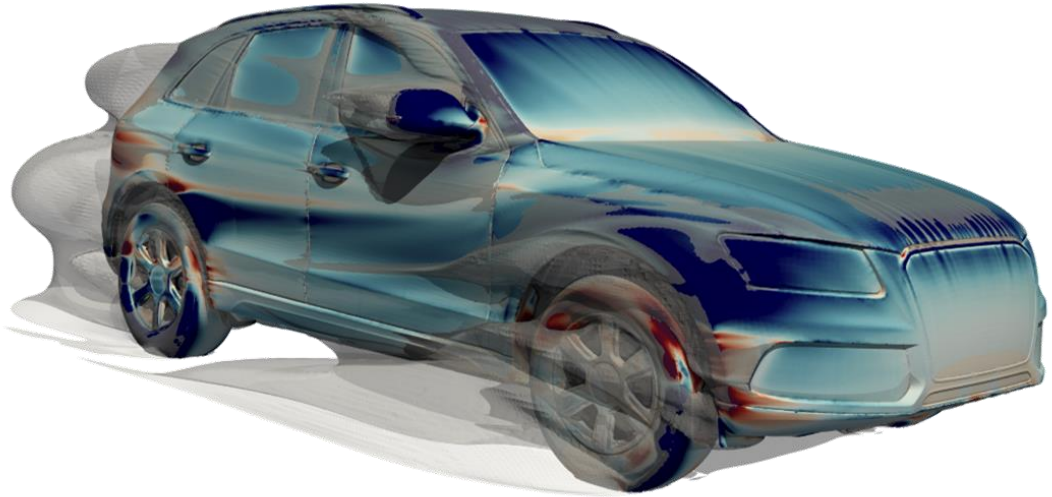
报告来源：2019年IDAJ中国CAE/MBD技术大会

ICSC 2019

iconCFD®

iconCFD Optimize:
From validation to industrial application



Geometry courtesy of Audi AG, I/EK-44

Prepared by:

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Technology ● Process ● Consulting

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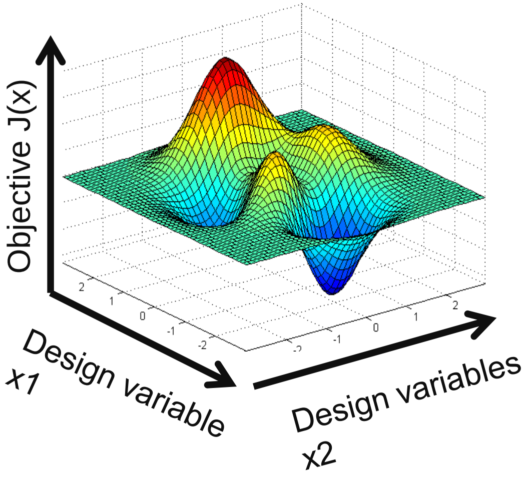
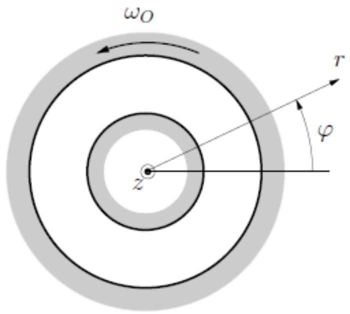
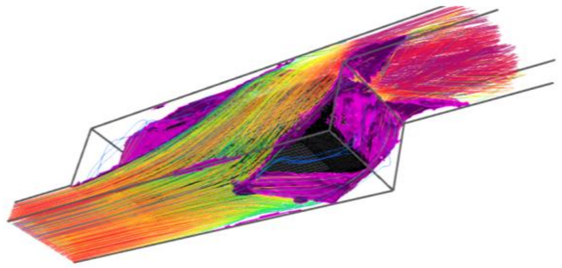
AGENDA

- Introduction
- Key features
- Adjoint Validations Cases
- Applications Cases
- Concluding Remarks

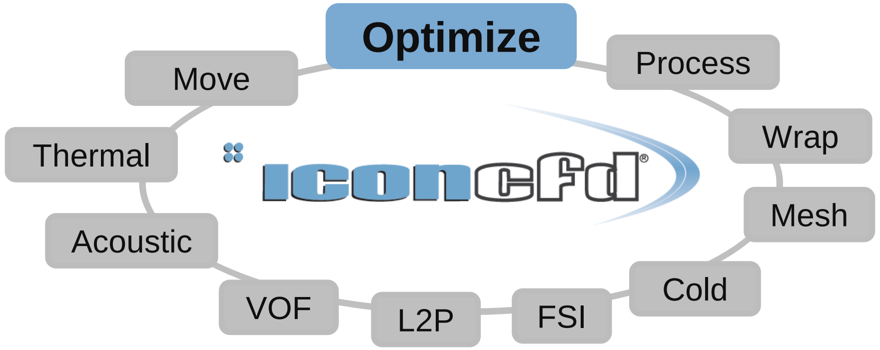




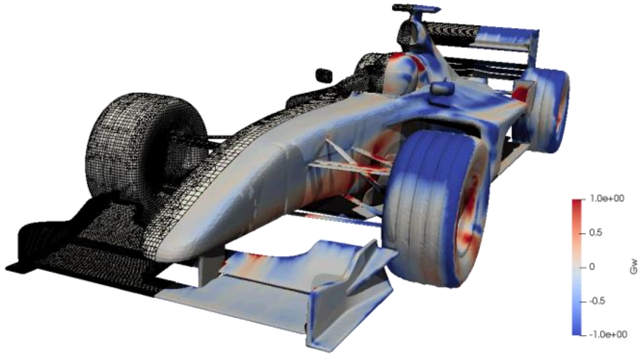


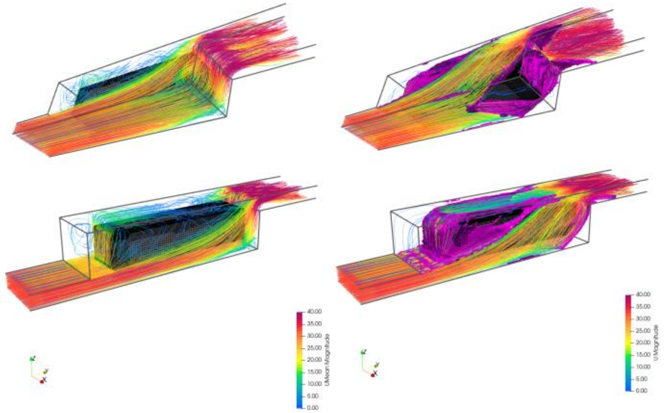
Geometry courtesy of TUM

INTRODUCTION
WHAT IS iconCFD® Optimize?



- Module part of the iconCFD® Product
- Adjoint based automatic optimization
- **Two main types of applications:**
  - **Shape optimization**
    - Free Form Deformation
    - Marginal modifications
    - Typical use case: external aero, drag reduction
  - **Topology optimization**
    - Solid/fluid volume fraction (or level sets)
    - Significant modifications, creative forms
    - Typical use case: internal flow, power loss reduction





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INTRODUCTION
ADJOINT VS FINITE DIFFERENCES

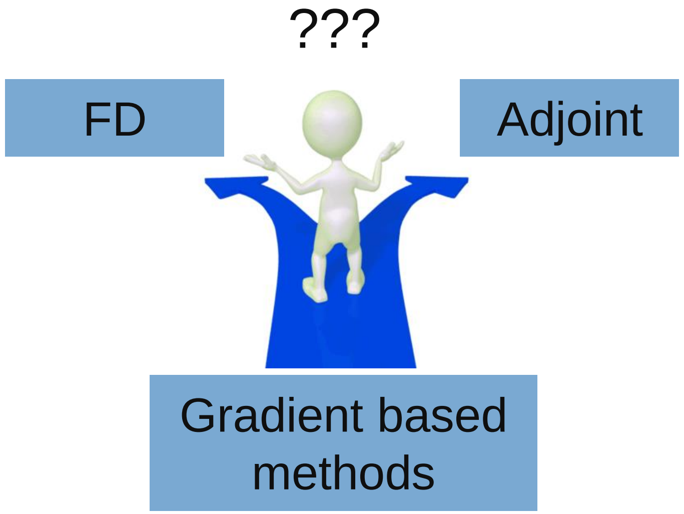
- Standard finite difference based method has a complexity that scales with the number of design parameters $\mathbb{D}$:

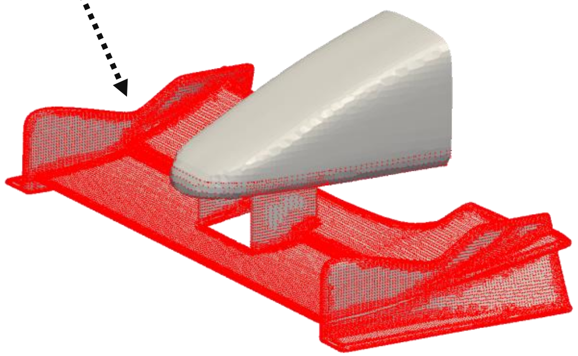
$$\frac{d\mathcal{F}}{d\,\mathbb{D}_i} = \frac{\mathcal{F}(\mathbb{U}(\mathbb{D}+h\delta_i),\mathbb{D}+h\delta_i)-\mathcal{F}(\mathbb{U},\mathbb{D})}{h}$$

- For shape optimization this is generally impracticable

- Adjoint approach addresses the issue

- The extra cost consists “only” in assembling and solving the so-called adjoint equations, **regardless of the number of design parameters**





F1 wing: 120,000 points

INTRODUCTION
INC. NAVIER-STOKES ADJOINT EQUATIONS

"Adjoint Momentum" Flow Term

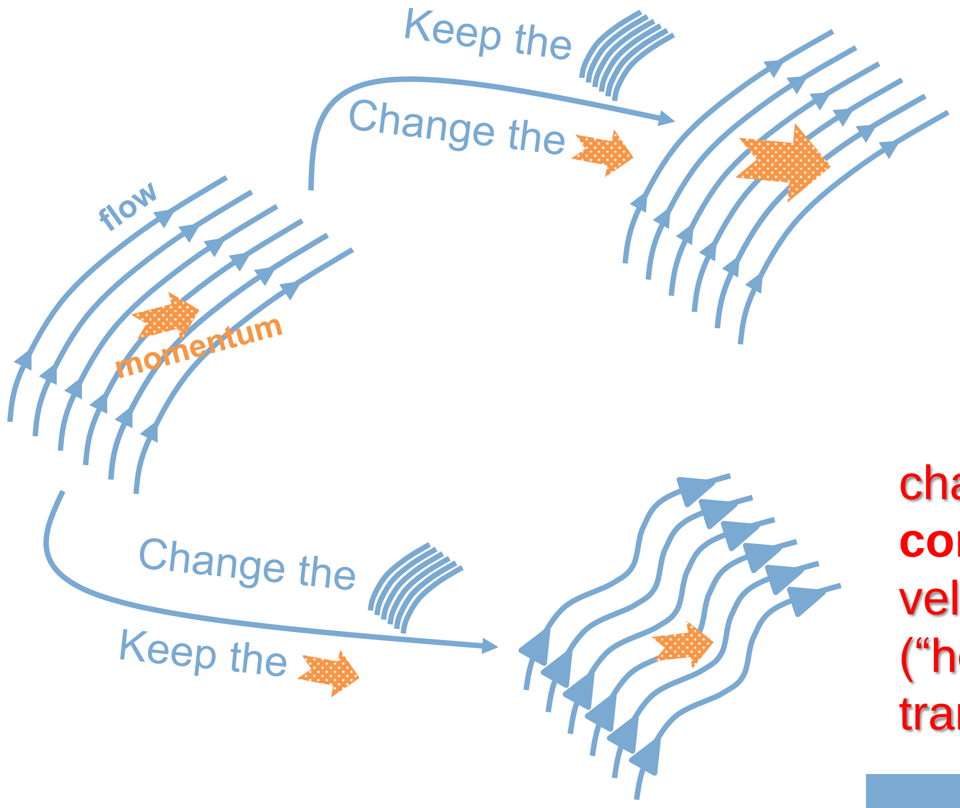
$$\begin{cases} -\nabla.(\nu\,\nabla\mathbb{u}_a) + \nabla.(-\mathbb{u}_a\otimes\mathbb{u}) + \nabla\mathbb{p}_a \\ \qquad + (\nabla^T\mathbb{u})\;\mathbb{u}_a = 0 \\ \nabla\cdot\mathbb{u}_a = 0 \end{cases}$$

Momentum "Adjoint Flow" Term

$\mathbb{u}_a$: adjoint velocity

$\mathbb{p}_a$: adjoint pressure

Neglected by most adjoint codes



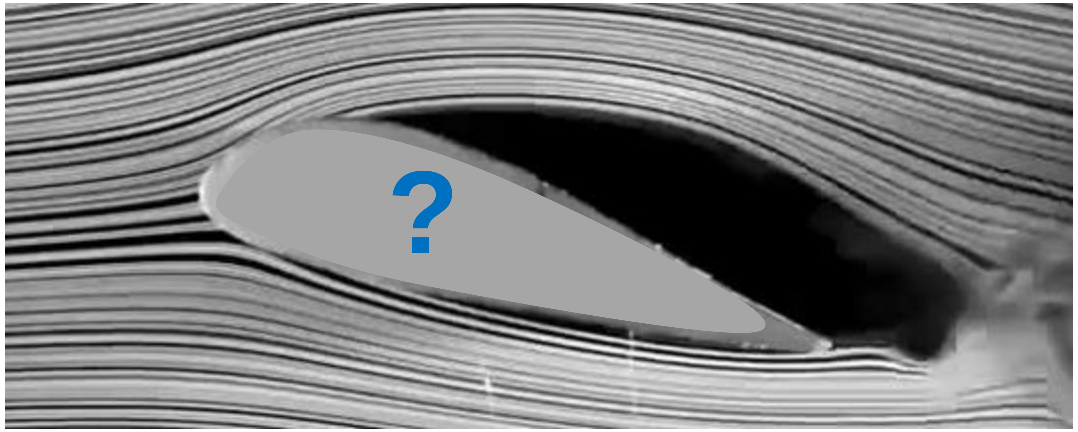
change of **convected** momentum ("what" is transported)

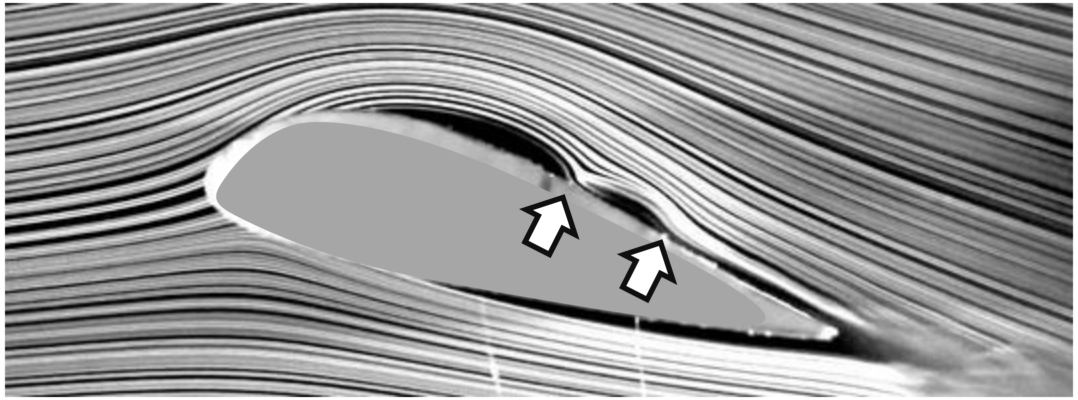
change of **convective velocity ("how" it is transported)**

