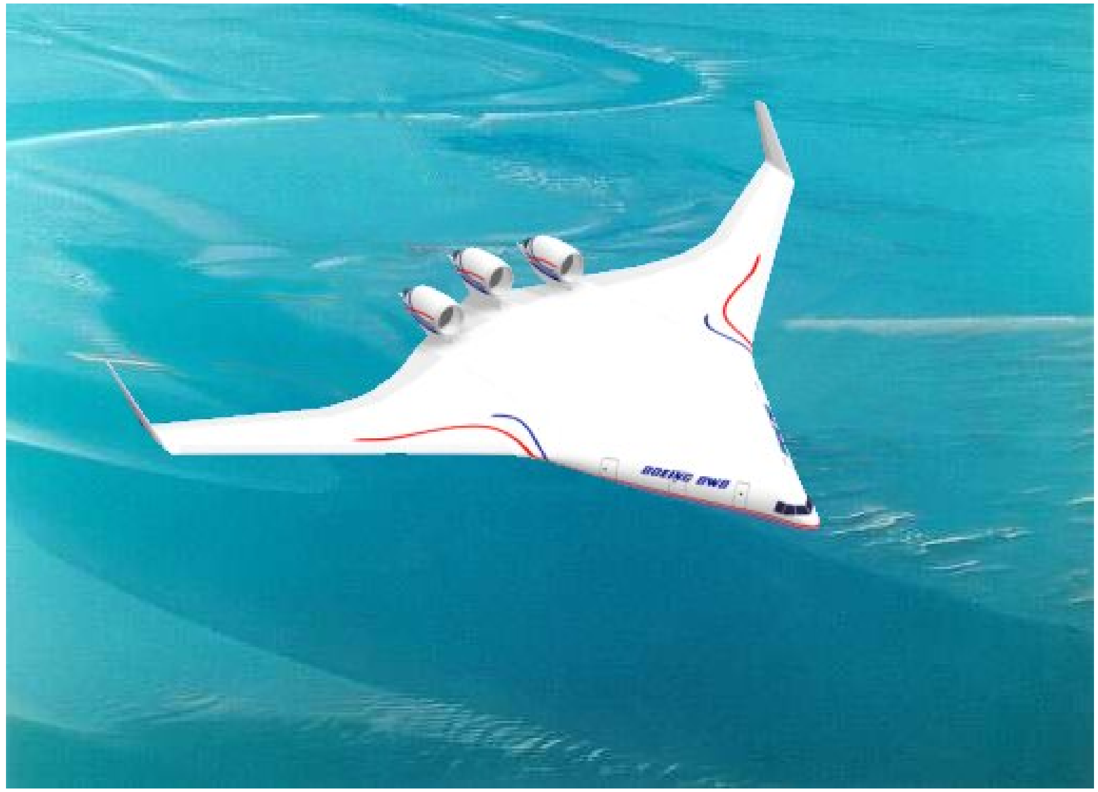
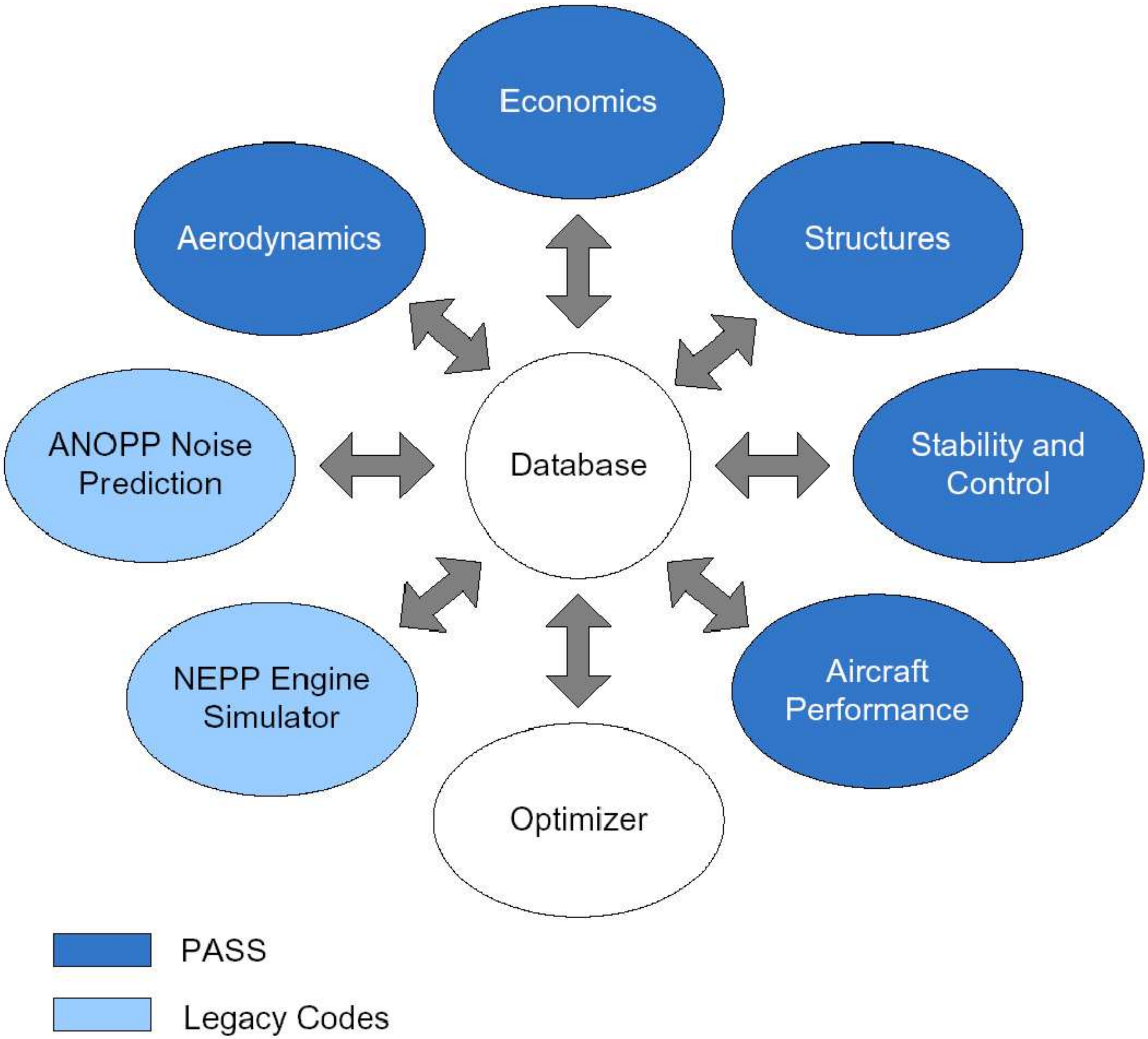
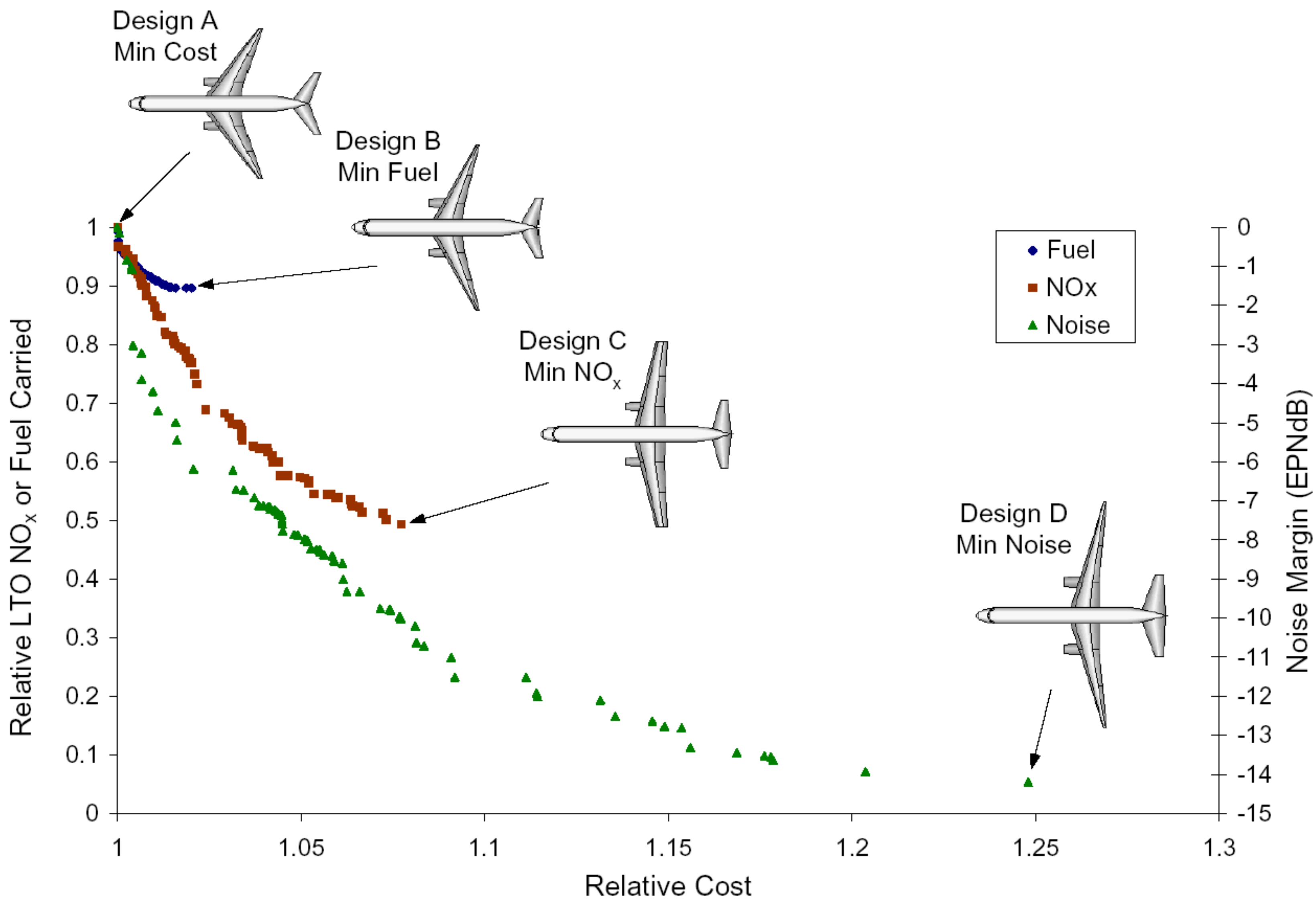


