Optimization of Aerodynamic Shapes

Matthias Schramm[1,2], Lena Vorspel[2], Bernhard Stoevesandt[1], Joachim Peinke[1,2]
[1]Fraunhofer IWES, [2]ForWind

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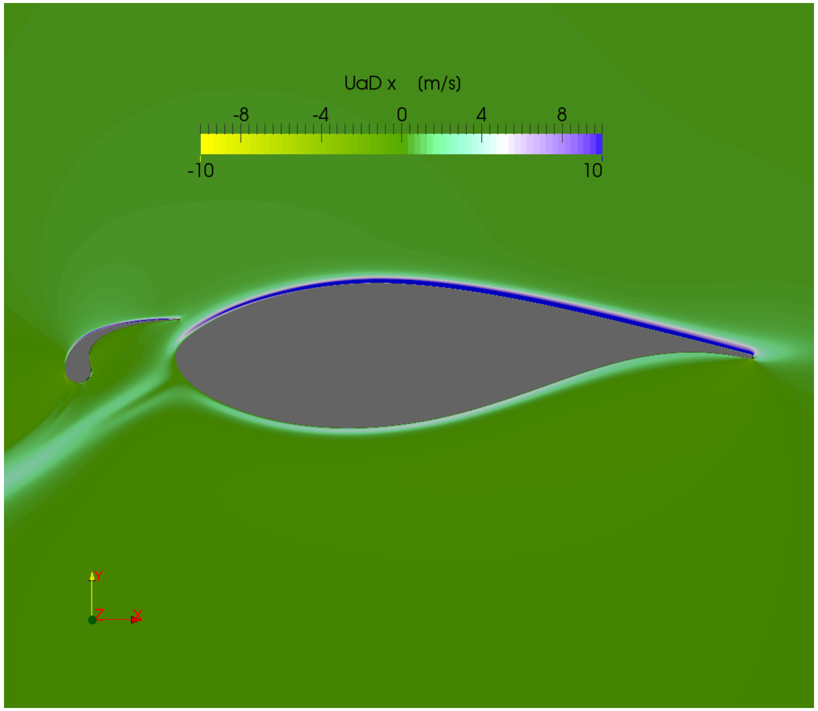


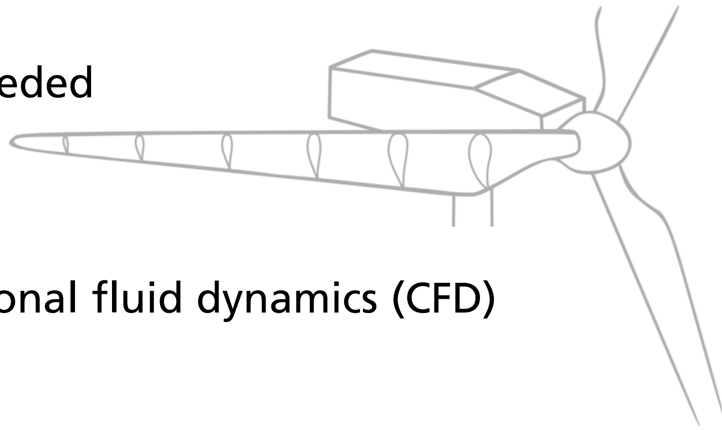
ForWind
Fraunhofer IWES
DLR Deutsches Zentrum für Luft- und Raumfahrt e.V. in der Helmholtz-Gemeinschaft
Research Alliance Wind Energy

Agenda

- Motivation
- Adjoint approach
- Verification of the gradients
- Optimization of thick airfoil
- Validation and optimization of leading edge slat
- Conclusions & Outlook

Motivation

- Rotor blades are complex geometries → no intuitive design possible
- Optimization is necessary
- Blades consists of airfoils → airfoil optimization needed



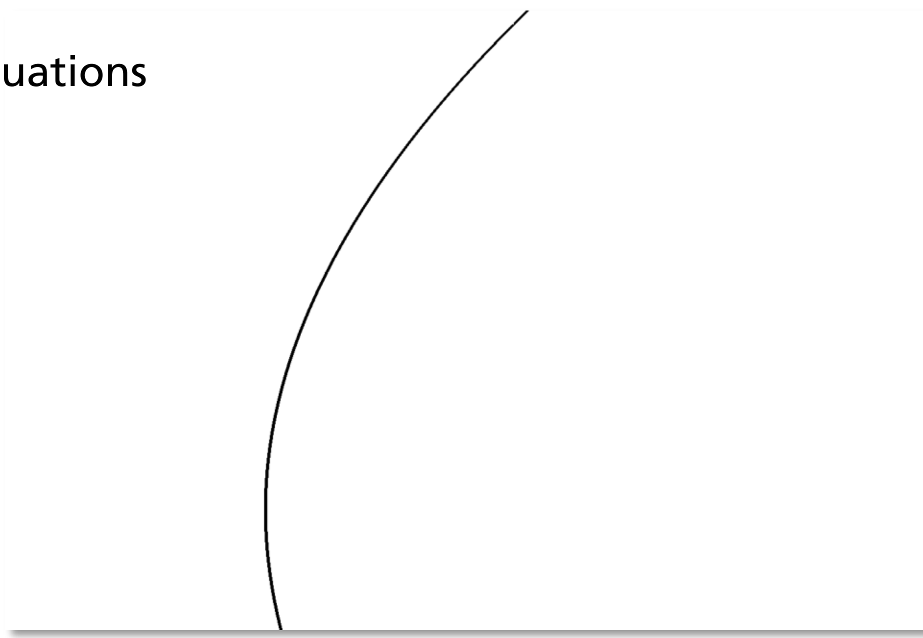
- High accuracy for prediction of loads → computational fluid dynamics (CFD)

- CFD + conventional optimization → expensive

  → adjoint approach

Gradient-Based Optimization: Traditional Approach

- Optimization using gradients
- Traditionally by finite differences
- More design parameters → more evaluations
- Every time full CFD necessary
- Computationally expensive



