Airfoil Shape Optimization Using Output-Based Adapted Meshes

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Outline

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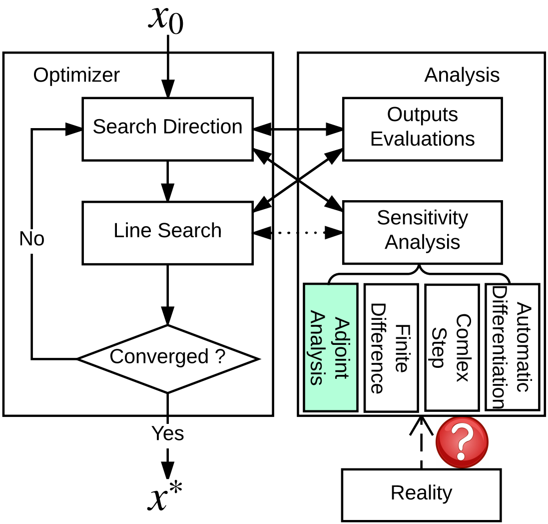
Aerodynamic Shape Design/Optimization

Design/Optimization: Numerical Optimization + CFD Analysis



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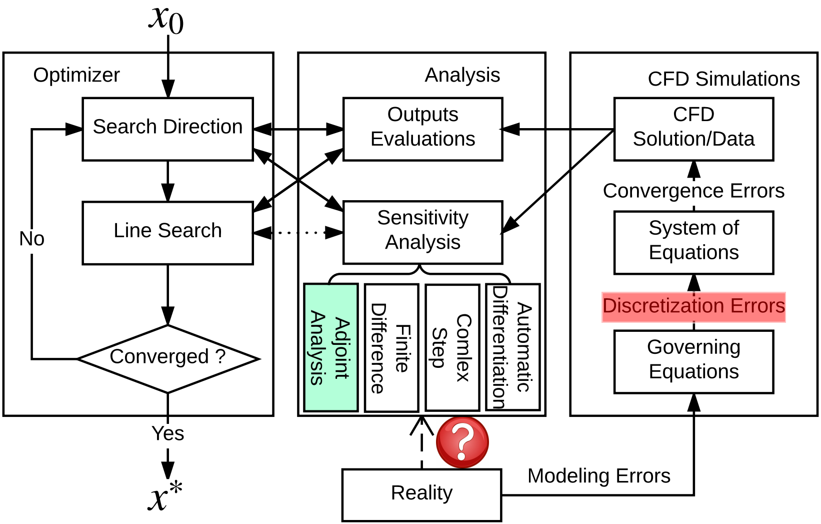


Improving Optimization Accuracy and Efficiency

Traditional methods

- a *priori* mesh: numerical error not controlled during optimization
- fixed fidelity: optimizing on fixed mesh resolution

Proposed method

- Multi-fidelity optimization: reduce the computational resources at the early stages of optimization
- Adjoint based error estimation and mesh adaptation: actively control the numerical error during the optimization
- $\xrightarrow{Integration}$ Multi-fidelity optimization driven by error estimation and mesh adaptation:
  Initial shape $\Rightarrow$ Optimal design, Coarse mesh $\Rightarrow$ Fine mesh
  Goal: prevent over-refining and over-optimizing

Outline

Optimization Problem Formulation

General optimization problem

- Determine the design variables $\mathbf{x}$ that minimize the objective function J:

$$\begin{aligned} \min_{\mathbf{x}} \quad & J(\mathbf{U}, \mathbf{x}) \\ \text{s.t.} \quad & \mathbf{R}^{\mathrm{e}}(\mathbf{U}, \mathbf{x}) = \mathbf{0} \\ & \mathbf{R}^{\mathrm{ie}}(\mathbf{U}, \mathbf{x}) \geq \mathbf{0} \end{aligned}$$

- $\mathbf{U}$ denotes the flow variables, $\mathbf{R}^{\mathrm{e}}$ and $\mathbf{R}^{\mathrm{ie}}$ are the equality and inequality constraints.

Aerodynamic optimization

- Objective and constraints are aerodynamic outputs
- Physical feasibility: Flow variables $\mathbf{U}$ are solved within a feasible design space Ω to satisfy the flow equations,

$$\mathbf{R}(\mathbf{U}, \mathbf{x}) = \mathbf{0}, \quad \forall\, \mathbf{x} \in \Omega$$

Adjoint and Design Equations

Objective and trim constraints

- Objective outputs: directly targeted for mesh adaptation, denoted as J^{adapt}
- Trim constraints: We only consider the equality constraints $\mathbf{R}^{\text{e}}$ and active inequality constraints $\mathbf{R}_{\text{a}}^{\text{ie}}$,

$$\mathbf{R}^{\text{trim}} = [\mathbf{R}^{\text{e}}\ \mathbf{R}_{\text{a}}^{\text{ie}}]^T = \mathbf{J}^{\text{trim}} - \bar{\mathbf{J}}^{\text{trim}} = \mathbf{0}$$

Augmented Lagrangian functions

The adjoint-based optimization is equivalent to searching for the stationary point of the augmented Lagrangian function,

$$\mathcal{L}(\mathbf{U}, \mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = J^{\text{adapt}}(\mathbf{U}, \mathbf{x}) + \boldsymbol{\lambda}^T \mathbf{R}(\mathbf{U}, \mathbf{x}) + \boldsymbol{\mu}^T \mathbf{R}^{\text{trim}}(\mathbf{U}, \mathbf{x})$$

where $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$ are Lagrange multipliers associated with the flow equations and the trim constraints, respectively

Optimality Condition

- First-order optimality (Karush-Kuhn-Tucker) condition

$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}} = \frac{\partial J^{\text{adapt}}}{\partial \mathbf{x}} + \boldsymbol{\lambda}^T \frac{\partial \mathbf{R}}{\partial \mathbf{x}} + \boldsymbol{\mu}^T \frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{x}} = \mathbf{0} \qquad \text{optimal design}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{U}} = \frac{\partial J^{\text{adapt}}}{\partial \mathbf{U}} + \boldsymbol{\lambda}^T \frac{\partial \mathbf{R}}{\partial \mathbf{U}} + \boldsymbol{\mu}^T \frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{U}} = \mathbf{0} \qquad \text{coupled adjoint}$$

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\lambda}} = \mathbf{R}(\mathbf{U}, \mathbf{x}) = \mathbf{0} \qquad \text{physics feasibility}$$

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\mu}} = \mathbf{R}^{\text{trim}}(\mathbf{U}, \mathbf{x}) = \mathbf{0} \qquad \text{trim condition}$$

- Always physically feasible: $\mathbf{R}(\mathbf{U}, \mathbf{x}) = \mathbf{0}$
- Choose coupled adjoints variables, such that,

$$\frac{\partial \mathcal{L}}{\partial \mathbf{U}} = \mathbf{0} \Rightarrow \boldsymbol{\lambda}^T = -\left(\frac{\partial J^{\text{adapt}}}{\partial \mathbf{U}} + \boldsymbol{\mu}^T \frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{U}} \right) \frac{\partial \mathbf{R}}{\partial \mathbf{U}}^{-1}$$
$$= (\boldsymbol{\Psi}^{\text{adapt}} + \boldsymbol{\Psi}^{\text{trim}} \boldsymbol{\mu})^T$$

Reduced optimality condition

- Coupled adjoints: $\boldsymbol{\lambda}^T = (\boldsymbol{\Psi}^{\text{adapt}} + \boldsymbol{\Psi}^{\text{trim}}\boldsymbol{\mu})^T$, where

$$\frac{\partial \mathbf{R}}{\partial \mathbf{U}}^T \boldsymbol{\Psi}^{\text{adapt}} + \frac{\partial J^{\text{adapt}}}{\partial \mathbf{U}}^T = \mathbf{0}, \qquad \frac{\partial \mathbf{R}}{\partial \mathbf{U}}^T \boldsymbol{\Psi}^{\text{trim}} + \frac{\partial \mathbf{J}^{\text{trim}}}{\partial \mathbf{U}}^T = \mathbf{0}$$

- Sensitivity Analysis

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \mathbf{x}} &= \frac{\partial J^{\text{adapt}}}{\partial \mathbf{x}} + \boldsymbol{\lambda}^T \frac{\partial \mathbf{R}}{\partial \mathbf{x}} + \boldsymbol{\mu}^T \frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{x}} \\
&= \frac{\partial J^{\text{adapt}}}{\partial \mathbf{x}} + (\boldsymbol{\Psi}^{\text{adapt}})^T \frac{\partial \mathbf{R}}{\partial \mathbf{x}} + \boldsymbol{\mu}^T \left[\frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{x}} + (\boldsymbol{\Psi}^{\text{trim}})^T \frac{\partial \mathbf{R}}{\partial \mathbf{x}} \right] \\
&= \frac{dJ^{\text{adapt}}}{d\mathbf{x}} + \boldsymbol{\mu}^T \frac{d\mathbf{J}^{\text{trim}}}{d\mathbf{x}}
\end{aligned}$$

- Reduced optimality condition:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \mathbf{x}} &= \frac{dJ^{\text{adapt}}}{d\mathbf{x}} + \boldsymbol{\mu}^T \frac{d\mathbf{J}^{\text{trim}}}{d\mathbf{x}} = \mathbf{0} \\
\frac{\partial \mathcal{L}}{\partial \boldsymbol{\mu}} &= \mathbf{R}^{\text{trim}} = \mathbf{0}
\end{aligned}$$

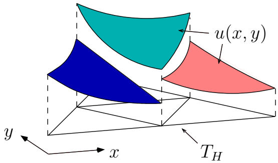
Outline

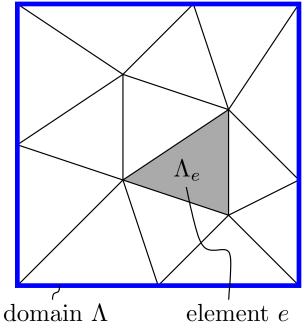
Discretization

- Conservation law: $\partial_t \mathbf{u} + \nabla \cdot \vec{\mathbf{H}}(\mathbf{u}, \nabla \mathbf{u}) = \mathbf{0}$
  where $\underbrace{\vec{\mathbf{H}}}_{\text{total flux}} = \underbrace{\vec{\mathbf{F}}(\mathbf{u})}_{\text{inviscid flux}} + \underbrace{\vec{\mathbf{G}}(\mathbf{u}, \nabla \mathbf{u})}_{\text{viscous flux}}$

- DG approx of order p_e on each element:

$$\mathbf{u}_h(\vec{x}) = \sum_{e=1}^{N_e} \sum_{n=1}^{N_p} \mathbf{U}_{e,n} \phi_{e,n}(\vec{x})$$





N_e	=	# of elements
p_e	=	approx order on element e
N_{p_e}	=	# of basis fcns on element e
$\phi_{e,n}(\vec{x})$	=	n^{th} basis fcn of order p_e on e
$\mathbf{U}_{e,n}$	=	coefficients vector of n^{th} basis function on element e

Outline

Output-Based Error Estimation

For a given configuration (design) $\mathbf{x}$, the outputs (objective and constraints) are based on a **pure** CFD flow solve.