MAFT

INTRODUCTION
UNDERSTANDING THE ADJOINT VELOCITY

- Often viewed as an “abstract” mathematical artefact, but it has a clear “physical” interpretation
- It tells you where and how to inject momentum optimally wrt your given objective
- Then it defines an ideal **virtual jet actuators map**





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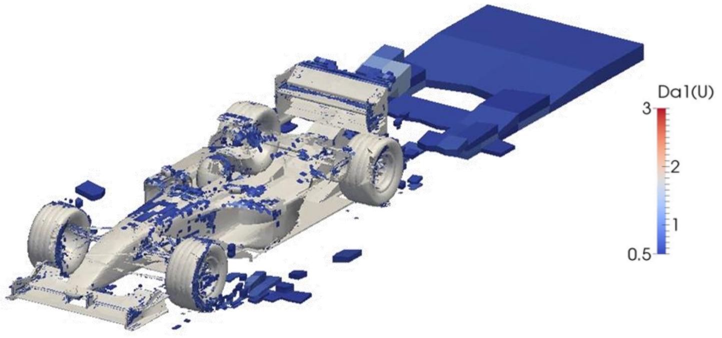
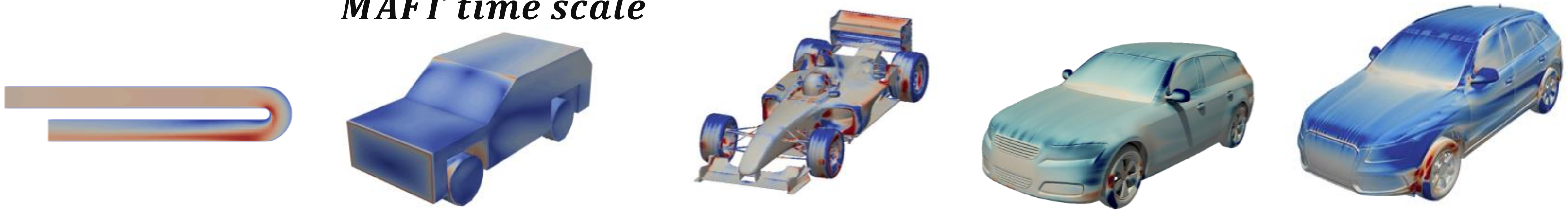
Key Features

[iconCFD® Optimize]

KEY FEATURES
STABILIZED MAFT FORMULATION



- MAFT may be very stiff, especially close the ground and walls
- Adjoint Damköhler number : $\mathbb{Da} = \dfrac{flow\ time\ scale}{MAFT\ time\ scale}$



	U-bend	ToyCar	Formula 1	DrivAer	Industrial vehicle
Cell Count	150k	1500k	3000k	40000k	50000k
Da avg	0.08	0.065	0.15	0.03	0.10
Da max	2.51	4.45	**20.57**	11.85	**24.85**

KEY FEATURES

STABILIZED MAFT FORMULATION

- Most adjoint codes neglect the MAFT, at least close to the walls.
- This is inconsistent.

- **iconCFD Optimize** uses Stabilized MAFT formulation:

$$-\nabla.(\nu\, \nabla \mathbb{u}_a) + \nabla.(-\mathbb{u}_a \otimes \mathbb{u}) + \mathbb{K}\, \mathbb{u}_a + \nabla p_a + \boxed{\alpha\, \mathbb{Da}\, \boldsymbol{\mathcal{R}}(\mathbb{u}_a)} = 0$$

- Selective relaxation, asymptotically consistent
- This allows to run with **high order convection**

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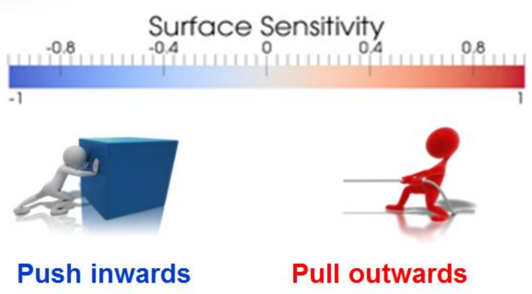
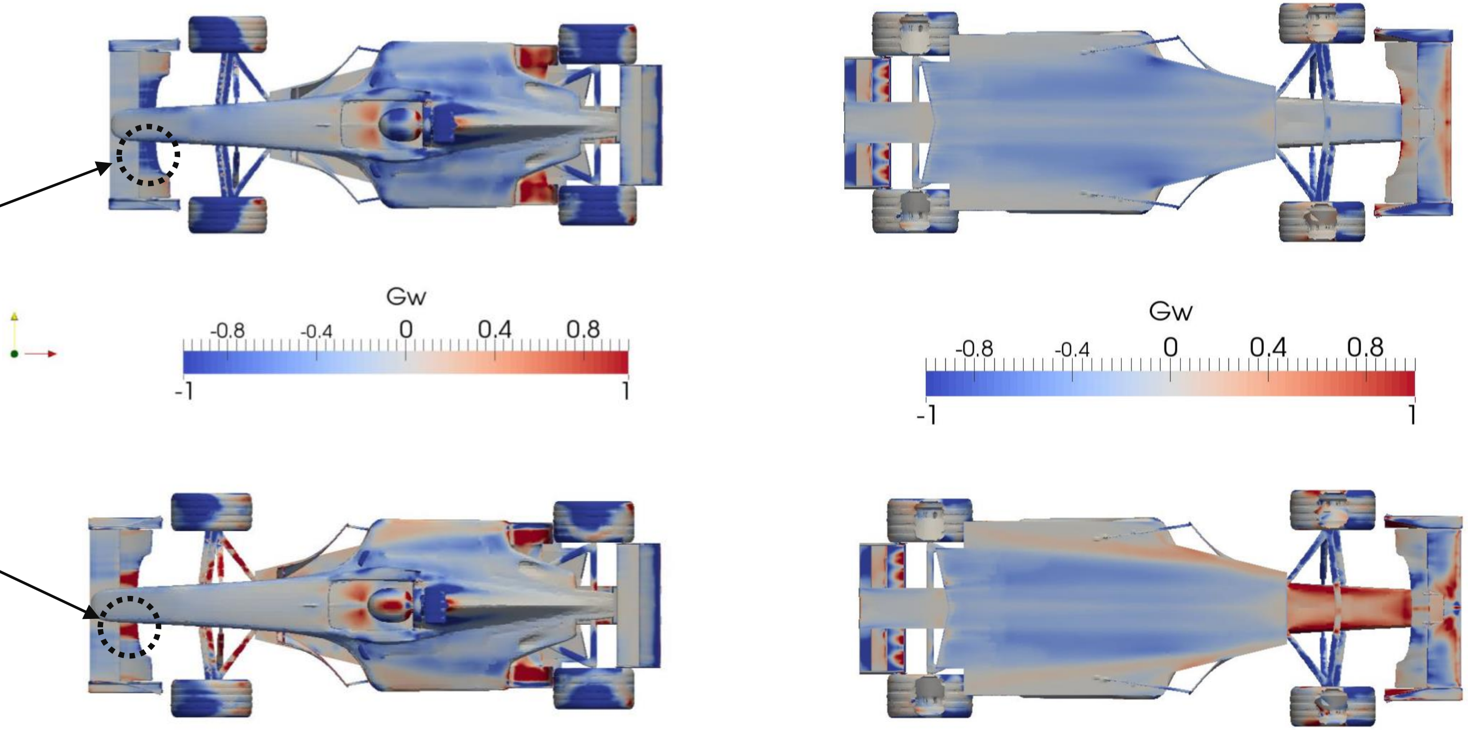
KEY FEATURES
STABILIZED MAFT FORMULATION



- Drag optimization, Formula 1 (Re = 3,5M, 3M cells)
  - **Without MAFT:**



Sensitivity signs are opposite!

  - **With MAFT:**

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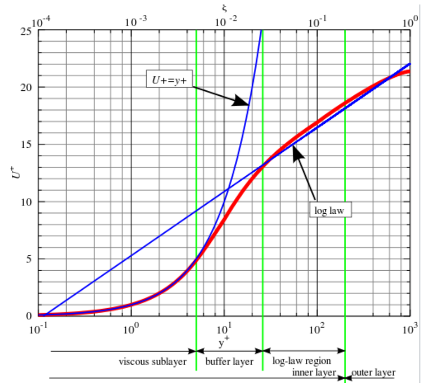
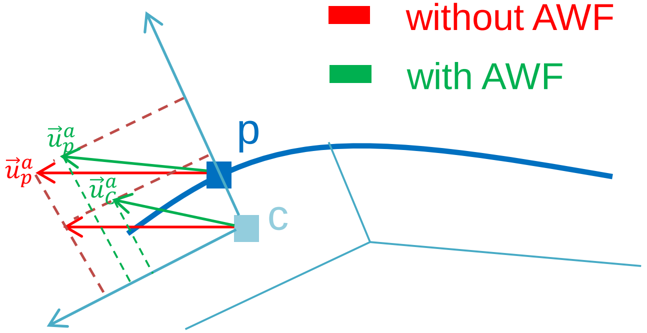
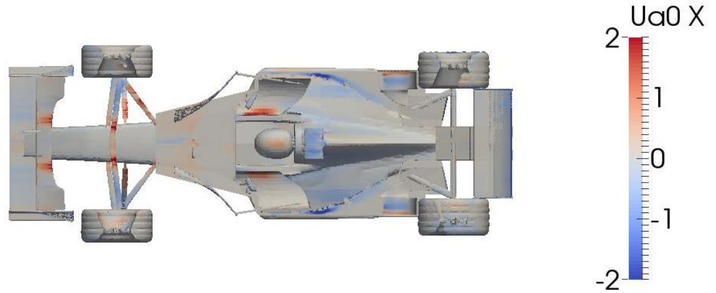
KEY FEATURES
UNIVERSAL ADJOINT WALL FUNCTION



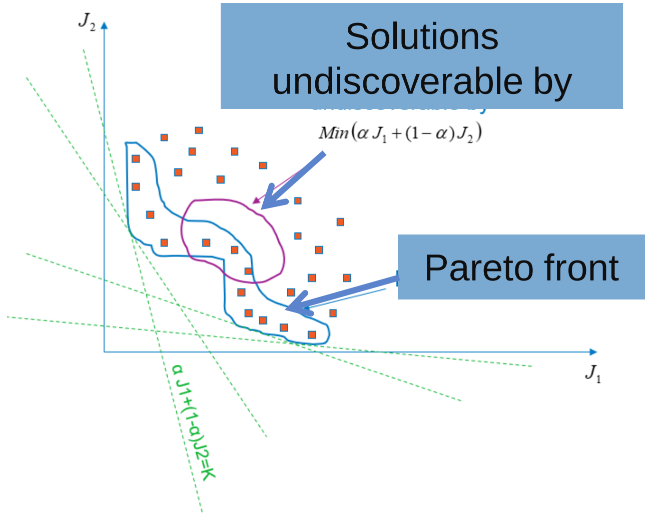
Regime	Universal law of the wall	Universal adjoint wall function
$y^+ \approx 1$	$\|u_c^+\| = y^+$	$u_p^a + d = 0$
$y^+ \geq 30$	$\|u_c^+\| = \dfrac{\ln y^+}{k} + C^+$	$u_p^a + d = (r-1)\dfrac{u_c \otimes u_c}{\|u_c\|^2}(u_c^a + d)$



- Leads to a modification of the adjoint shear stress in the flow direction only
- Both standard and Spalding versions available



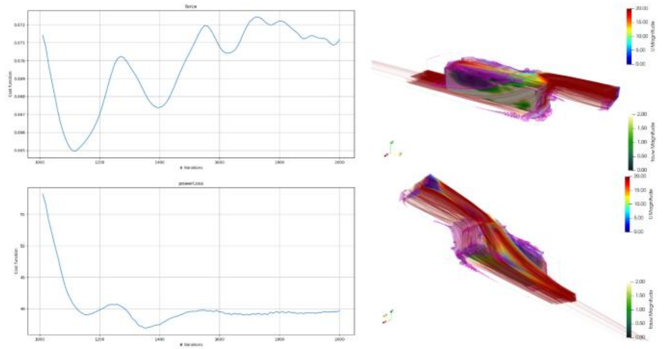
KEY FEATURES
MULTI-OBJECTIVE OPTIMIZATION



- **Scalarization approach** : $\mathcal{F} \leftarrow \lambda\, \mathcal{F}_1 + (1-\lambda)\, \mathcal{F}_2$
  - Might miss the most interesting points on the Pareto front
  - How to select λ ?

