One-shot robust optimisation with grid adaptation using adjoint sensitivities

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Motivation

- Aerodynamic optimisation is limited by computational cost
- Grid adaptation can reduce computational cost
- Robust optimal design is needed

Research tasks:

- Develop one-shot optimisation coupled with adjoint based grid adaptation
- Develop robust optimisation coupled with grid adaptation

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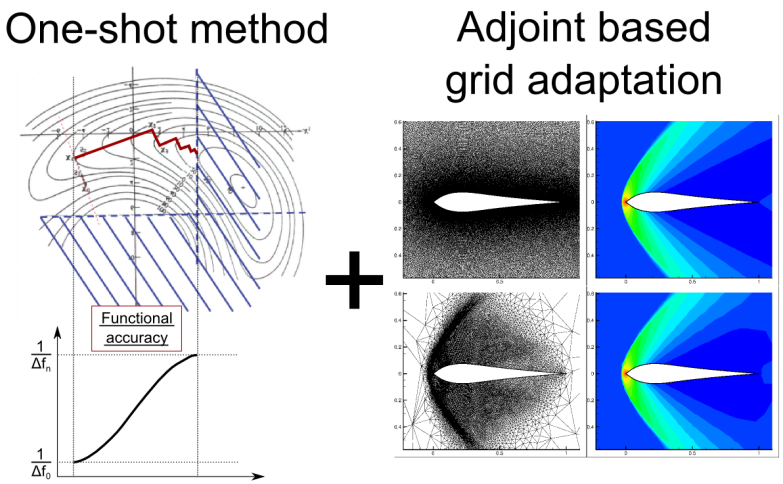
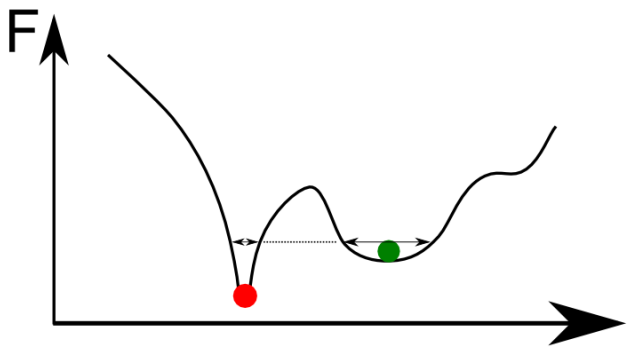
Research tasks

- One-shot optimisation coupled with adaptation



- Reduced cost of robust optimisation



Adjoint solver

$$\left(\frac{\partial \mathrm{R}}{\partial \mathrm{Q}}\right)^{\mathrm{T}} \mathrm{v} = \left(\frac{\partial \mathrm{L}}{\partial \mathrm{Q}}\right)^{\mathrm{T}},$$

$$\mathrm{A}^{\mathrm{T}}\mathrm{v} = \mathrm{g}.$$

$$\frac{\mathrm{dL}}{\mathrm{d}\alpha} = \frac{\partial \mathrm{L}}{\partial \alpha} + \mathrm{g}^{\mathrm{T}}\mathrm{u} = \frac{\partial \mathrm{L}}{\partial \alpha} + \mathrm{v}^{\mathrm{T}}\mathrm{f}$$

1. Implicit adjoint solver developed by WUT
   - solving $\mathrm{A}^{\mathrm{T}}\mathrm{v} = \mathrm{g}$ using sparse Jacobian
   - 0.1 factor of CPU consumption compared to primal calculation
2. ANSYS Fluent v14 adjoint solver

Adaptation indicator

- Adaptation indicator: adjoint · Hesjan

$$e_k = \sum_i^n (|v_i| \cdot |h^T \mathcal{H}_i h|) \cdot V_i \qquad (1)$$

where: i - flow variable, k - node

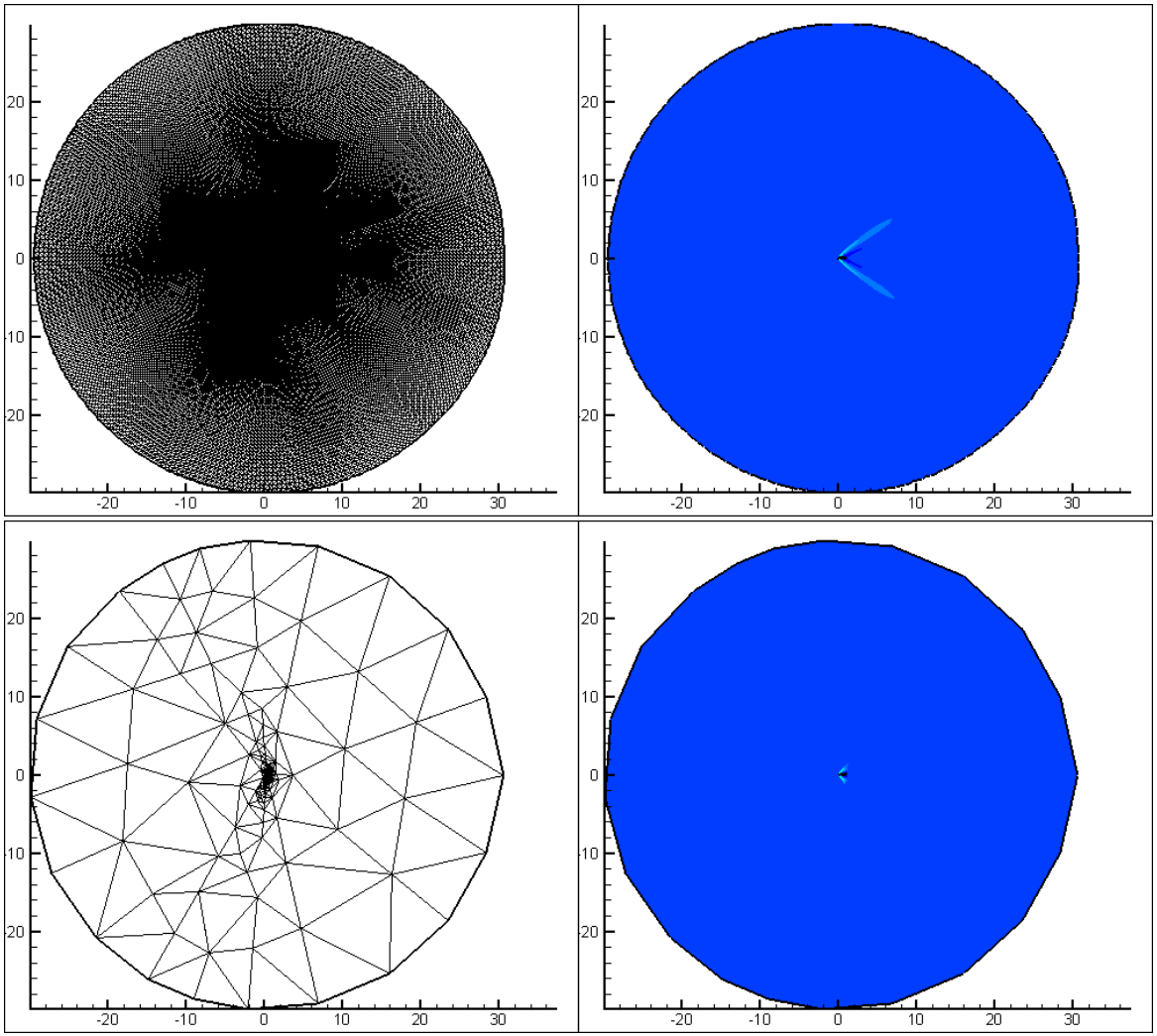
- Adaptation indicator - scaling

$$a_k = \left(\frac{e_k \cdot N}{\delta_{lim}} \right)^{\omega} \qquad (2)$$

- Separate ω for coarsening and refinement gives better convergence
- New edge length h_k:

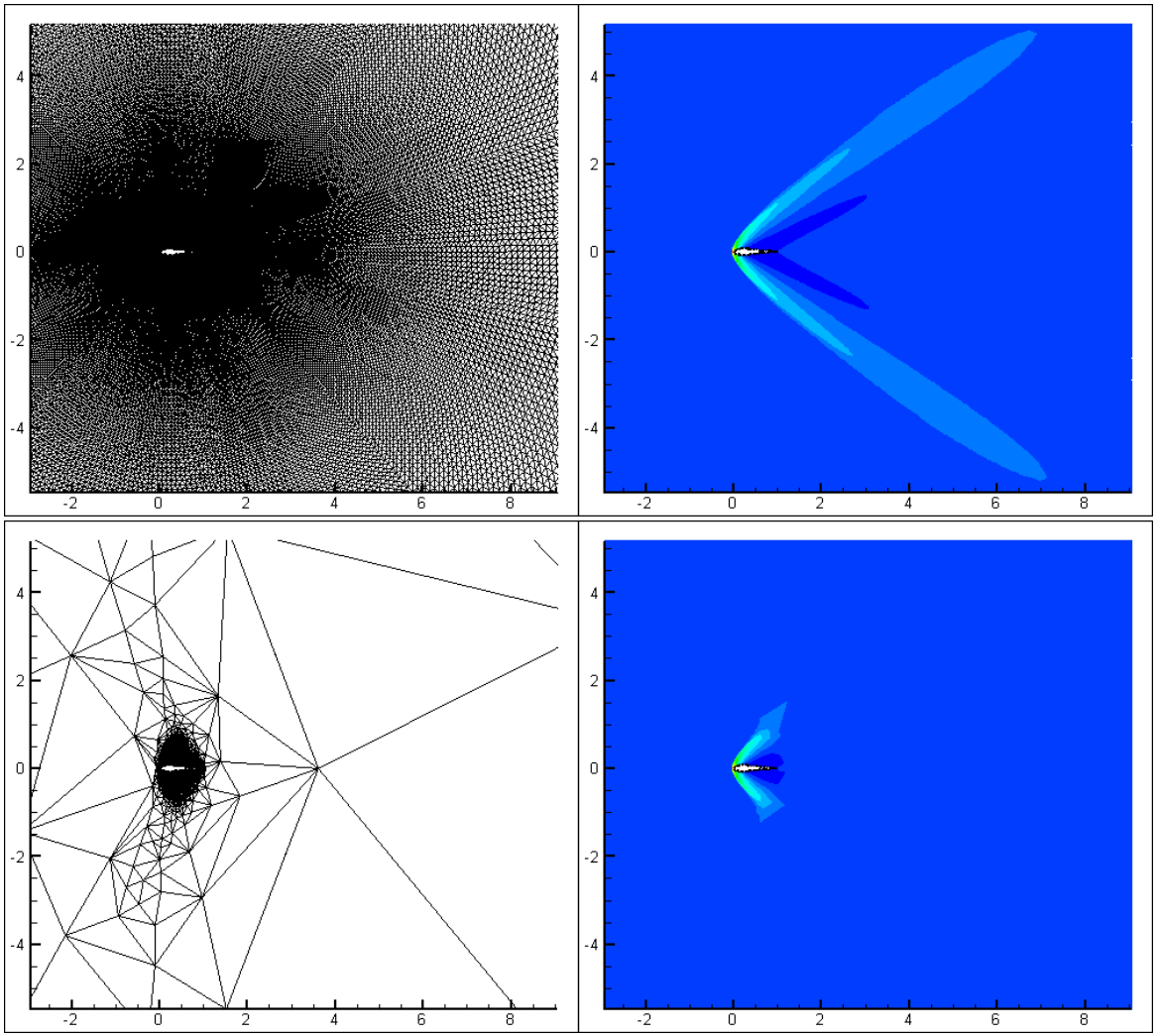
$$h_{new} = h_{old} \cdot \frac{1}{a_k} \qquad h_{min} < h_{new} < h_{max} \qquad (3)$$

Adaptation - comparison with uniformly refined grids, M = 2.0



142000 nodes, 19000 nodes.