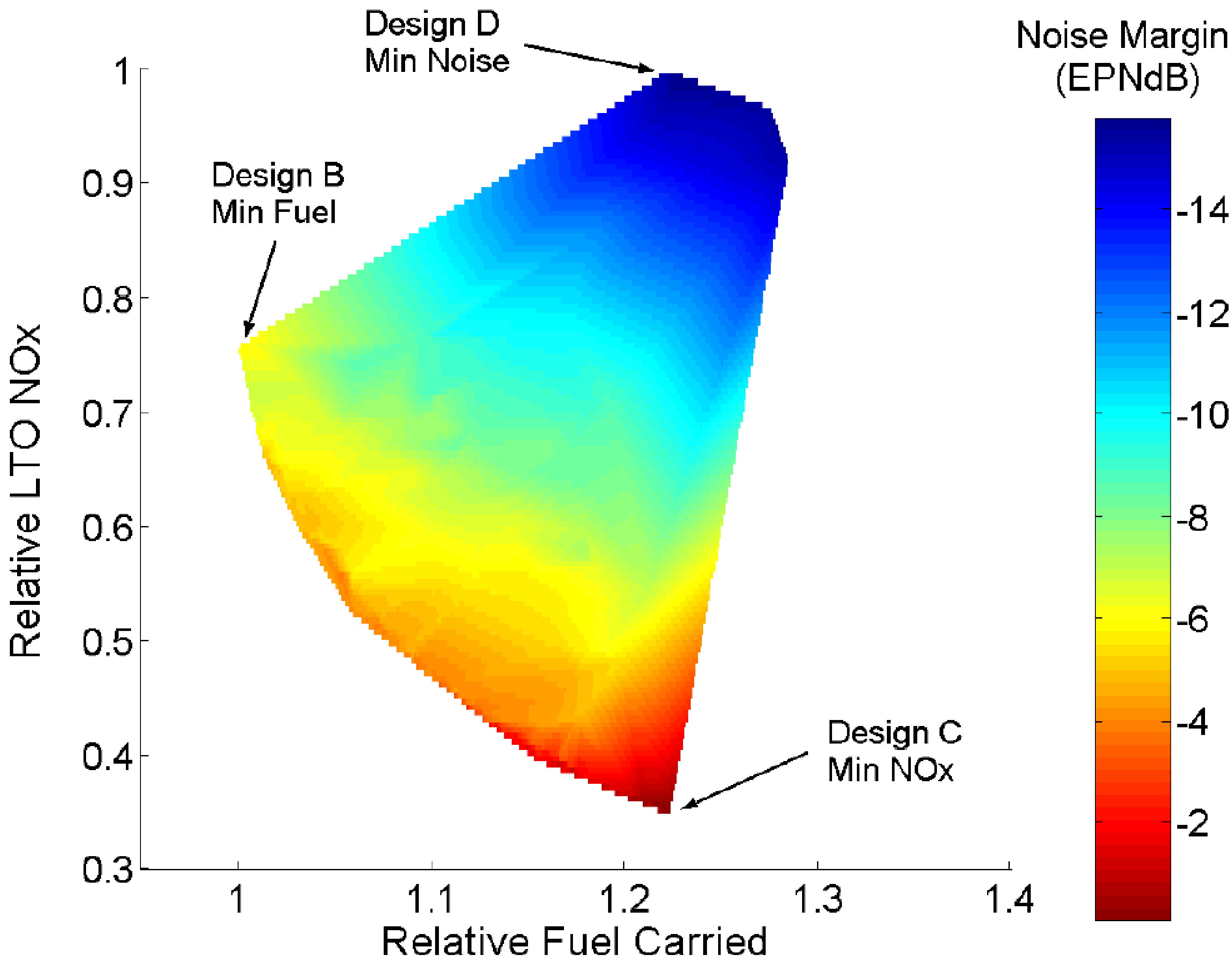
Blended-wing-body (BWB)


Economics
Aerodynamics
Structures
ANOPP Noise Prediction
Database
Stability and Control
NEPP Engine Simulator
Aircraft Performance
Optimizer
PASS
Legacy Codes