Output Error: $\delta J = J_H(\mathbf{U}_H, \mathbf{x}) - J(\mathbf{U}, \mathbf{x})$

This is the difference between J computed with the discrete system solution, $\mathbf{U}_H$, and J computed with the *exact* solution, $\mathbf{U}$.

Error Surrogate: $\delta J = J_H(\mathbf{U}_H, \mathbf{x}) - J_h(\mathbf{U}_h, \mathbf{x})$

The difference between outputs on coarse and fine discretizations.

$$\text{coarse space:} \rightarrow \underbrace{\mathbf{R}_H(\mathbf{U}_H, \mathbf{x}) = \mathbf{0}}_{N_H \text{ flow equations}} \rightarrow \underbrace{\mathbf{U}_H}_{\text{state} \in \mathbb{R}^{N_H}} \rightarrow J_H(\mathbf{U}_H, \mathbf{x})$$

$$\text{fine space:} \rightarrow \underbrace{\mathbf{R}_h(\mathbf{U}_h, \mathbf{x}) = \mathbf{0}}_{N_h \text{ flow equations}} \rightarrow \underbrace{\mathbf{U}_h}_{\text{state} \in \mathbb{R}^{N_h}} \rightarrow J_h(\mathbf{U}_h, \mathbf{x})$$

Adjoint-based Error Estimation

- State injection: $\mathbf{U}_h^H = \mathbf{I}_h^H \mathbf{U}_H$
- $\mathbf{U}_h^H$ will generally not satisfy the fine-space equations,

$$\mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x}) \neq \mathbf{0}$$

- Recall the definition of the output adjoint, $\frac{\partial \mathbf{R}}{\partial \mathbf{U}}^T \boldsymbol{\Psi} + \frac{\partial J}{\partial \mathbf{U}}^T = \mathbf{0}$. $\boldsymbol{\Psi}$ relates the residual perturbation to an output perturbation,

$$\delta J = \underbrace{\frac{\partial J}{\partial \mathbf{U}} \delta \mathbf{U} = \overbrace{-\boldsymbol{\Psi}^T \frac{\partial \mathbf{R}}{\partial \mathbf{U}} \delta \mathbf{U}}^{\text{residual linearization}}}_{\text{adjoint definition}} \approx -\boldsymbol{\Psi}^T \delta \mathbf{R}$$

$$\begin{aligned} \delta J &= J_H(\mathbf{U}_H, \mathbf{x}) - J_h(\mathbf{U}_h, \mathbf{x}) = J_h(\mathbf{U}_h^H, \mathbf{x}) - J_h(\mathbf{U}_h, \mathbf{x}) \\ &\approx -\boldsymbol{\Psi}_h^T \delta \mathbf{R}_h = -\boldsymbol{\Psi}_h^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x}) \end{aligned}$$

- Error (Adapt) indicator: the error is localized in each element and serves as an adaptation indicator, $\eta_e = |\boldsymbol{\Psi}_{h,e}^T \mathbf{R}_{h,e}(\mathbf{U}_h^H, \mathbf{x})|$

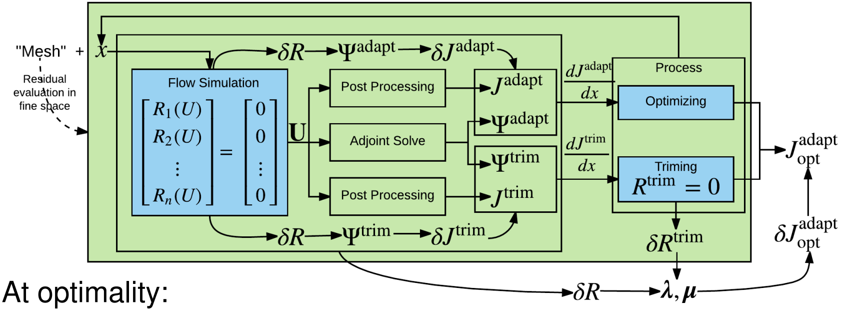
Error Estimation and Mesh Adaptation for Optimization

- Numerical error affects both objective and constraint outputs.
- How to estimate the error and adapt the mesh efficiently?
- Both errors can be obtained via adjoints.
- Possible adaptation strategies:
  1. Adapt only on the objective
     Error due to inexact constraints satisfaction
  2. Adapt equally on the objective and constraints
     Inefficient, expensive to keep all outputs very accurate
  3. Adapt on combined/weighted outputs
     The weights? Adapt more on objective/constraints?
  4. Adapt on the optimization problem (coupled adjoint)

$$\text{coarse space: } \mathbf{x}_0 \rightarrow \text{optimization} \rightarrow \underbrace{\mathbf{x}_H^*, \mathbf{U}_H}_{\text{optimal design}} \rightarrow J_H(\mathbf{U}_H, \mathbf{x}_H^*)$$

$$\text{fine space: } \mathbf{x}_0 \rightarrow \text{optimization} \rightarrow \underbrace{\mathbf{x}_h^*, \mathbf{U}_h}_{\text{optimal design}} \rightarrow J_h(\mathbf{U}_h, \mathbf{x}_h^*)$$

Error Estimation and Mesh Adaptation for Optimization



At optimality:

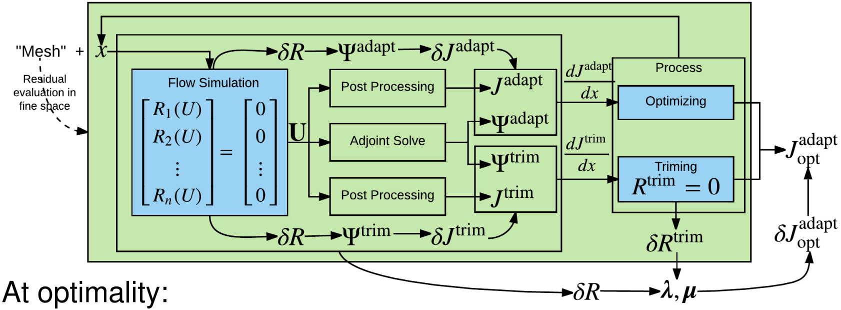
$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}} = \frac{\partial J^{\text{adapt}}}{\partial \mathbf{x}} + \boldsymbol{\lambda}^T \frac{\partial \mathbf{R}}{\partial \mathbf{x}} + \boldsymbol{\mu}^T \frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{x}} = \mathbf{0}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{U}} = \frac{\partial J^{\text{adapt}}}{\partial \mathbf{U}} + \boldsymbol{\lambda}^T \frac{\partial \mathbf{R}}{\partial \mathbf{U}} + \boldsymbol{\mu}^T \frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{U}} = \mathbf{0}$$

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\lambda}} = \mathbf{R}(\mathbf{U}, \mathbf{x}) = \mathbf{0}$$

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\mu}} = \mathbf{R}^{\text{trim}}(\mathbf{U}, \mathbf{x}) = \mathbf{0}$$

Error Estimation and Mesh Adaptation for Optimization



At optimality:

$$
\begin{aligned}
\delta J_{\text{opt}}^{\text{adapt}} &= -\boldsymbol{\lambda}_h^T \delta \mathbf{R}_h - \boldsymbol{\mu}_h^T \delta \mathbf{R}_h^{\text{trim}} \\
&= -\boldsymbol{\lambda}_h^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x}_H) - \boldsymbol{\mu}_h^T \mathbf{R}_h^{\text{trim}}(\mathbf{U}_h^H, \mathbf{x}_H) \\
&= -(\boldsymbol{\Psi}_h^{\text{adapt}} + \boldsymbol{\Psi}_h^{\text{trim}} \boldsymbol{\mu}_h)^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x}_H) - \boldsymbol{\mu}_h^T \underbrace{\left(\mathbf{J}_h^{\text{trim}}(\mathbf{U}_h^H, \mathbf{x}_H) - \bar{\mathbf{J}}^{\text{trim}}\right)}_{\approx \mathbf{0}} \\
&= \delta J^{\text{adapt}}(\mathbf{x}_H) + \boldsymbol{\mu}_h^T \delta \mathbf{J}^{\text{trim}}(\mathbf{x}_H)
\end{aligned}
$$

Note: $\mathbf{J}_h^{\text{trim}}(\mathbf{U}_h^H, \mathbf{x}_H) = \mathbf{J}_H^{\text{trim}}(\mathbf{U}_H, \mathbf{x}_H) = \bar{\mathbf{J}}^{\text{trim}} = \mathbf{J}_h^{\text{trim}}(\mathbf{U}_h, \mathbf{x}_h)$

Error Estimation and Mesh Adaptation for Optimization

Optimality error estimation

$$\frac{dJ^{\text{adapt}}}{d\mathbf{x}} + \boldsymbol{\mu}^T \frac{d\mathbf{J}^{\text{trim}}}{d\mathbf{x}} = \mathbf{0}$$

$$\delta J^{\text{adapt}}_{\text{opt}} = \underbrace{\delta J^{\text{adapt}}(\mathbf{x}_H)}_{\text{objective error only}} + \underbrace{\boldsymbol{\mu}_h^T \delta \mathbf{J}^{\text{trim}}(\mathbf{x}_H)}_{\text{inexact constraints satisfaction}}$$

What does μ mean?
It is the objective sensitivity w.r.t constraints and measures how much the constraints error can affect the optimal objective.

