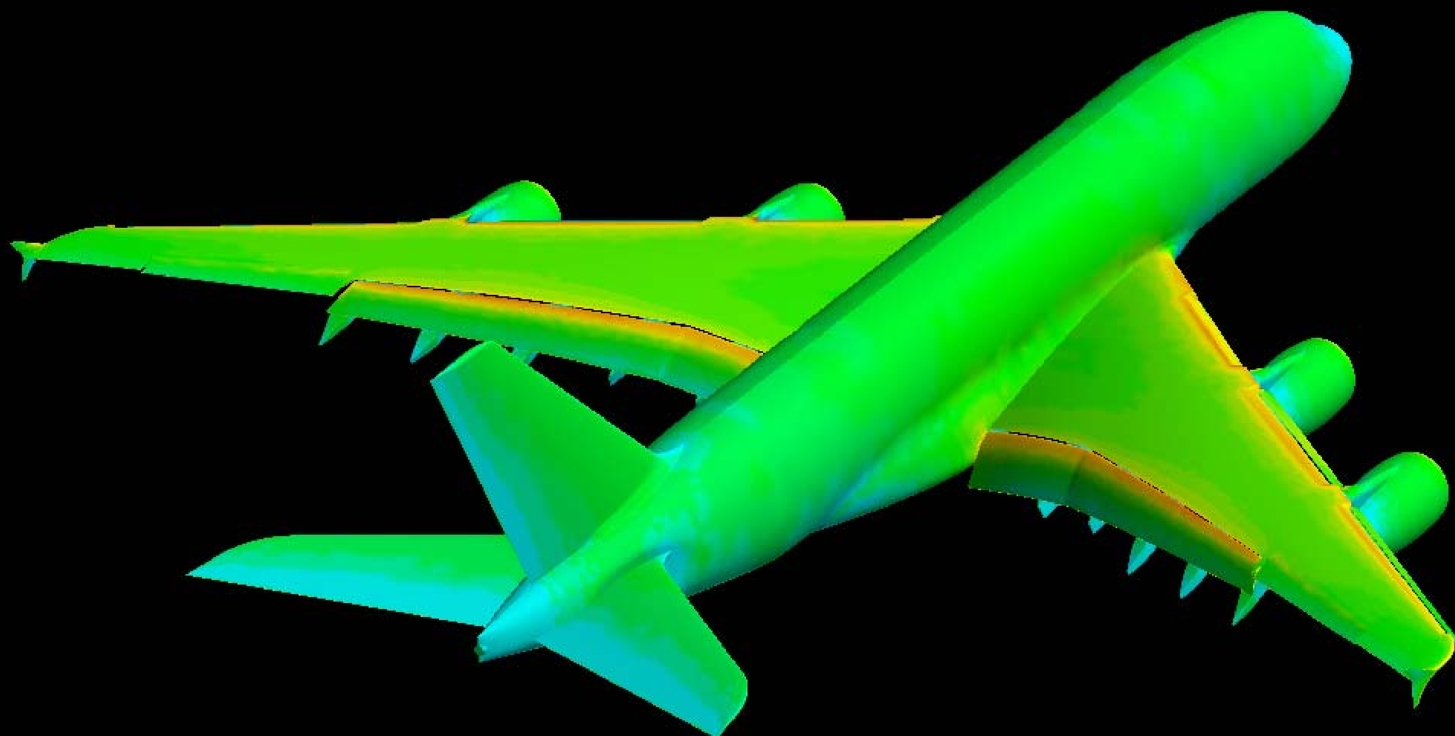
Need and Use of Multiobjective Optimization in Large Scale Engineering Applications



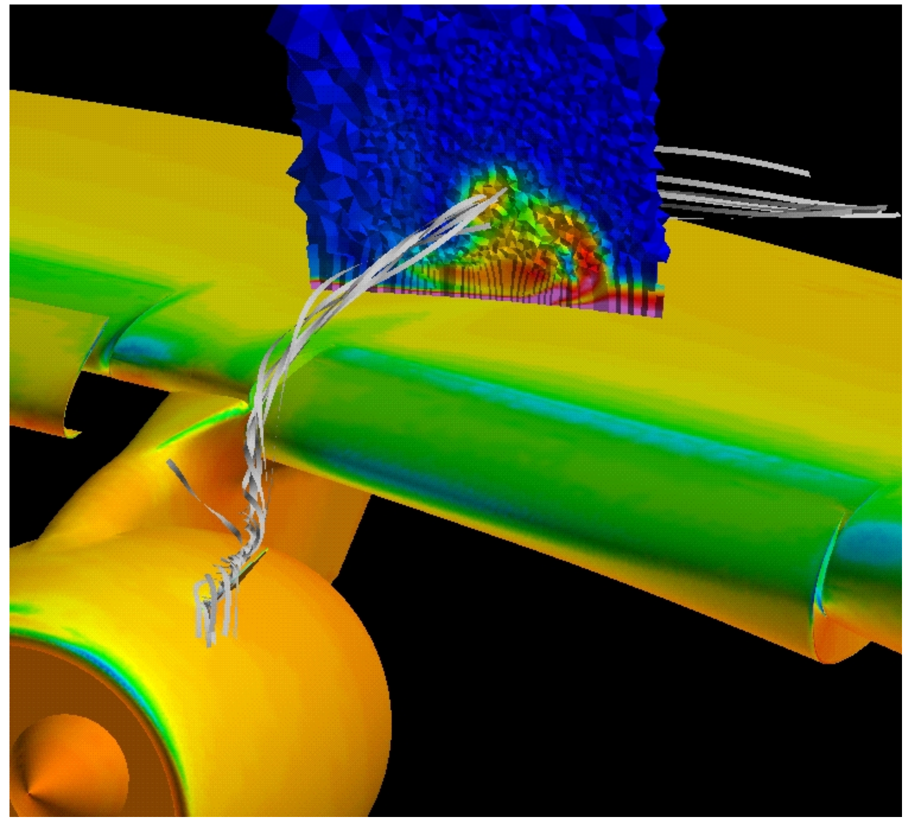
N. Kroll

DLR (German Aerospace Center)
Institute of Aerodynamics and Flow Technology
Braunschweig

Need and Use of Multiobjective Optimization in Aircraft Design

Outline

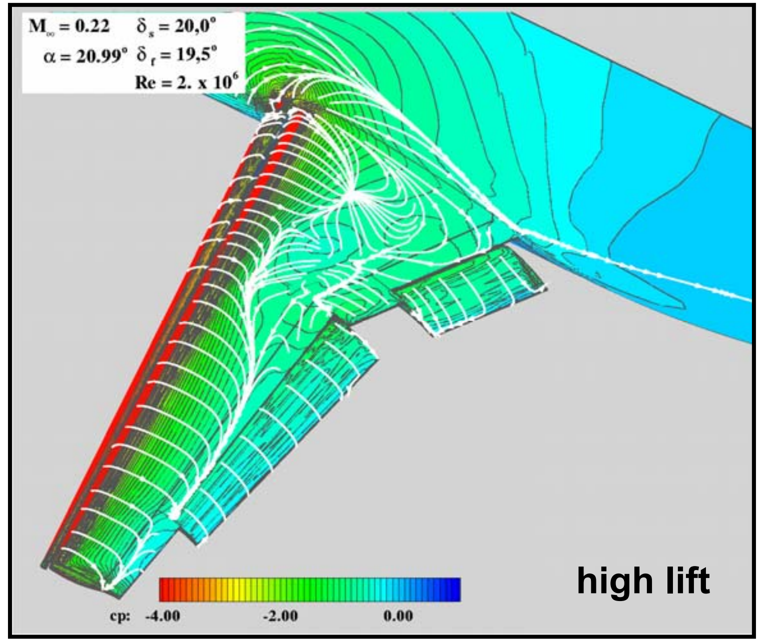
- **Role of CFD in Aircraft Design**
- **Shape optimization**
  examples, requirements
- **Multiobjective optimization**
  examples, need for research
- **Conclusion**

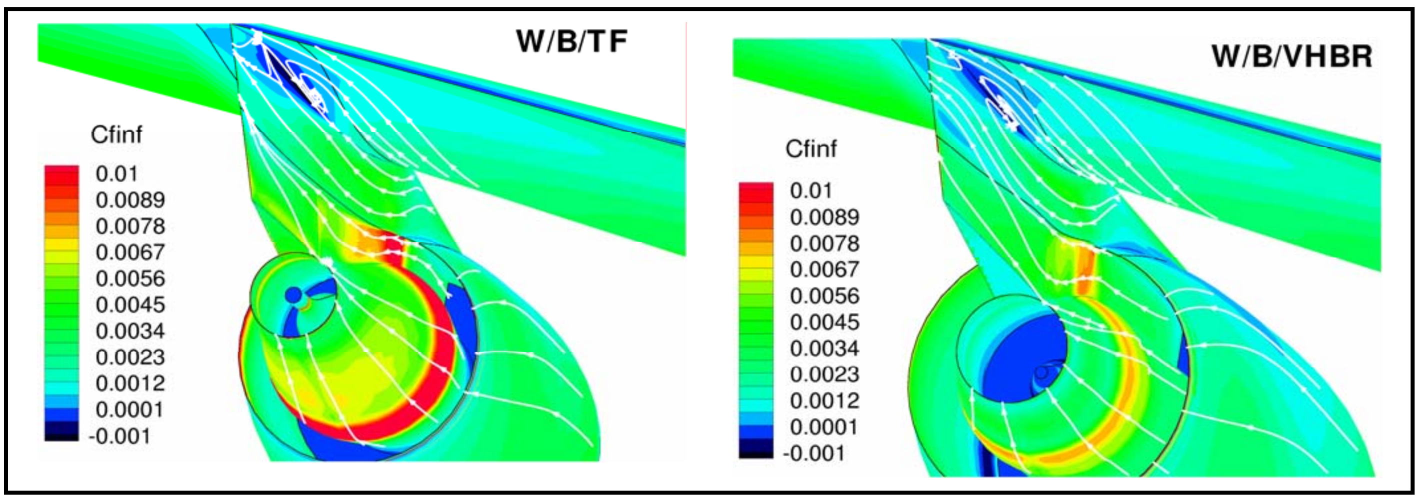


Role of Computational Fluid Dynamics (CFD) in Aerodynamic Aircraft Design

Objectives of CFD

- detailed analysis of complex flow fields
- cost efficient configuration studies
- shape optimization
- extrapolation of wind tunnel results to free flight conditions



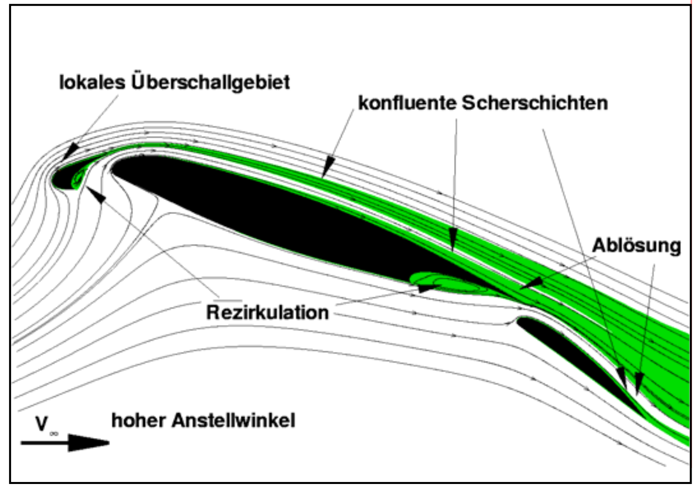


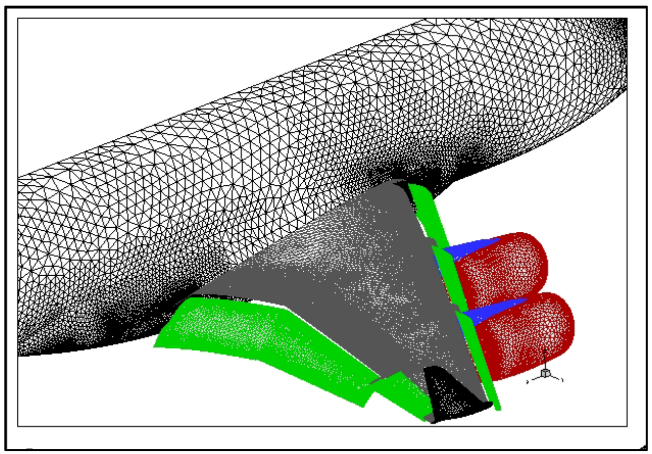
engine integration

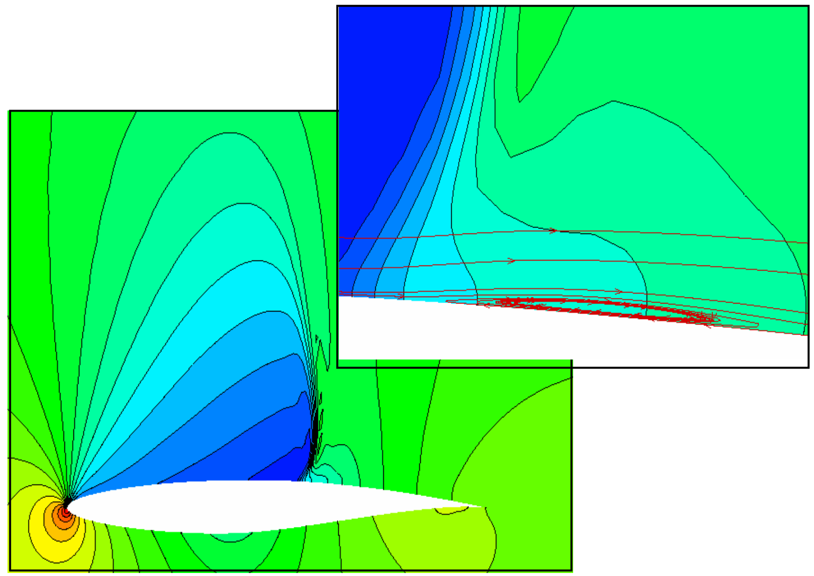
Use of CFD in Aerodynamic Aircraft Design

Requirements on CFD

- high level of physical modeling
  - compressible flow
  - transonic flow
  - laminar - turbulent flow
  - high Reynolds numbers (60 million)
  - large flow regions with flow separation
  - steady / unsteady flows
- complex geometries
- short turn around time







Use of CFD in Aerodynamic Aircraft Design

Consequences for "Detailed Design Phase"

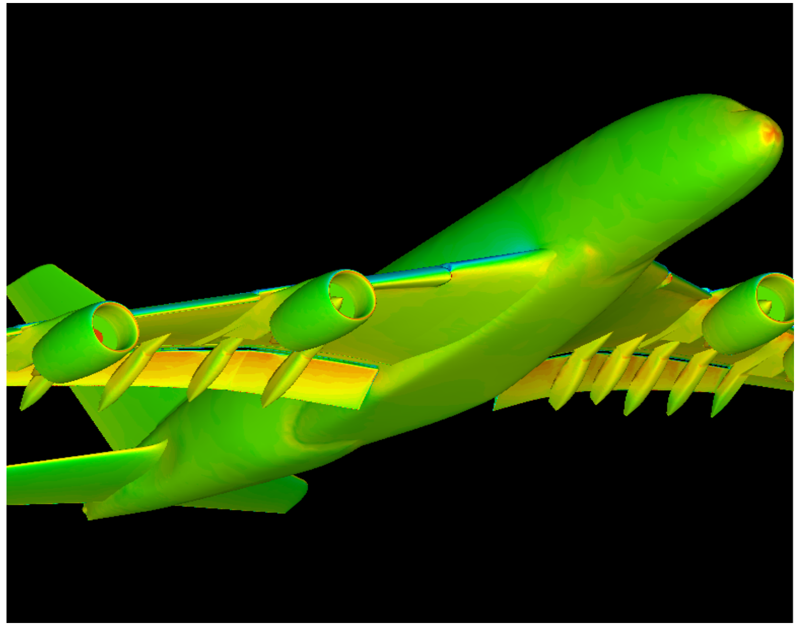
- solution of 3D compressible Reynolds averaged Navier-Stokes equations
- turbulence models based on transport equations (2 – 6 eqn)
- models for predicting laminar-turbulent transition
- flexible grid generation techniques with high level of automation (block structured grids, overset grids, unstructured/hybrid grids)
- link to CAD-systems
- efficient algorithms (multigrid, grid adaptation, parallel algorithms...)
- large scale computations (~ 10 - 25 million grid points)