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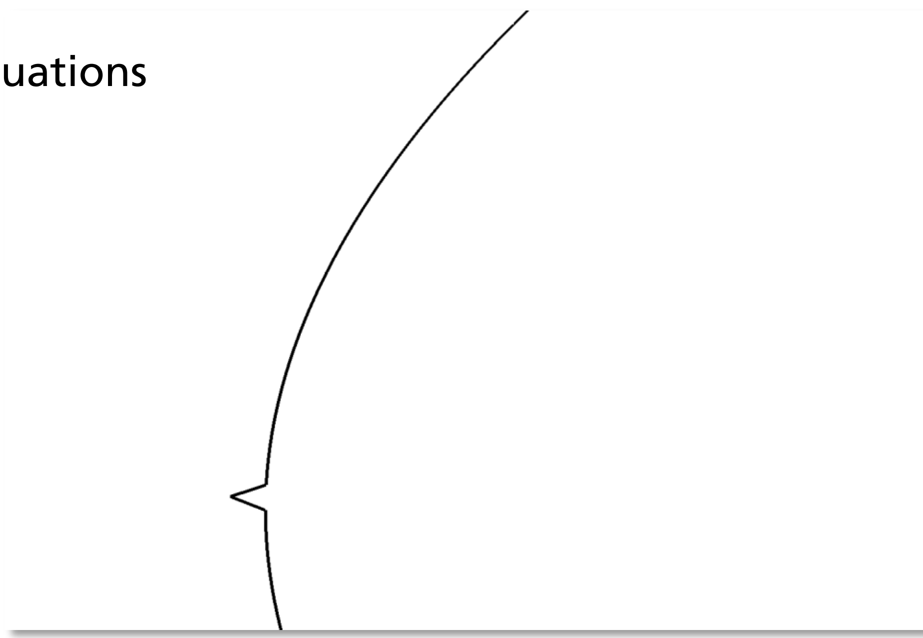

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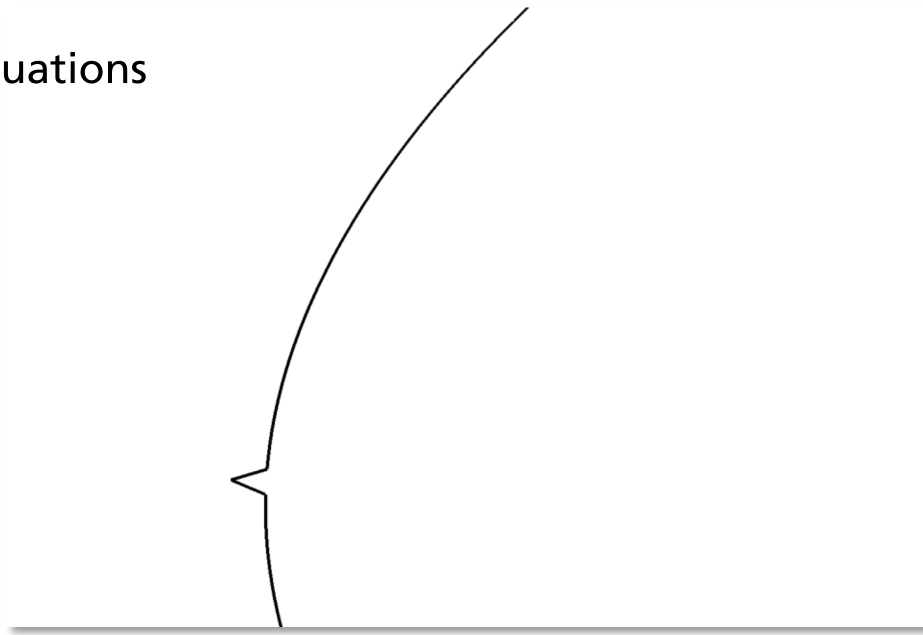

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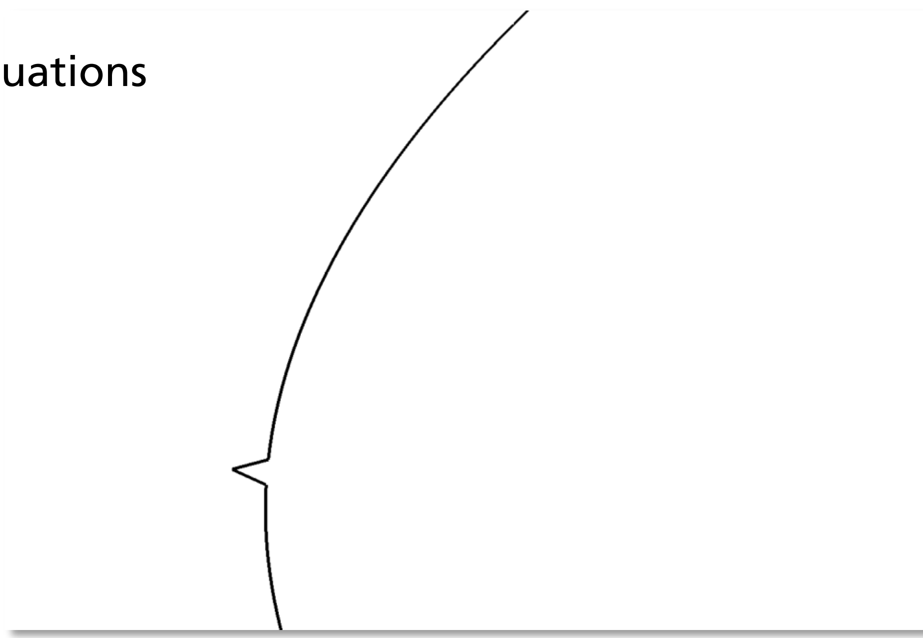

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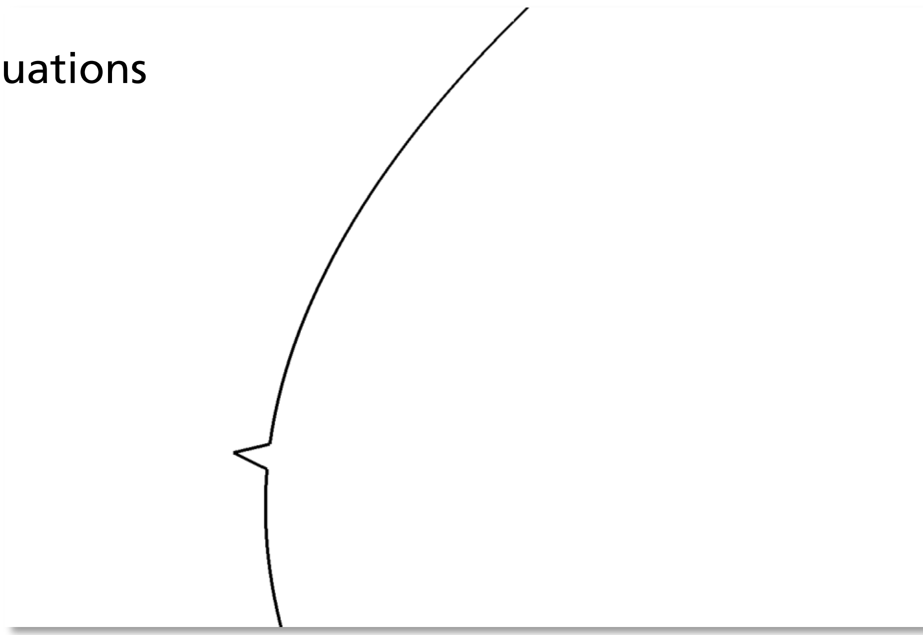

