Industrial Requirements for Aircraft Design

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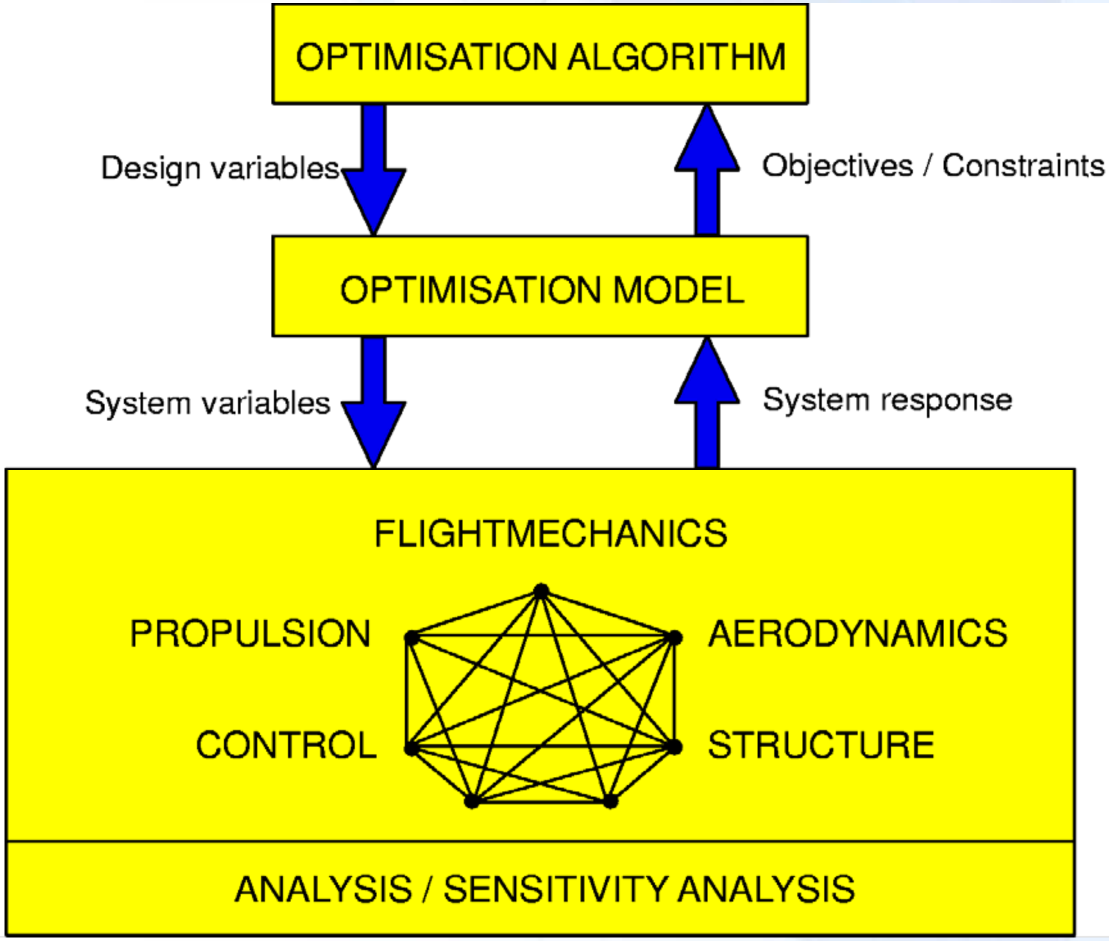
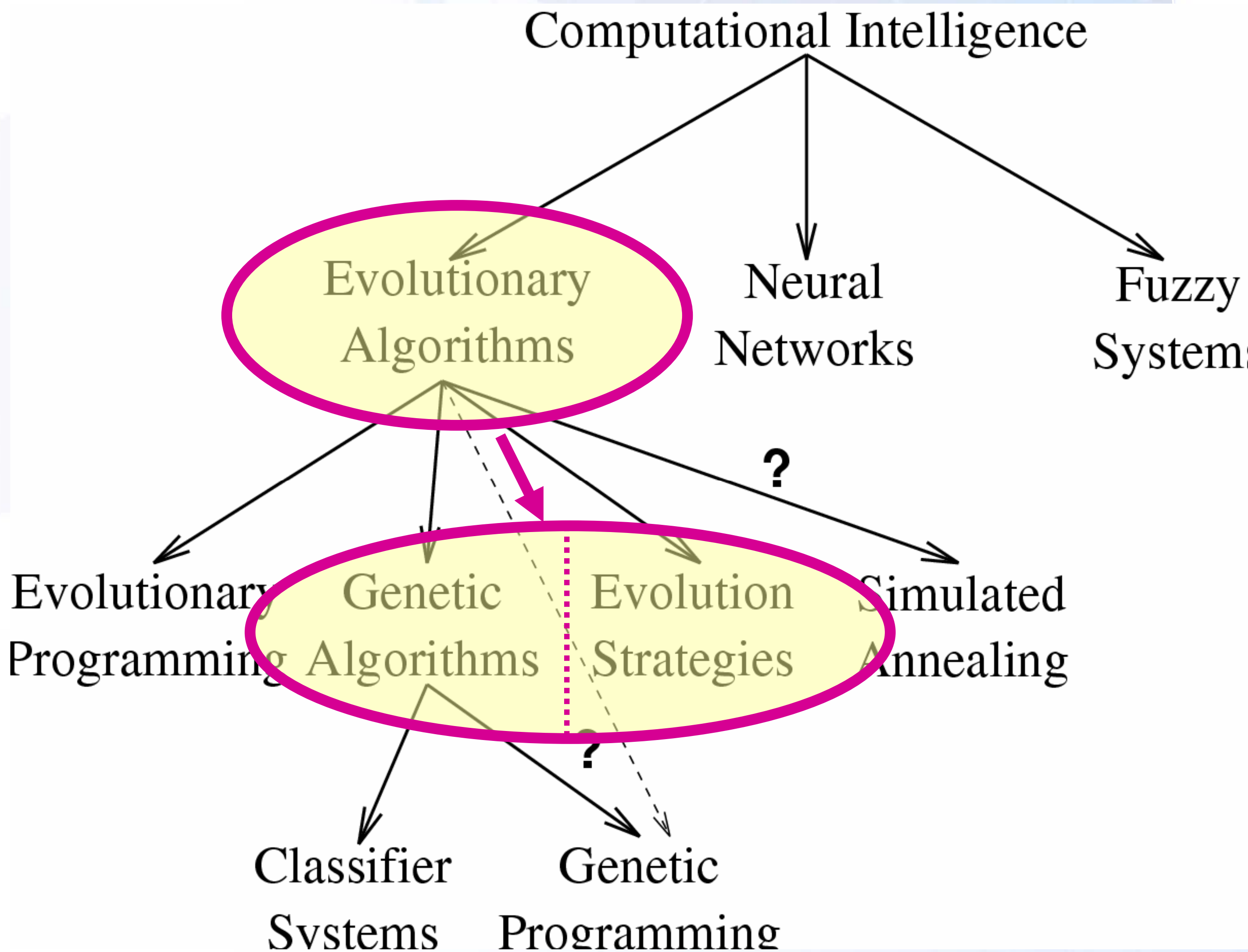
Introduction

- Aircraft design
- Optimisation with evolutionary algorithms
- Pareto frontier – a modelling and engineering challenge – based on
- Airfoil optimisation
- Flap optimisation
- Multi-disciplinary optimisation
- Wing optimisation with CATIA_v5

Network of influences in aircraft design optimisation



Optimisation using evolutionary algorithms



Idea: Mimic natural evolution (1/2)

1. **Set of candidate solutions (individuals):** *Population*

2. **Generating candidates**
   - *Reproduction*: Copying an individual
   - *Crossover* (*Recombination*): ≥ 2 parents $\rightarrow \geq 2$ children
   - *Mutation*: 1 parent $\rightarrow$ 1 child

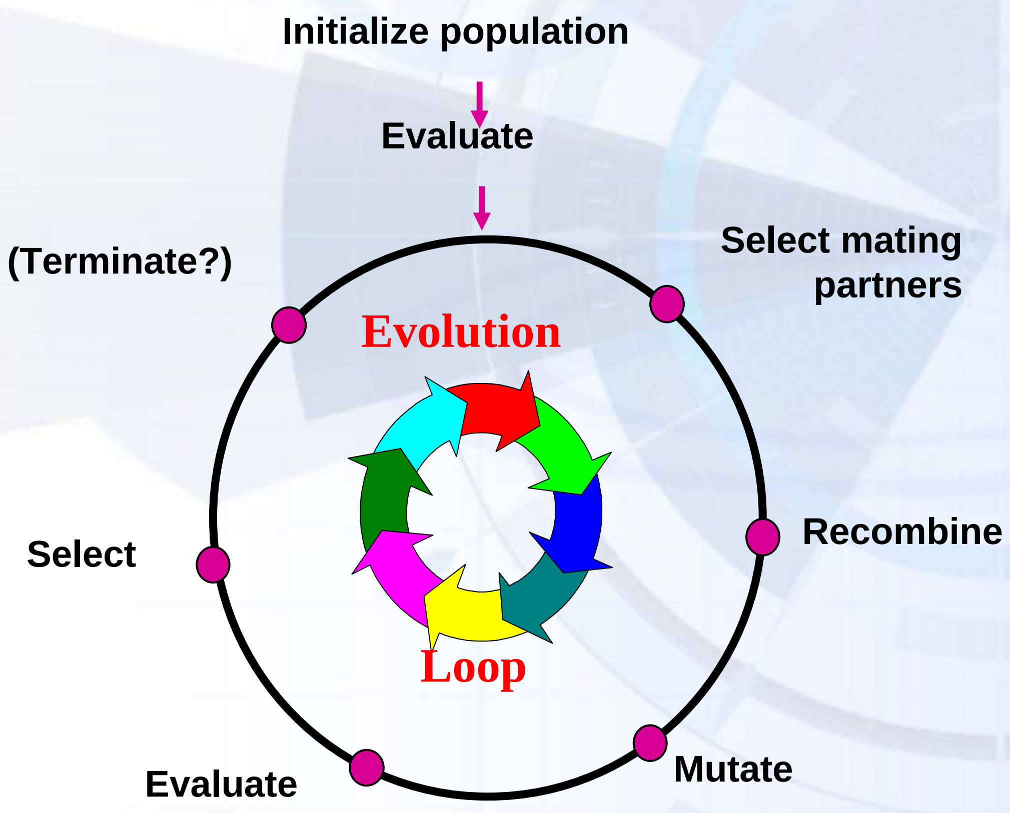
3. **Quality measure of individuals:**
   Fitness function, objective function

4. **Survival-of-the-fittest principle**

History:

1962	L.J. Fogel:	*Evolutionary Programming*
1962	Holland:	*Genetic Algorithms*
1965	Rechenberg & Schwefel:	*Evolution Strategies*

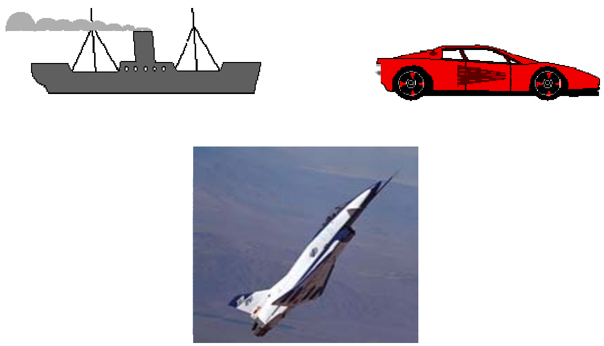
Idea: Mimic natural evolution (1/2)



The Optimiser

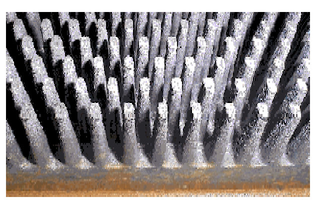
The FRONTIER technology stems from a former EU ESPRIT project with the (targeted) design sectors:

Industrial products

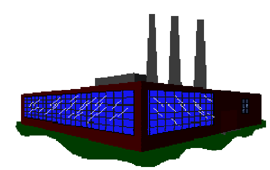


Consumer Products

Industrial Equipment



Manufacturing Processes



The Optimiser

- *FRONTIER* addresses design optimisation problems which have one or **several objectives** to be optimised simultaneously
- Tradeoffs conducted by *FRONTIER* are expressed in terms of the limiting **Pareto boundaries** in objective space
- *FRONTIER*'s **decision support tool (MCDM)** helps to clarify the relative importance of the objectives (non-dominated individuals on Pareto bd)
- GUI supported, based on **JAVA and CORBA** for parallel design evaluation
- Current version is FRONTIER_v3.1
  featuring genetic algorithms, evolutionary strategies, gradient based methods together with response-surface approaches, kriging, neural nets, and robust design

„Work-around“ for optimisation

- Problem recognition
- Problem building blocks
- Analysis tool for running optimisation problem **automatically**
- Definition of
  - Design parameters (Input to analysis – will be provided by optimiser)
  - Constraints
  - Objective function(s)
  - Other parameters going to be monitored
- For shape optimisation:
  - Parameterisation
  - Mesh generation

ES versus GA

- Often real-value search spaces, $\Re^n$.
- Emphasis on mutation: n-dimensional, normally distributed, expectation zero.
- Different recombination operators.
- Deterministic selection: (μ,λ) , $(\mu+\lambda)$
- Self-adaptation of strategy parameters.
- Creation of offspring surplus, i.e., $\lambda >> \mu$.