Mesh adaptation implementation

Adapt (error) indicator: $\eta_\kappa = |\boldsymbol{\Psi}^T_{h,\kappa} \mathbf{R}_{h,\kappa}(\mathbf{U}^H_h, \mathbf{x}_H)|$

Combined indicator: $\eta_{\kappa,\text{opt}} = \eta^{\text{adapt}}_\kappa + |\boldsymbol{\mu}|^T \boldsymbol{\eta}^{\text{trim}}_\kappa$

$\boldsymbol{\Psi}_h$: reconstructing the coarse-space adjoints $\boldsymbol{\Psi}_H$

$\boldsymbol{\mu}_h$: extracted from the optimizer on the coarse space

Outline

Multi-fidelity Optimization with Error Control

Geometry and Mesh

- Airfoil parameterization: Hicks-Henne basis function
- Design parameters: airfoil shape + angle of attack
- Mesh movement: Radial Basis Function (RBF) interpolation

Optimization Algorithm

- Sequential Least Squares Programming (SLSQP)
- Broyden-Fletcher-Goldfarb-Shanno (BFGS) Hessian update
- Inexact line search: weak Wolfe condition

Multi-fidelity Optimization with Error Control

Geometry and Mesh

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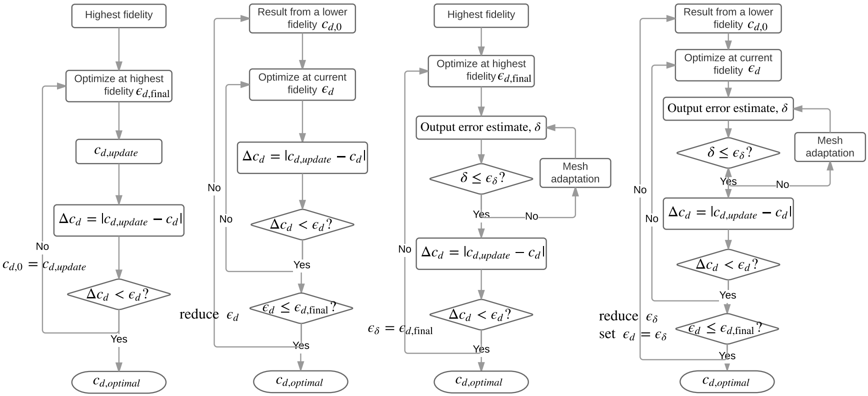

Outline

Laminar, Subsonic Flow (nearly feasible starting point)

NACA 0012, $Re = 5000$, $M_\infty = 0.5$, $\alpha_0 = 0^\circ$
$J^{\text{adapt}} = c_d$, $J^{\text{trim}} = c_l$, $\bar{J}^{\text{trim}} = 0.02$, $A \geq A_{min}$

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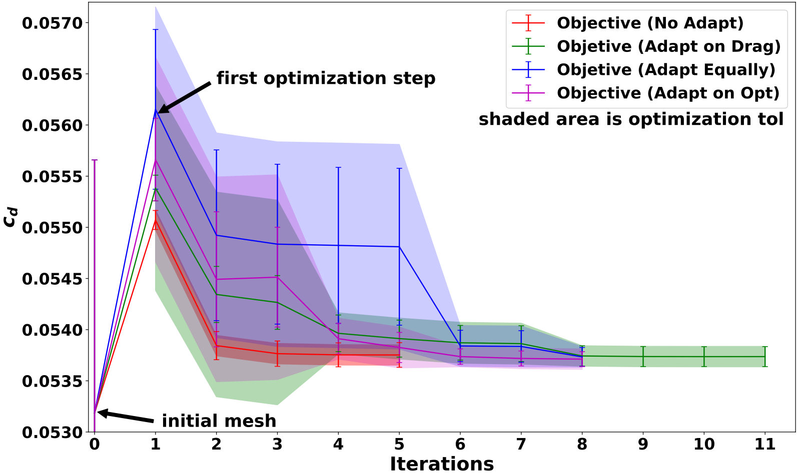

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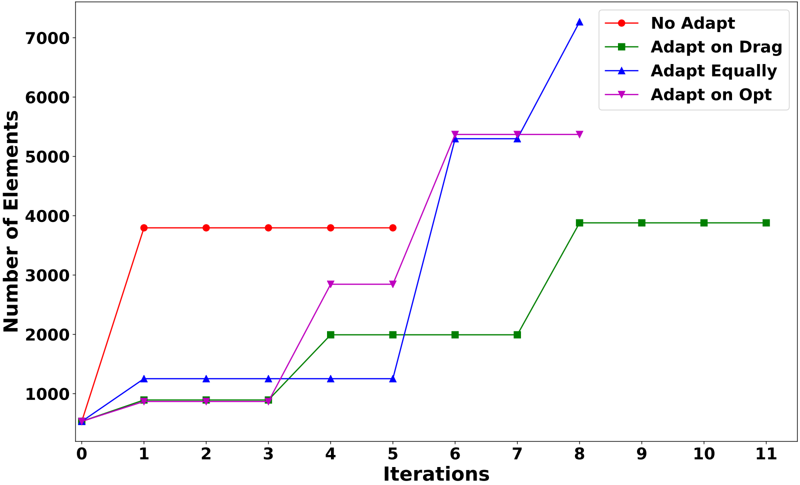
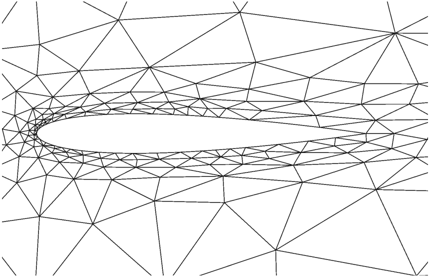
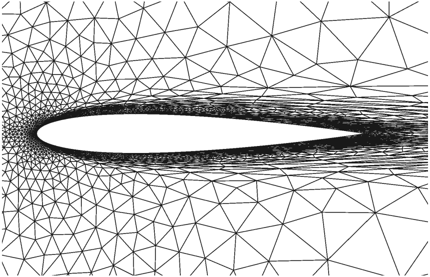


Mesh Evolution



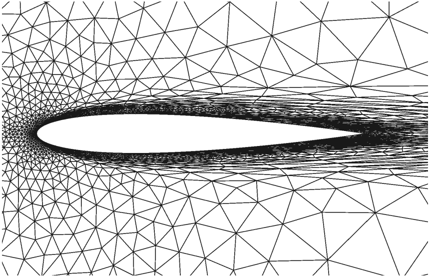
initial mesh (533 elements)

Mesh Evolution



no adapt (3796 elements)

Mesh Evolution



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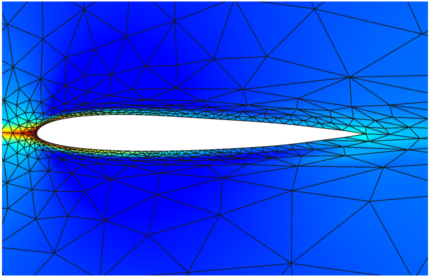
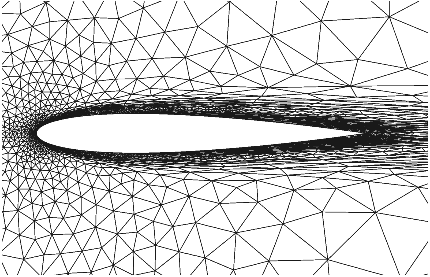


drag adapt (894 elems, Ψ^{adapt})

Mesh Evolution



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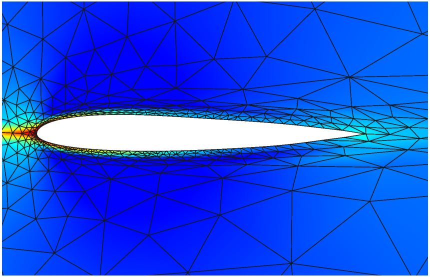

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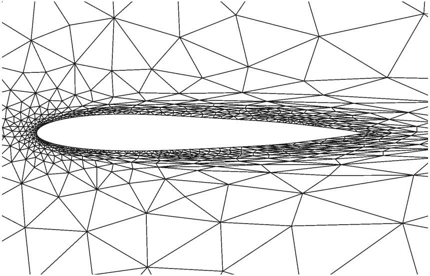
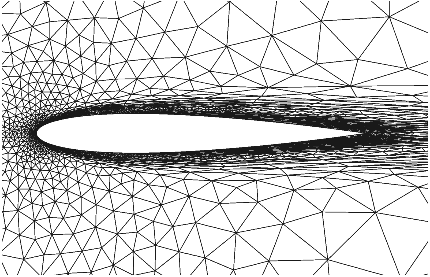


adapt equally (1253 elements)

Mesh Evolution



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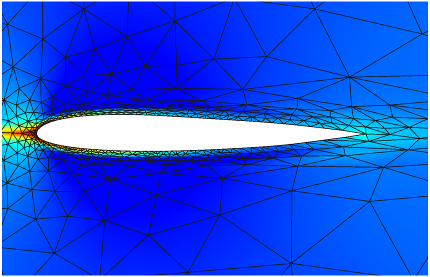
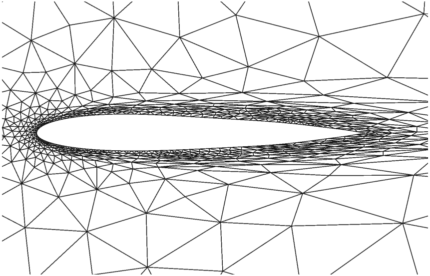
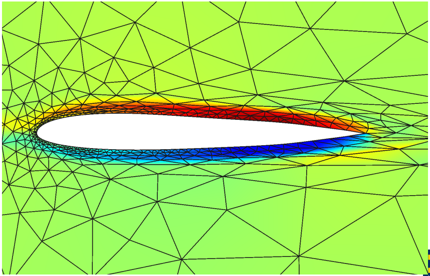


drag adapt (894 elems, Ψ^{adapt})