Gradient-Based Optimization: Adjoint Approach

- Solving a few more equations

$$\text{Min.} \quad I(\mathbf{u}, p, \beta) \quad \text{w.r.t.} \quad \mathbf{R}(\mathbf{u}, p, \beta) = 0$$

$$L := I + \int_\Omega (\mathbf{\Psi}^{\mathbf{u}}, \Psi^p) \cdot \mathbf{R}$$

$$\delta L = \Big(\frac{\partial I}{\partial \beta} + \int_\Omega (\mathbf{\Psi}^{\mathbf{u}}, \Psi^p) \cdot \frac{\partial \mathbf{R}}{\partial \beta}\Big)\delta\beta$$

$$\Big[\; + \Big(\frac{\partial I}{\partial \mathbf{u}} + \int_\Omega (\mathbf{\Psi}^{\mathbf{u}}, \Psi^p) \cdot \frac{\partial \mathbf{R}}{\partial \mathbf{u}}\Big)\delta\mathbf{u} + \Big(\frac{\partial I}{\partial p} + \int_\Omega (\mathbf{\Psi}^{\mathbf{u}}, \Psi^p) \cdot \frac{\partial \mathbf{R}}{\partial p}\Big)\delta p \; \Big] = 0$$

Adjoints in CFD

Gradient-Based Optimization: Adjoint Approach

- Solving a few more equations and each single point can be design parameter

Min. $I(\mathbf{u}, p, \beta)$ w.r.t. $\mathbf{R}(\mathbf{u}, p, \beta) = 0$

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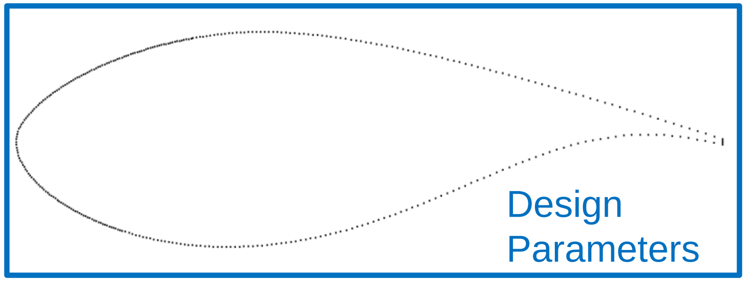
Adjoints in CFD



Gradient-Based Optimization: Adjoint Approach

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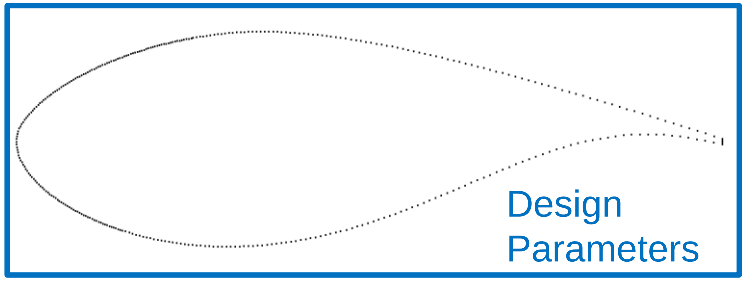
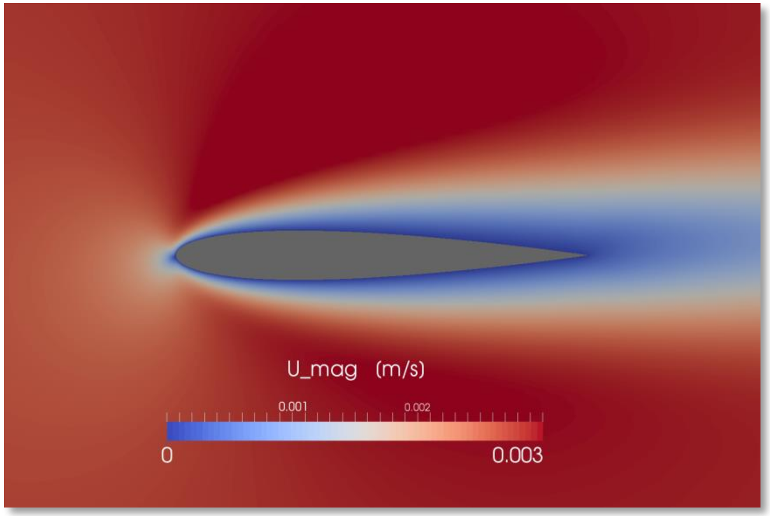
Adjoints in CFD



- Computation of gradient independent from number of design parameters
- Only two solver runs for each gradient necessary
- Arbitrary amount design parameters possible

Setup of Verification Case

- NACA 0012
- Re = 2,000
- AoA=3°
- Laminar flow, $y^{+}<1$
- Approx. 55,000 cells, 350 faces on airfoil
- OpenFOAM-2.3.0