- In many cases, one would like to optimize a given objective (the « primary one ») but « keep an eye » on a secondary one
- **Optimize Both Favour One (OBFO)**

$$d = \underset{\mathbb{d}/\|\mathbb{d}\|=1}{\operatorname{argmin}} (\nabla \mathcal{F}_1 \cdot \mathbb{d})$$
$$s.t. \quad \nabla \mathcal{F}_2 \cdot d \leq \alpha\, \|\boldsymbol{\nabla} \mathcal{F}_2\| \qquad \alpha \in [0,1[$$



Ref. *"Combined Drag and Cooling Optimization of a Car Vehicle with an Adjoint-Based Approach" SAE 2018-01-0721 - G. Pierrot, J. Papper (ICON) T. Han, S. Kaushik (GM)*

Adjoint Validation Cases
[iconCFD® Optimize]

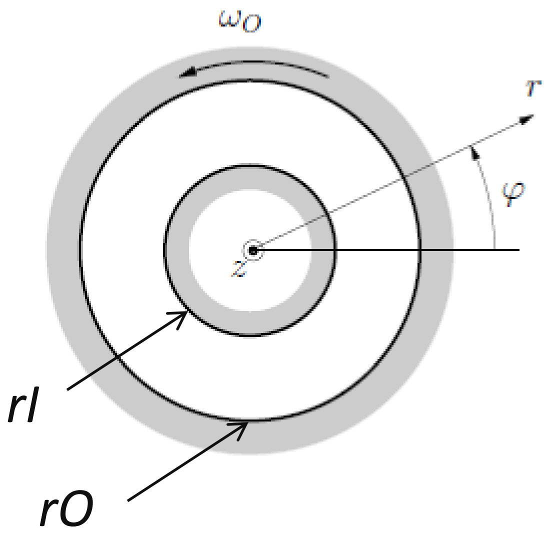
VALIDATION CASES
2D AXISYMMETRIC COUETTE FLOW

- **Analytical flow solution :**

$$U^r(r) = 0\,, \quad U^\varphi(r) = \alpha\left(r - \frac{r_I^2}{r}\right)\,,$$

$$p(r) = p(r_I) + \rho\,\alpha^2\left[\frac{r^2}{2} + 2\,r_I^2\,\ln\left(\frac{r_I}{r}\right) - \frac{r_I^4}{2r^2}\right]\,,$$

$$\alpha = \frac{\omega_O}{1-(r_I/r_O)^2}\,.$$



- **Analytical adjoint solution :**
  - **Cost function: reduce torque on inner cylinder**

$$\begin{aligned}\hat{U}^\varphi(r) &= \hat{\alpha}\left(\frac{r}{r_O^2} - \frac{1}{r}\right)\\ \hat{p}(r) &= \hat{p}(r_I) + \rho\,\alpha\hat{\alpha}\left[\frac{r_I^2 - r^2}{r_O^2} + 2\,\ln\left(\frac{r}{r_I}\right)\right]\,,\end{aligned}$$

$$\hat{\alpha} = \frac{r_I}{(r_I/r_O)^2 - 1}\,.$$

Ref. *“Adjoint Navier-Stokes Methods for Hydrodynamic Shape Optimisation” PhD thesis A.Stück - 2011*

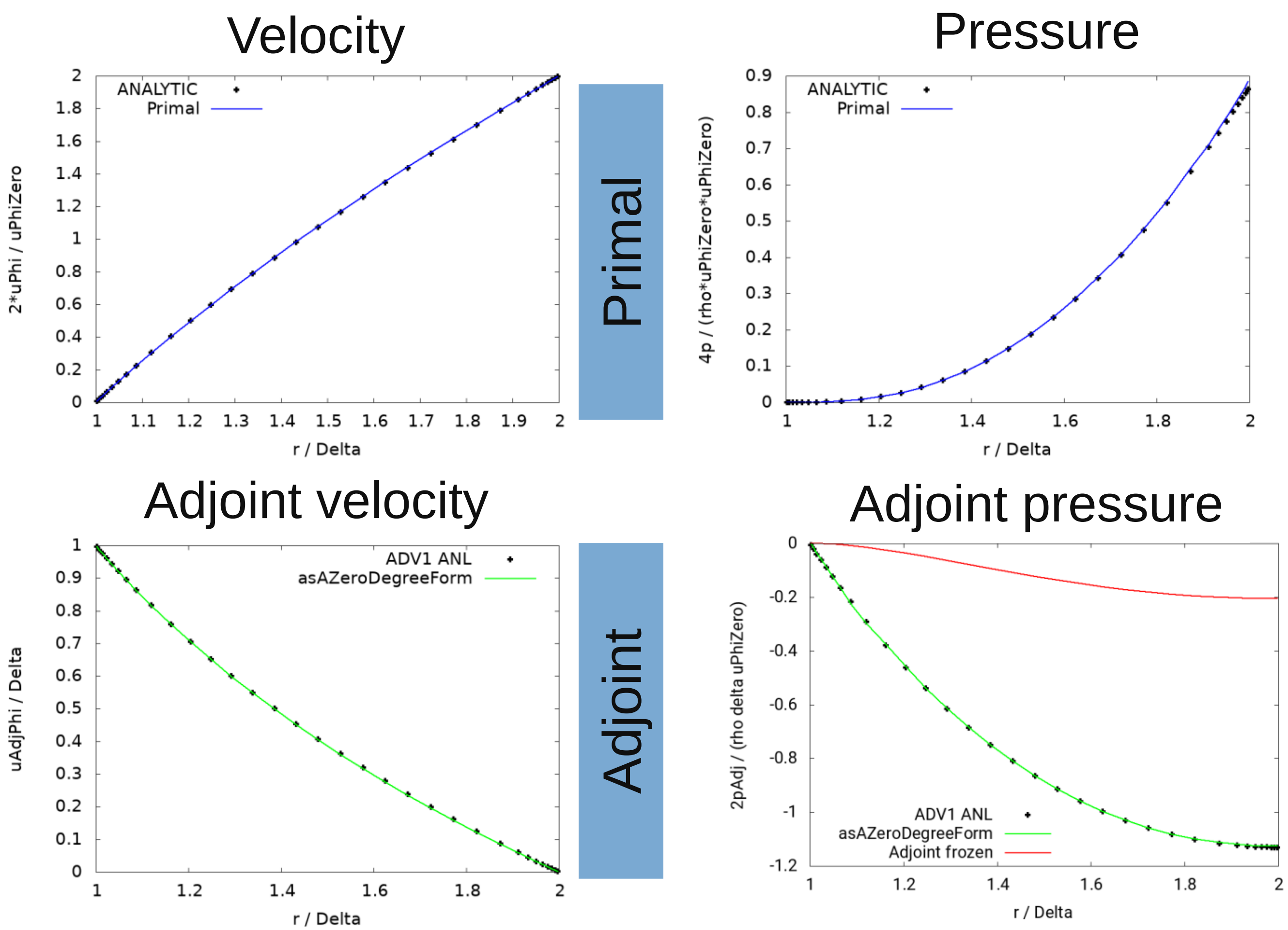
VALIDATION CASES
2D AXISYMMETRIC COUETTE FLOW

- Non-dimensional plot of pressure and velocity analytical solutions vs. Simulation

  - • ANALYTIC
  - — PRIMAL
  - — ADJOINT

- Excellent agreement between analytical and ICON solutions..

- ..When MAFT is NOT neglected

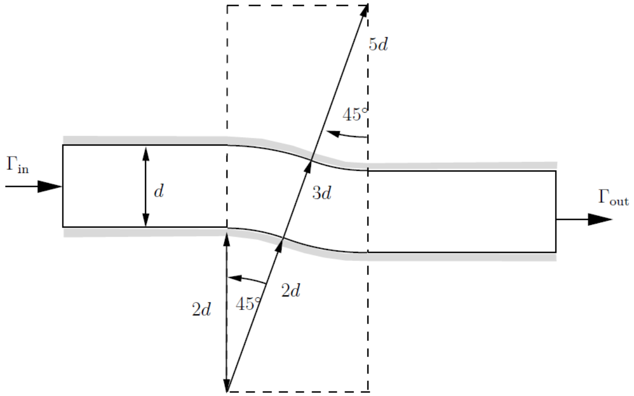


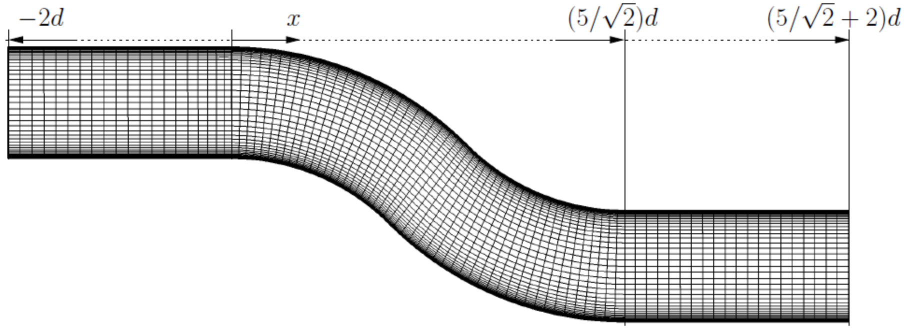
VALIDATION CASES

2D BEND DUCT

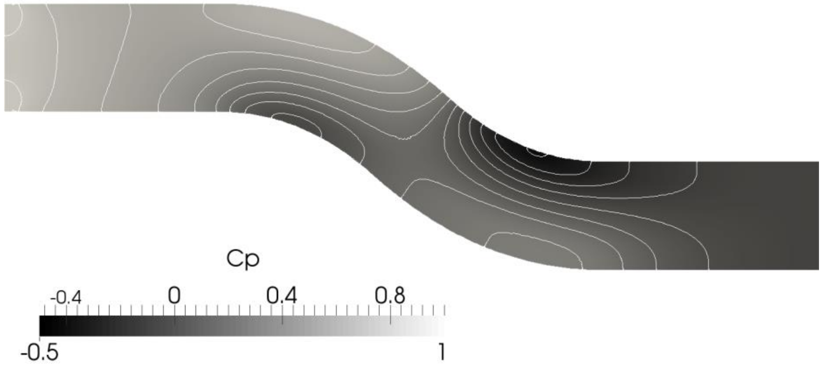
- 2D Bend duct in laminar flow
- Re = 500
- Cost function: Reduce power loss

$$J_\Gamma = \int_{\Gamma_O} \left(p + \frac{\rho}{2} U_i^2\right) U_j \, \mathrm{d}\Gamma_j \, .$$





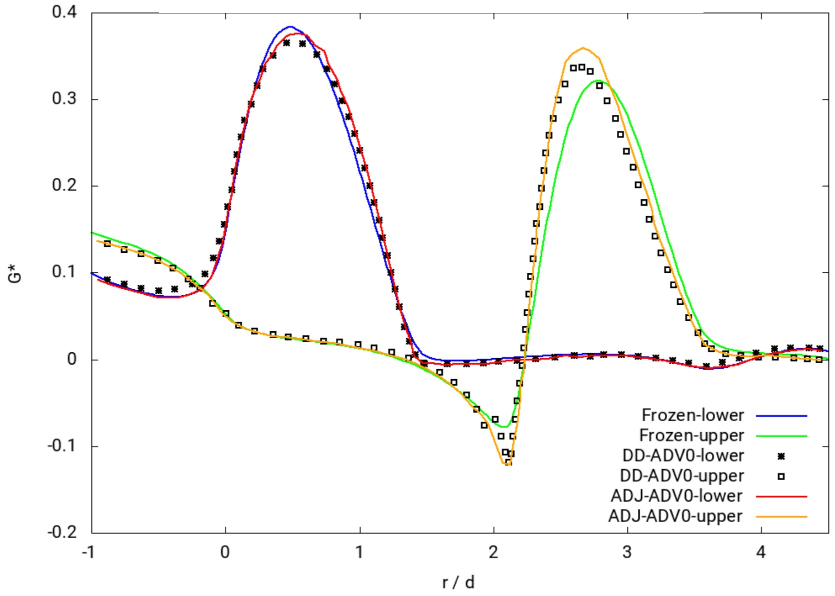
Primal solution



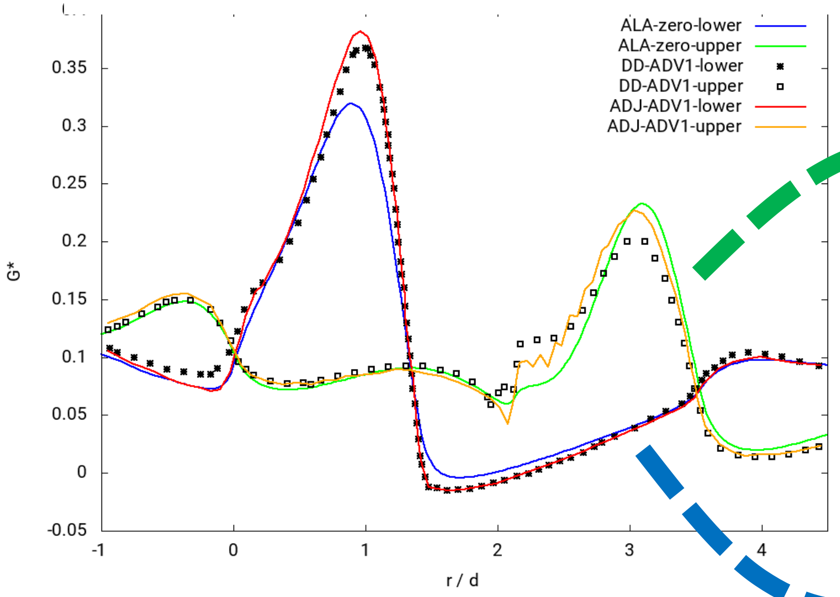
VALIDATION CASES
2D BEND DUCT

- Validation against Direct Differentiation method
- Very good agreement (given the different convection schemes)

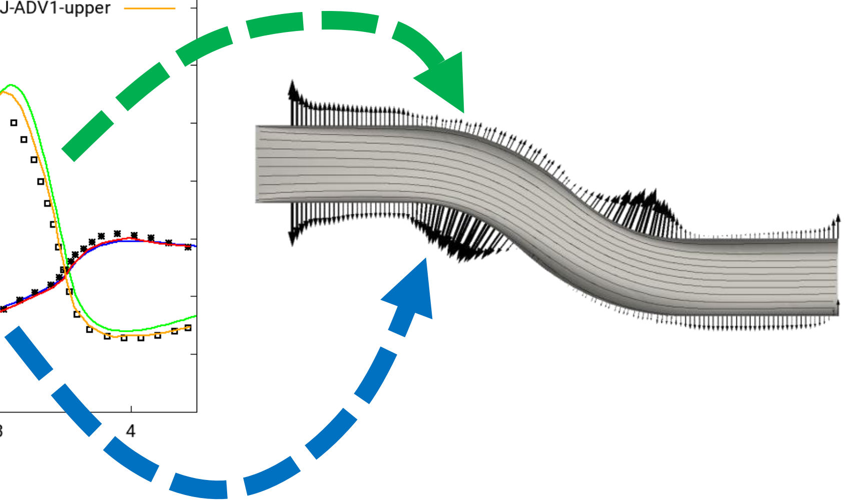
No MAFT



MAFT



Sensitivity vectors and velocity streamlines



Applications Cases
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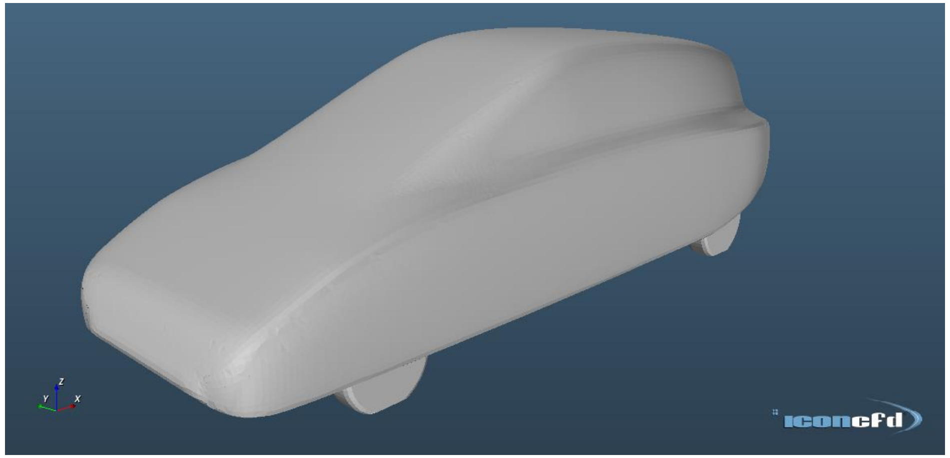
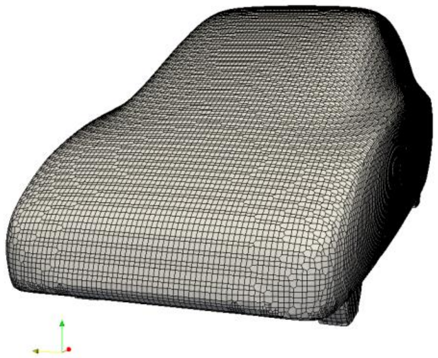
APPLICATION CASES
ASMO