Pareto fronts of fuel carried, emissions and noise vs. operating cost



Pareto surface of emissions vs. fuel carried vs. noise

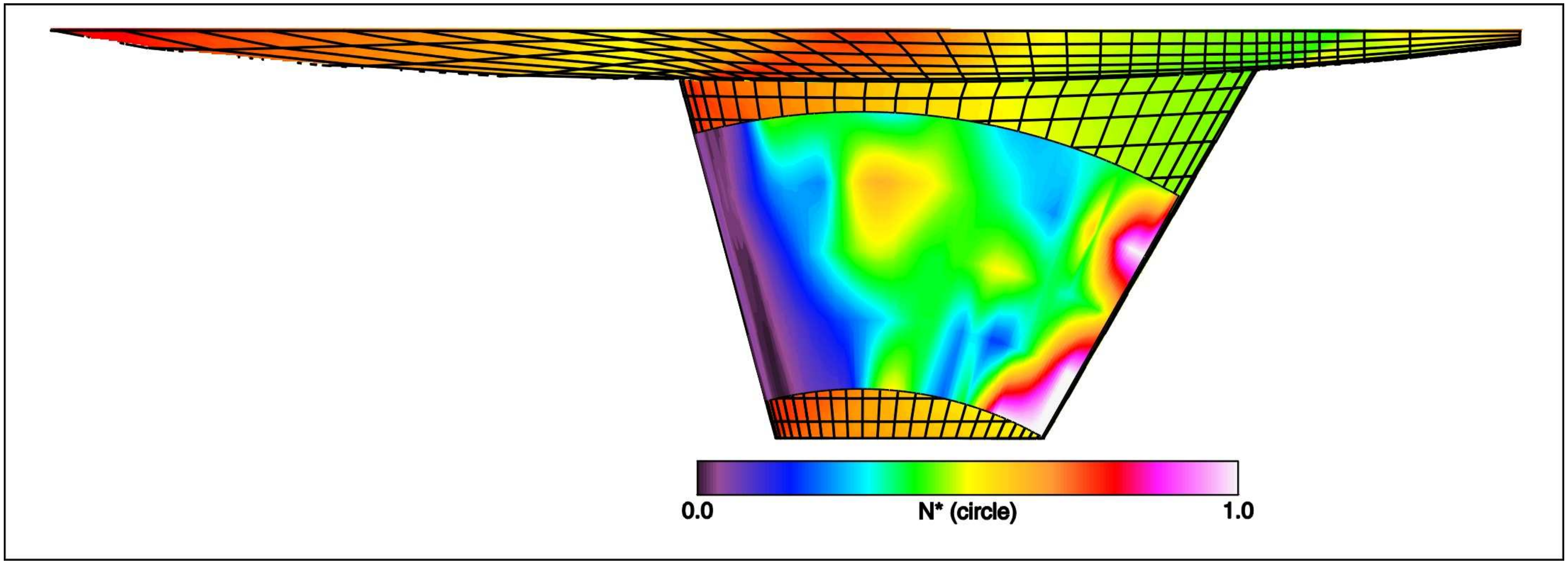


Aerodynamic Design of a Natural Laminar Flow Business Jet (P.Sturdza and I.Kroo, Stanford) [7]

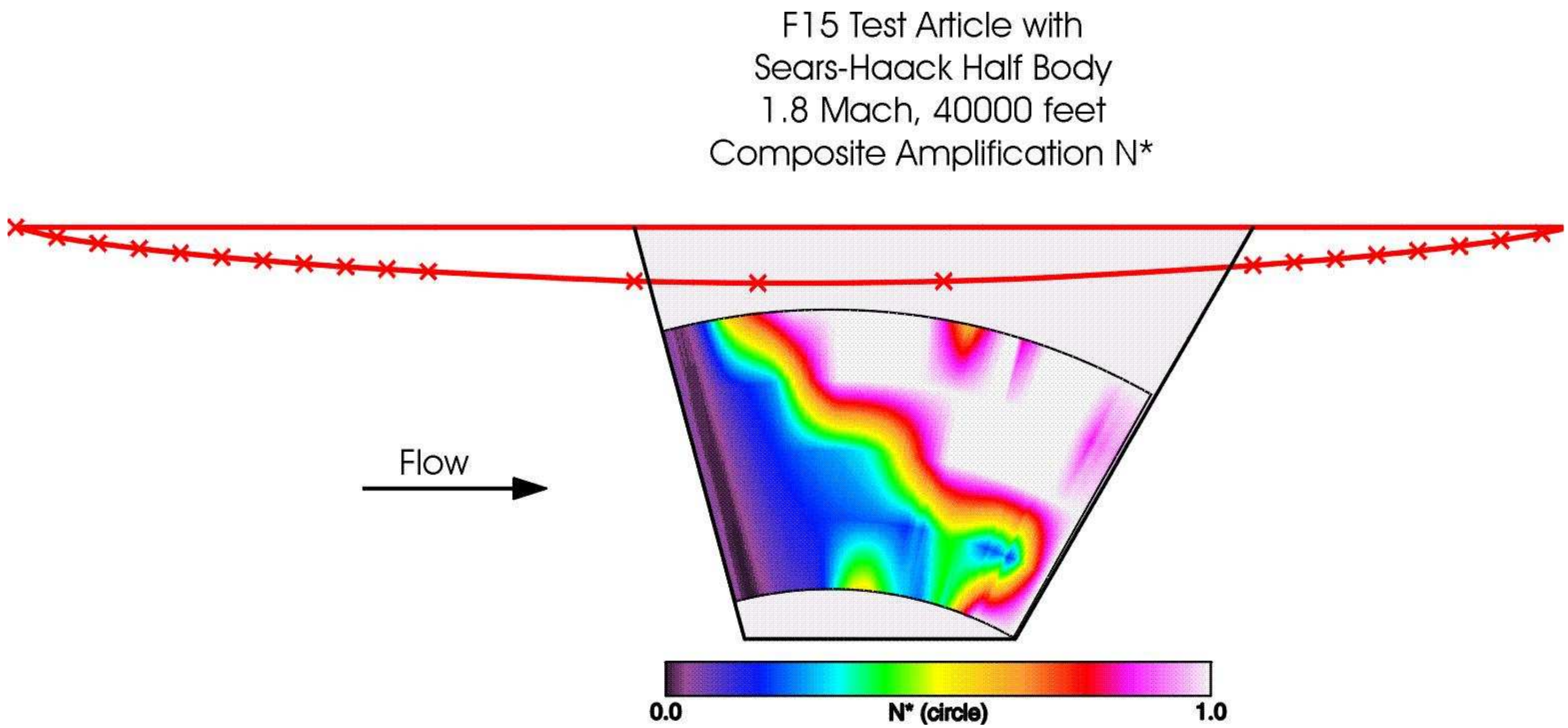
ASSET Corporation configuration. $M = 1.5$; Cruise Altitude: 50,000 feet; Payload: 6-8 Passengers; Range: 5,000 nautical miles; Weight: 100,000 lbs; L/D = 9–10; Wings designed with low sweep for natural laminar flow.

A CFD Euler code was combined with a boundary-layer solver to compute the flow on a wing-body. The fuselage spoils the laminar flow that can normally be maintained on a thin, low sweep wing in supersonic flow. The goal is to reshape the fuselage at the wing-body junction to maximize the extent of laminar flow on the wing.