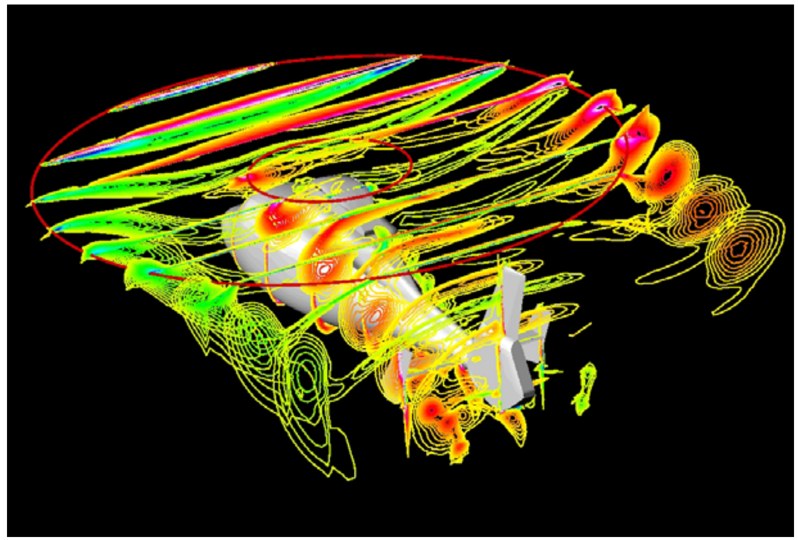
DLR Software MEGAFLOW

MEGAFLOW

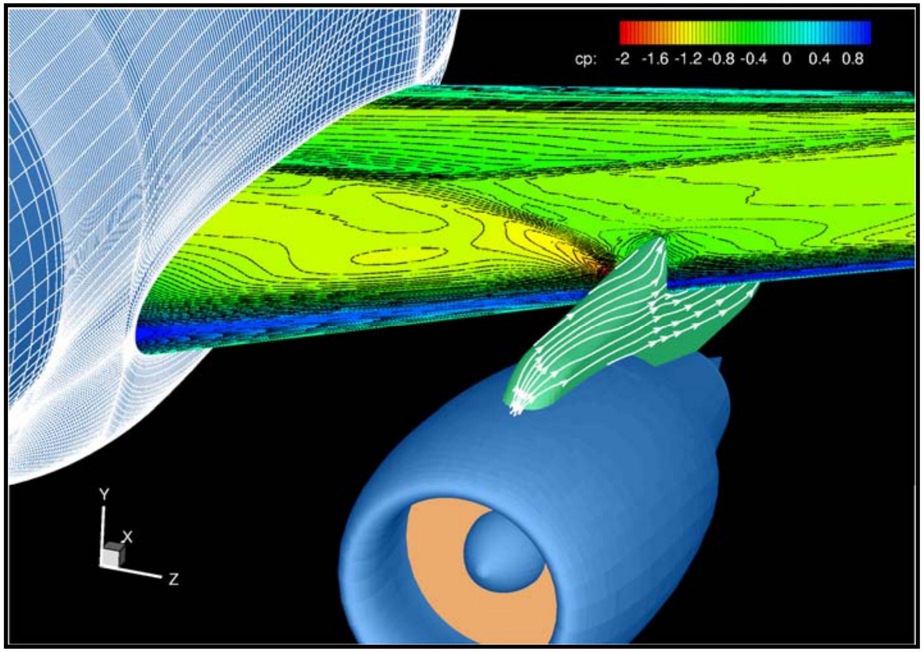
National CFD software dedicated for aerodynamic aircraft applications which

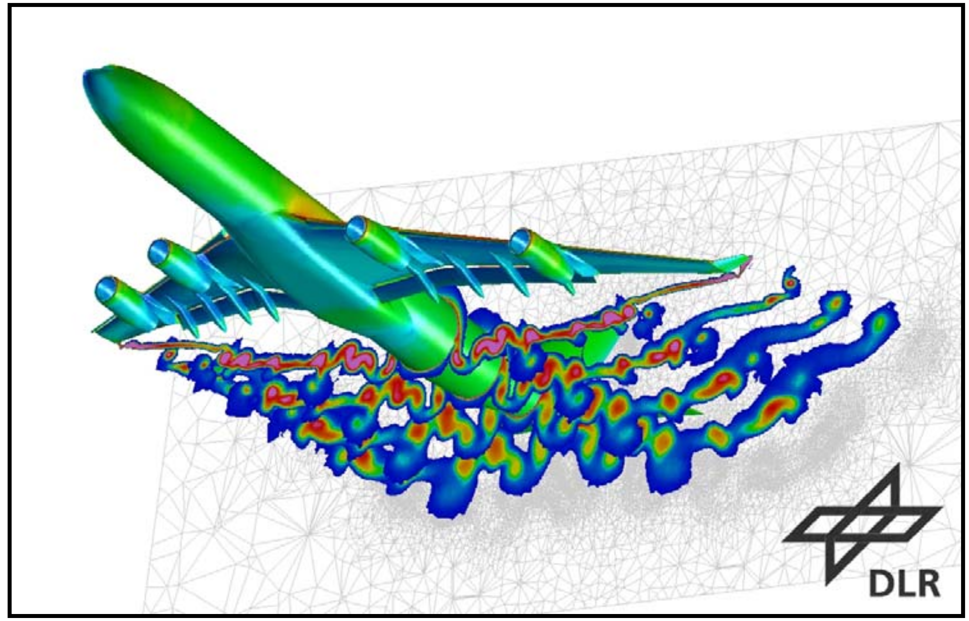
- allows Navier-Stokes computations for 3D complex configurations at cruise and high-lift conditions
- establishes numerical flow simulation as a routinely used tool at DLR and in German aircraft industry
- CFD kernel for multidisciplinary simulation and optimization
- serves as a development platform for universities





MEGAFLOW Software





Structured RANS solver FLOWer

- block-structured grids
- moderate complex configurations
- fast algorithms (unsteady flows)
- design option

Unstructured RANS solver TAU

- hybrid grids
- very complex configurations
- grid adaptation
- fully parallel software

Reynolds-Averaged Navier-Stokes Solver FLOWer

Physical model

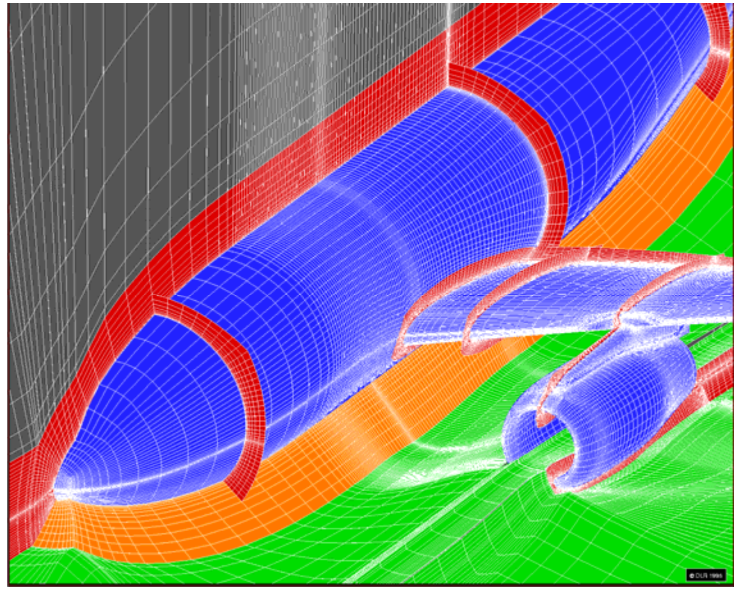
- 3D compressible Navier-Stokes equations
- arbitrarily moving bodies
- steady and time accurate flows
- state-of-the-art turbulence models (RSM)

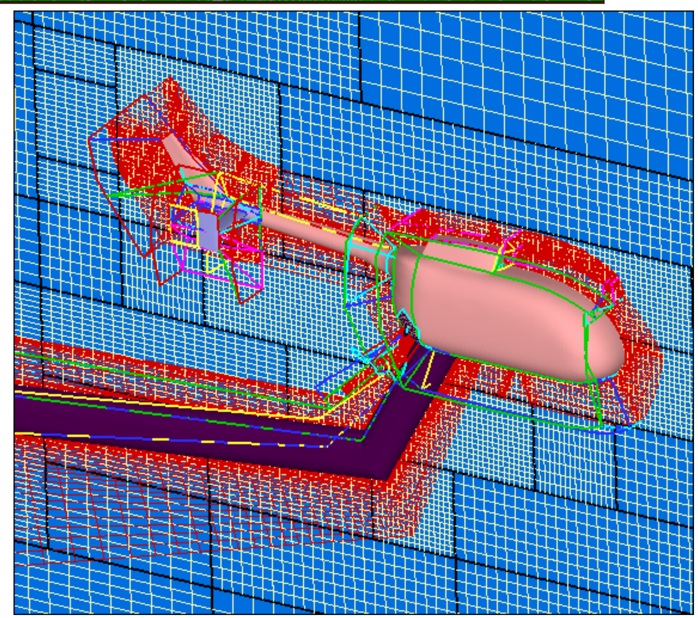
Grid strategy

- block-structured grids
- discontinuous block boundaries
- overset grids (Chimera)
- deforming grids

Numerical algorithms

- 2nd order finite volume discretization (cell centered & cell vertex option)
- central and upwind schemes
- multigrid
- implicit treatment of turbulence equations
- implicit schemes for time accurate flows
- preconditioning for low speed flow
- vectorization & parallelization
- adjoint solver

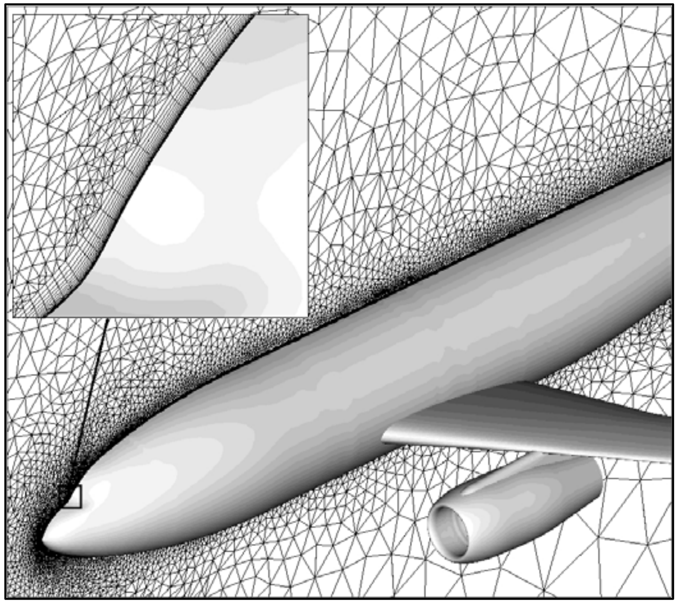




Reynolds-Averaged Navier-Stokes Solver TAU

Physical model

→ 3D compressible Navier-Stokes equations
→ arbitrarily moving bodies
→ steady and time accurate flows
→ state-of-the-art turbulence models

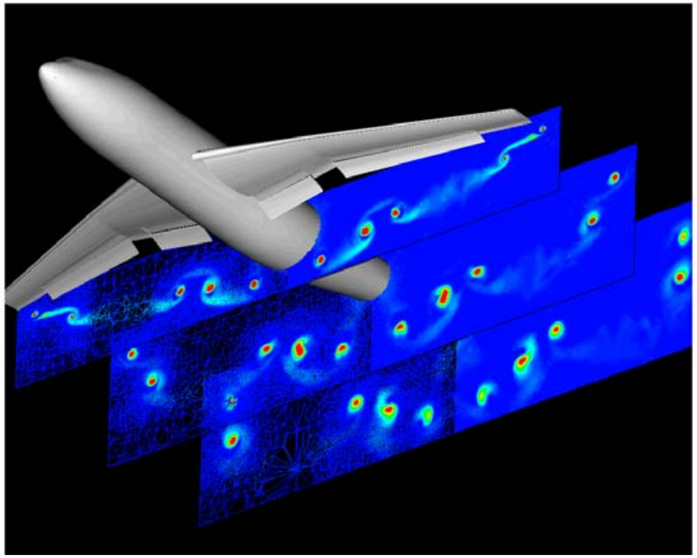


Grid strategy

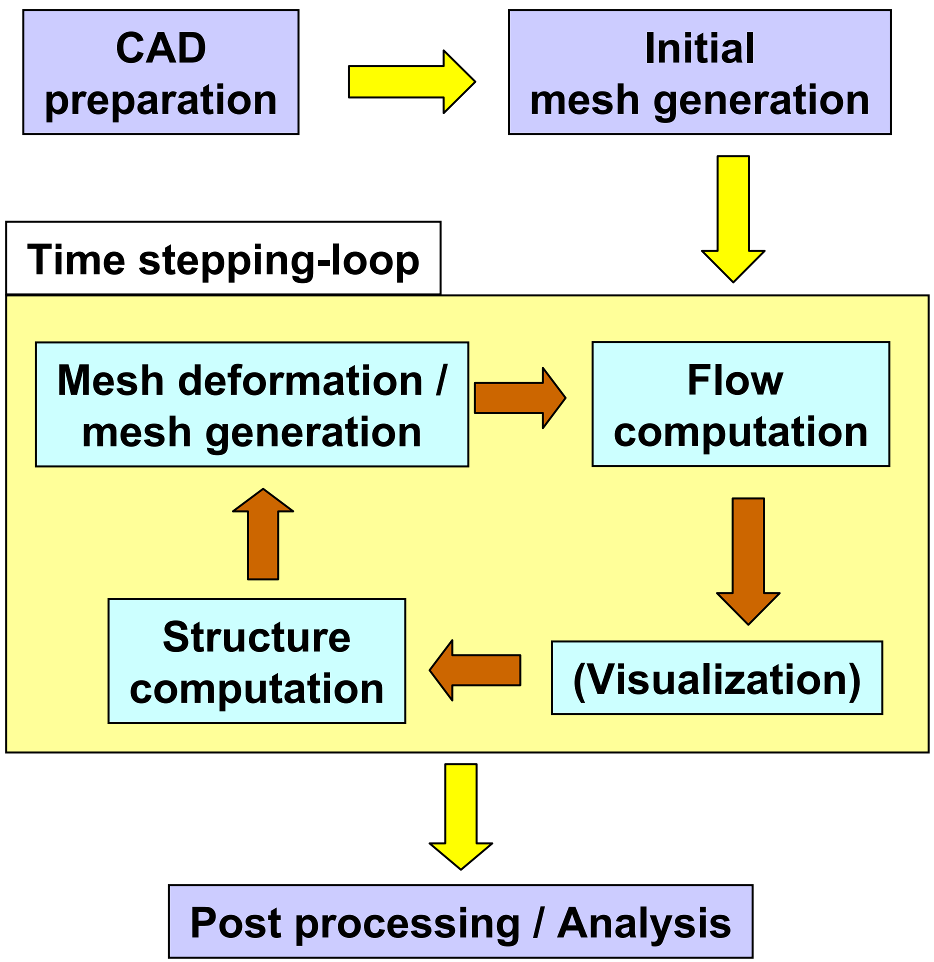
→ unstructured/hybrid grids
→ semi-structured sublayers
→ overset grids (Chimera)
→ deforming grids
→ grid adaptation (refinement, de-refinement)

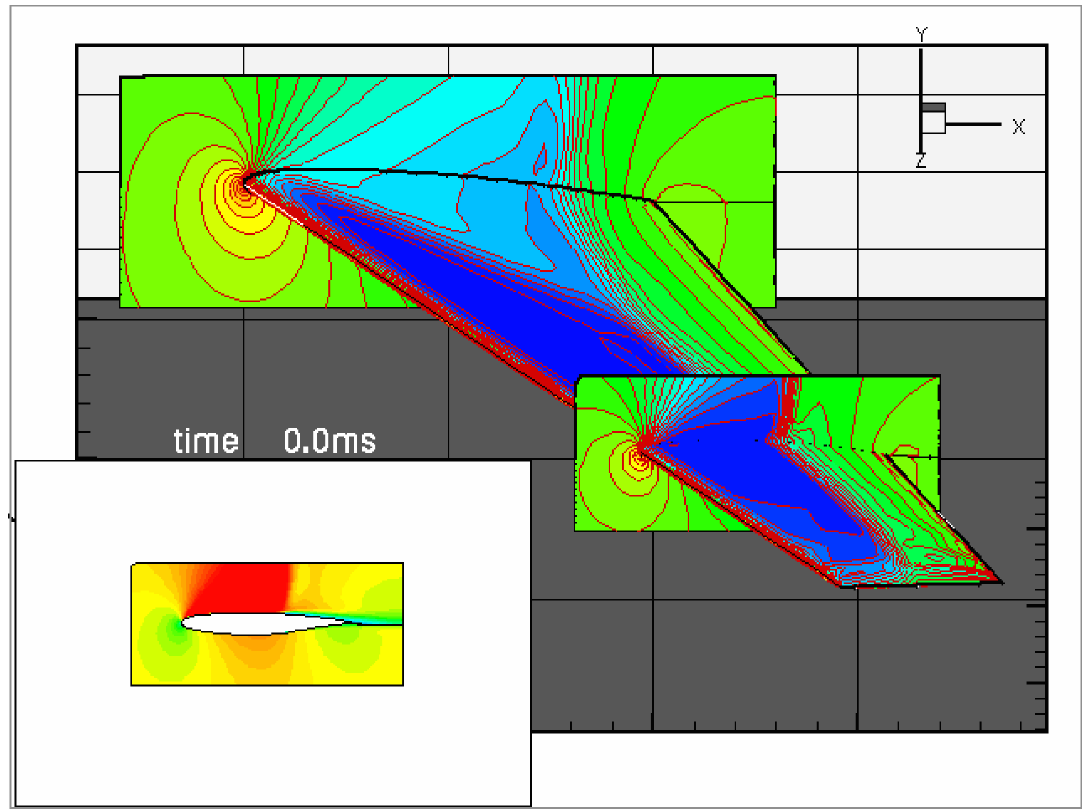
Numerical algorithms

→ 2nd order finite volume discretization based on dual grid approach
→ central and upwind schemes
→ multigrid based on agglomeration
→ implicit schemes for time accurate flows
→ preconditioning for low speed flow
→ optimized for cash and vector processors
→ MPI parallelization