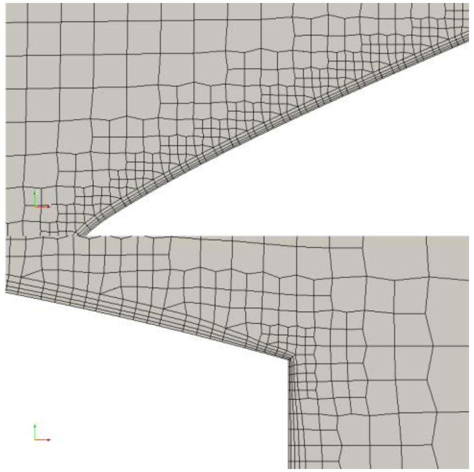
- **Case summary**
  - Geometry: “ASMO” body (square back, smooth surface, boat tailing, underbody-diffuser)

Ref. *S. Perzon, L. Davidson - ACFD 2000 Beijing, 2000*

  - Setup: static condition, Uinlet = 50m/s, Re ~ 1.7e6, turb. RKE
  - Objective: drag reduction through 2 iterative morphing cycles
  - Setting:
    - Wheels: static
    - Body: morphing
- **Model**
  - Mesh size: 28.6M / y+ ~ 30-50
  - Adjoint setting: frozen + MAFT as a zero degree form
  - Max displacement / radius : 5mm / 10mm





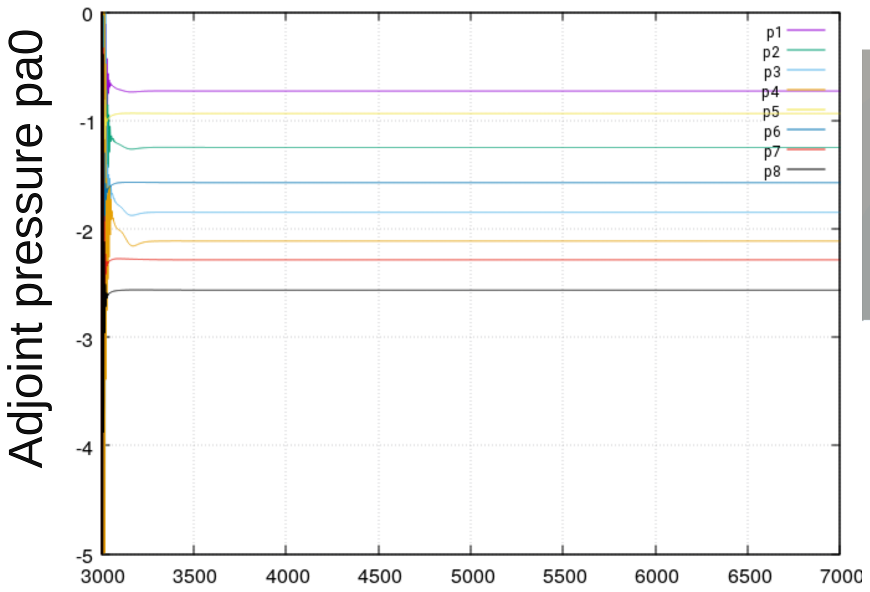


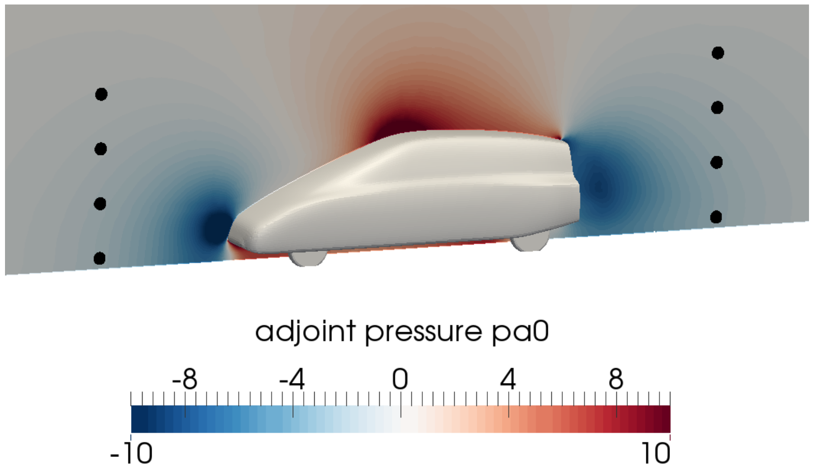
ASMO model

APPLICATION CASES
ASMO

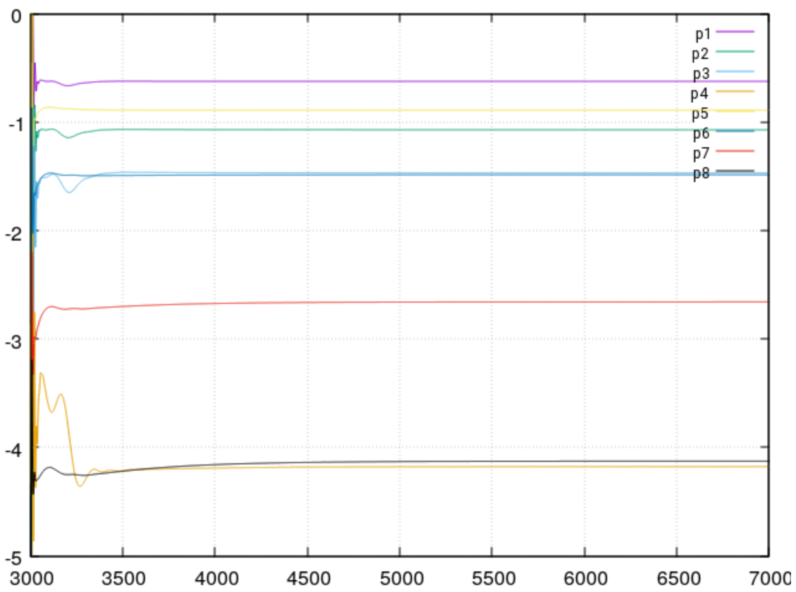
- **Comparison frozen vs. MAFT**
  - Probes were used to monitor the convergence of the adjoint state
  - Evolution of adjoint pressure confirms the convergence is reached for both frozen and MAFT settings

Adjoint pressure at probe locations
Frozen adjoint solution



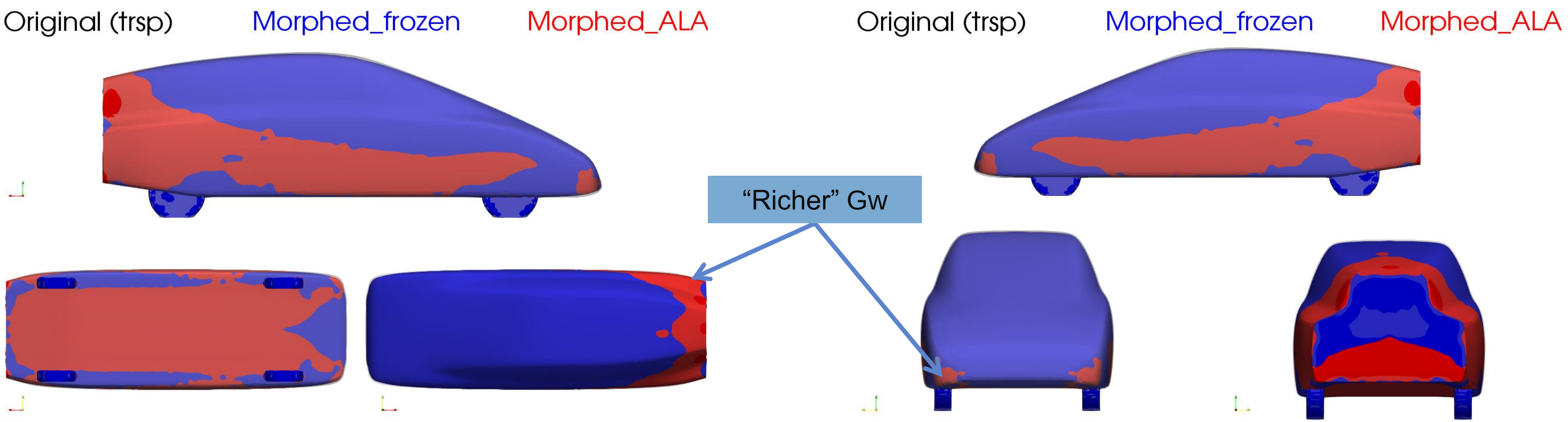


Adjoint pressure at probes locations
MAFT adjoint solution



APPLICATION CASES
ASMO

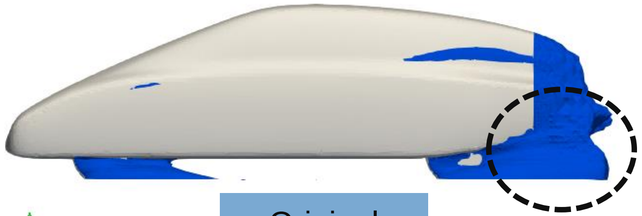
- **Comparison with/without MAFT**
  - Very different morphed surfaces
  - MAFT Gw provides “richer” information (balance of positive and negative Gw)



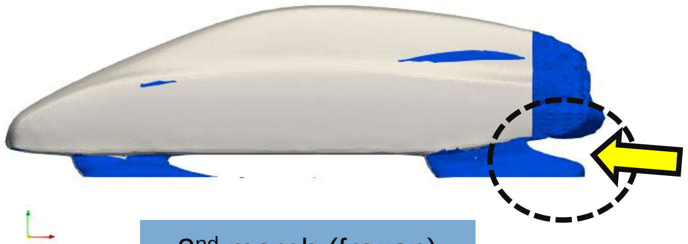
APPLICATION CASES
ASMO

- **Comparison frozen vs. MAFT**
  - Drag reduction observed in both cases after 2 cycles of morphing
  - After 2 morphing loops:
    - -20.9 counts for frozen model
    - -30.7counts for MAFT model

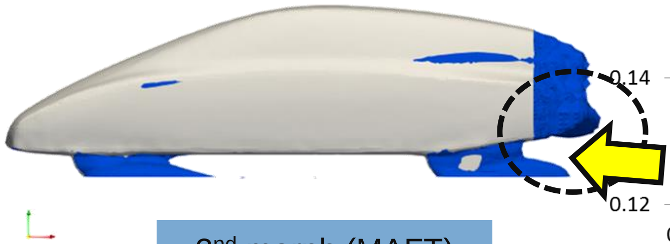
Contour of iso coefficient of total pressure



Original

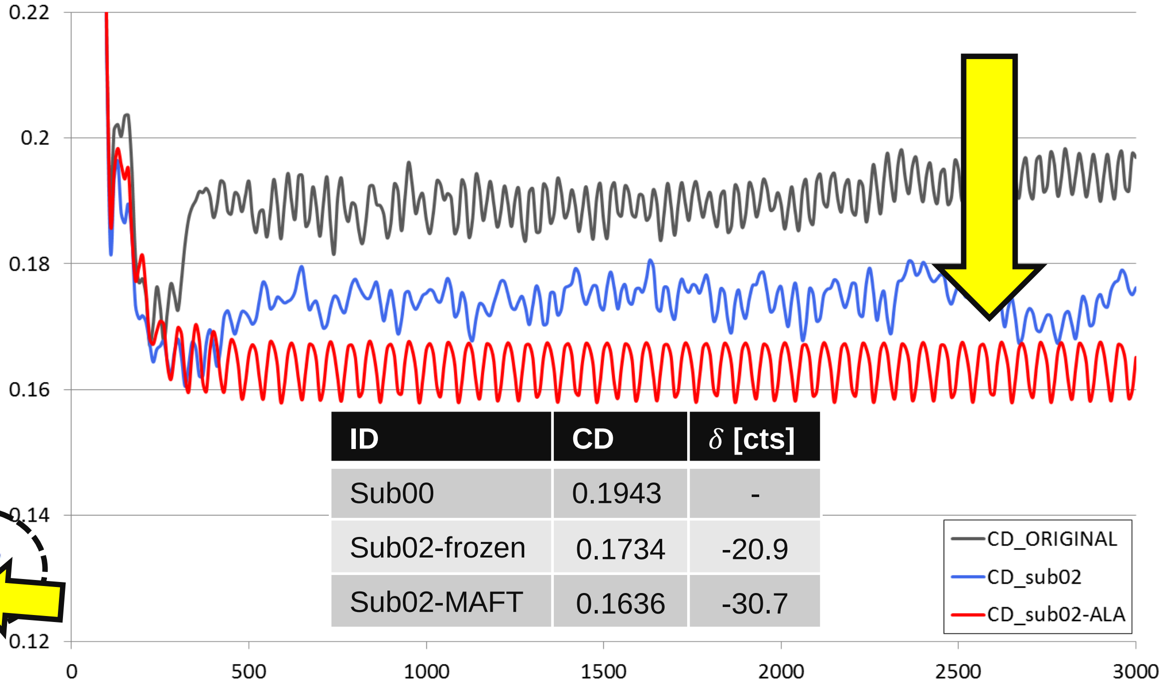


2nd morph (frozen)



2nd morph (MAFT)

ASMO drag coefficient evolution



ID	CD	δ [cts]
Sub00	0.1943	-
Sub02-frozen	0.1734	-20.9
Sub02-MAFT	0.1636	-30.7

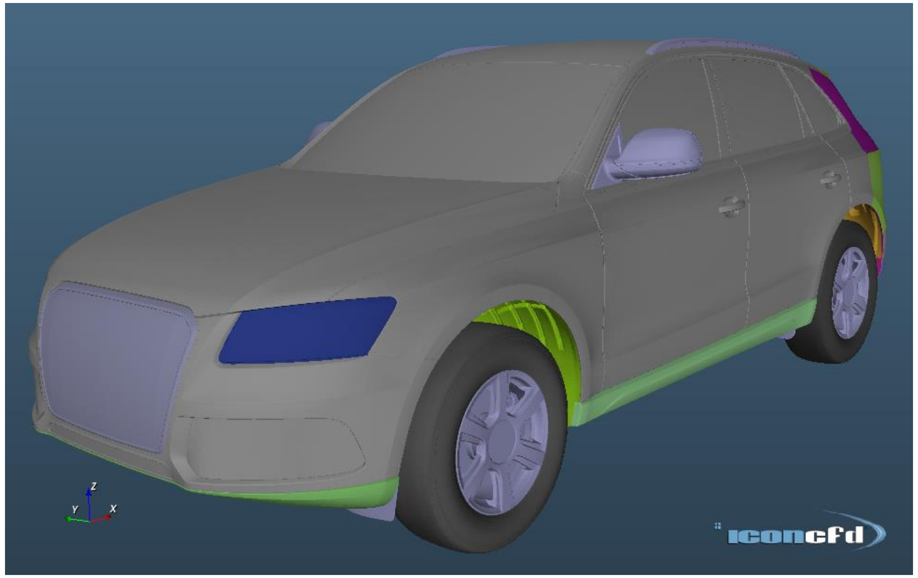
APPLICATION CASES
AUDI Q5

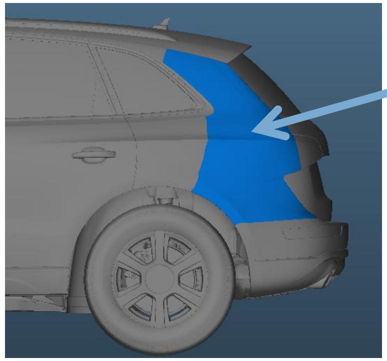
- **Case summary**
  - Geometry: Audi Q5 SUV
  - Setup: static condition, Uinlet = 38.89m/s, Re ~ 6.9e6, turb. RKE
  - Objective: evaluation of adjoint solution (for drag reduction) with an averaged transient primal flow solution
  - Configuration: static conditions (wheel, ground)

