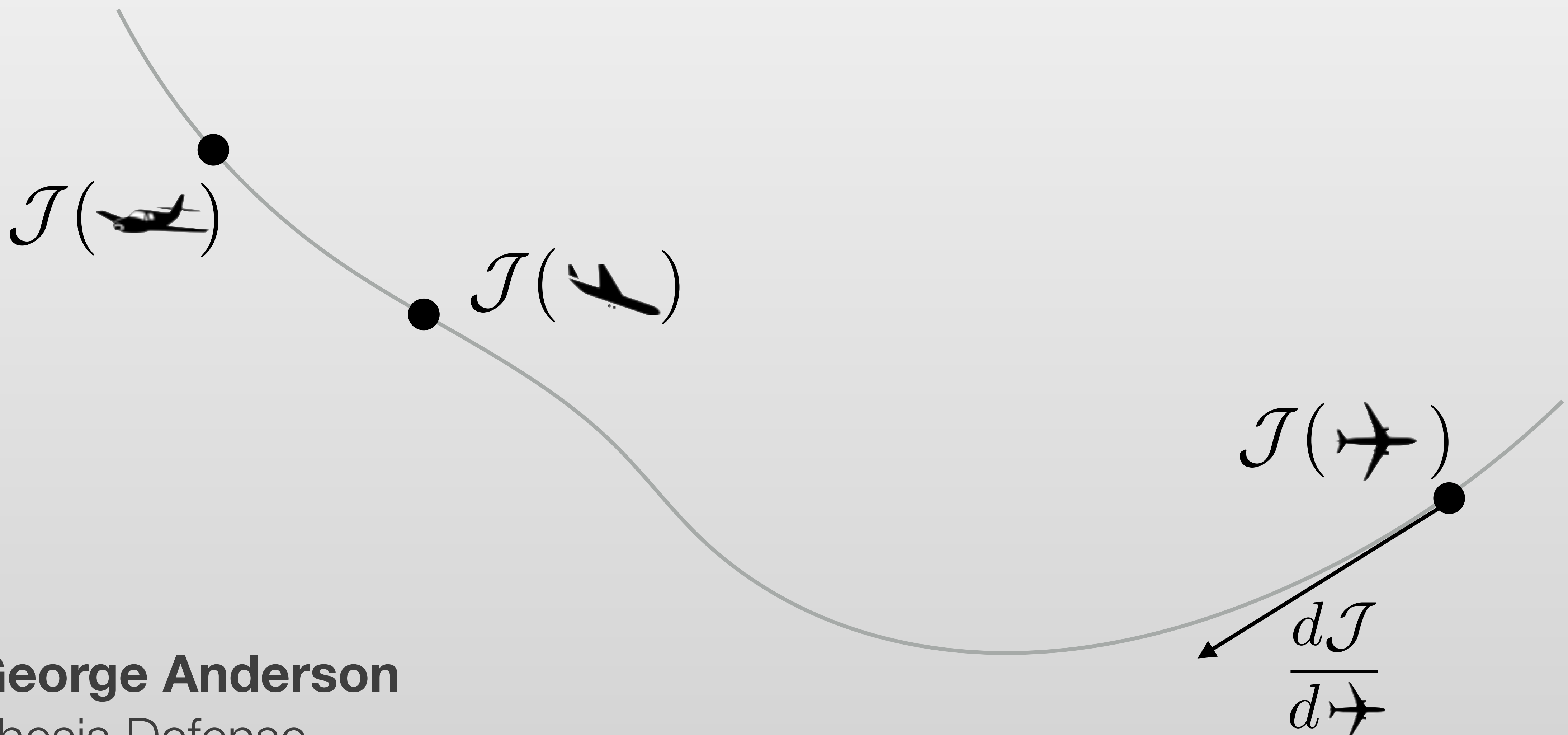
Shape Optimization
in Adaptive Search Spaces



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Thesis Defense
4 September 2015
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Outline

1. Introduction to Shape Parameterization
2. Automatic Adaptive Parameterization
3. Verification Studies
4. Design Examples

Aerodynamic Shape Optimization

Designer-driven

1. Define **goals**:
   Minimize objective
   Subject to constraints

$$\min_{S} \mathcal{J}(S)$$
$$\mathcal{C}_j(S) \leq 0$$

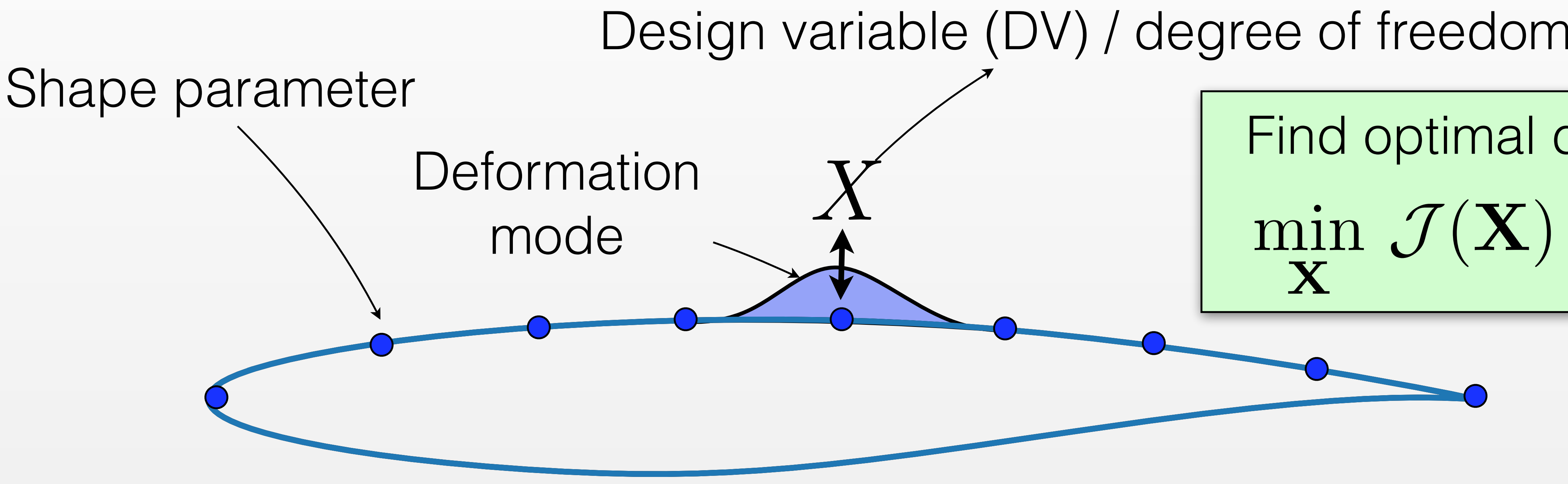
2. Select **design variables**
   (shape parameterization)

High-fidelity (expensive) **analysis**

Automated

3. Numerical **optimizer** iteratively modifies shape to improve performance

Shape Parameterization

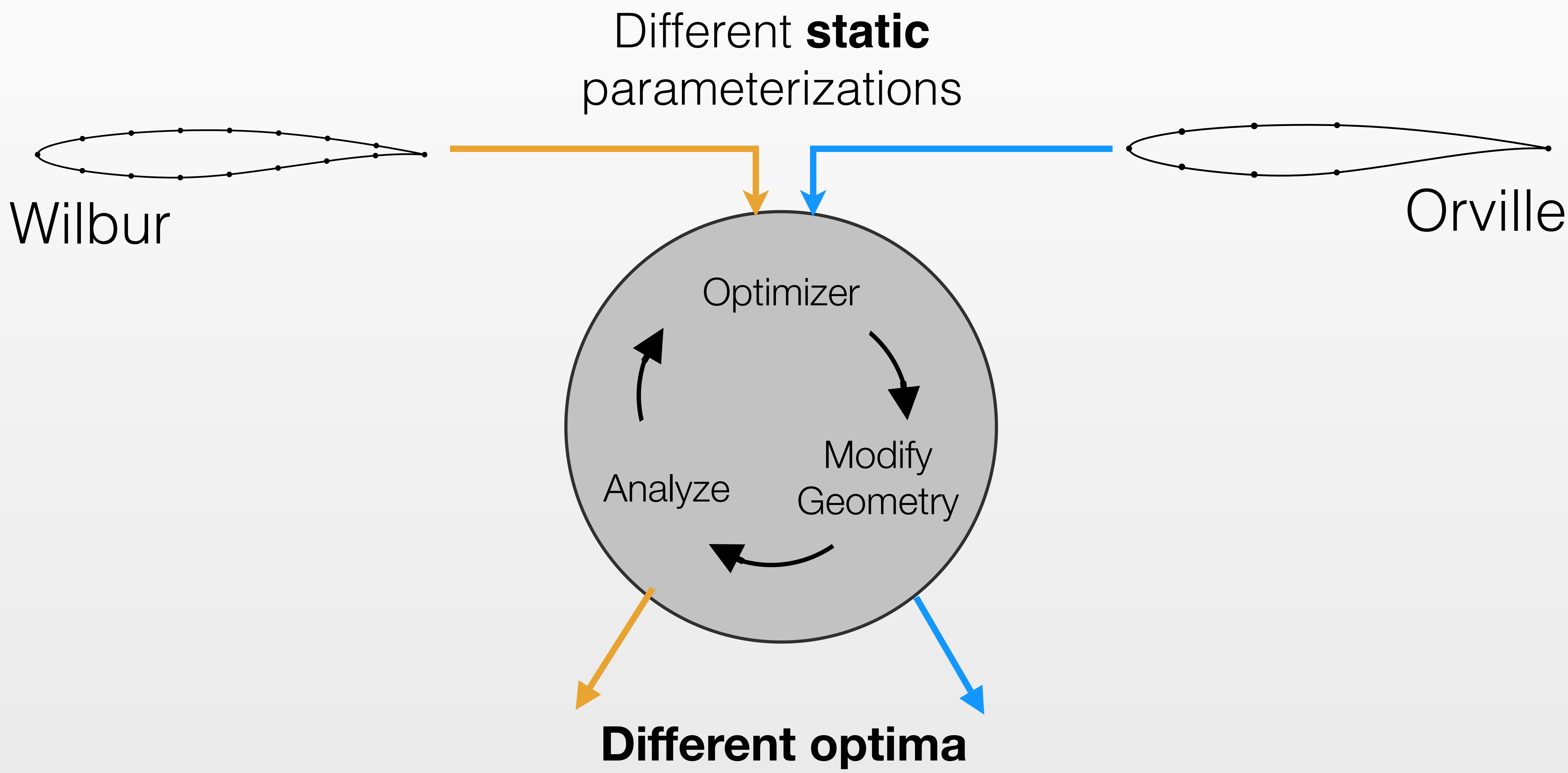


Find optimal deformation

$$\min_{\mathbf{X}} \mathcal{J}(\mathbf{X})$$

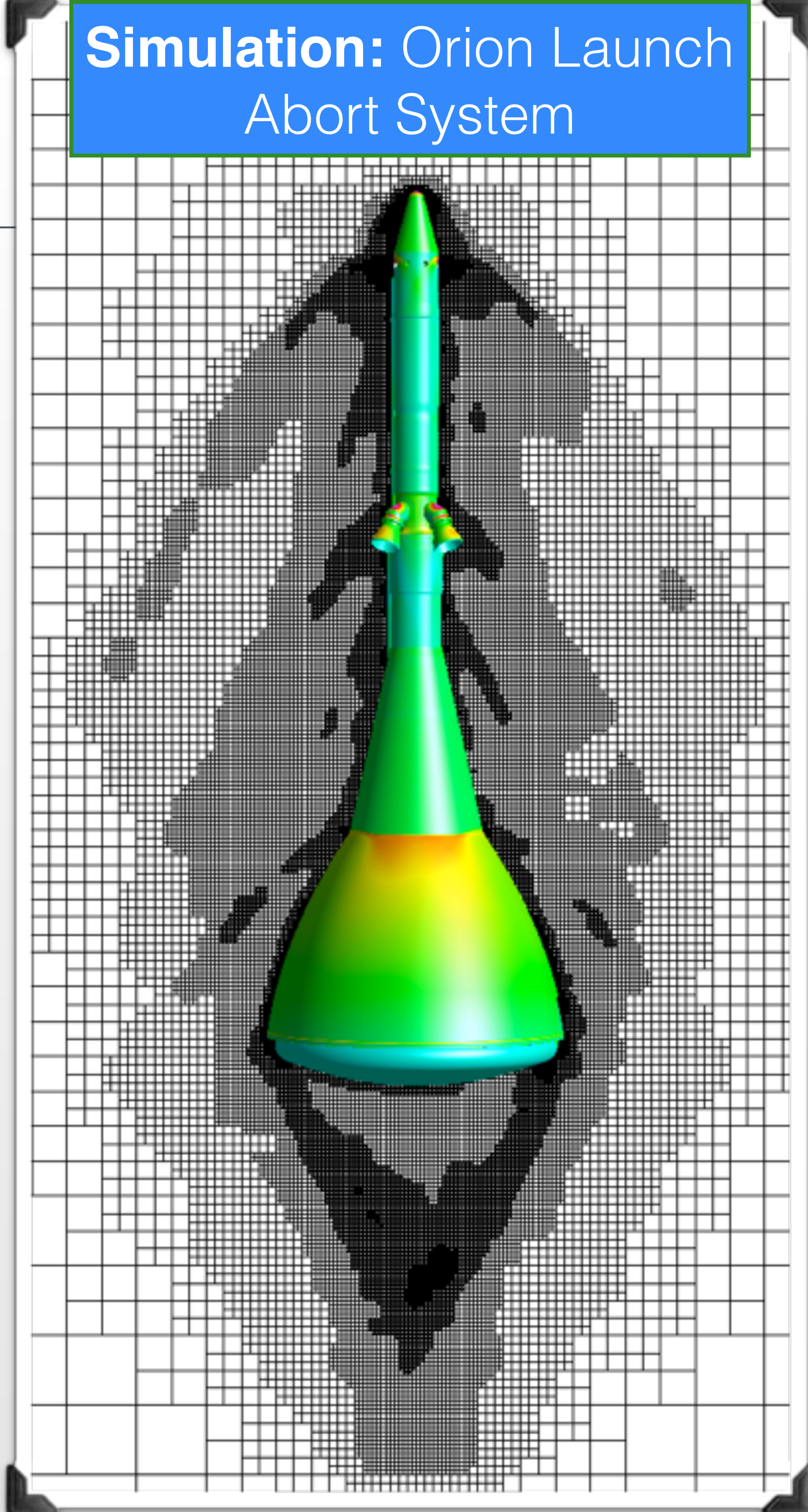
- Shape parameterization reduces continuous design space into finite search space
- Reduces range of reachable shapes

Static Parameterization



Motivation

- Design of complex vehicles in unfamiliar settings, driven by high-fidelity simulations.
- Choice of shape parameters impacts:
  - **Bias** towards familiar designs.
  - Ability to approximate the continuous optimal solution. (Want *more* DOF)
  - Optimization **cost.** (Want *fewer* DOF)



Objective

Research Goal:

Develop system for automatic, adaptive shape parameterization refinement during optimization

Requirements:

- Gradually approach continuous optimum (**convergent**)
- Without *a priori* knowledge (**automated**)
- Using as few design variables as possible (**adaptive**)

Previous Work

Progressive (uniform "h"-refinement)	**Redistribution** (*"r"-refinement*)
Gradually **increase resolution**	Improve **distribution** of shape control
(1991) *Kohli and Carey* — Multi-fidelity shape representation for structural optimization	**(2004, 2006)** *Desideri and El Majd, Duvigneau* — Minimize total variation of Bezier/FFD control points
(1993) *Marco et al.* — Aerodynamic optimization with nested parameters	**(2012)** *Hwang and Martins* — Equally distribute arc-length of curve between B-spline control points

These approaches are **insensitive to the goals of aerodynamic optimization.**

Previous Work

Towards **goal-oriented** adaptation:

- **(2011)** *Han and Zingg* — **Discrete** refinement approach
  - **Restrictions:** Single-component design, only localized constraints, can only add one new variable at a time
- **(2014)** *Poole and Allen* — **Redistribution** approach
  - **Restrictions:** Only geometric matching of airfoils
- **(2015)** *Anderson* — **Discrete adaptation** approach appropriate for general aerodynamic design problems

Contributions

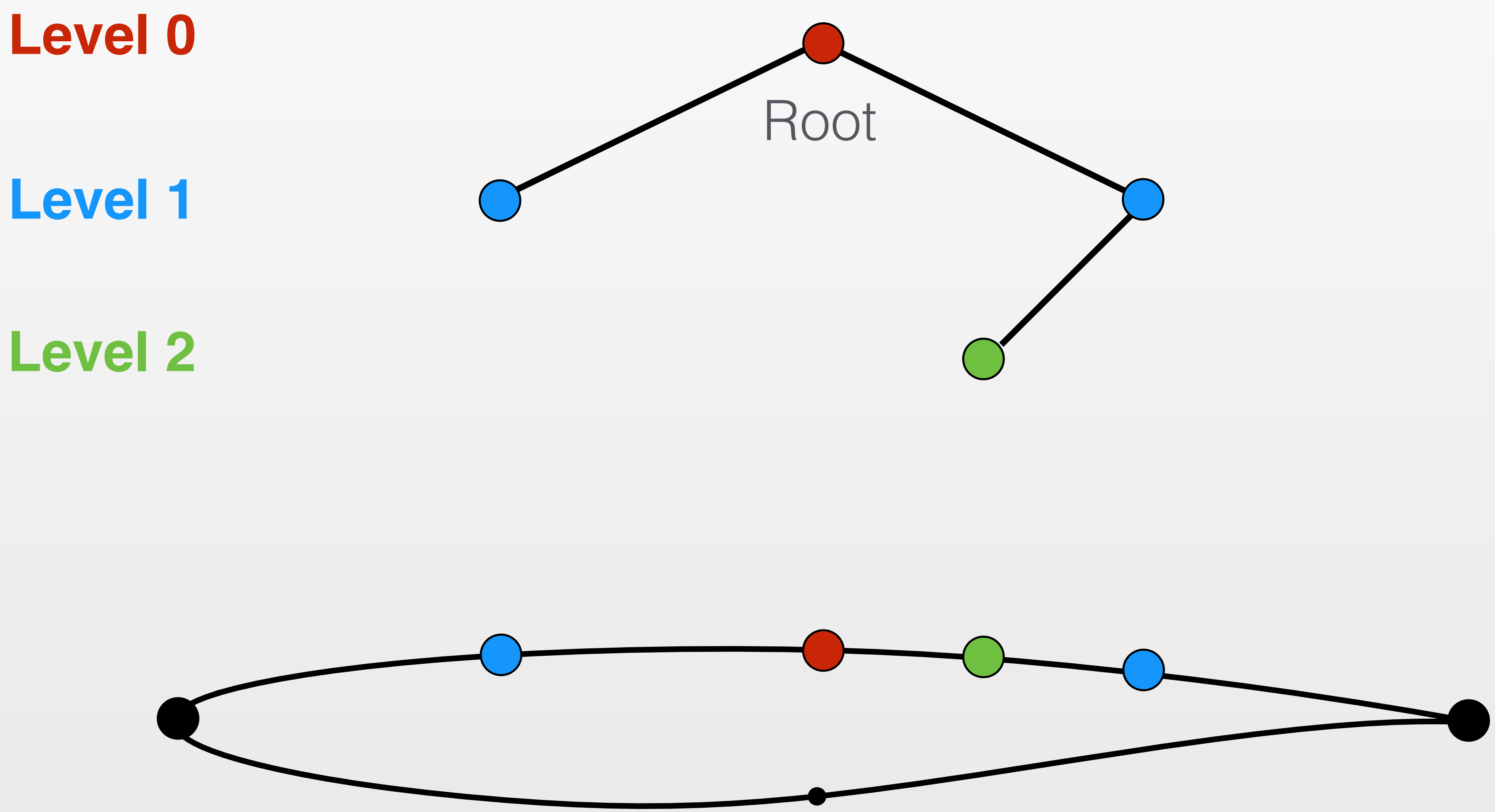
- Complete **system** for automatic, adaptive parameterization
- Novel **refinement indicator** that enables adaptive parameterization for general problems:
  - Multiple components
  - Multiple classes of shape control
  - High curvature variation in design space
  - General constraints
- Several new algorithms and strategies to accelerate and automate adaptation
- First **verification** of robust convergence of adaptation
- **Implementation,** testing in a production design environment

Outline

- ✓ Introduction
- **Adaptive Parameterization**
  - **Discrete Adaptation (How?)**
  - Refinement Indicator (Where?)
  - Adaptation Strategy
- Verification
- Design Examples

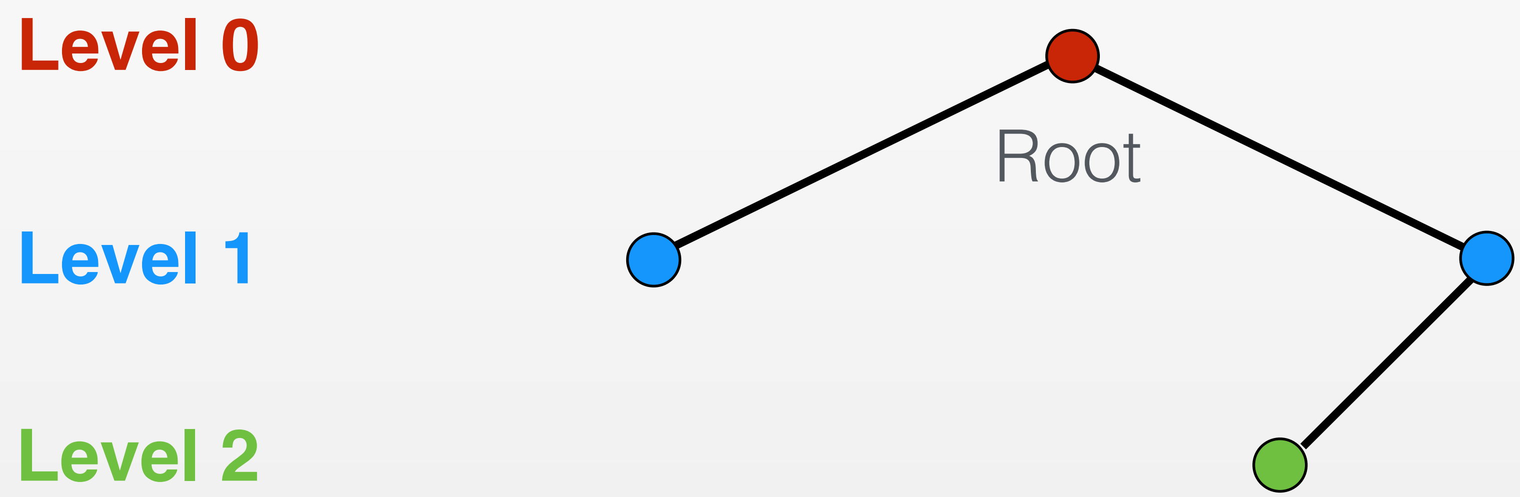
Shape Control Refinement

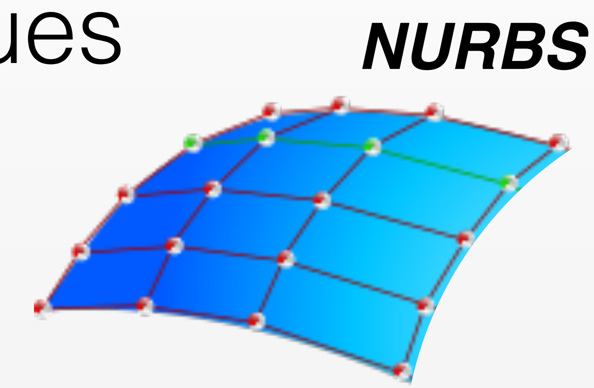
View shape parameterization as **binary tree:**