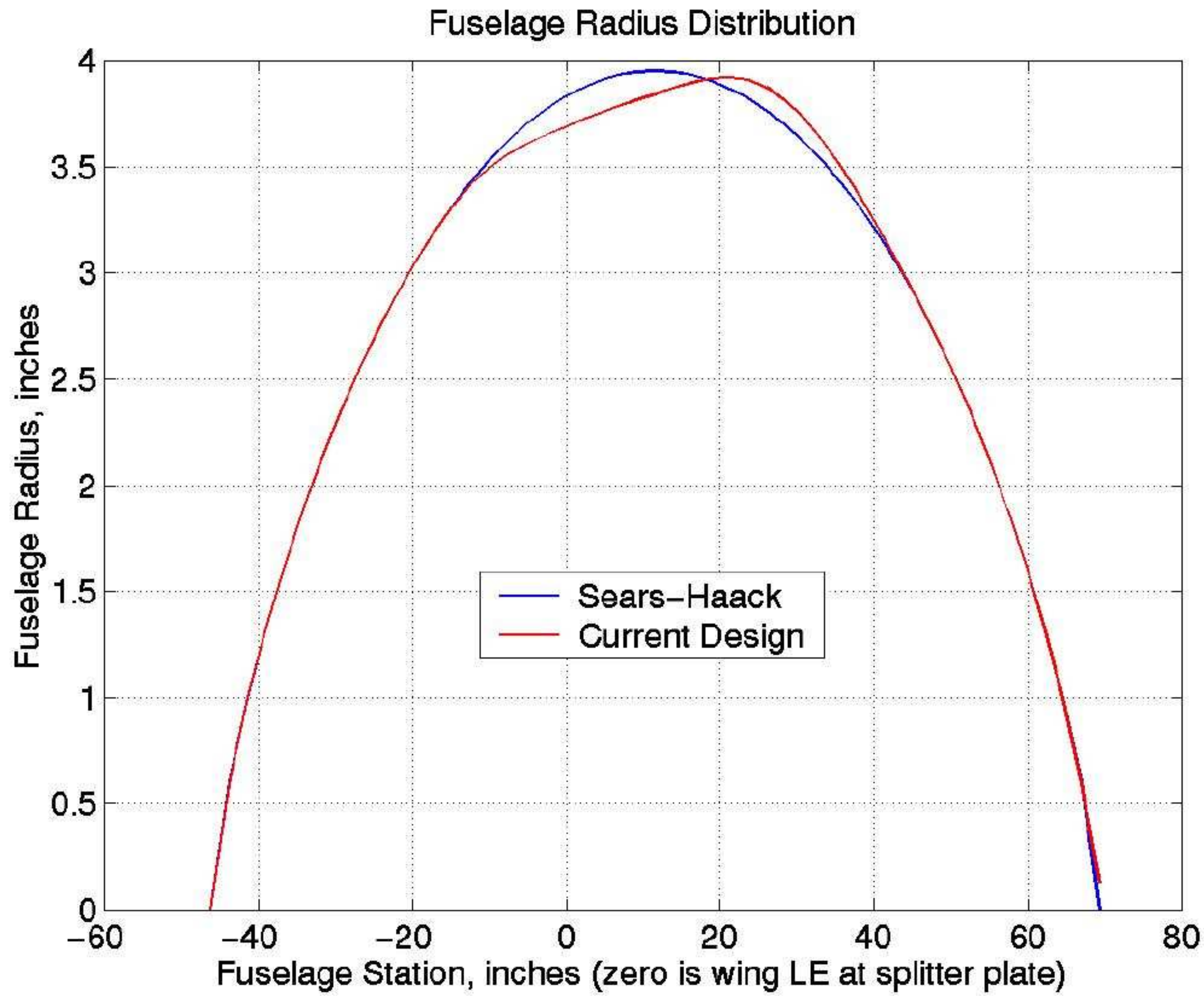
Three design variables were used initially, with quadratic response surfaces and a trust region update algorithm.



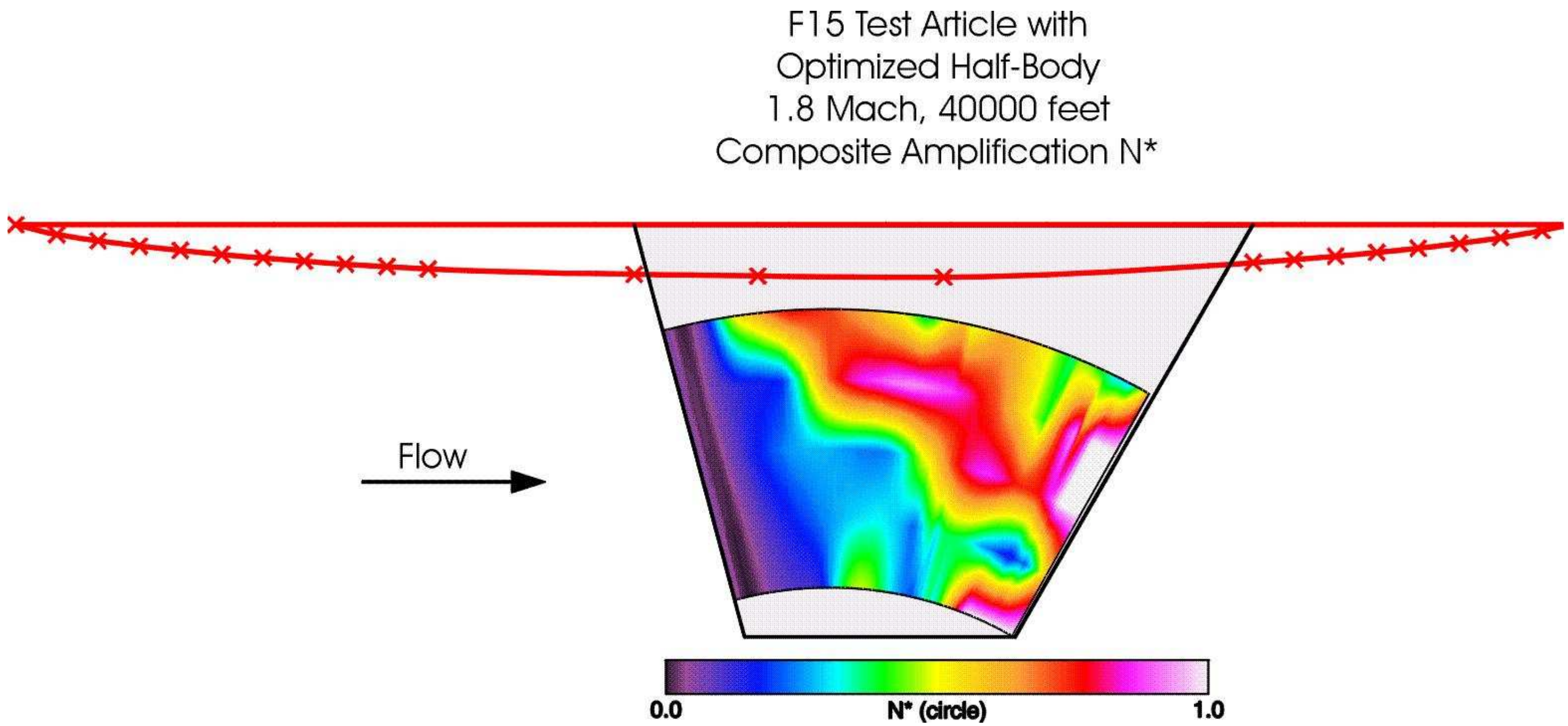
The boundary-layer solution appears superimposed on the inviscid Euler pressures on the surface grid.