  - Note: the Q5 is vehicle that is already very well optimized aerodynamically

- **Model**
  - Mesh size: 63 M / y+ ~ 40-50
  - Adjoint setting: without ("frozen") and with MAFT term

AUDI Q5 SUV Model



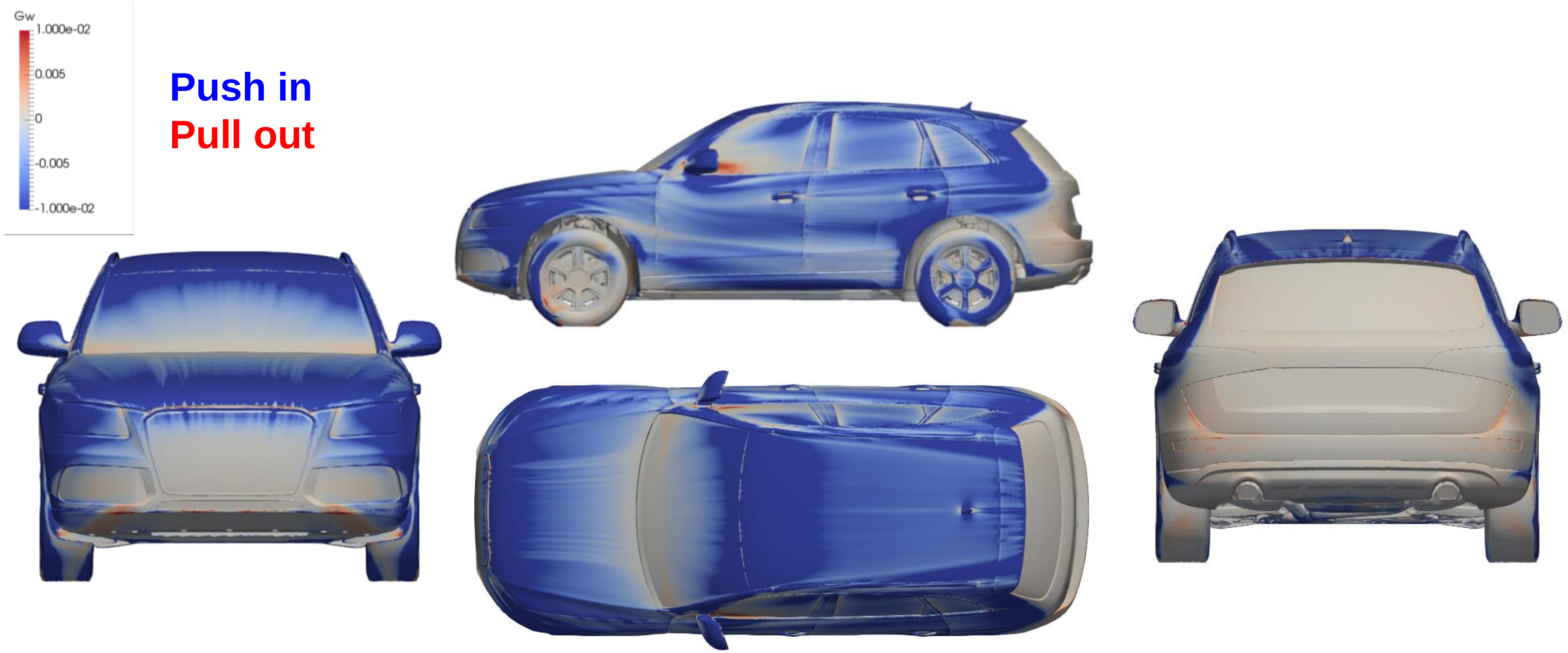


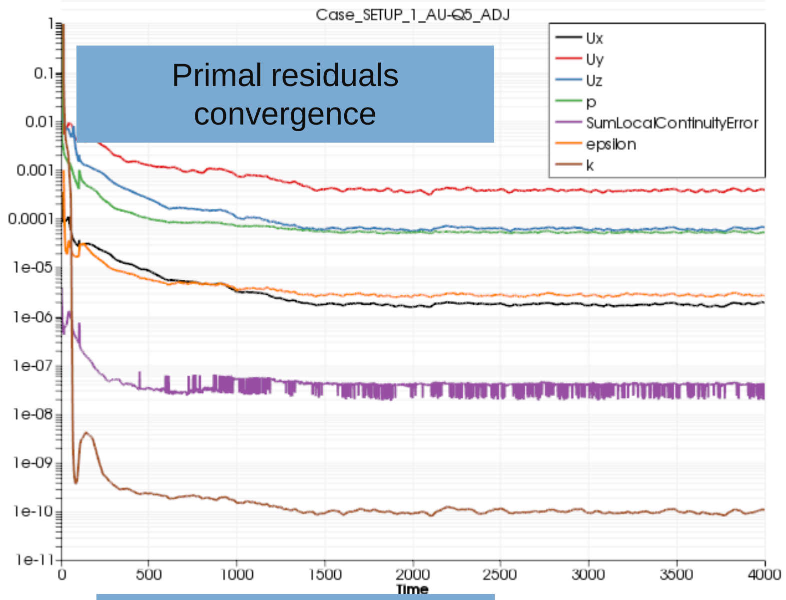
D-Pillar

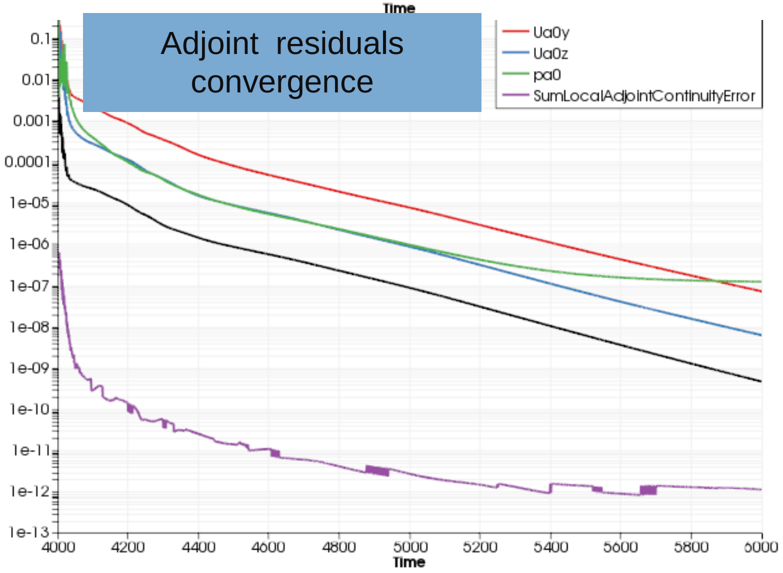
Geometry courtesy of Audi AG, I/EK-44

APPLICATION CASES
AUDI Q5

- **Primal RANS / adjoint solution without MAFT term ("frozen")**
  - Symmetrical sensitivities

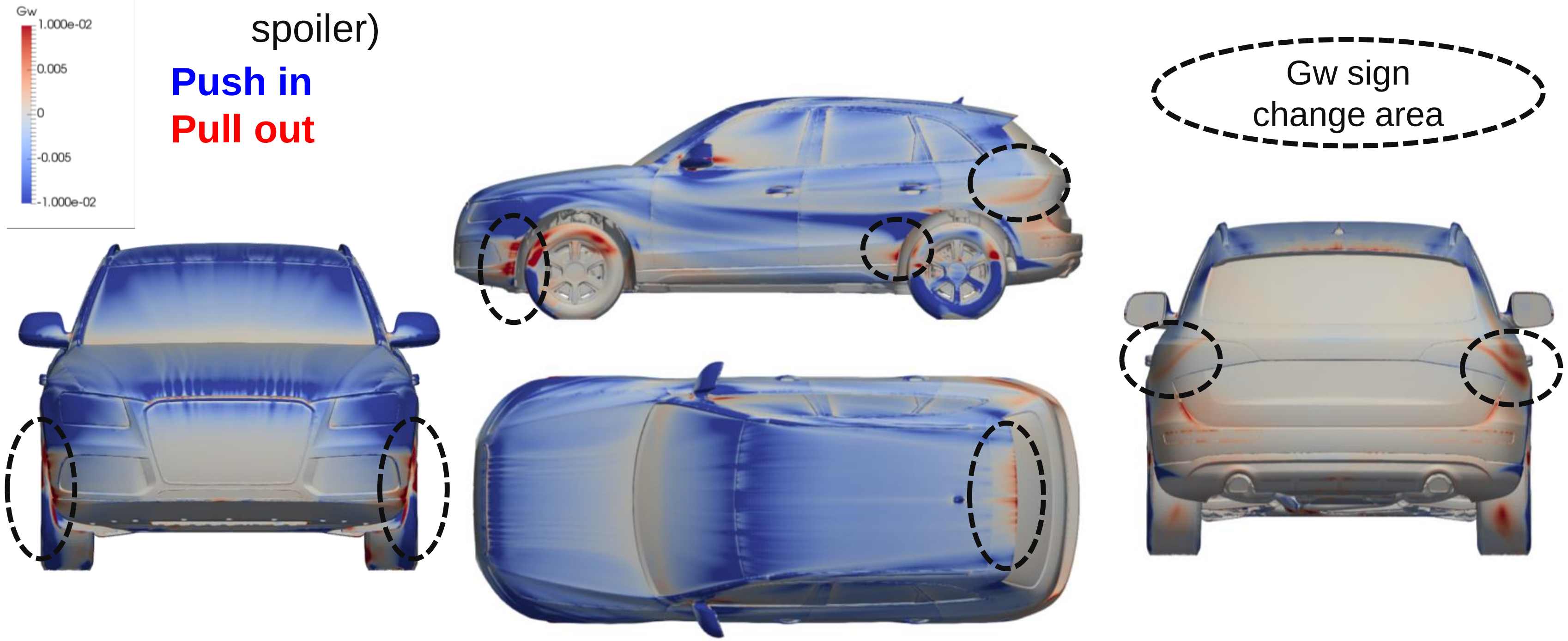


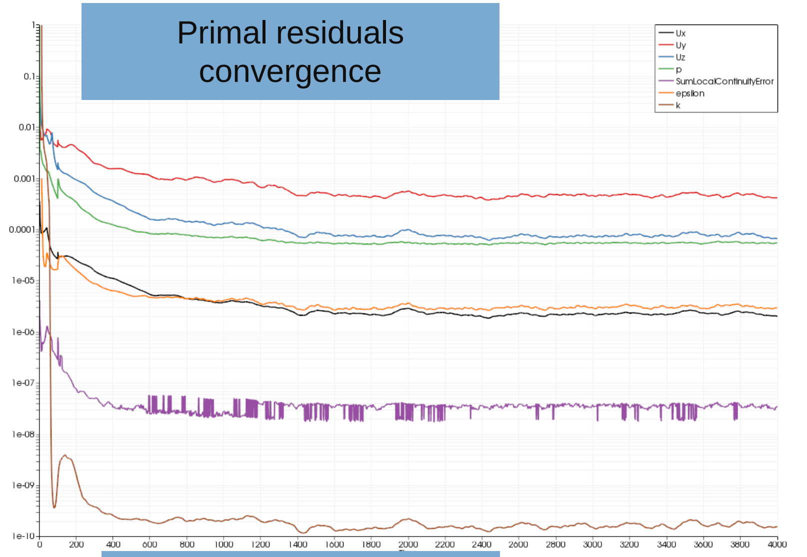


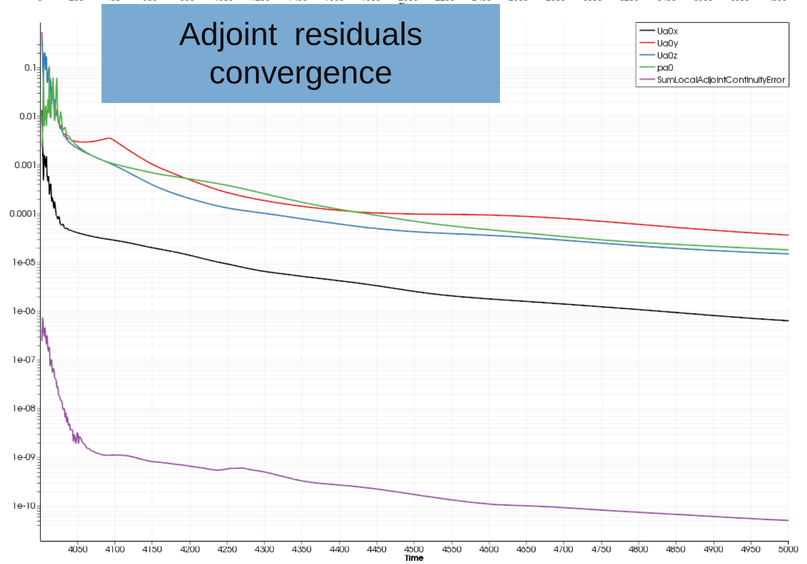


APPLICATION CASES
AUDI Q5

- **Primal RANS / adjoint solution with MAFT term**
  - Difference with “frozen” solution, MAFT term carries “richer” information
  - Sensitivity sign changes in key area (upstream front wheel arch, D-pillar, spoiler)