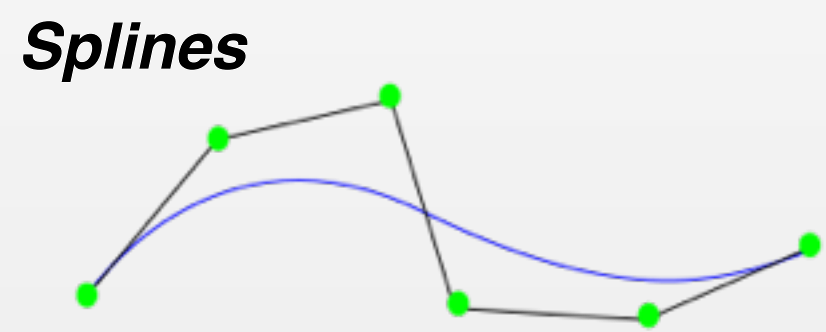


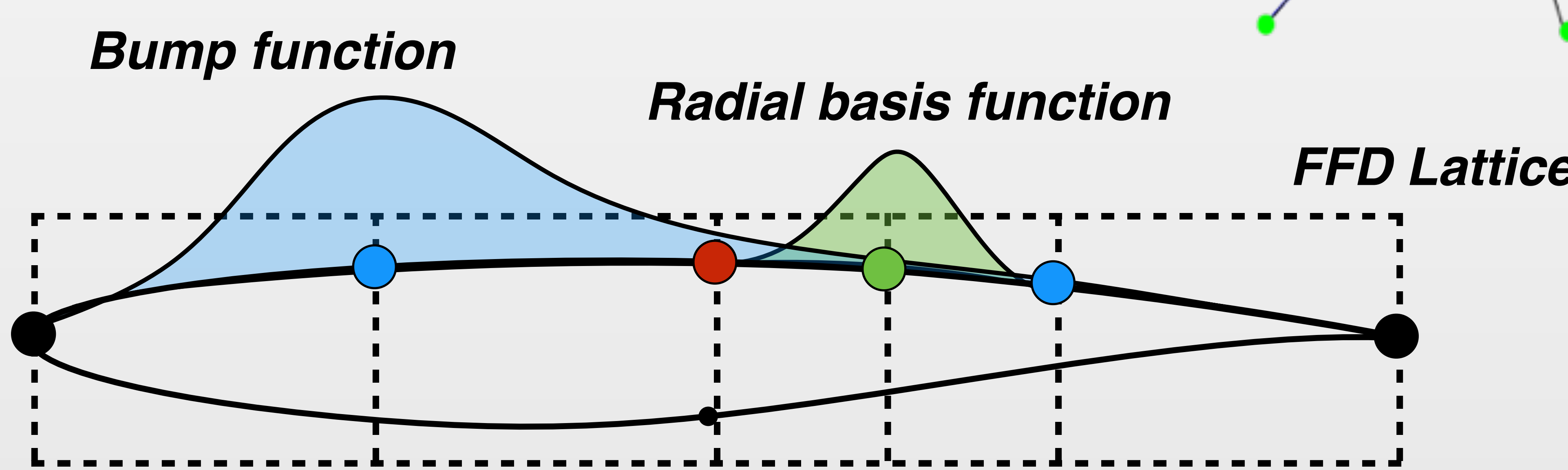
Shape Control Refinement

Applicable to most parameterization techniques



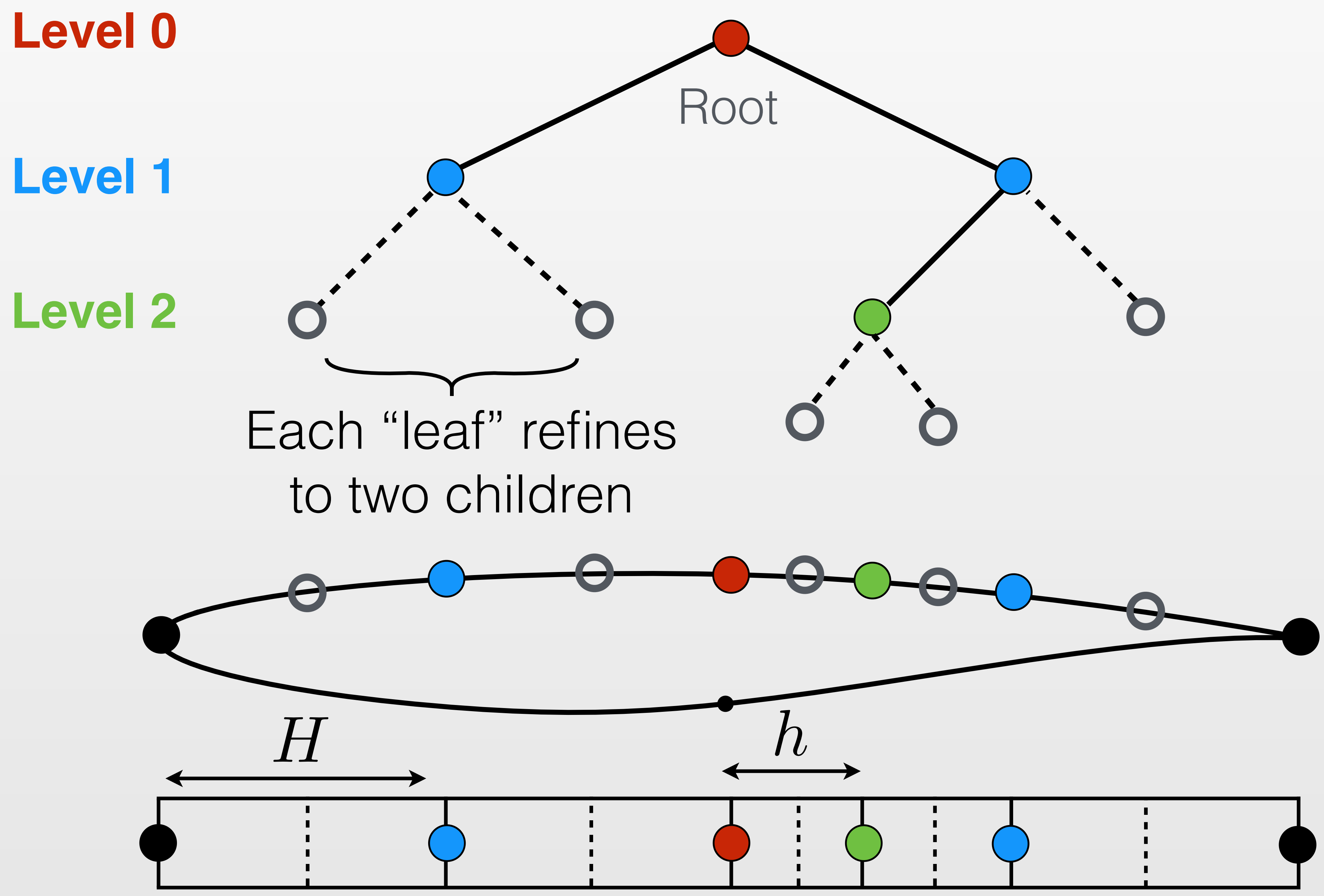




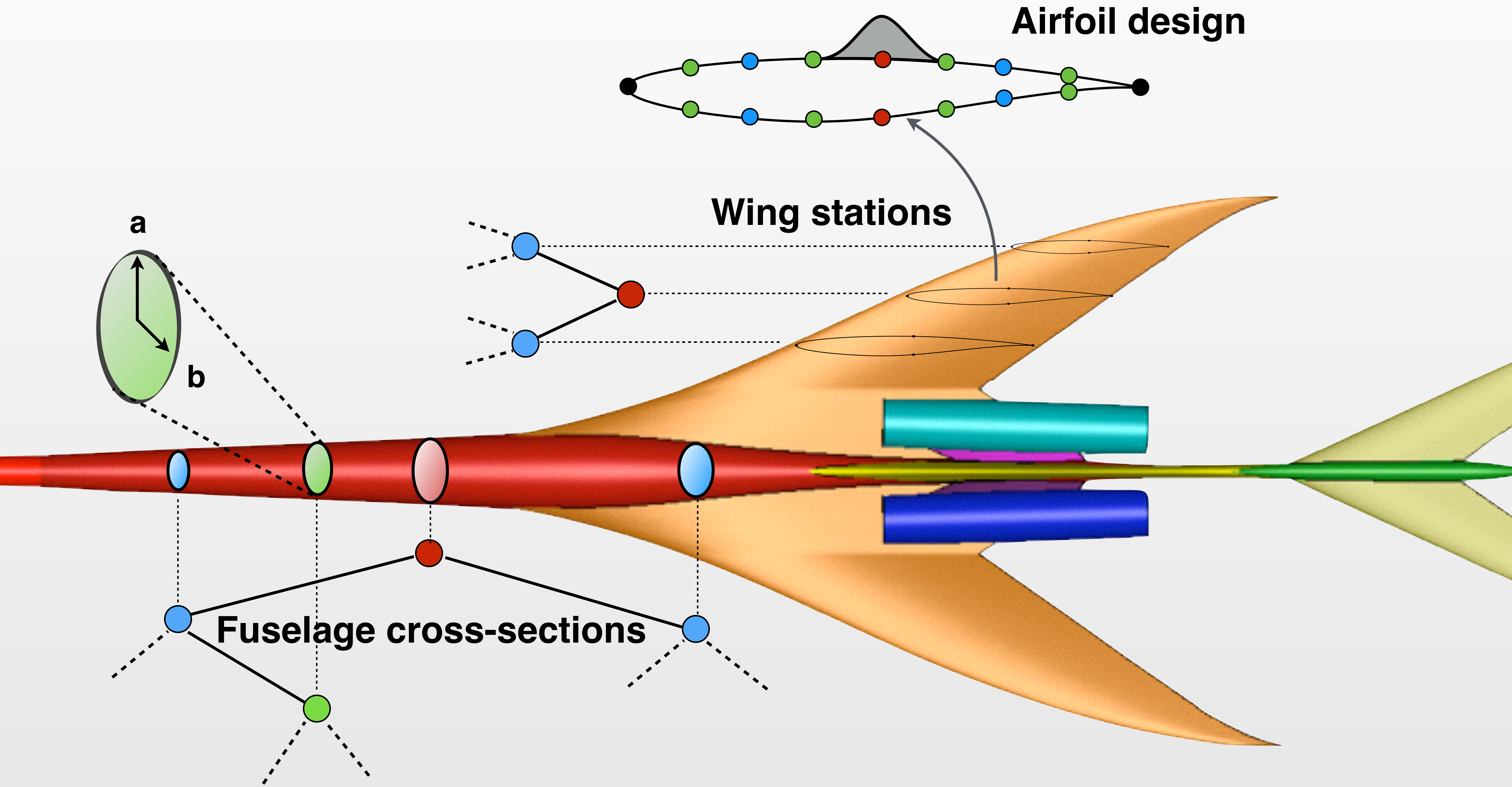


Shape Control Refinement

View shape parameterization as **binary tree:**



Configuration Design



Outline

- ✓ Introduction
- **Adaptive Parameterization**
  - ✓ Discrete Adaptation
  - **Refinement Indicator**
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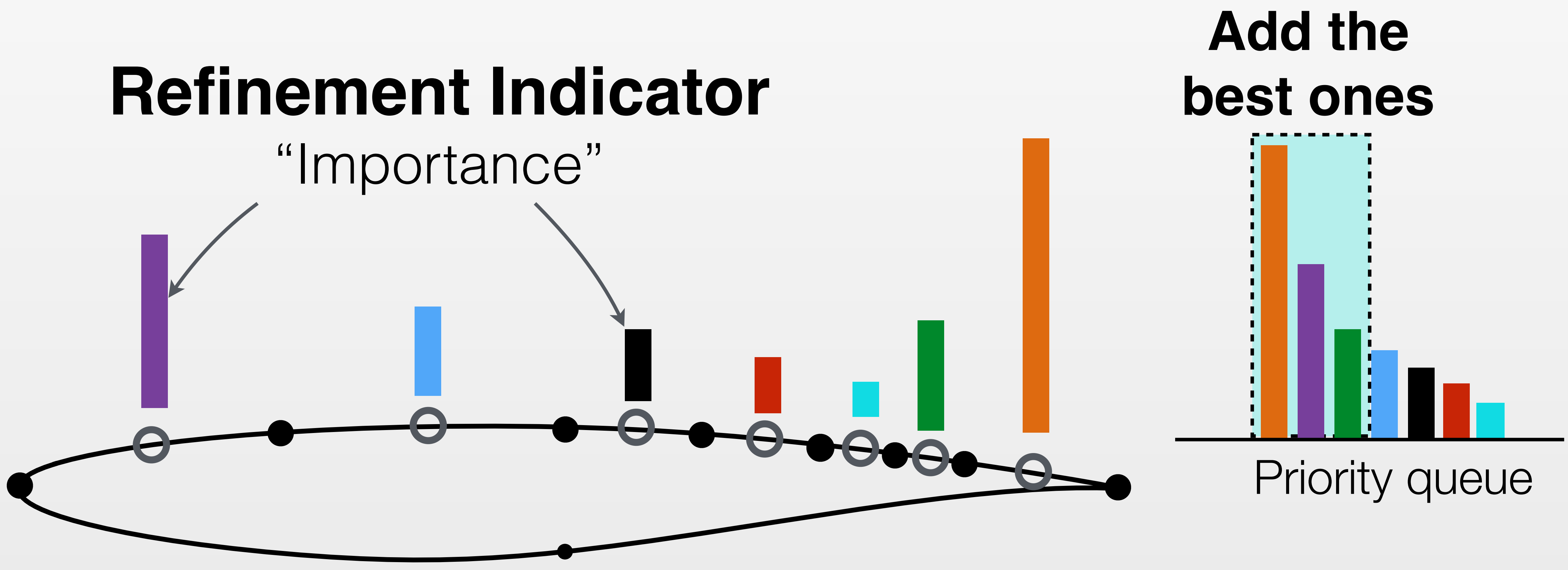
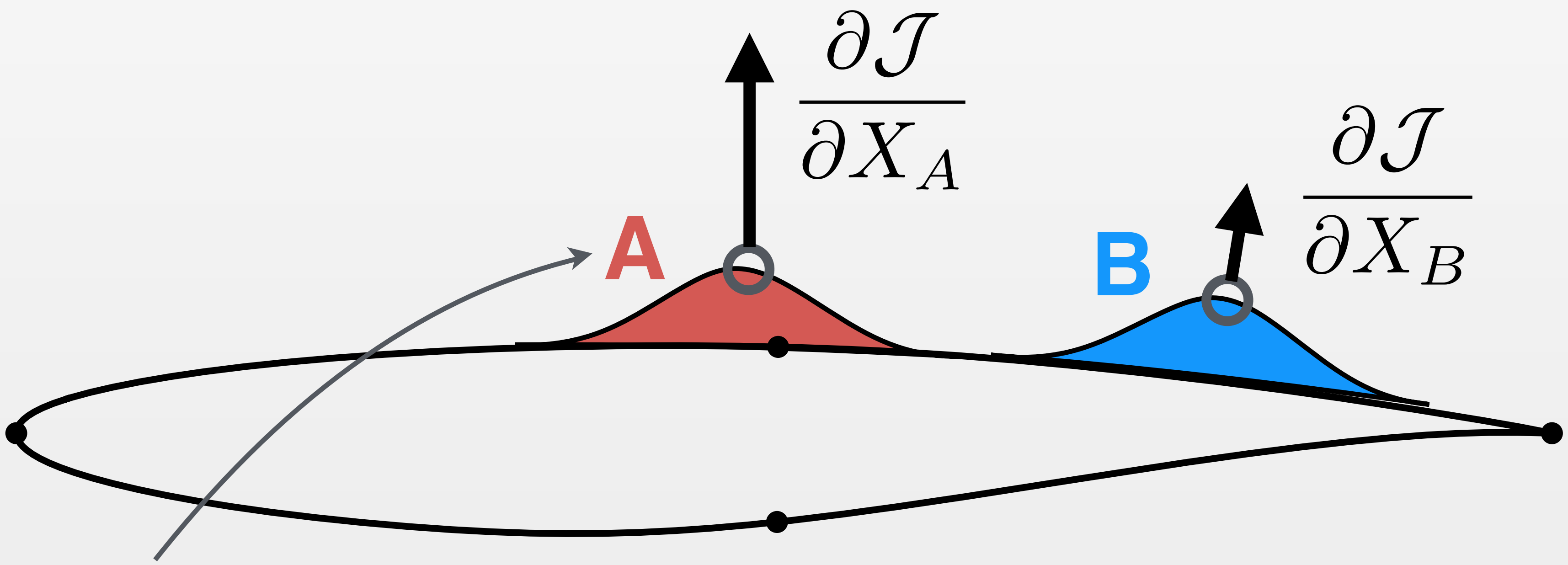
Adaptive Refinement

Goal: Determine **most important** candidate parameters



Previous Approach

- (2011) Han and Zingg rank parameters by magnitude of **objective gradient** with respect to **candidate** design variables.[†]



Prefer A, because objective is more **sensitive** to it**.**

[†] (2011) X. Han, D. Zingg. *"An Evolutionary Geometry Parametrization for Aerodynamic Shape Optimization." AIAA 2011-3536*

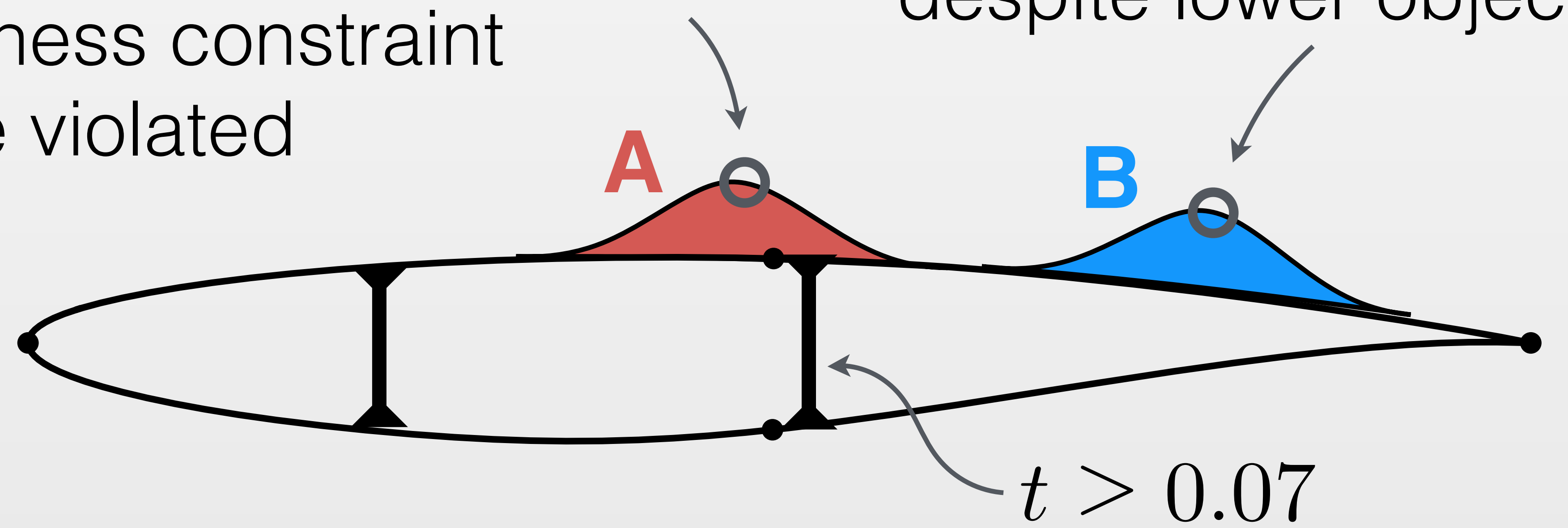
Limitations of Previous Approach

- **Ignores constraints**

Inconsistent units
Ignores curvature variation
Insensitive to redundancy

Drag is **more sensitive** to **A**, but thickness constraint would be violated

B offers **more real potential**, despite lower objective gradient



Limitations of Previous Approach

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- **Inconsistent units**

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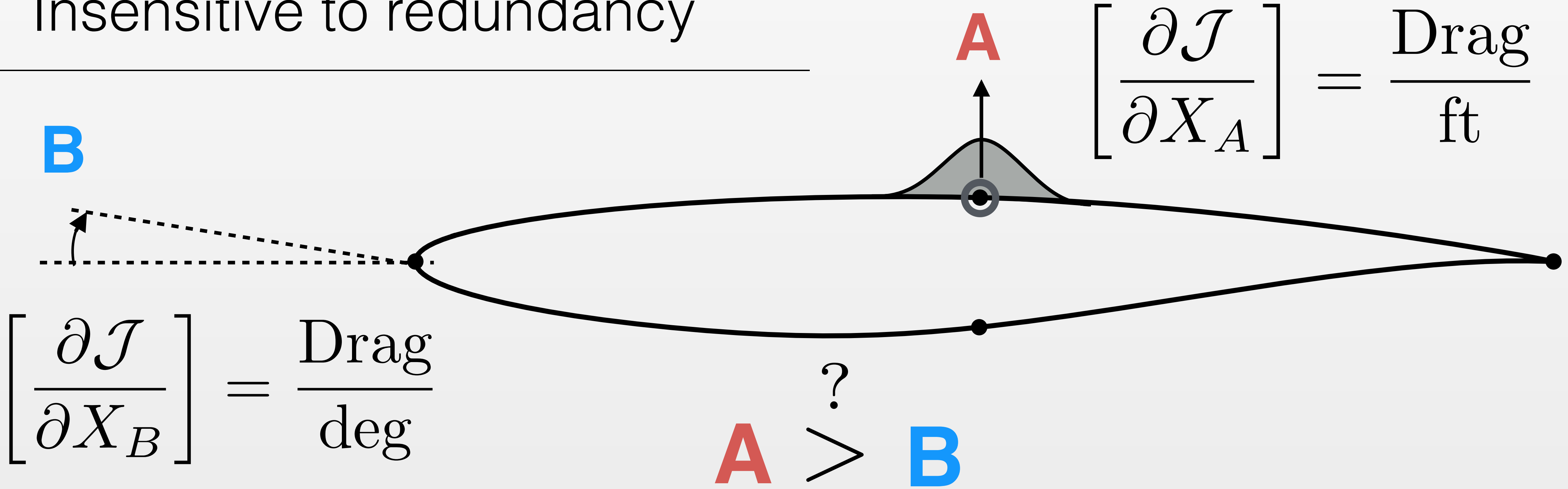
Insensitive to redundancy

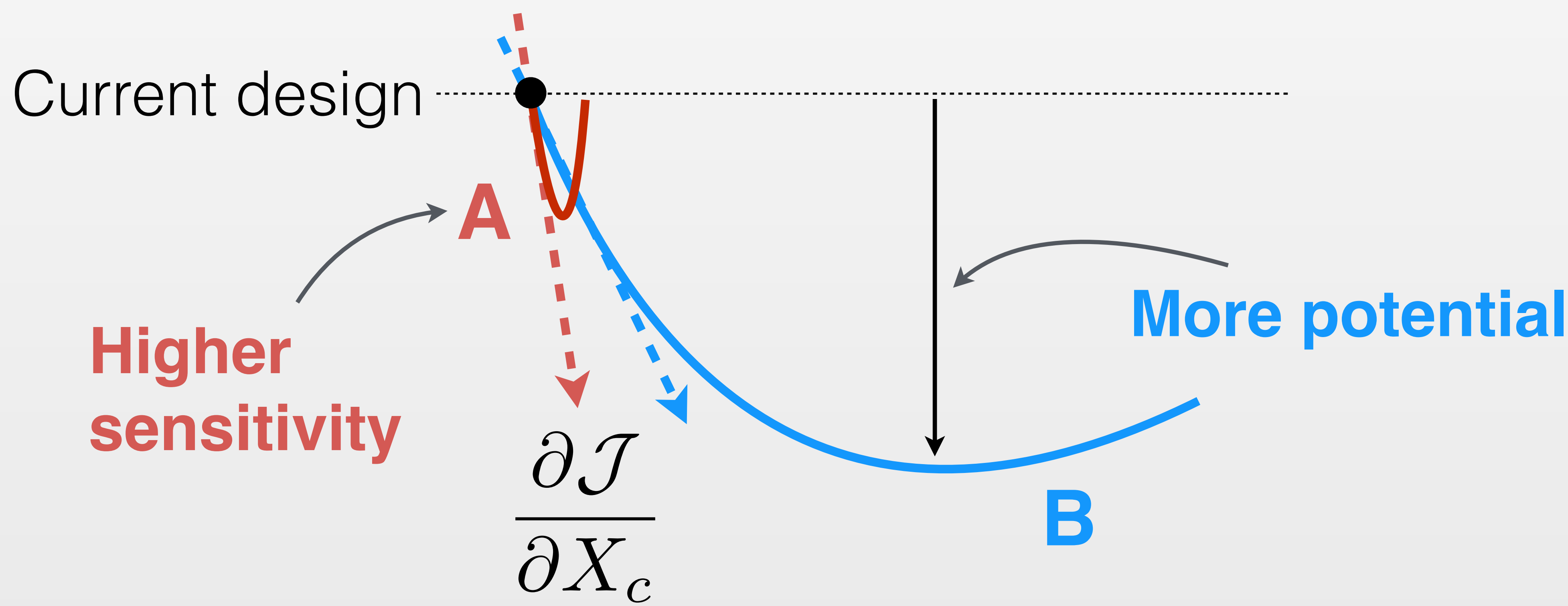


Limitations of Previous Approach

Ignores constraints
Inconsistent units

- **Ignores curvature variation** $\frac{\partial^2 \mathcal{J}}{\partial X_c^2}$

Insensitive to redundancy

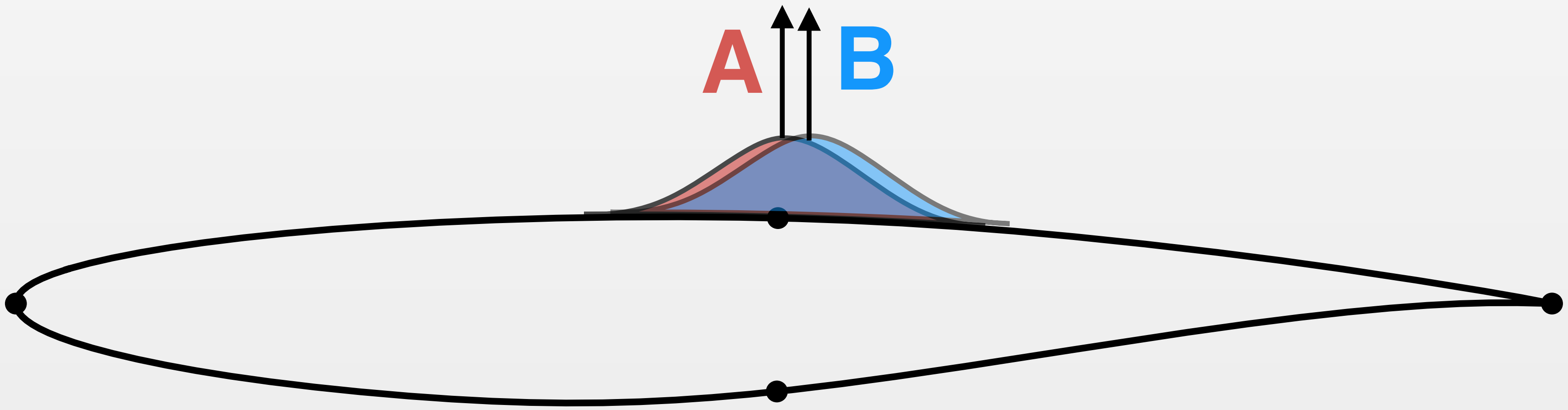


Limitations of Previous Approach

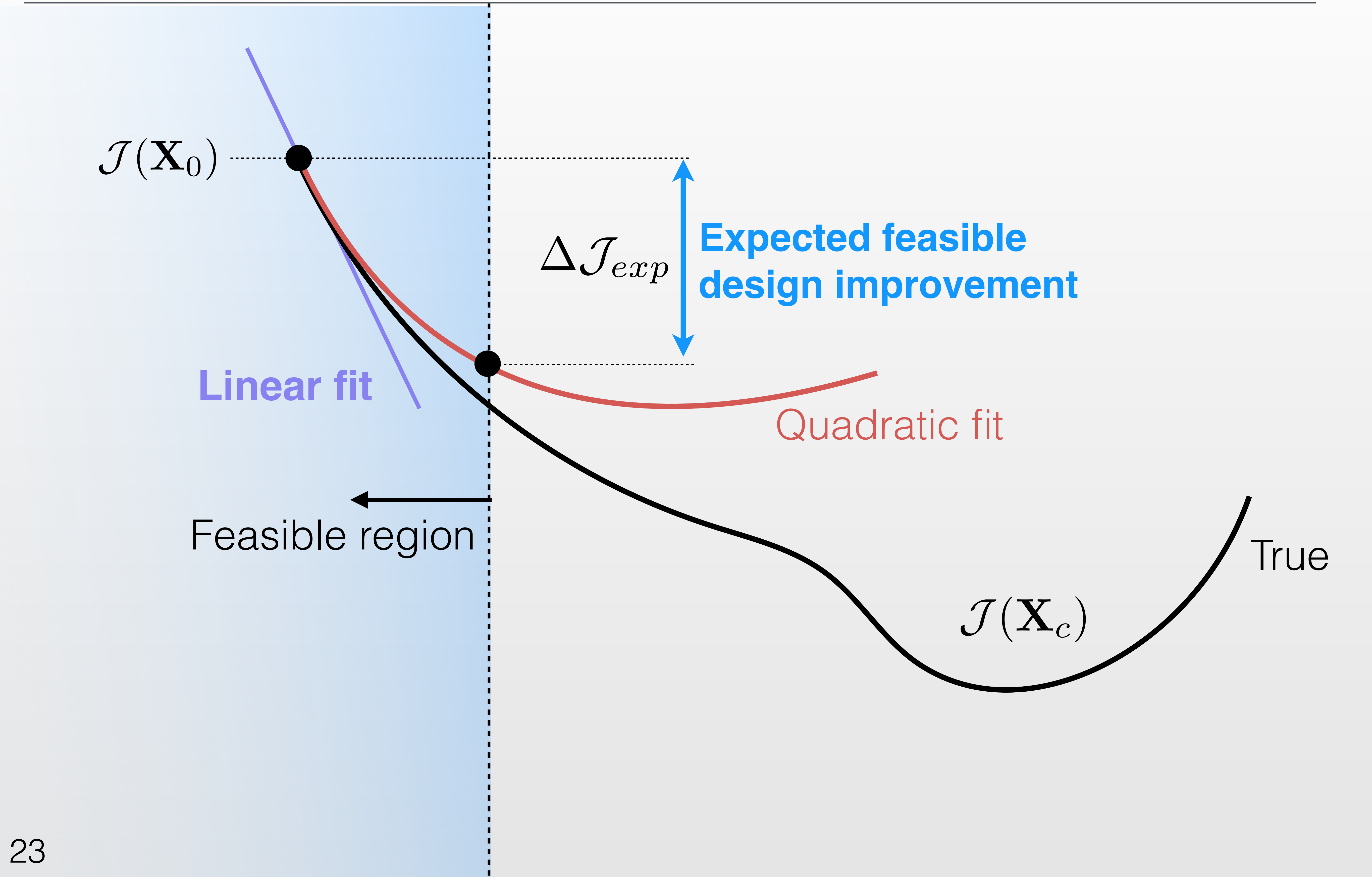
Ignores constraints
Inconsistent units
Ignores curvature variation