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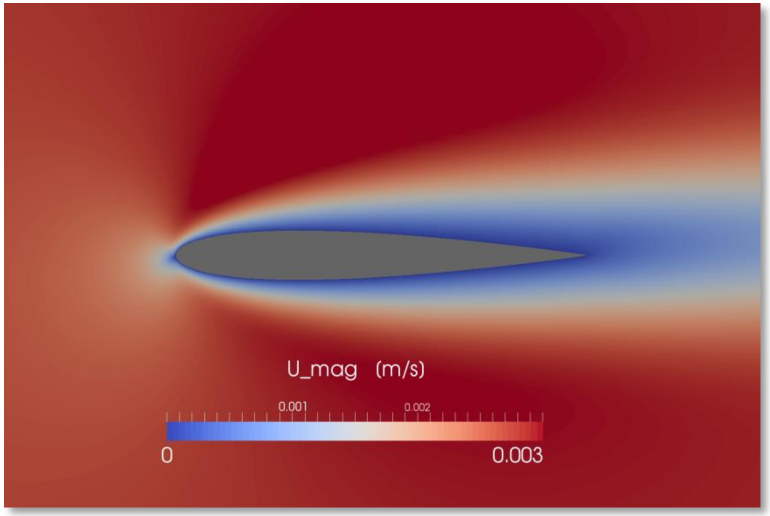
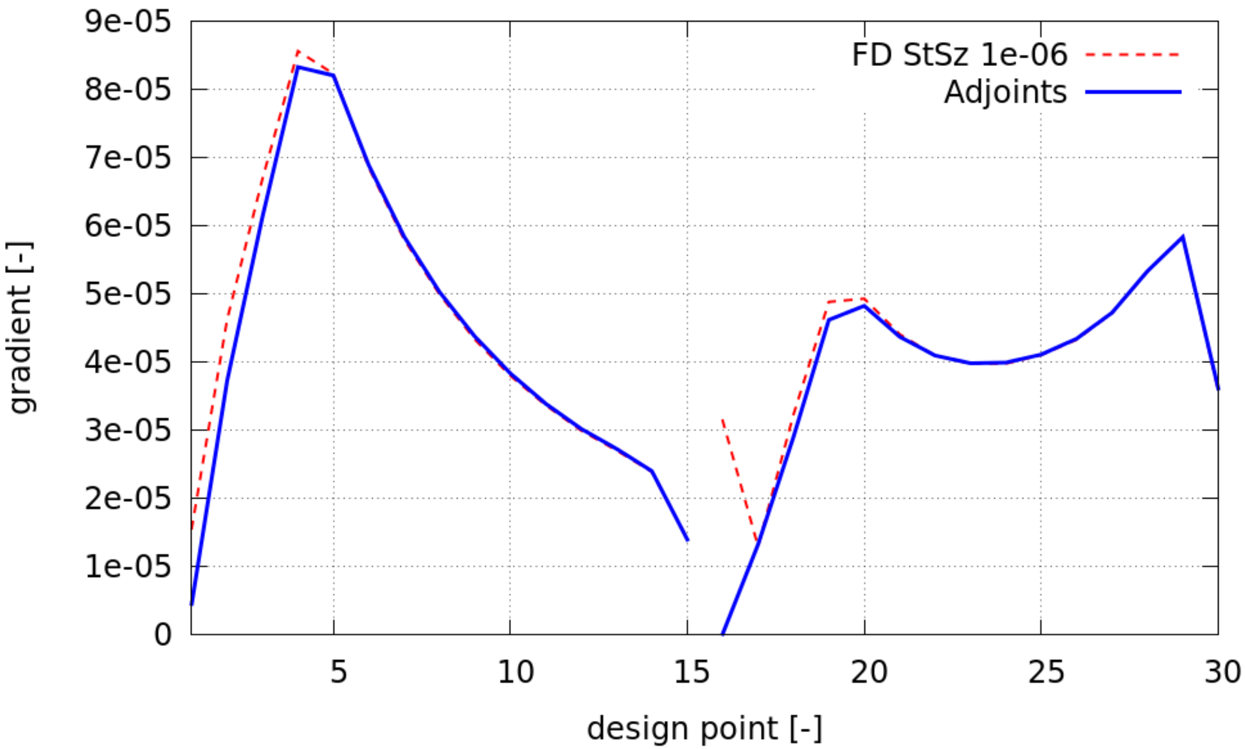


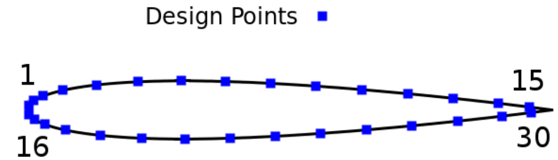
- Gradients from the adjoint approach compared with gradients obtained by finite differences FD (forward, 1st order)
- Finite differences:

Fine mesh → small mesh movement → small force changes → high convergence → expensive computation

Verification of Gradients

- Evaluation at selected design points only (→ expensive FD)