Adaptation - comparison with uniformly refined grids, M = 2.0



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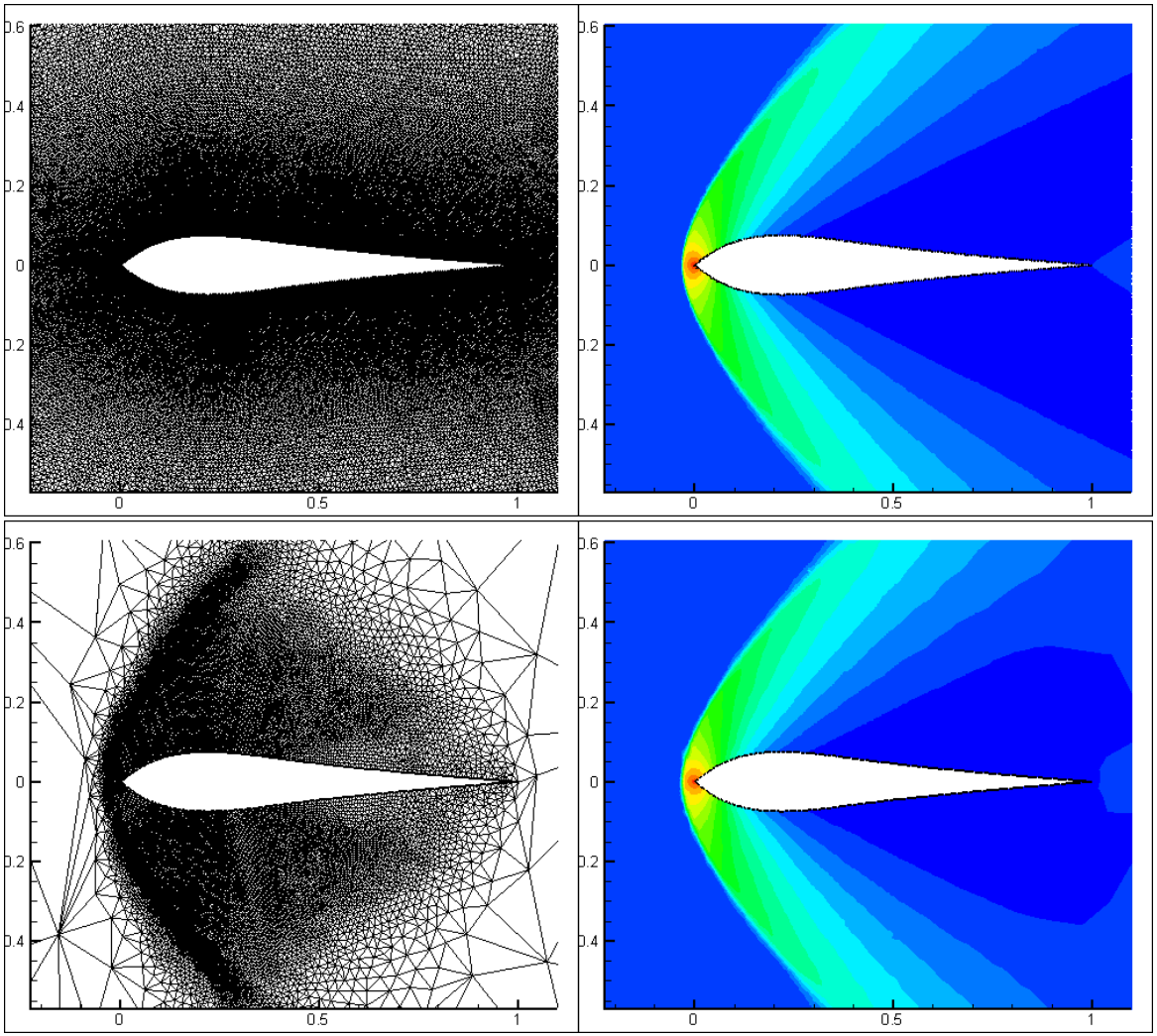
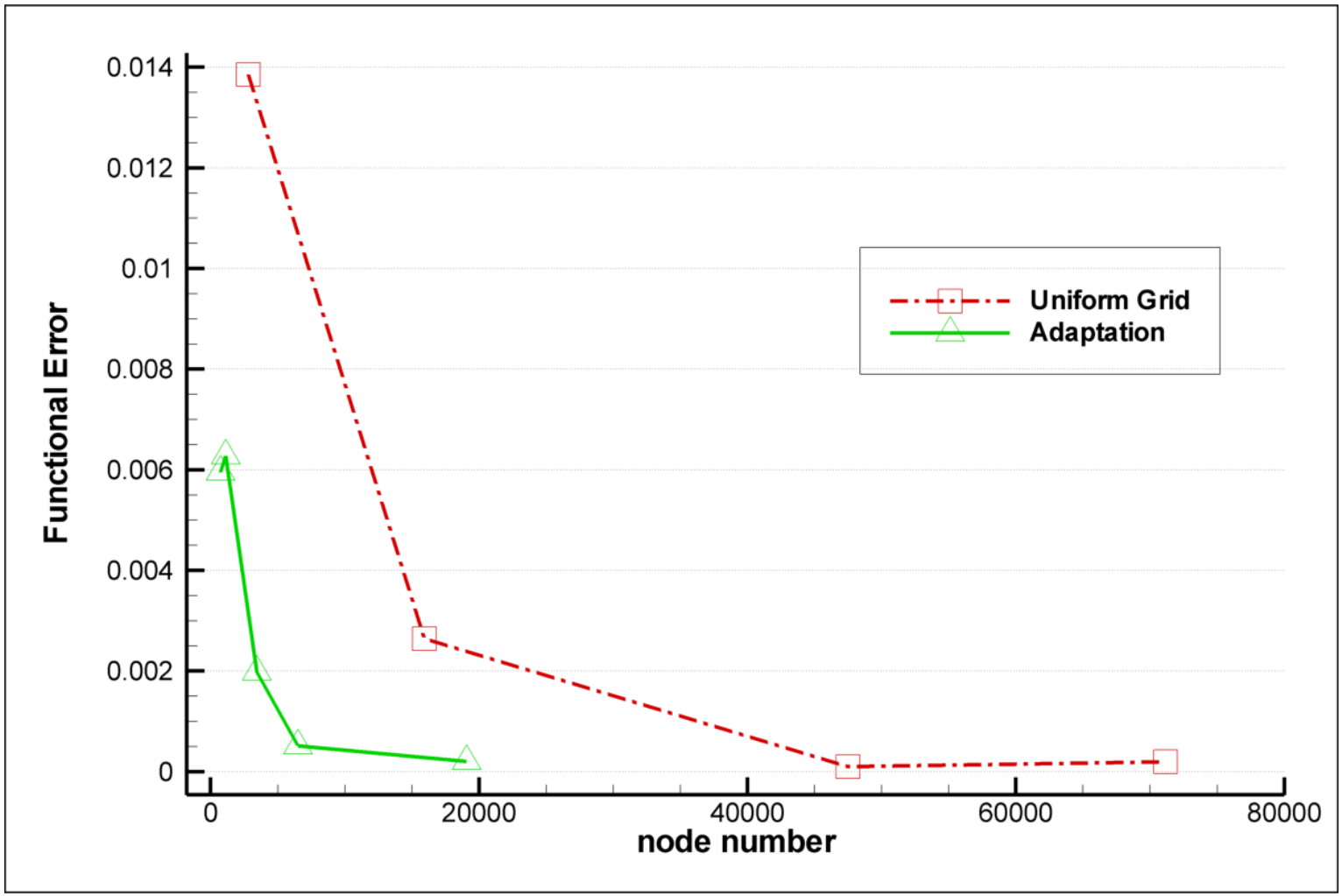


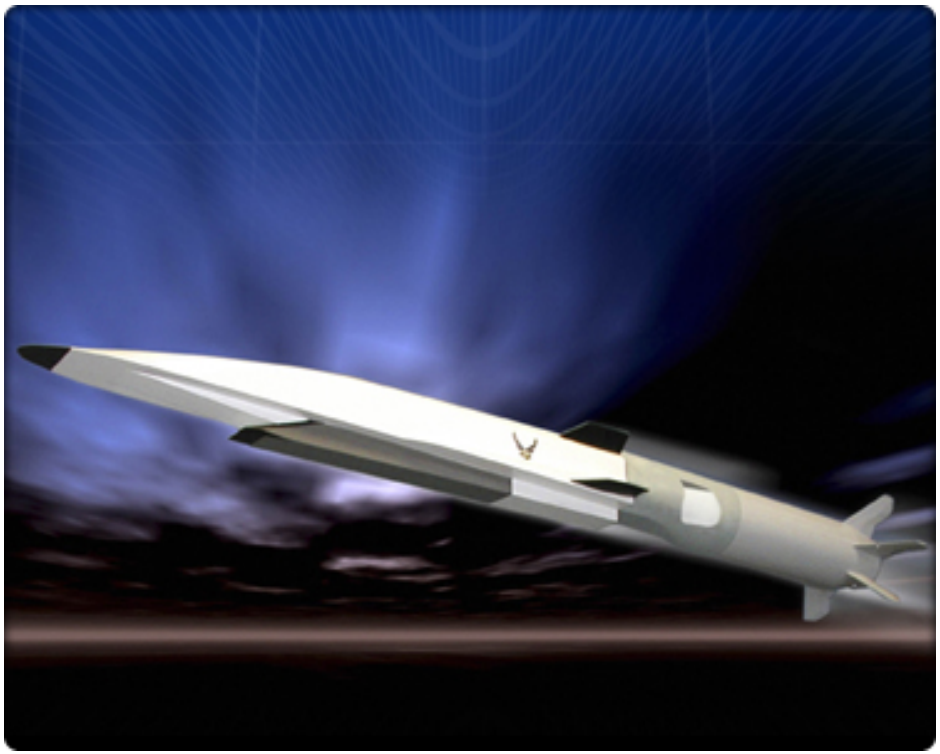
142000 nodes, 19000 nodes.