Evolutionary Strategies

- Often binary search spaces, $\{0,1\}^m$
- Mutation by means of bit inversion; low probability p.
- Emphasis on recombination.
- Probabilistic selection.
- *Constant* control parameters.
- No offspring surplus.

Genetic algorithms

Multi-objective optimisation

Minimise

$$f(x) = \left(f_1(x), f_2(x), \ldots., f_n(x)\right)$$

with

$$x = \left(x, \ldots., x\right) \in X \quad (e.g. \Re^n),$$

$$f(x) \in \Re^n, \qquad \text{m,n} \in \aleph$$

Then

$$a \ \underline{\text{dominates}} \ \text{b} \ :\Leftrightarrow$$

$$\forall \text{i} \in \{1,\ldots,\text{n}\}: \ \text{f}_\text{i}(\text{a}) \leq \text{f}_\text{i}(\text{b}) \ \wedge$$

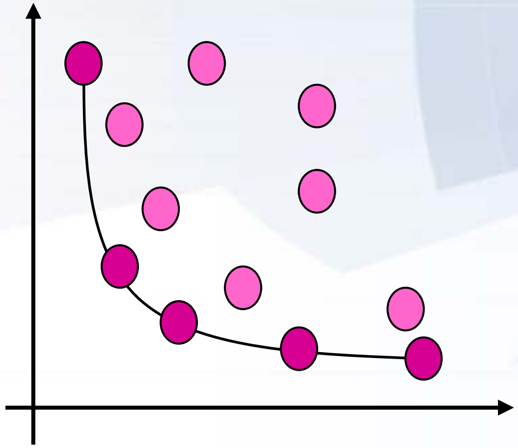
$$\exists \ \text{j} \in \{1,\ldots,\text{n}\}: \ \text{f}_\text{j}(\text{a}) < \text{f}_\text{j}(\text{b}).$$

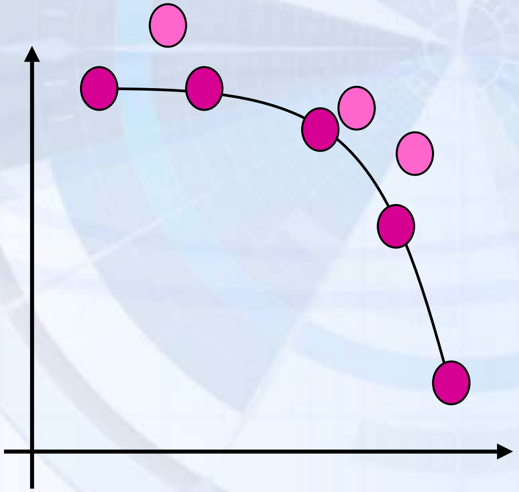
In case of minimisation, for maximisation using > accordingly

Multi-objective optimisation

Non-dominated vectors/solutions/individuals define

Pareto-Front (convex, concave)





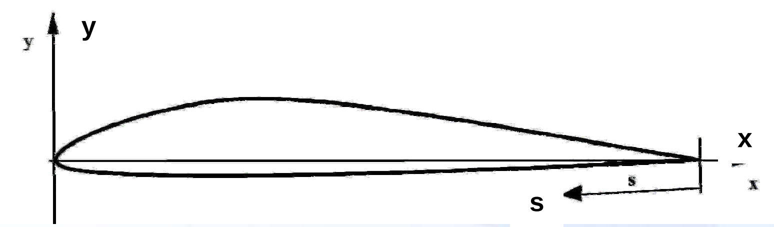
Let's assume an example …

Inverse 2-point airfoil design - Test Case Description

- Minimisation of an objective function which is the difference between computed/optimised pressure distribution at two different design points with pre-defined target pressures (originally proposed by T. Labruyere, NLR)

- The objective function reads:

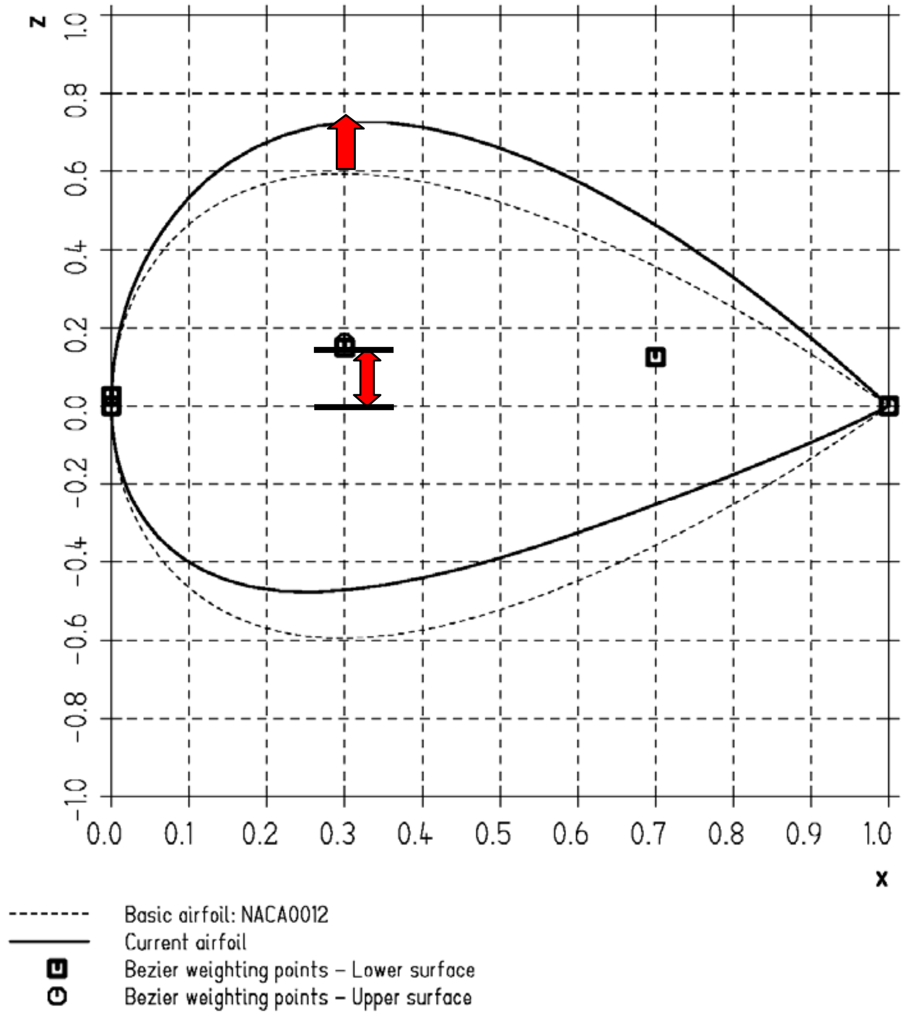
$$F(\alpha_1, \alpha_2, x(s), y(s)) = \sum_{n=1}^{2} \left[W_n \int_0^1 \left(C_p^n(s) - C_{p,target}^n(s) \right)^2 ds \right]$$



Geometry Parameterisation - Bezier Splines

Illustrative example for parametrisation

- Starting airfoil: NACA4412 or arbitrary
- Cubic Bezier Splines with a variable number of control/weighting points
- y-values of Bezier control points being added/subtracted from starting airfoil contour



Inverse 2-point airfoil design - Test Case Description

Two different design conditions (i=1,2):

i=1: Typical **high-lift** airfoil at subsonic conditions

i=2: Typical high-speed/**low drag** airfoil at transonic conditions

Case	i=1	i=2
Ma	0.20	0.77
Re	$5x10^6$	10^7
Incidence	10.8^o	1.0^o
X_{trans}/c	0.03	0.03

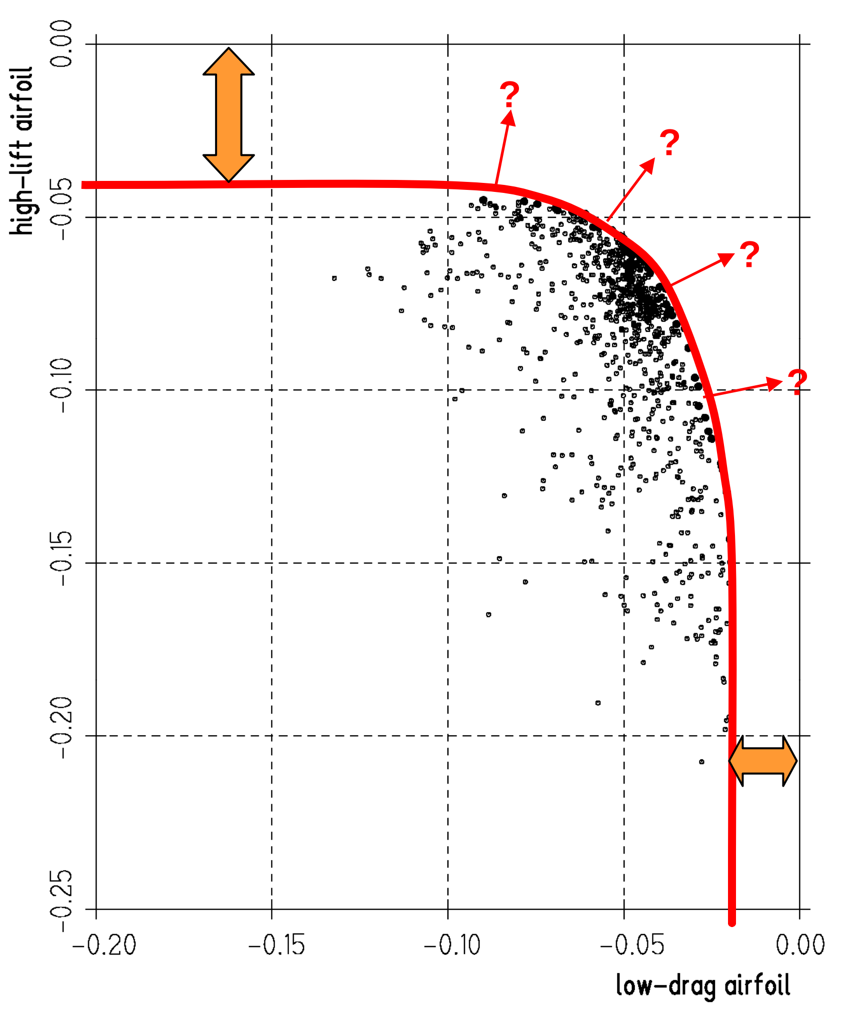
Inverse 2-point airfoil design - Parameterisation

Axes values:
Objective function =
Difference in pressure

Pareto "gap" due to

Parameterisation !!!