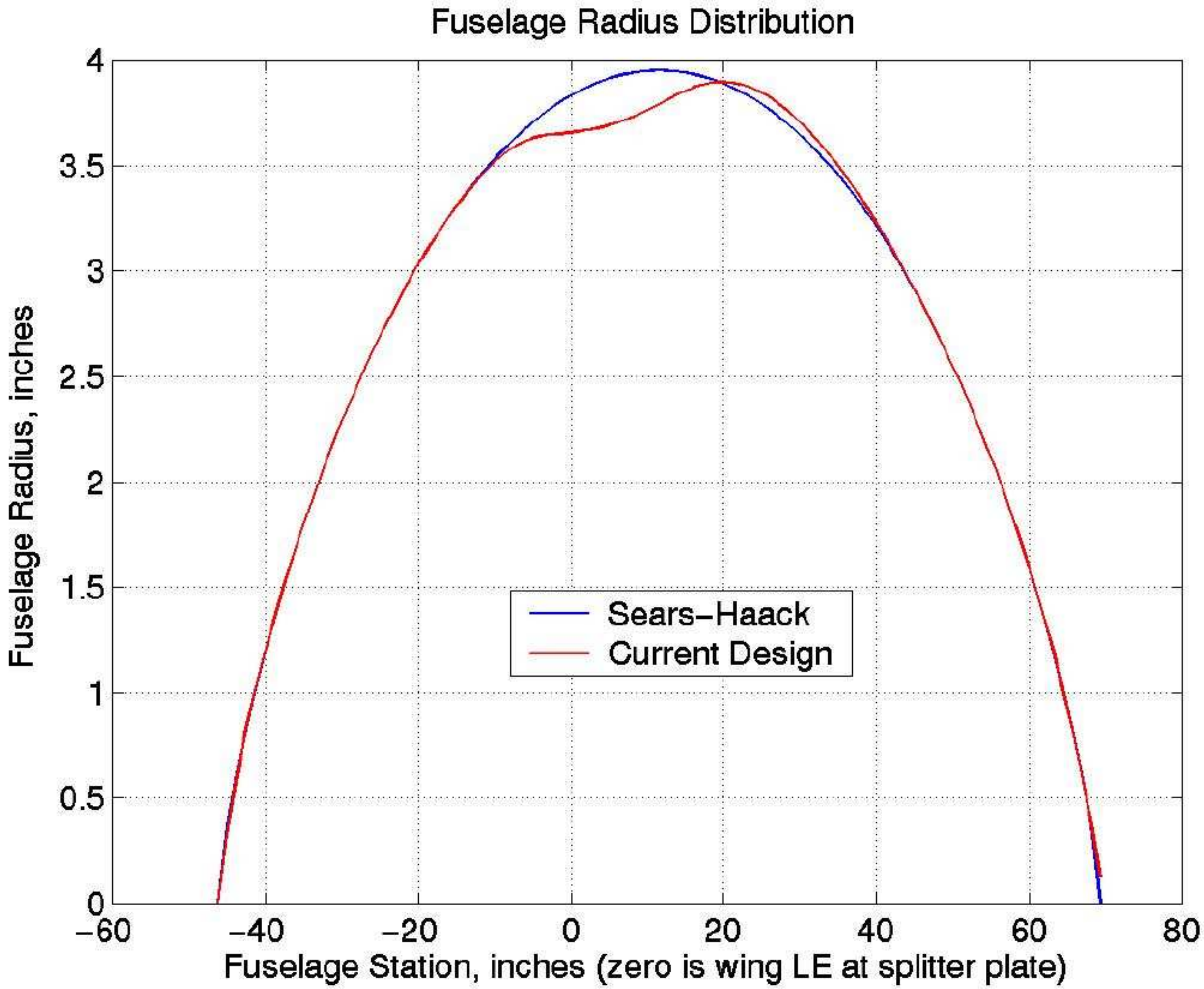
Baseline design: a Sears–Haack body with wing results in early transition (the white areas in the boundary-layer solution). N^* is the measure of laminar instability, with 1.0 (white) being the prediction of transition. The flow is then turbulent from the first occurrence of $N^* = 1$ to the trailing edge irrespective of further values of N^*.



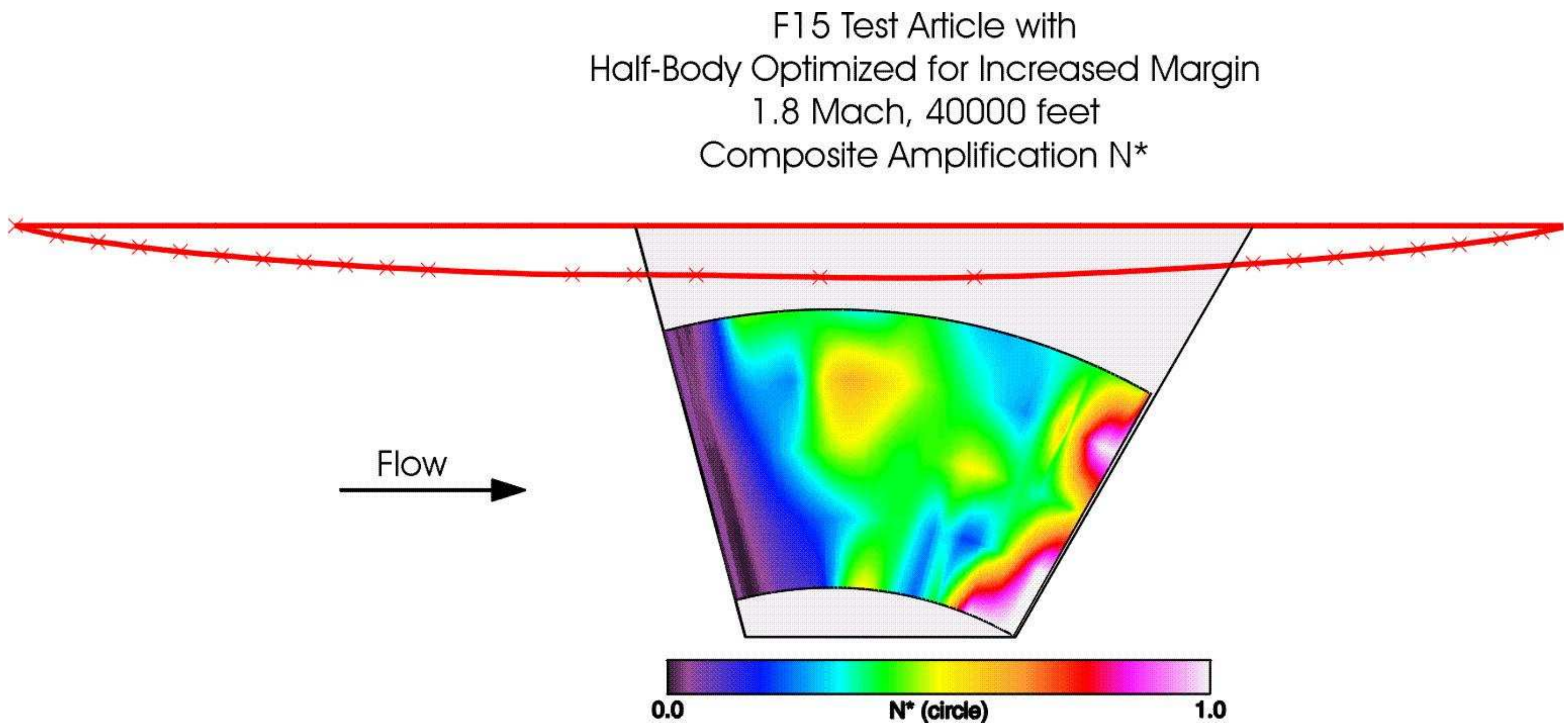
From the nose at left, to the tail at right, this is the radius of the original (blue) and re-designed (red) fuselage after two iterations.



With only 3 design variables (the crosses on the fuselage outline that sit on the wing) and two iterations (not even near a converged optimization) the improvement is dramatic.



With five design variables, and a few more trust-region update cycles, a better solution is found.