- **Insensitive to redundancy**

Either one would be useful, but **not both**



New Refinement Indicator



Expected Feasible Design Improvement

KKT system

$$\begin{bmatrix} \mathcal{H} & \frac{\partial \boldsymbol{\mathcal{C}}^a}{\partial \mathsf{S}} \\ \left(\frac{\partial \boldsymbol{\mathcal{C}}^a}{\partial \mathsf{S}}\right)^\mathsf{T} & \bar{\mathbf{0}} \end{bmatrix} \begin{pmatrix} \delta \mathsf{S}^\star \\ \boldsymbol{\lambda} \end{pmatrix} = \begin{pmatrix} -\frac{\partial \mathcal{J}}{\partial \mathsf{S}} \\ \mathbf{0} \end{pmatrix}$$

Hessian: $\mathcal{H}$

Gradients of active constraints: $\frac{\partial \boldsymbol{\mathcal{C}}^a}{\partial \mathsf{S}}$

Objective gradients: $\frac{\partial \mathcal{J}}{\partial \mathsf{S}}$

Lagrange multipliers: $\boldsymbol{\lambda}$

Solve for **Newton step** to predicted optimum

$$\delta \mathsf{S}^\star = -\mathcal{H}^{-1}\left(\frac{\partial \mathcal{J}}{\partial \mathsf{S}} + \boldsymbol{\lambda}\frac{\partial \boldsymbol{\mathcal{C}}^a}{\partial \mathsf{S}}\right)$$

Quadratic Taylor expansion

$$\mathcal{J}(\mathsf{S}_0 + \delta\mathsf{S}) \approx \mathcal{J}(\mathsf{S}_0) + \left\langle \frac{\partial \mathcal{J}}{\partial \mathsf{S}}, \delta\mathsf{S} \right\rangle + \frac{1}{2}\langle \mathcal{H}\delta\mathsf{S}, \delta\mathsf{S}\rangle + \dots$$

Gradient: $\frac{\partial \mathcal{J}}{\partial \mathsf{S}}$

Hessian: $\mathcal{H}$

Refinement Indicator

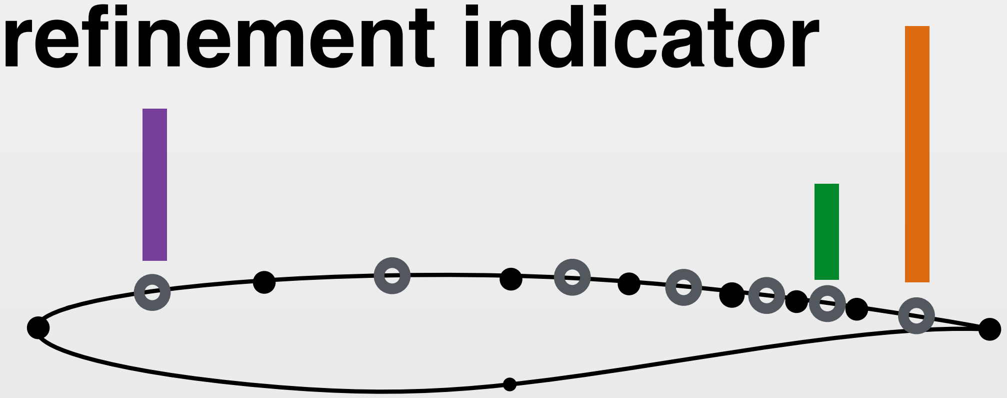
$$\Delta \mathcal{J}_{exp}^{\infty} = \frac{1}{2} \left\langle \left(\frac{\partial \mathcal{J}}{\partial \mathsf{S}} + \boldsymbol{\lambda} \frac{\partial \mathcal{C}^a}{\partial \mathsf{S}} \right), \mathcal{H}^{-1} \left(\frac{\partial \mathcal{J}}{\partial \mathsf{S}} + \boldsymbol{\lambda} \frac{\partial \mathcal{C}^a}{\partial \mathsf{S}} \right) \right\rangle$$

Expected feasible objective reduction in **candidate** search space:

KKT stationarity
0 at optimum

$$I \equiv \Delta \mathcal{J}_{exp}^{\infty} = \frac{1}{2} \left\langle \left(\frac{\partial \mathcal{J}}{\partial \mathbf{X}_c} + \boldsymbol{\lambda} \frac{\partial \mathcal{C}^a}{\partial \mathbf{X}_c} \right), (\mathcal{M}\mathcal{H})^{-1} \underbrace{\left(\frac{\partial \mathcal{J}}{\partial \mathbf{X}_c} + \boldsymbol{\lambda} \frac{\partial \mathcal{C}^a}{\partial \mathbf{X}_\mathbf{c}} \right)}_{} \right\rangle$$

Use as **refinement indicator**



Has sensible **units**

$$[I] = \frac{\text{Drag}}{\text{ft}} \left(\frac{\text{ft}^2}{\text{Drag}} \right) \frac{\text{Drag}}{\text{ft}} = \text{Drag}$$

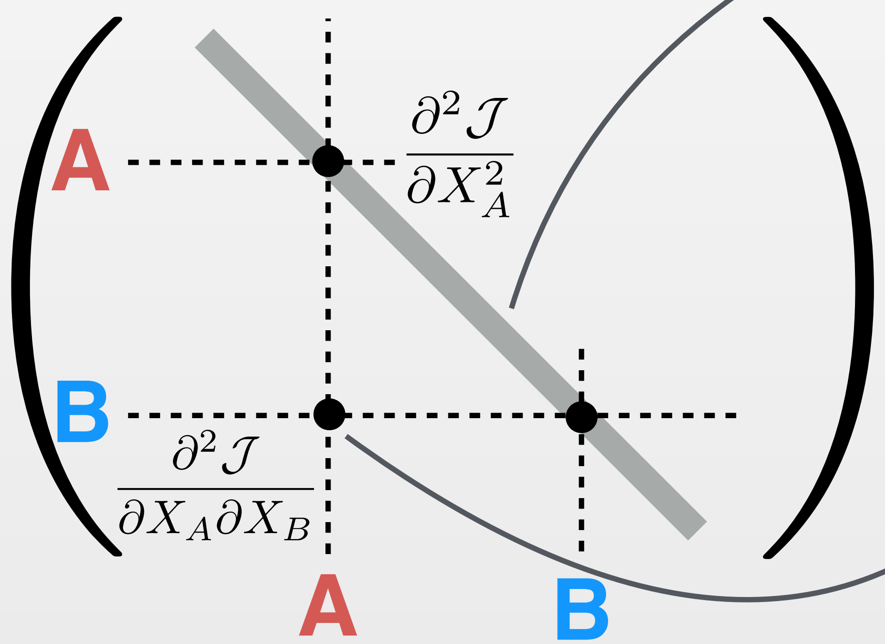
"expected drag reduction"

Refinement Indicator

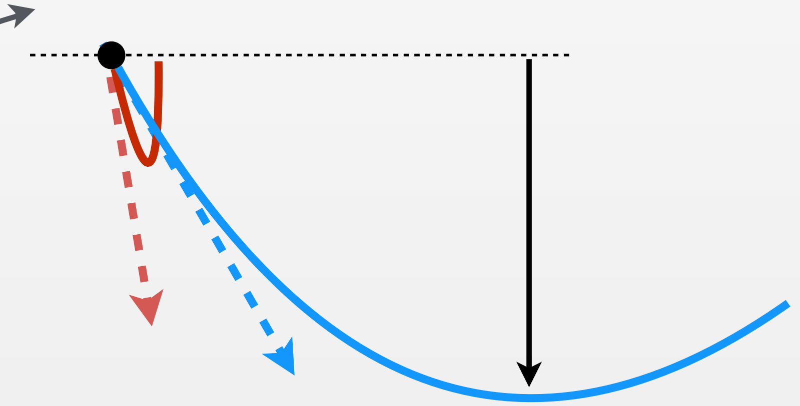
$$I = \frac{1}{2}\left\langle \left(\frac{\partial \mathcal{J}}{\partial \mathbf{X}_c} + \boldsymbol{\lambda}\frac{\partial \mathcal{C}^a}{\partial \mathbf{X}_c}\right), (\mathcal{M}\mathcal{H})^{-1}\left(\frac{\partial \mathcal{J}}{\partial \mathbf{X}_c} + \boldsymbol{\lambda}\frac{\partial \mathcal{C}^a}{\partial \mathbf{X}_\mathbf{c}}\right)\right\rangle$$

Explicitly accounts for **constraints**

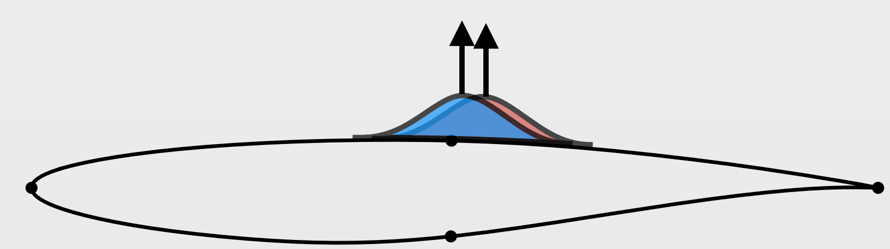
Hessian matrix



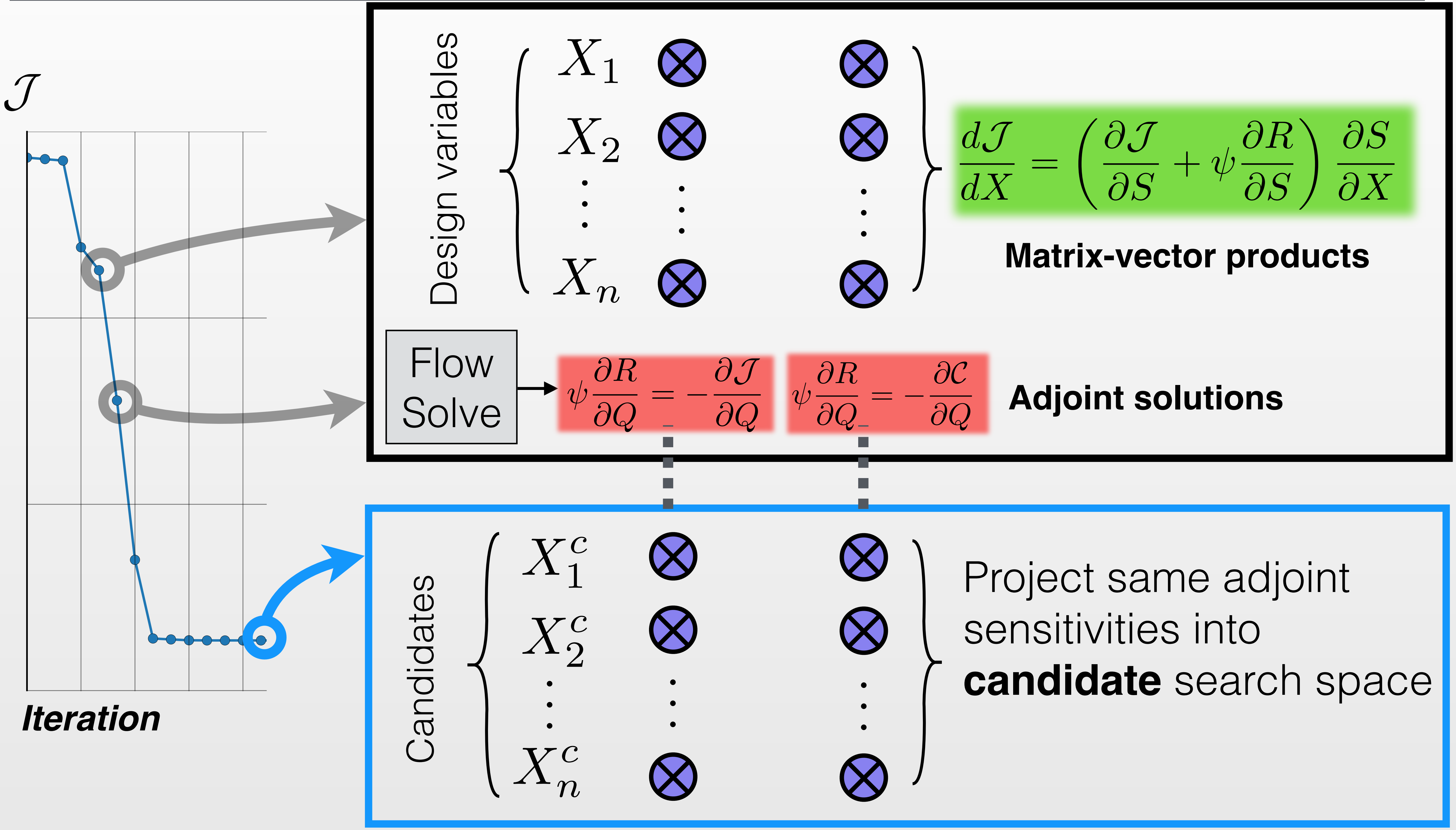
Accounts for **curvature** variation



Detects **redundancy**



Indicator Computation — Gradients



Indicator Computation — Hessian Estimation

$$I = \frac{1}{2}\left\langle \left(\frac{\partial \mathcal{J}}{\partial \mathbf{X}_c} + \boldsymbol{\lambda} \frac{\partial \mathcal{C}^a}{\partial \mathbf{X}_c} \right), (\mathcal{M}\mathcal{H})^{-1} \left(\frac{\partial \mathcal{J}}{\partial \mathbf{X}_c} + \boldsymbol{\lambda} \frac{\partial \mathcal{C}^a}{\partial \mathbf{X}_{\mathbf{c}}} \right) \right\rangle$$

Estimate Hessian from **quasi-Newton** approximation in previous space

BFGS

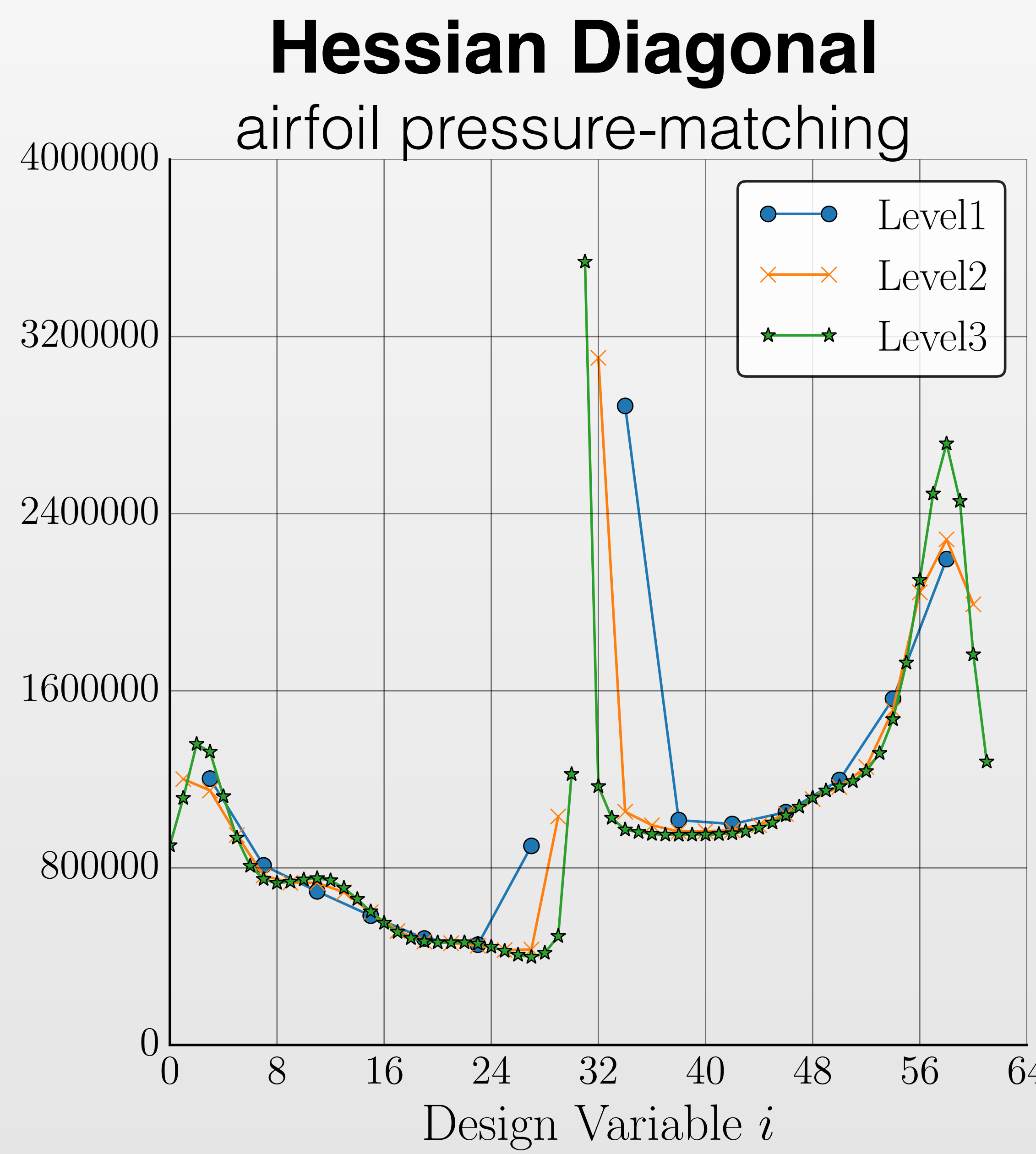
$$\mathbf{B}_0^k = \mathbf{I}$$

$$\mathbf{B}_n^k \approx \mathbf{H}_n^k$$

$$\mathbf{H}_0^{k+1} \approx \mathcal{P}(\mathbf{B}_n^k)$$

Prolong to finer space

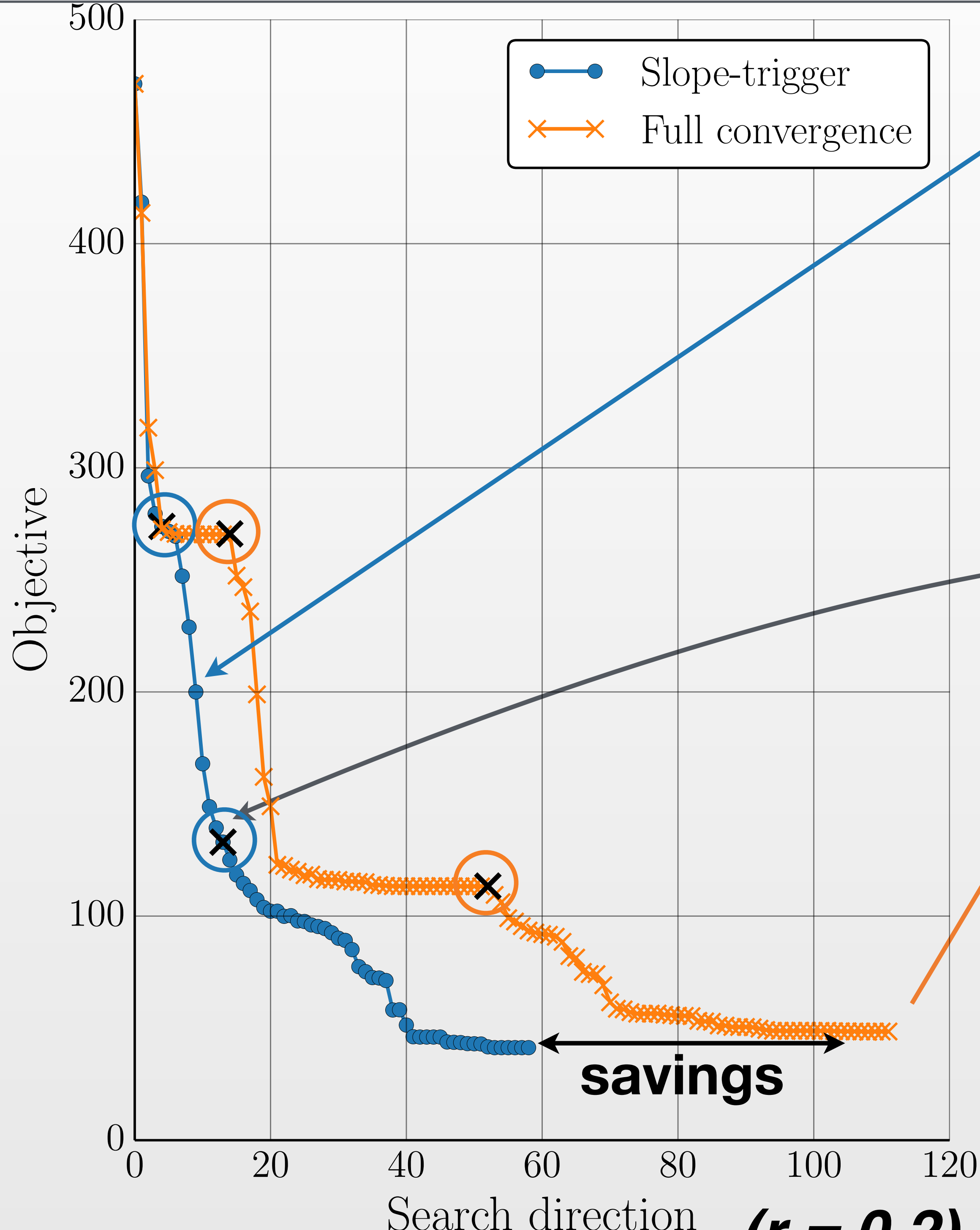
(see dissertation)



Outline

- ✓ Introduction
- **Theory and Approach**
  - ✓ Discrete Adaptation
  - ✓ Refinement Indicator
  - **Adaptation Strategy**
- Verification
- Design Examples

When to refine?



(r = 0.2)

Slope Reduction:

Deceleration of design improvement

- **Trigger** detects diminishing returns on **computational** time:

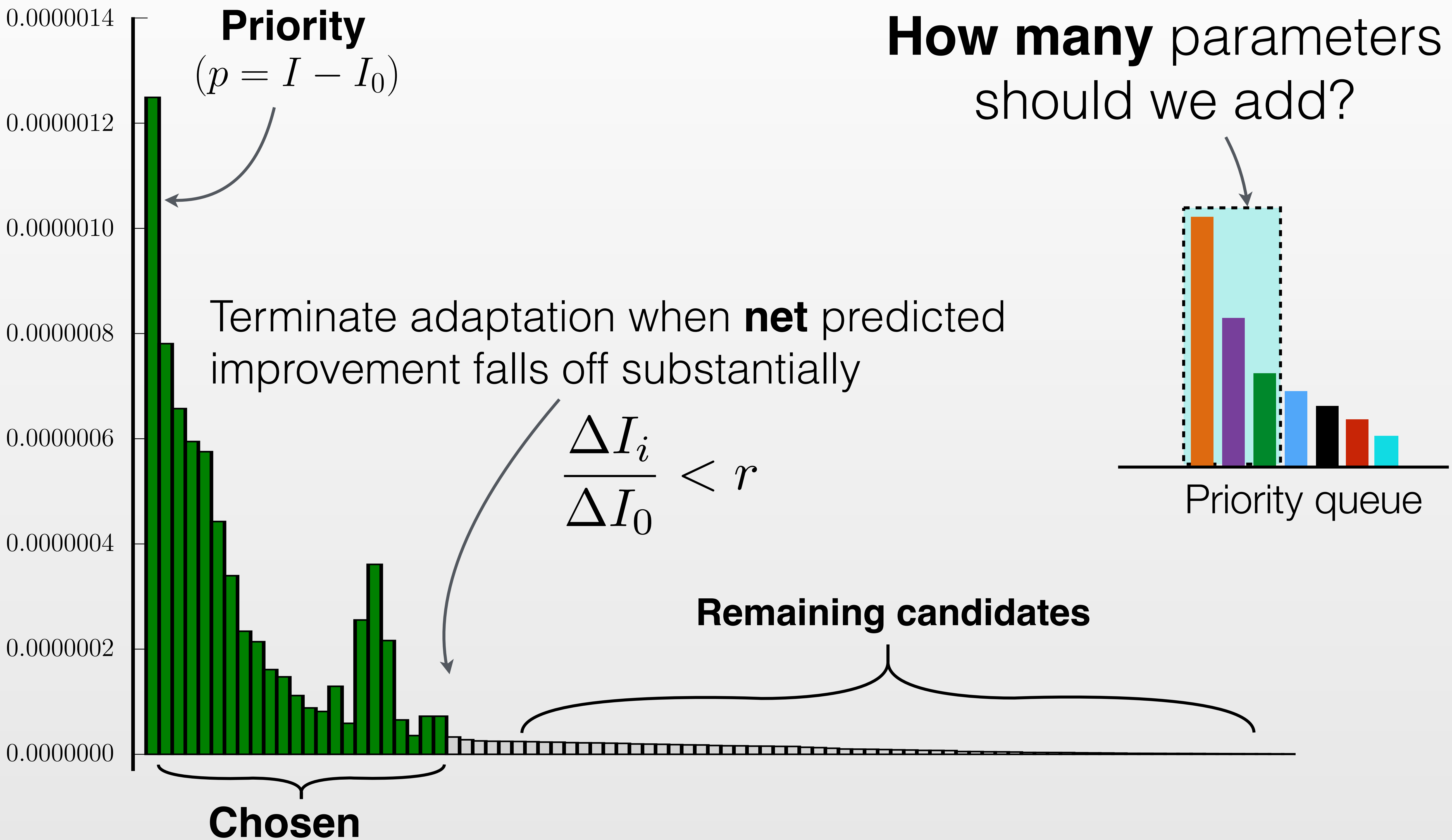
$$\frac{\Delta \mathcal{J}_i}{\max_k (\Delta \mathcal{J}_k)} < r$$

Convergence:

Sufficient optimality (KKT conditions)

- Maximally exploits parameters

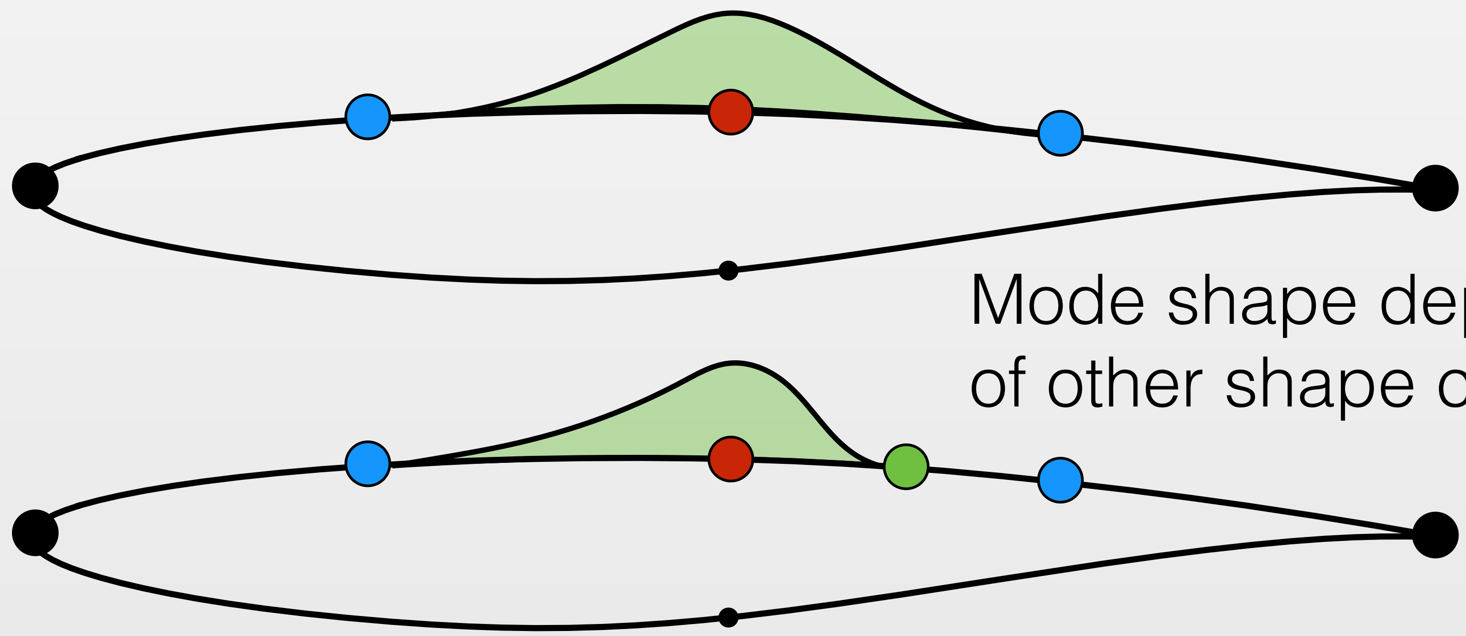
Growth rate



How many parameters should we add?