APPLICATION CASES
AUDI Q5

Gw from the FKFS 2015 paper after 150 000iterations

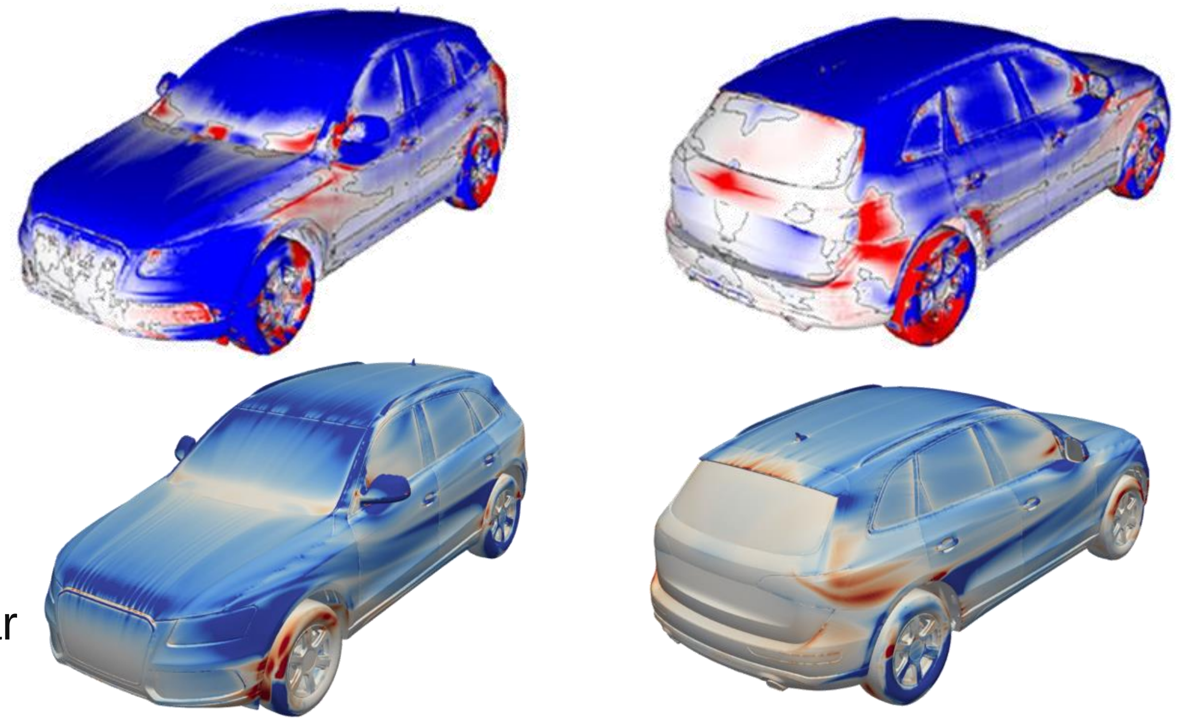
- **Comparison with an alternative method**
  - Reference publication:

Ref.

  “Aerodynamic vehicle optimization using the continuous adjoint method” – T. Blacha FKFS 2015

  - Stable sensitivities after 150,000 iterations

- **Using iconCFD Optimize**
  - Stable sensitivities after 1,000 iterations only
  - Extra information (sign change) on spoiler / D-pillar

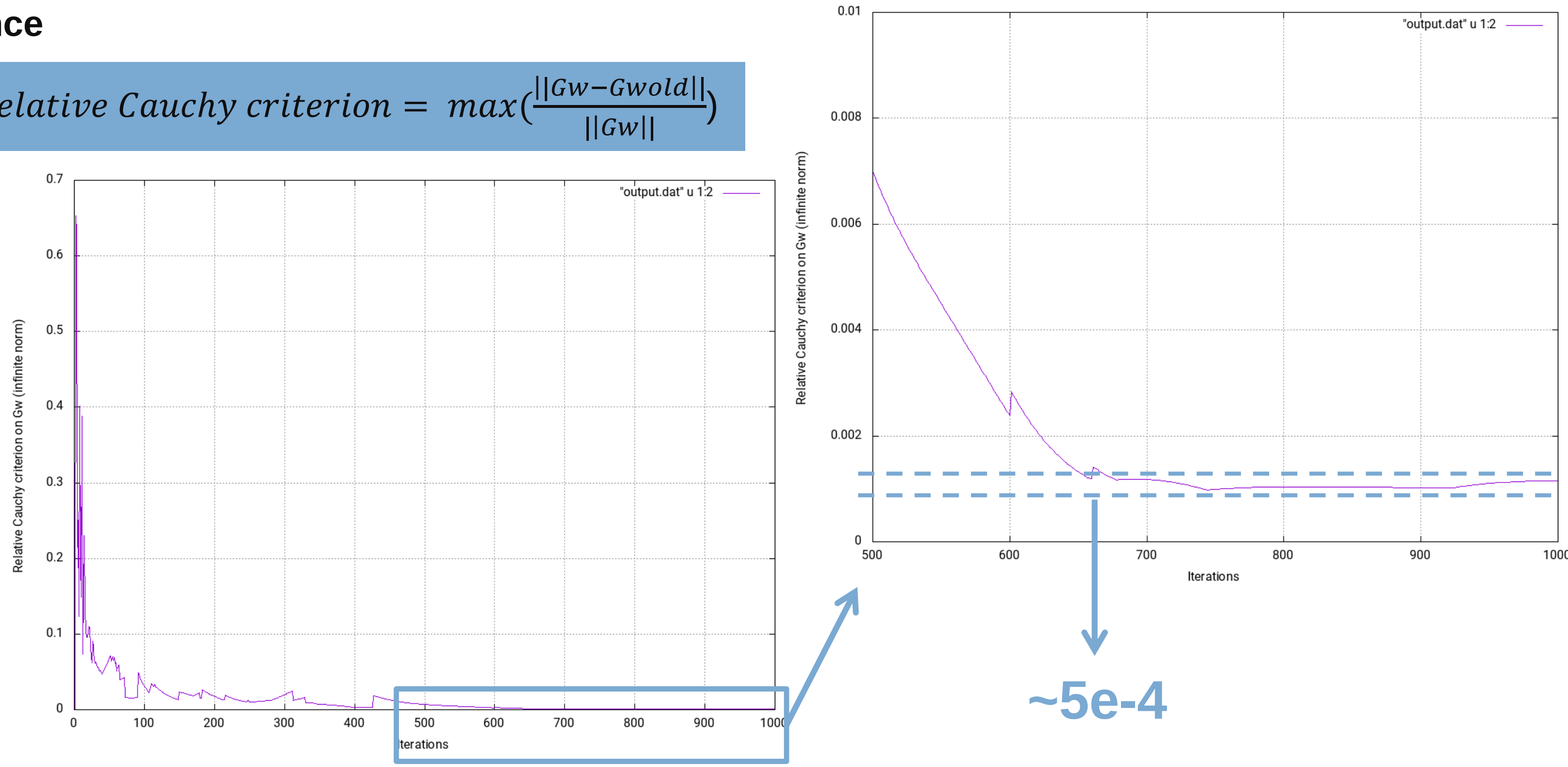


Gw from iconCFD Optimize after 1000 iterations

APPLICATION CASES
AUDI Q5

- **Adjoint convergence (with MAFT term)**
  - Evolution of variation of sensitivities over 1000 iterations of adjoint solver
  - **Proof of adjoint solution convergence**
  - Indicator monitored :

$$Gw\ relative\ Cauchy\ criterion = max\left(\frac{||Gw - Gwold||}{||Gw||}\right)$$



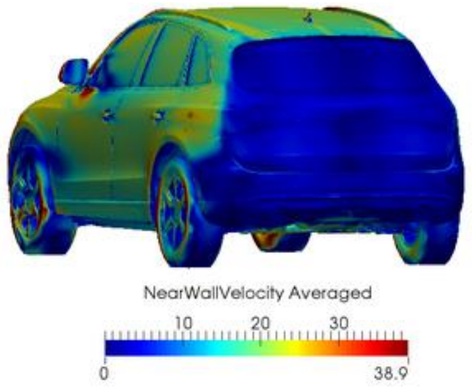
APPLICATION CASES
AUDI Q5

- **Transient primal based adjoint solution**
  - RANS initialization for 1,500 iterations
  - 5.0sec physical time primal solution
  - Adjoint solution based on averaged primal flow (last 2.0sec)

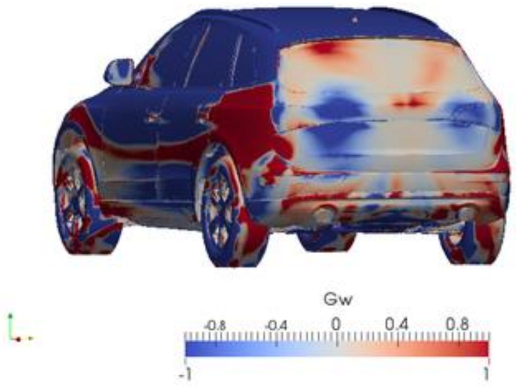
- **Local morphing of the D-pillar only**
  - Maximum displacement of 5mm

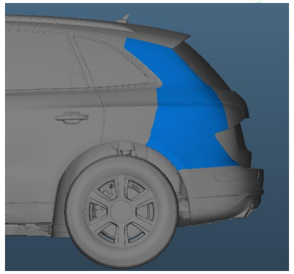
- **Drag reduction**
  - **-1.3 counts in a single loop**

Near wall velocity [m/s]



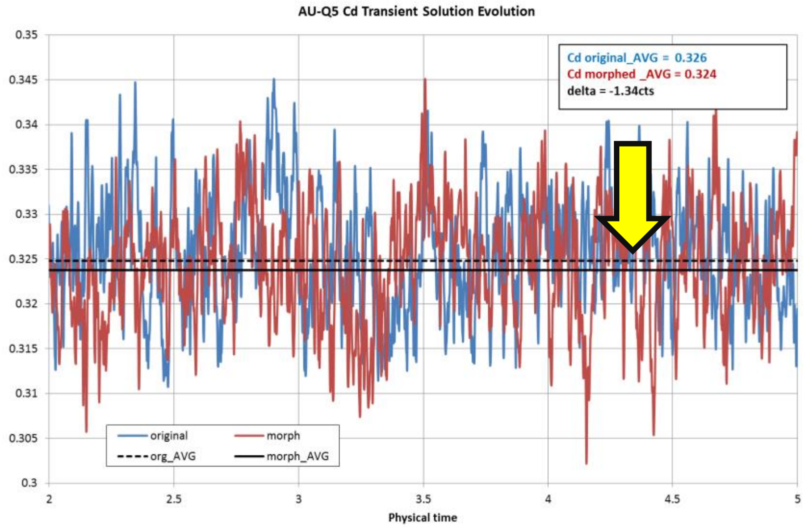
Surface sensitivities





D-Pillar

Morphed surface (blue)

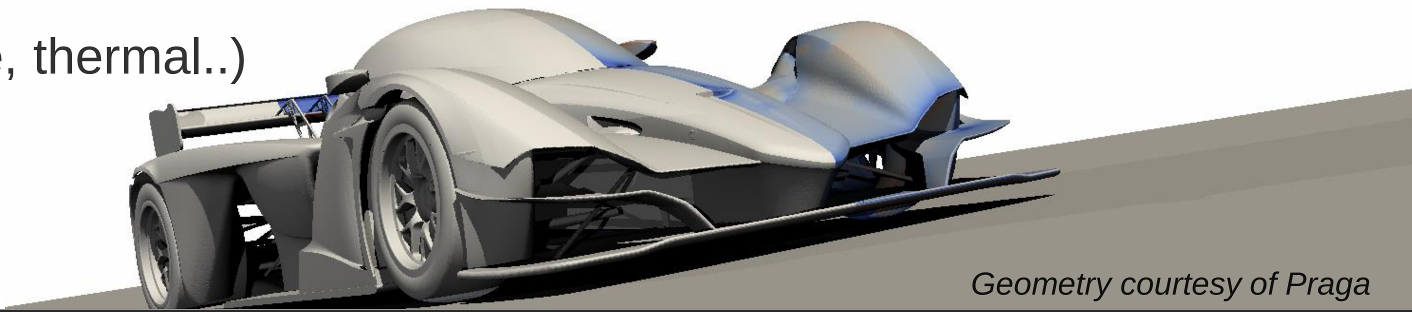


CONCLUDING REMARKS
iconCFD® Optimize

- State-of-the-art shape and topology optimization capabilities

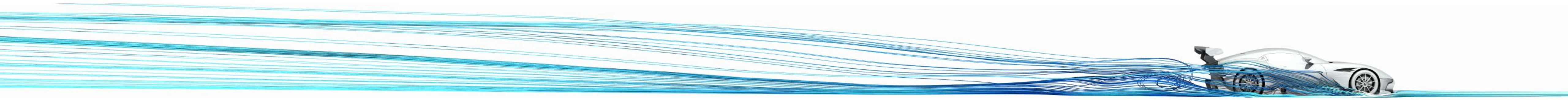
- Unique features:
  - Stabilized MAFT
  - Universal adjoint wall function
  - OBFO

- Next steps:
  - More model supports (MRF, turbulence, thermal..)
  - Improved morpher performance
  - Transient adjoint



Geometry courtesy of Praga

THANK YOU



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报告来源：2019年IDAJ中国CAE/MBD技术大会

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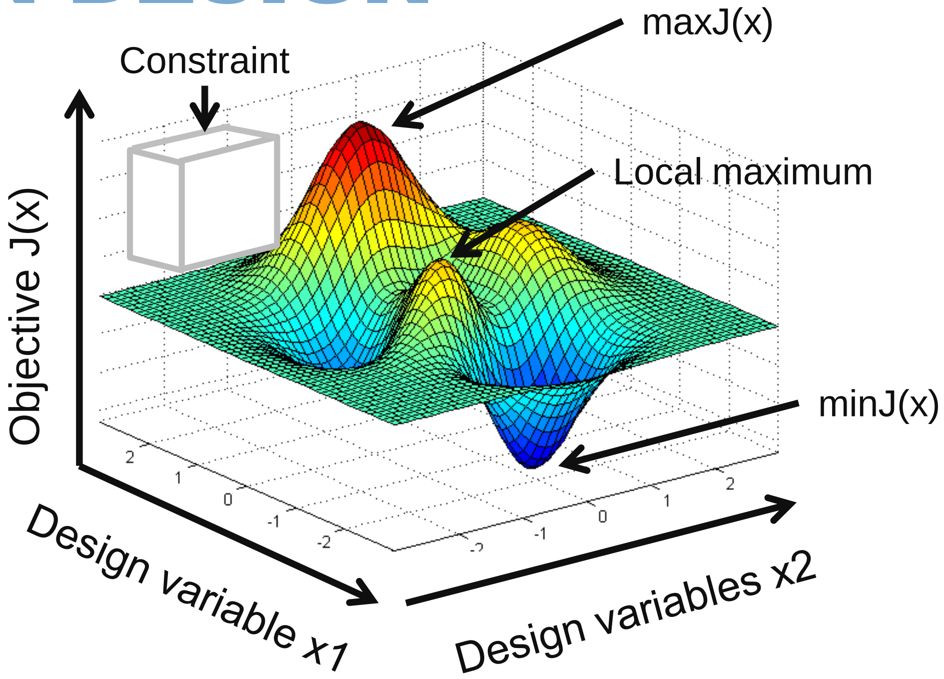
INTRODUCTION
OPTIMIZATION METHODS IN DESIGN

- Used for over 40 years
- Some problems can be simply visualised but most engineering problems are multi-dimensional
- We are looking for a minimum or a maximum of the objective function, bounded by several constraints, in a certain design space, defined by the design parameters



Find the objective function minJ(x)
with respect to x1 and x2

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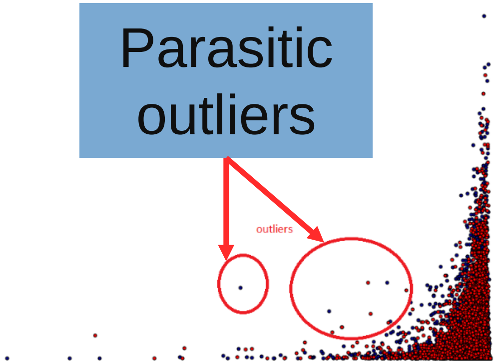
NEW FEATURES
OUTLIERS BASED GW NORMALIZATION

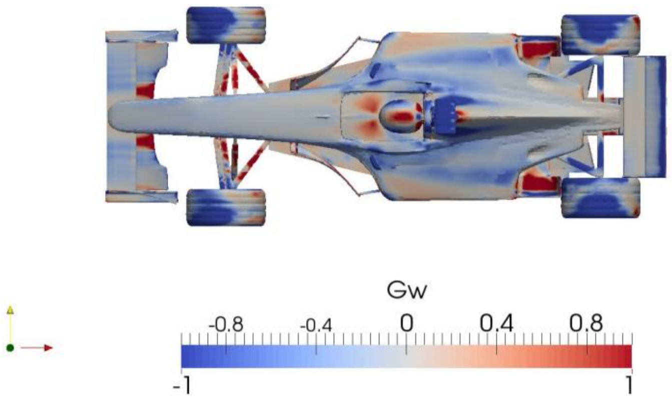
- Shape sensitivity may be difficult to visualize due to the presence of **outliers** (very high and localized peaks)



- Identification of outliers based on **MAD** (Mean Absolute Deviation)

$$|G_w| > \mathcal{M} + \mathrm{n} * MAD$$

- Standardized Gw visualization: **-1 < Gw < 1**



INTRODUCTION
HOW DOES THAT WORK ?