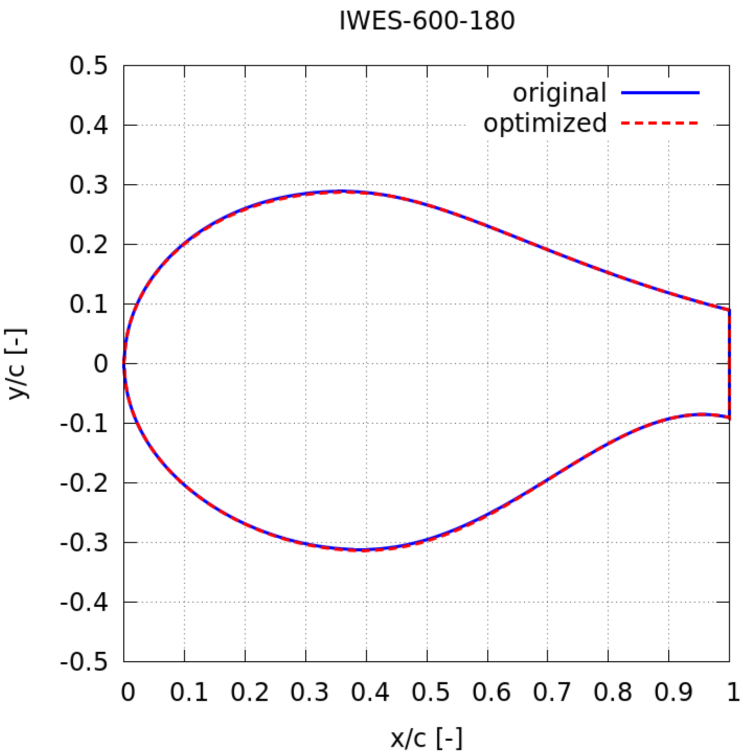


Generally good agreement

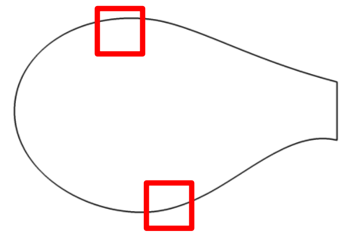
Design point 16 critical

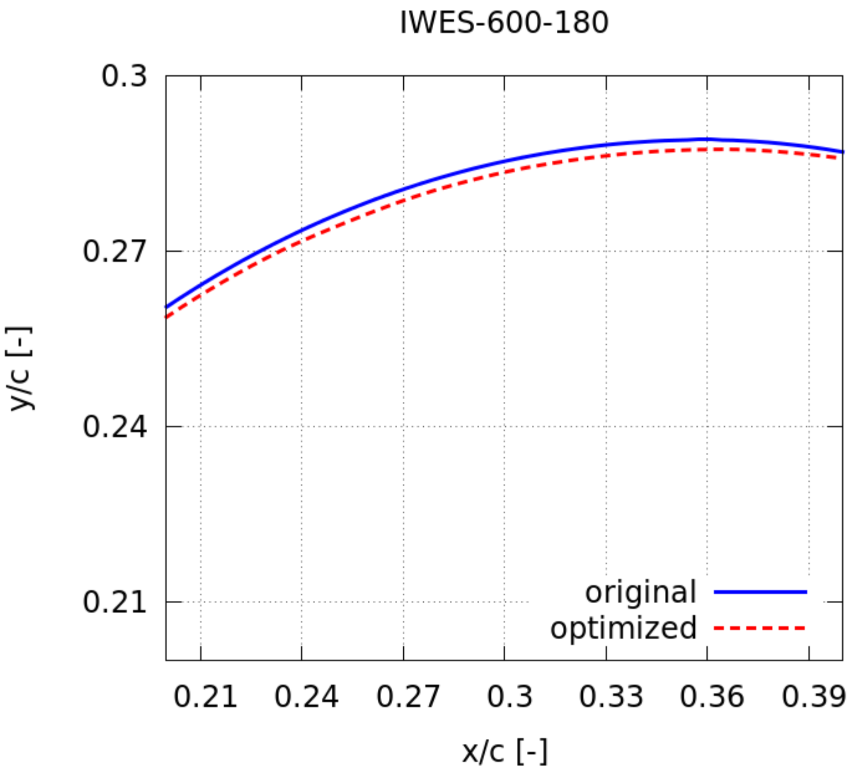
Drag Reduction of IWES 600-180

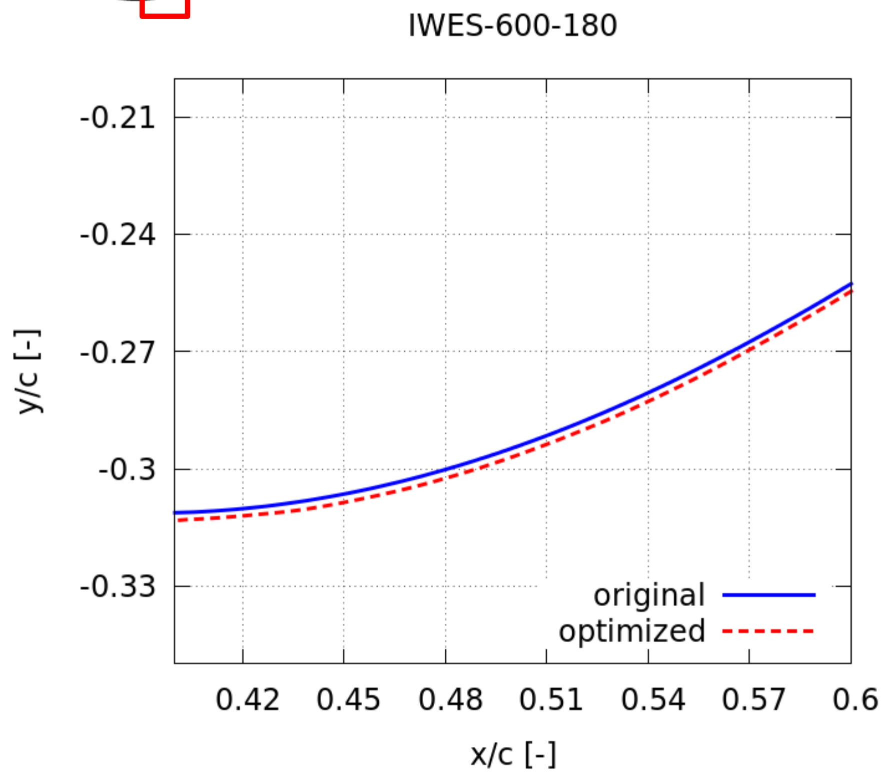
- IWES 600-180
- Re = $3 \cdot 10^6$, AoA = 12°
- Objective: min $I=½\cdot(c_d-0.15)^2$ w.r.t. $c_l \geq c_{l,0}$
- Spalart-Allmaras turbulence model
- Optimization including adjoints to turbulence model
- Drag reduction > 3%