Adding Multiple Parameters

- **Adaptation:** "Find the best *N* out of *M* parameters"
- Properly a **combinatorial optimization** problem
  - Not separable for most deformers
  - But conducive to approximate solutions
- I use an approximate **constructive** (greedy) algorithm†

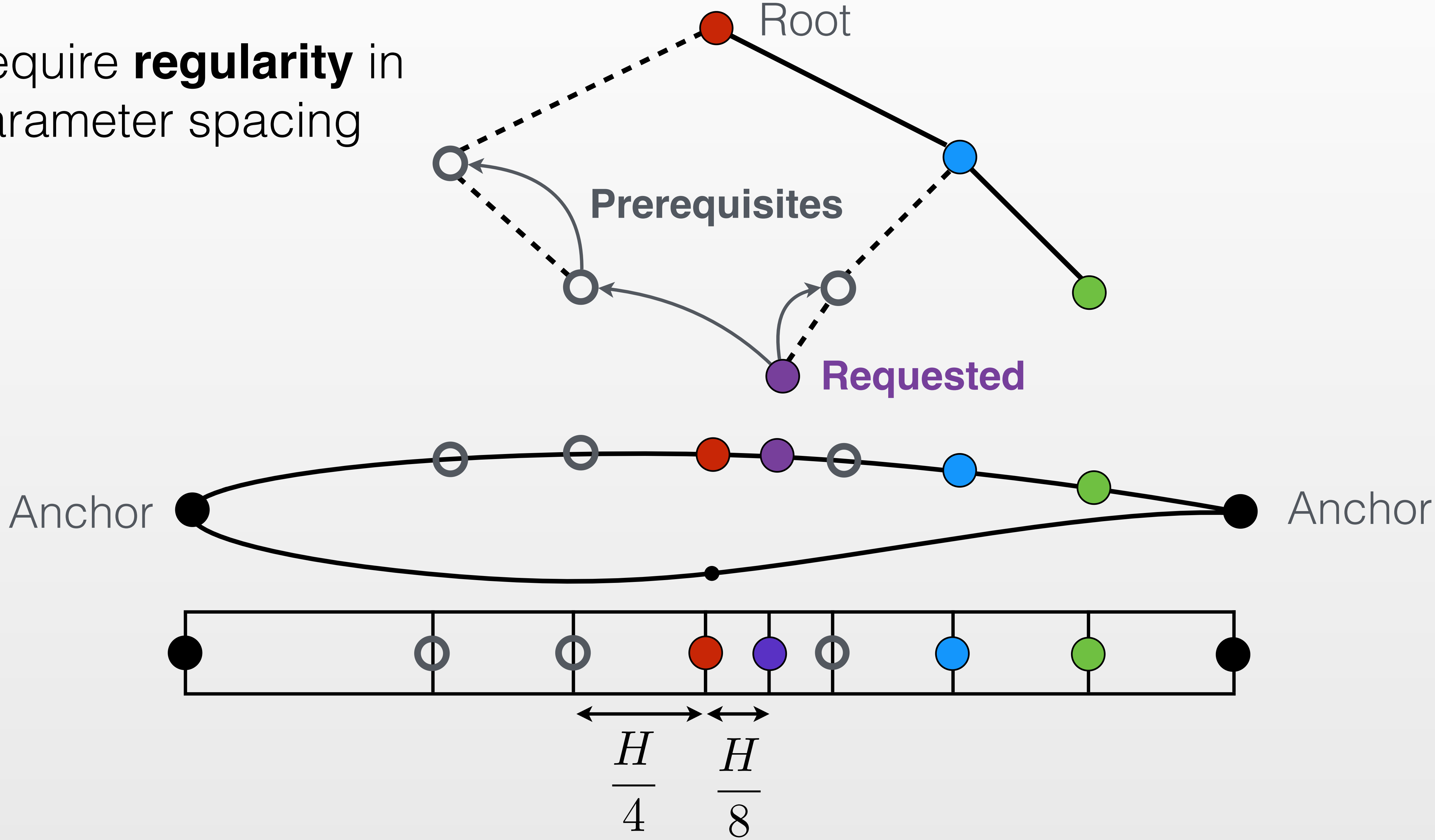


Mode shape depends on locations of other shape controllers

† (2015) **Anderson**, G.R., Aftosmis, M. J. *"Adaptive Shape Control for Aerodynamic Design." AIAA 2015-0398*

Regularity

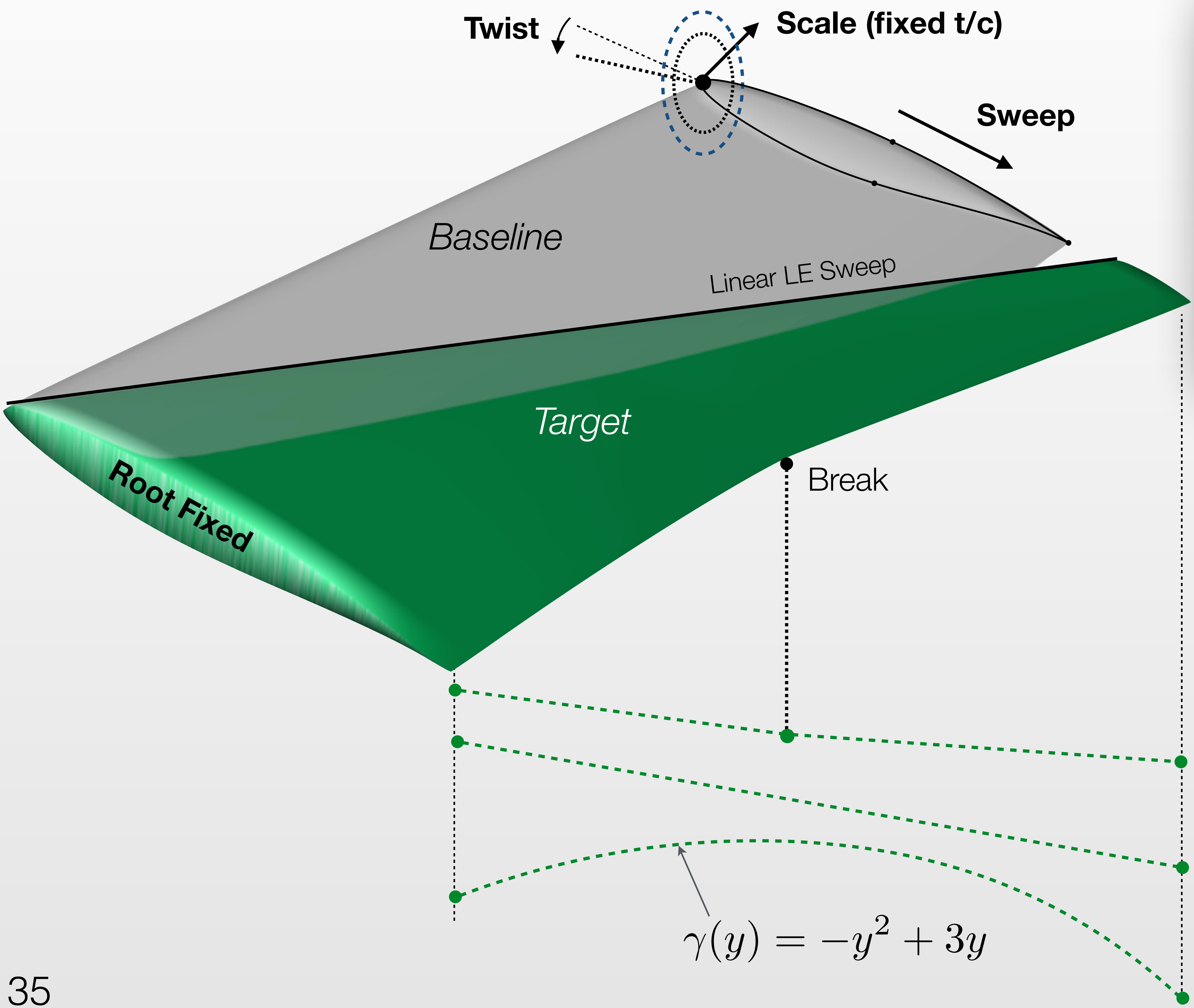
Require **regularity** in parameter spacing



Outline

- ✓ Introduction
- ✓ Theory and Approach
- **Verification**
  - **Correctness —** Does the indicator predict actual design improvement?
  - **Robustness —** Does the approach always converge to the continuous optimum?
- Design Examples

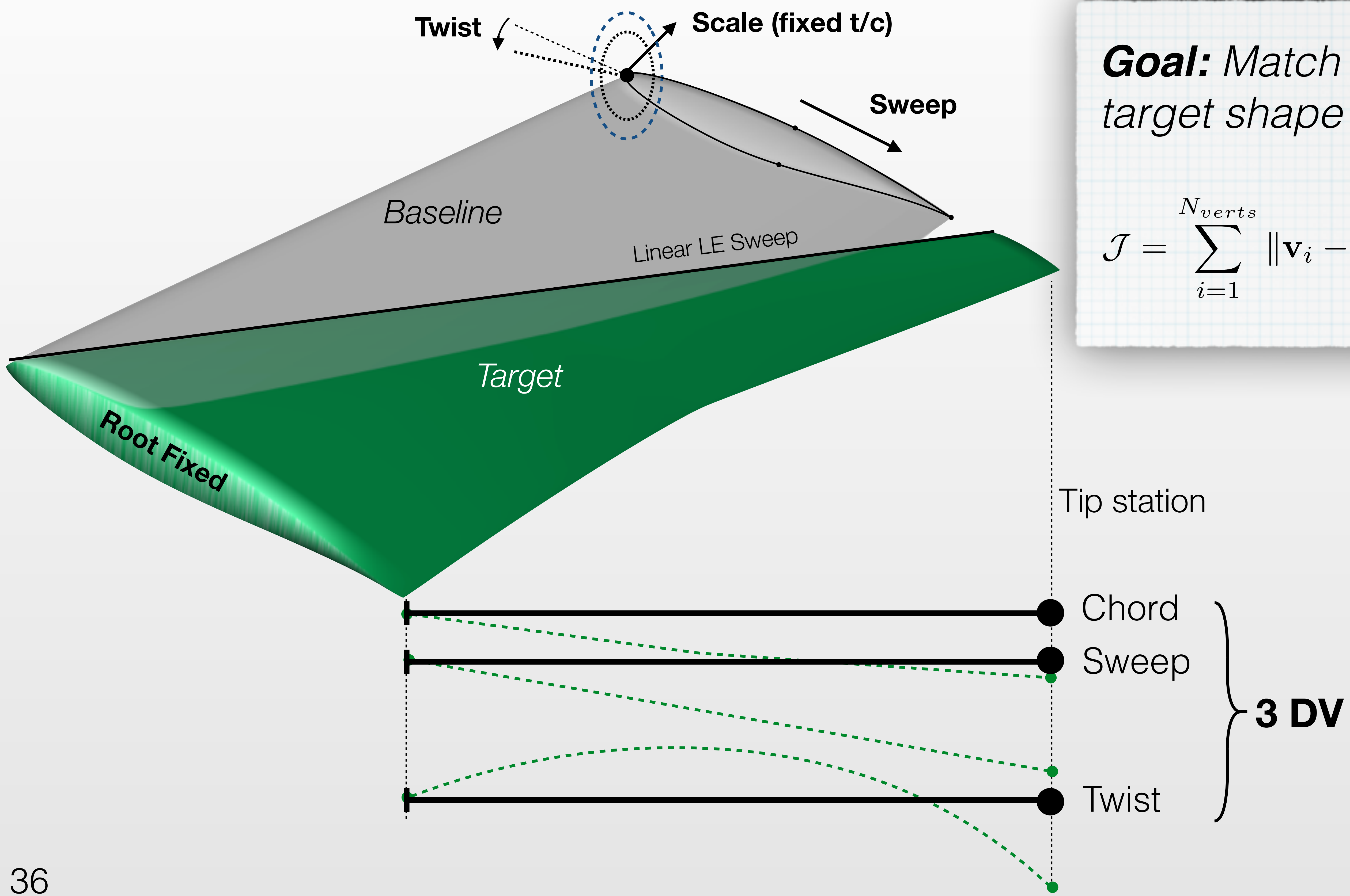
Verification Study 1: Geometric Shape Matching



Goal: *Match target shape*

$$\mathcal{J} = \sum_{i=1}^{N_{verts}} \|\mathbf{v}_i - \mathbf{v}_i^*\|^2$$

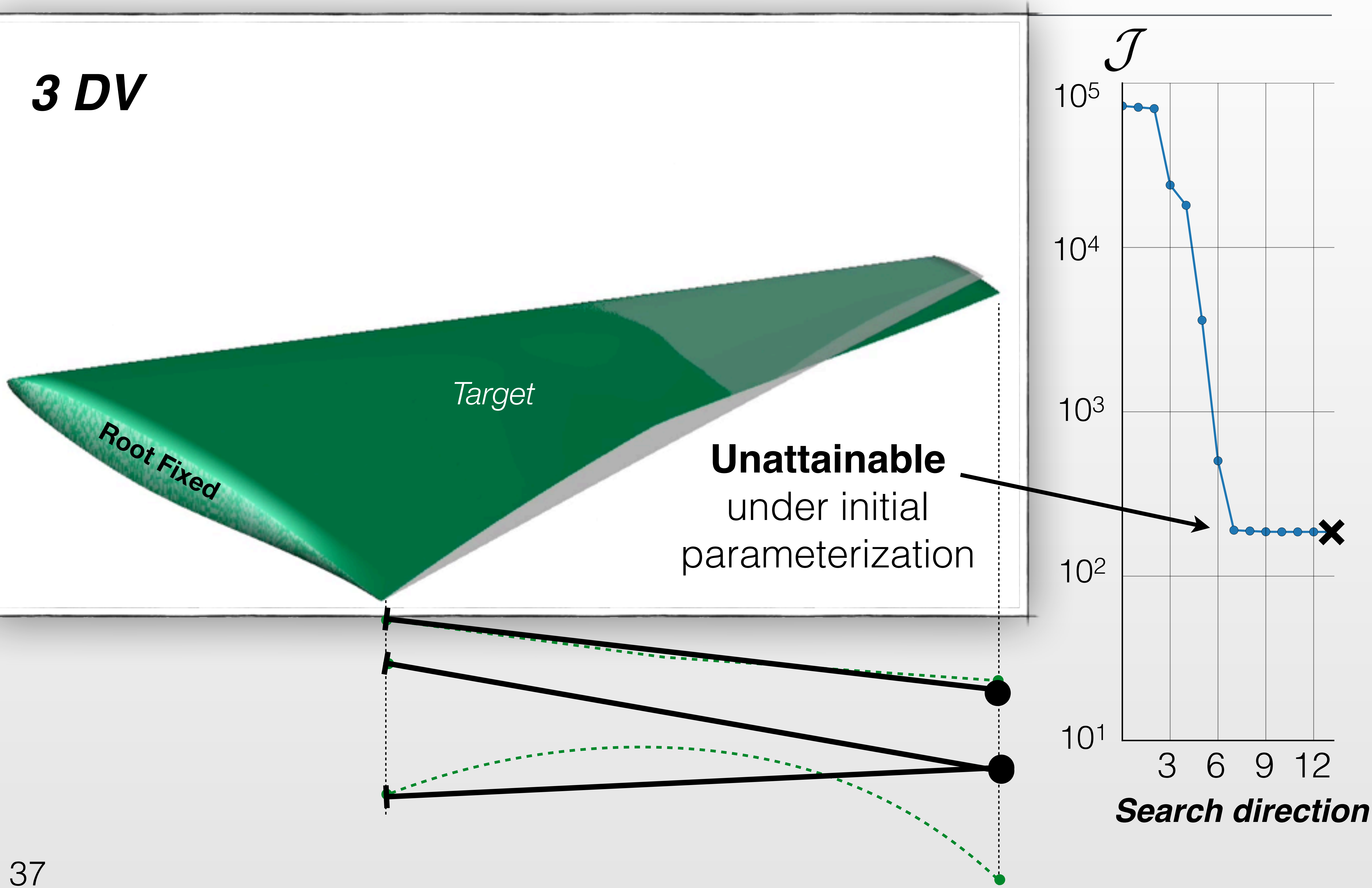
Initial Parameterization



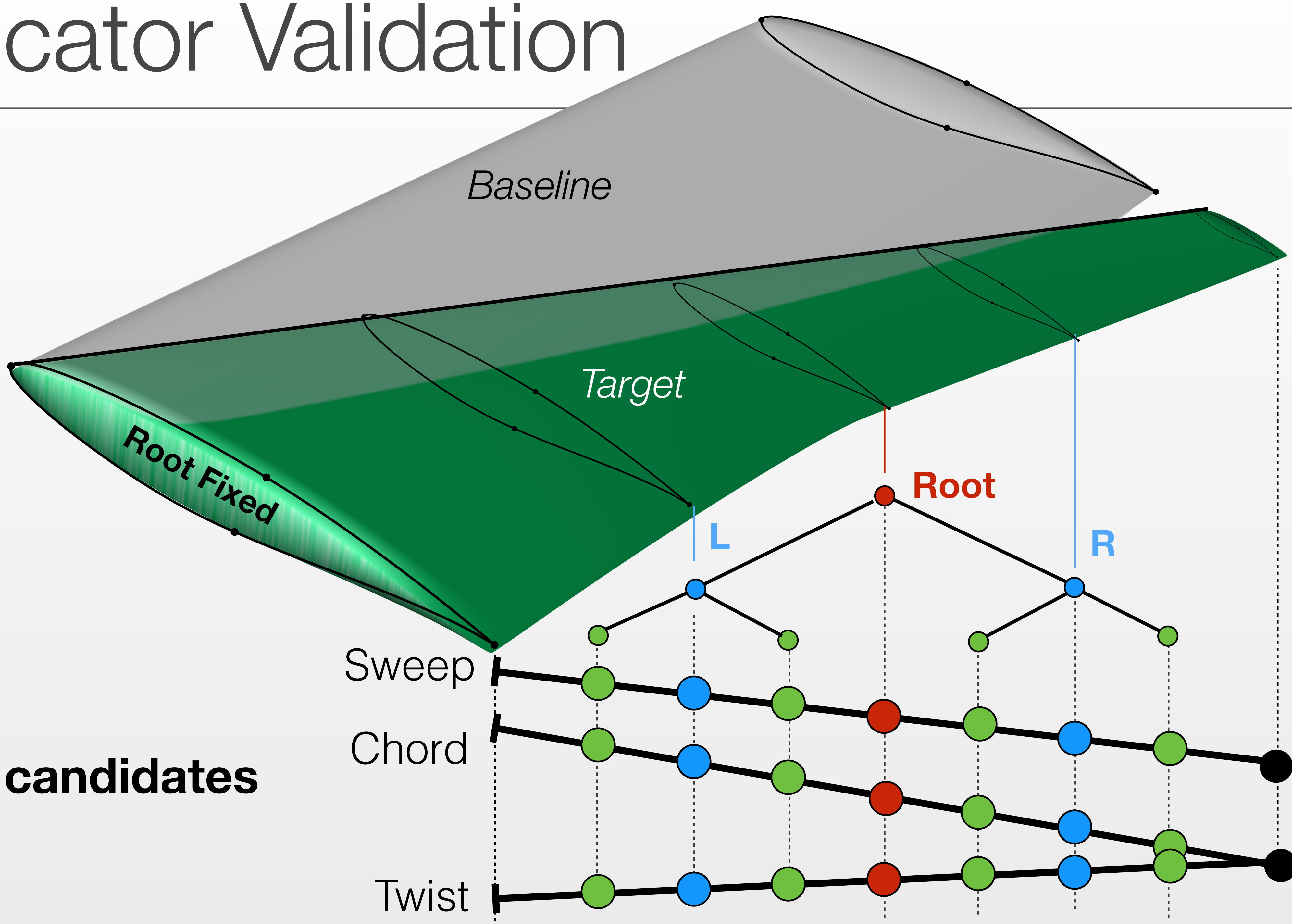
Goal: *Match target shape*

$$\mathcal{J} = \sum_{i=1}^{N_{verts}} \|\mathbf{v}_i - \mathbf{v}_i^*\|^2$$

Shape Matching under Initial Parameterization



Indicator Validation



21 candidates

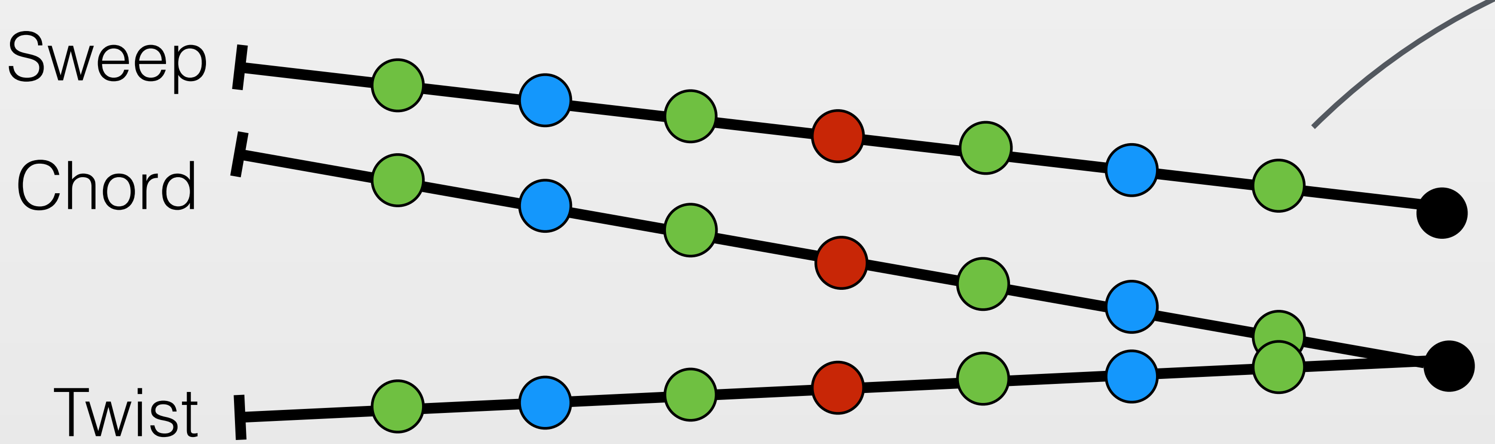
Indicator Validation

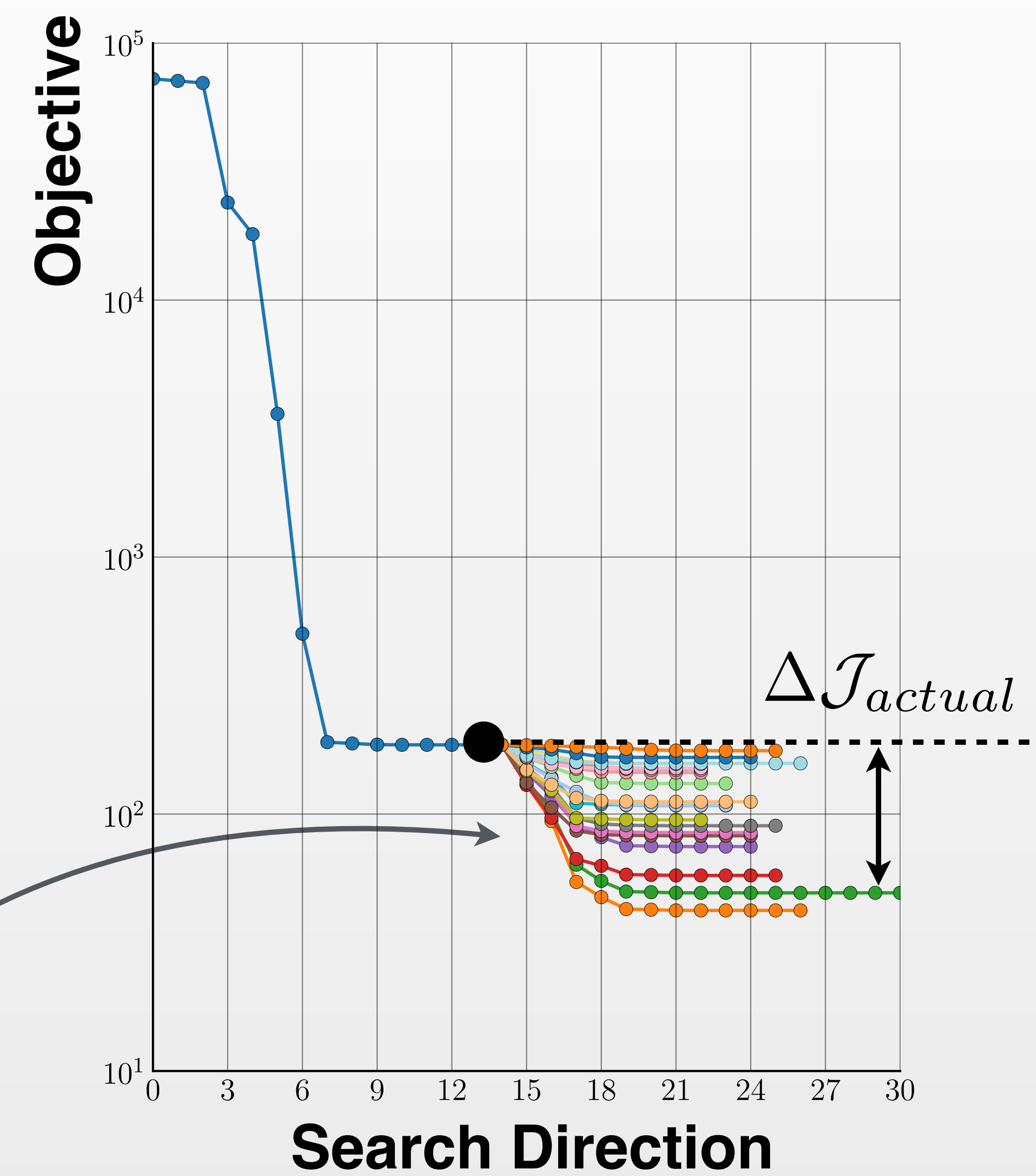
For each candidate:

1. **Predict** design improvement.
   With indicator:

$$I = \frac{1}{2}\left\langle \left(\frac{\partial \mathcal{J}}{\partial \mathbf{X}_c} + \boldsymbol{\lambda}\frac{\partial \mathcal{C}^a}{\partial \mathbf{X}_c}\right), (\mathcal{M}\mathcal{H})^{-1}\left(\frac{\partial \mathcal{J}}{\partial \mathbf{X}_c} + \boldsymbol{\lambda}\frac{\partial \mathcal{C}^a}{\partial \mathbf{X_c}}\right)\right\rangle$$

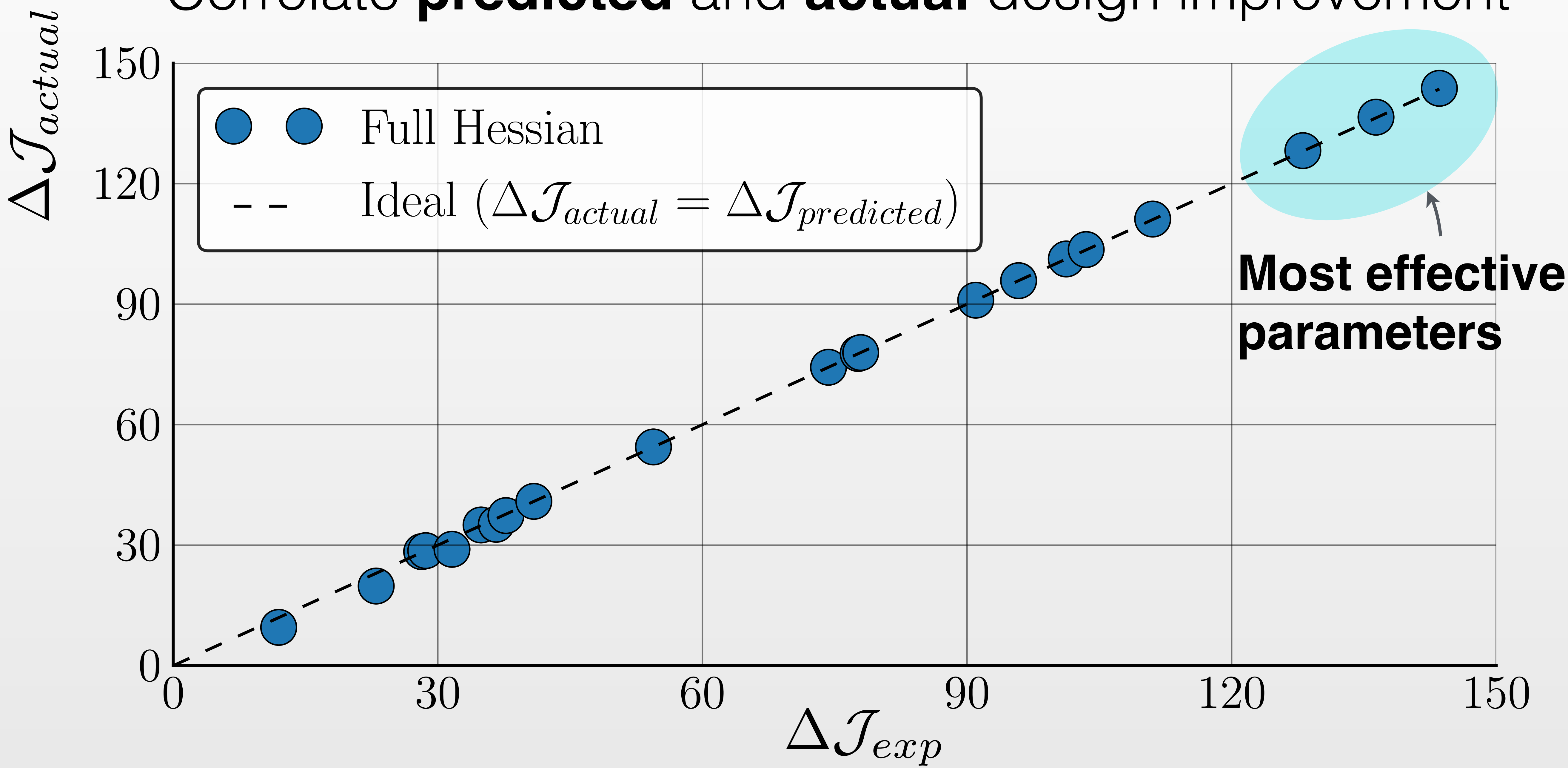
2. Measure **actual** improvement.
   Run optimization for each candidate.