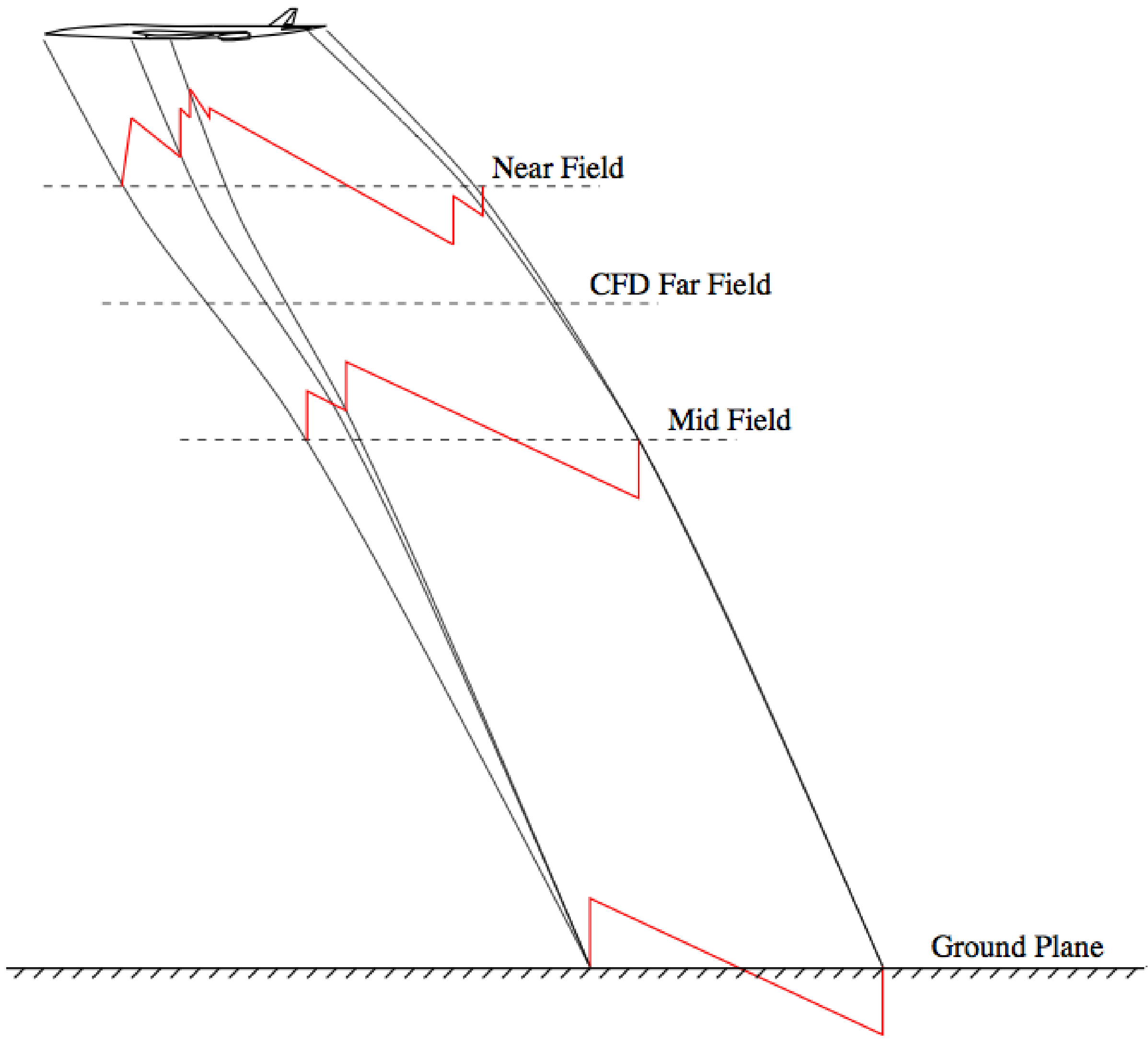
The boundary layer is much farther from transition to turbulent flow as can be seen by comparing the green and yellow colors on this wing with the red and violet colors two figures ago. Also notice how subtle the reshaping of the fuselage is.

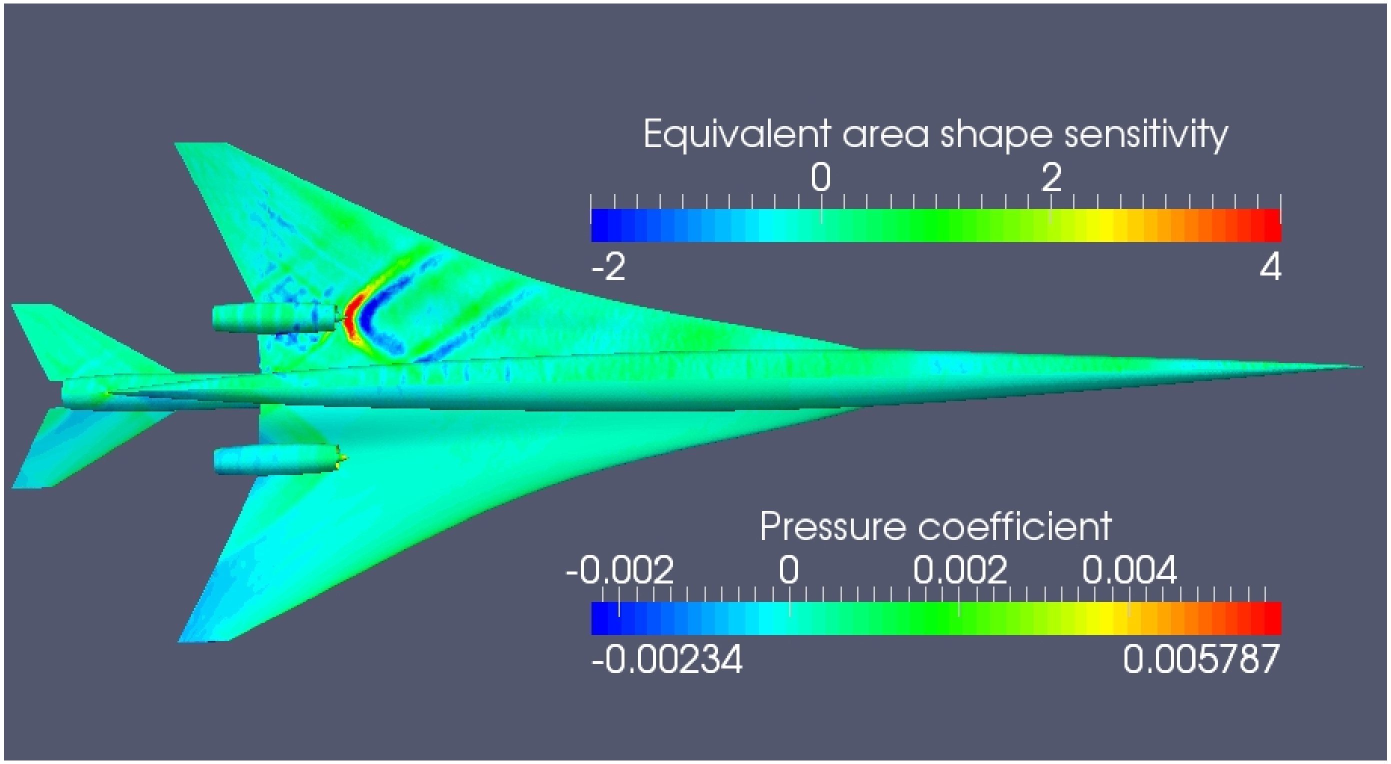
Low-Boom Supersonic Aircraft Design (F. Palacios, J. Alonso, M. Colonno, J. Hicken and T. Lukaczyk) [11]

The goal in low-boom design is to reduce the strength of the sonic boom sufficiently to permit supersonic flight overland. The idea is to make subtle changes to the shape of the aircraft that lead to changes in the sonic boom at ground level.

NASA N+2 project: Lockheed-Martin configuration

Objective: reduce sonic boom strength on the ground by changing shape and weight of the aircraft.