Fluid / Structure Coupling





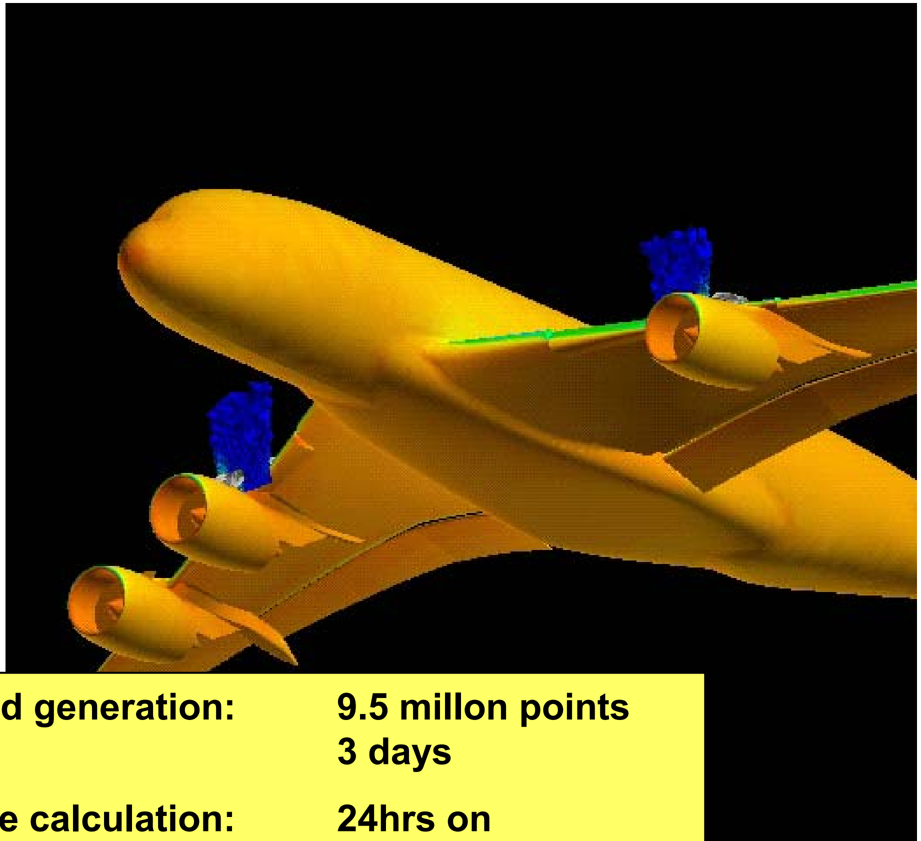
FLOWer-Code

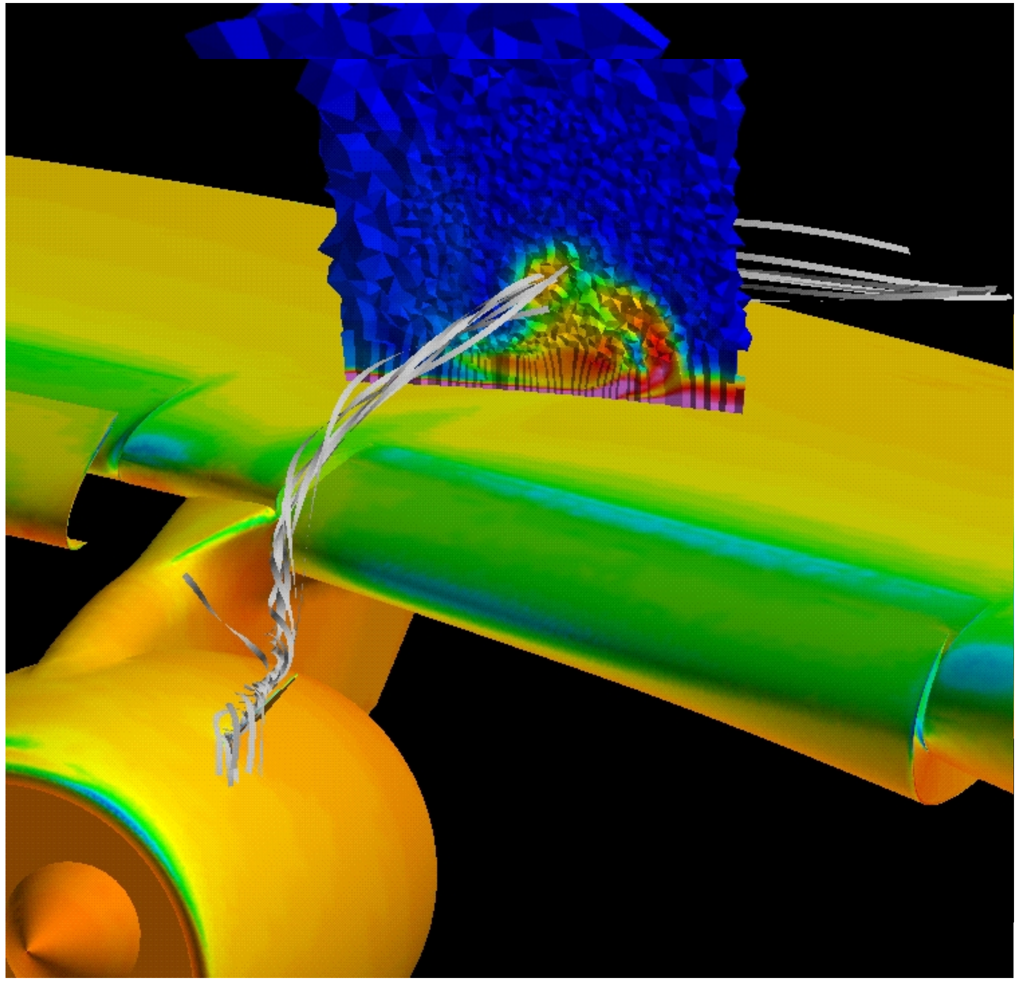
RWTH Aachen

Complex High- Lift Configurations

Megaliner landing configuration

Influence of nacelle strakes





grid generation:	**9.5 millon points** **3 days**
one calculation:	**24hrs on** **64 Proc. PC-Cluster**

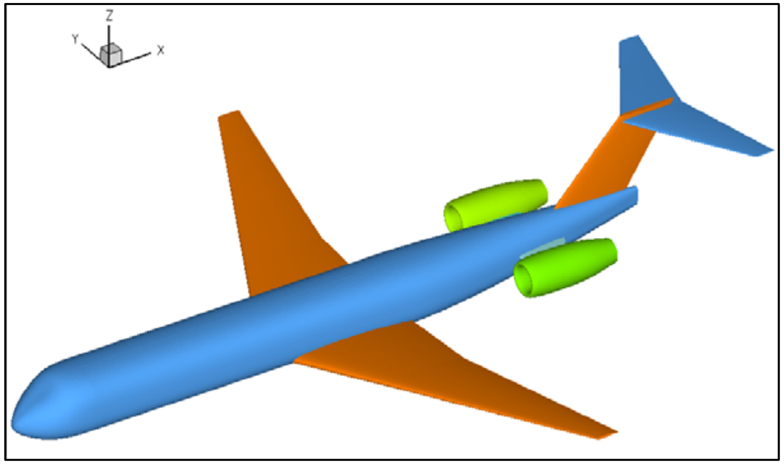
TAU computations

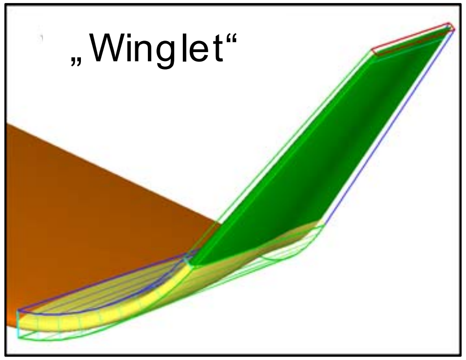
Brodersen

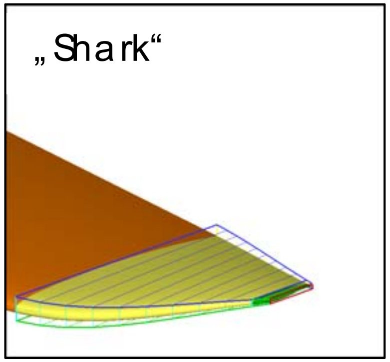
Aerodynamic Shape design

Approach

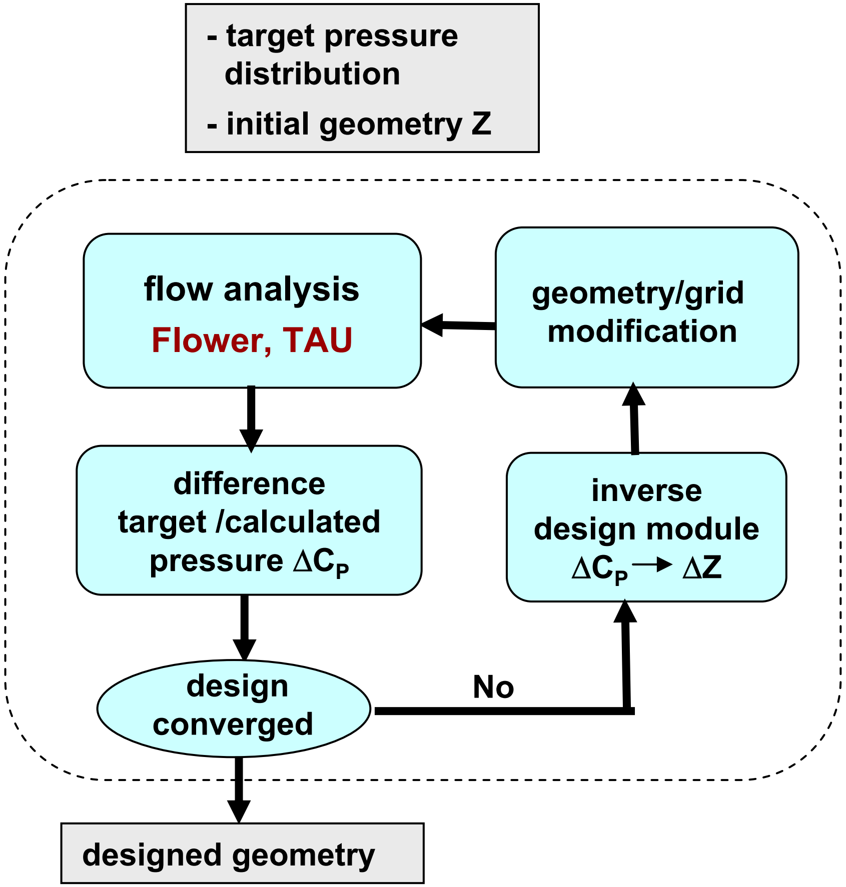
- **analysis of different geometries**
- **inverse design** (ill-posed problem)
- **numerical shape optimization**
  - **single discipline optimization**
    - single point
    - multi point
  - **multidisciplinary optimization**
    - single/multi point, single objective
    - single/multi point, multi objective