Adaptation efficiency



Optimisation + adaptation
Wave Rider testcase

- Mach = 2.0, inviscid flow
- Optimisation task - minimize drag with constant lift
- Gradient based L-BFGS-B optimiser
- 4 design variables



source: boeing.com

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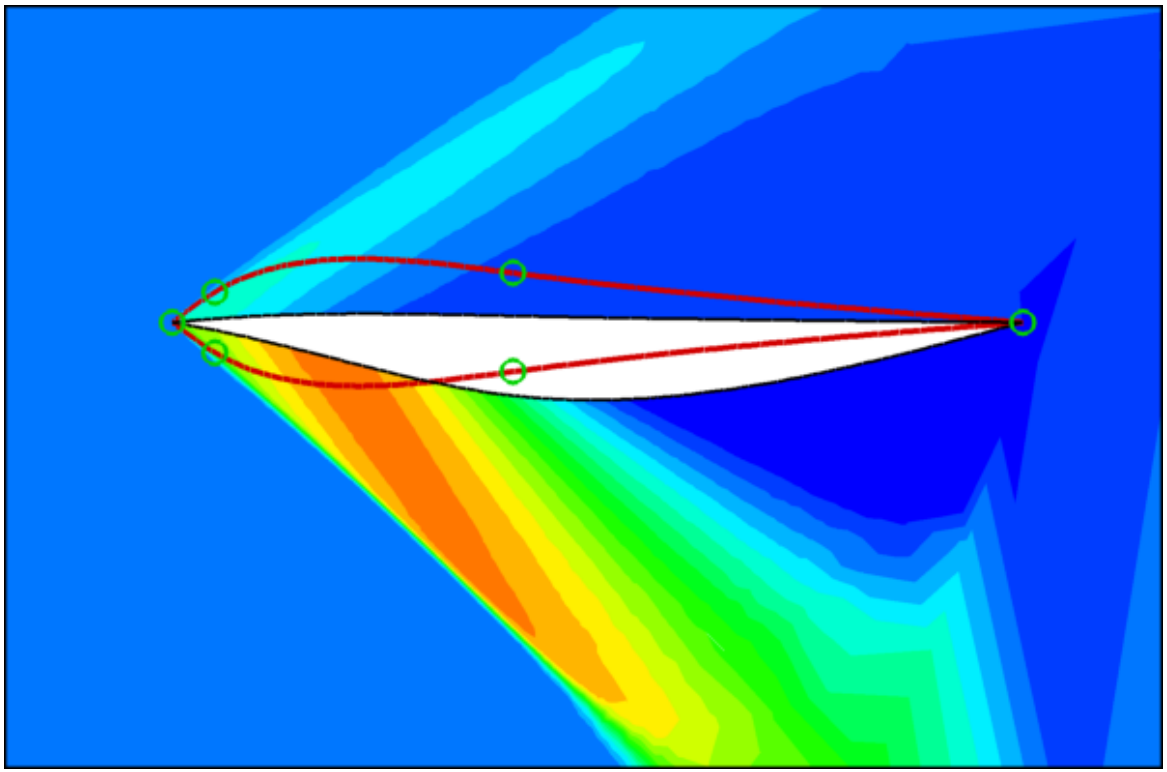
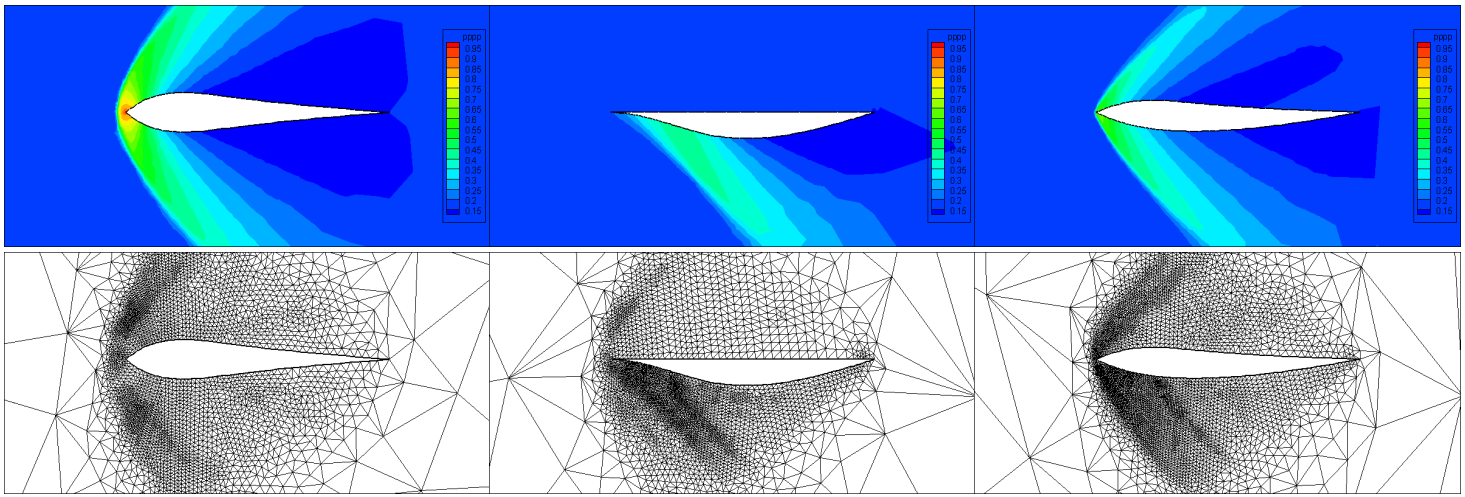
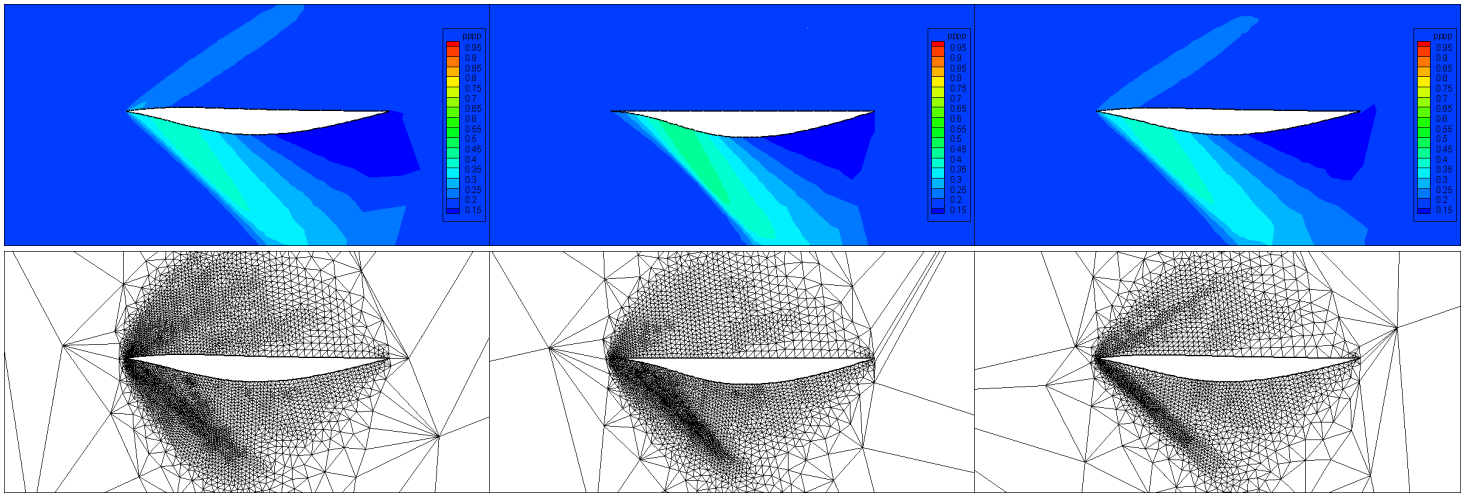


Optimisation + adaptation, error = const

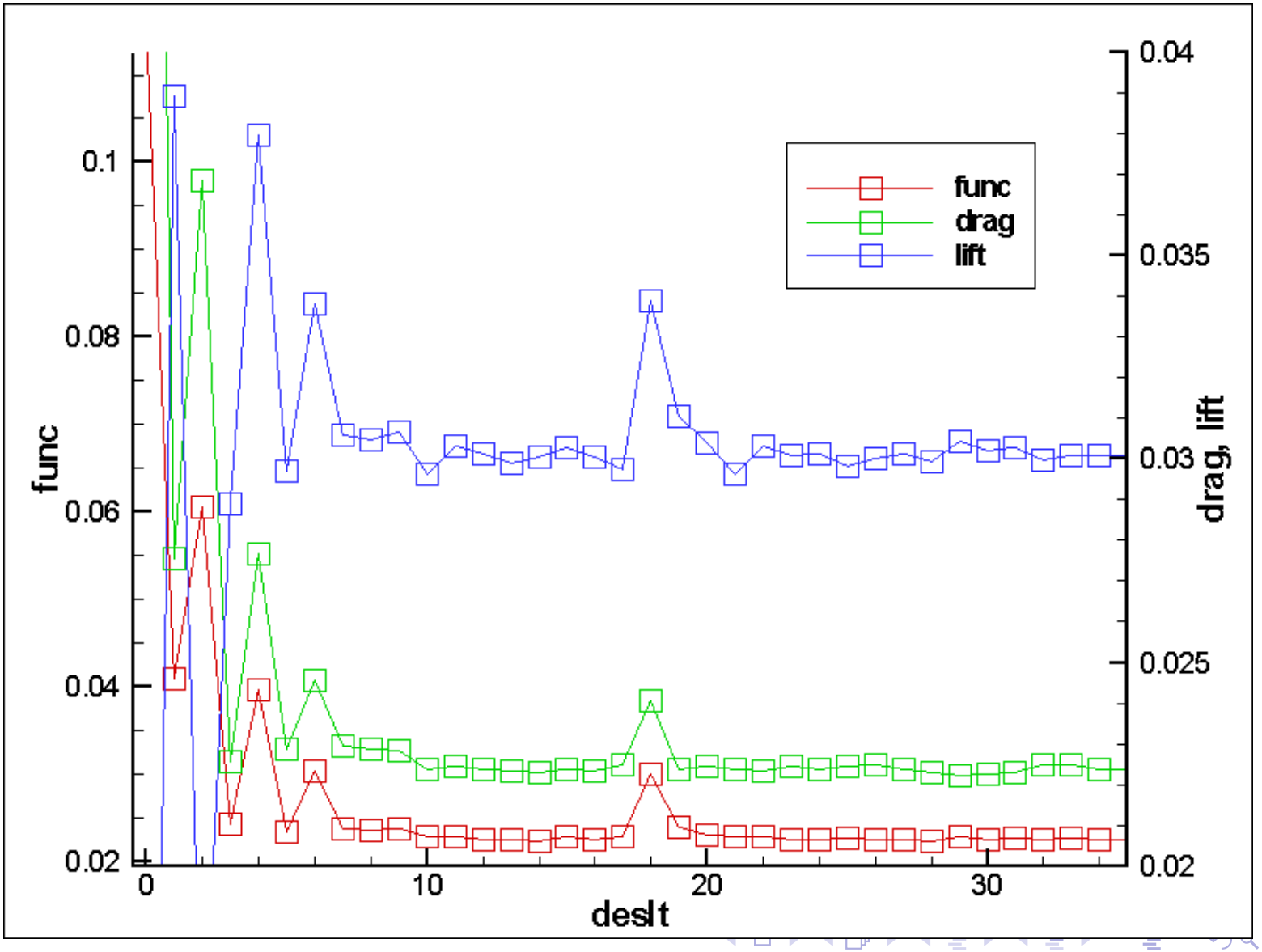


iteration: 1 iteration: 2 iteration: 3



iteration: 4 iteration: 5 iteration: 34

Optimisation + adaptation, error = const
Convergence history:



One-shot method

Cost of single design iteration depends on:

- mesh size, number of nodes
- solution accuracy, residual stop criteria

Total cost of optimisation can decreased by:

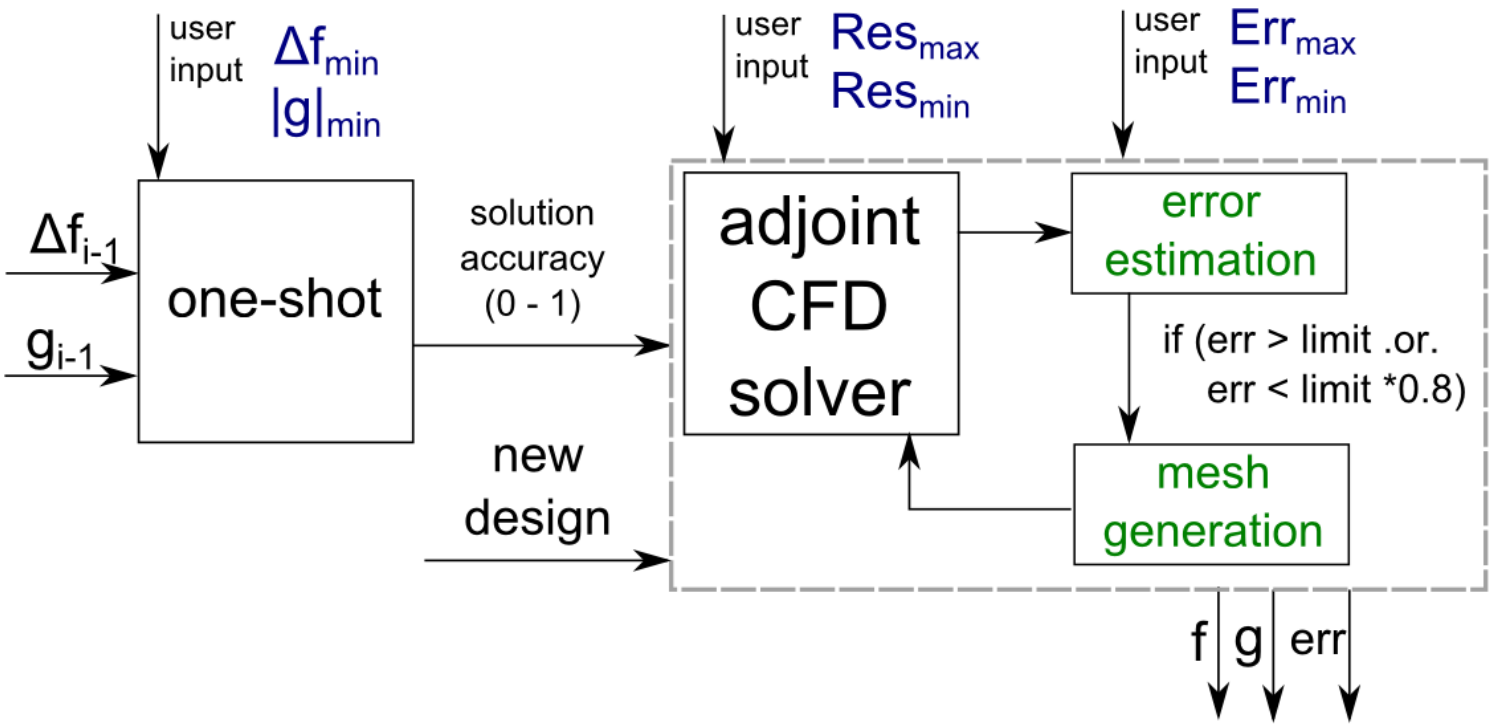
- solving CFD with minimal acceptable accuracy
- using mesh with lowest acceptable number of nodes

One-shot Wolfe condition:

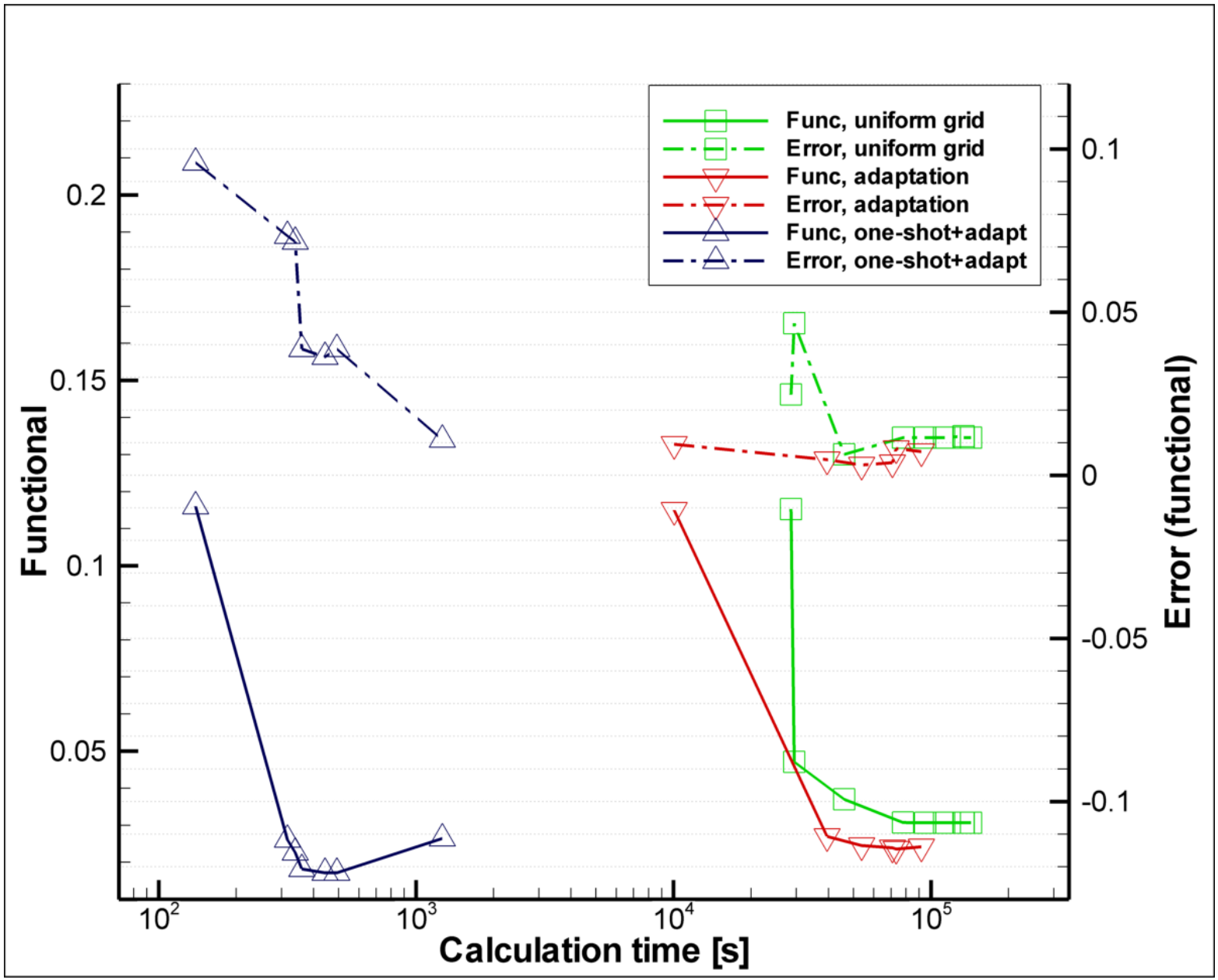
- estimation of accuracy acceptable by optimiser:

$$\mathrm{acc} \sim \min\left(\log\left(\frac{|\mathrm{g}|}{\mathrm{g_{min}}}\right), \log\left(\frac{|\Delta \mathrm{f}|}{\Delta \mathrm{f_{min}}}\right)\right)$$