But what about different optimisation/Pareto scenarios ?



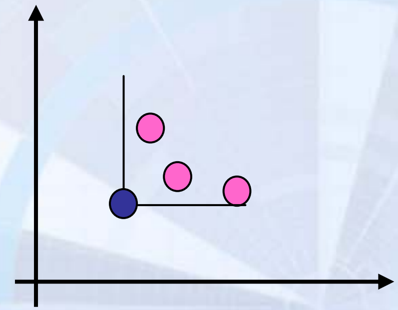
Multi-objective optimisation with DES single parent optimisation

Mode I

Selection criteria:

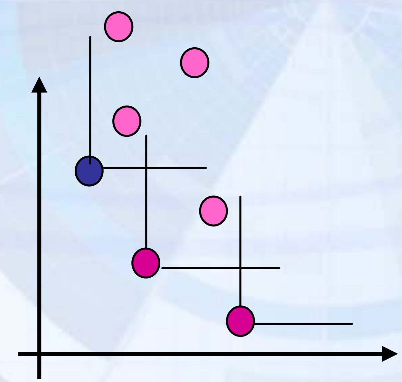
1. Dominance

   Only **one non-dominated individual**: parent of the next generation, otherwise



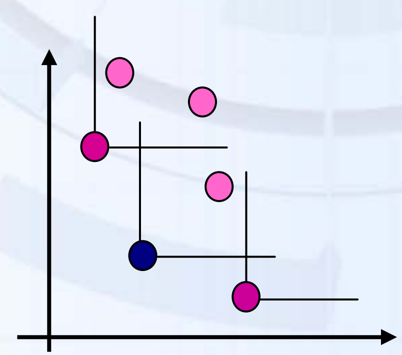
2. Number of individuals dominated

   Only **one individual with maximum number of individuals dominated**: parent of the next generation, otherwise



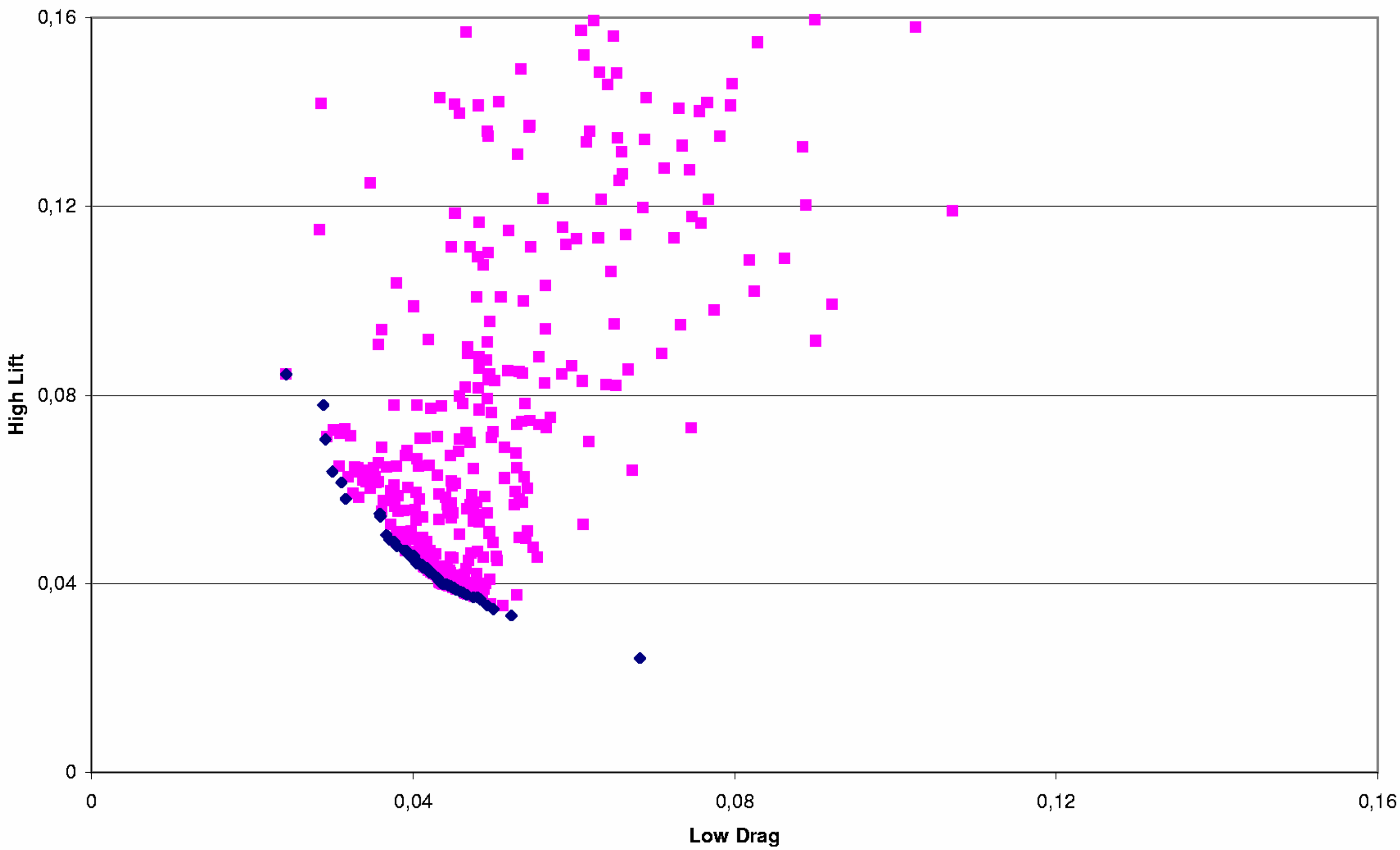
3. Distance to origin of search space

   Individual with shortest distance to origin of search space: parent of next generation



Multi-objective optimisation with DES single parent optimisation

Mode I with (1+10) strategy



Multi-objective optimisation with DES single parent optimisation

Mode II

Selection criteria:

1. Dominance

   Only **one non-dominated individual**:

   parent of the next generation, otherwise

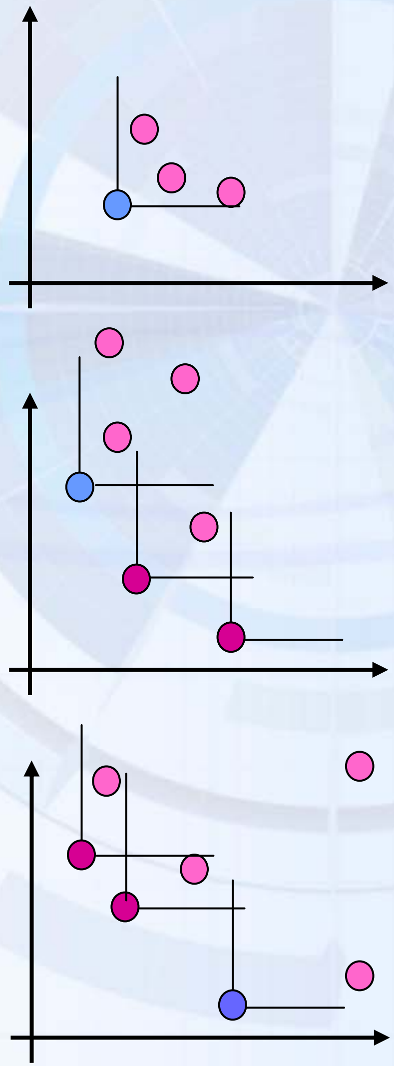
2. Number of individuals dominated

   Only **one individual with maximum number of individuals dominated**:

   parent of the next generation, otherwise

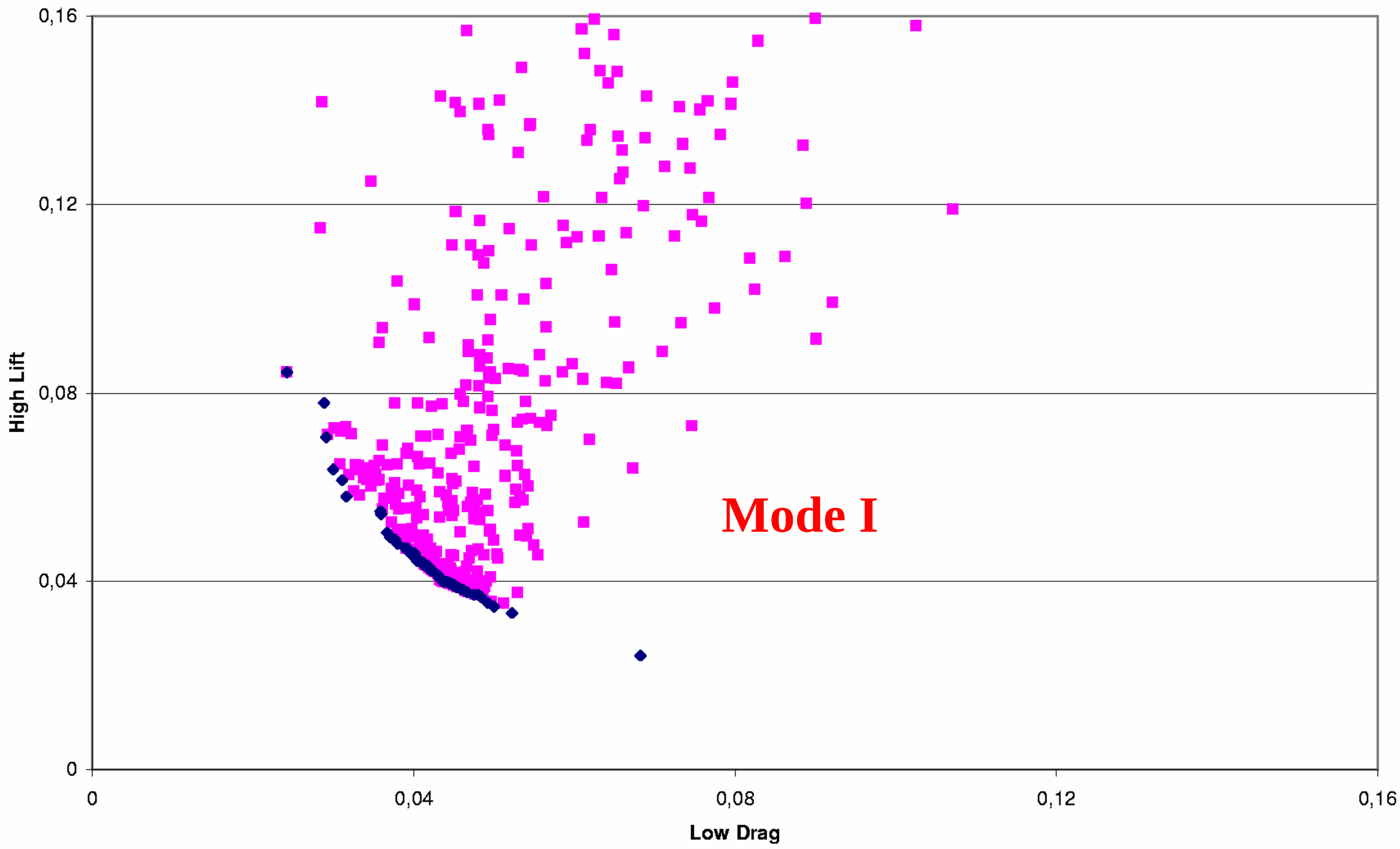
3. Distance to other individuals

   Individual with **largest distance to other individuals** with the above properties: parent of next generation