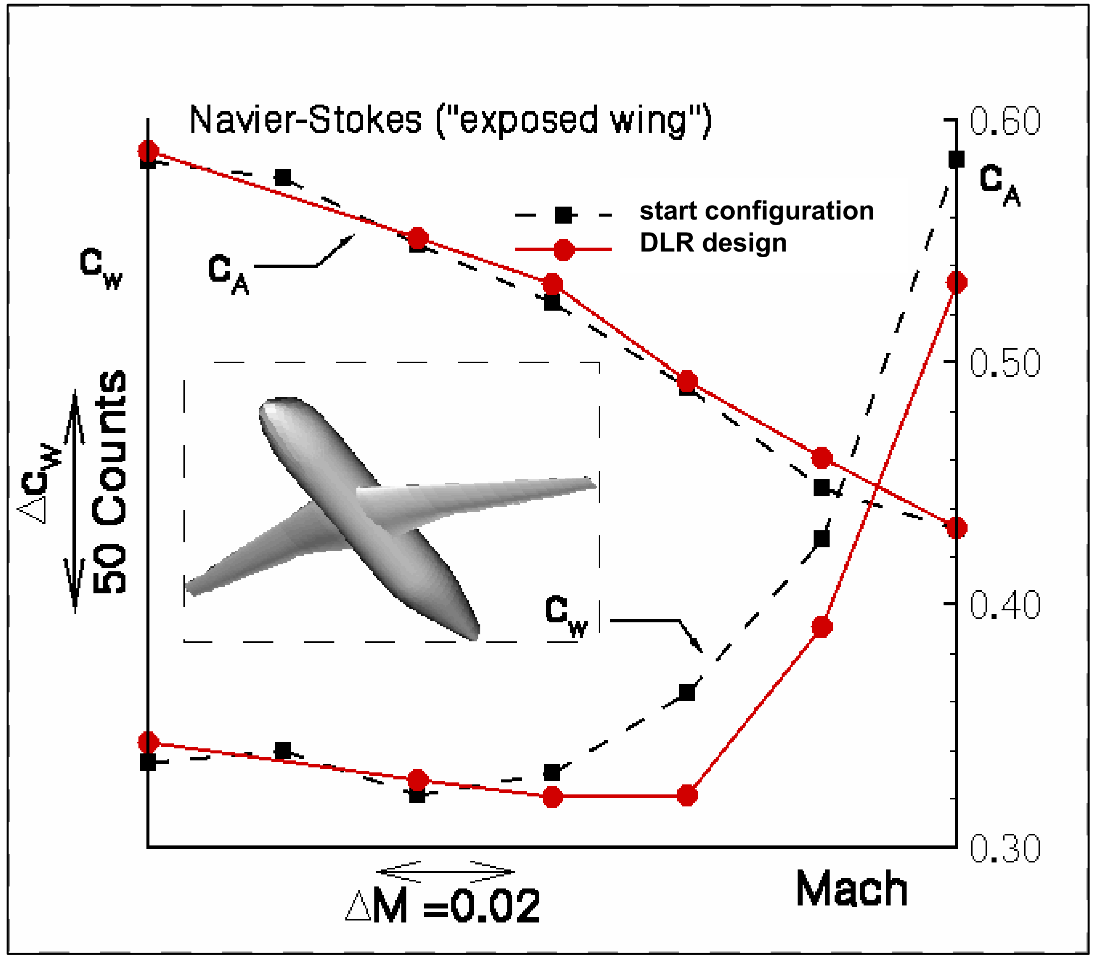




Inverse Design



***Objective*: drag rise improvement**
***Configuration*: F/D 728/928 (n=1.0g)**

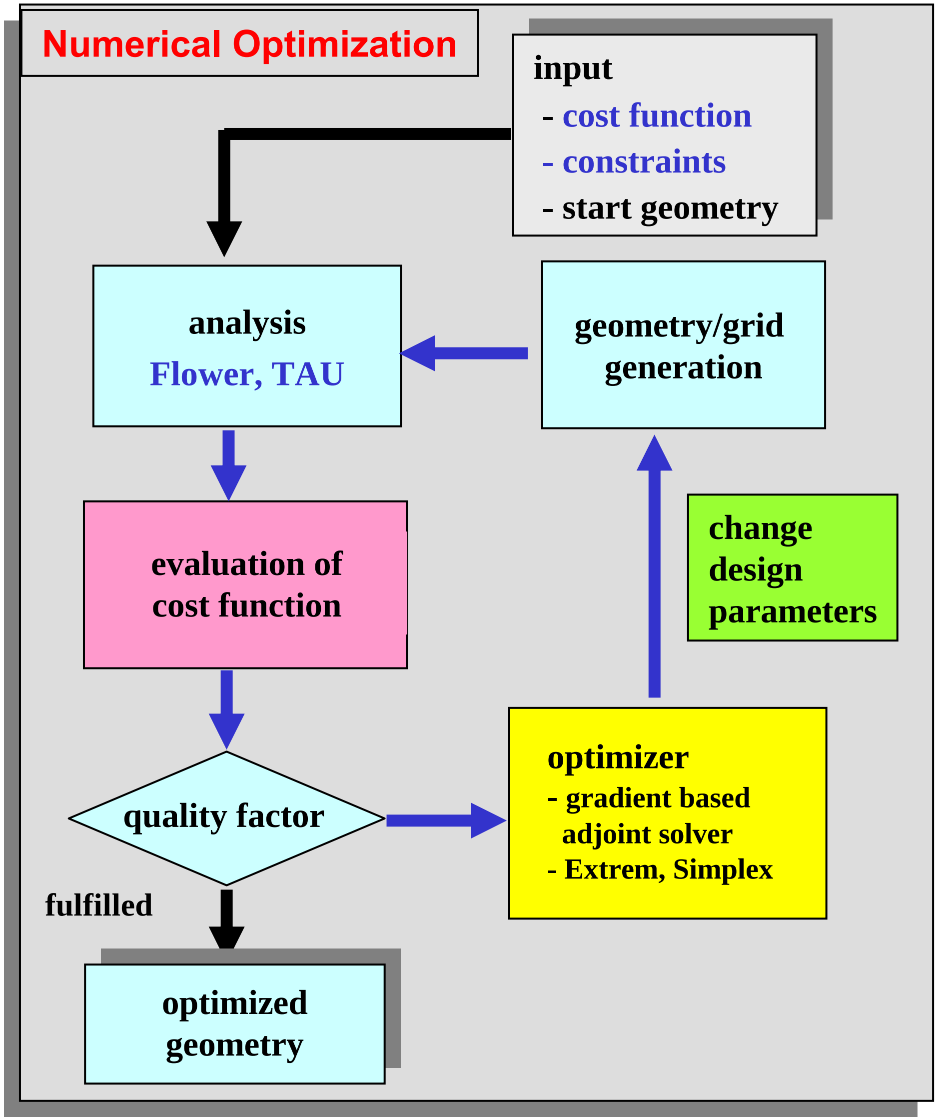


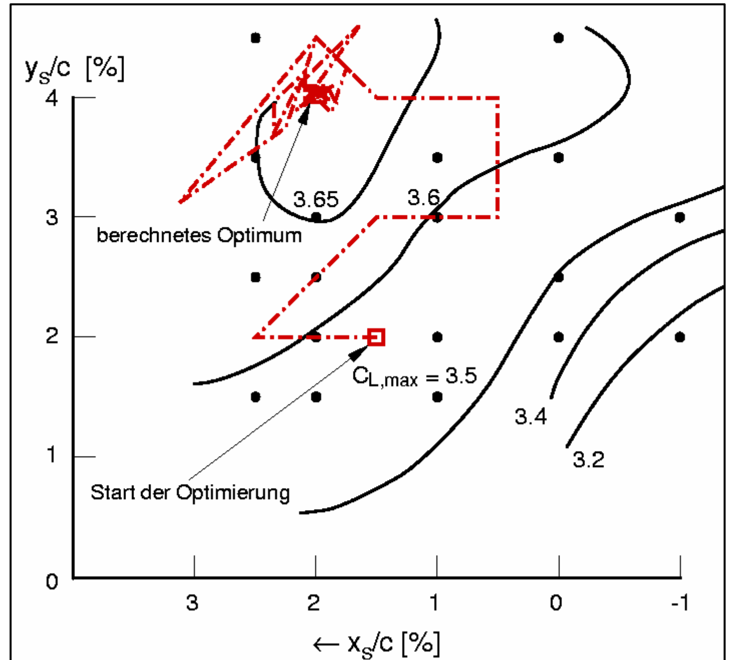
Application

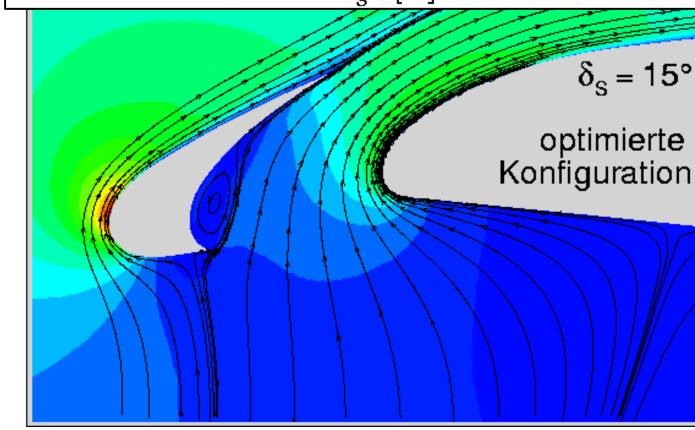
- airfoil, isolated wings
- wing/body
- isolated and integrated nacelles

Streit

Aerodynamic Shape Optimization







setting optimization, $C_{a_{max}}$

M=0.197, Re=3.52x10^6

Wild

Numerical Optimization of High-Lift 3-Element Airfoil

single point, single discipline, single objective

Application

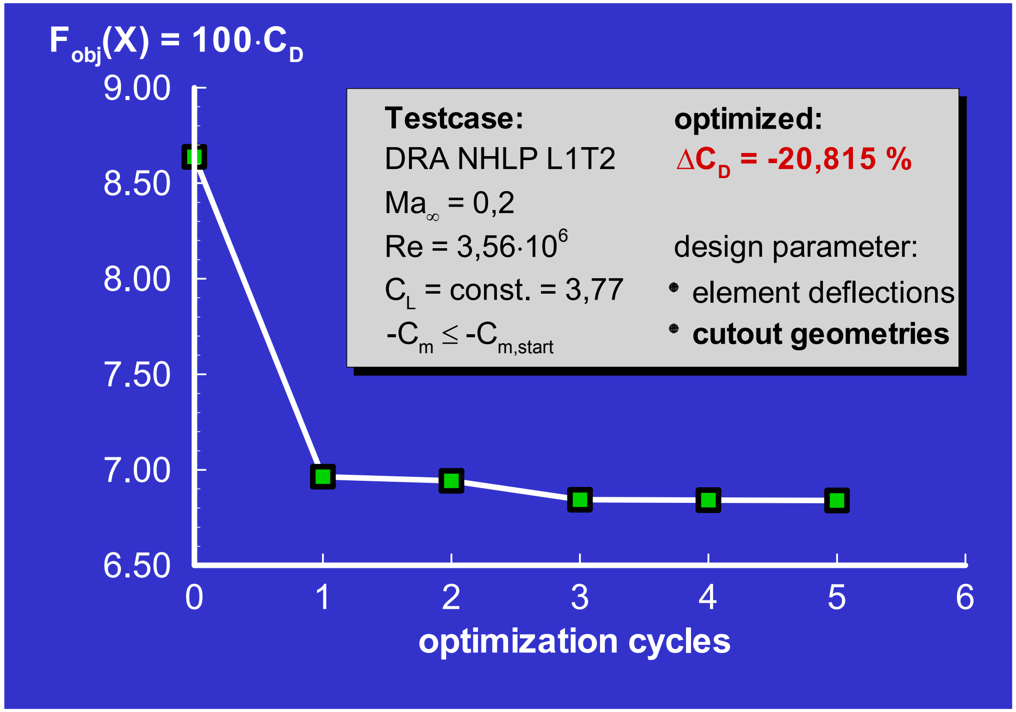
- drag optimization for 3-element airfoil
- take-off configuration (M_∞=0.2, Re=3.52x10^6)

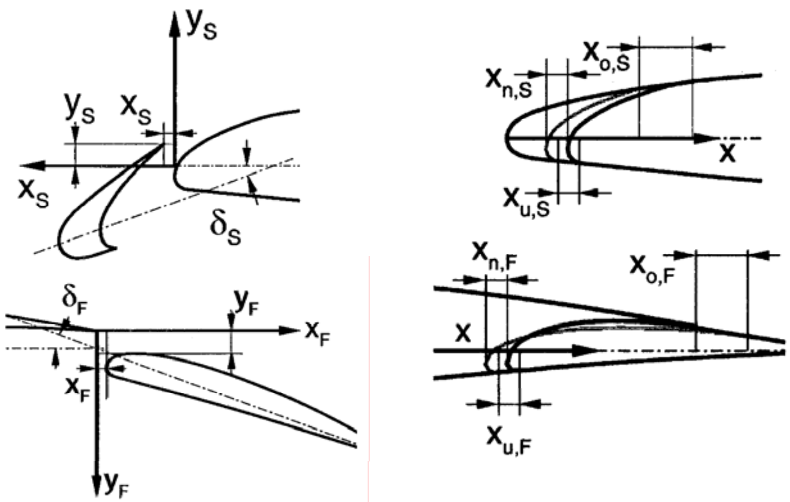
Cost function:

- minimum drag with constant lift and constraint pitching moment

Design parameters (12)

- element position & deflection
- element-size variations





Computational effort:
50 hrs, 4 procs NEC SX5.

~ 24 hrs, 12 procs PC-Cluster

Wild

Optimization of SCT Configuration

Drag reduction at constant lift

- Mach number = 2.0
- lift coefficient = 0.1207

Design variables

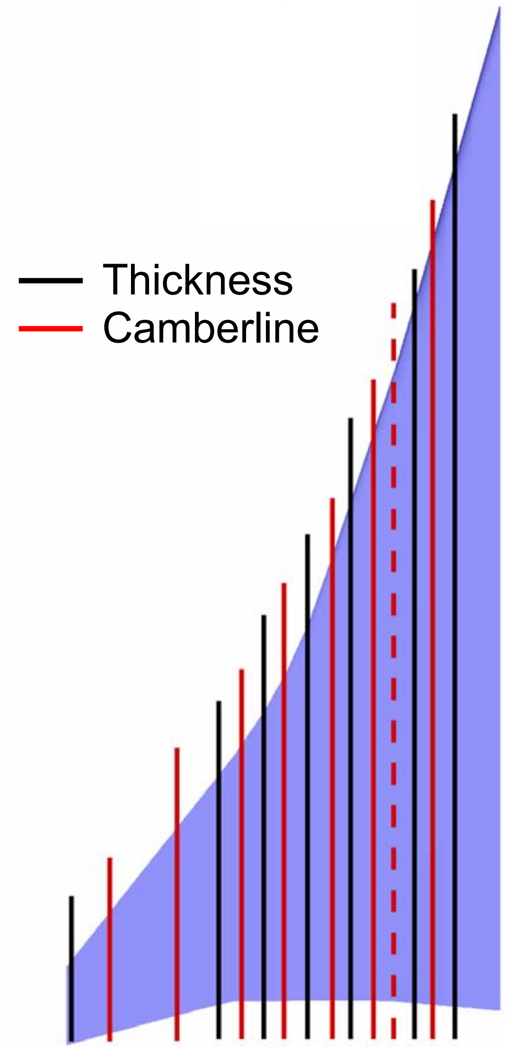
Fuselage	10 parameters
twist deformation:	10 parameters
camberline (8 sections):	32 parameters
thickness (8 sections) :	32 parameters
angle of attack:	1 parameter
	85 parameters

Geometric constraints

- minimum wing thickness distribution along the spanwise direction
- minimum fuselage radius

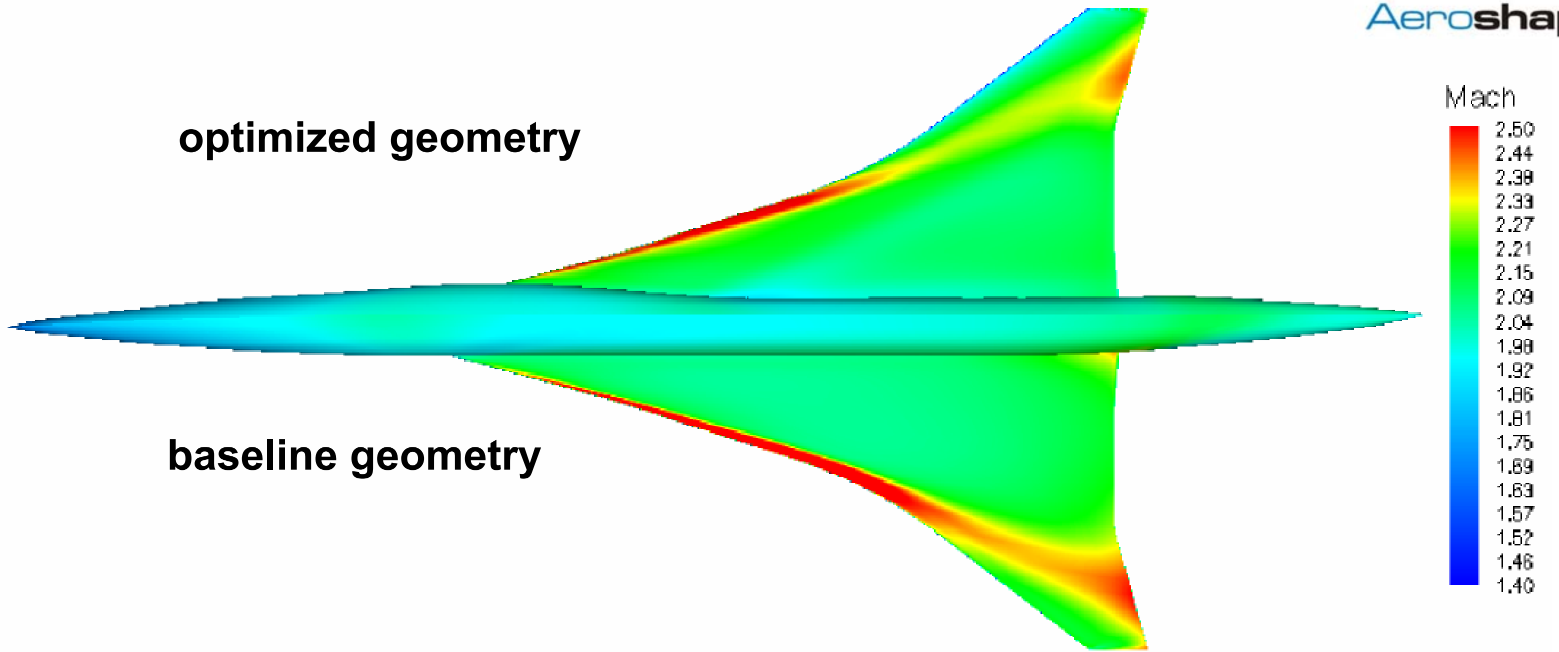
Approach

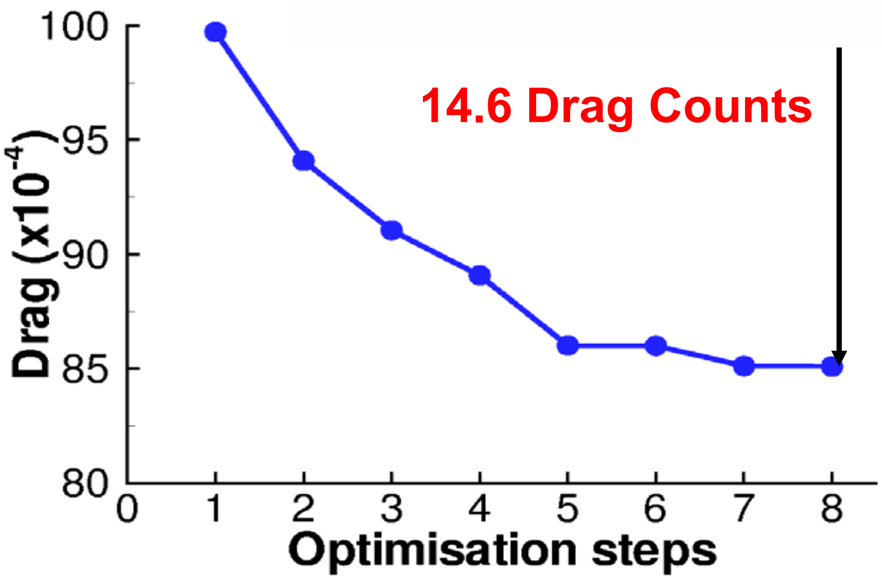
- inviscid flow computation
- Euler adjoint for calculation of flow sensitivities
- 230.000 points