Detail View of Shapes





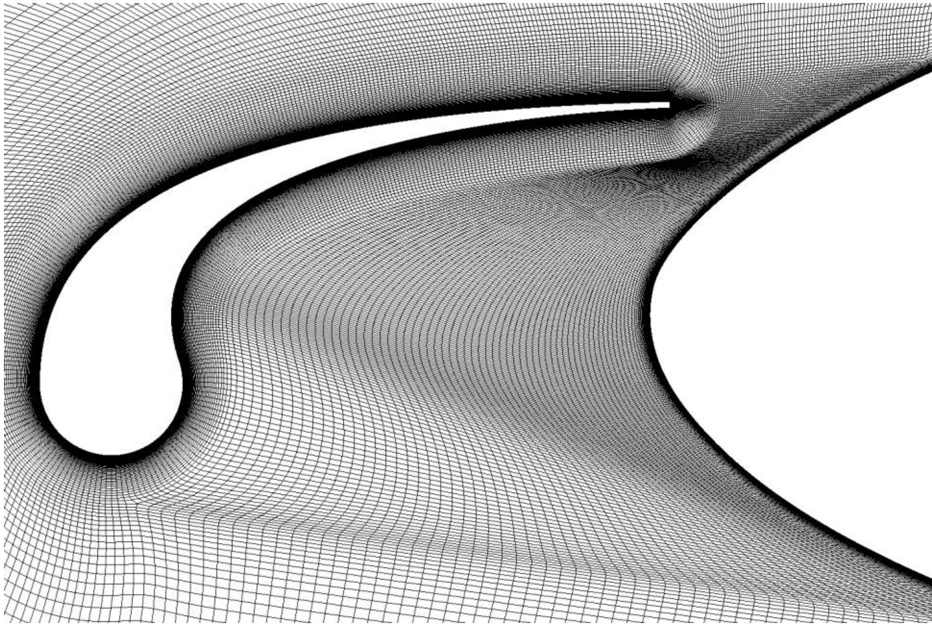


- Pure numerical problem, no wind tunnel data existing
- Shape moves downwards

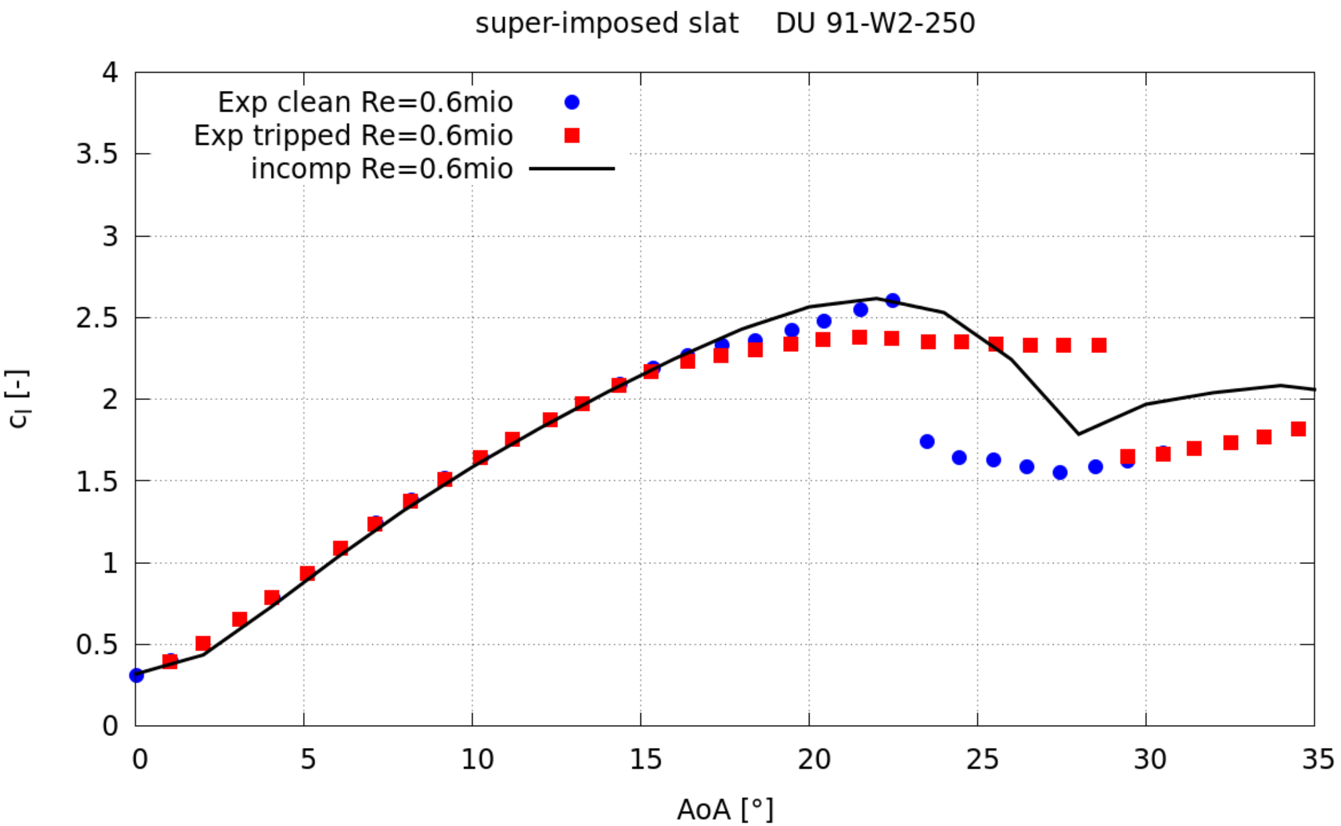
Setup for Leading Edge Slat

- Comparison with experimental data from wind tunnel in Oldenburg
- $Re=0.6\cdot10^6$, incompressible solver
- $Re=7.89\cdot10^6$, incompressible and compressible solver (Ma>0.3)

- Spalart-Allmaras turbulence model, $y^+<1$
- 480 faces on slat, 700 faces on airfoil, 160,000 cells in total
- Block-structured O-mesh
- Radius 25·chord