Multi-objective optimisation with DES single parent optimisation

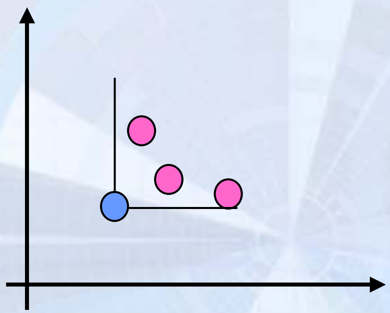
Mode II with (1+10) strategy



Multi-objective optimisation with DES single parent optimisation

Mode III

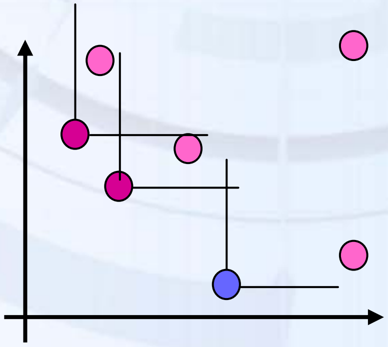
Selection criteria:



1. Dominance
   Only **one non-dominated individual**: parent of the next generation, otherwise

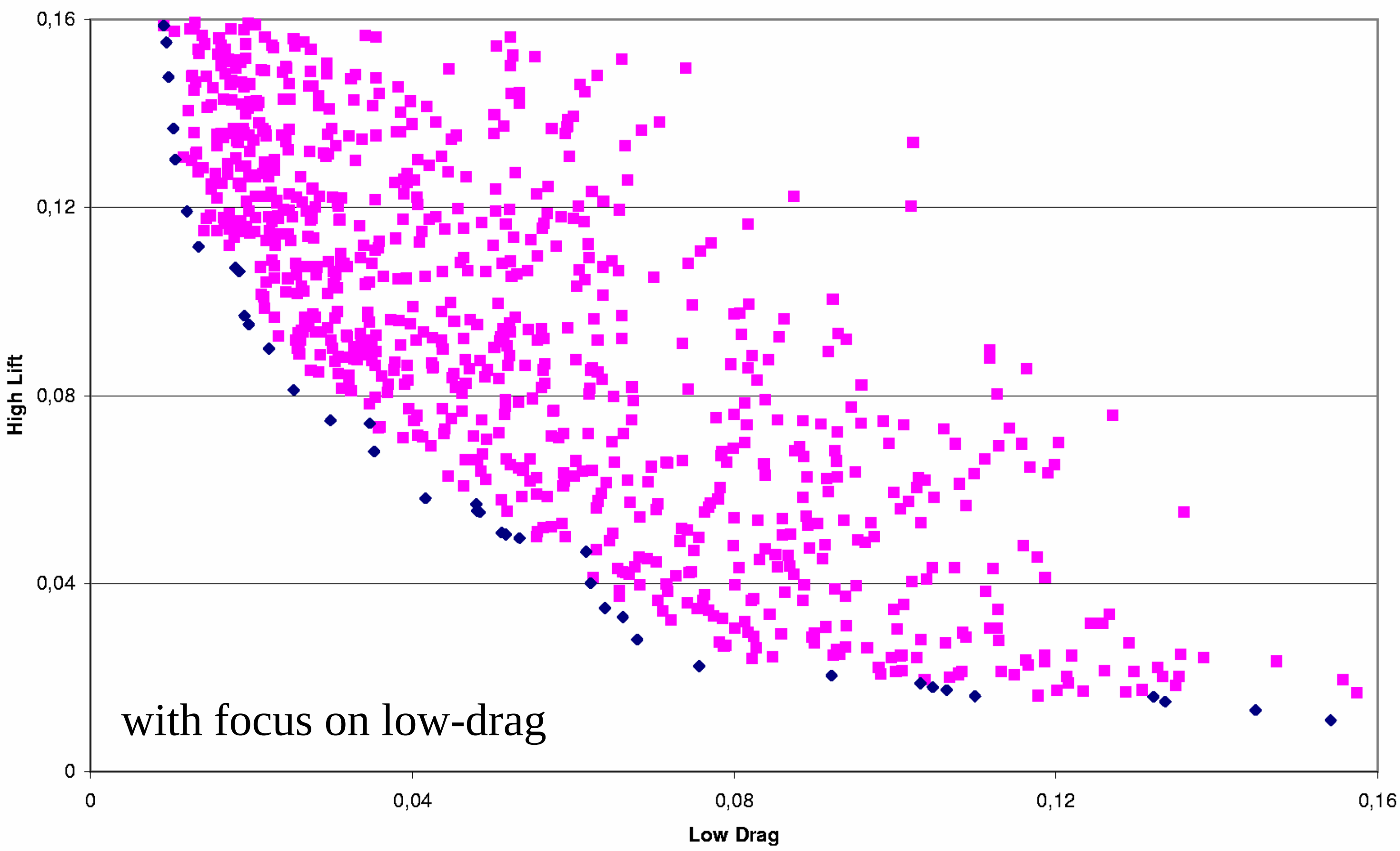
2. Number of individuals dominated
   Only **one individual with maximum number of individuals dominated**: parent of the next generation, otherwise

3. Distance to other individuals
   Individual with **largest distance to other individuals** with the above properties: parent of next generation



Multi-objective optimisation with DES single parent optimisation

Mode III with (1+10) strategy)



Inverse 2-point airfoil design - Numerical approach

Navier-Stokes method in use:

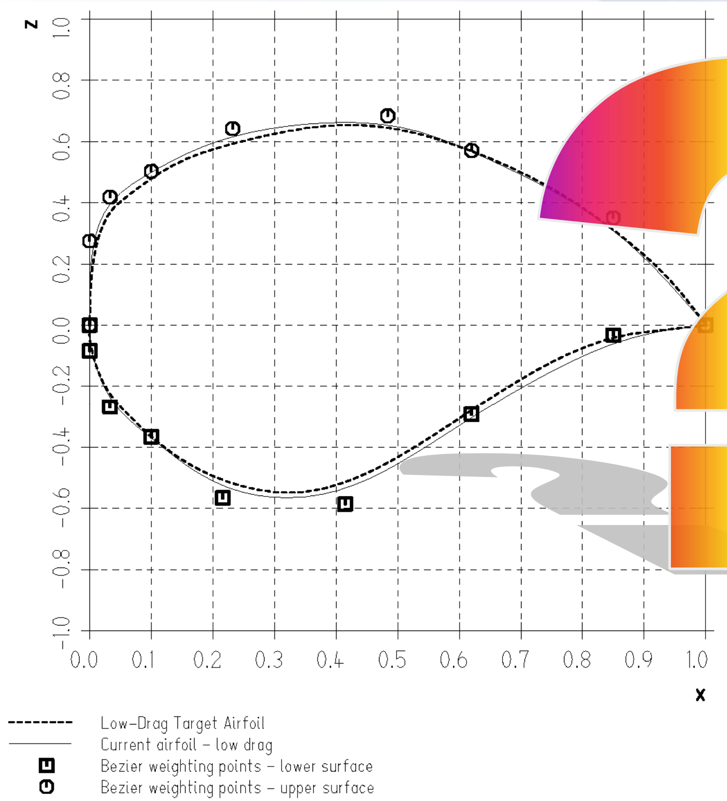
- 2D (full) Navier-Stokes method
- Finite volume approach
- Runge-Kutta method (3.1 scheme) with 2nd and 4th-order damping
- Multigrid/multi level approach
- 1/2-equation turbulence models:
  Johnson-Coakley for transonic flow
  Johnson-King for subsonic flow

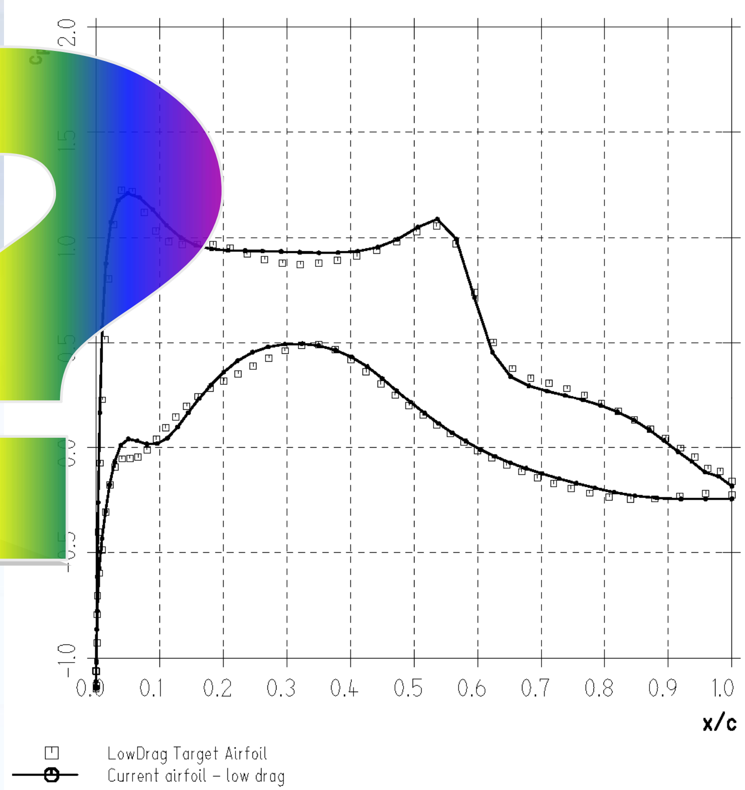
==

- Mesh resolution has been set to the lowest possible level (with respect to predictive accuracy) of 128x32 mesh points
- Computation time for one individual: < 60 sec. on a PC
- Starting airfoil: NACA4412 (gradient based method or „scratch“ in case of EA)

Inverse airfoil design - GA results (64x16)

Only transonic case, individual 946 as ‚best‘ re-design





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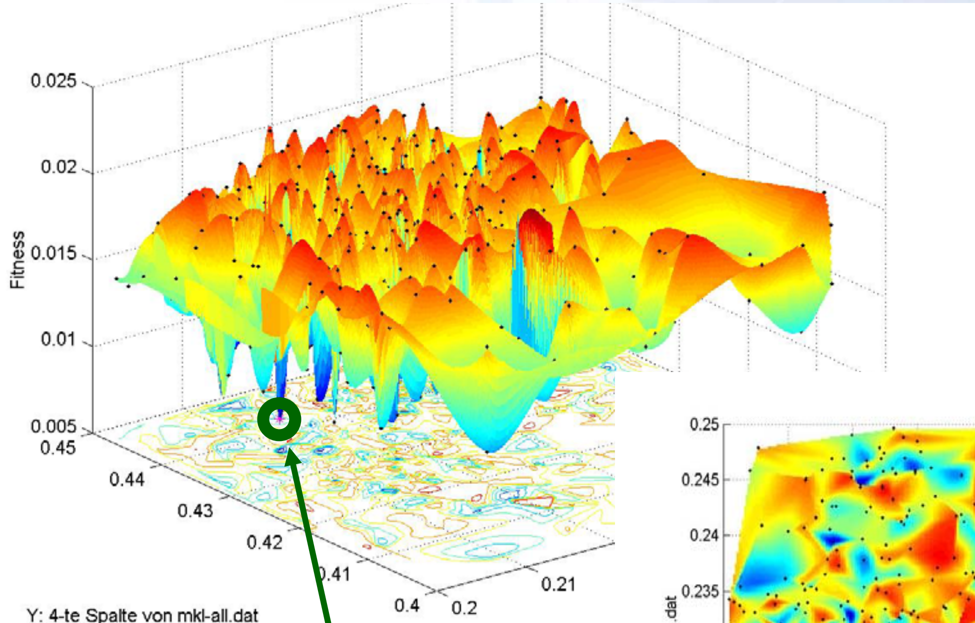
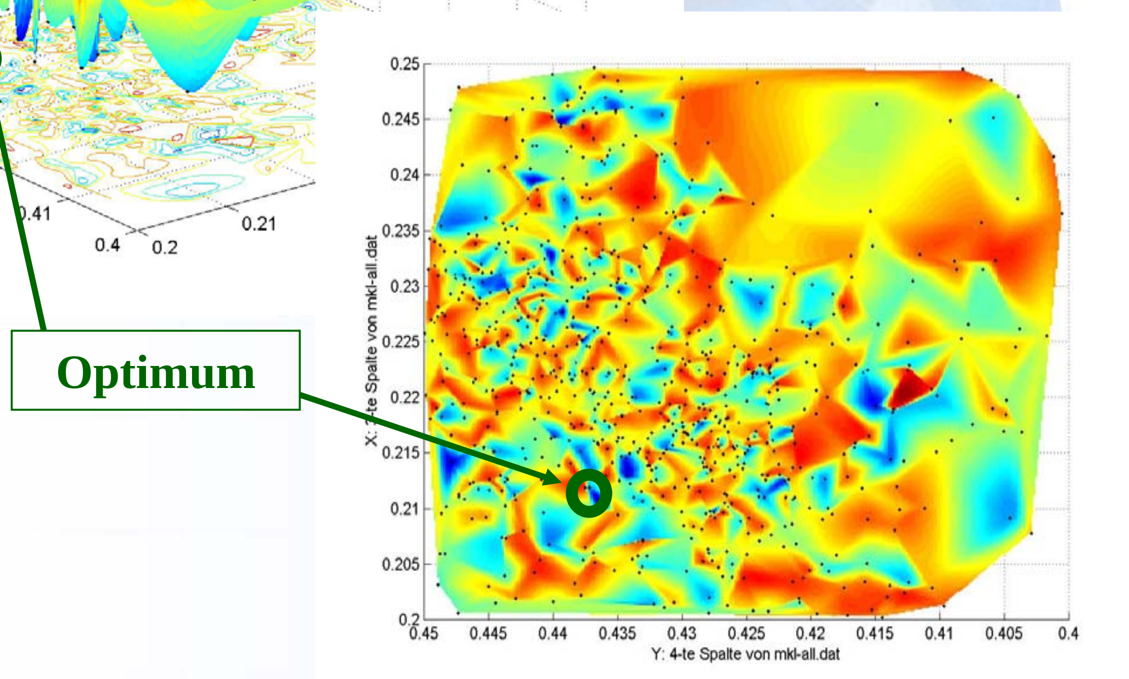
Inverse airfoil design - ES results