One-shot method

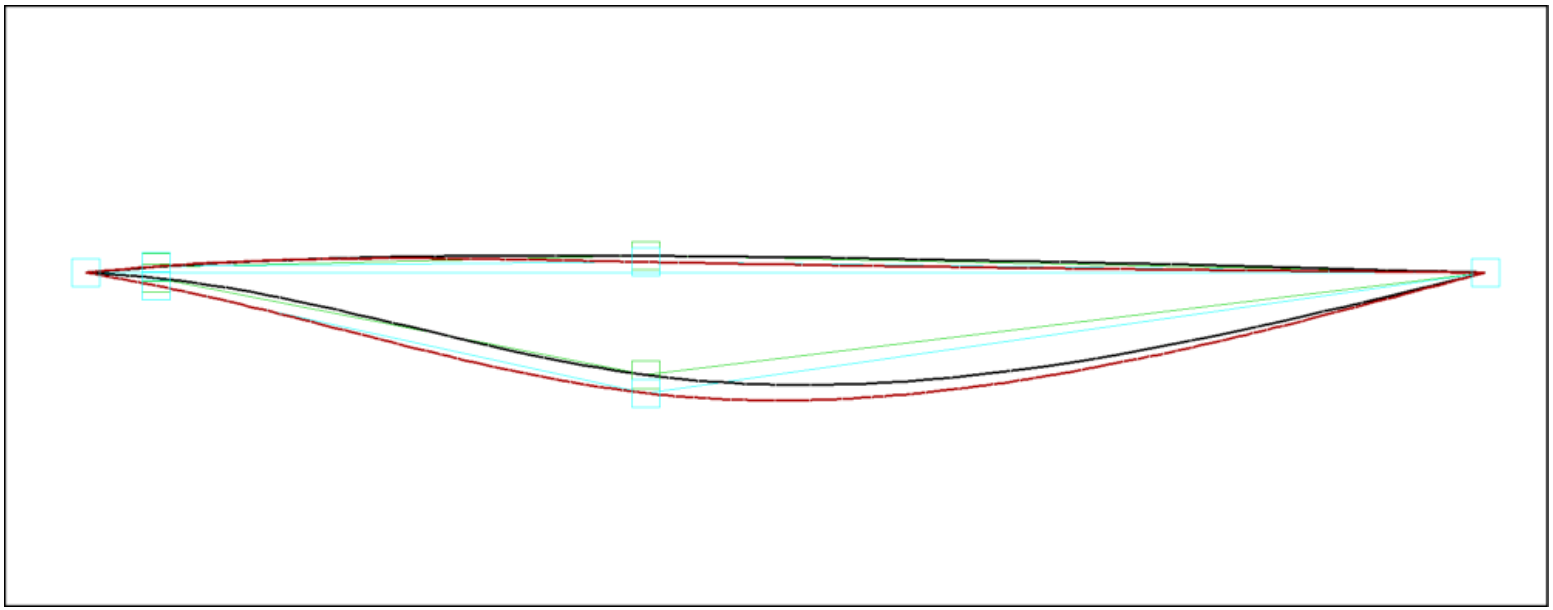


Wave-rider: one-shot + adaptation



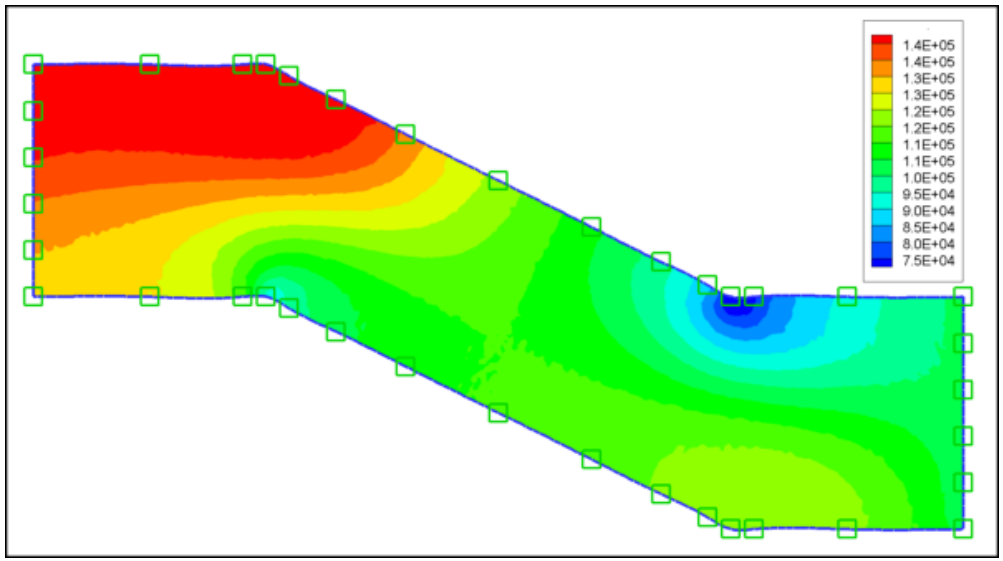
One-shot + adaptation, comparison

Difference in final design between one-shot and constant error.



One-shot + adaptation
2D sband testcase

- Optimisation task - minimize pressure drop
- Gradient based L-BFGS-B optimiser, 14 des. var.
- ANSYS Fluent v14 adjoint solver
- Laminar flow, Re = 300
- Simplified adaptation - adjoint solver convergence problems



Sband: one-shot + adaptation, performance

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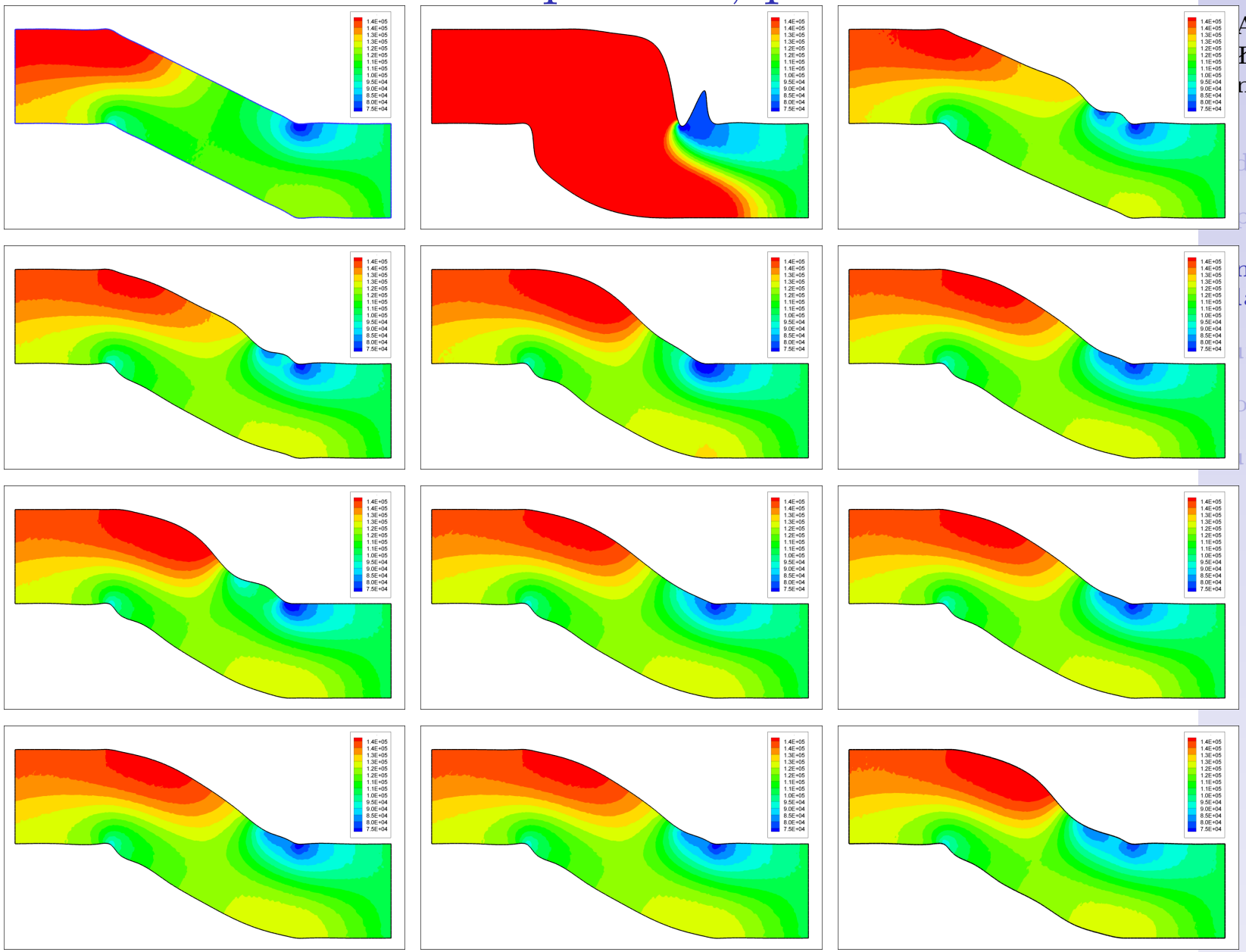
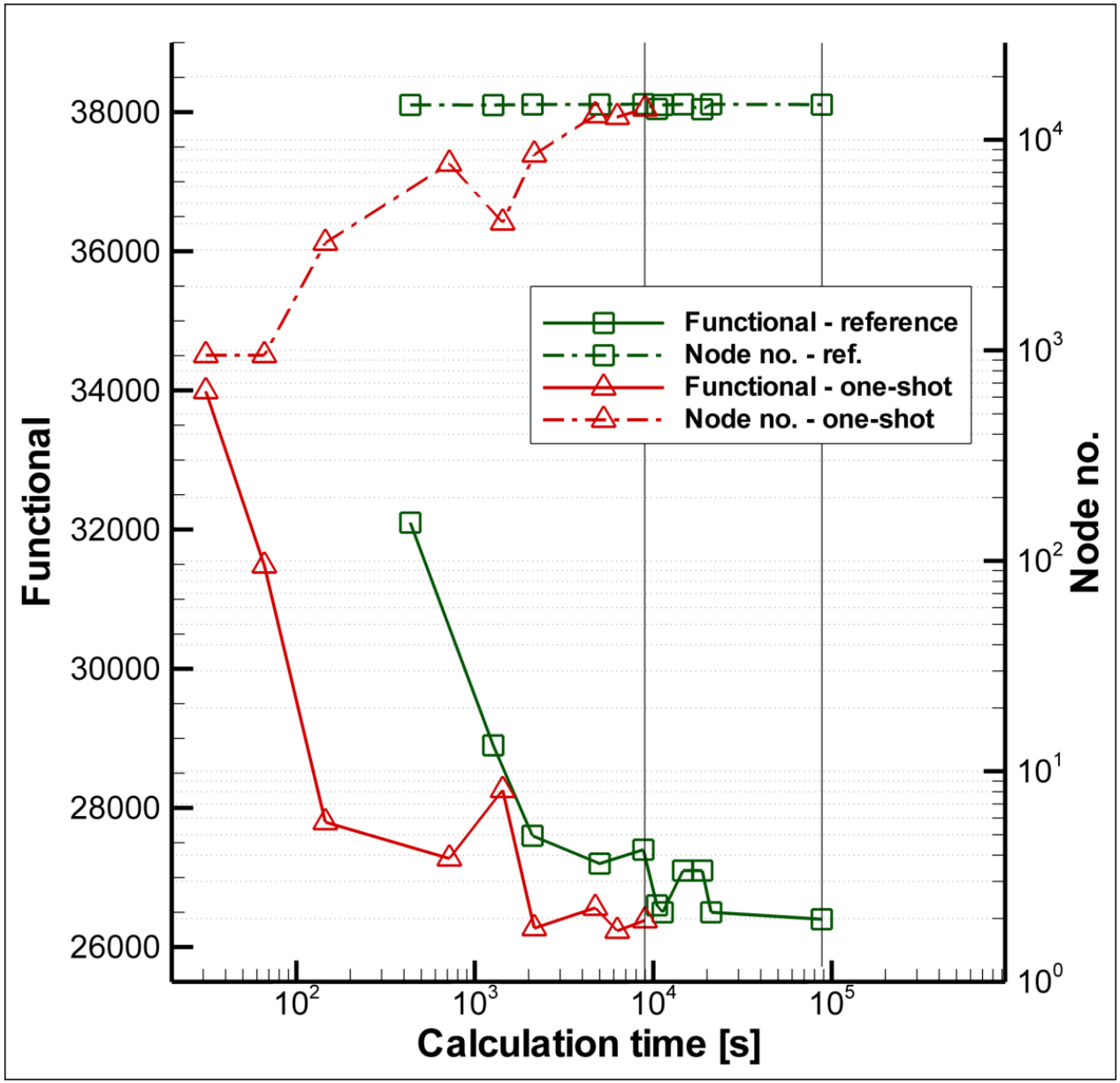