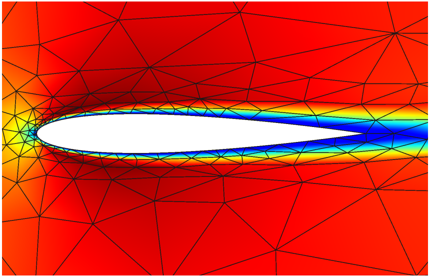


adapt equally (1253 elements)



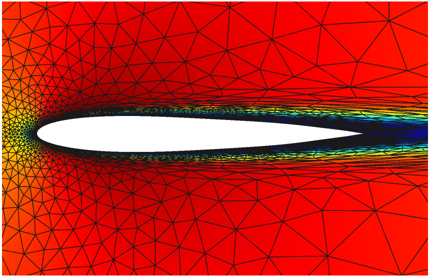
opt adapt (869 elems, Ψ^{trim})

Optimized design (Mach Contour $0 \sim 0.6$)



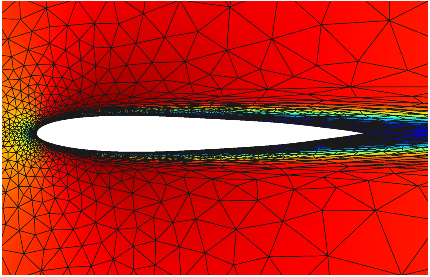
initial airfoil ($\alpha = 0°$)

Optimized design (Mach Contour $0 \sim 0.6$)

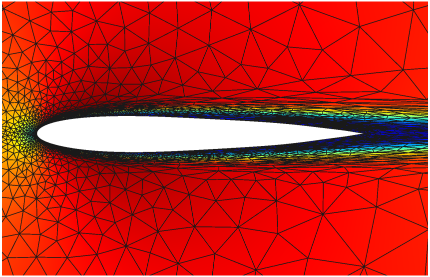


no adapt ($\alpha = 0.27^{\circ}$)

Optimized design (Mach Contour $0 \sim 0.6$)

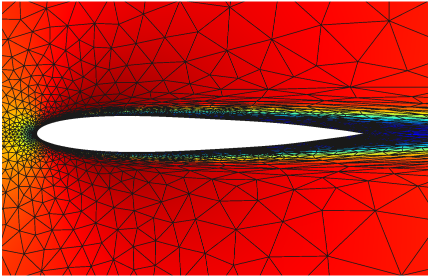


no adapt ($\alpha = 0.27°$)

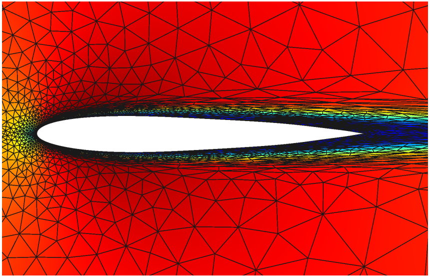


adapt on drag ($\alpha = 0.30°$)

Optimized design (Mach Contour $0 \sim 0.6$)



no adapt ($\alpha = 0.27°$)



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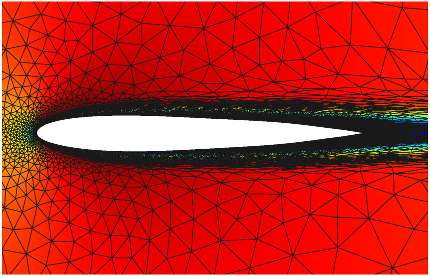
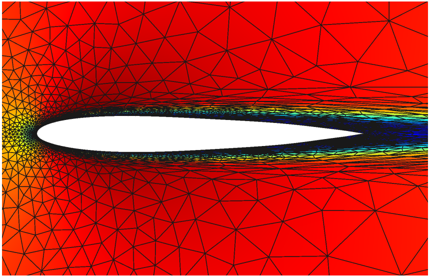
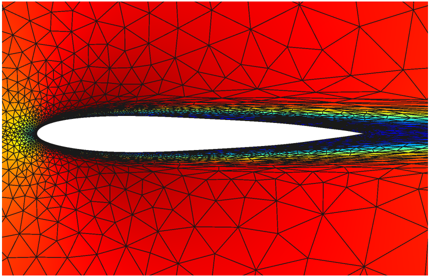


adapt equally ($\alpha = 0.25°$)

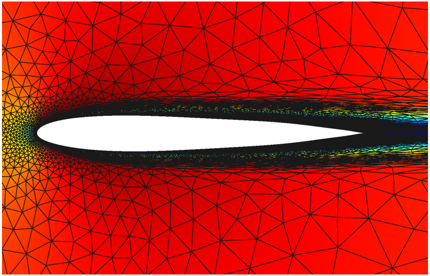
Optimized design (Mach Contour $0 \sim 0.6$)



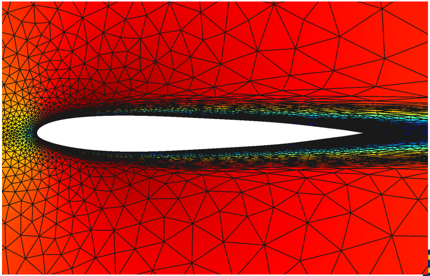
no adapt ($\alpha = 0.27°$)



adapt on drag ($\alpha = 0.30°$)

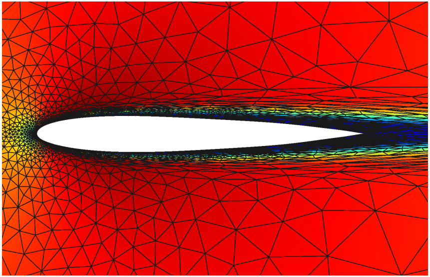


adapt equally ($\alpha = 0.25°$)

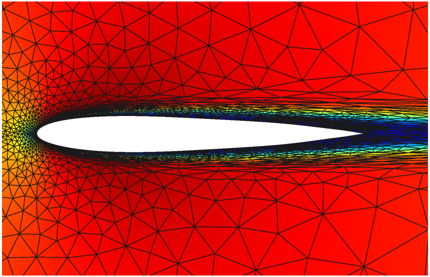


adapt on opt ($\alpha = 0.24°$)

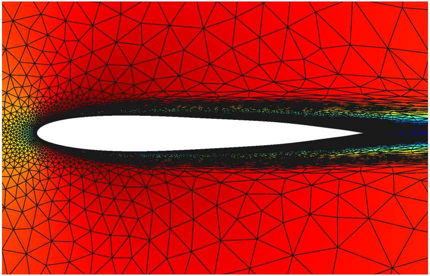
Optimized design (Mach Contour $0 \sim 0.6$)



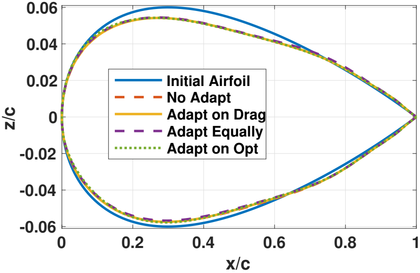
no adapt ($\alpha = 0.27°$)



adapt on drag ($\alpha = 0.30°$)



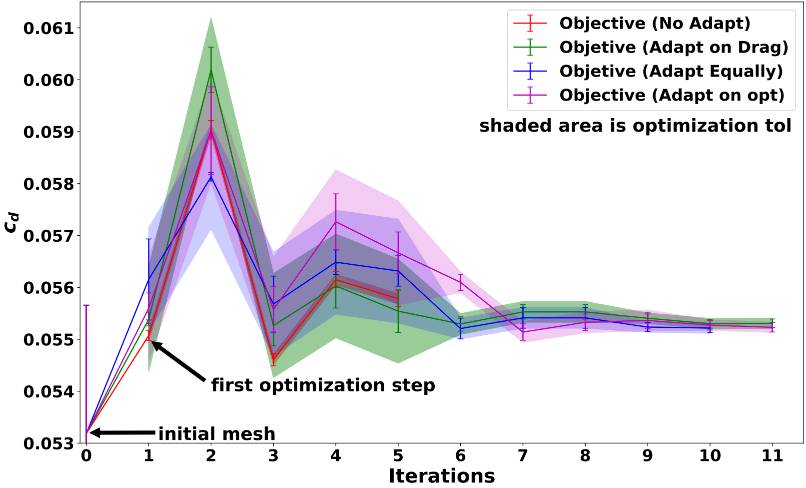
adapt equally ($\alpha = 0.25°$)



final design

Laminar, Subsonic Flow (infeasible starting point)

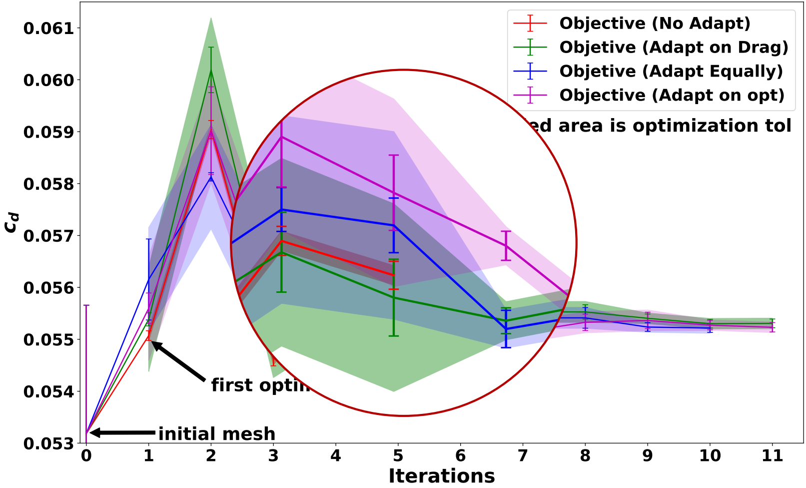
NACA 0012, $Re = 5000$, $M_\infty = 0.5$, $\alpha_0 = 0^\circ$
$J^{\text{adapt}} = c_d$, $J^{\text{trim}} = c_l$, $\bar{J}^{\text{trim}} = 0.1$, $A \geq A_{min}$