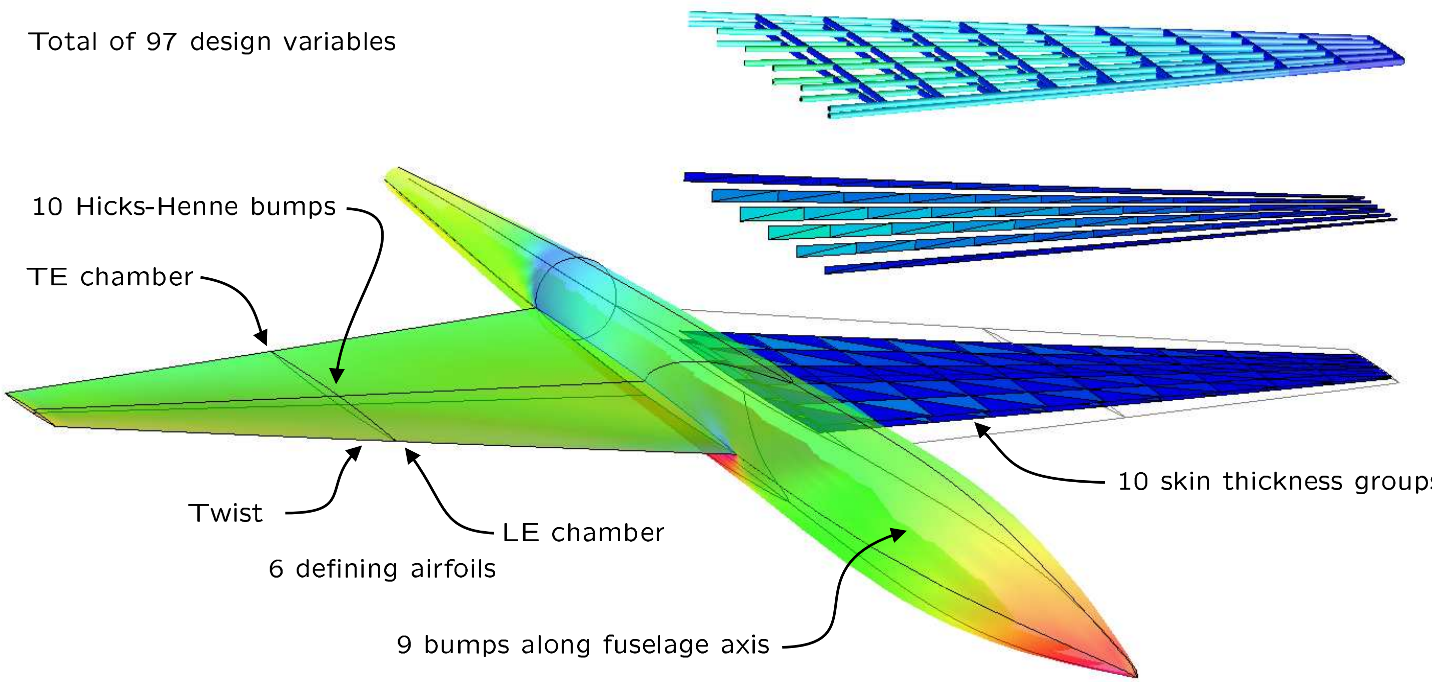




Pressure field (lower half) and equivalent-area shape sensitivity fields.

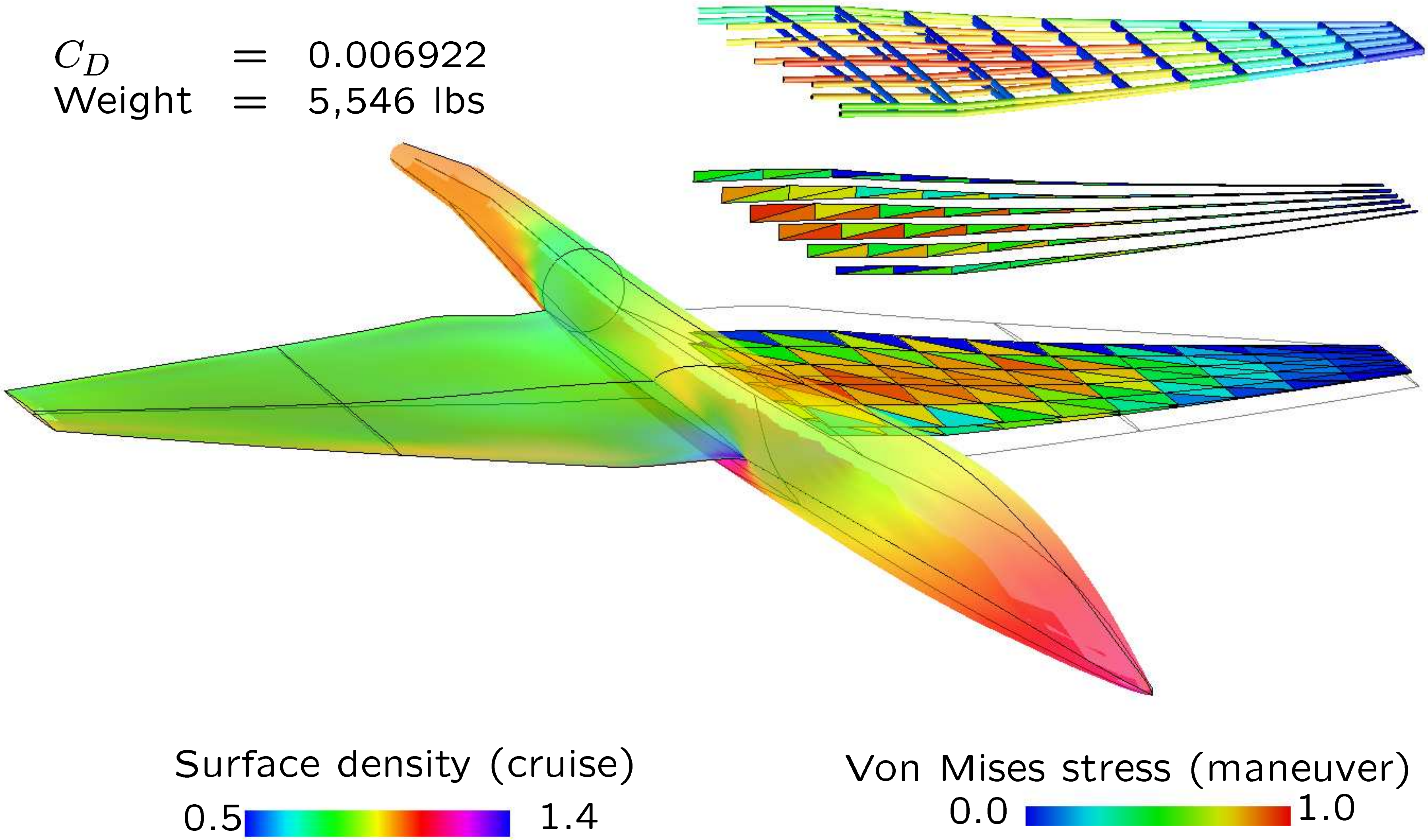
Aero-Structural Design of a Supersonic Business Jet (J.Martins, UTIAS / J.Alonso, Stanford / J.Reuther, NASA) [8, 9]