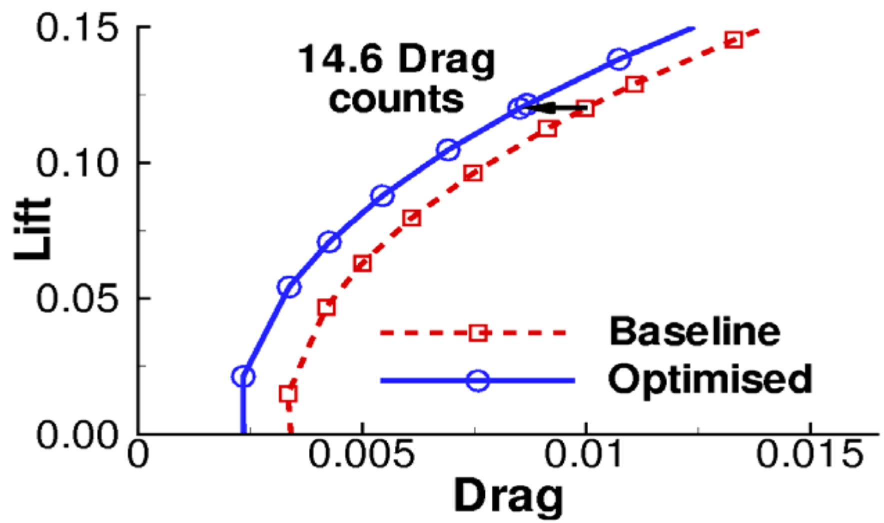


Brezillion, Gauger

Optimization of SCT Configuration



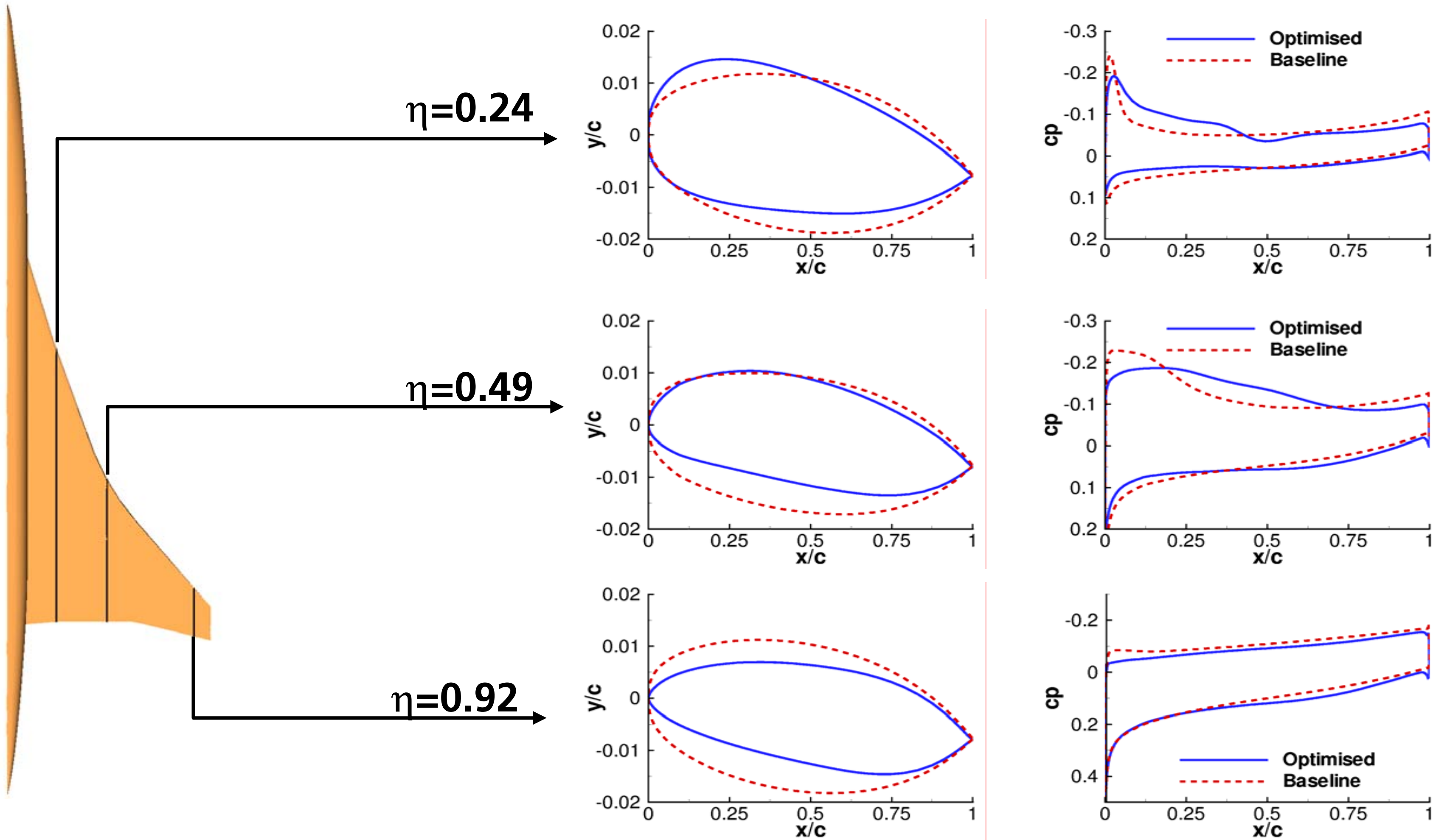




Brezillion, Gauger

Optimization of SCT Configuration

Wing section and pressure distribution



Multipoint airfoil optimization RAE2822

$$I = \sum_{i=1}^{2} W_i C_d(\alpha_i, M_i)$$

Objective function

- Reduction of drag in 2 design points

Design points

- 1 : M_∞=0.734, CL = 0.80 , α = 2.8°, Re=6.5×10^6, xtrans=3%, W_1=2
- 2 : M_∞=0.754, CL = 0.74 , α = 2.8°, Re=6.2×10^6, xtrans=3%, W_2=1

Constraints

- No lift decrease, no change in angle of incidence
- Variation in pitching moment less than 2% in each point
- Maximal thickness constant and at 5% chord more than 96% of initial
- Leading edge radius more than 90% of initial
- Trailing edge angle more than 80% of initial

Multipoint airfoil optimization RAE2822

$$I = \sum_{i=1}^{2} W_i C_d(\alpha_i, M_i)$$

Parameterization

- 20 design variables changing camberline, Hicks-Henne functions

Optimization strategy

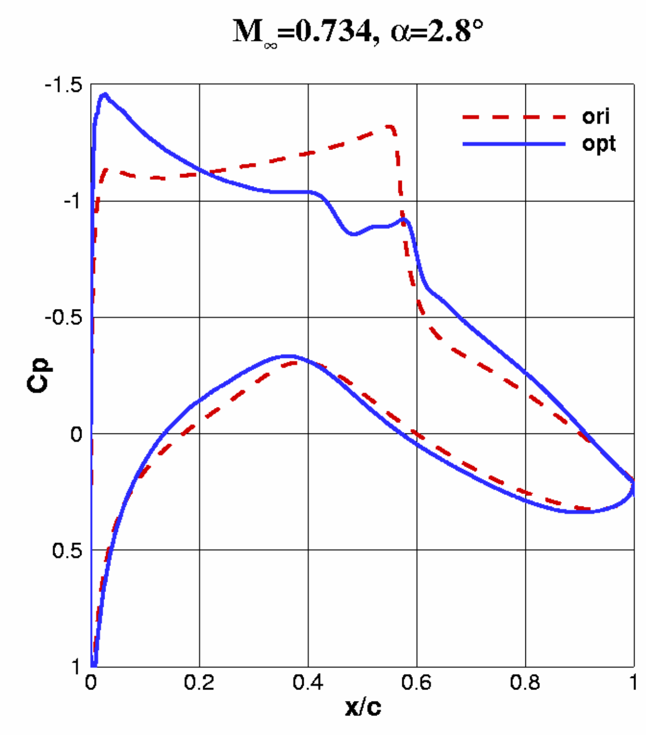
- Constrained SQP, Synaps Pointer Pro; W_1=2, W_2=1
- Navier-Stokes solver FLOWer, Baldwin/Lomax turbulence model
- Gradients provided by FLOWer Adjoint, based on Euler equations

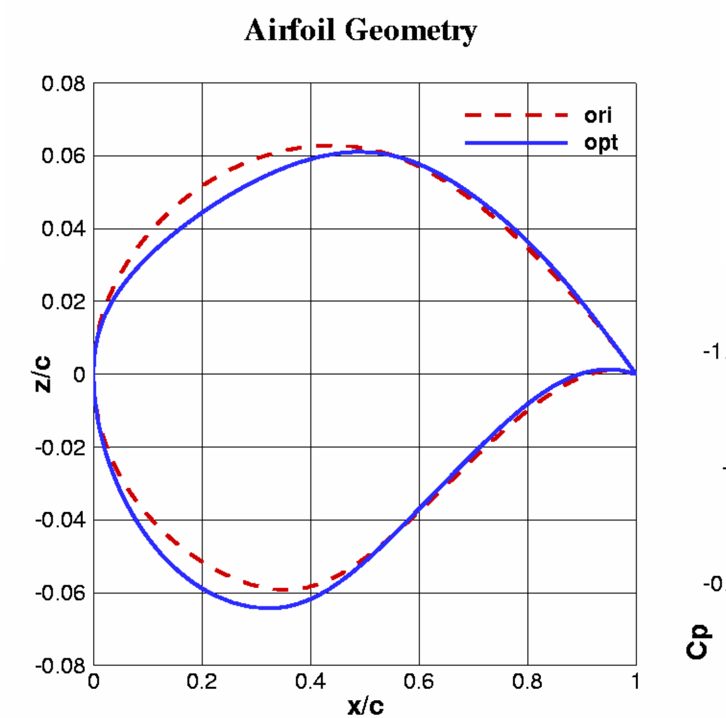
Results

Pt	α	M_i	cl^t	cd^t ($.10^{-4}$)	cl	cd^t ($.10^{-4}$)	$\Delta cd/cd^t$	$\Delta cl/cl^t$	$\Delta cm/cm^t$
1	2.8	0.734	0.811	197.1	0.811	135.5	-31.2%	0%	+1.6%
2	2.8	0.754	0.806	300.8	0.828	215.0	-27.4%	+2.7%	+2.0%

Multipoint airfoil optimization RAE2822

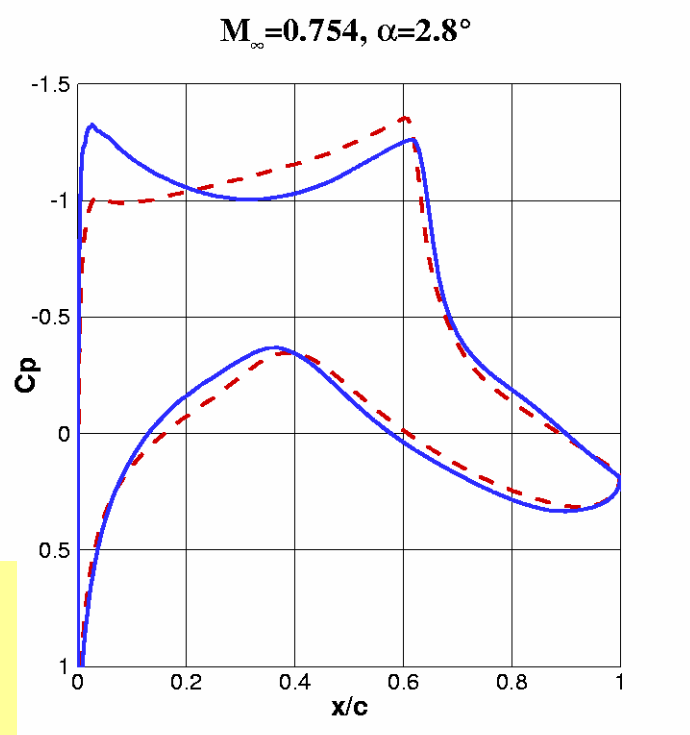
1. design point





shape geometry

2. design point



$$I = \sum_{i=1}^{2} W_i C_d(\alpha_i, M_i)$$

Remark: weights W_1 and W_2 not necessarily known

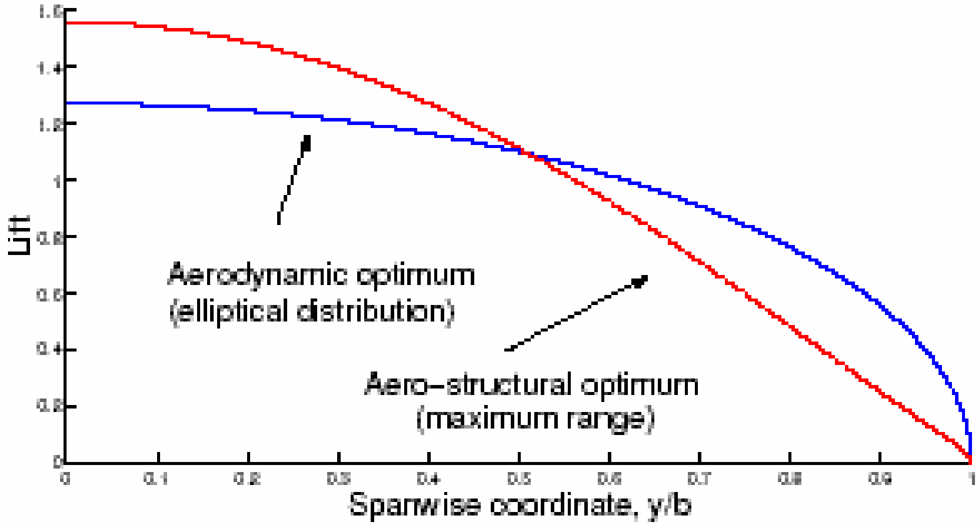
Brezillion

Aerodynamic Shape Optimization

Requirements

- multi-point design, multi-objective optimization, multidisciplinary optimization
- large number of design variables
- physical and geometrical constraints
- complex configurations
- efficient parametrization techniques based on CAD model
- meshing & mesh deformation techniques ensuring grid quality
- compressible Navier-Stokes equations with accurate models for turbulence and transition
- efficient flow solvers
- efficient and robust optimization algorithms
- automatic framework

Multidisciplinary Optimization
Motivation



Natural laminar flow supersonic business jet configuration
(pics: Alonso et al., AIAA-2002-5402)

Multidisciplinary Optimization

Motivation

Wing deflection up to 7% of wing span!

Deflected aerodynamic optimal shape can be worse than the initial …

Boeing 737-800 at ground and in cruise (Ma = 0.76)

Aero-Structure MDO - Example

Range R:

$$R \propto \frac{C_L}{C_D} \ln \frac{W}{W-F} = \frac{C_L}{C_D} \ln \left(\frac{1+\lambda\, ks}{1+\lambda\, ks - \frac{F}{W_0}} \right)$$

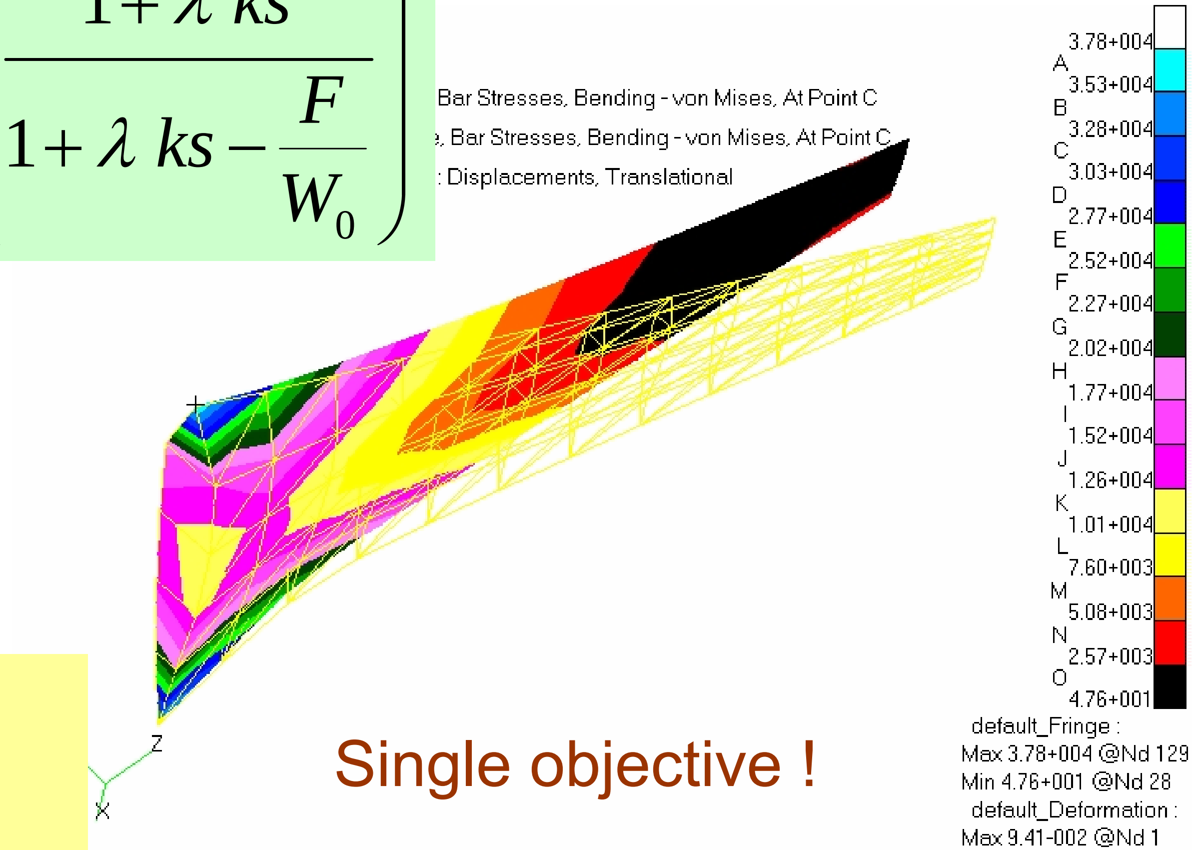
Fuel Weight F

Weight W:

$$W = W_0 (1+\lambda\, ks)$$

$$ks = \frac{1}{\beta} \ln\left(\sum_n \exp\left(\beta \frac{\sigma_n - \sigma_0}{\sigma_0}\right)\right)$$

$\lambda=0.2$, $\sigma_0 = 30.000$ and $\beta=40$



Single objective !