- Generic **state equation** : $\mathcal{R}(\mathbb{U},\mathbb{D}) = 0 \quad (\mathbb{U}\ :\ \text{state vector},\ \mathbb{D}\ :\ \text{design parameters})$
- From linear theory, applying a small parameters perturbation $\mathbb{D} \leftarrow \mathbb{D} + \delta\mathbb{D}$ yields :

$$\mathcal{R}(\mathbb{U}+\delta\mathbb{U},\mathbb{D}) = -\frac{\partial\mathcal{R}}{\partial\mathbb{D}}\delta\mathbb{D}$$

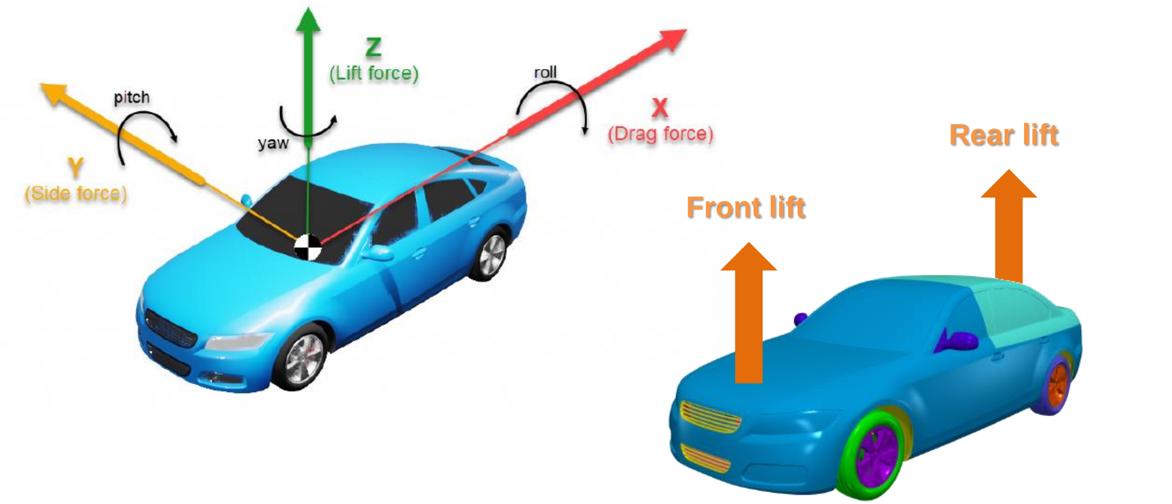
- **Corollary** : modifying the design parameters amounts to adding an equivalent source term to the state equation
- **Take away message** : we only have to measure the impact of adding a source term on the cost function in order to compute the gradient
- **This is exactly what adjoint does!**

INTRODUCTION
MORE PRECISELY

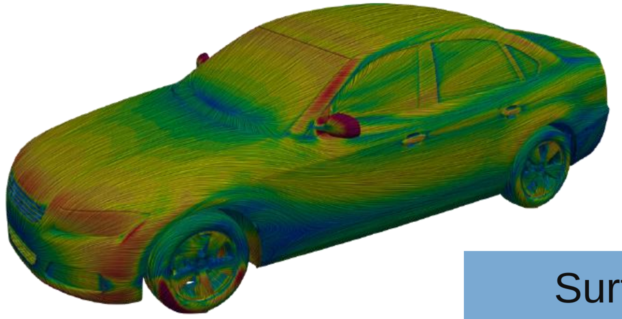
- Shifted **state equation** : $\mathcal{R}'(\mathbb{U},\mathbb{D}) = \mathcal{R}(\mathbb{U},\mathbb{D}) - \mathbb{S} = 0$ ($\mathbb{S}$: source term)
- Modified optimization problem, now $\mathbb{S}$ is the design parameters field : $\mathcal{G}(\mathbb{U},\mathbb{S}) \leftarrow \mathcal{F}(\mathbb{U},\mathbb{D})$
- We can show that : $\left(\frac{d\mathcal{G}}{d\mathbb{S}}\right)^T = \left(\frac{\partial\mathcal{R}}{\partial\mathbb{U}}\right)^{-T}\left(\frac{\partial\mathcal{F}}{\partial\mathbb{U}}\right)^T = -\mathbb{U}_a$
- The adjoint state reflects the sensitivity of the cost function to the addition of a source term
- **The adjoint velocity tells you where to inject momentum!**

NEW FEATURES
COST FUNCTIONS

- **Torque :** $\mathbb{T} = \int_{\mathcal{S}_{\mathbb{T}}} \{\bar{\bar{\sigma}}\,\vec{n} \wedge (\vec{x} - \vec{c})\} \cdot \vec{d}$
  - Front/rear lift /side force



- **Friction :** $\mathbb{F} = \int_{\mathcal{S}_{\mathbb{F}}} \|\bar{\bar{\sigma}}\,\vec{n} - (\bar{\bar{\sigma}}\,\vec{n} \cdot \vec{n})\,\vec{n}\|$



Surface streamlines

- **Targets types :** minimum, maximum, target, drift

Geometry courtesy of TUM

NEW FEATURES
QUASI-TRANSIENT ADJOINTS

- State of the art external aero uses DES ➔ transient simulations
- Fully transient adjoint still beyond reach on industrial cases
- Intermediate approach :

Flow is solved transient

$$\partial_t \boldsymbol{u} + \boldsymbol{\nabla}.(\boldsymbol{u} \otimes \boldsymbol{u}) + \boldsymbol{\nabla}.\Big(-(\nu + \nu_t)\big(\boldsymbol{\nabla u} + \boldsymbol{\nabla}^T\boldsymbol{u}\big)\Big) + \boldsymbol{\nabla}\mathrm{p} = \boldsymbol{0}$$
$$\boldsymbol{\nabla}.\boldsymbol{u} = 0$$

U and p are time-averaged, ν_t is discarded

$$\{\langle u\rangle, \langle p\rangle\}$$

$$\frac{\partial\tilde{\nu}}{\partial t} + u_j\frac{\partial\tilde{\nu}}{\partial x_j} = C_{b1}[1-f_{t2}]\tilde{S}\tilde{\nu} + \frac{1}{\sigma}\{\nabla\cdot[(\nu+\tilde{\nu})\nabla\tilde{\nu}] + C_{b2}|\nabla\tilde{\nu}|^2\} - \left[C_{w1}f_w - \frac{C_{b1}}{\kappa^2}f_{t2}\right]\left(\frac{\tilde{\nu}}{d}\right)^2 + f_{t1}\Delta U^2$$

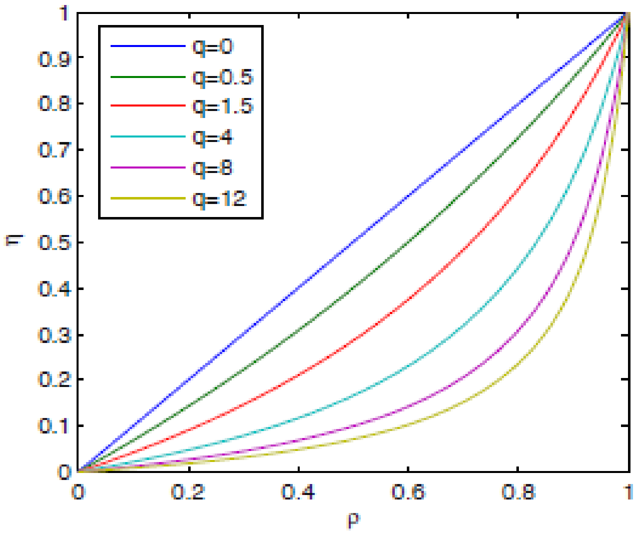
$$\tilde{\nu}$$

RANS turbulence model is run until convergence on time averaged U and p to get the consolidated turbulent viscosity to be used by the adjoint solver

NEW FEATURES
TOPOLOGY OPTIMIZATION

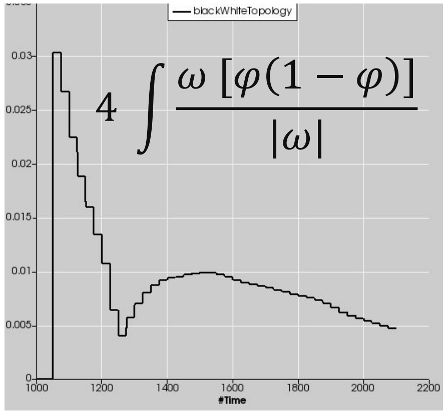
- Improved algorithm controls
  - RAMP curvature parameter (q)
  - α_{max} based on Da number
  - Step size selection
  - Primal/adjoint alternate steps layout

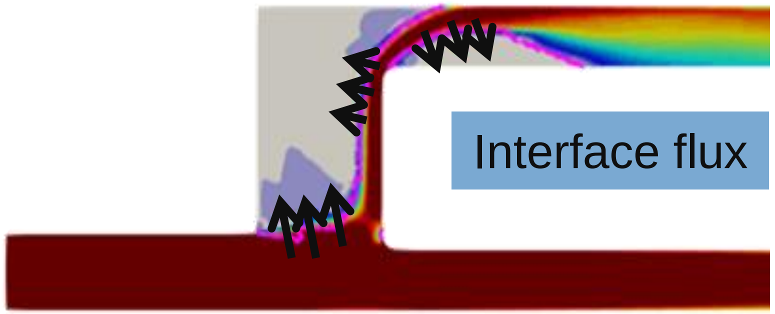
$$\alpha = \frac{\alpha_{max}\,\phi}{1 + q(1-\phi)}$$



- **Black/White Topology** and **InterfaceFlux** function objects

Black/white topology



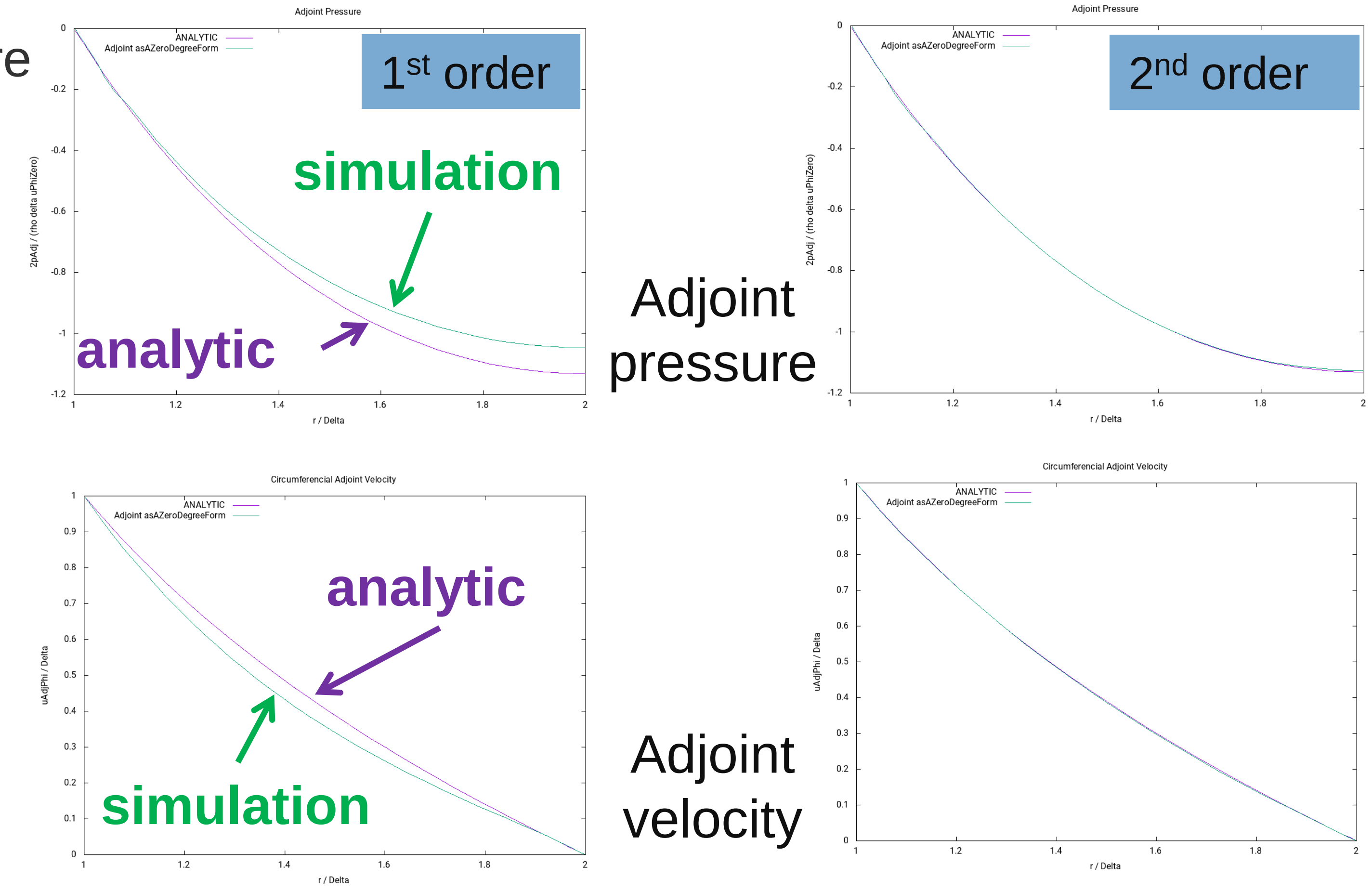


VALIDATION CASES

1^{st} vs. 2^{nd} ORDER CONVECTION SCHEME

- Non-dimensional plot of pressure and velocity analytical solutions vs. Simulation