Laminar, Subsonic Flow (infeasible starting point)

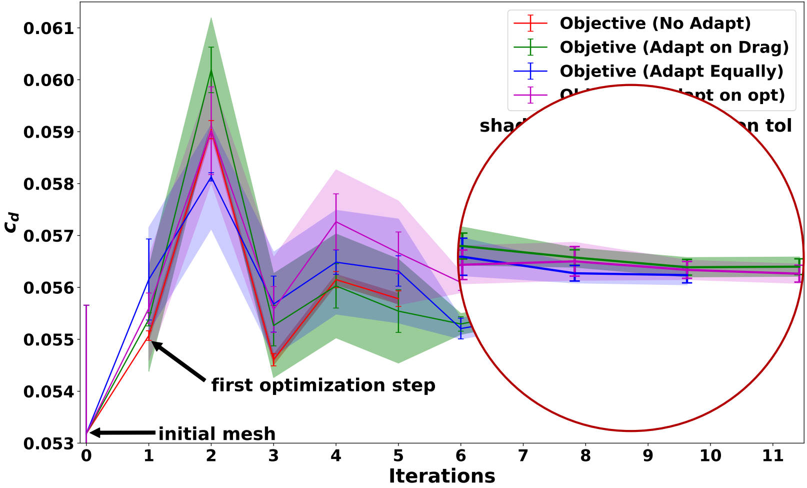
NACA 0012, $Re = 5000$, $M_\infty = 0.5$, $\alpha_0 = 0^\circ$

$J^{\text{adapt}} = c_d$, $J^{\text{trim}} = c_l$, $\bar{J}^{\text{trim}} = 0.1$, $A \geq A_{min}$



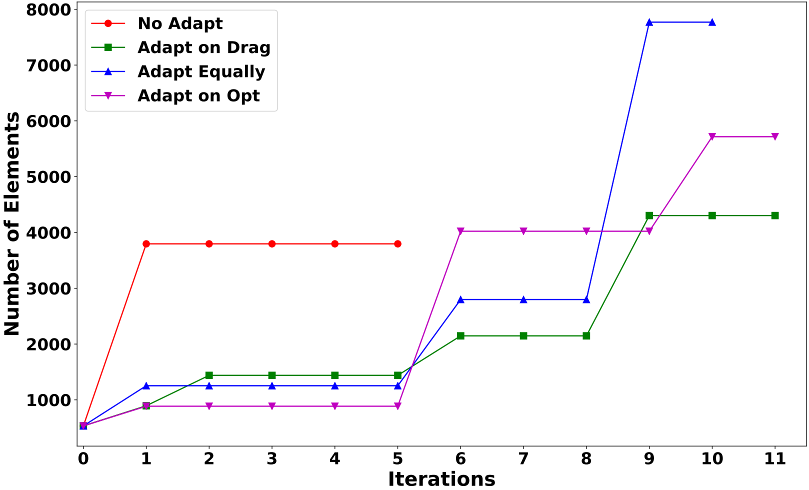
Laminar, Subsonic Flow (infeasible starting point)

NACA 0012, $Re = 5000$, $M_\infty = 0.5$, $\alpha_0 = 0^\circ$
$J^{\text{adapt}} = c_d$, $J^{\text{trim}} = c_l$, $\bar{J}^{\text{trim}} = 0.1$, $A \geq A_{min}$

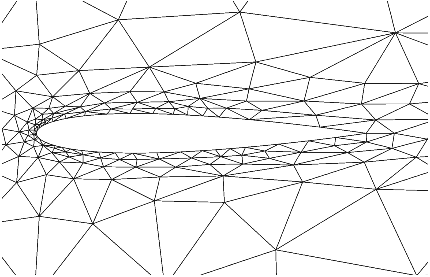


Laminar, Subsonic Flow (infeasible starting point)

NACA 0012, $Re = 5000$, $M_\infty = 0.5$, $\alpha_0 = 0°$
$J^{\text{adapt}} = c_d$, $J^{\text{trim}} = c_l$, $\bar{J}^{\text{trim}} = 0.1$, $A \geq A_{min}$

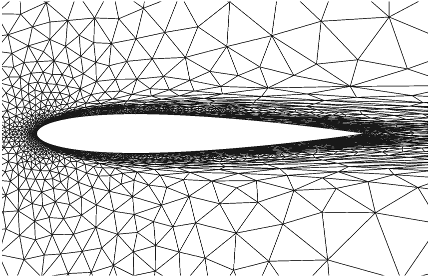


Mesh Evolution



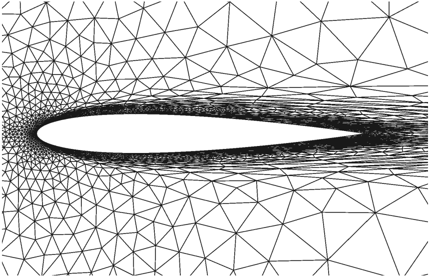
initial mesh (533 elements)

Mesh Evolution

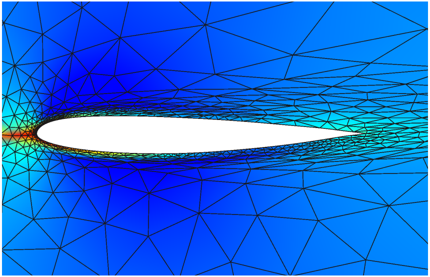


no adapt (3796 elements)

Mesh Evolution

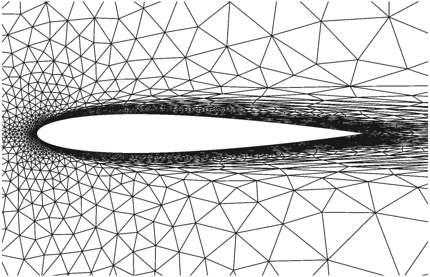


no adapt (3796 elements)

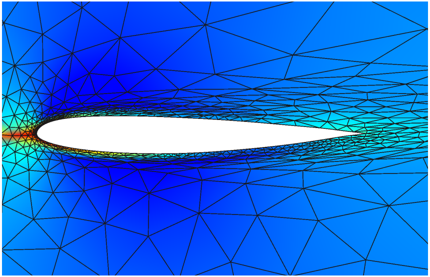


drag adapt (1439 elems, $\mathbf{\Psi}^{\text{adapt}}$)

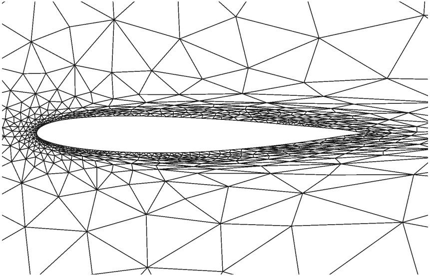
Mesh Evolution



no adapt (3796 elements)

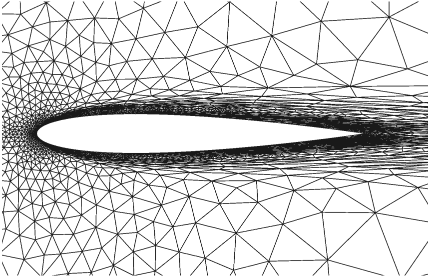


drag adapt (1439 elems, Ψ^{adapt})

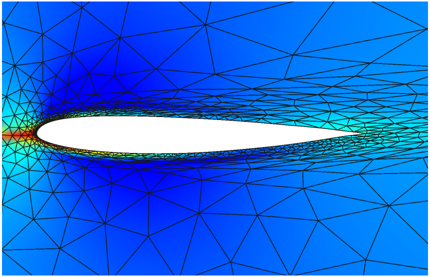


adapt equally (1253 elems)

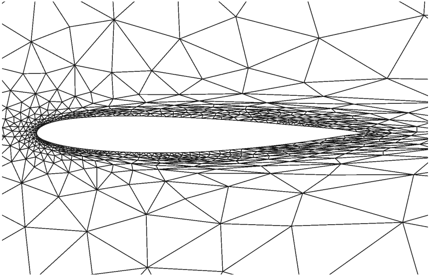
Mesh Evolution



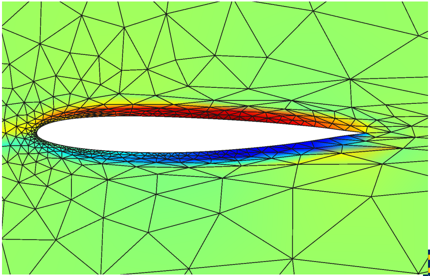
no adapt (3796 elements)



drag adapt (1439 elems, Ψ^{adapt})

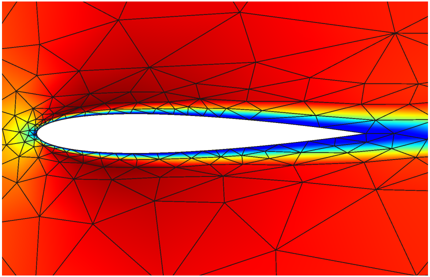


adapt equally (1253 elems)



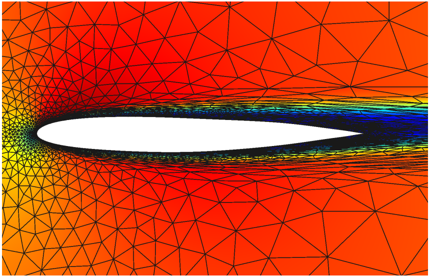
opt adapt (886 elems, Ψ^{trim})

Optimized design (Mach Contour $0 \sim 0.6$)



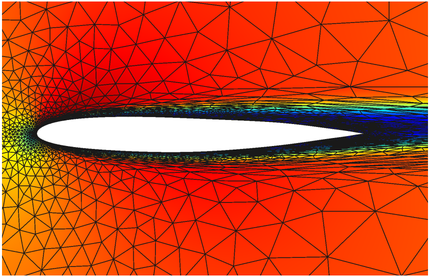
initial airfoil ($\alpha = 0^\circ$)

Optimized design (Mach Contour $0 \sim 0.6$)