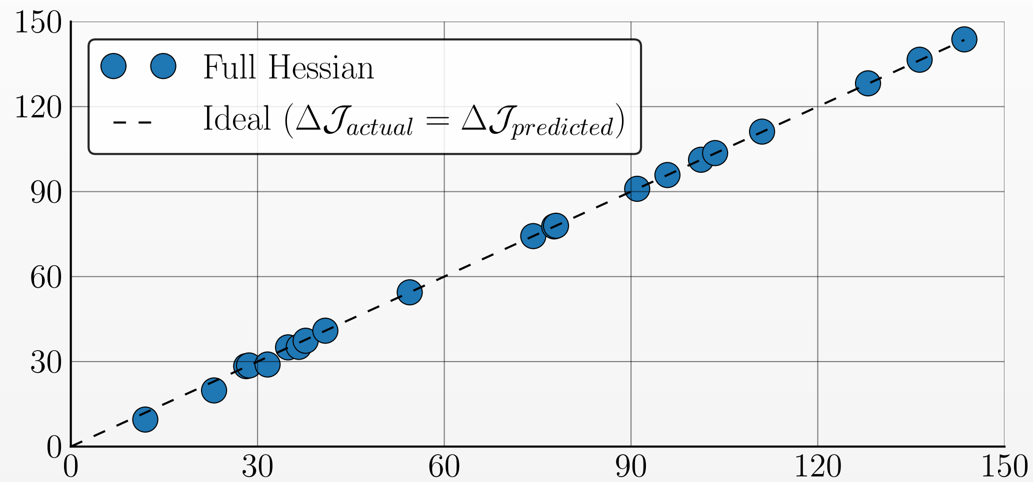
Indicator Validation

Correlate **predicted** and **actual** design improvement



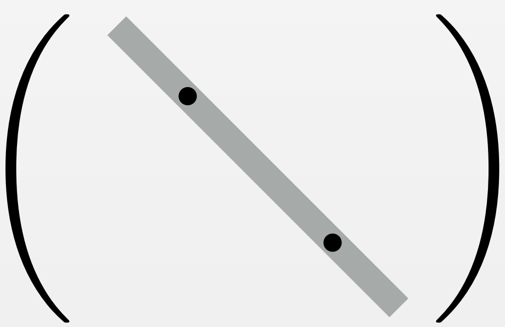
Approximations

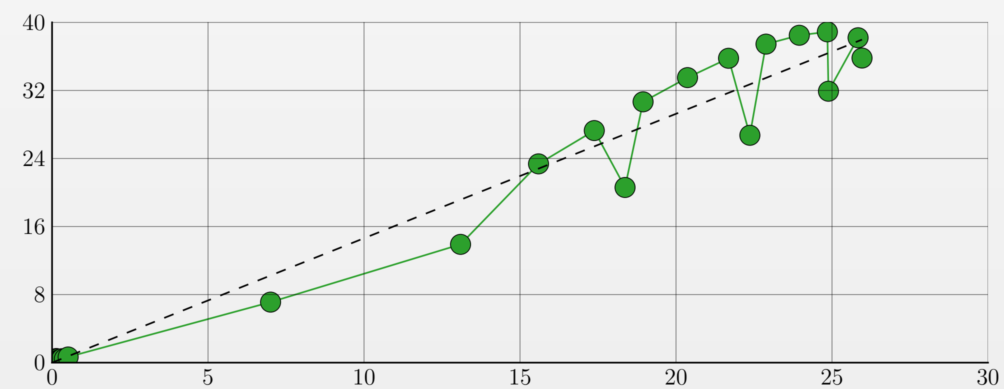
Exact Hessian



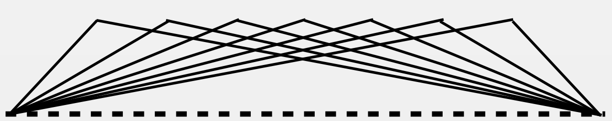
Excellent prediction

Diagonal



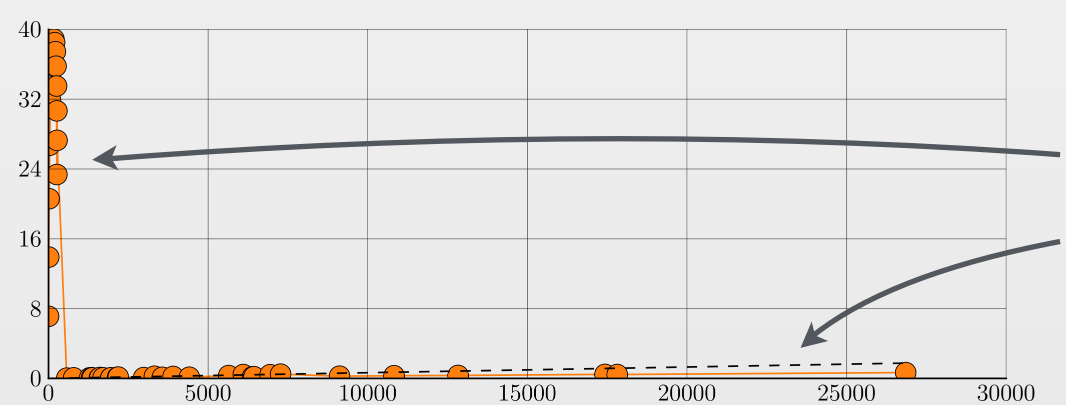


Acceptable — some redundancy



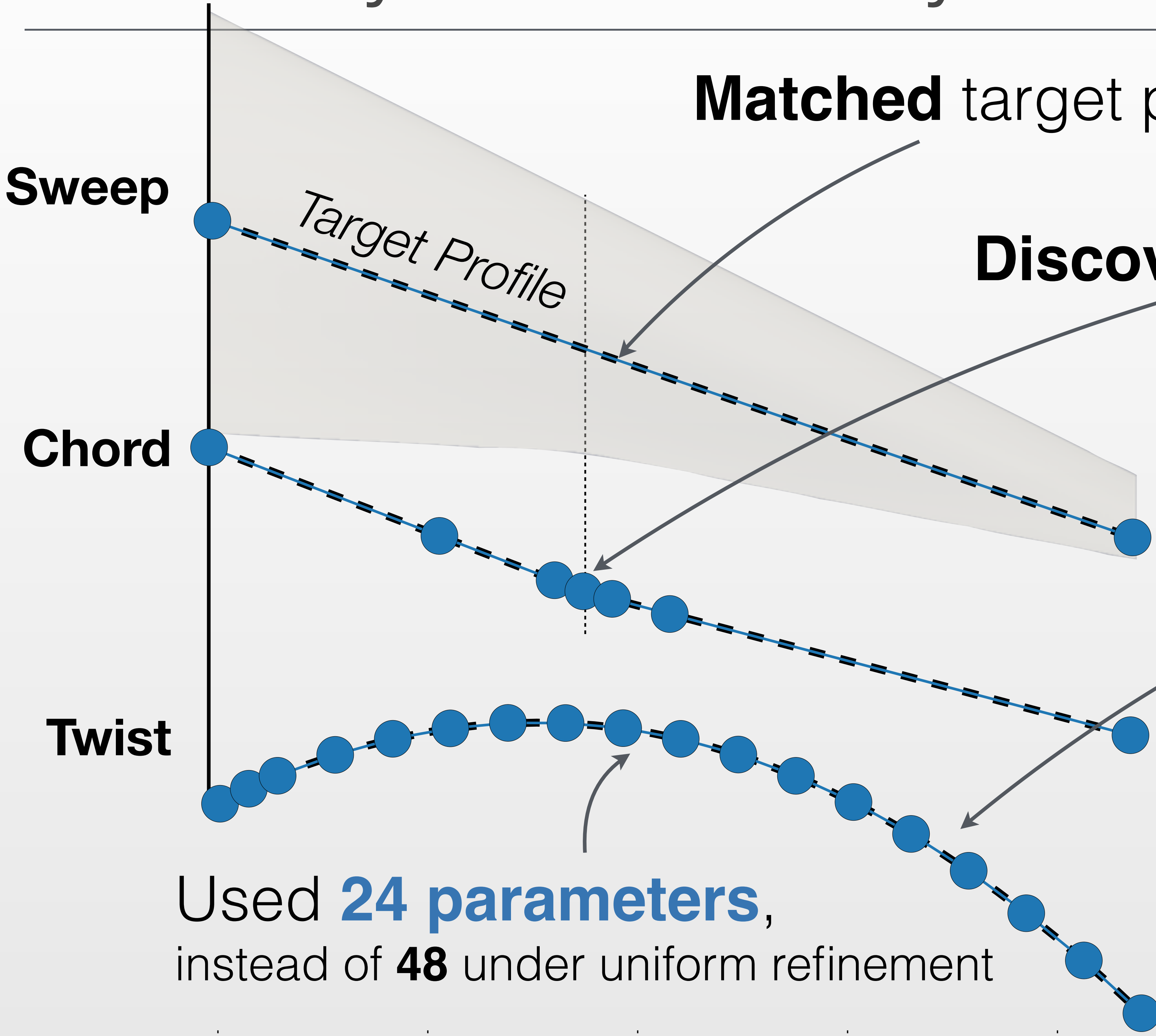
Identity

$$\begin{pmatrix} 1 & & & & \\ & 1 & & & \\ & & 1 & & \\ & & & 1 & \\ & & & & 1 \end{pmatrix}$$



Poor ranking — systematic difference between classes of shape control

Recovery of Necessary Parameters



Matched target profiles

Discovered wing break

Uniform twist control
minimized interpolation error

Balanced adaptation
of three different classes of shape control

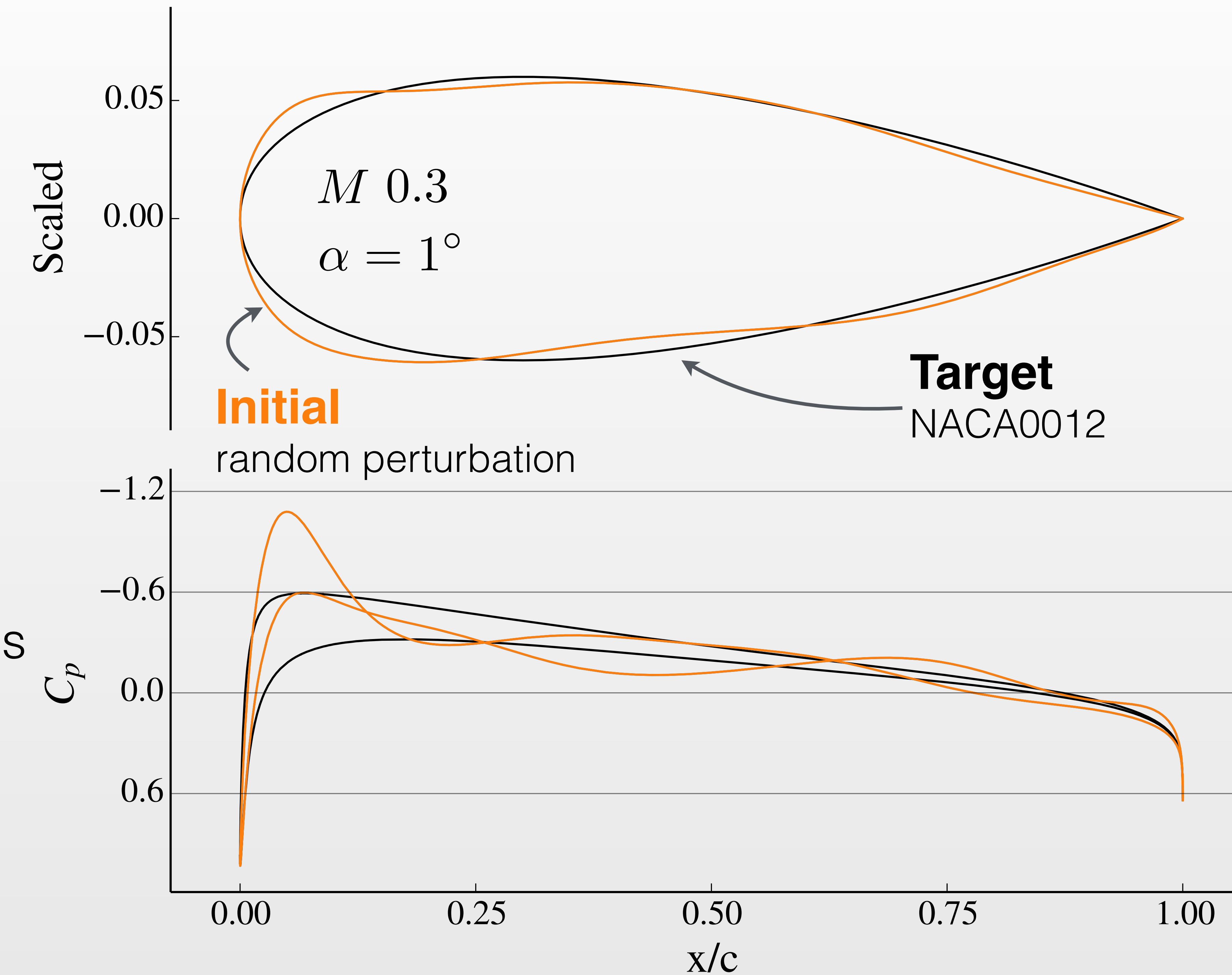
Used **24 parameters**,
instead of **48** under uniform refinement

Verification Study 2: Pressure Signature Matching

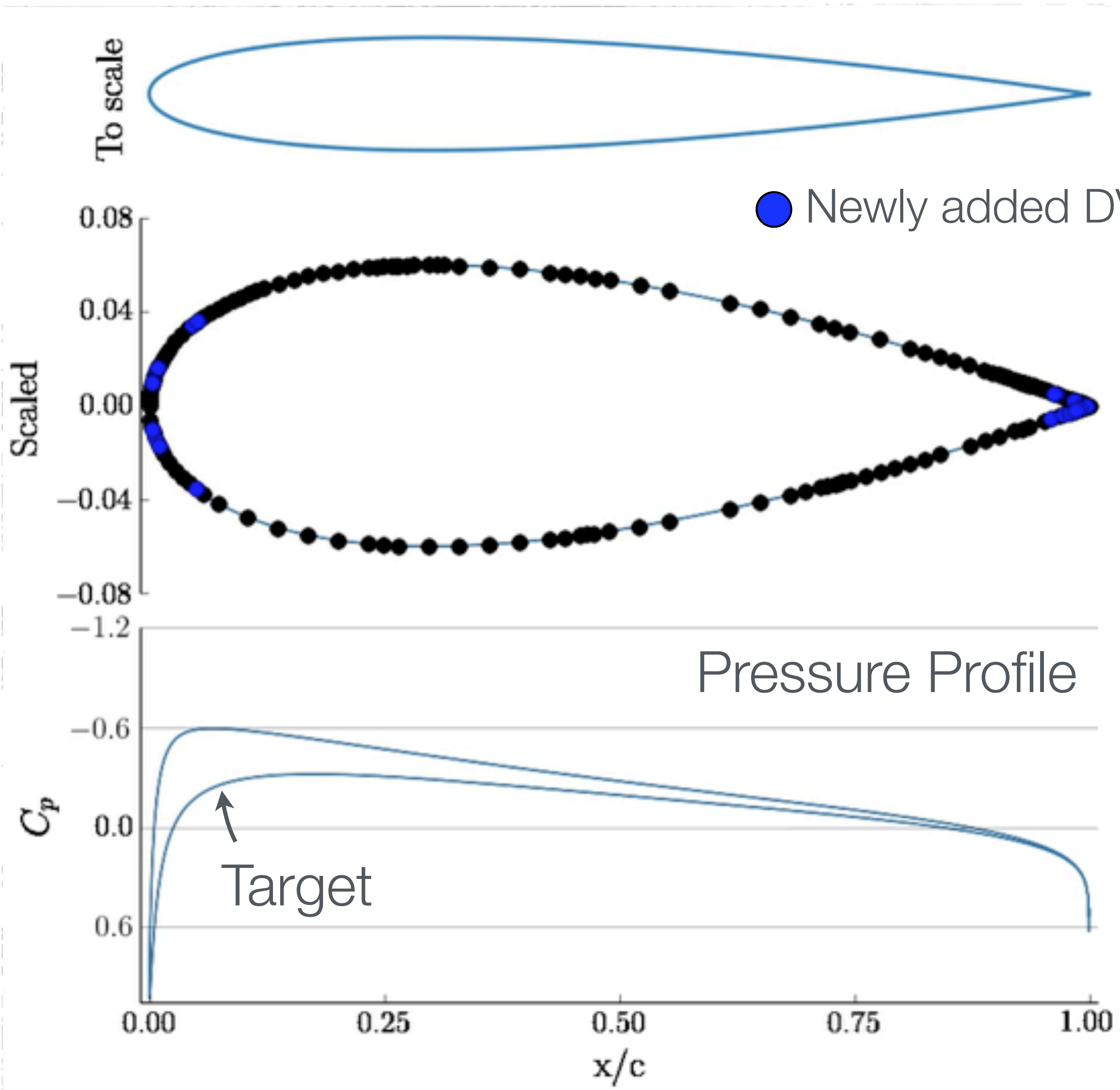
Objective:
Match target pressure profile

$$\mathcal{J} = \frac{1}{2}\sum_{i=1}^{N_{verts}} (p_i - p_i^*)^2$$

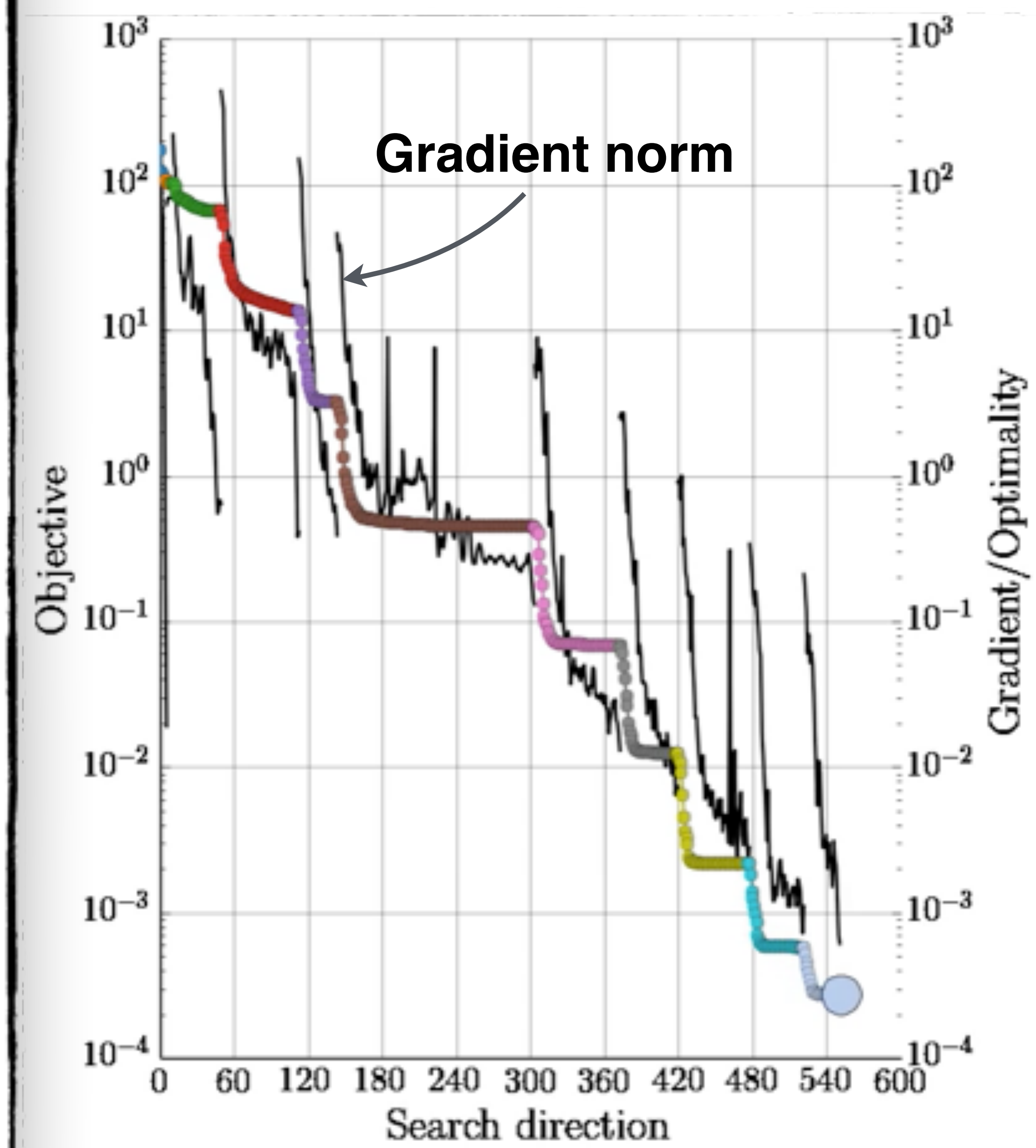
Parameterization:
2D Radial basis functions (localized bumps)
Flow Solver: Cart3D
Optimizer: SNOPT