A. Fazzolari

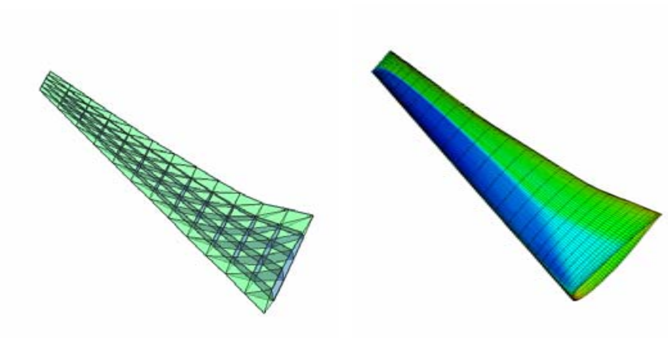
Aero-Structure MDO - Example

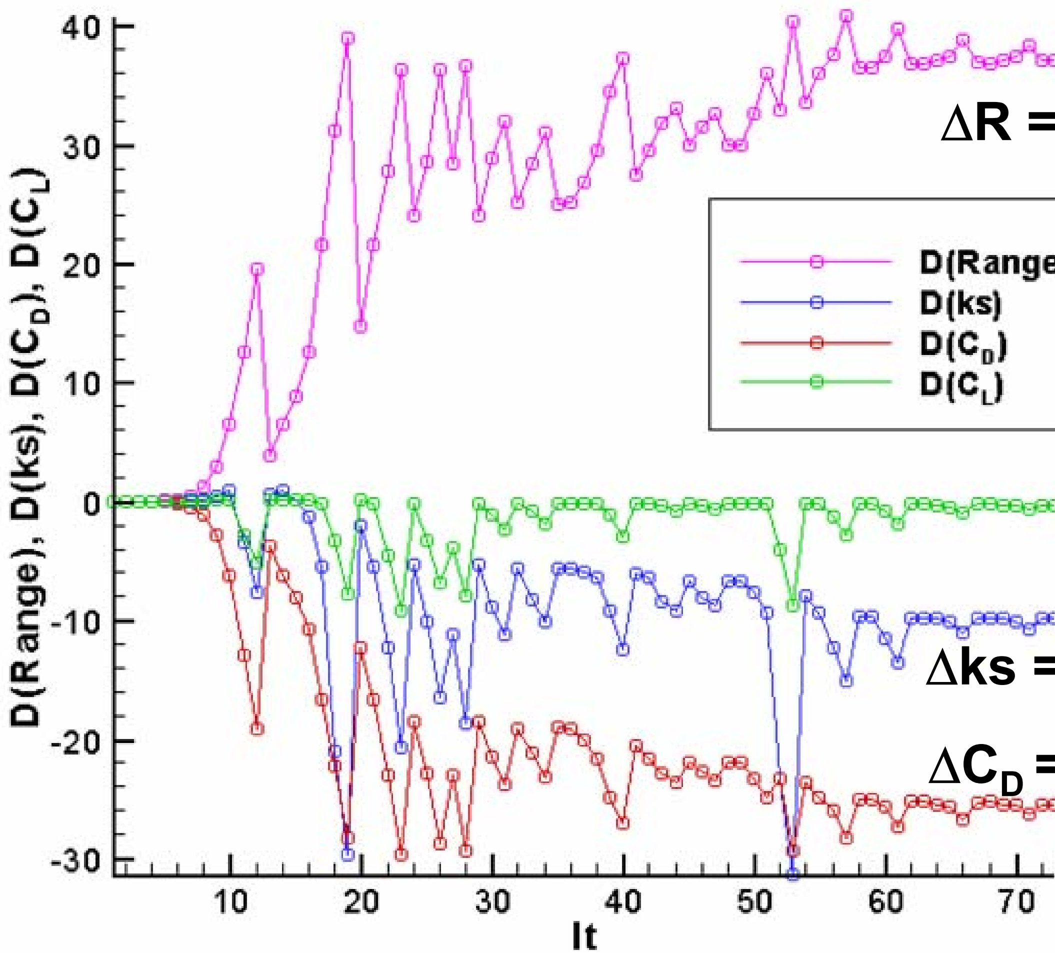
AMP wing

240 design variables (control points free form deformation)

Ma=0.78
alpha=2.83

Range maximization by constant lift





ΔR = +37 %

Δks = -10 %

ΔC_D = -25 %

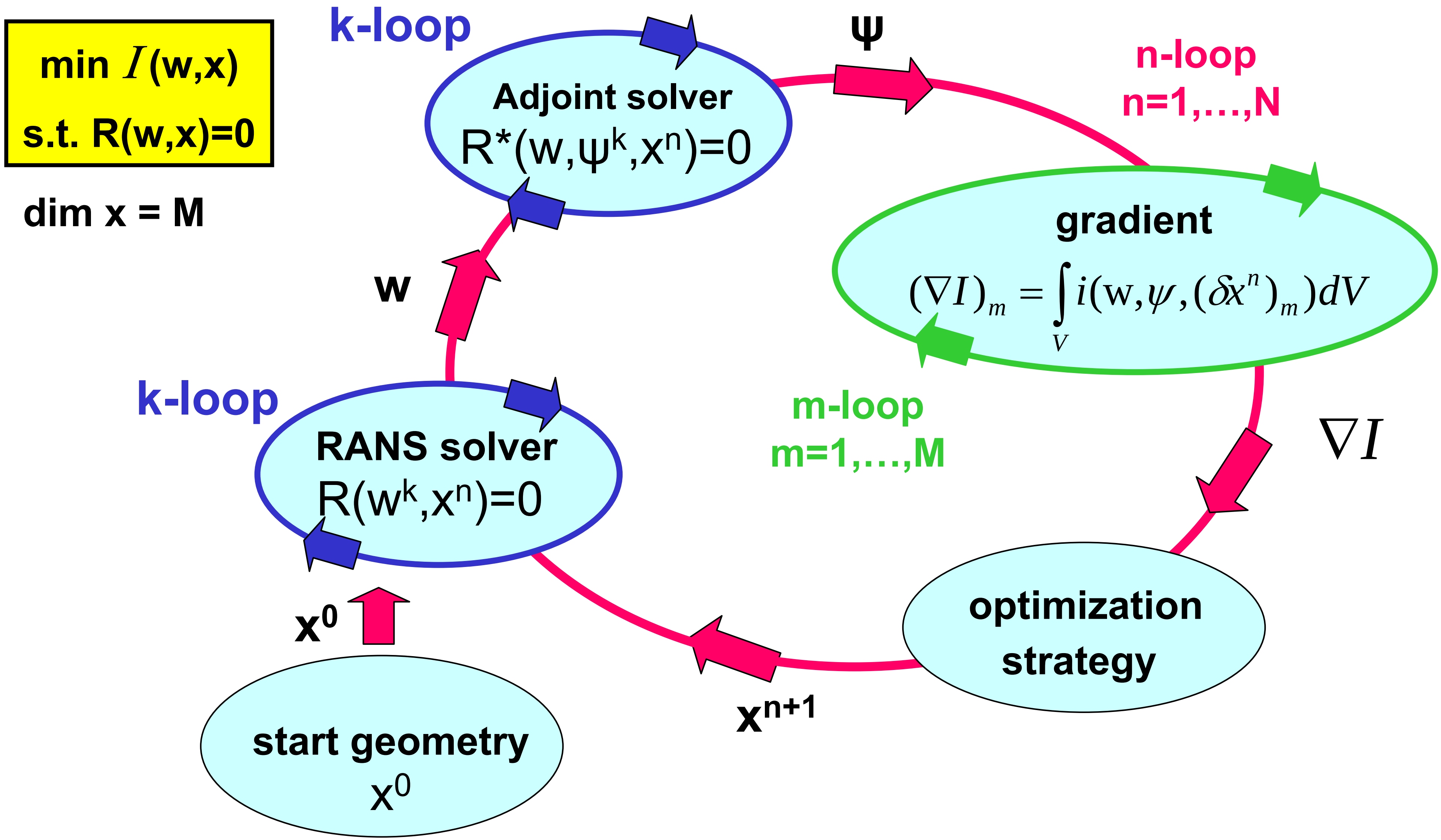
feasible direction method

Single Criterion Optimization

Status:

- efficient gradient based optimization available
- determination of gradients/sensitivities based on adjoints
- “accurate” approximation of Hessian often not possible
- problem: treatment of constraints

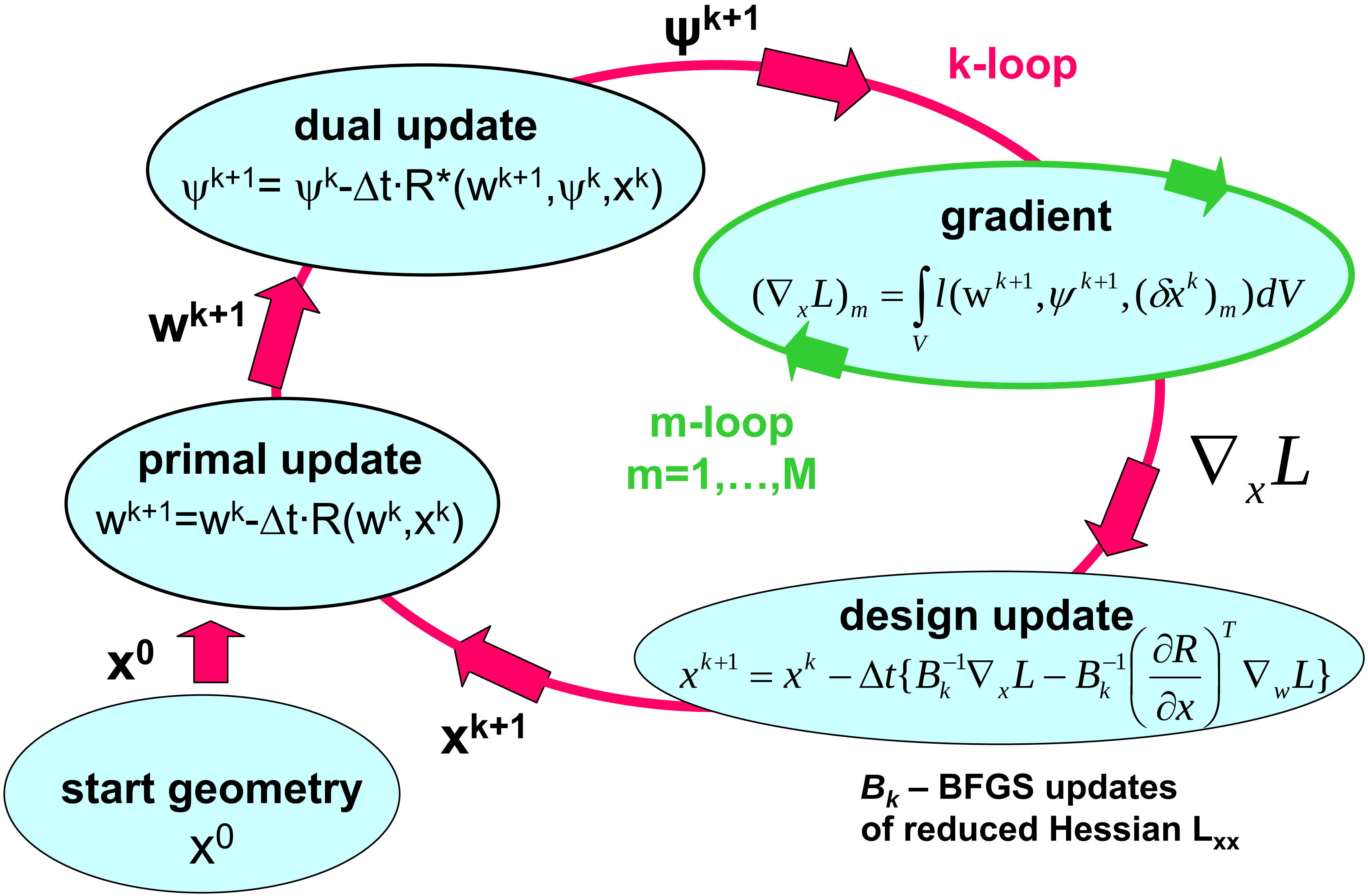
Adjoint Based Optimization



Simultaneous Pseudo-Time stepping - One Shot Approach

DLR

University of Trier



Schulz et al.

Simultaneous Pseudo-Time stepping - One Shot Approach

DLR

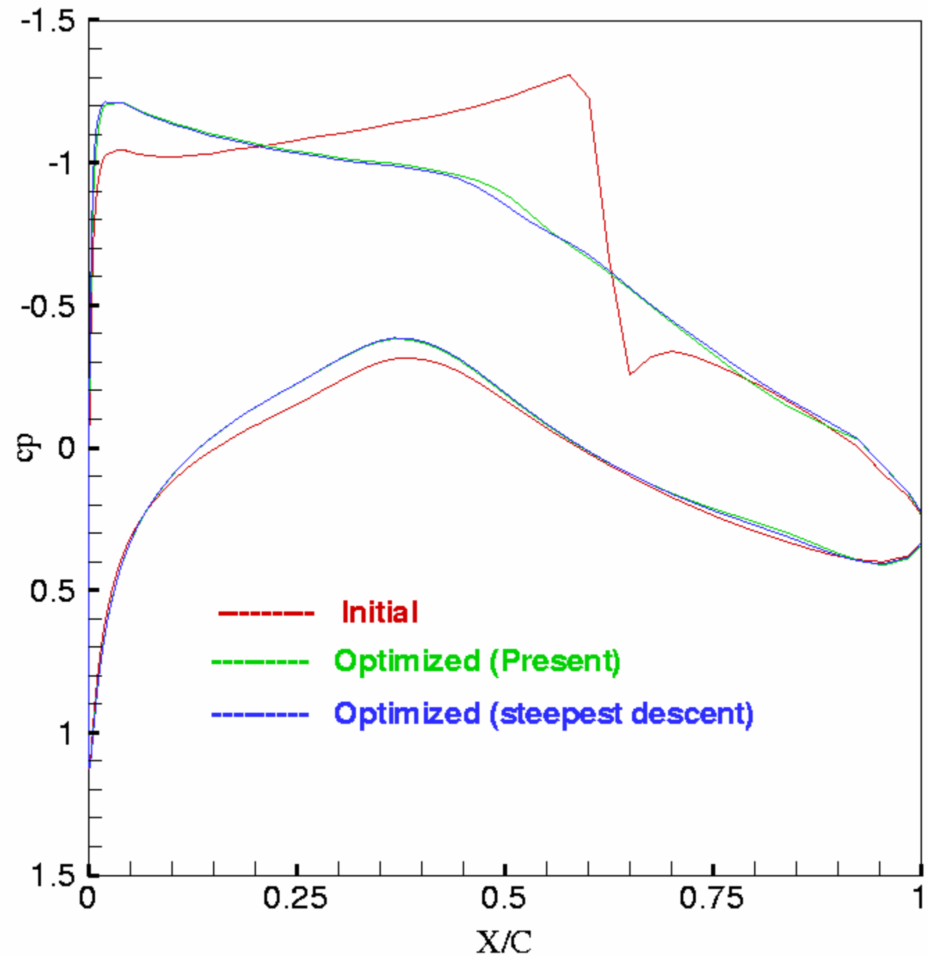
University of Trier

Optimization problem

- drag reduction for RAE 2822
- inviscid flow
- M=0.73, a=2^0

Tools

- FLOWer
- FLOWer adjoint



Optimization at the cost of 4 flow simulations!

Schulz et al.

Coupled Aero-Structure Adjoint

Aerodynamics,
e.g Euler Eqn.: $R_A = 0$

Structure:

$$R_S = Ku - f = 0$$

K: Symmetric stiffness matrix
f: Aerodynamic force
u: Displacement vector
x: Vector of Design variables

ψ_A : **Aerodynamic Adjoint**

ψ_S : **Structure Adjoint**

~: Lagged ...

Conventional Gradient:

$$\frac{dC_D}{dx} = \frac{\partial C_D}{\partial x} + \frac{\partial C_D}{\partial w}\frac{\partial w}{\partial x} + \frac{\partial C_D}{\partial u}\frac{\partial u}{\partial x}$$

Aero/Structure Adjoint System:

$$\left(\frac{\partial R_A}{\partial w}\right)^T \psi_A = \frac{\partial C_D}{\partial w} - \left(\frac{\partial R_S}{\partial w}\right)^T \tilde{\psi}_S$$

$$\left(\frac{\partial R_S}{\partial u}\right)^T \psi_S = \frac{\partial C_D}{\partial u} - \left(\frac{\partial R_A}{\partial u}\right)^T \tilde{\psi}_A$$

Adjoint Gradient:

$$\frac{dC_D}{dx} = \frac{\partial C_D}{\partial x} - \psi_A^T \frac{\partial R_A}{\partial x} - \psi_S^T \frac{\partial R_S}{\partial x}$$