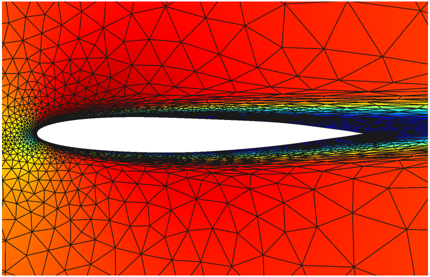


no adapt ($\alpha = 2.53°$)

Optimized design (Mach Contour $0 \sim 0.6$)

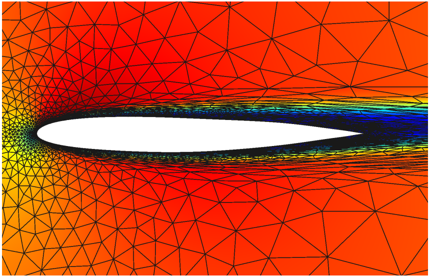


no adapt ($\alpha = 2.53°$)

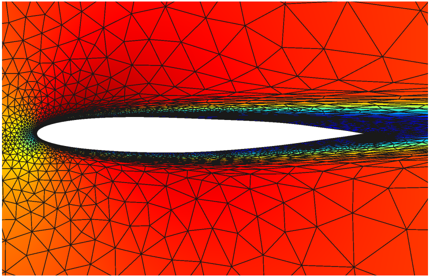


adapt on drag ($\alpha = 2.46°$)

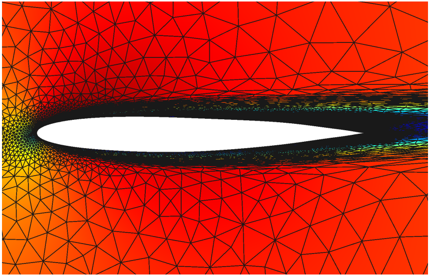
Optimized design (Mach Contour $0 \sim 0.6$)



no adapt ($\alpha = 2.53^\circ$)

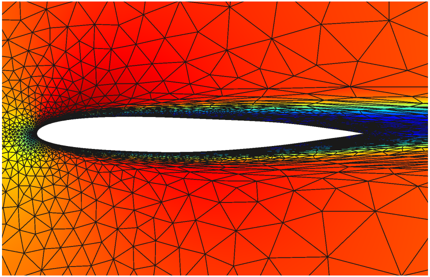


adapt on drag ($\alpha = 2.46^\circ$)

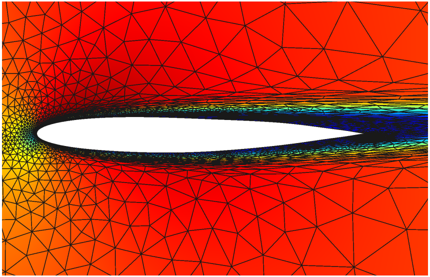


adapt equally ($\alpha = 2.39^\circ$)

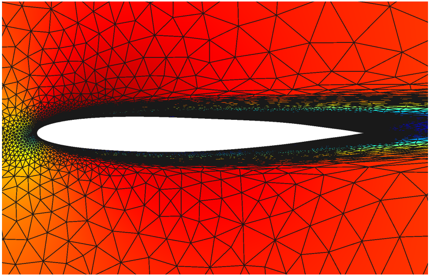
Optimized design (Mach Contour $0 \sim 0.6$)



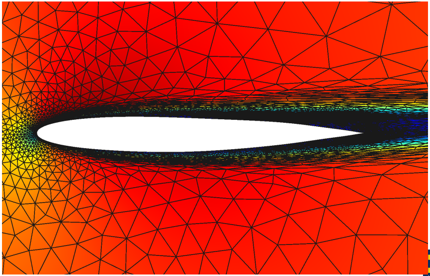
no adapt ($\alpha = 2.53°$)



adapt on drag ($\alpha = 2.46°$)

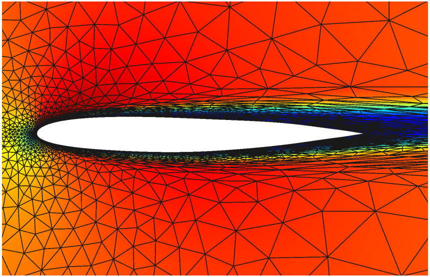


adapt equally ($\alpha = 2.39°$)

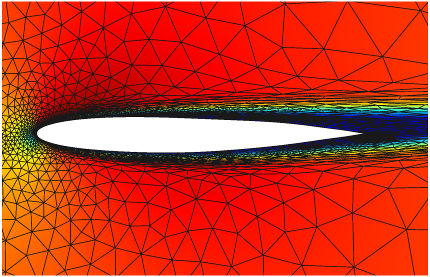


adapt on opt ($\alpha = 2.40°$)

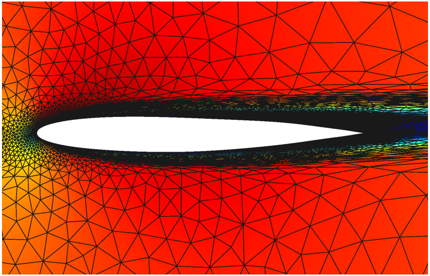
Optimized design (Mach Contour $0 \sim 0.6$)



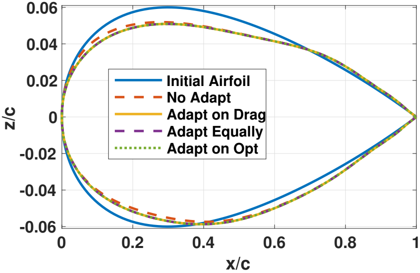
no adapt ($\alpha = 2.53°$)



adapt on drag ($\alpha = 2.46°$)



adapt equally ($\alpha = 2.39°$)

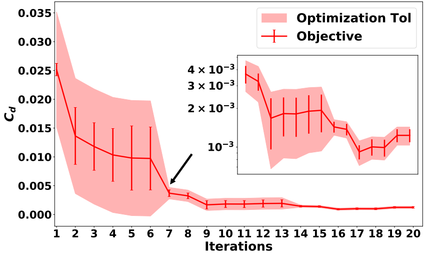


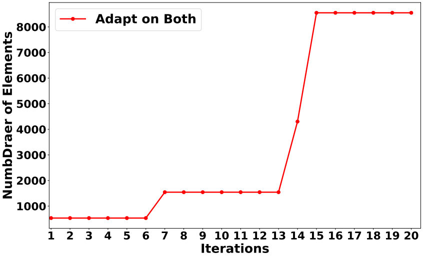
final design

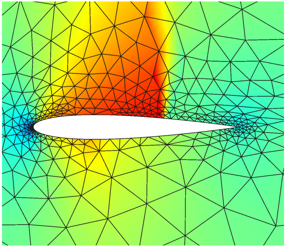
Inviscid, Transonic Flow

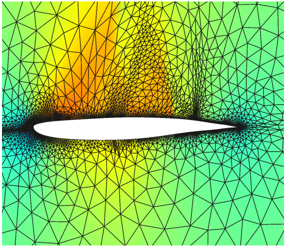
NACA 0012, $M_\infty = 0.8$, $\alpha_0 = 1.25^\circ$

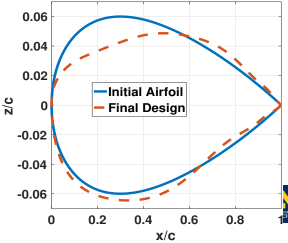
$J^{\text{adapt}} = c_d$, $J^{\text{trim}} = c_l$, $\bar{J}^{\text{trim}} = 0.4$, $A \geq A_{min}$



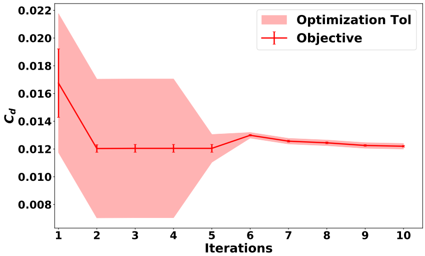


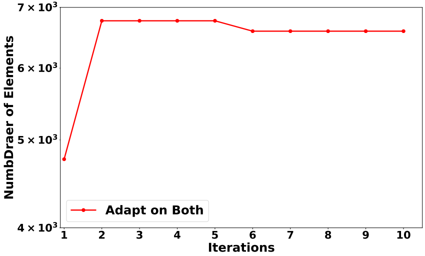


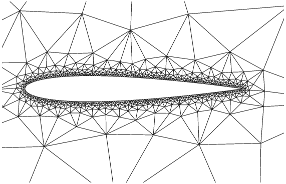




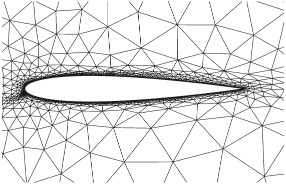
NACA 0012, $Re = 10^6$, $M_\infty = 0.15$, $\alpha_0 = 6^\circ$
$J^{\text{adapt}} = c_d$, $J^{\text{trim}} = c_l$, $\bar{J}^{\text{trim}} = 0.6$, $A \geq A_{min}$



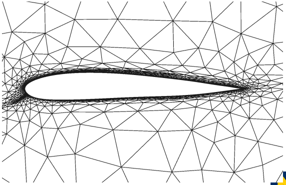




initial mesh



first step mesh

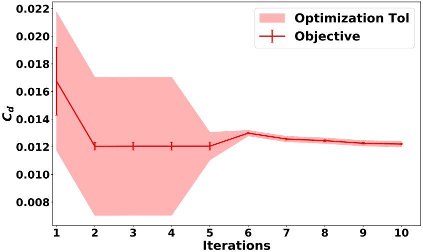


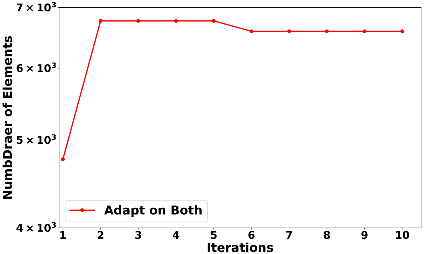
final mesh

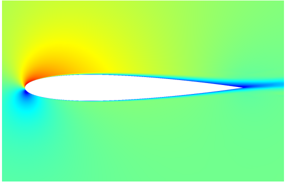
Turbulent, Low-Speed Flow

NACA 0012, $Re = 10^6$, $M_\infty = 0.15$, $\alpha_0 = 6^\circ$

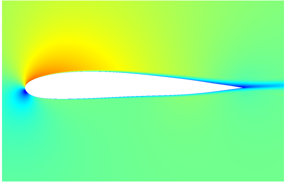
$J^{\text{adapt}} = c_d$, $J^{\text{trim}} = c_l$, $\bar{J}^{\text{trim}} = 0.6$, $A \geq A_{min}$