Sband: one-shot + adaptation, performance



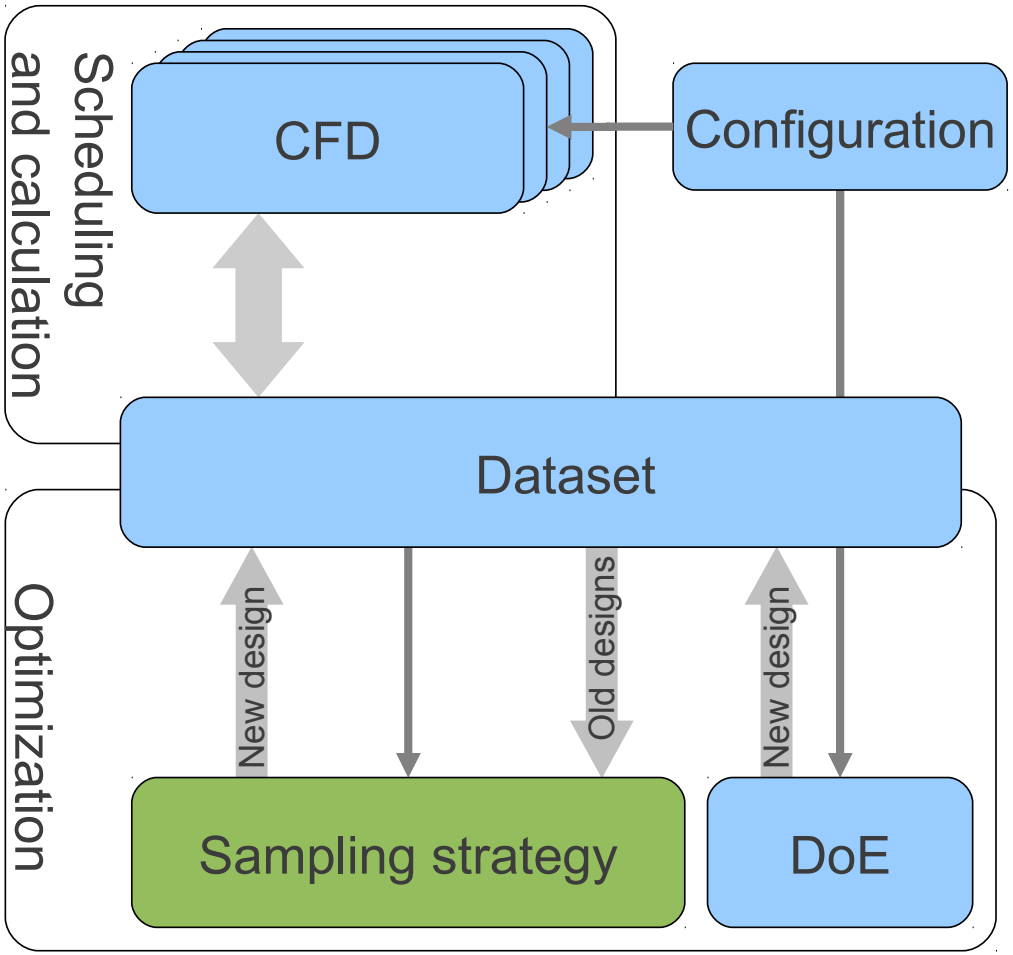
Summary one-shot+adaptation coupling

- Faster optimisation from 10 to 100 times is obtained
- Adaptation is keeping accuracy at desired level
- Coupling one-shot method with adaptation can significantly reduce overall optimisation cost

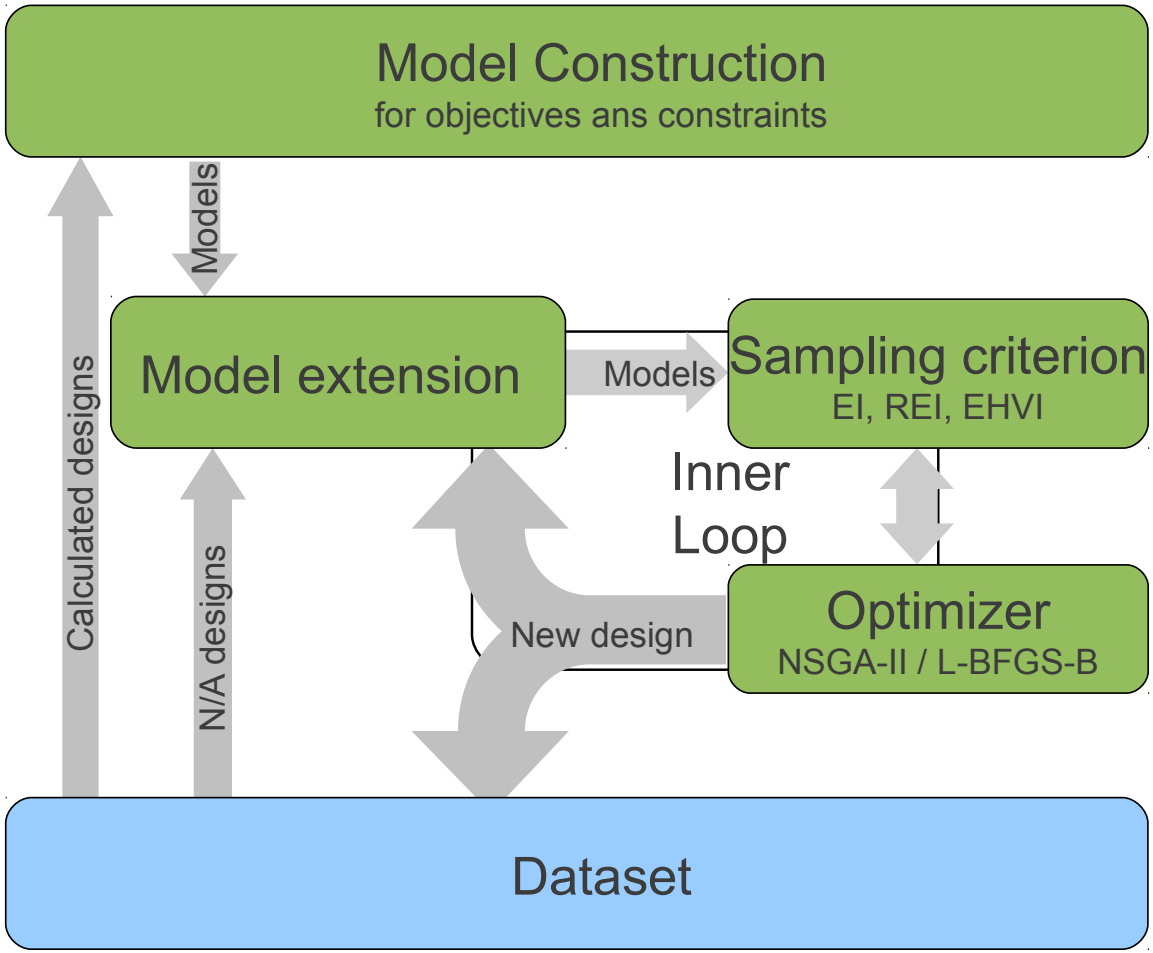
Problems

- One-shot performance is case-sensitive and depends on user input parameters
- Optimisation algorithm performane is affected, Hessian approximation is affected by changing accuracy of functional and gradient