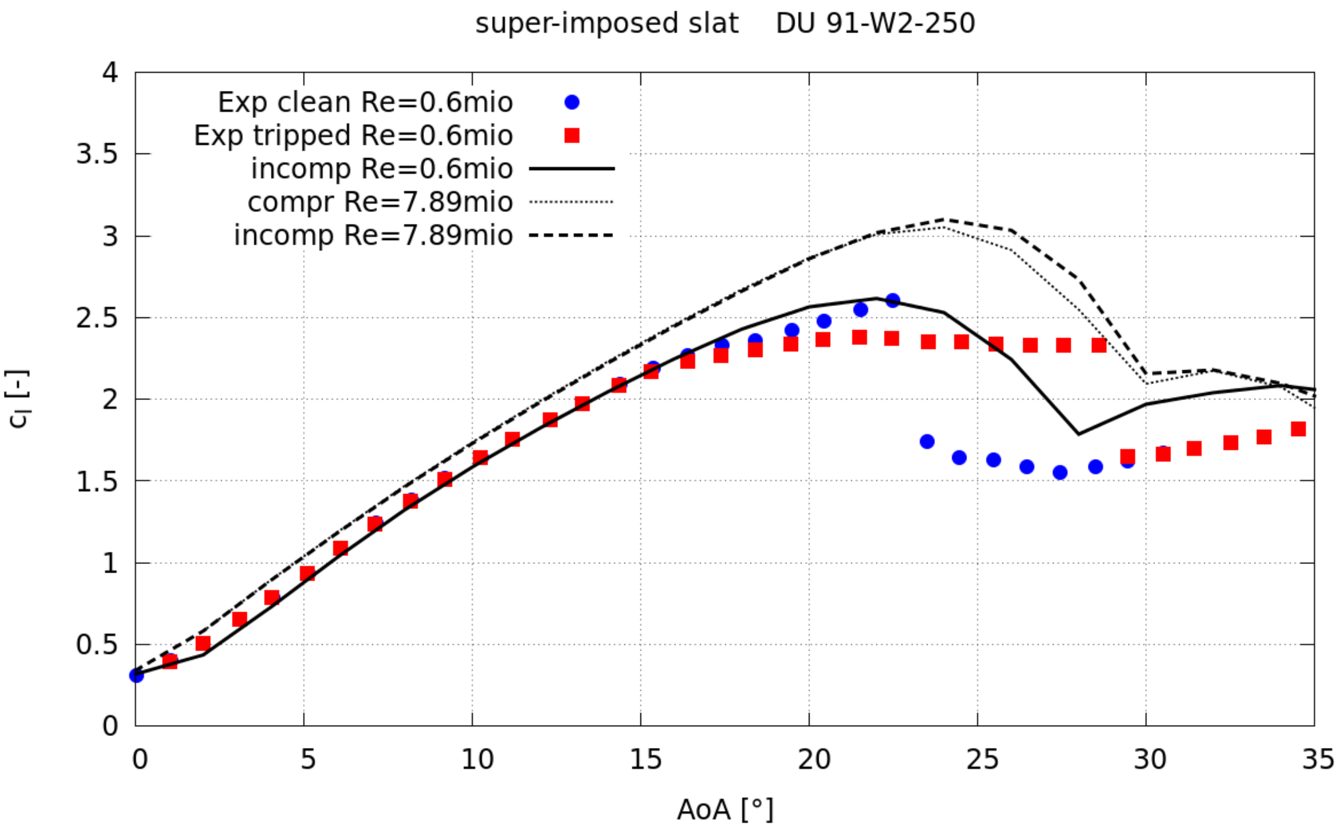


Validation for Leading Edge Slat



- Differences in stall

Validation for Leading Edge Slat

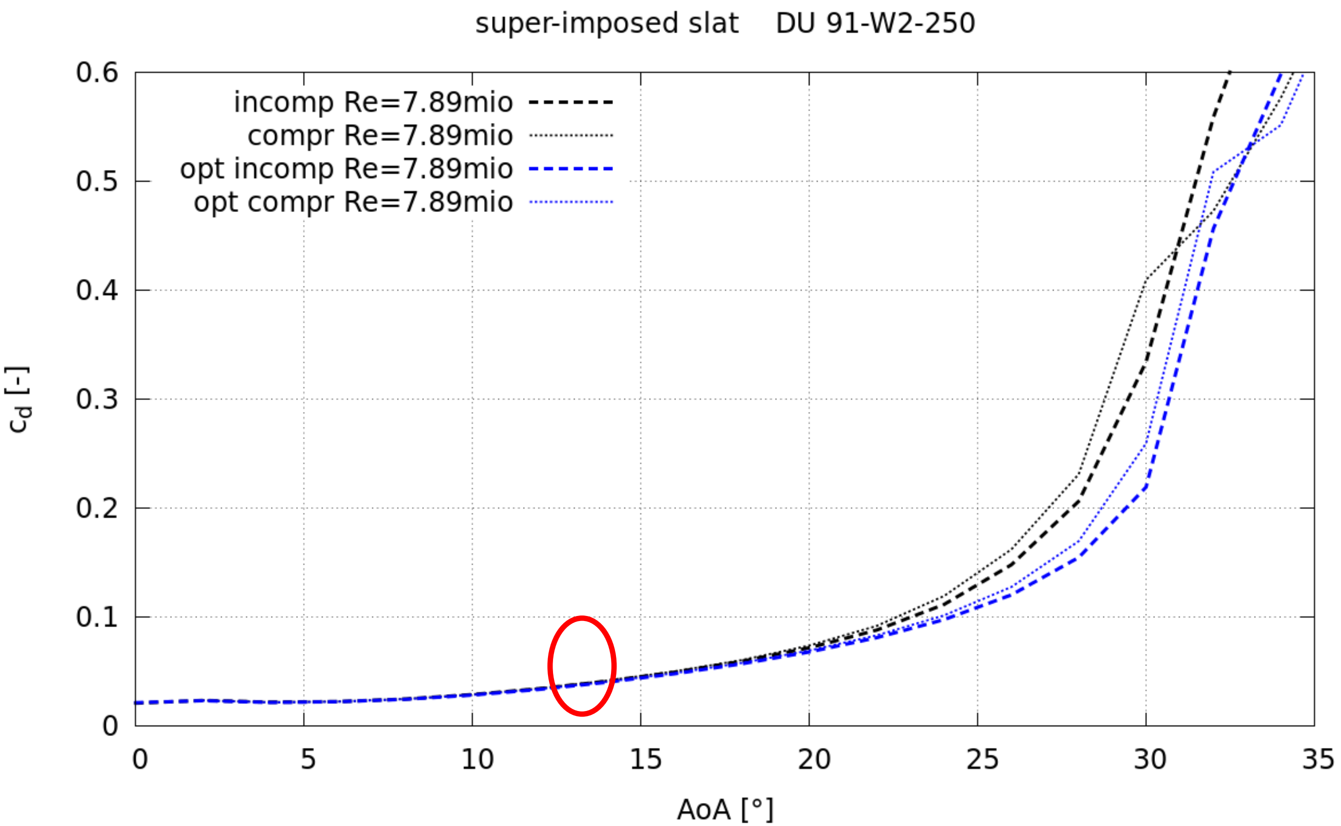


- Similarities in linear range
- Differences between compressible and incompressible solvers

Optimization of Leading Edge Slat

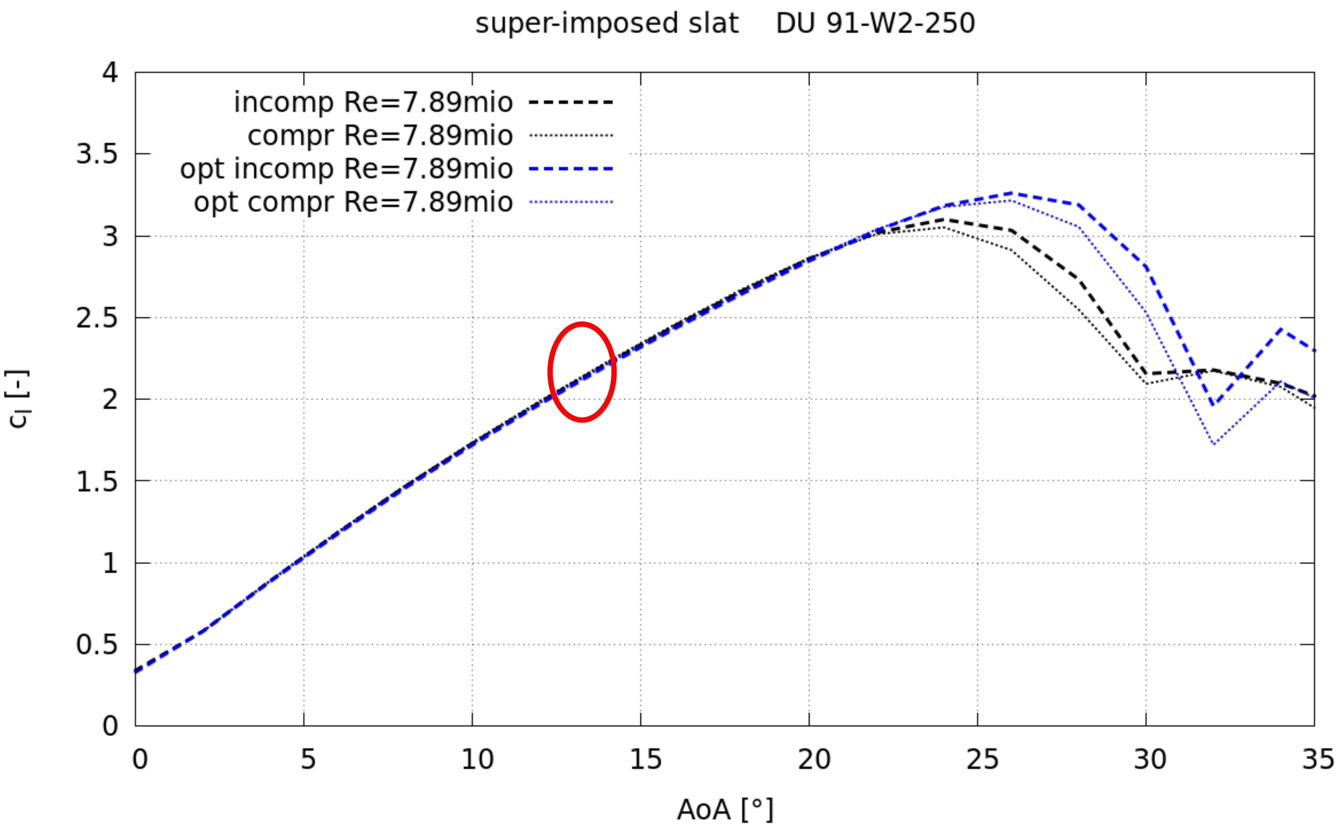
- $Re=0.6\cdot10^6$, $AoA=13^\circ$
- Objective: min $I=c_d$ w.r.t. $c_l \geq c_{l,0}$
- Optimization at low $Re=0.6\cdot10^6$, incompressible solver
  - (optimization framework more stable at low Re)
- Check design at high $Re=7.89\cdot10^6$, compressible solver
  - (final slat on 80m blade)
- Drag reduction > 2% at $AoA=13^\circ$