Fitness vs. first and second design parameter - transonic case

Inverse 2-point airfoil design - GA results (64x16)

Individual 25 is the best non-dominated individual for the high lift airfoil with objective function values of:

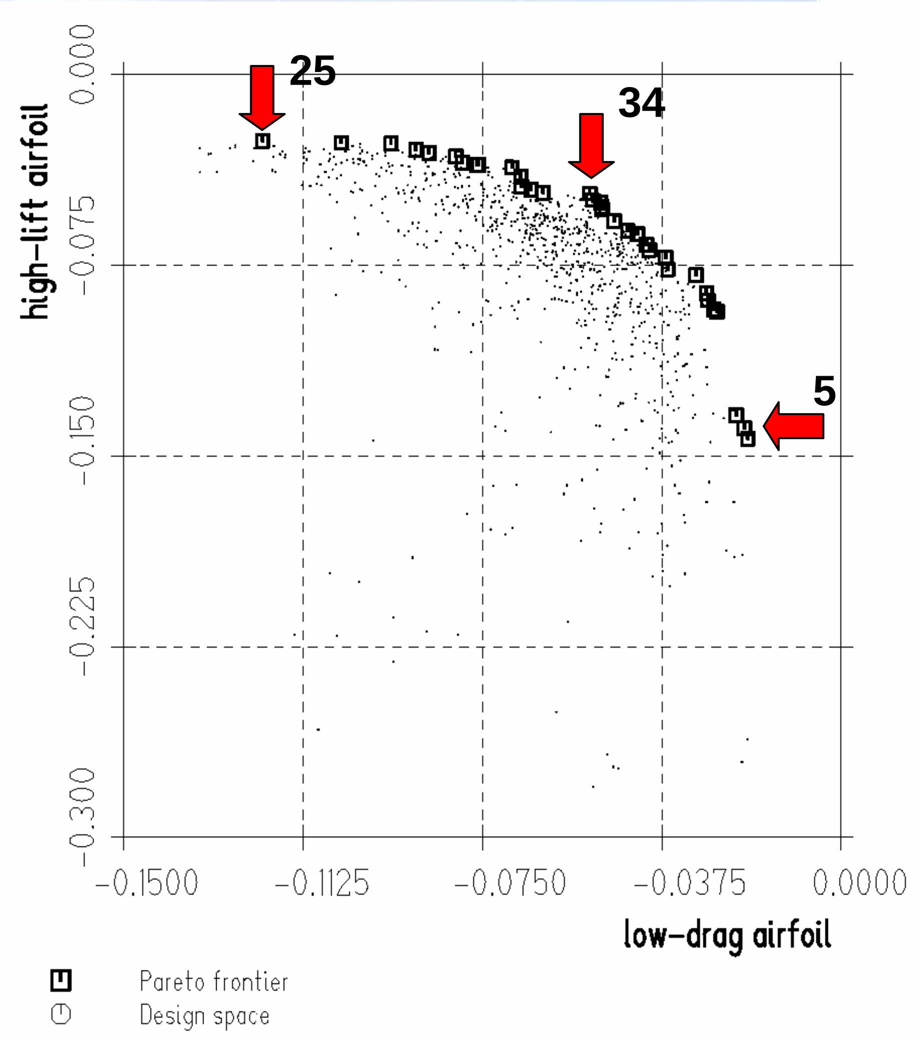
LD: $1.21 \cdot 10^{-1}$

HL: $2.60 \cdot 10^{-2}$

Individual 5 denotes the best low-drag, non-dominated individual with objective function values of:

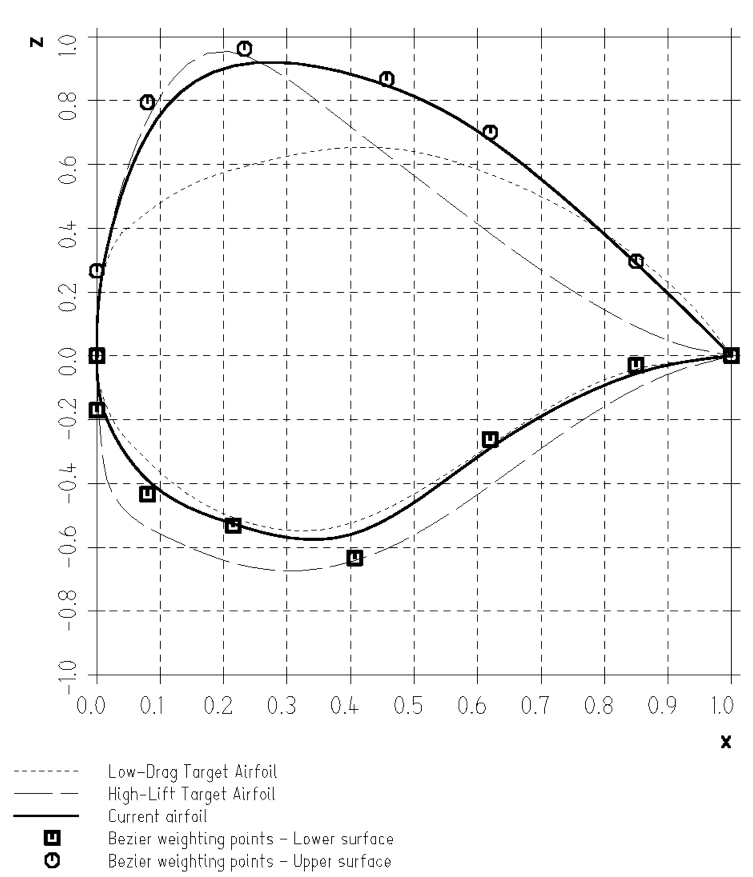
LD: $2.03 \cdot 10^{-2}$

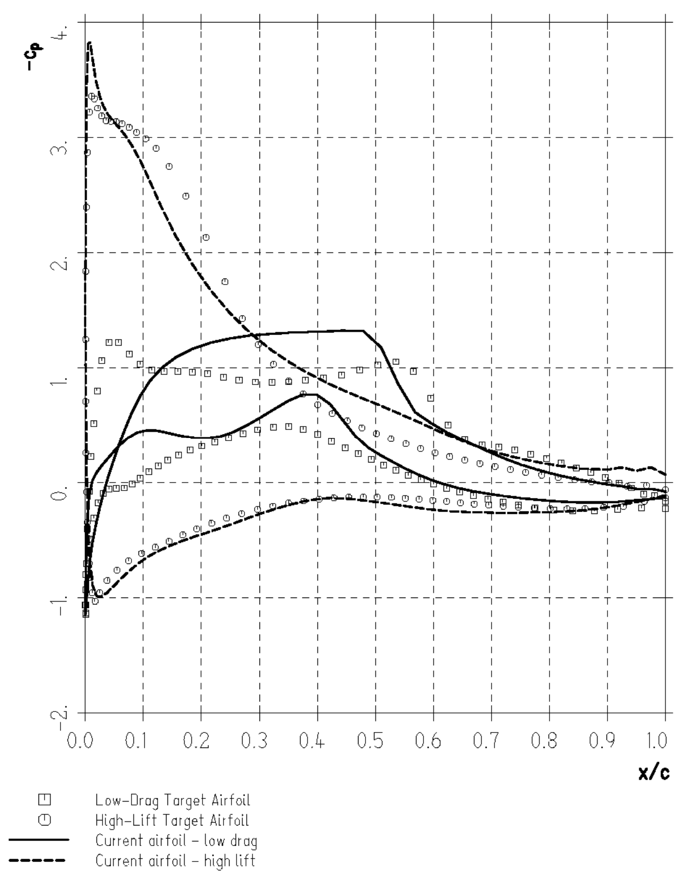
HL: $1.39 \cdot 10^{-1}$



Inverse 2-point airfoil design - GA results (64x16)

Non-dominated **individual 34** from Pareto frontier as an engineering compromise between low-drag and high-lift airfoil





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By the way: Airfoil (RAE2822) drag minimisation

A three-point design

Design points:

1. $M_1 = 0.734,\ \alpha_1 = 2.8°$, Re = 6.5 x 10^6
2. $M_2 = 0.754,\ \alpha_2 = 2.8°$, Re = 6.2 x 10^6
3. $M_3 = 0.680,\ \alpha_3 = 1.8°$, Re = 5.7 x 10^6

Objective:

$$OBJ = 2\,C_d(\alpha_1, M_1) + C_d(\alpha_2, M_2) + C_d(\alpha_3, M_3)$$

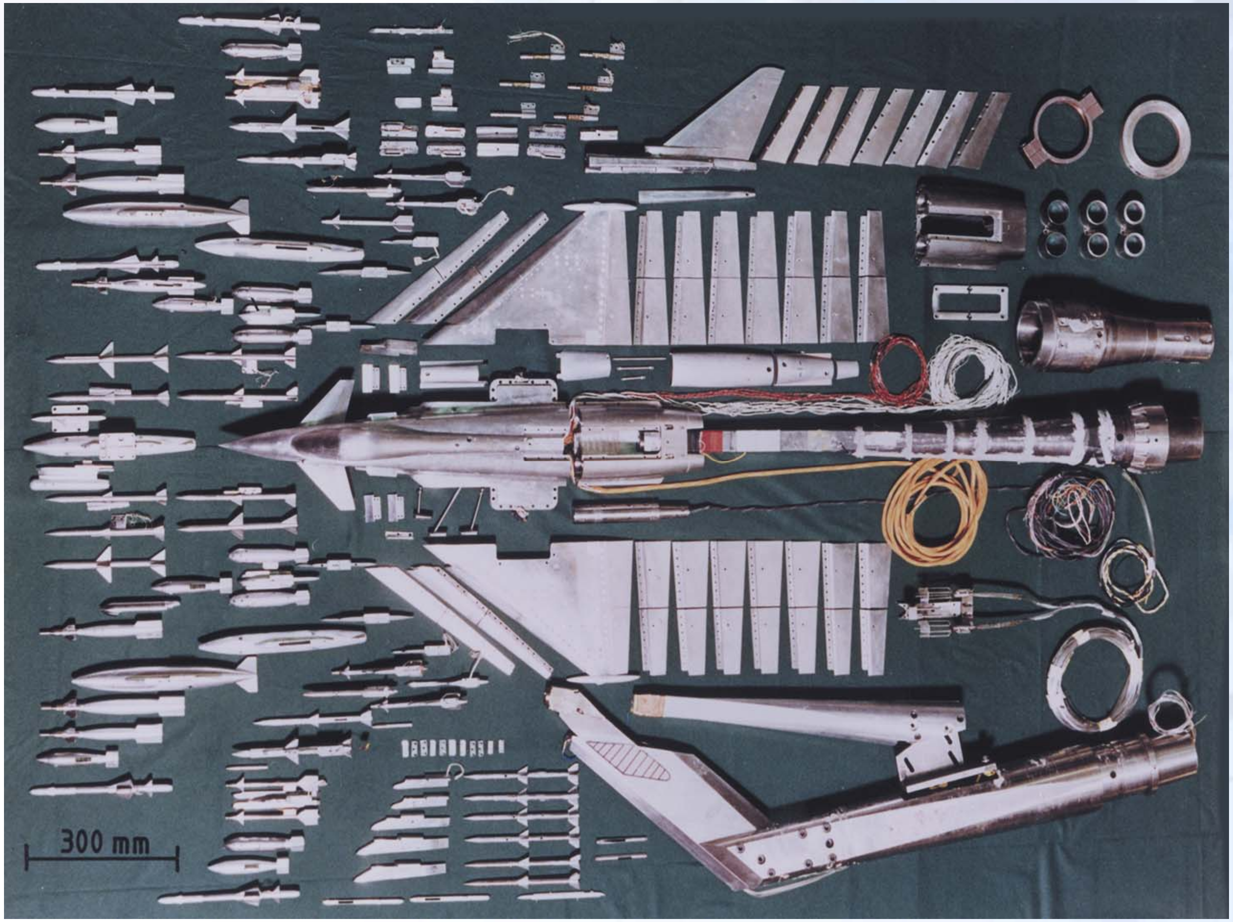
Constraints:

1. $C_l(\alpha_1, M_1) \geq C_l^t(\alpha_1, M_1)$,
2. $C_m(\alpha_1, M_1) \simeq C_m^t(\alpha_1, M_1)$ - variation of $\pm 2\%$ allowed,
3. $C_l(\alpha_2, M_2) \geq C_l^t(\alpha_2, M_2)$,
4. $C_m(\alpha_2, M_2) \simeq C_m^t(\alpha_2, M_2)$ - variation of $\pm 2\%$ allowed,
5. $C_l(\alpha_3, M_3) \geq C_l^t(\alpha_3, M_3)$,
6. $C_m(\alpha_3, M_3) \simeq C_m^t(\alpha_3, M_3)$ - variation of $\pm 2\%$ allowed,
7. $\mathrm{leading-edge-radius} \geq 0.9\,\mathrm{l.e.r}^t$,
8. $\mathrm{trailing-edge-angle} \geq 0.8\,t.e.a^t$,
9. $\mathrm{thickness}(5\%) \geq 0.96\,\mathrm{th.}^t(5\%)$.

Optimisation of <u>canard</u> and <u>leading edge flap</u> settings

Optimisation of canard and leading edge flap settings

„Experimental optimisation“



Optimisation of canard and leading edge flap settings

Model:

- Aerodynamic Data set
- With trim algorithm according to N. Moritz

Design parameters:

- **Canard angle (-40^o to 10^o; step size = 1^o)**
- **Leading edge flap angle: -20^o to 0^o; step size = 1^o ; -20.0^o re-set to -19.5^o**
- Angle-of-attack: -10^o to 40^o; step size = 2^o
- Mach number: 1.2

Optimisation of canard and leading edge flap settings

Objectives:

Lift = C_L ➔ Maximum

Drag = C_D ➔ Minimum

Constraints:

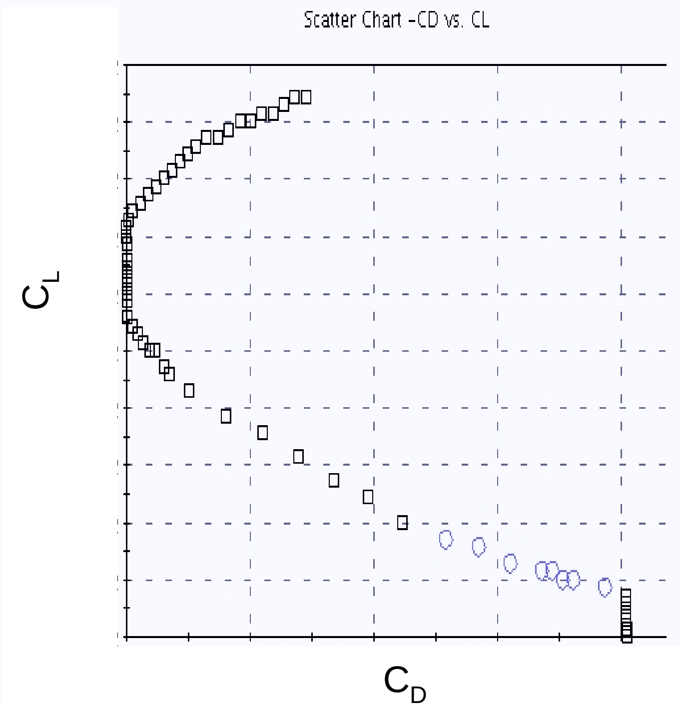
- trimability within t.e. flap deflection limits
- foreplane shear load limits
- actuator load limits
- sufficient rudder effectiveness (t.e. flap/canard)
- load factor (nz) limits
- wing dihedral dcl/dβ limits (lateral stability)
- long. stability constraints (dcm/dα)

Optimisation of canard and leading edge flap settings

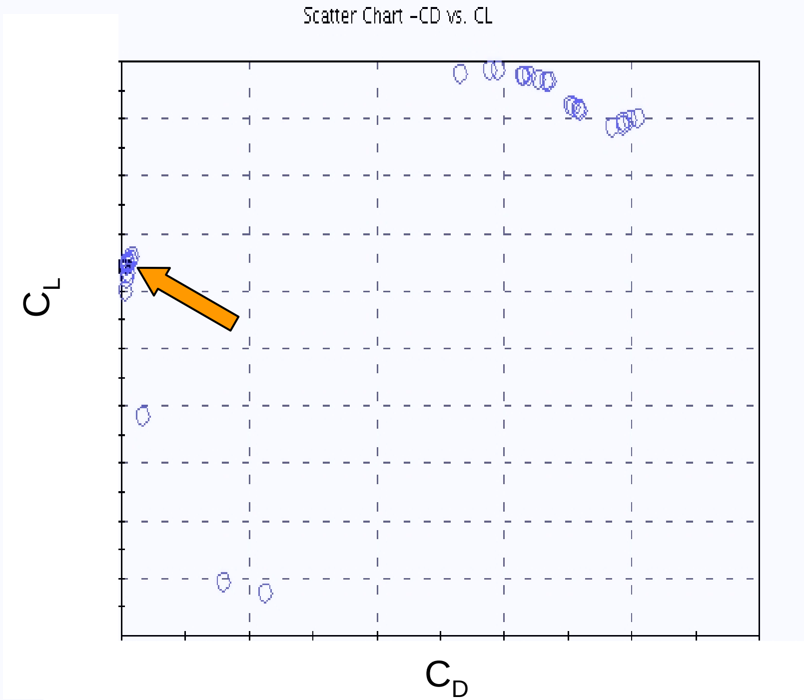
Trimming of loads

Mach = 1.2, Alt. = 30,000 ft, Canard setting: “real”, **$C_{d,min}$ search**

NZ = –0.5



NZ = 2.0



X31 wing performance optimisation

Multi-objective, multi-disciplinary optimisation

- **Maximisation of roll rate** and
- **Minimisation of structural weight** for various relevant loads
- Use of GA approach
- Spanwise divided & deflected flaps
- Continuous and discrete design parameter

X31 wing performance optimisation

The test case is based on the following flow and structure parameters:

Flow parameters:

Mach-number	[-]	= 1.2
Stagnation_pressure	[N/m**2]	= 102100.0

Structural constraints:

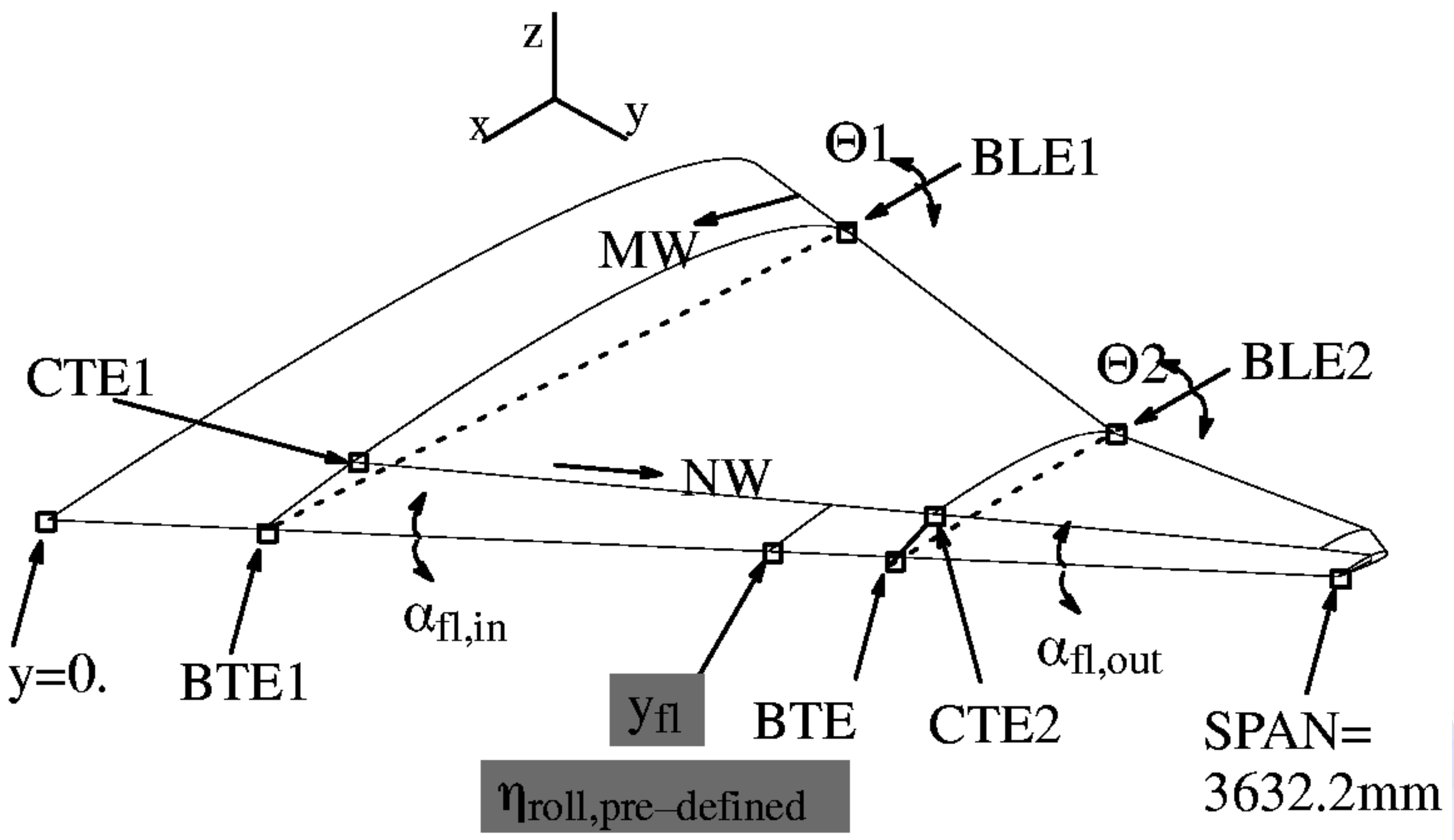
Max. Inb_flap_setting	[deg]	= 15.0
Max. Outb_flap_setting	[deg]	= 15.0
Max. Inb_hinge_moment	[Nm]	= 4500.
Max. Outb_hinge_moment	[Nm]	= 4500.