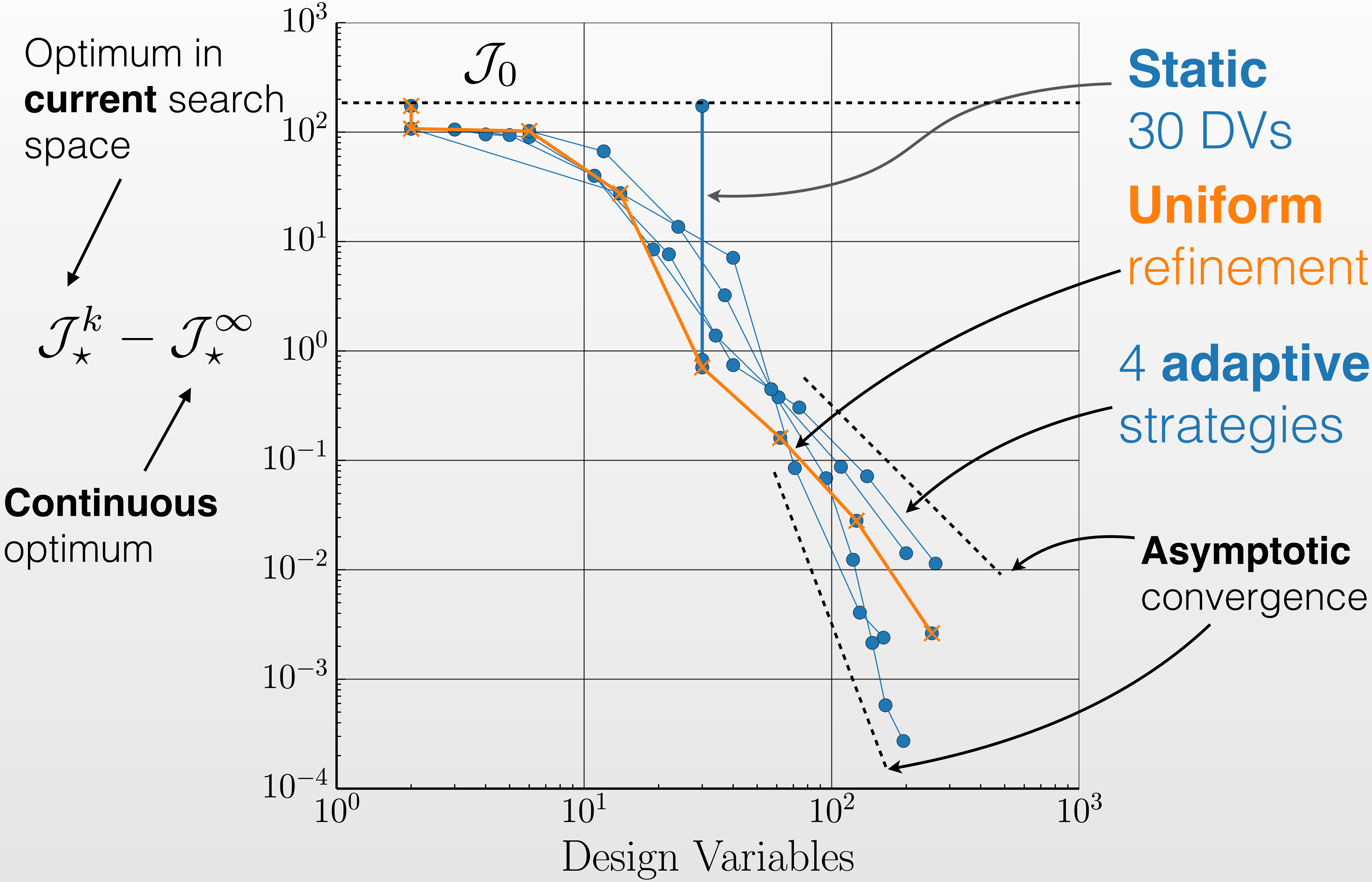
Video — Results



Objective Convergence



Convergence to Continuous Optimum

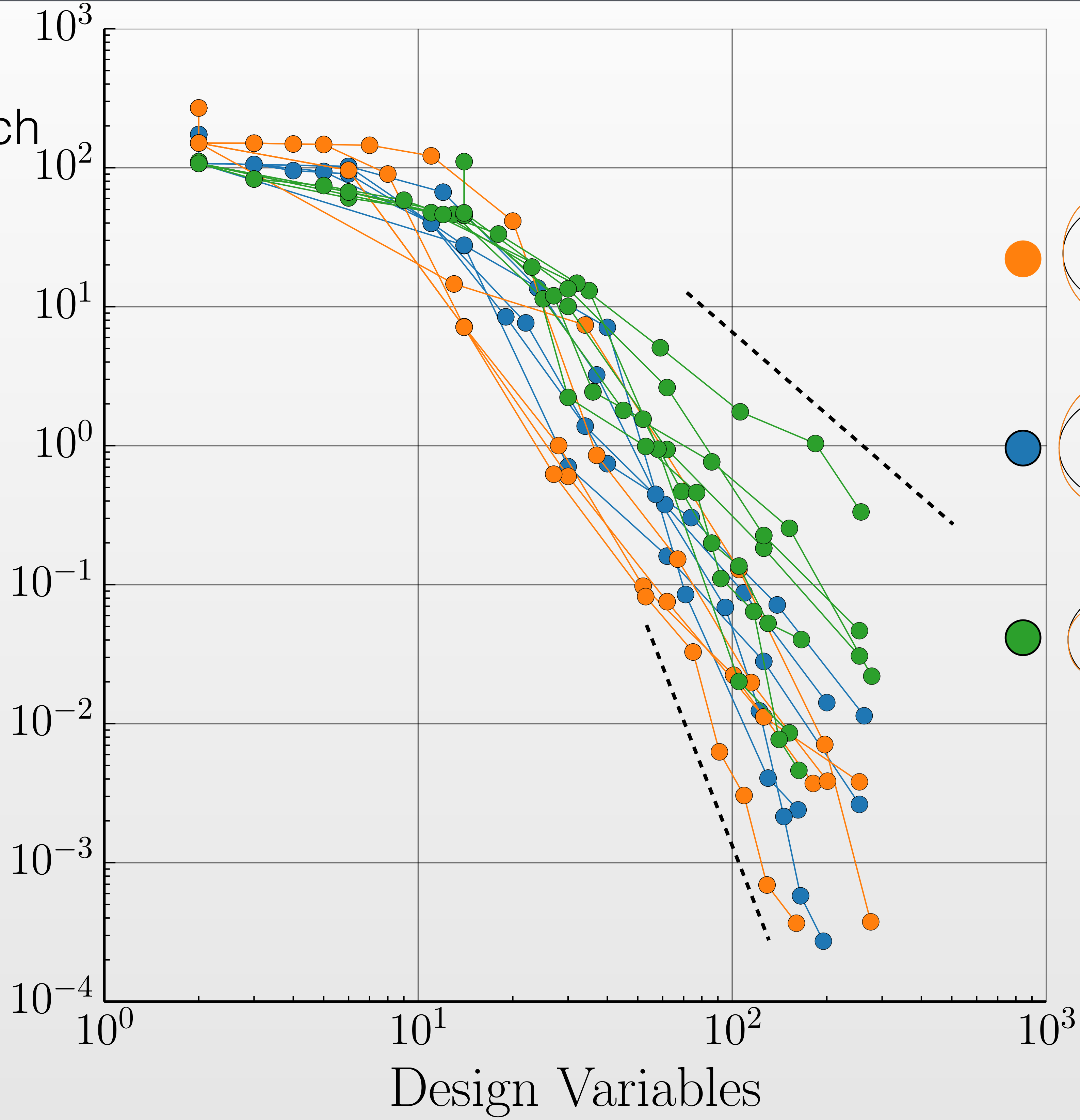


Convergence to Continuous Optimum

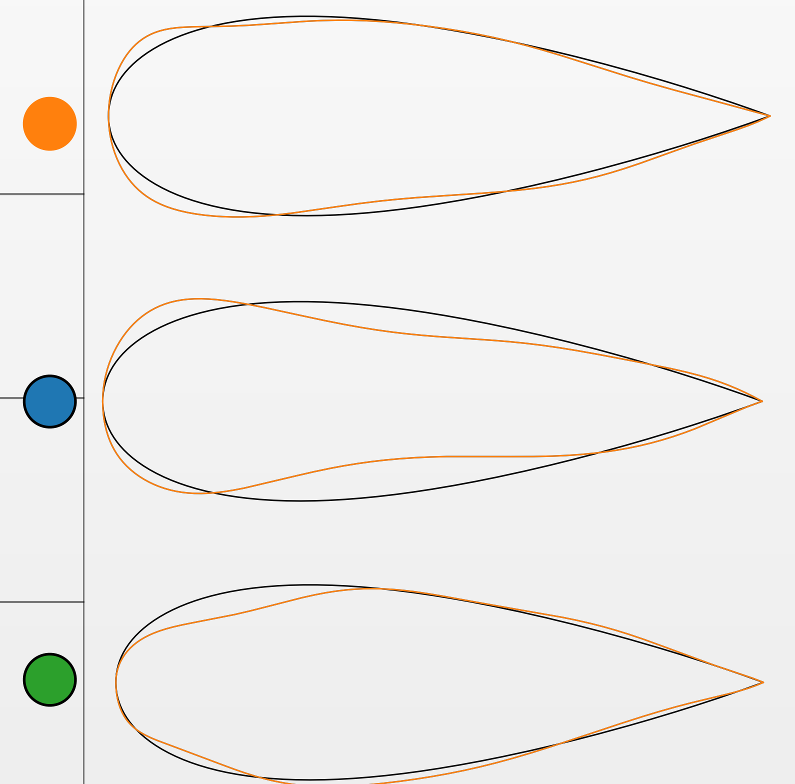
Optimum in **current** search space

$$\mathcal{J}_\star^k - \mathcal{J}_\star^\infty$$

Continuous optimum



Random initial airfoils



Convergence Rate

Efficient in **use of design variables**

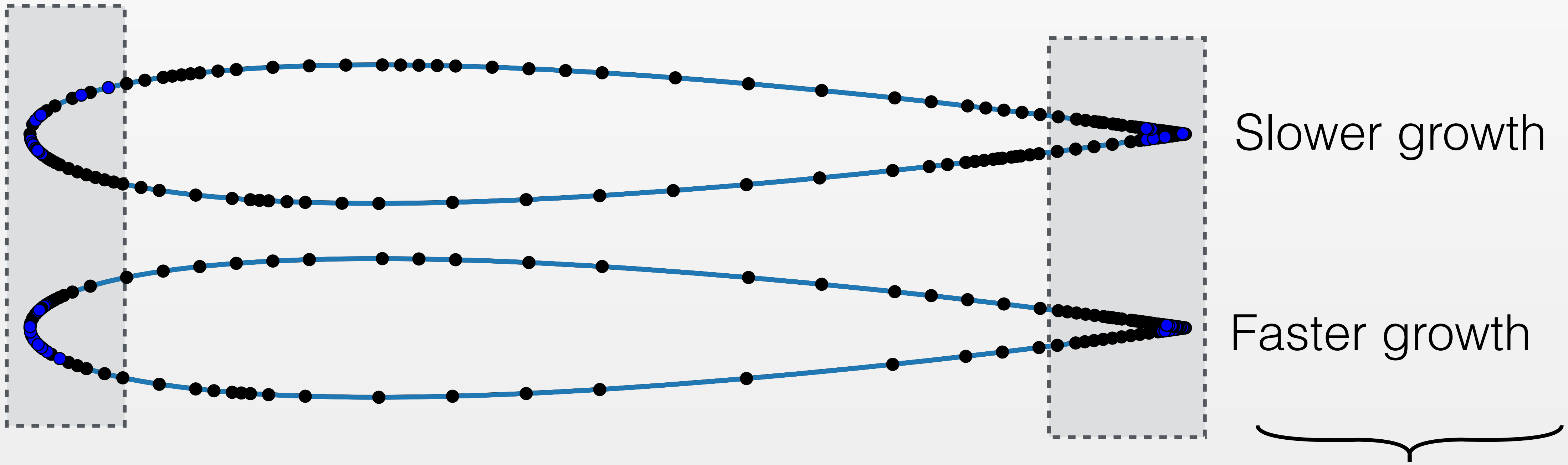
Asymptotic convergence rate of $\mathcal{J}_\star^k - \mathcal{J}_\star^\infty$

Case	**Uniform**	**Adaptive** Strategy 1	Strategy 2
1	2.6	8.3	5.0
2	2.4	5.2	5.6
3	2.7	5.7	4.7
mean	**2.6**	**5.75**	
$\frac{\Delta\mathcal{J}}{\Delta N_{DV}}$*	$\sim$ **6**$\times$	$\sim$ **54**$\times$	

* Reduction in objective for $2\times$ increase in N_{DV}

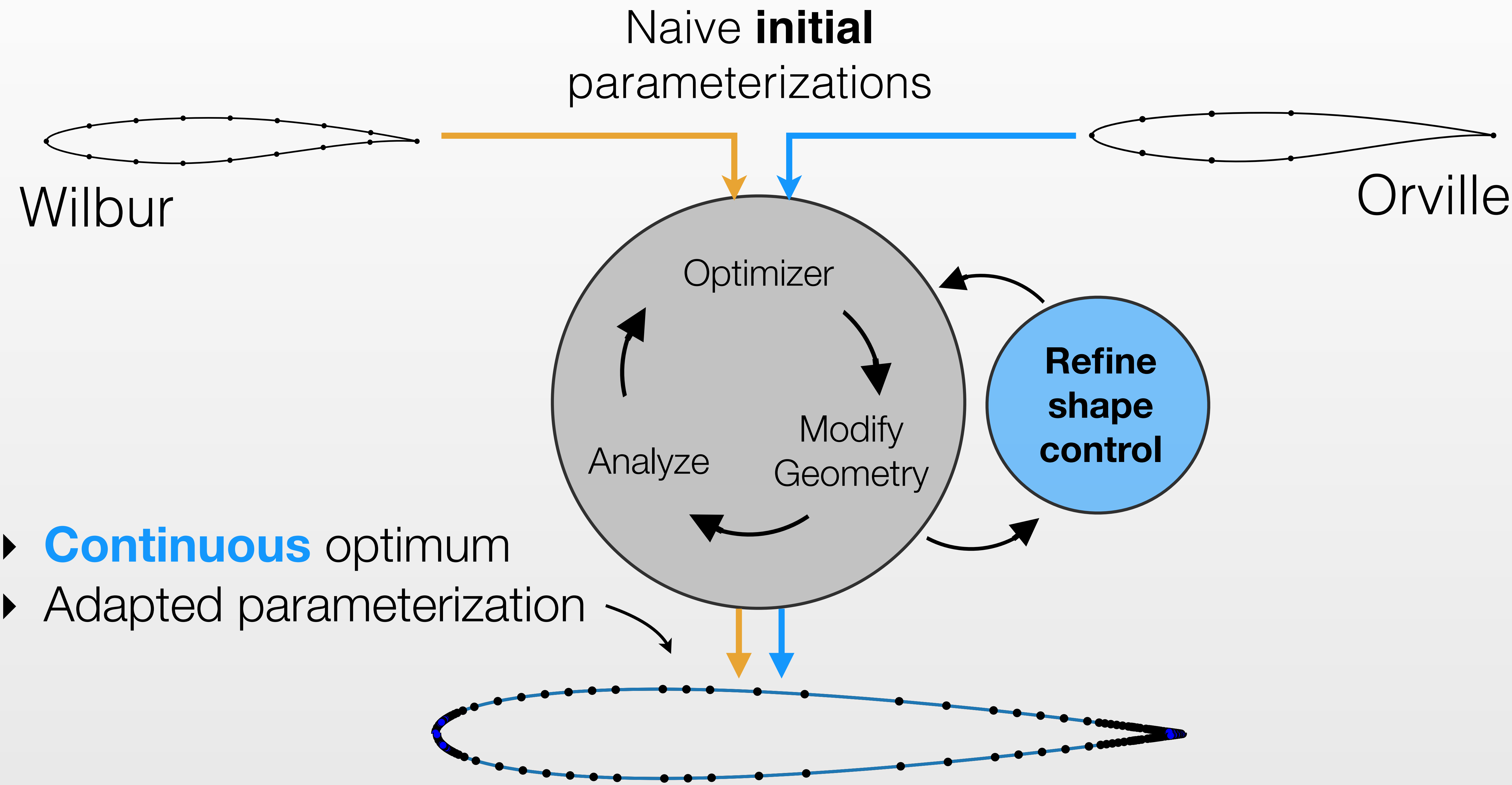
Refinement Patterns

Automatic shape control **clustering** at leading and trailing edges



Different adaptation strategies result in **similar patterns**

Adaptive System

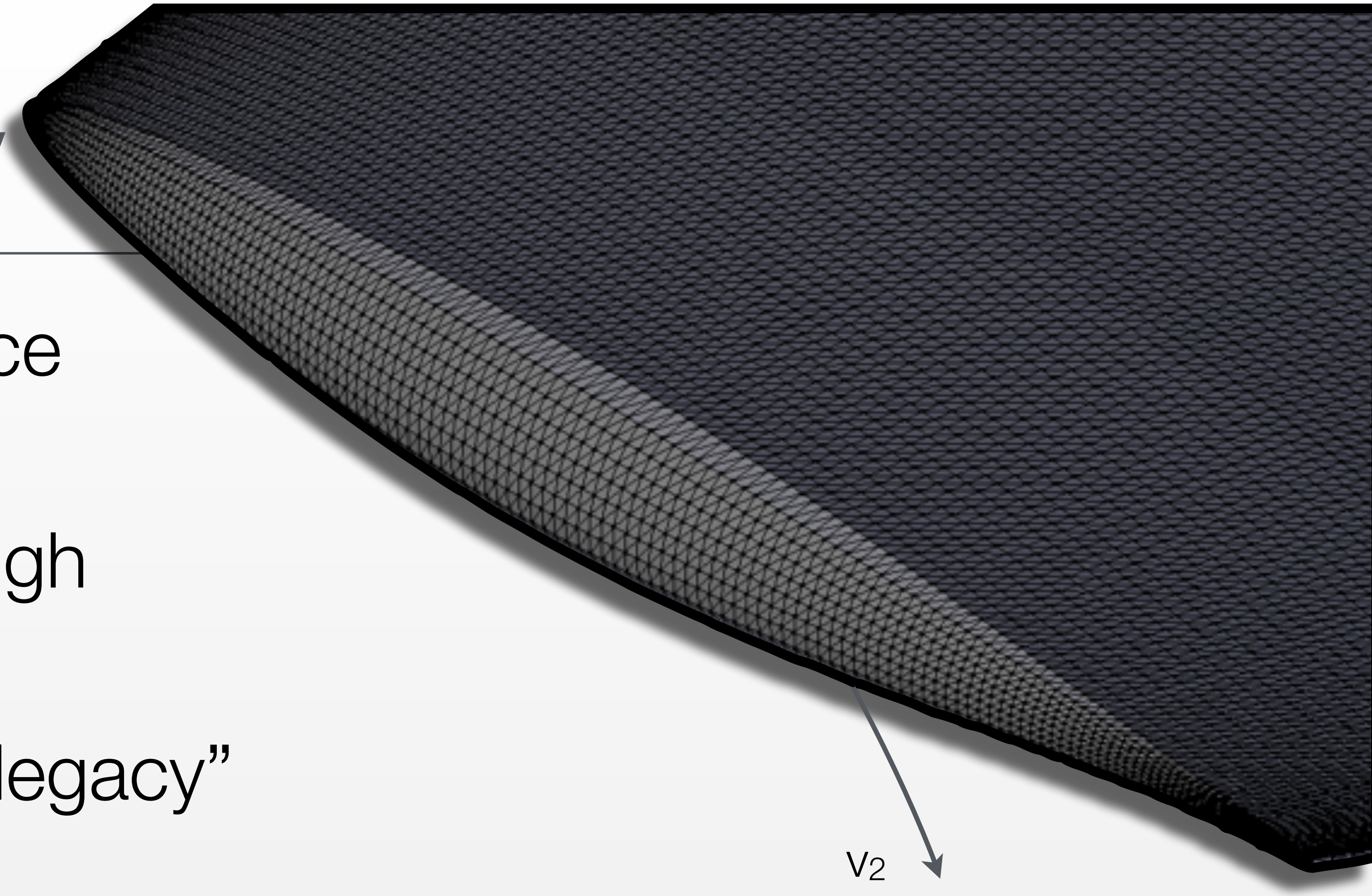


- **Continuous** optimum
- Adapted parameterization

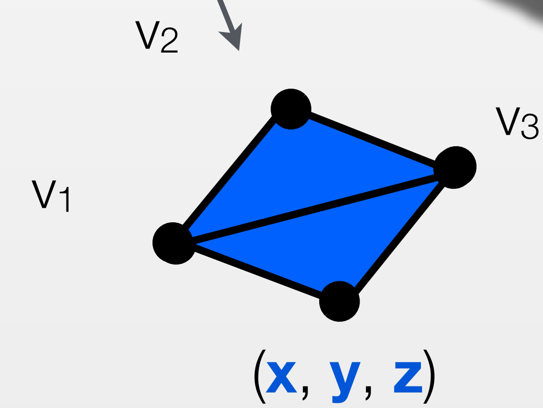
Outline

- ✓ Introduction
- ✓ Theory and Approach
- ✓ Verification
- **Design Examples**
  - *Implementation*
  - *Sonic boom signature matching*
  - *Adaptive flaps for Truss-braced wing*

Discrete Geometry



- Direct manipulation of surface tessellations
  - CFD-ready — always high resolution
  - Allows optimization of “legacy” geometries



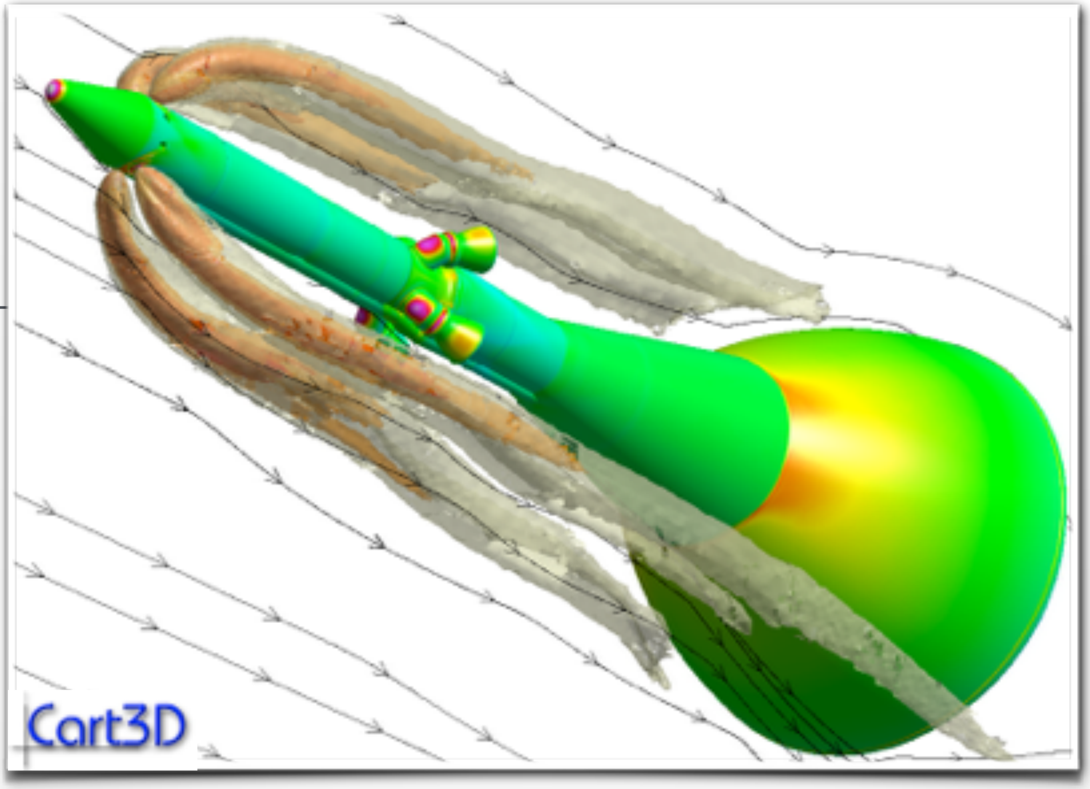
blender

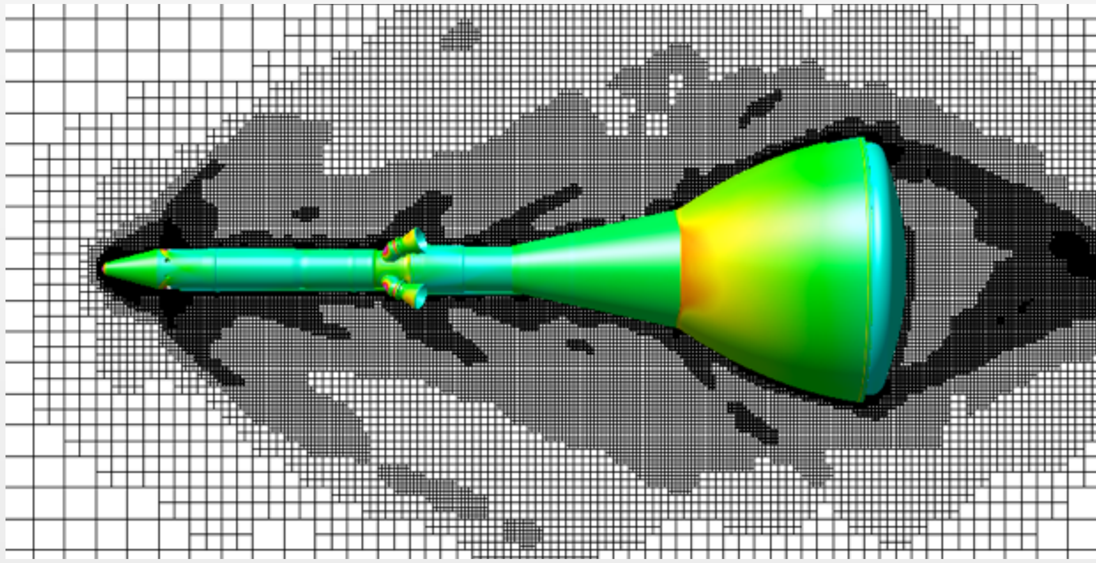
- Serves as **geometry engine** for optimization
- Script-driven surface mesh deformation
- Implemented a number of custom deformation techniques

- *(2012)* ***Anderson*** *and Aftosmis, “****Parametric Deformation of Discrete Geometry for Aerodynamic Shape Design****”. AIAA Paper 2012-0965.*

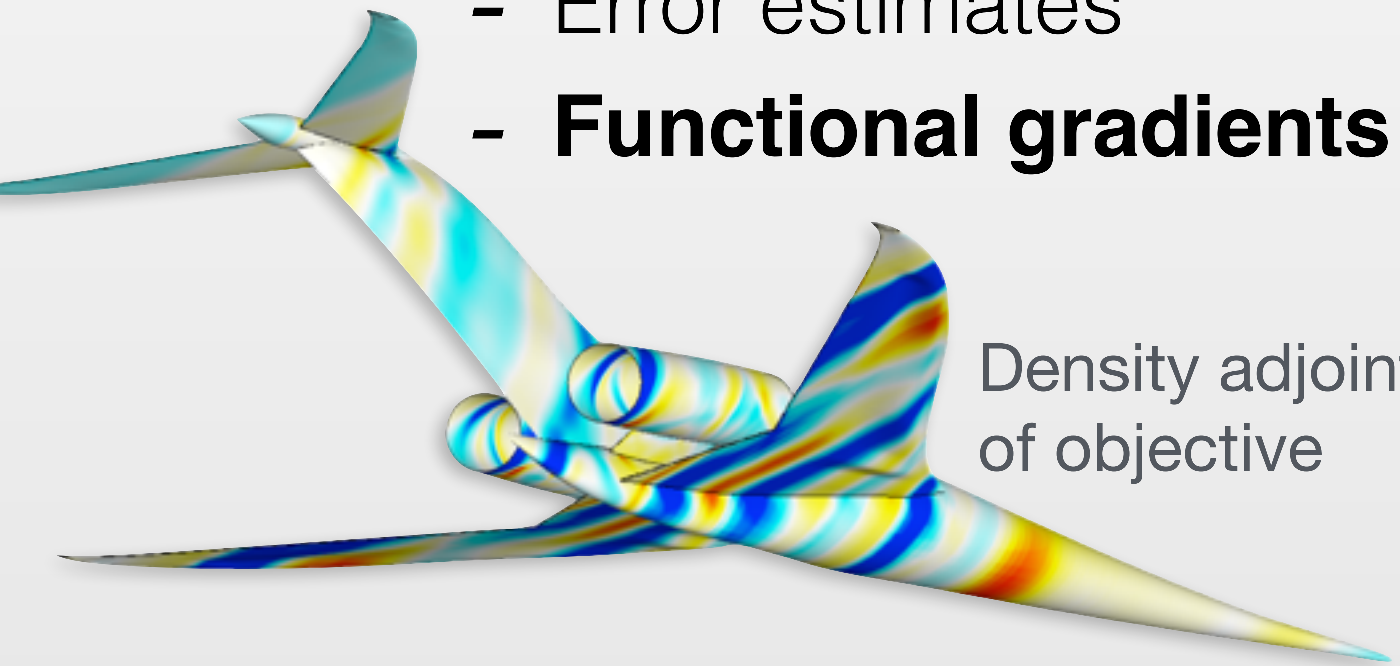
Cart3D

- Cartesian cut-cell method with automated meshing of complex configurations
- Inviscid solver with adjoint-driven
  - Adaptive meshing
  - Error estimates
  - **Functional gradients**