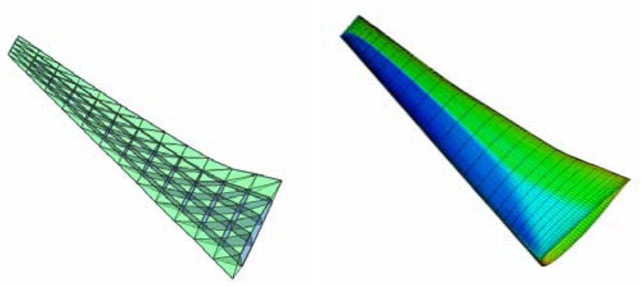
Coupled Aero-Structure Adjoint

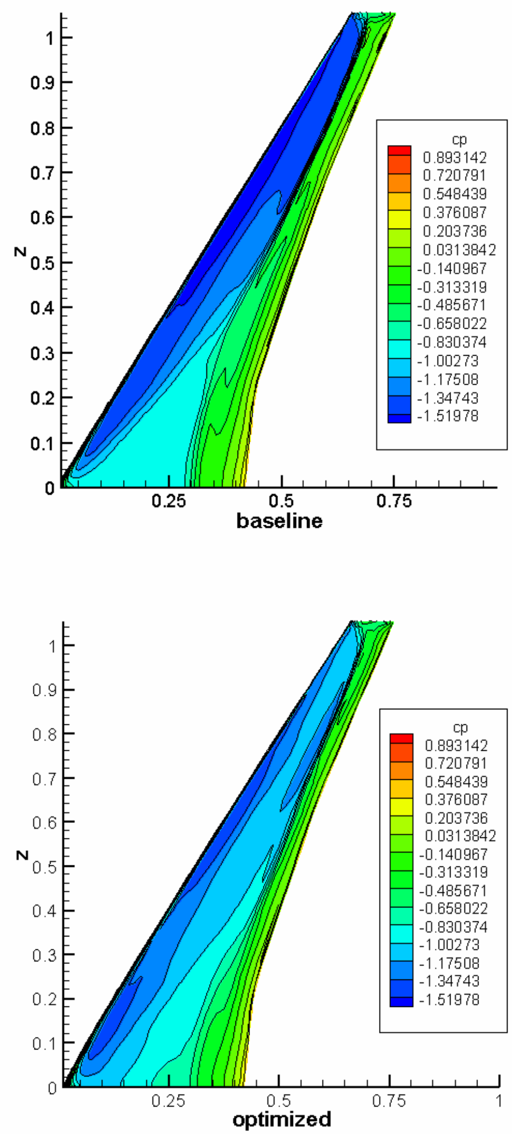
AMP wing

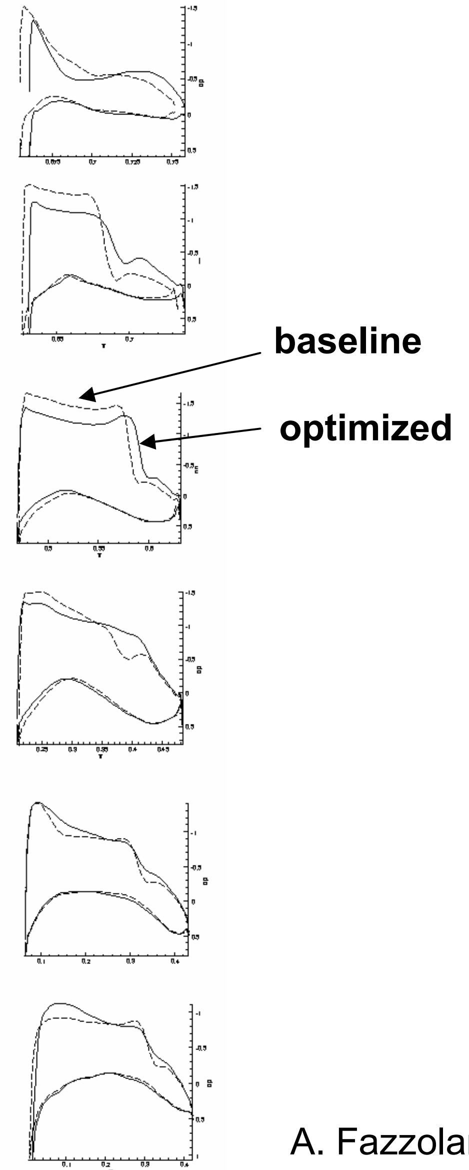
240 design variables (control points free form deformation)

Ma=0.78
alpha=2.83

Drag reduction by constant lift







A. Fazzolari

Multiobjective Optimization

- In aircraft design very often a single objective does not adequately represent the design problem
- Vector of objective functions must be traded off
  (Aircraft design: Maximize lift/drag & minimize structural weight)
- The relative importance of the objectives is not generally known until the system's capabilities are determined and the tradeoffs are understood

- Multi-objective strategies are need which are reliable, efficient and which offers the engineer to express preferences throughout the optimization cycle
- Multi-objective optimization leads to a set of compromised solutions

Multiobjective Optimization

Problem description

$$\min F(X)$$

$$X \in R^n$$

$$F : R^n \rightarrow R^m$$

subject to constraints

$$G_i(X) = 0 \qquad i = 1,\dots.M$$

$$H_k(X) \leq 0 \qquad k = 1,\dots.N$$

Remark

- F is vector
- if any of components of F(X) are competing, no unique optimum

Multiobjective Optimization

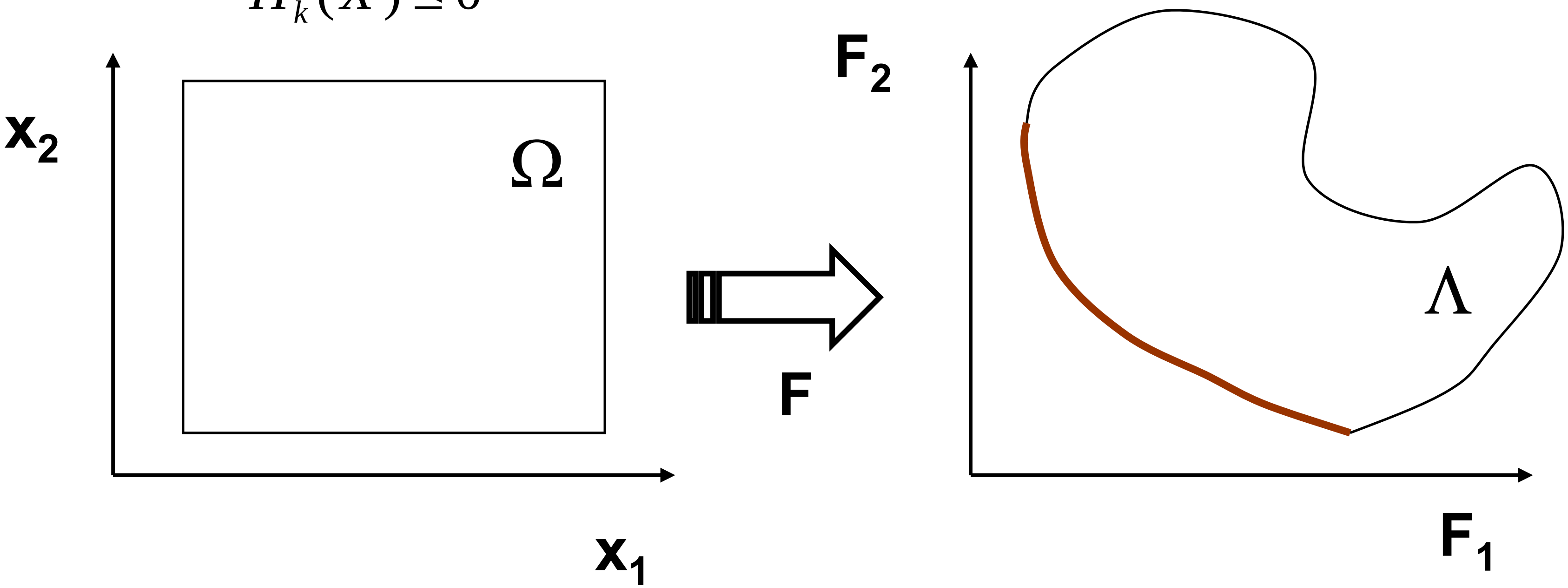
feasible region

$$\Omega = \{X \in R^n\}$$

subject to

$$G_i(X) = 0$$

$$H_k(X) \leq 0$$



Multiobjective Optimization

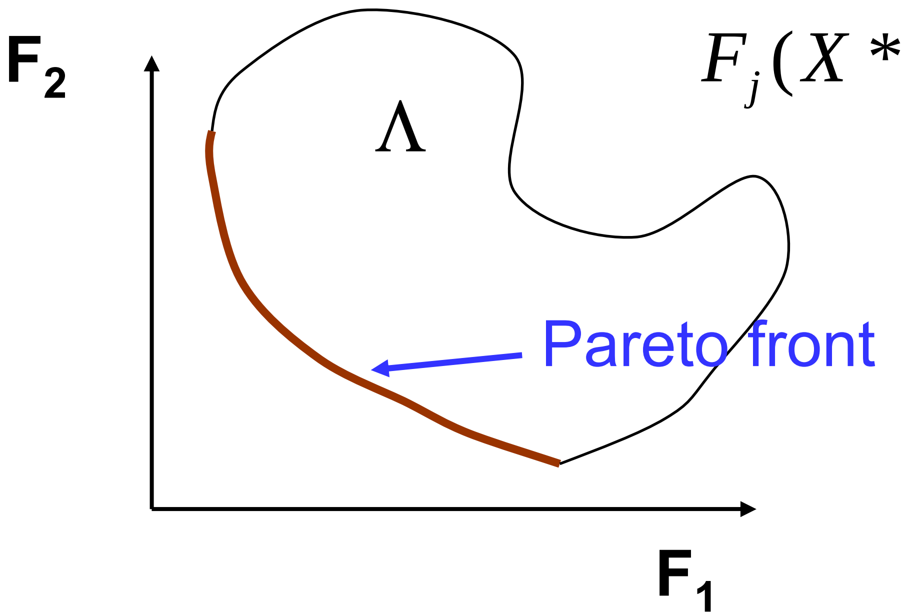
Concept of Pareto optimality

Definition

A point $X^* \in \Omega$ is a local Pareto optimal point if for some neighborhood of X^* there does not exist a ΔX such that $(X^* + \Delta X) \in \Omega$ and

$$F_i(X^* + \Delta X) \leq F_i(x^*) \qquad i = 1, \ldots, m$$

$$F_j(X^* + \Delta X) < F_j(X^*) \qquad \text{for some } j$$

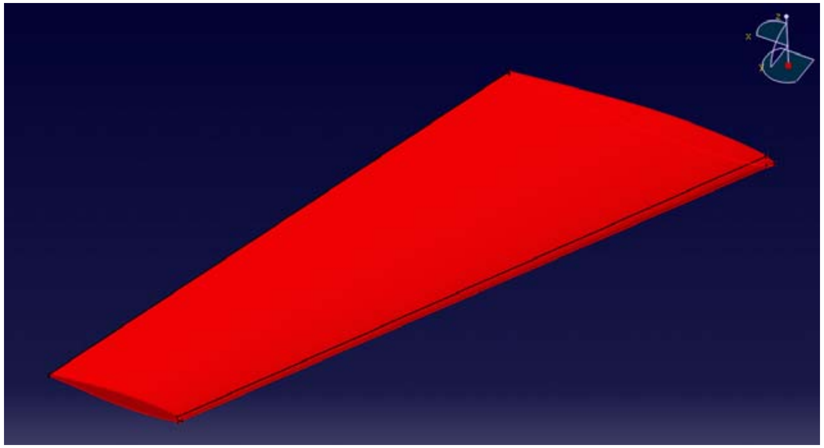


How to determine Pareto points

- **Genetic algorithms**
- **Weighted Sum Strategy**
- **Normal Boundary Intersection method**
- **…….**

Multiobjective Optimization - Example

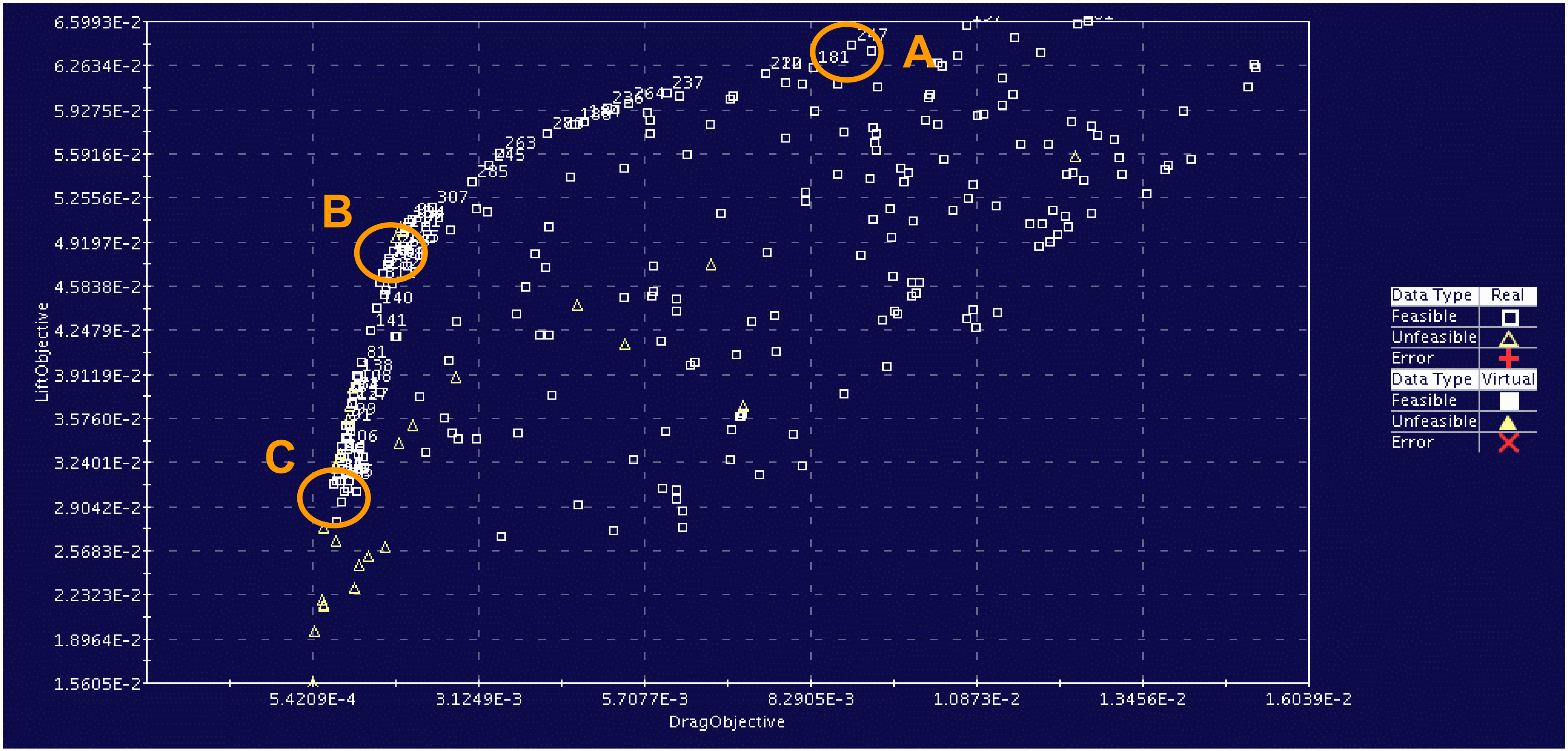
Shape optimization of wing plan form



- flow condition: M = 0.85, a = 1°
- inviscid flow (Euler)
- computational mesh: 630.000 nodes
- multi objective optimization:
  - maximize lift and minimize drag
- design parameters:
  - sweep angle (range: -60° to +60°)
  - half span (range: 0.750 [m] to 1.250 [m])
  - aspect ratio (defined by const. wing plan area constraint)
  - taper ratio (range: 0.2 to 0.8)
- design constraints:
  - pitching moment restricted to range –0.025 to +0.0001

Genetic Algorithm

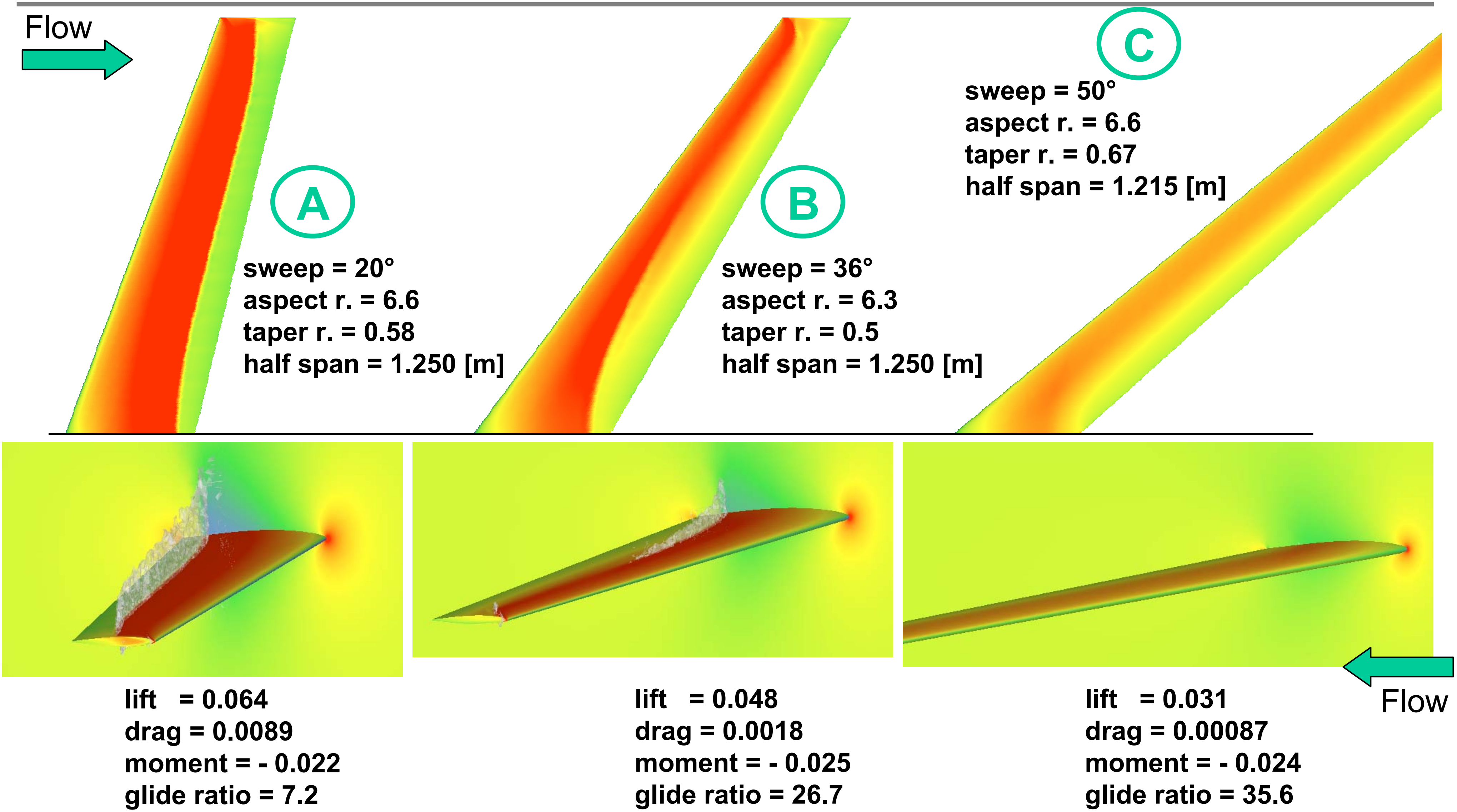
Wing plan form optimization



Pareto Front

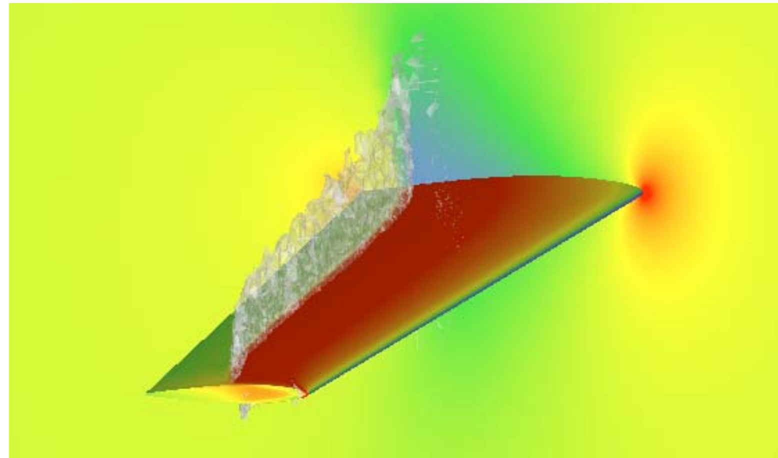
EADS

Multiobjective Optimization - Example



EADS-M: Deister

Multiobjective Optimization - Example



Shape optimization of wing plan form

Computational effort:

- for one design evaluation:
  50 min (4 XEON 2.6 GHz processors)
  - complete mesh generation time: approx. 15 min.
  - complete flow simulation time: 35 min.
- 12 concurrent design evaluations using 4 processors each
- 30 design generations

- all together 360 design evaluations in less than 25 h

but just 5 design variables and inviscid flow !

Alternatives ????

DLR

Multiobjective Optimization

Academic test case

Test case definition : 2 variables - 2 objectives

$a = 0.5\sin(1) - 2.0\cos(1) + 1.0\sin(2) - 1.5\cos(2)$

$b = 0.5\sin(x) - 2.0\cos(x) + 1.0\sin(y) - 1.5\cos(y)$

$c = 1.5\sin(1) - 1.0\cos(1) + 2.0\sin(2) - 0.5\cos(2)$

$d = 1.5\sin(x) - 1.0\cos(x) + 2.0\sin(y) - 0.5\cos(y)$

$Obj1 = -(1+(a-b)^2 + (c-d)^2)$

$Obj2 = -(x+3)^2 - (y+1)^2$

$x,y \in [-\pi,\pi]$

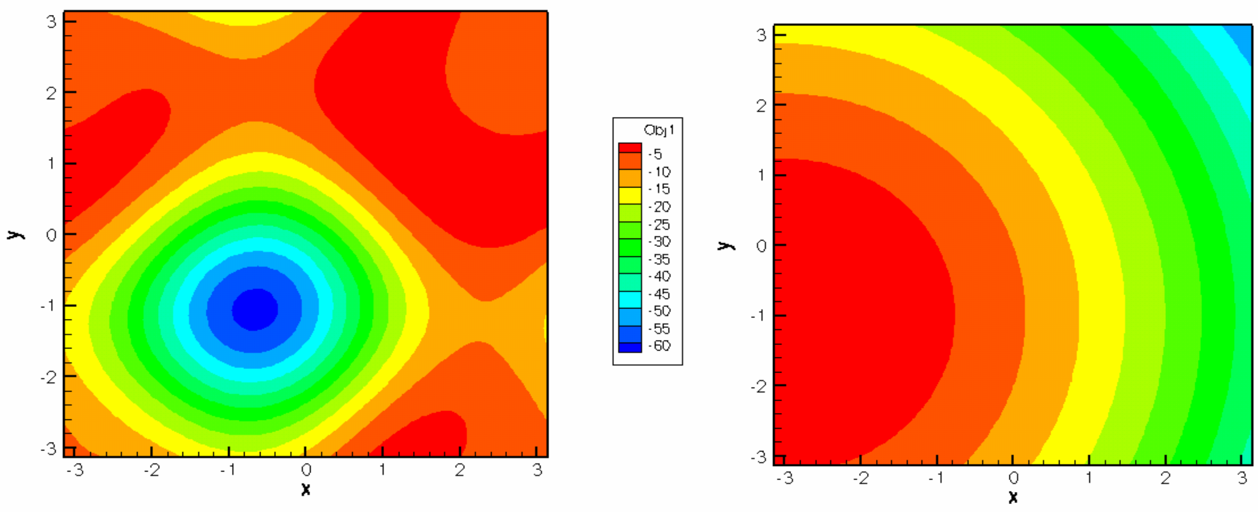
Two objective functions to be maximised

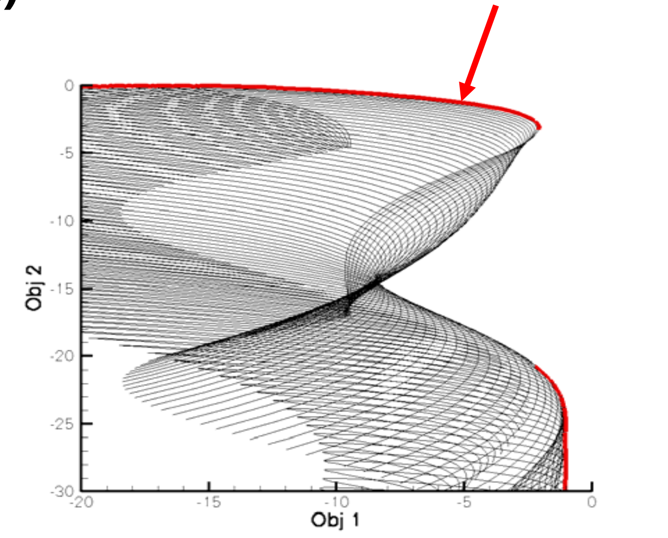
Multiobjective Optimization

Academic test case

Visualisation of the design space (101x101 evaluations)

Pareto front





Obj1 and Obj2 in the design space **Obj1 vs. Obj2**

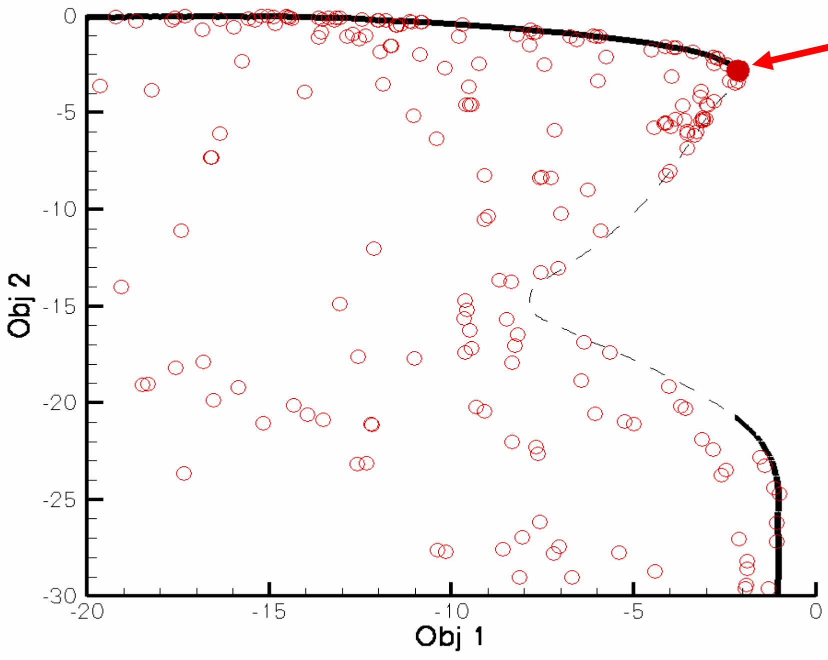
Multiobjective Optimization

Academic test case

Multi-objective optimisation using Genetic Algorithm

- **Latin Square DOE**
- **Population size of 64 individuals (i.e. 64 concurrent evaluations could be performed in parallel)**
- **6 generations**
- **383 evaluations**

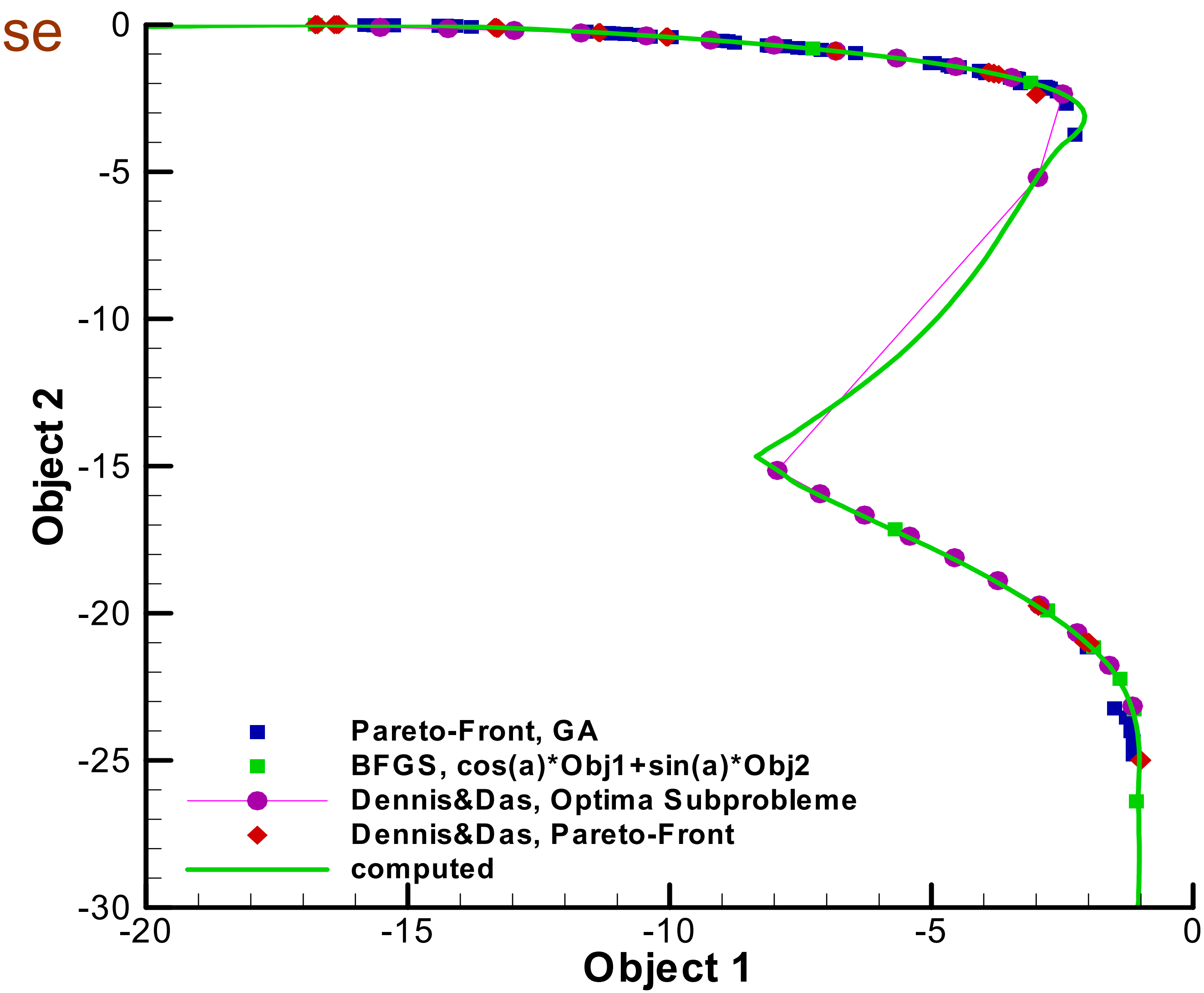
Almost the complete Pareto front is captured within a single run !



Global Optimum from a mono-obj. form. (obtained after post processing)

Multiobjective Optimization

Academic test case



Dennis & Das:

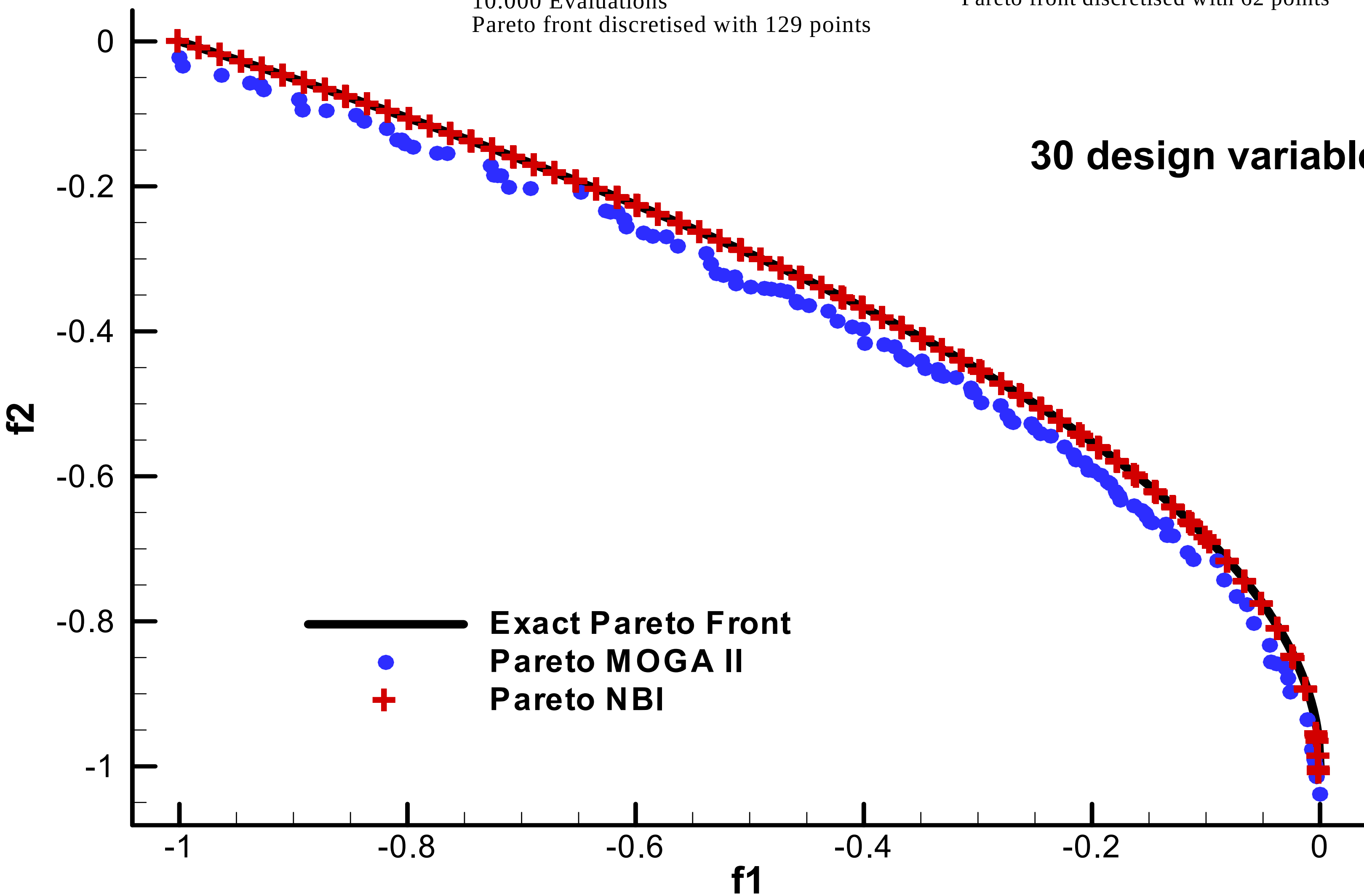
- use warm start for sub problems (starting point, gradients)

Multiobjective Optimization

ZDT1 Test Case

MOGA II
Population = 100
Generation = 100
10.000 Evaluations
Pareto front discretised with 129 points

NBI
Pareto front discretised with 62 points



DLR

Concluding Remarks

- Shape optimization is essential for future aircraft design
- Shape design requires multidisciplinary optimization (>>> multiobjective optimization, Pareto front)
- "Efficient" methods for single objective optimization are available or under development (adjoint sensitivities, Newton-type methods, one shot methods,,,)
- Multidisciplinary optimization based on high-fidelity CFD solvers not practical, appropriate deterministic methods are missing