Robust Optimisation Framework — Data-flow

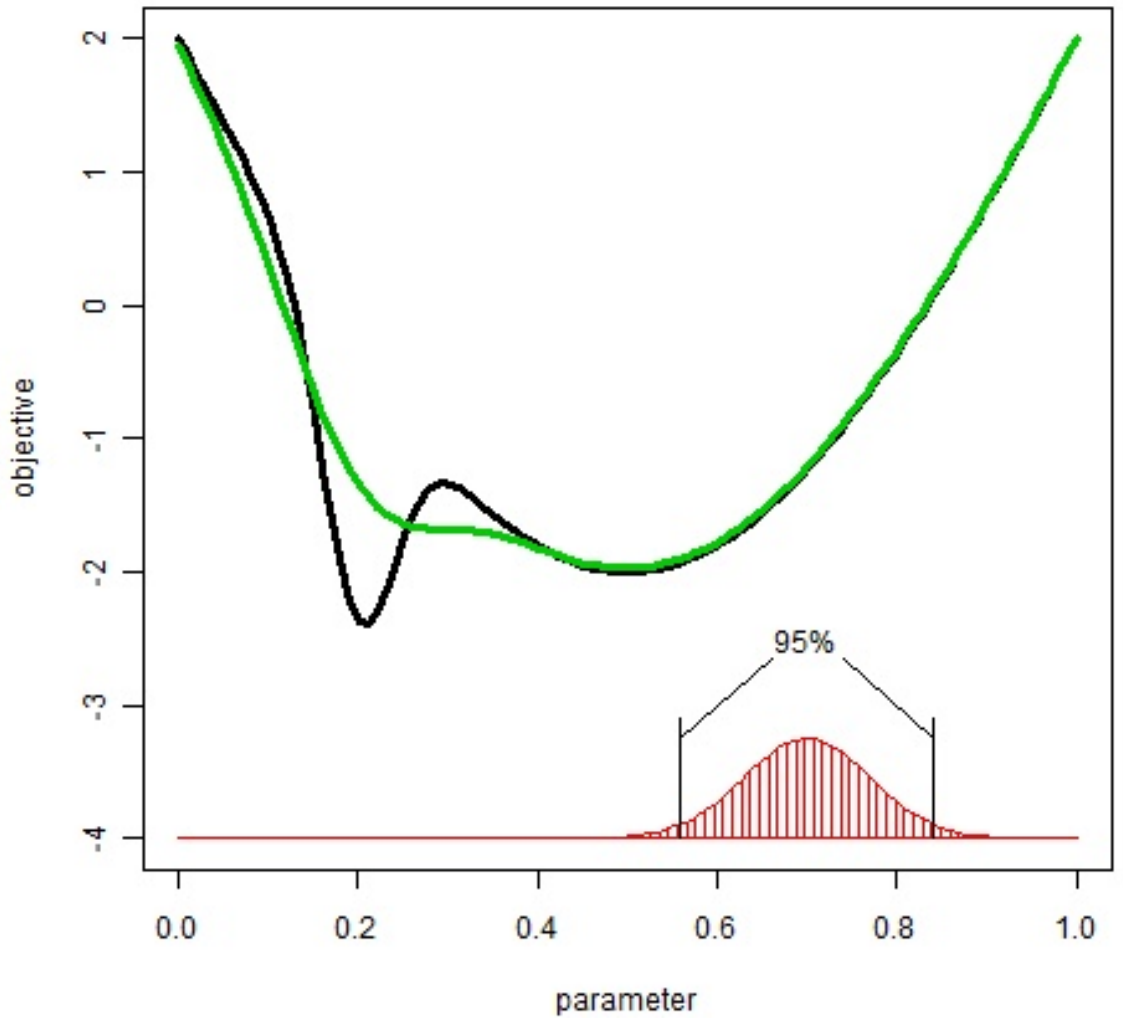


Robust Optimisation Framework — Generating new designs

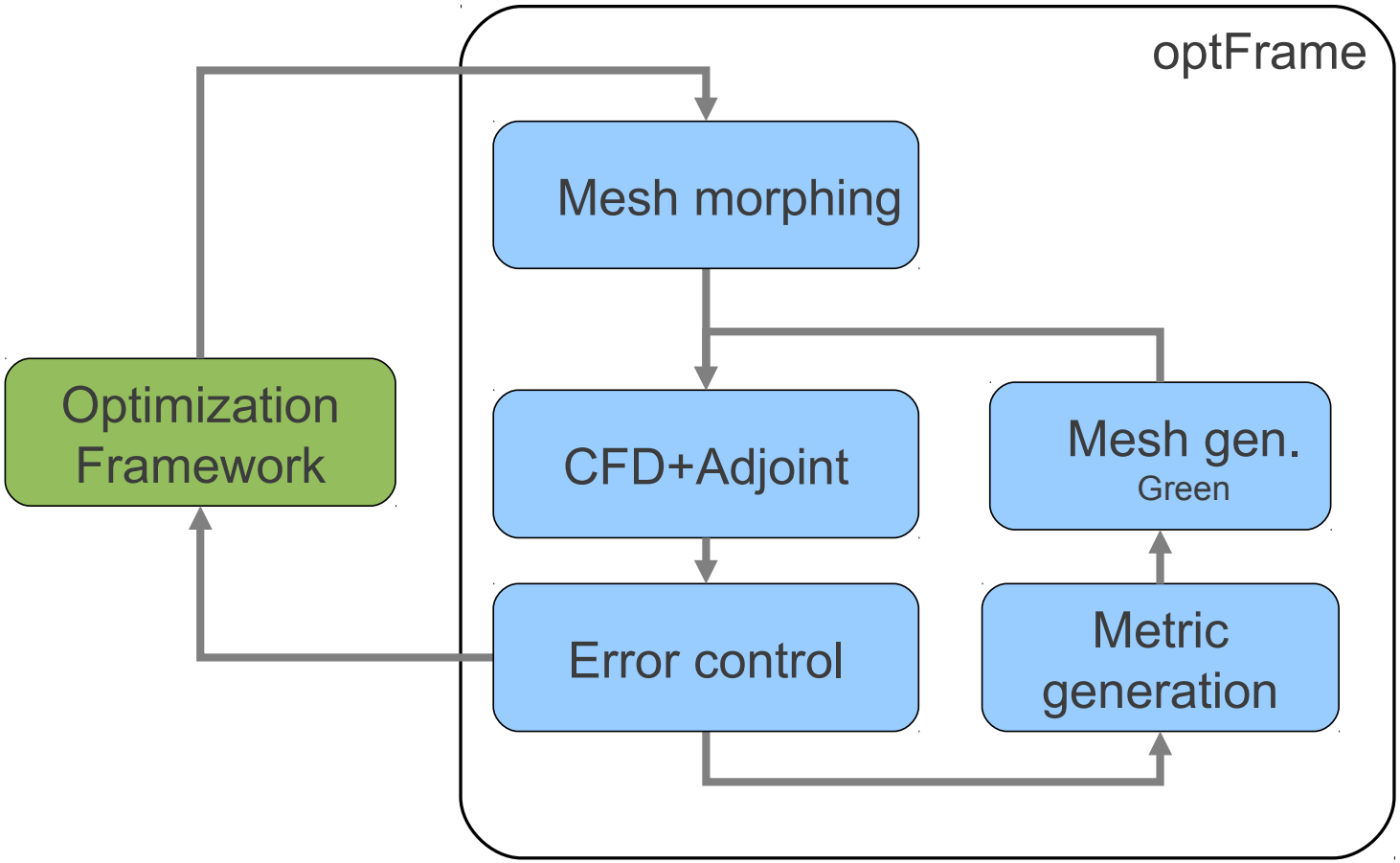


Robust optimisation concept

- Kriging approximation is smoothing the functional
- Uncertainty level provided by a user

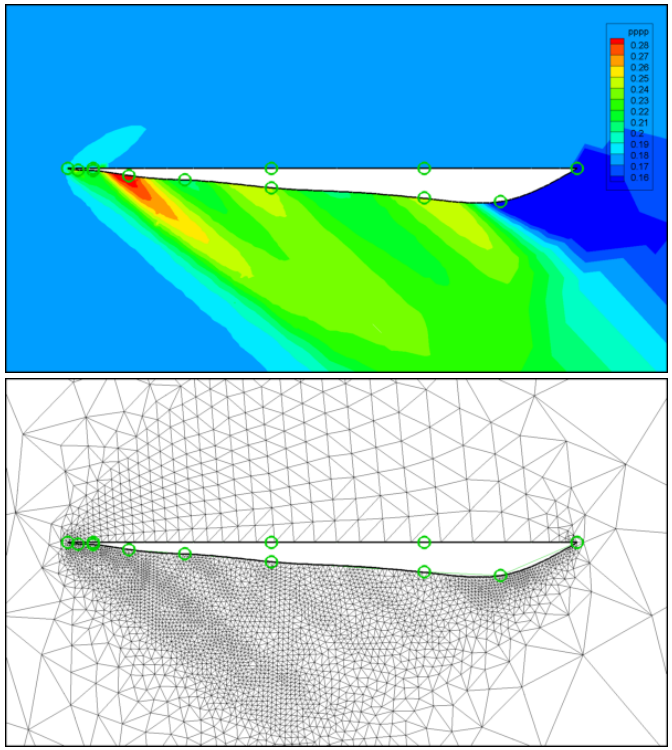


Wave-rider — Optimization loop



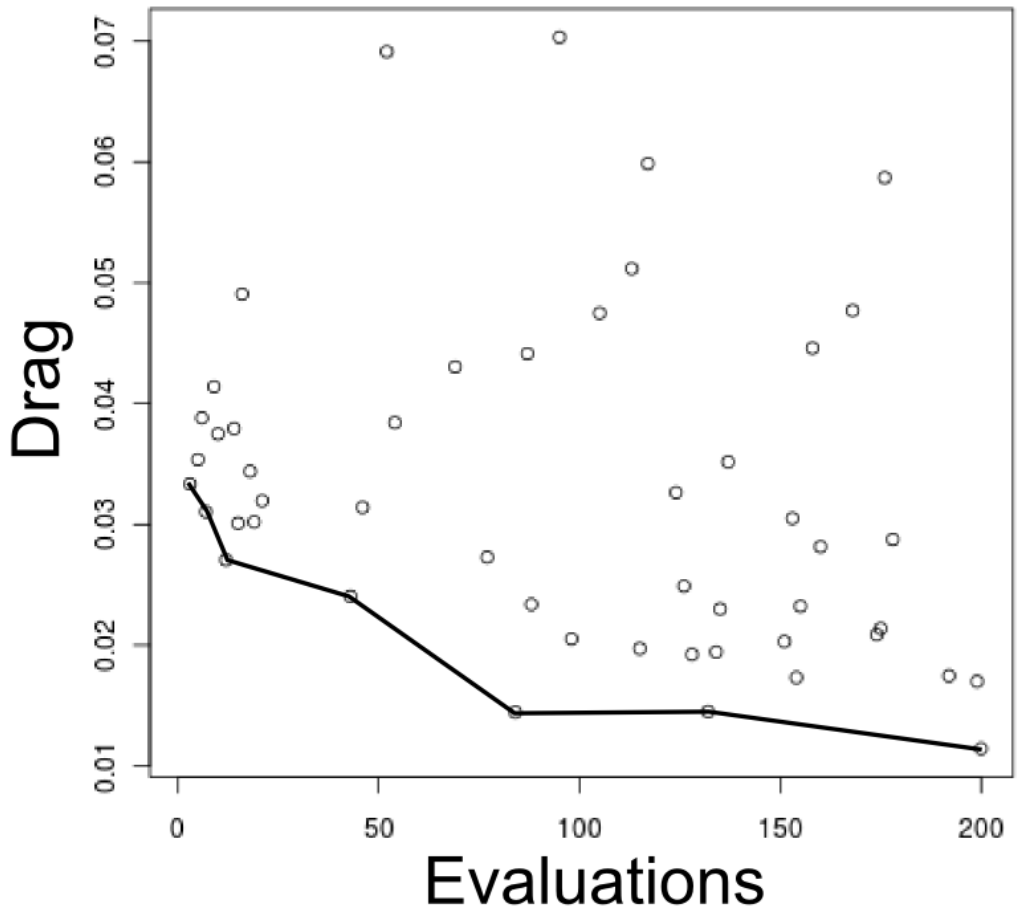
Wave-rider Testcase

- M = 2.0, inviscid flow
- Kriging based optimiser
- 7 design variables



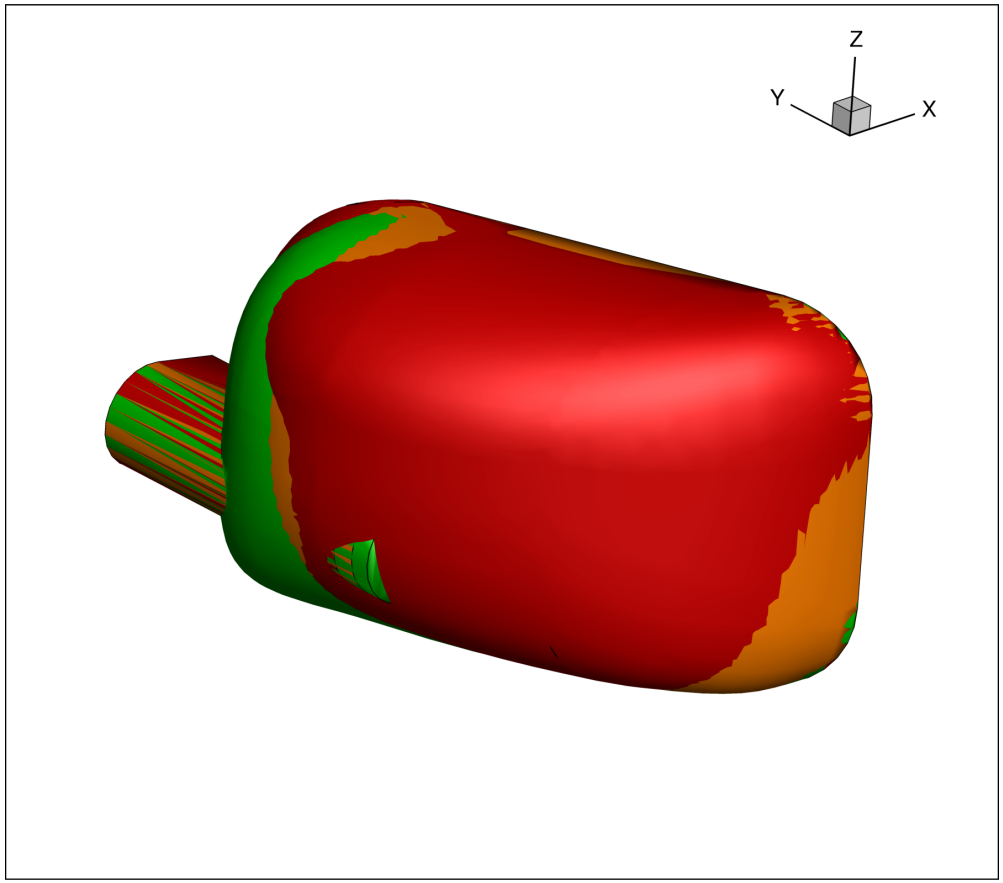
Wave-rider — Optimization convergence

- 7 desing var. 200 runs. 94 crashed.