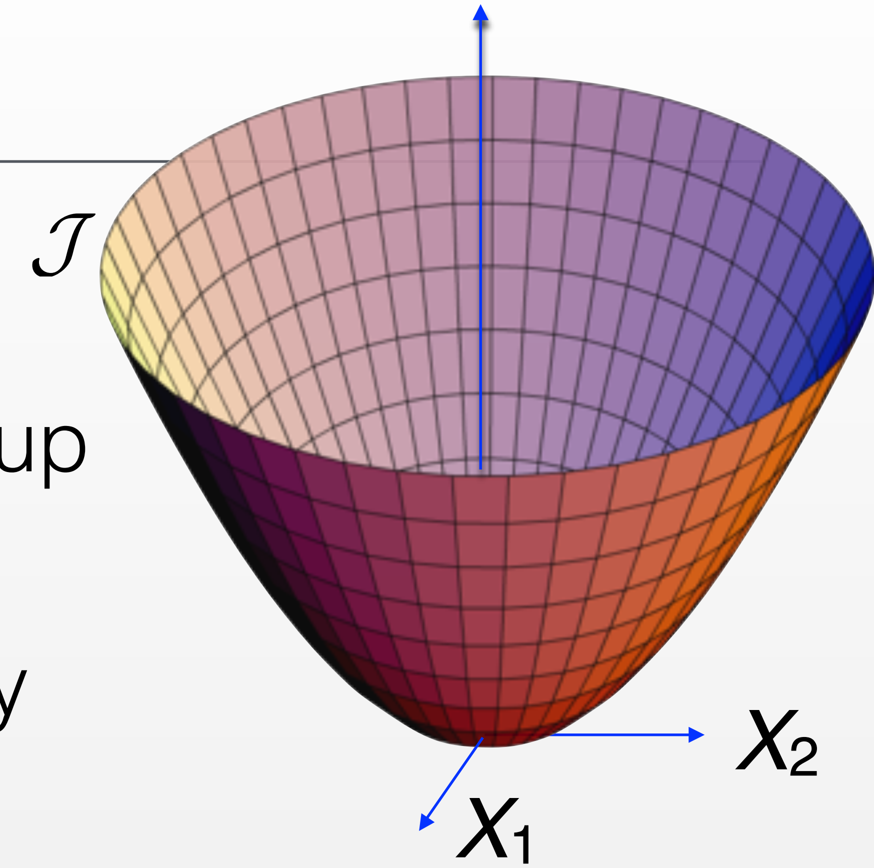


Output-adaptive meshing



Density adjoint of objective

Optimizer



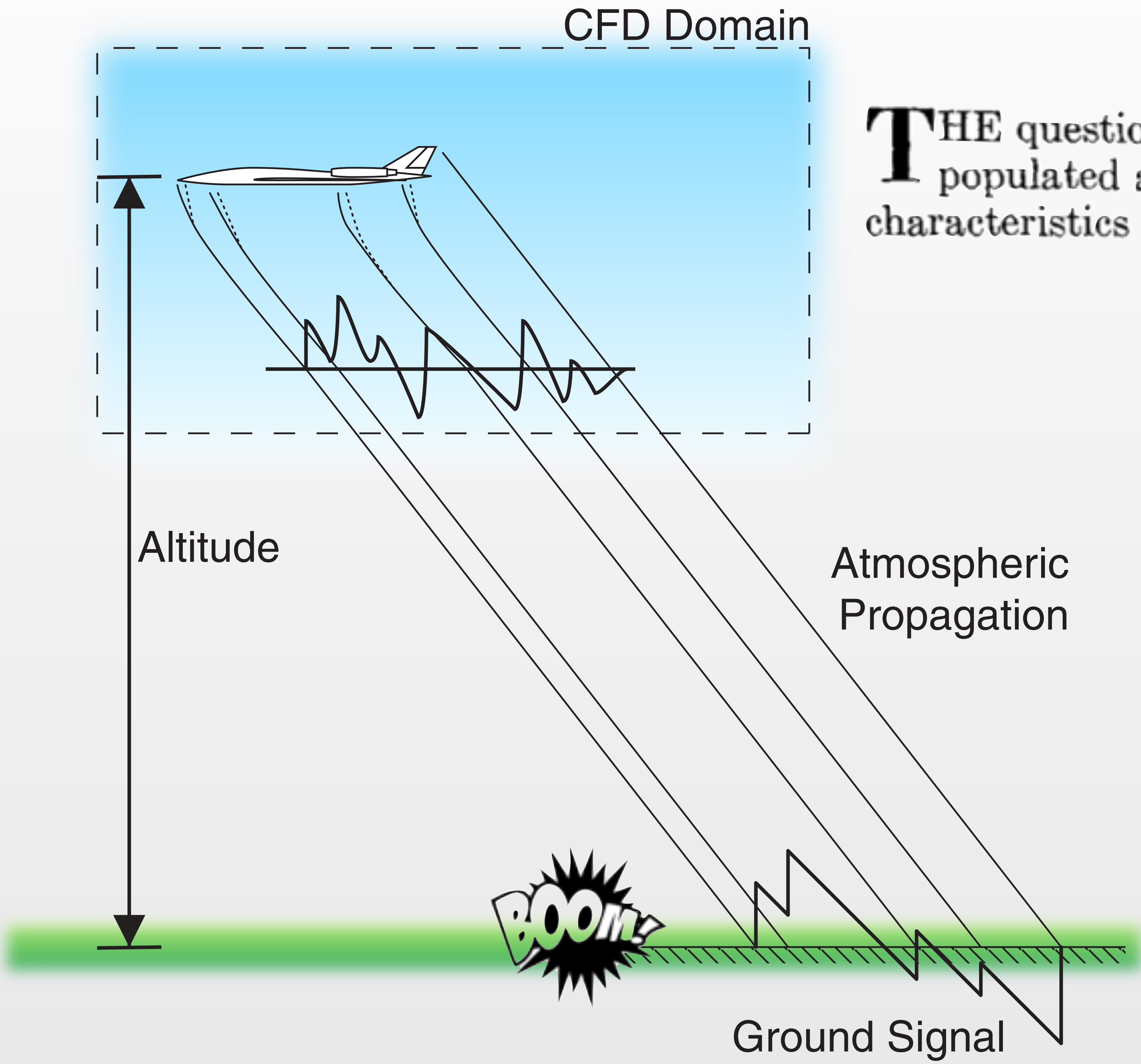
SNOPT — Sparse **N**onlinear **Opt**imizer

- **Quasi-Newton** method — gradually builds up Hessian approximation
- **SQP** method — handles nonlinear inequality constraints
- Use full-memory BFGS (test cases involve <1000 DVs)

Can also use any general gradient-based optimizer:

- SLSQP, SciPy, Knitro, pyOpt…

Boom Design



THE question of whether flights of supersonic aircraft over populated areas will ever be acceptable depends upon the characteristics of the sonic booms of these aircraft.

~ A. R. George and Richard Seebass
October 1971

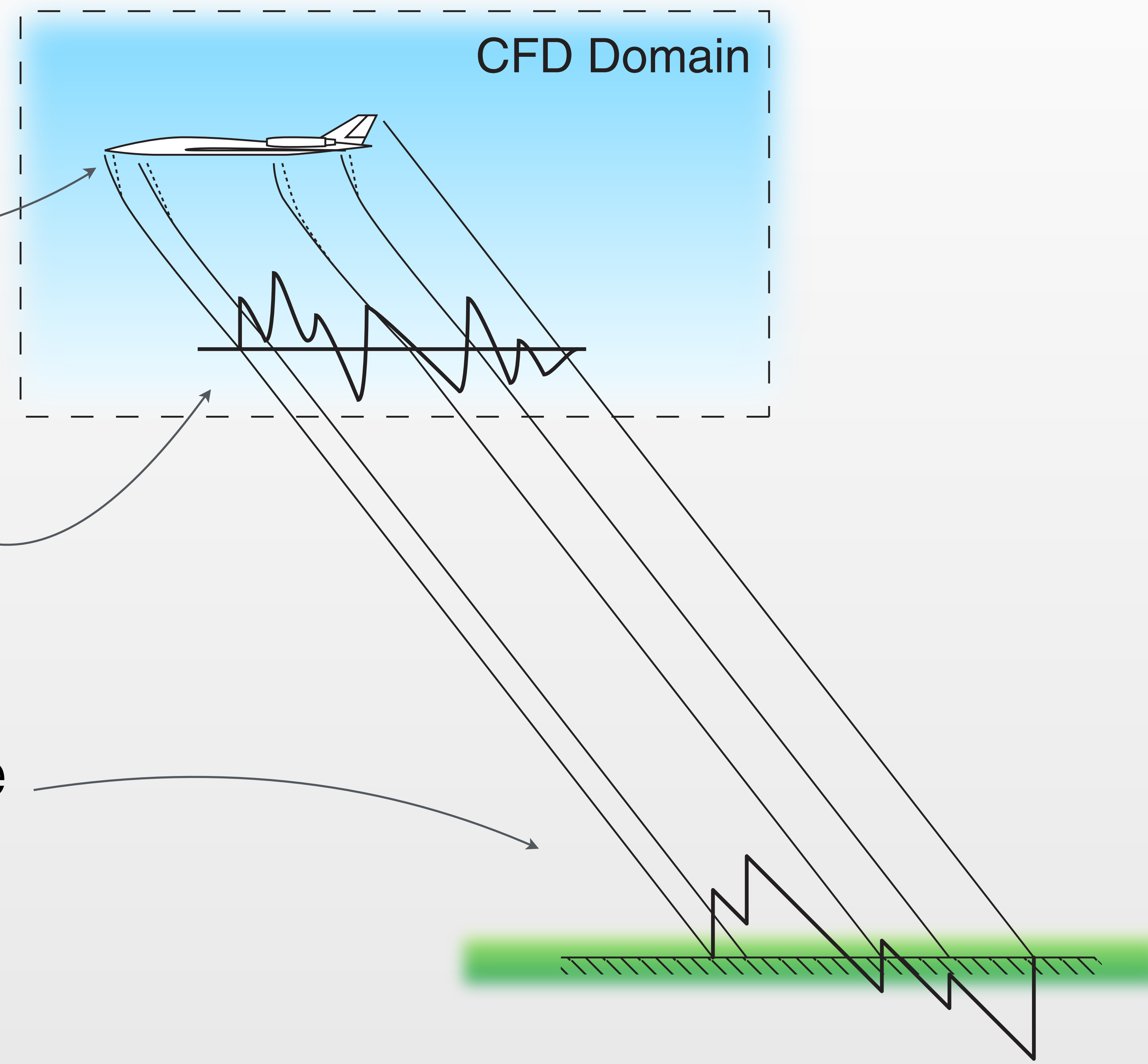
Inverse Design Procedure

3. **Reshape vehicle** to match the near-field signal

$$\mathcal{J} = \frac{1}{p_\infty^2} \int (p - p_{\text{target}})^2 dS$$

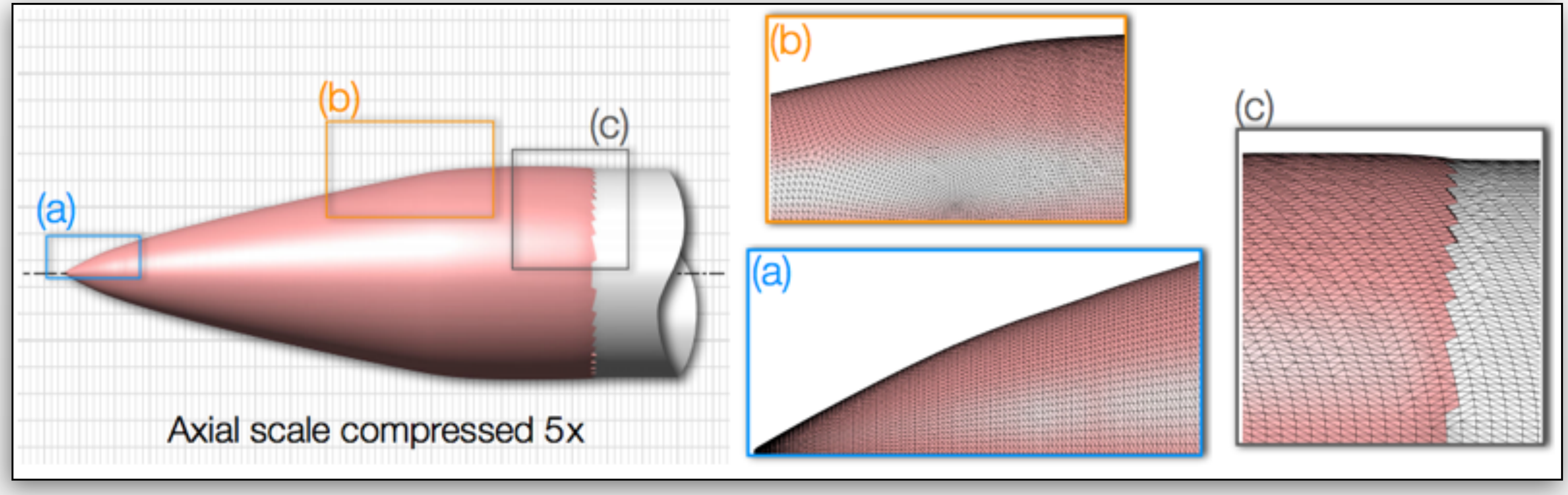
2. Find **near-field signal** that meets these requirements