Baseline configuration and design variables



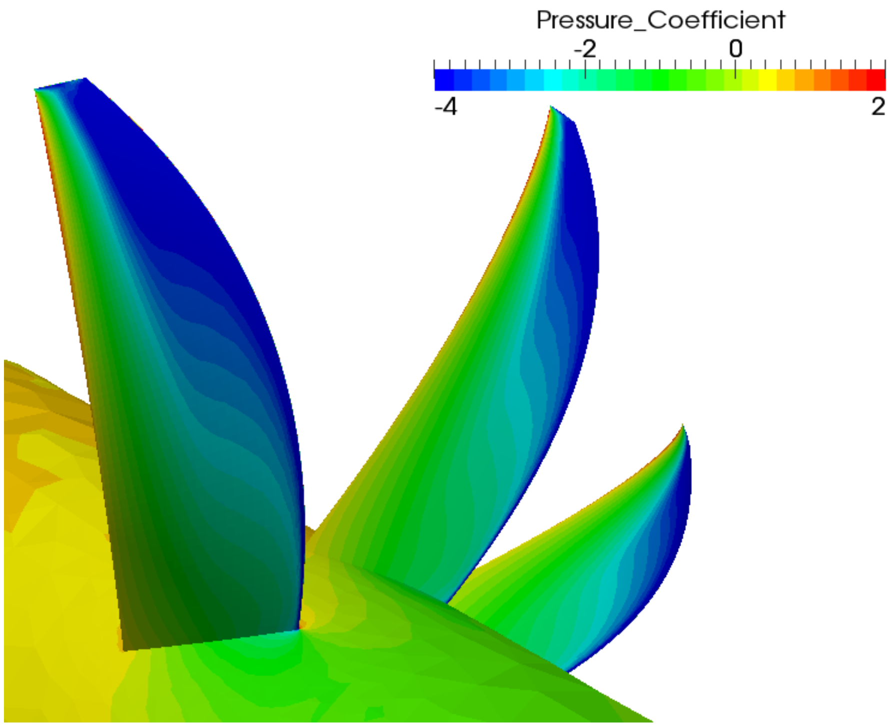
Optimized design

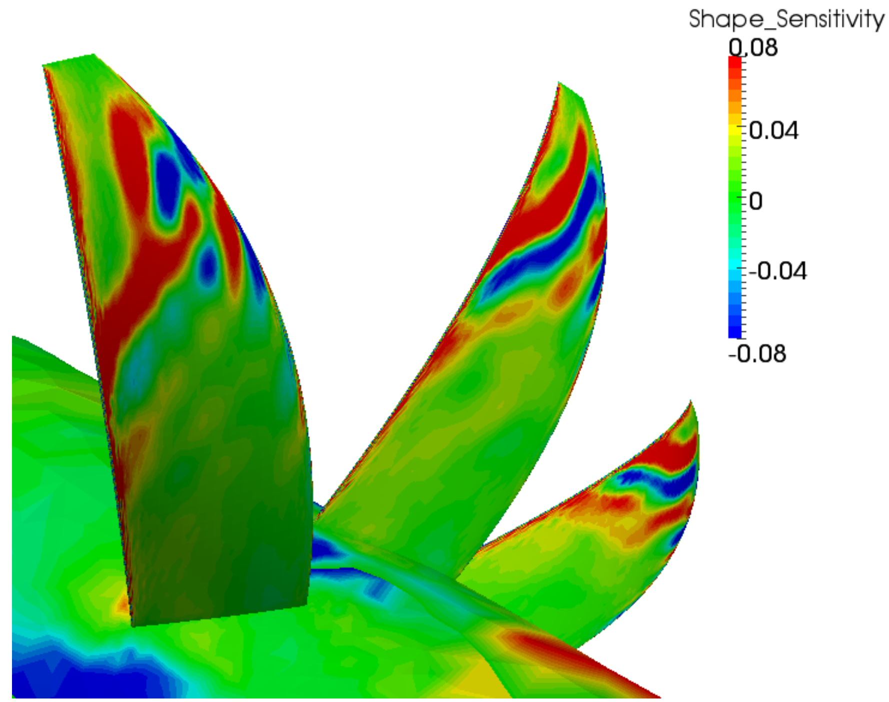
$$
\begin{aligned}
C_D &= 0.006922 \\
\text{Weight} &= 5{,}546 \text{ lbs}
\end{aligned}
$$



Design of Efficient, Quite Open Rotors (T. Economon and J. Alonso, Stanford)

Open-rotor engines offer significantly improved fuel efficiency relative to ducted turbofan engines (perhaps as high as 25%). However, these engines also produce unacceptable noise. In this work, high-fidelity CFD is coupled to an aeroacoustic model to analyze the performance and noise of a rotor. This analysis will then be placed inside an optimization framework to shape the geometry of the rotor.





Design of Low-Cost Launch Vehicles (M. Colonno, J.Alonso, Stanford, SpaceX)

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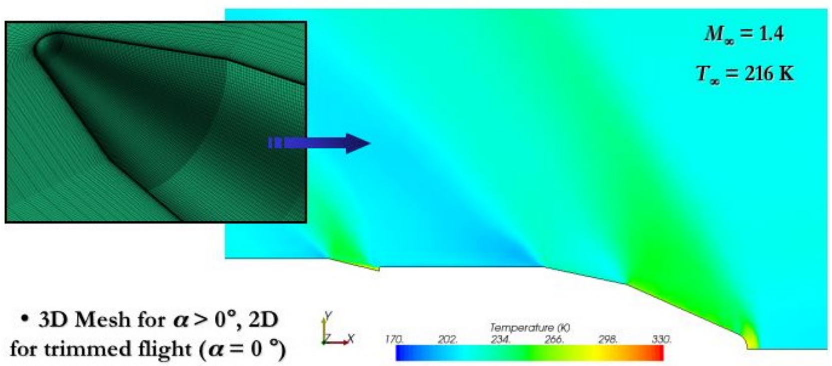

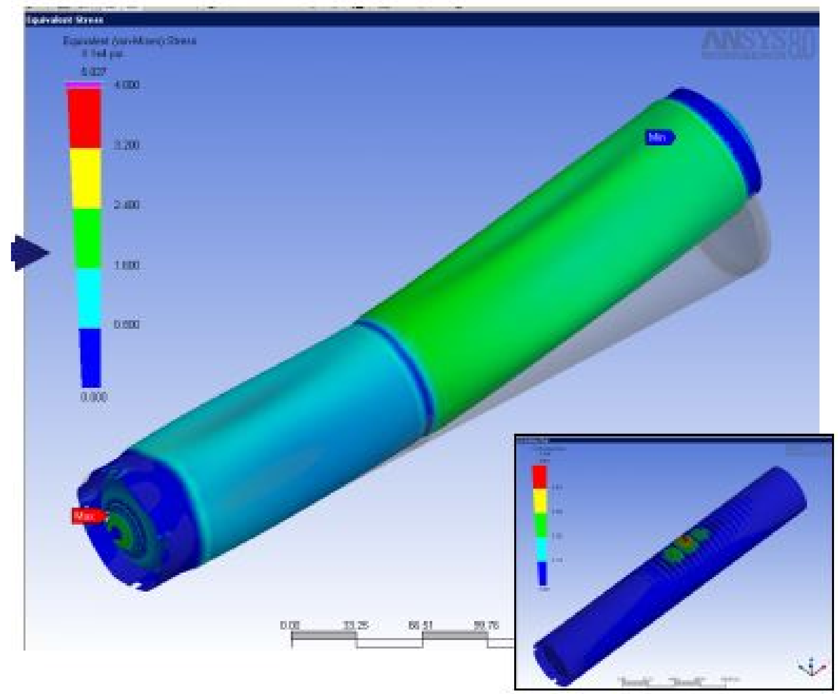

Cost: Current U.S. LV's $ 40,000 /kg to LEO. Small improvements yield big rewards.

Performance: Payload mass to orbit depends exponentially on many vehicle parameters.

Coupled environments: Wide-ranging aerodynamic, thermal, and structural loading tightly coupled.

High-fidelity Aerostructural Optimization of a Subsonic Transport (G. Kenway, G. Kennedy, and J. Martins)

Problem: Maximize the Breguet range of the Common Research Model configuration (approx. dimensions of B777) subject to aerostructural constraints.

$$\max \frac{V}{c}\frac{L}{D}\ln\left(\frac{W_1}{W_2}\right)$$

Variables: free-form shape variables (154), twist variables (6), tail rotation angle (2), angle of attack (2), and structural thickness (160).

Constraints: $L_{\text{cruise}} \geq$ MTOW, $L_{\text{maneuver}} \geq 2.5$MTOW, $C_{m,\text{cruise}} = 0$, $C_{m,\text{maneuver}} = 0$, $\text{KS}_{\text{maneuver}} \leq 1$, and 27 wing thickness constraints.

References

[1] N. Alexandrov and M. Y. Hussaini, editors. *Multidisciplinary Design Optimization: State-of-the-Art*. SIAM, 1997.

[2] N. M. Alexandrov and R. M. Lewis. Comparative properties of collaborative optimization and other approaches to MDO. In *Proceedings of the First ASMO UK / ISSMO Conference on Engineering Design Optimization*, 1999.

[3] N. E. Antoine and I. M. Kroo. Aircraft optimization for minimal environmental impact. *Journal of Aircraft*, 41(4):790–797, 2004.

[4] J. E. Hicken and D. W. Zingg. Aerodynamic optimization algorithm with integrated geometry parameterization and mesh movement. *AIAA Journal*, 48(2):400–413, Feb. 2010.

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