Optimization of Leading Edge Slat



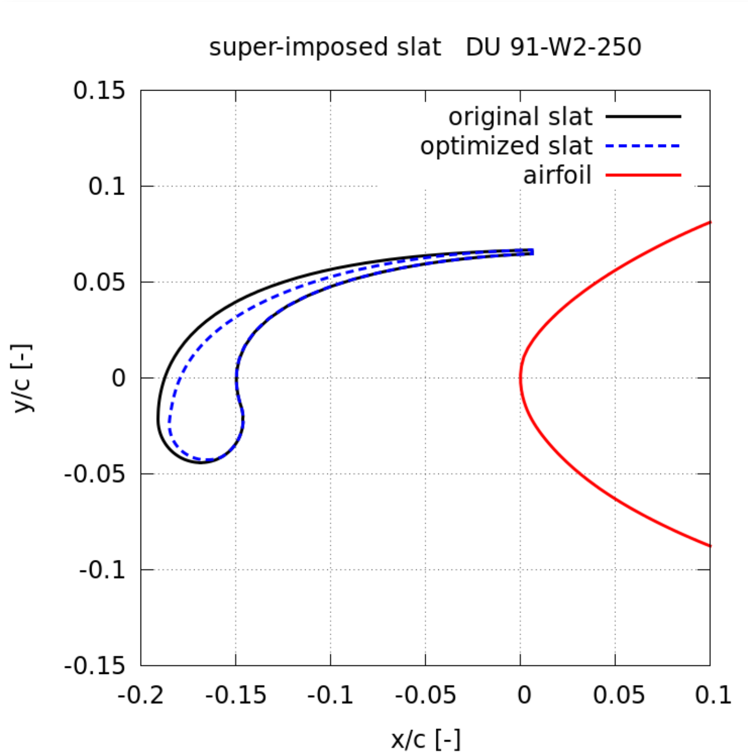
- Lower drag at higher angles of attack
- Drag reduction > 2% at AoA=13°

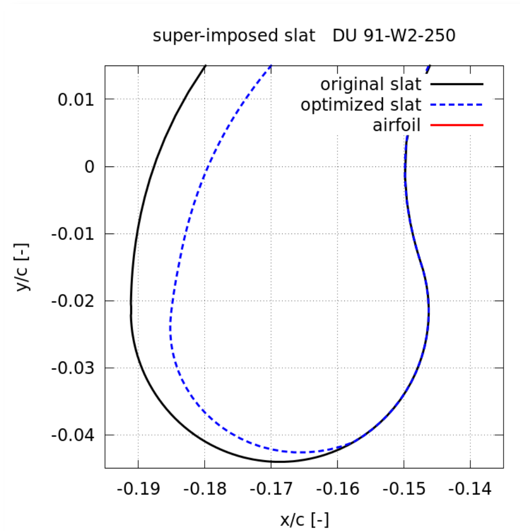
Optimization of Leading Edge Slat

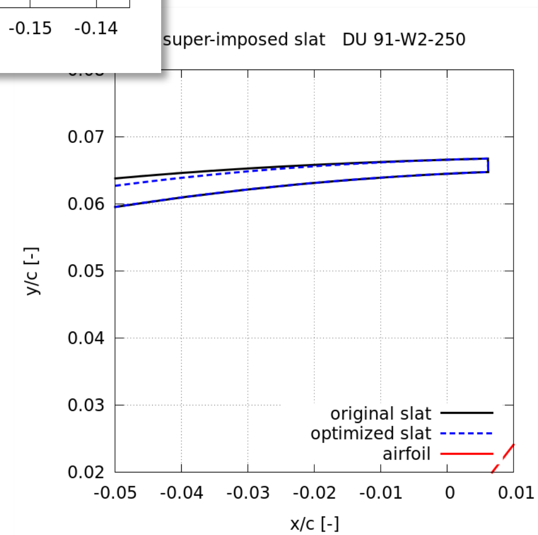


- Higher maximum lift
- Max. lift at higher angle of attack

Detail View of Shapes







- Thinner shape, same position
- Increase in c_l^3/c_d^2 of approx. 3% at AoA=13°

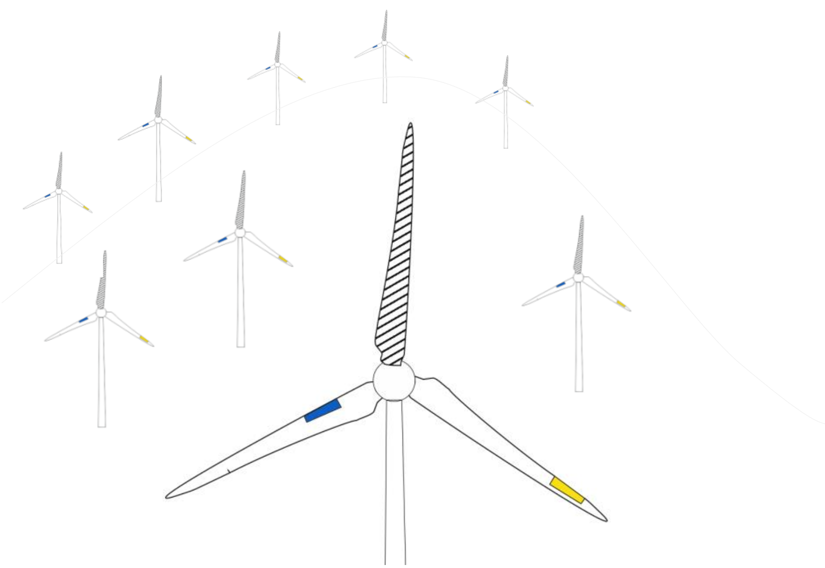
Conclusions & Outlook

- Implementation of adjoints for shape optimization in OpenFOAM
- Verification of gradients
- Numerical optimization of thick airfoil
- Validation and optimization of leading edge slat

- Extension of framework for the use of constraints

Thank you for attention!

matthias.schramm@iwes.fraunhofer.de



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