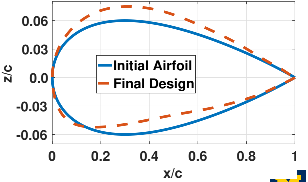




initial design



final design



airfoil shape

Outline

Conclusion

Conslusions:

- Numerical error should be carefully controlled as the shape and mesh change during the optimization
- We integrate output-based error estimation and mesh adaptation with a traditional gradient-based algorithm
- Error tolerance serves as the optimization tolerance at each fidelity, fidelity increases through mesh adaptation.
- Coupled adjoint error estimation offers a more efficient way to adapt the mesh for constrained optimization problem
- Prevent over-refining and over-optimizing during optimization

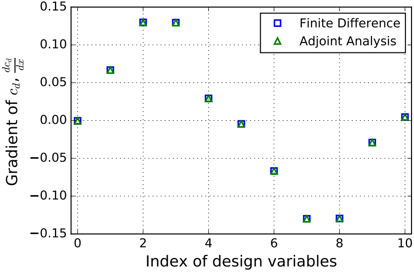
Future Work:

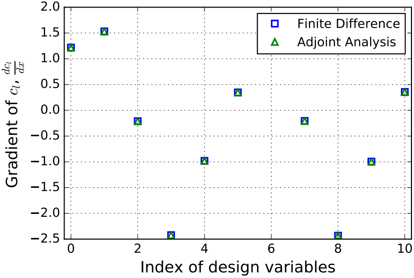
- Develop improved and automated fidelity increase strategy
- Avoid overshot refinement, allow more mesh redistribution and coarsening, optimize mesh during the optimization
- Combined with h-p refinement

Acknowledgments

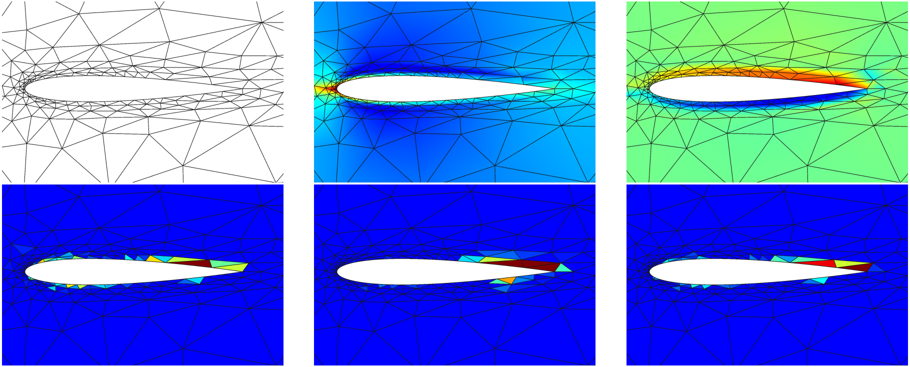
Department of Energy
DE-FG02-13ER26146/DE-SC0010341
Boeing Company, with technical monitor Dr. Mori Mani
— Thank you —

Sensitivity Verification



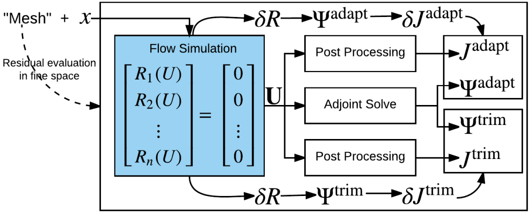


Adapt Indicator

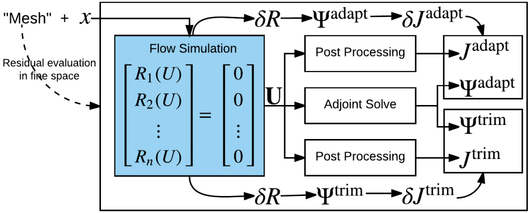


Complete Error Estimation

Error Estimation and Mesh Adaptation for Optimization



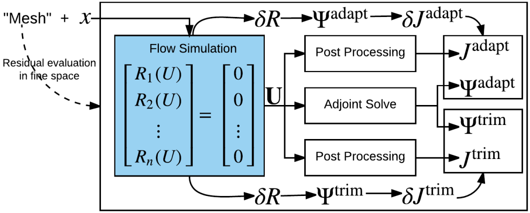
Error Estimation and Mesh Adaptation for Optimization



Flow problem:

$$\begin{aligned} \delta J &\approx J_h(\mathbf{U}_h^H, \mathbf{x}) - J_h(\mathbf{U}_h, \mathbf{x}) \\ &= -\boldsymbol{\Psi}_h^T \delta \mathbf{R}_h \\ &= -\boldsymbol{\Psi}_h^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x}) \end{aligned}$$

Error Estimation and Mesh Adaptation for Optimization

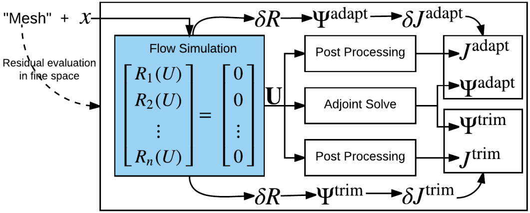


Flow problem:

$$\delta J \approx J_h(\mathbf{U}_h^H, \mathbf{x}) - J_h(\mathbf{U}_h, \mathbf{x})$$
$$= -\mathbf{\Psi}_h^T \delta \mathbf{R}_h$$
$$= -\mathbf{\Psi}_h^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x})$$

During optimization:

Error Estimation and Mesh Adaptation for Optimization



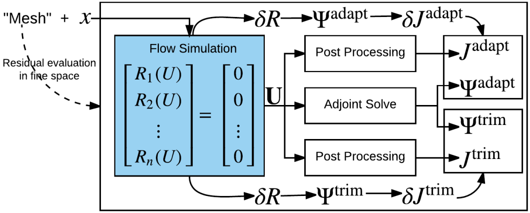
Flow problem:

$$\delta J \approx J_h(\mathbf{U}_h^H, \mathbf{x}) - J_h(\mathbf{U}_h, \mathbf{x})$$
$$= -\boldsymbol{\Psi}_h^T \delta \mathbf{R}_h$$
$$= -\boldsymbol{\Psi}_h^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x})$$

During optimization:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}} = \frac{\partial J^{\text{adapt}}}{\partial \mathbf{x}} + \boldsymbol{\lambda}^T \frac{\partial \mathbf{R}}{\partial \mathbf{x}} + \boldsymbol{\mu}^T \frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{x}} \neq \mathbf{0}$$
$$\frac{\partial \mathcal{L}}{\partial \mathbf{U}} = \frac{\partial J^{\text{adapt}}}{\partial \mathbf{U}} + \boldsymbol{\lambda}^T \frac{\partial \mathbf{R}}{\partial \mathbf{U}} + \boldsymbol{\mu}^T \frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{U}} = \mathbf{0}$$
$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\lambda}} = \mathbf{R}(\mathbf{U}, \mathbf{x}) = \mathbf{0}$$
$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\mu}} = \mathbf{R}^{\text{trim}}(\mathbf{U}, \mathbf{x}) \neq \mathbf{0}$$

Error Estimation and Mesh Adaptation for Optimization



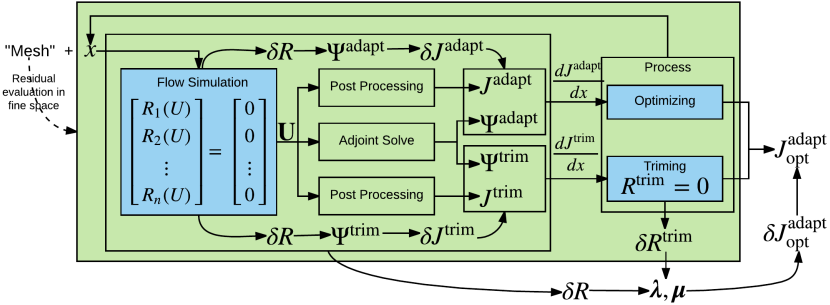
Flow problem:

$$\begin{aligned}\delta J &\approx J_h(\mathbf{U}_h^H, \mathbf{x}) - J_h(\mathbf{U}_h, \mathbf{x}) \\ &= -\boldsymbol{\Psi}_h^T \delta\mathbf{R}_h \\ &= -\boldsymbol{\Psi}_h^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x})\end{aligned}$$

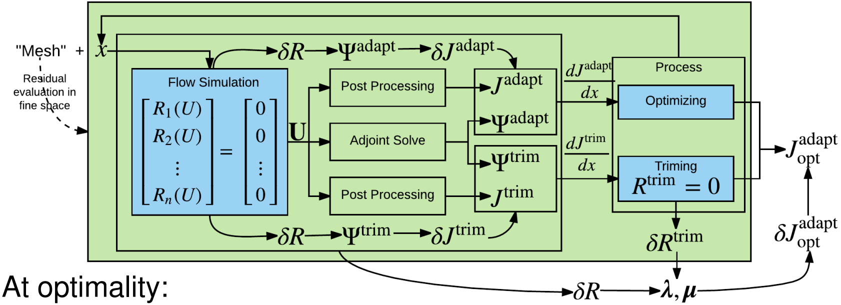
During optimization:

$$\begin{aligned}\delta J^{\text{adapt}} &= -\boldsymbol{\lambda}_h^T \delta\mathbf{R}_h - \boldsymbol{\mu}^T \delta\mathbf{R}_h^{\text{trim}} \\ &= -\boldsymbol{\lambda}^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x}) - \boldsymbol{\mu}^T \mathbf{R}_h^{\text{trim}}(\mathbf{U}_h^H, \mathbf{x}) \\ &= -(\boldsymbol{\Psi}_h^{\text{adapt}} + \boldsymbol{\Psi}_h \boldsymbol{\mu}_h)^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x}) - \boldsymbol{\mu}_h^T (J_h^{\text{trim}}(\mathbf{U}_h^H, \mathbf{x}) - J_h^{\text{trim}}(\mathbf{U}_h, \mathbf{x})) \\ &= \delta J^{\text{adapt}} + \boldsymbol{\mu}_h^T \underbrace{(-\boldsymbol{\Psi}_h^{\text{trim}})^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x})}_{\delta J^{\text{trim}}} - \boldsymbol{\mu}_h^T \delta J^{\text{trim}} \\ &= \delta J^{\text{adapt}}\end{aligned}$$