- 2^{nd} order adjoint gives better results than 1^{st} order



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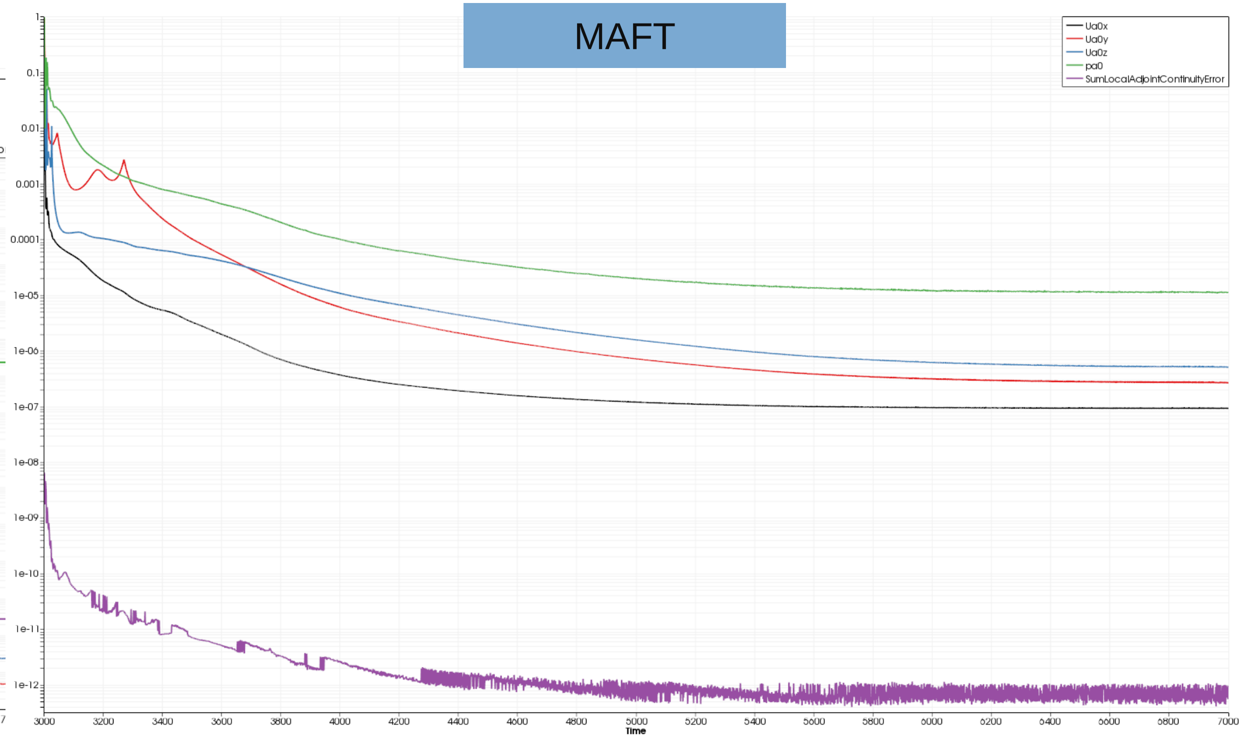
APPLICATION CASES
ASMO

- **Comparison frozen vs. MAFT**
  - Convergence of residuals expectedly lower for frozen vs. MAFT

Frozen

MAFT



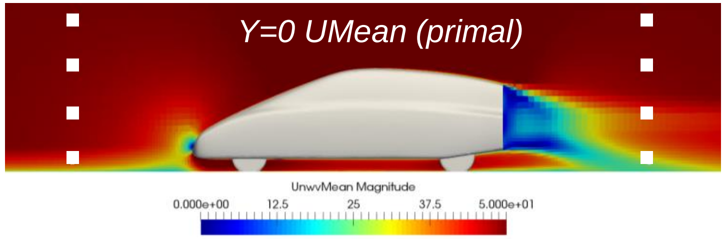
APPLICATION CASES

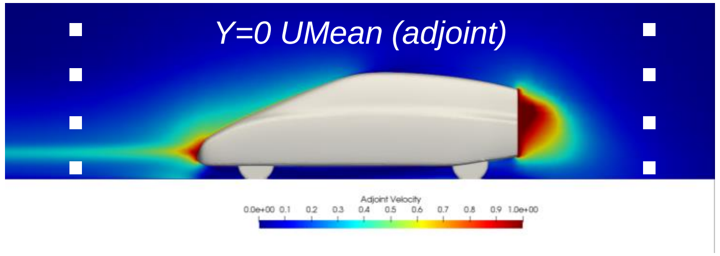
ASMO

- **Comparison frozen vs. MAFT**
  - Stable adjoint pressure at upstream/downstream probes for both frozen and MAFT solutions

Adjoint velocity at probe locations
Frozen adjoint solution

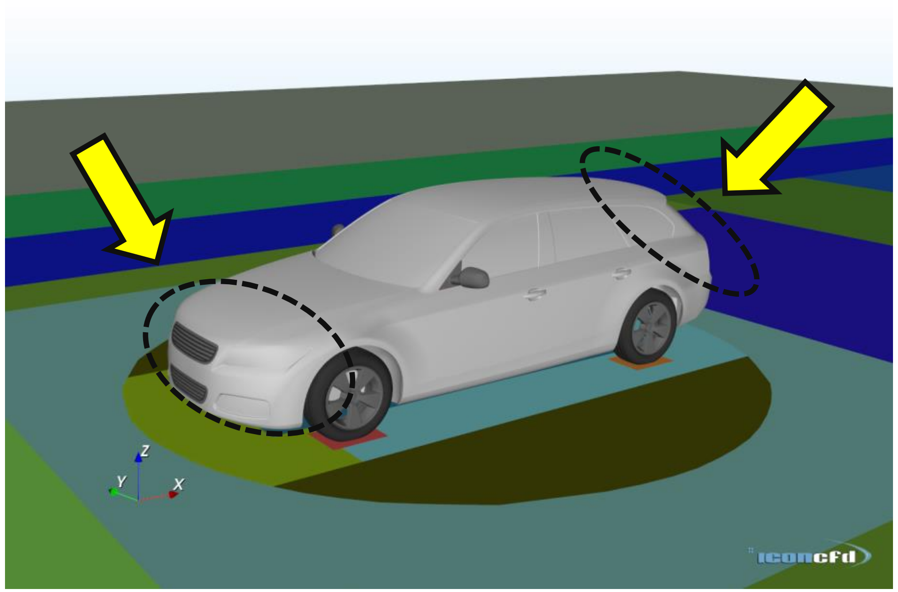
Adjoint velocity at probes locations
MAFT adjoint solution





APPLICATION CASES
DRIVAER

- **Case summary**
  - Geometry: TUM DrivAer Estate, semi-industrial case
  - Setup: Static condition, Uinlet = 30m/s, Re ~ 4.7e6, turb. RKE
  - Objective: drag reduction through one cycle of morphing
  - Setting:
    - Wheels: static
    - Front hood/bumper + rear-end pillar + spoiler: **morphing**
    - Body: follow
- **Model**
  - Mesh size: 30M / y+ ~ 40-50
  - Adjoint setting: frozen (no MAFT)
  - Max displacement / radius : 5mm / 10mm



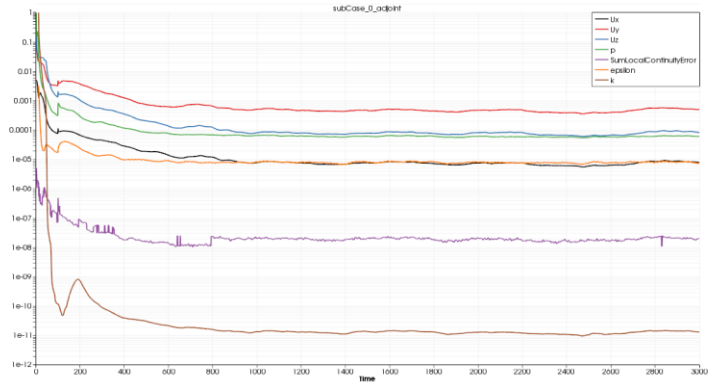
DrivAer Estate model (closed grilles) in ICON WT template – Moving conditions

Geometry courtesy of TUM

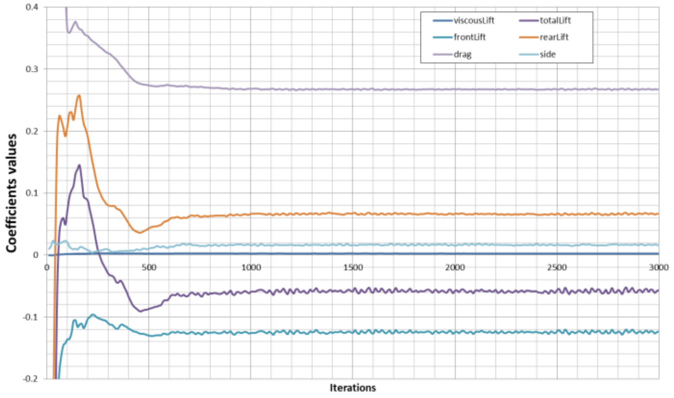
APPLICATION CASES
DRIVAER

- Primal solution
  - Level of convergence for the continuity residuals ~10^{-8}
  - Turbulence model: Realizable-kε
  - Robust solver (SIMPLEC)
- Original CD = 0.2675 (+/-0.5 counts)

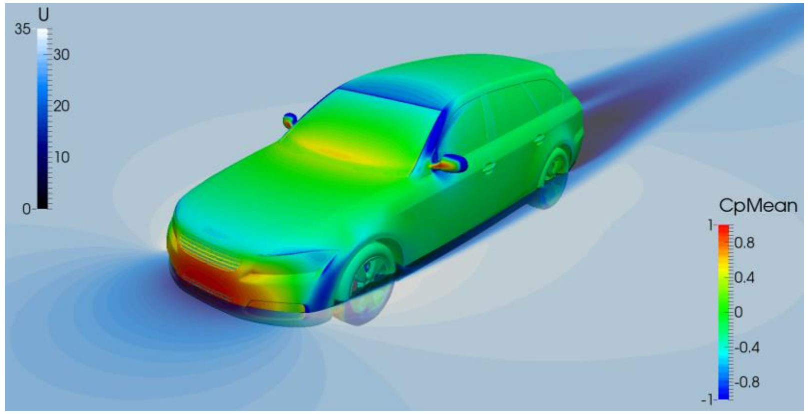
Primal residuals



Aerodynamic coefficient convergence



Primal flow solution

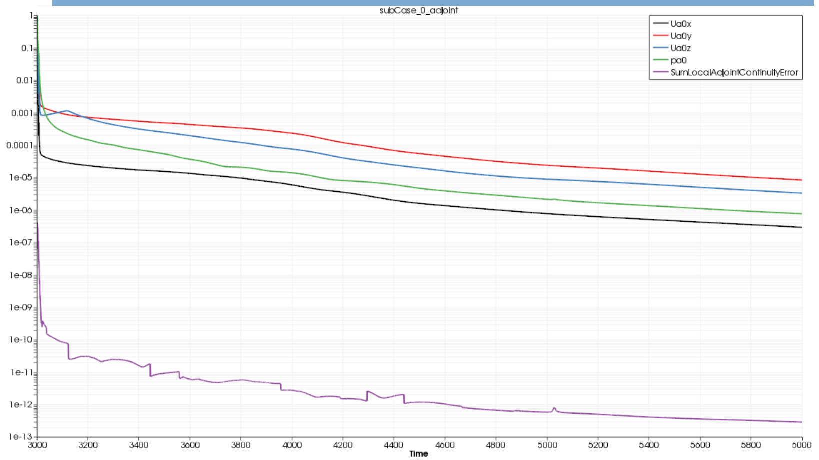


Geometry courtesy of TUM

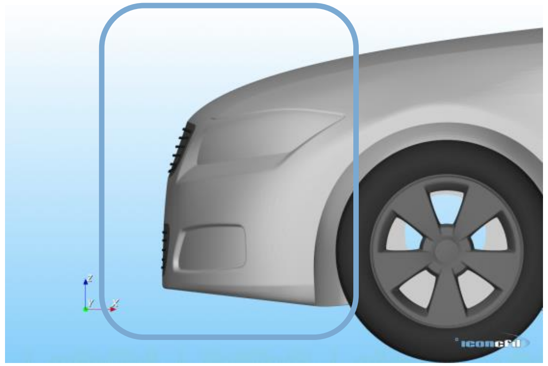
APPLICATION CASES
DRIVAER

- Adjoint solution
- Morphed geometry CD = 0.2643 (+/-0.6 counts)
- No modification of the cross section or mirrors
- **Drag reduction -3.2 counts in a single loop**

Adjoint residuals

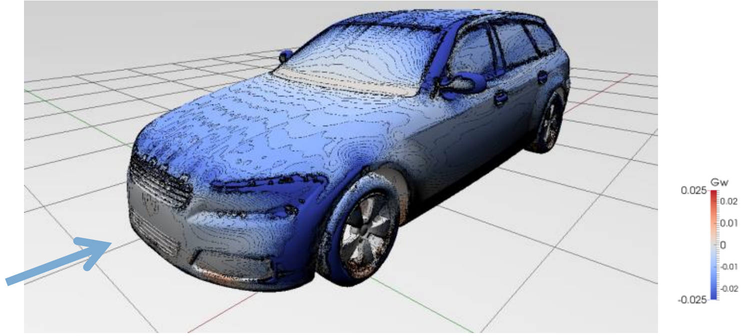


Front hood/bumper morphing

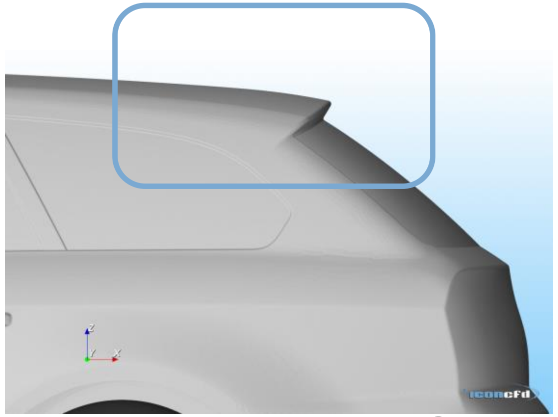


Push in
Pull out

Adjoint drag surface sensitivities



C-Pillar/spoiler morphing



Geometry courtesy of TUM

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