Design parameters:

	Min	Max	Base
Flap split:	1	3	3
Inboard Efficiency	0.2	0.5	151
Outboard Efficiency	0.2	0.5	252

X31 wing performance optimisation

Parameterisation



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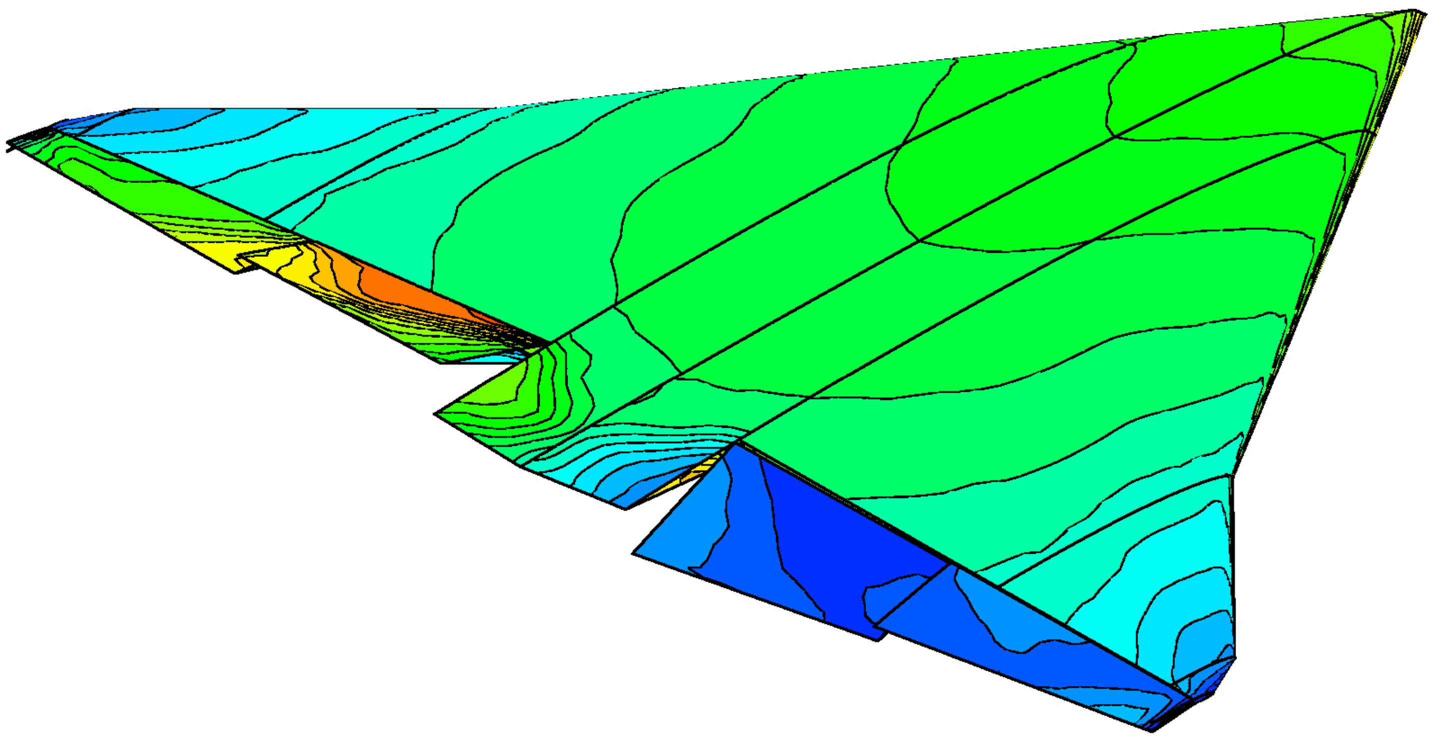
X31 wing performance optimisation

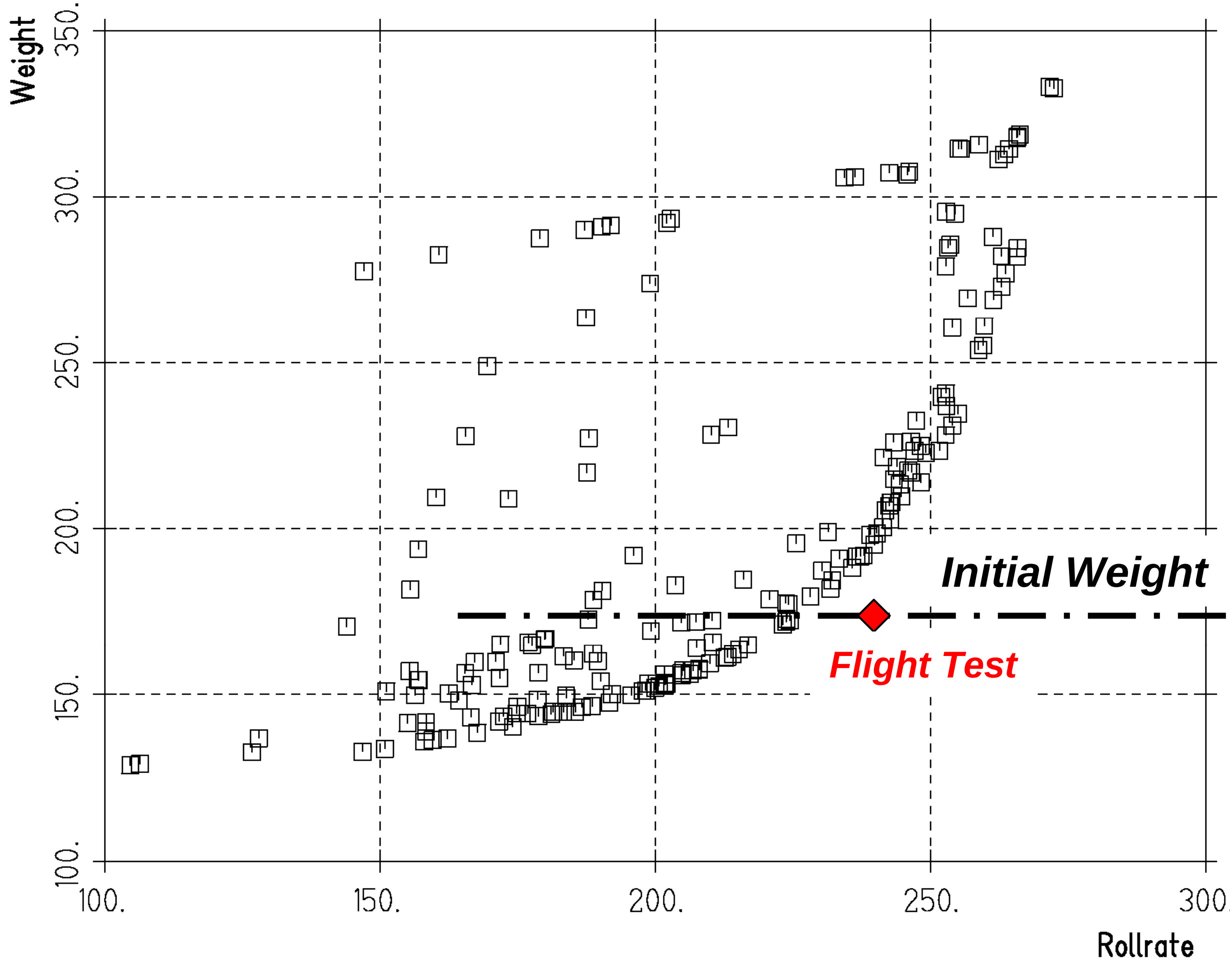
Results - CFD (HISSS-D Panel Method)

Ma=1.2 - α=5.53º - $\alpha_{flap,inboard}$=20.0º - $\alpha_{flap,outboard}$=10.0º

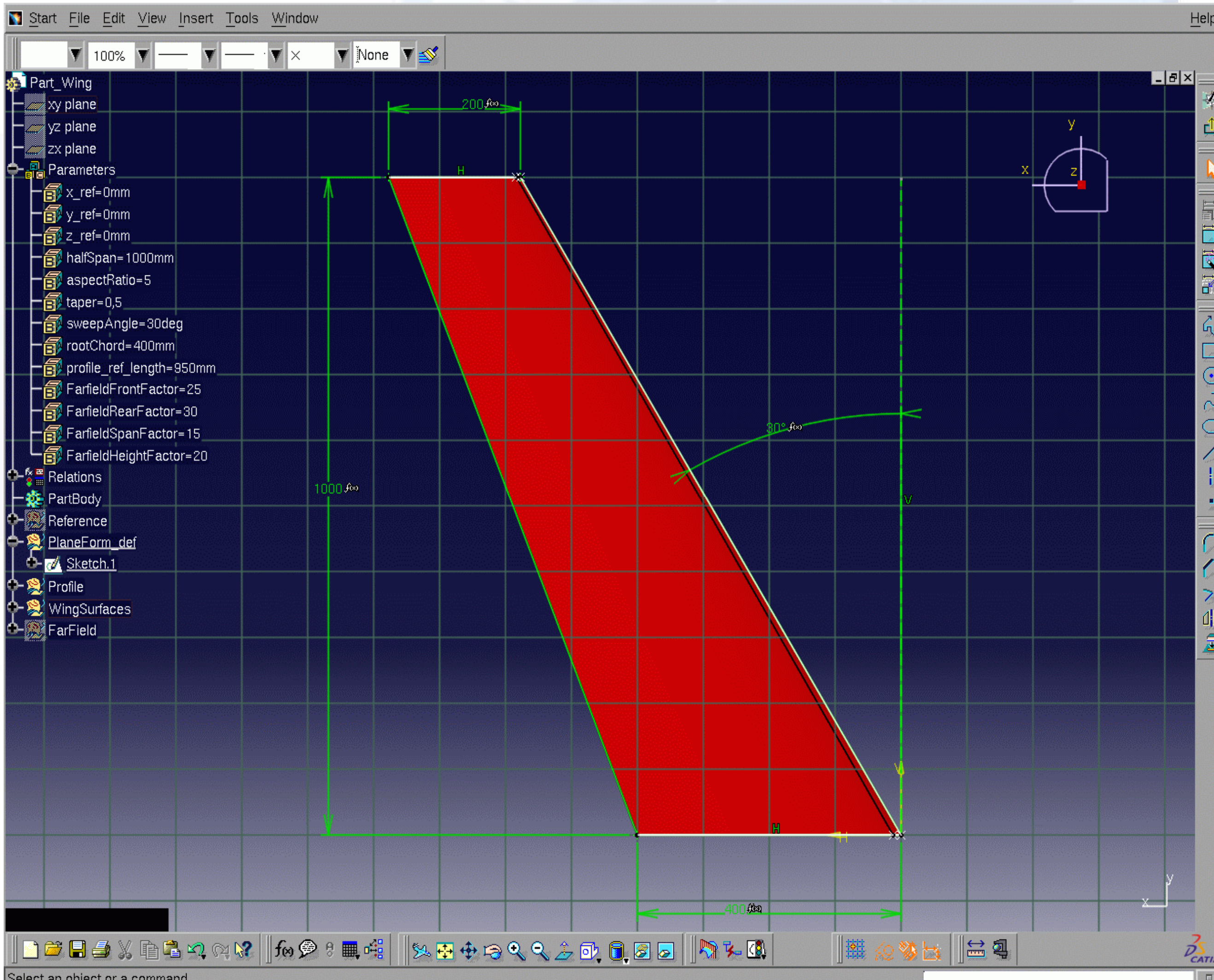


X31 wing performance optimisation

Results - Pareto Frontier



Inviscid shape optimisation of a wing planform – using CATIA_v5



Inviscid shape optimisation of a wing planform – using CATIA_v5

Flow conditions:
Mach= 0.85, angle of attack = 1°

Design parameters:

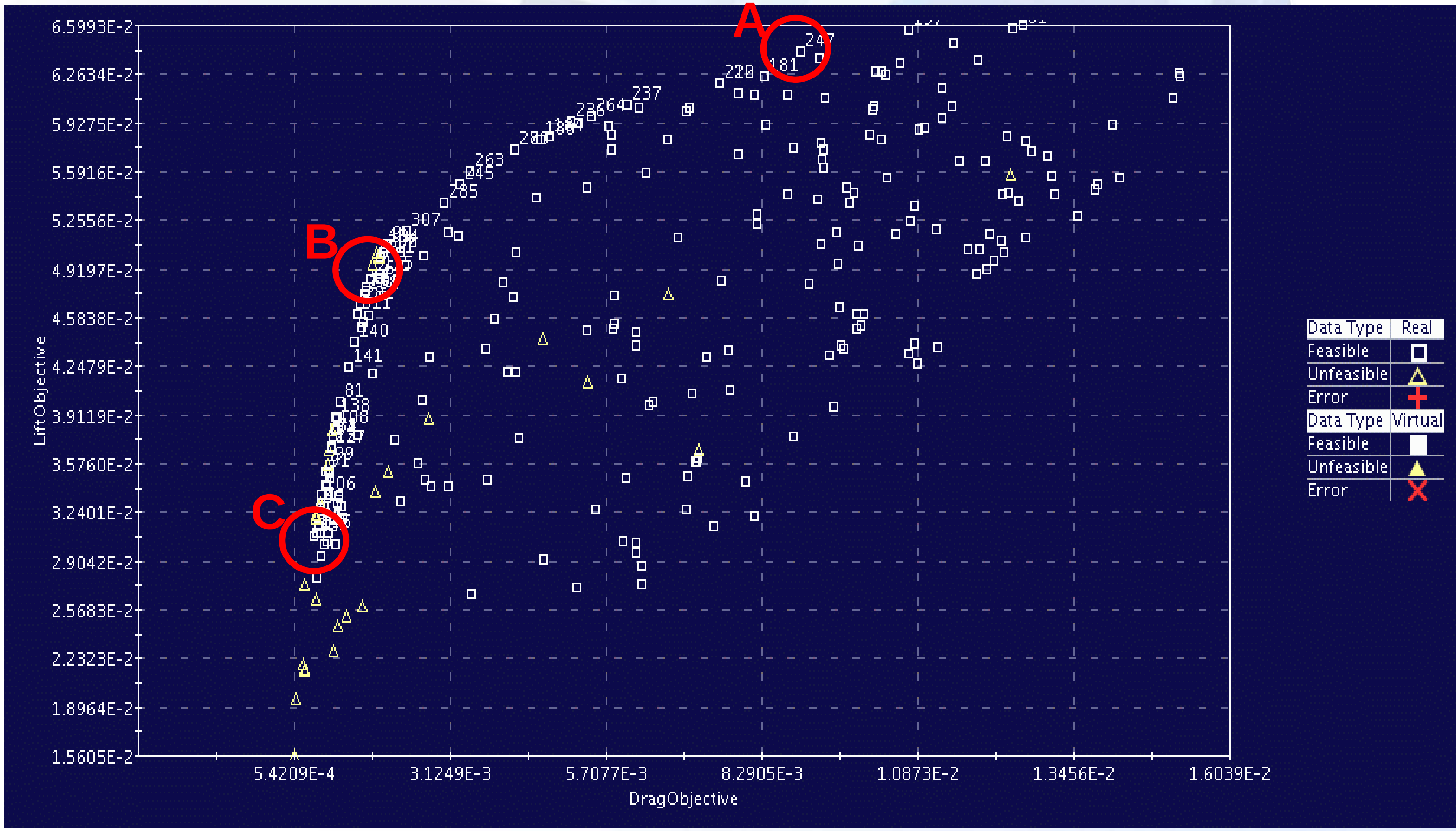
sweep angle	(range: -60° to +60°)
halfspan	(range: 0.750 m to 1.250 m)
aspect ratio	**(defined by const. wing plan area constraint)**
taper ratio	(range: 0.2 to 0.8)

Design constraints:

Pitching moment restricted to range –0.025 to +0.0001

Inviscid shape optimisation of a wing planform – using CATIA_v5

The correct approach: Wing area kept constant



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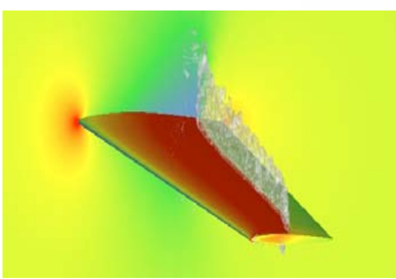
Inviscid shape optimisation of a wing planform – using CATIA_v5

Non-dominated individuals along the Pareto boundary @ A, B and C

A

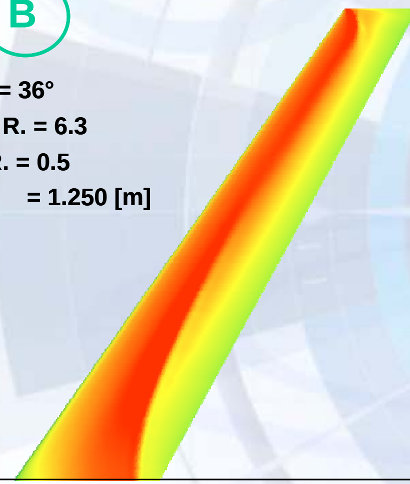
Sweep = 20°
Aspect R. = 6.6
Taper R. = 0.58
Halfspan = 1.250 [m]

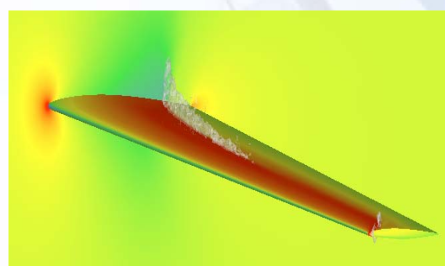


Lift = 0.064
Drag = 0.0089
Moment = - 0.022

B

Sweep = 36°
Aspect R. = 6.3
Taper R. = 0.5
Halfspan = 1.250 [m]

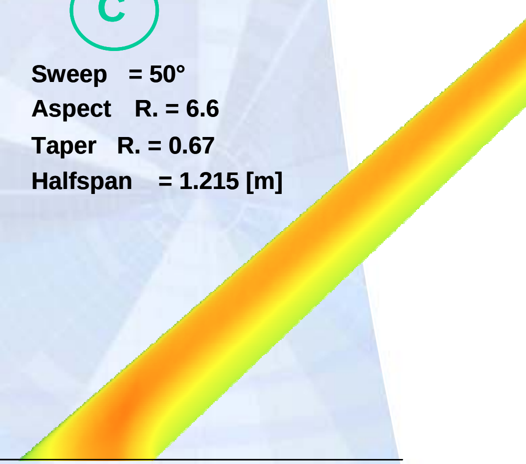


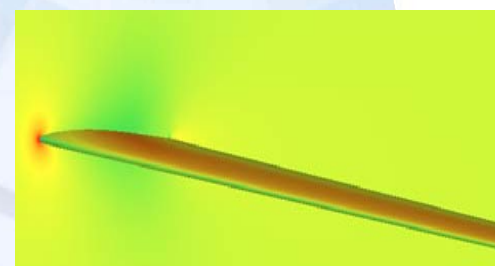


Lift = 0.048
Drag = 0.0018
Moment = - 0.025

C

Sweep = 50°
Aspect R. = 6.6
Taper R. = 0.67
Halfspan = 1.215 [m]

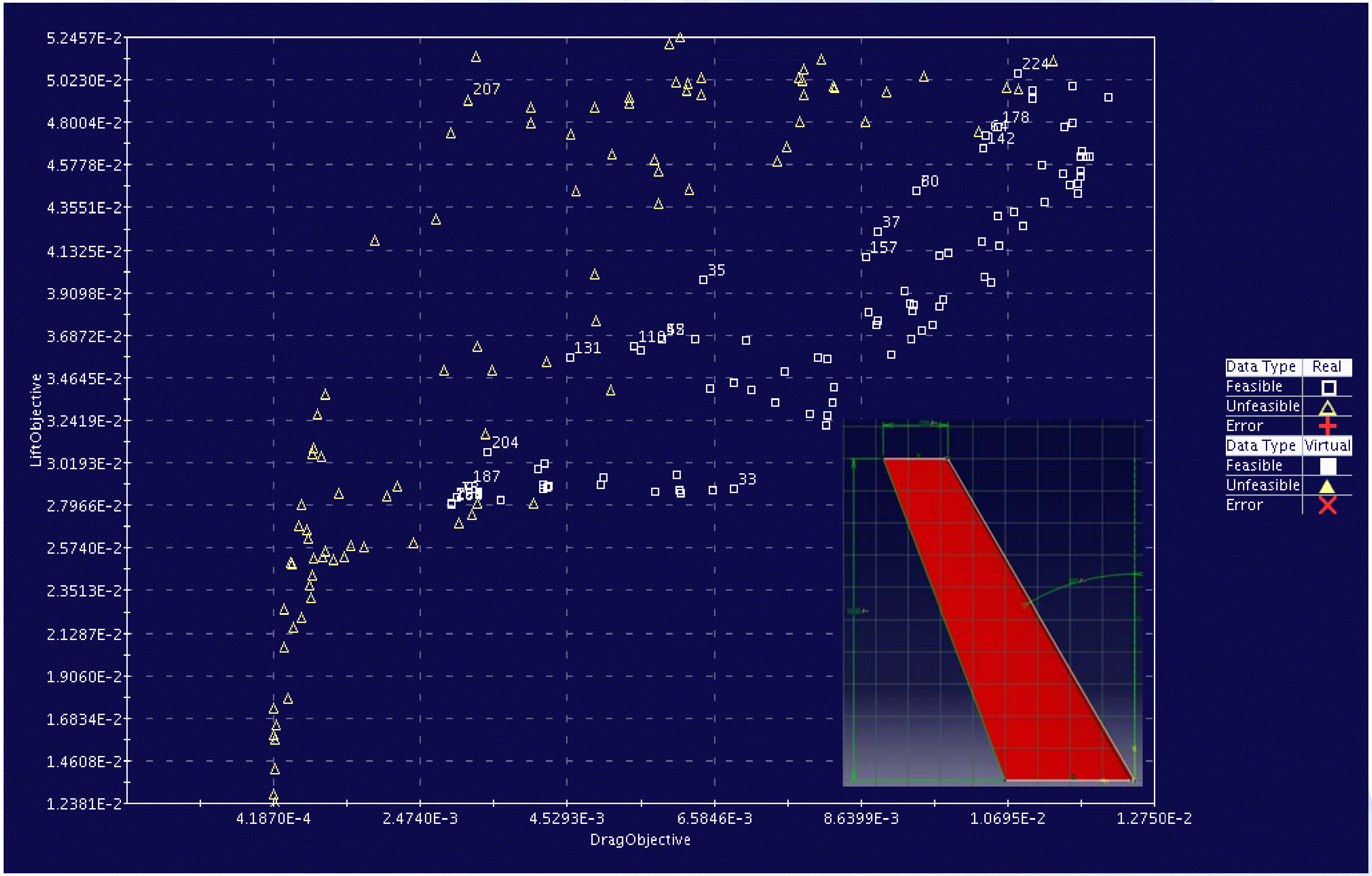




Lift = 0.031
Drag = 0.00087
Moment = - 0.024

Inviscid shape optimisation of a wing planform – using CATIA_v5

The wrong approach: Wing area not fixed !



Conclusions

- Use of evolutionary algorithms is an adequate optimisation means for varying applications (“non-adjoint“)
- including discrete design parameters,
- multi-objective and multi-disciplinary optimisation.

- ‘Pareto’-optimisation does not free the engineer from deciding on appropriate designs,
- but MCDM tools can be used for the latter

- Results presented clearly show the advantages of EAs,
- which does not necessarily mean that these methods are superior in all cases
- ‘Search’ mechanisms (MCDM) are welcome, as industry is looking at IMPROVEMENTS rather than at absolute optima, i.e.
- robust design is “more favourable”

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Questions?