Error Estimation and Mesh Adaptation for Optimization



Error Estimation and Mesh Adaptation for Optimization



At optimality:

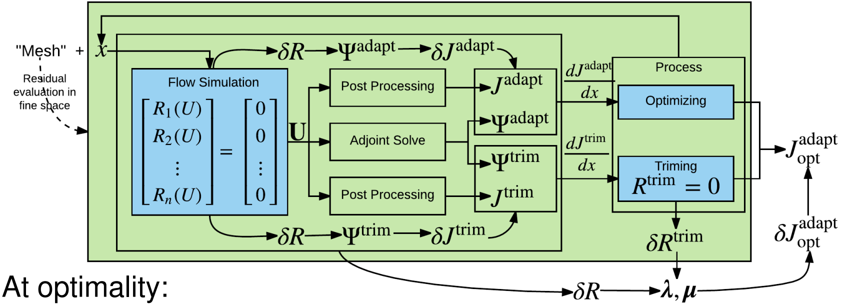
$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}} = \frac{\partial J^{\text{adapt}}}{\partial \mathbf{x}} + \boldsymbol{\lambda}^T \frac{\partial \mathbf{R}}{\partial \mathbf{x}} + \boldsymbol{\mu}^T \frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{x}} = \mathbf{0}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{U}} = \frac{\partial J^{\text{adapt}}}{\partial \mathbf{U}} + \boldsymbol{\lambda}^T \frac{\partial \mathbf{R}}{\partial \mathbf{U}} + \boldsymbol{\mu}^T \frac{\partial \mathbf{R}^{\text{trim}}}{\partial \mathbf{U}} = \mathbf{0}$$

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\lambda}} = \mathbf{R}(\mathbf{U}, \mathbf{x}) = \mathbf{0}$$

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\mu}} = \mathbf{R}^{\text{trim}}(\mathbf{U}, \mathbf{x}) = \mathbf{0}$$

Error Estimation and Mesh Adaptation for Optimization



At optimality:

$$
\begin{aligned}
\delta J^{\text{adapt}}_{\text{opt}} &= -\boldsymbol{\lambda}_h^T \delta \mathbf{R}_h - \boldsymbol{\mu}^T \delta \mathbf{R}_h^{\text{trim}} \\
&= -\boldsymbol{\lambda}^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x}_H) - \boldsymbol{\mu}^T \mathbf{R}_h^{\text{trim}}(\mathbf{U}_h^H, \mathbf{x}_H) \\
&= -(\boldsymbol{\Psi}_h^{\text{adapt}} + \boldsymbol{\Psi}_h \boldsymbol{\mu}_h)^T \mathbf{R}_h(\mathbf{U}_h^H, \mathbf{x}_H) - \boldsymbol{\mu}_h^T \underbrace{\left(J_h^{\text{trim}}(\mathbf{U}_h^H, \mathbf{x}_H) - \bar{J}^{\text{trim}}\right)}_{\approx 0} \\
&= \delta J^{\text{adapt}}(\mathbf{x}_H) + \boldsymbol{\mu}_h^T \delta J^{\text{trim}}(\mathbf{x}_H)
\end{aligned}
$$

Note: $J_h^{\text{trim}}(\mathbf{U}_h^H, \mathbf{x}_H) = J_H^{\text{trim}}(\mathbf{U}_H, \mathbf{x}_H) = \bar{J}^{\text{trim}} = J_h^{\text{trim}}(\mathbf{U}_h, \mathbf{x}_h)$

Error Estimation and Mesh Adaptation for Optimization

Optimality error estimation

$$\frac{dJ^{\text{adapt}}}{d\mathbf{x}} + \boldsymbol{\mu}^T \frac{d\mathbf{J}^{\text{trim}}}{d\mathbf{x}} = \mathbf{0}$$

$$\delta J^{\text{adapt}}_{\text{opt}} = \delta J^{\text{adapt}}(\mathbf{x}_H) + \boldsymbol{\mu}_h^T \delta J^{\text{trim}}(\mathbf{x}_H)$$

What does $\boldsymbol{\mu}$ mean?
It is the objective sensitivity w.r.t constraints and measures how much the constraints error can affect the optimal objective.

Mesh adaptation implementation

Adapt (error) indicator: $\eta_\kappa = |\boldsymbol{\Psi}^T_{h,\kappa} \mathbf{R}_{h,\kappa}(\mathbf{U}^H_h, \mathbf{x}_H)|$

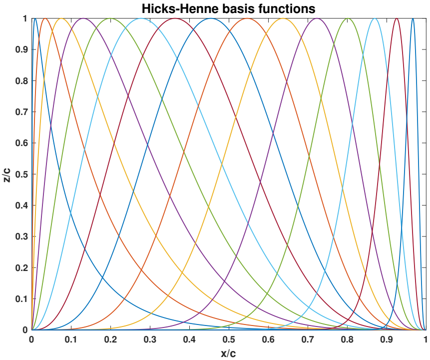
Combined indicator: $\eta_{\kappa,\text{opt}} = \underbrace{\eta^{\text{adapt}}_\kappa}_{\text{objective error only}} + \underbrace{|\boldsymbol{\mu}|^T \boldsymbol{\eta}^{\text{trim}}_\kappa}_{\text{inexact constraints satisfication}}$

$\boldsymbol{\Psi}_h$: reconstructing the coarse-space adjoints $\boldsymbol{\Psi}_H$

$\boldsymbol{\mu}_h$: extracted from the optimizer on the coarse space

Airfoil Parameterization

- Hicks-Henne basis functions: linear combination of "bump" functions added to the baseline airfoil



$$z = z_{\text{base}} + \sum_{i=0}^{n} a_i \phi_i(x)$$

$$\phi_i(x) = \sin^{t_i}(\pi x^{m_i})$$

$$m_i = \ln(0.5)/\ln(x_{M_i})$$

x : coord along the airfoil chord
z : vertical surface coord
x_{M_i} : maxima location
t_i : width of the bump function

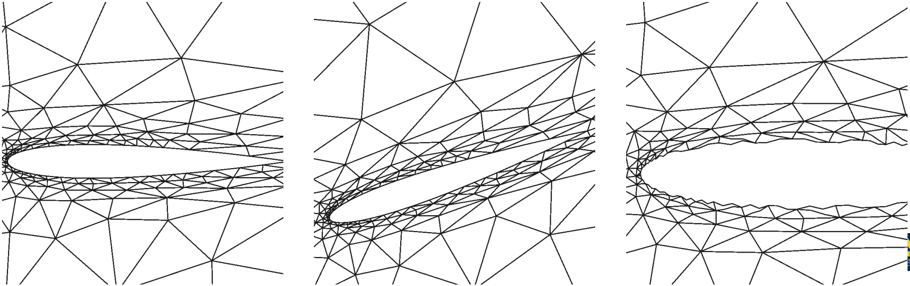
- Design parameters: $\mathbf{x} = [\alpha, a_1, a_2, \cdots, a_n]^T$
  Coefficients of Hicks-Henne basis + angle of attack α

Mesh Movement

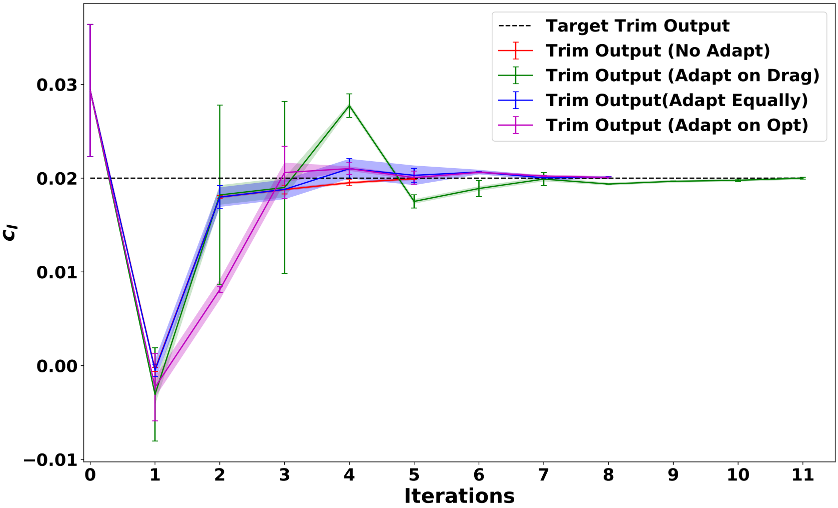
- Radial Basis Function (RBF): only depends on the distance from the origin or a center, e.g. $\phi(x) = e^{-x^2}$
- We can use a sum of RBFs $\phi(\|\vec{x}\|)$ and a polynomial $p(\vec{x})$ to interpolate the original function (mesh movement):

$$\vec{d}(\vec{x}) \approx \tilde{\vec{d}}(\vec{x}) = \sum_{i=1}^{N_b} \vec{r}_i \phi(\|\vec{x} - \vec{x}_i\|) + \vec{p}(\vec{x})$$

- Solving for a linear system $\mathcal{O}(N_b)$ of $\vec{r}_i$
- Mesh connectivity information not required



Constraints, Nearly Feasible Starting Point



Constraints, Infeasible Starting Point