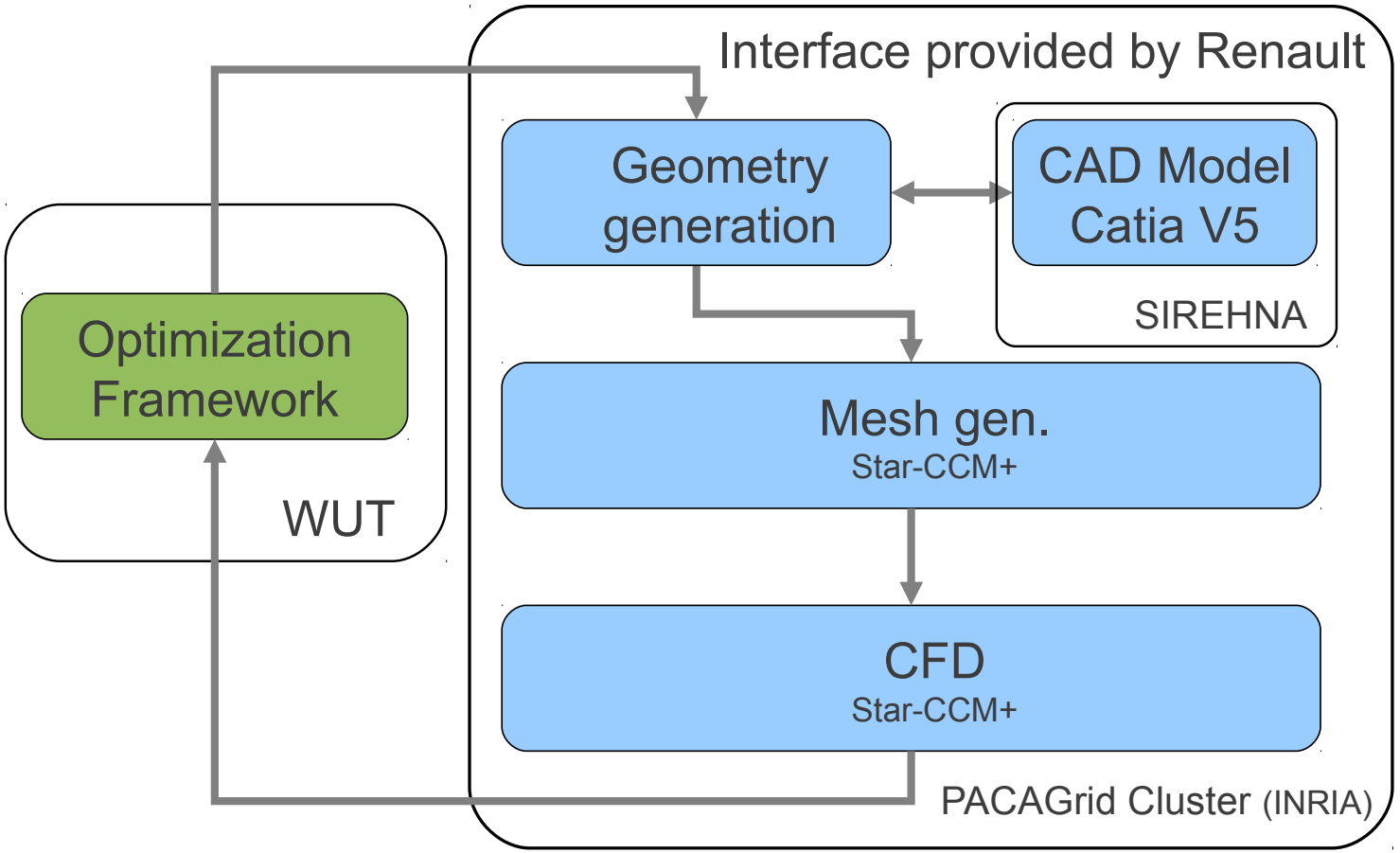


Renault side-mirror testcase

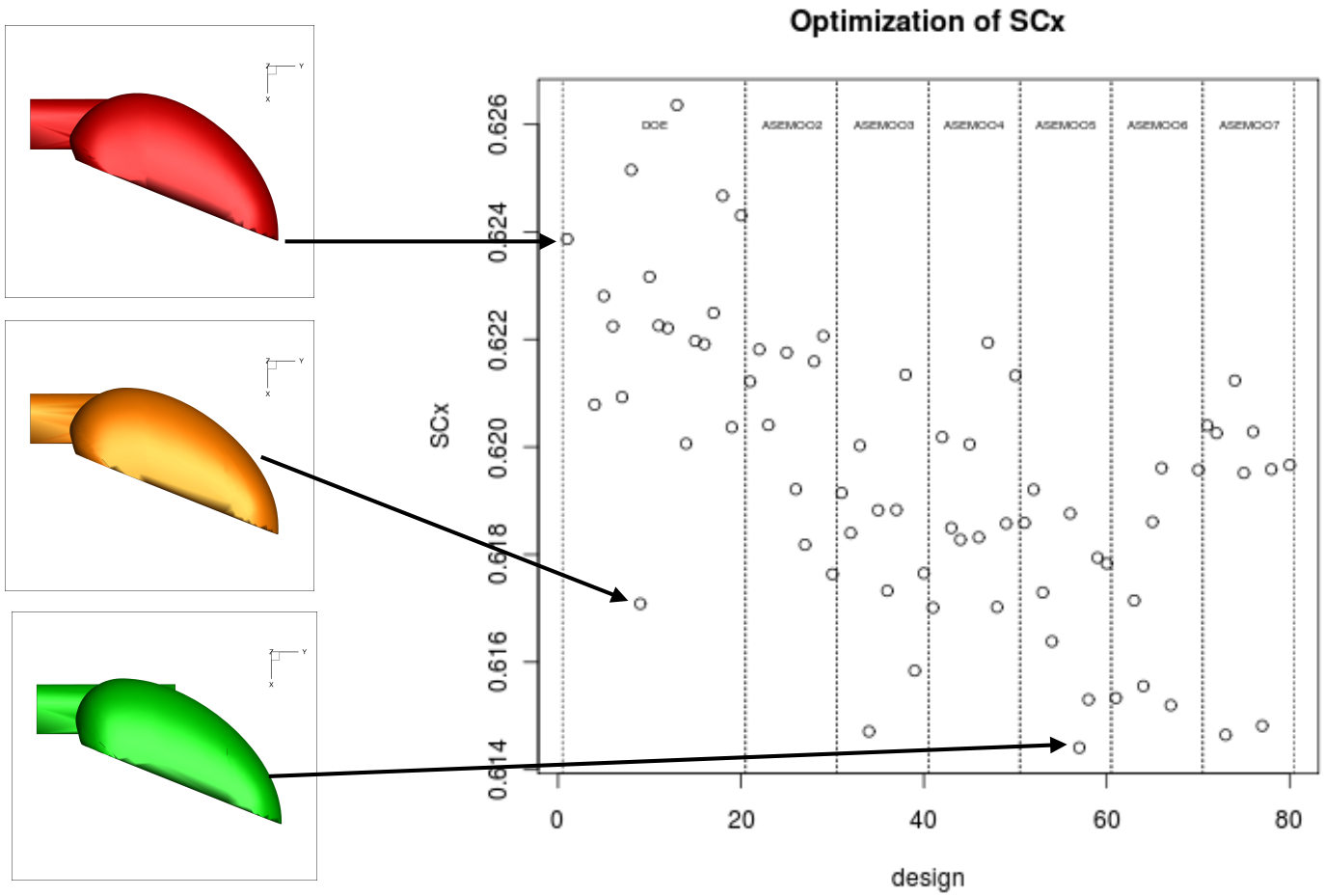
- Minimisation of turbulence in the wake
- Kriging based optimiser
- CAD based parametrisation, 8 desing var.



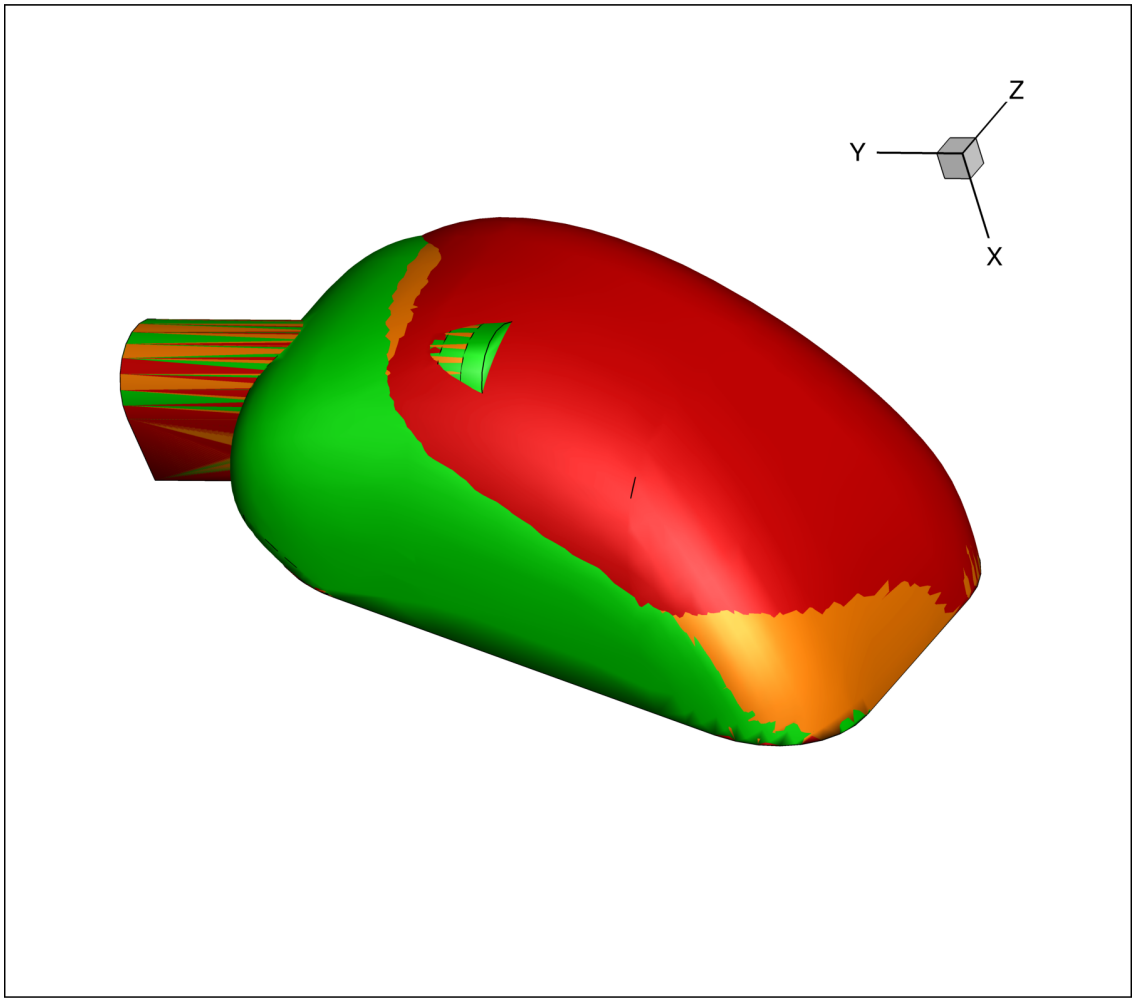
Side-mirror — Optimization Loop



Side-mirror — Optimization run



Side-mirror — Geometry comparison



Summary - Kriging based robust optimisation

- Robust design with respect to random parameter variations
- Easy integration with any toolchain (e.g. CAD parametrisation)
- Capable of using derivative information
- Faster global optimisation if compared to genetic algorithms

Limitations

- Moderate number of design var. (up to 30)