1. Determine acceptable noise characteristics at **ground**

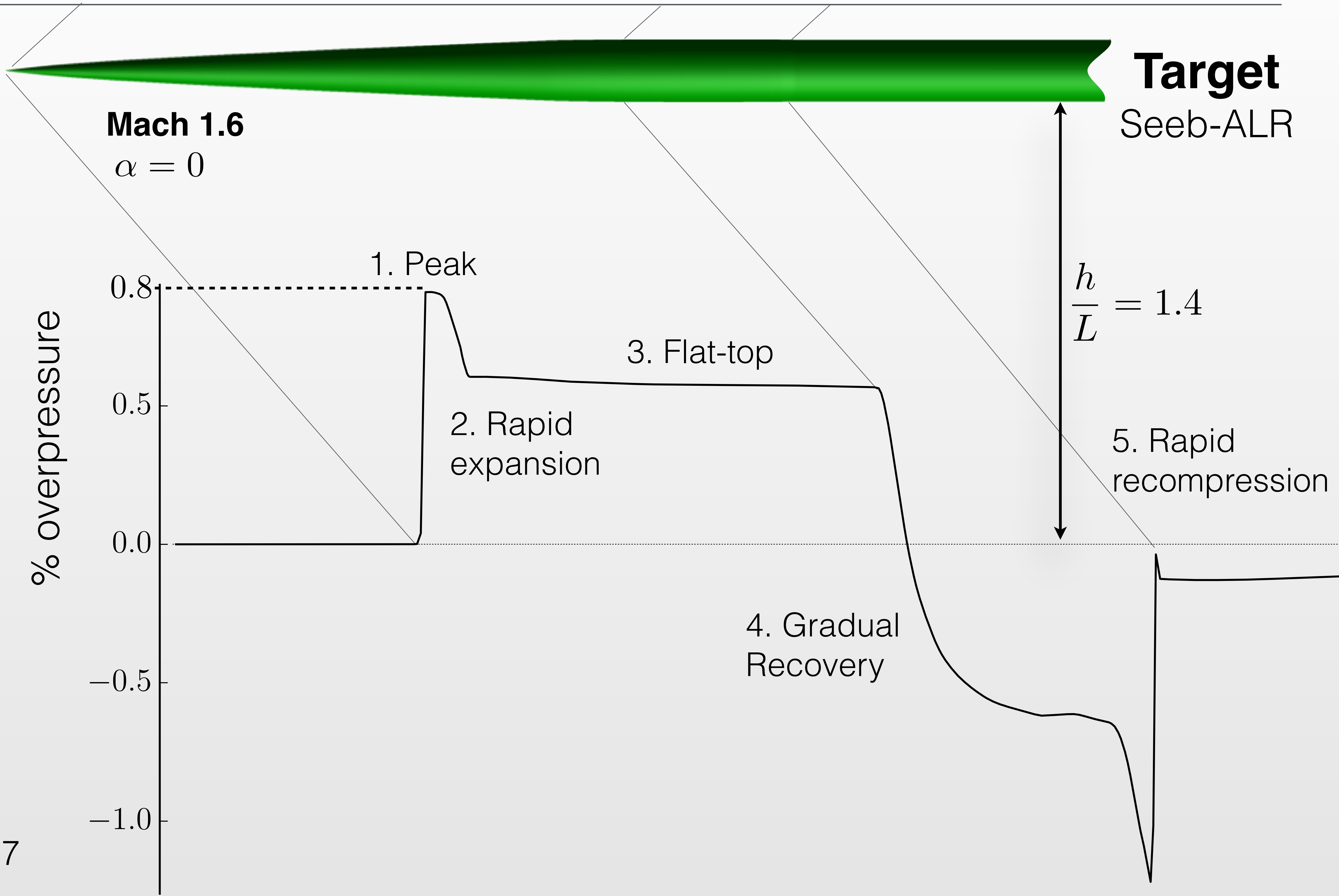


Seeb-ALR

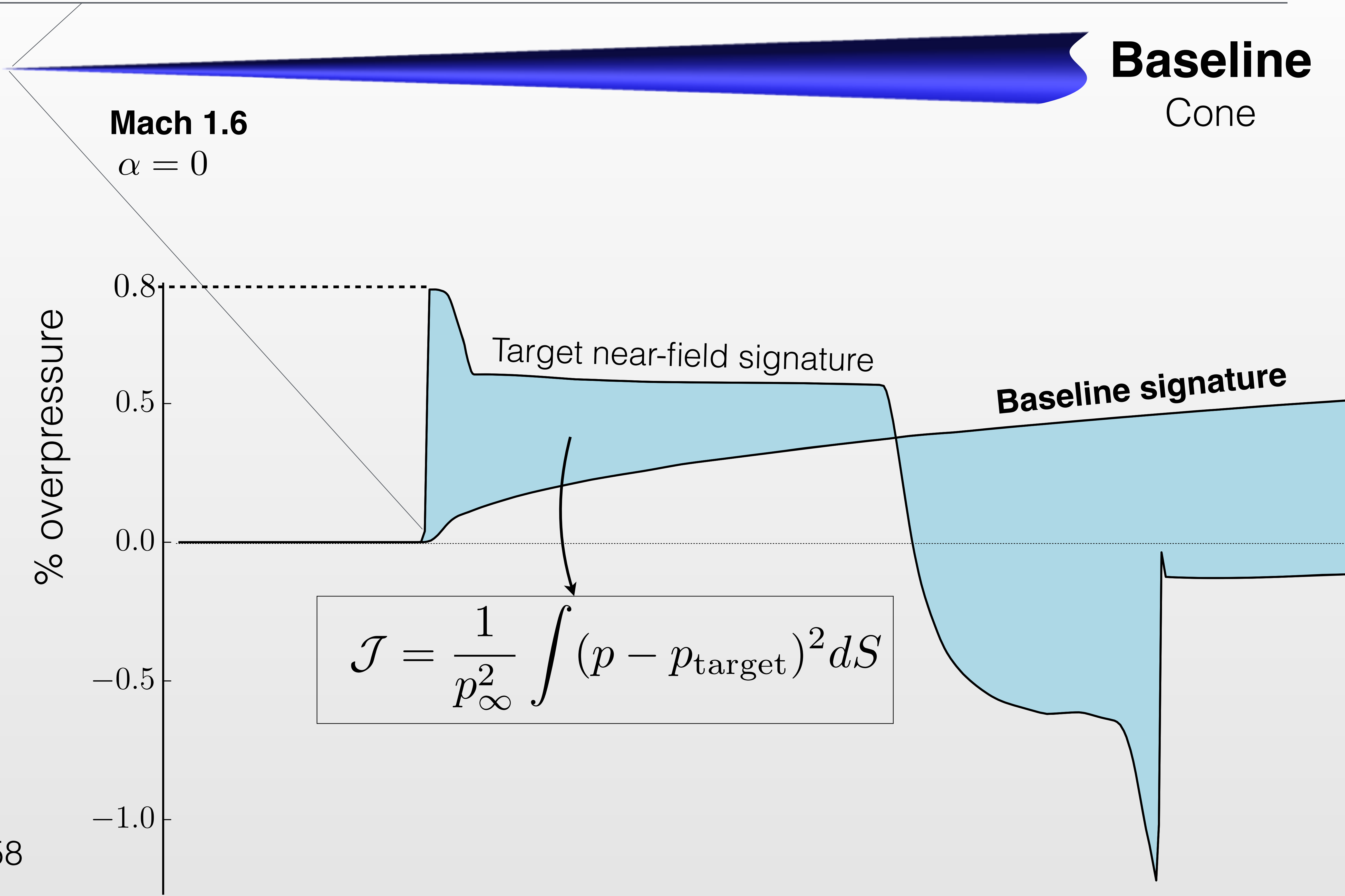
Target
Seeb-ALR



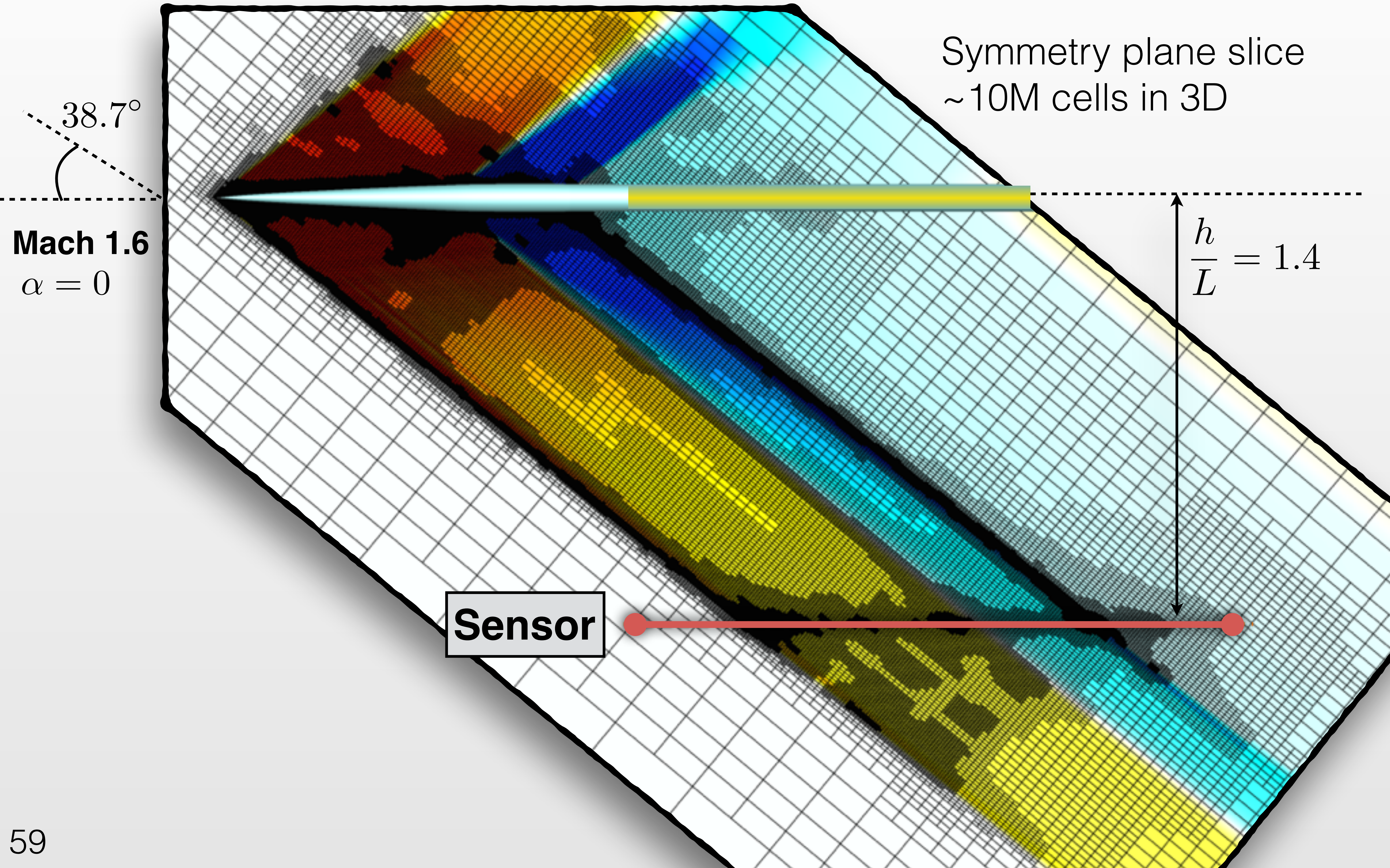
Target Nearfield Signature



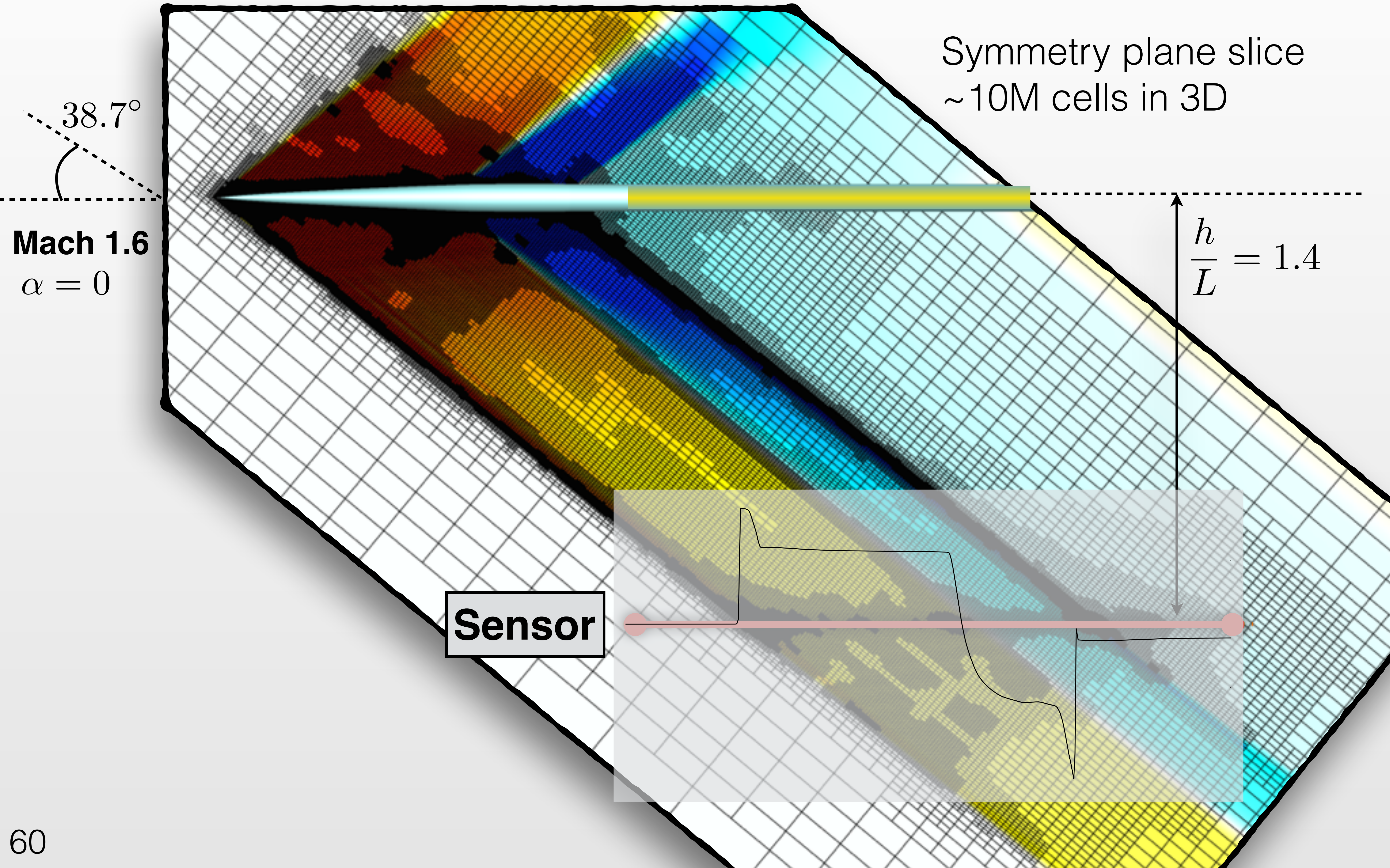
Baseline Geometry



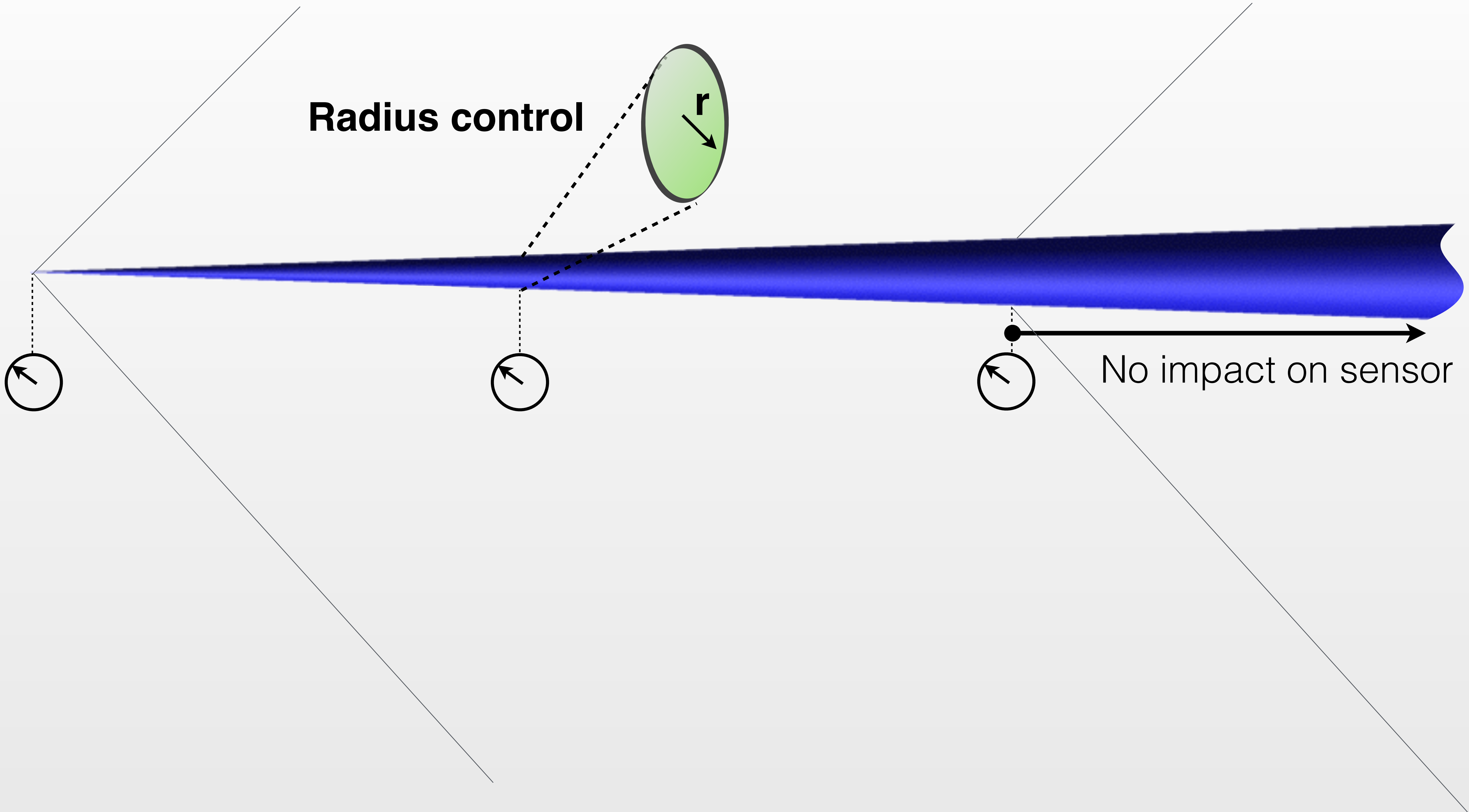
Mesh Adaptation



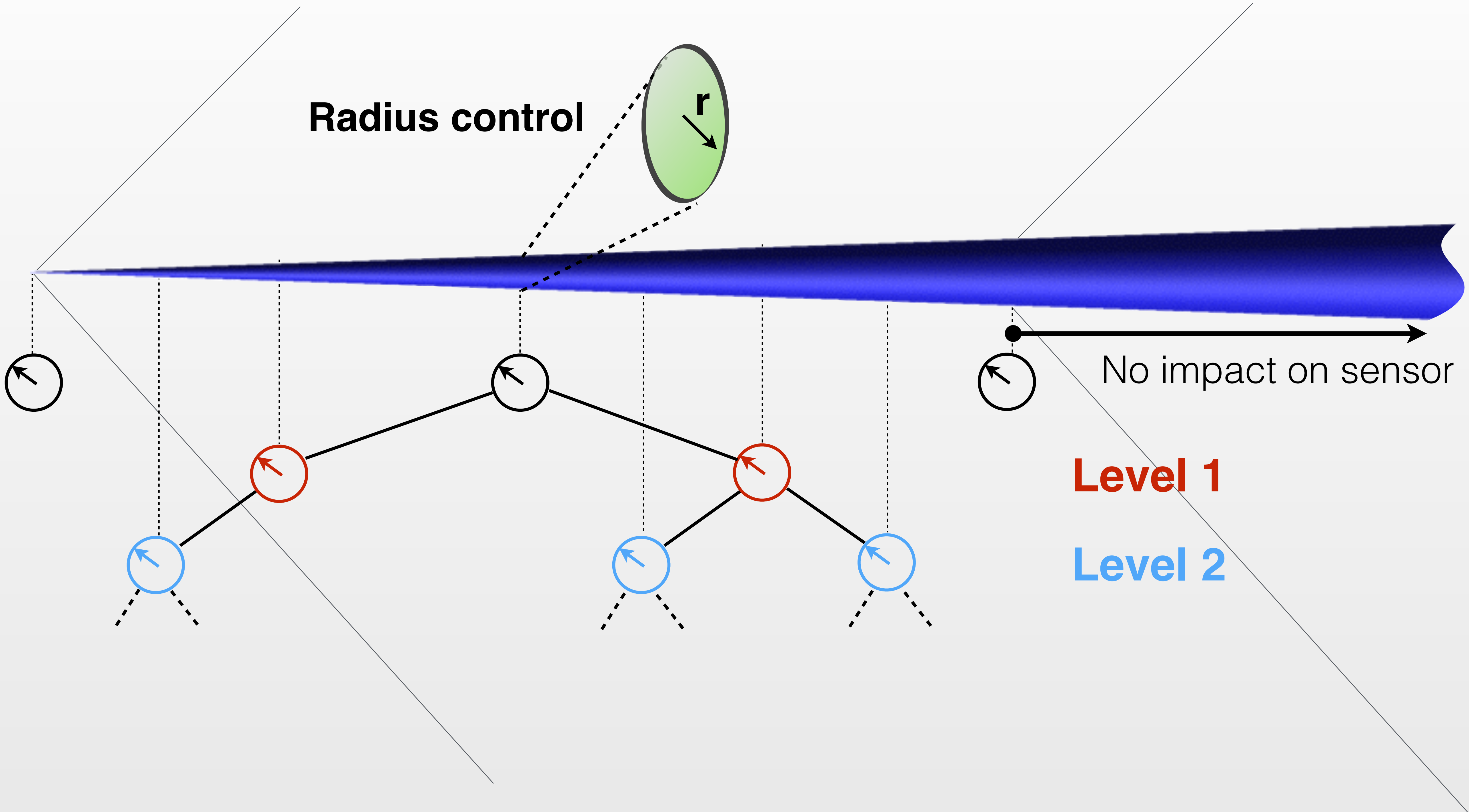
Mesh Adaptation



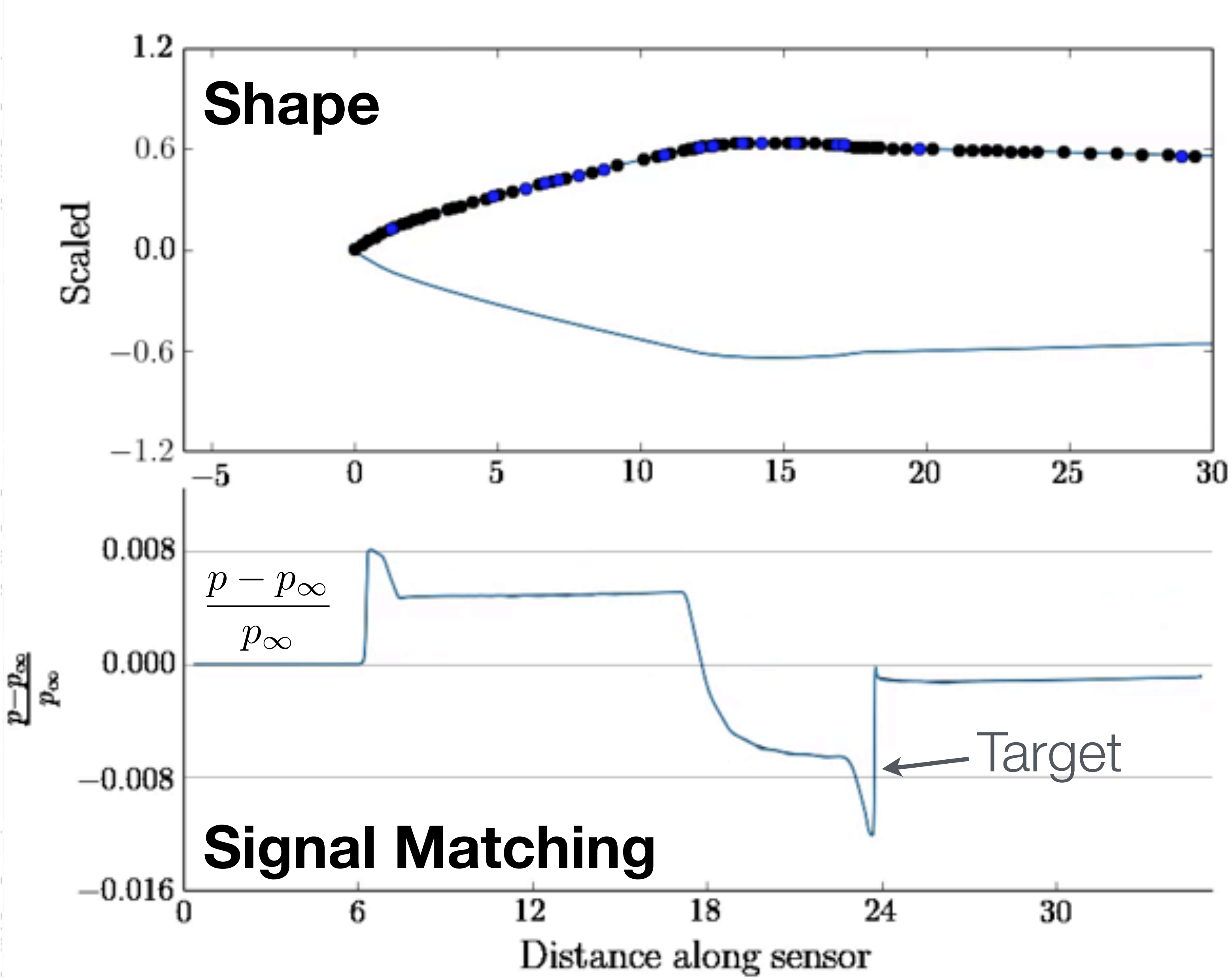
Adaptive Parameterization



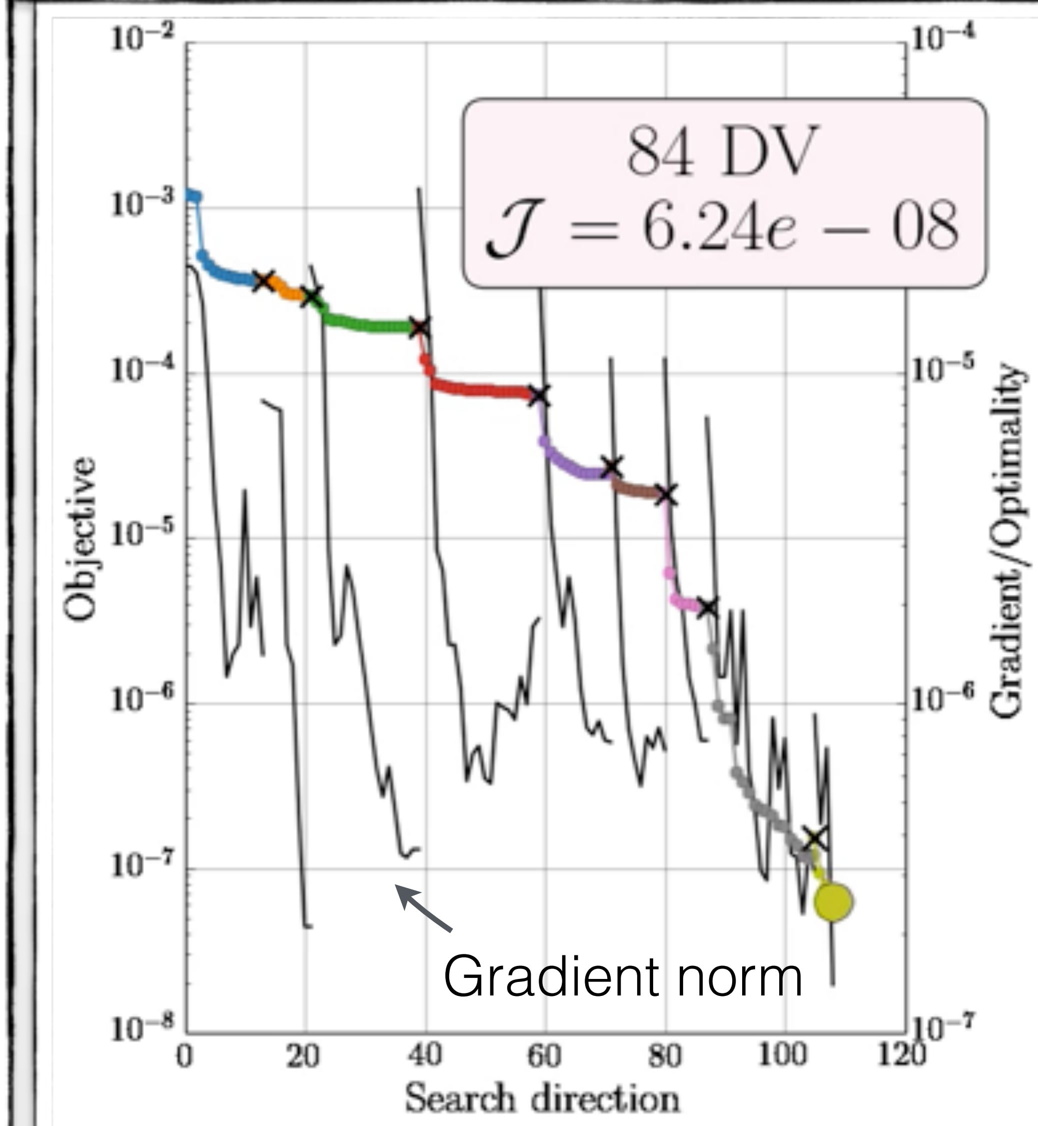
Adaptive Parameterization



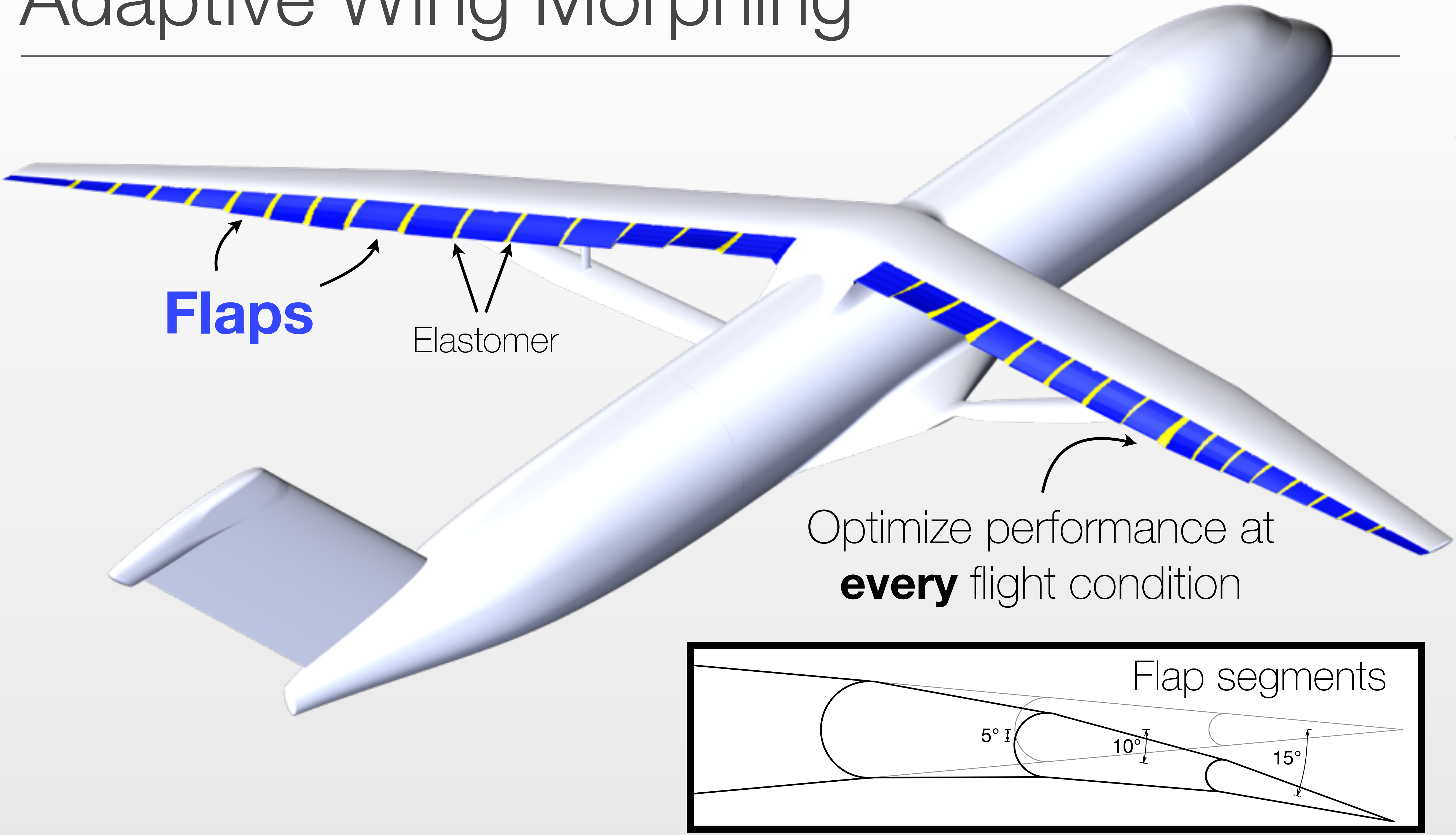
Video — Results



Objective Convergence

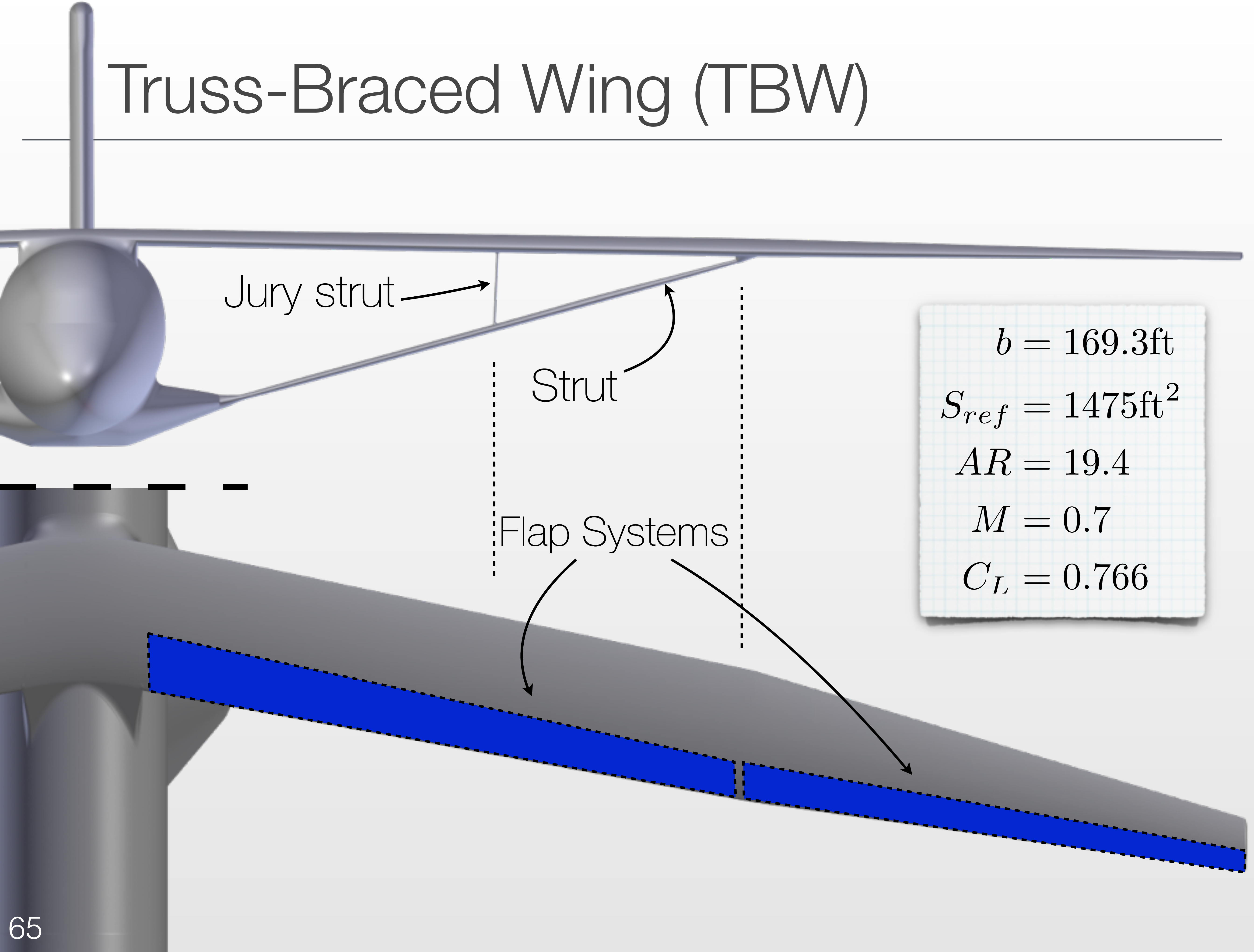


Adaptive Wing Morphing



(2015) *Rodriguez, Aftosmis, Nemec,* ***Anderson****,* ***"Optimized off-design performance of flexible wings with continuous trailing-edge flaps."*** *AIAA Paper 2015–1409, AIAA SciTech 2015, Kissimmee, FL.*

Truss-Braced Wing (TBW)

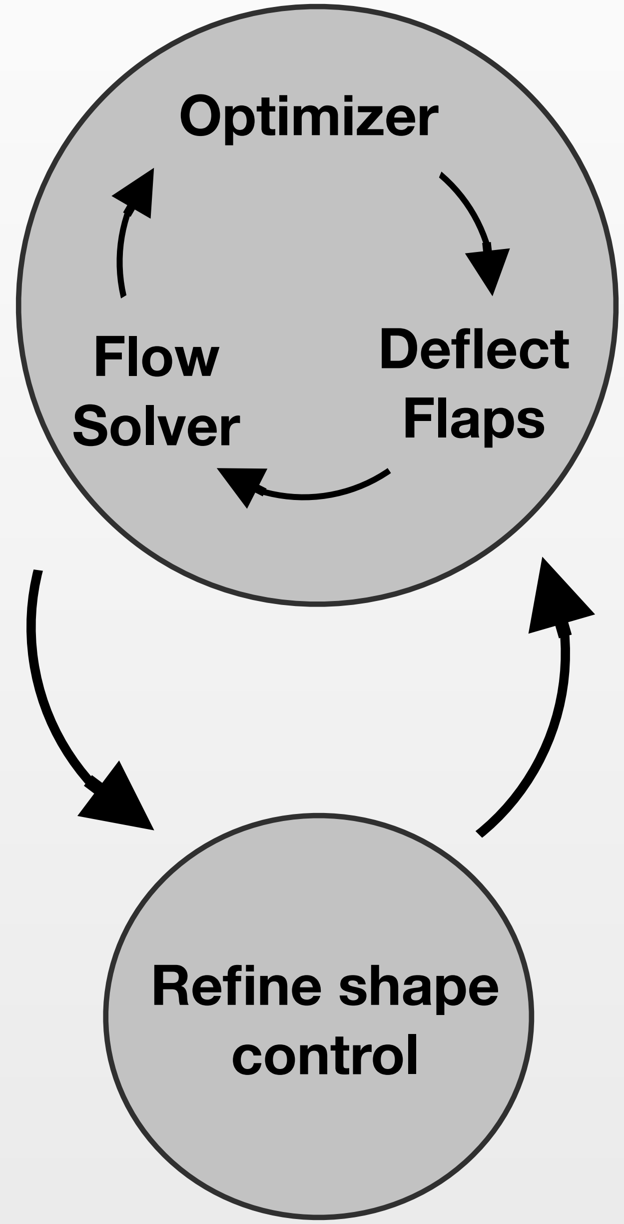


$$b = 169.3\text{ft}$$
$$S_{ref} = 1475\text{ft}^2$$
$$AR = 19.4$$
$$M = 0.7$$
$$C_L = 0.766$$

Flap Adaptation Procedure

1) **Morph:** Optimize flap deflections for minimum drag.

2) **Refine flap topology:** Add the one* additional flap that would best allow the drag to be reduced.



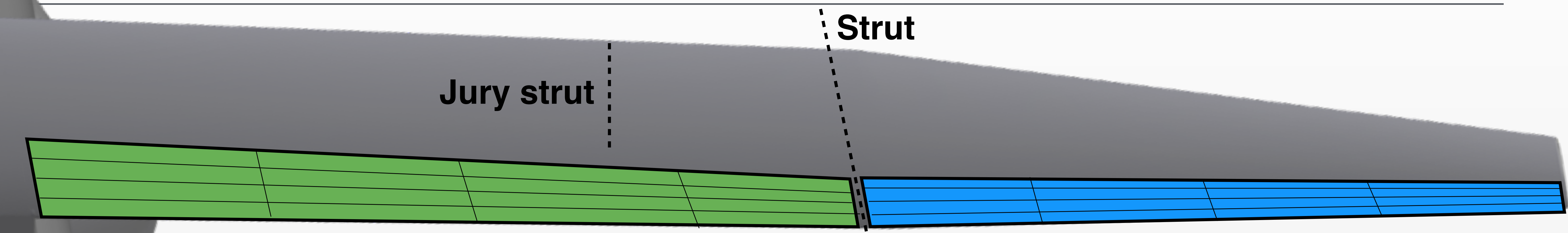
$$\mathcal{J} = C_D$$

$$M = 0.7$$

$$C_L = 0.766$$

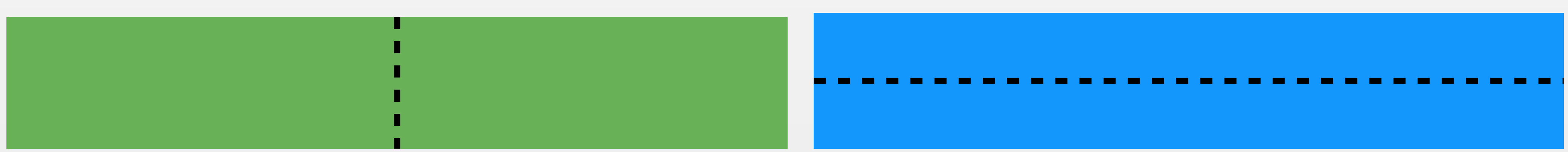
*Add flaps **one** at a time, because the cost associated with every flap is real — want to find **minimal** parameterization!

Flap Refinement



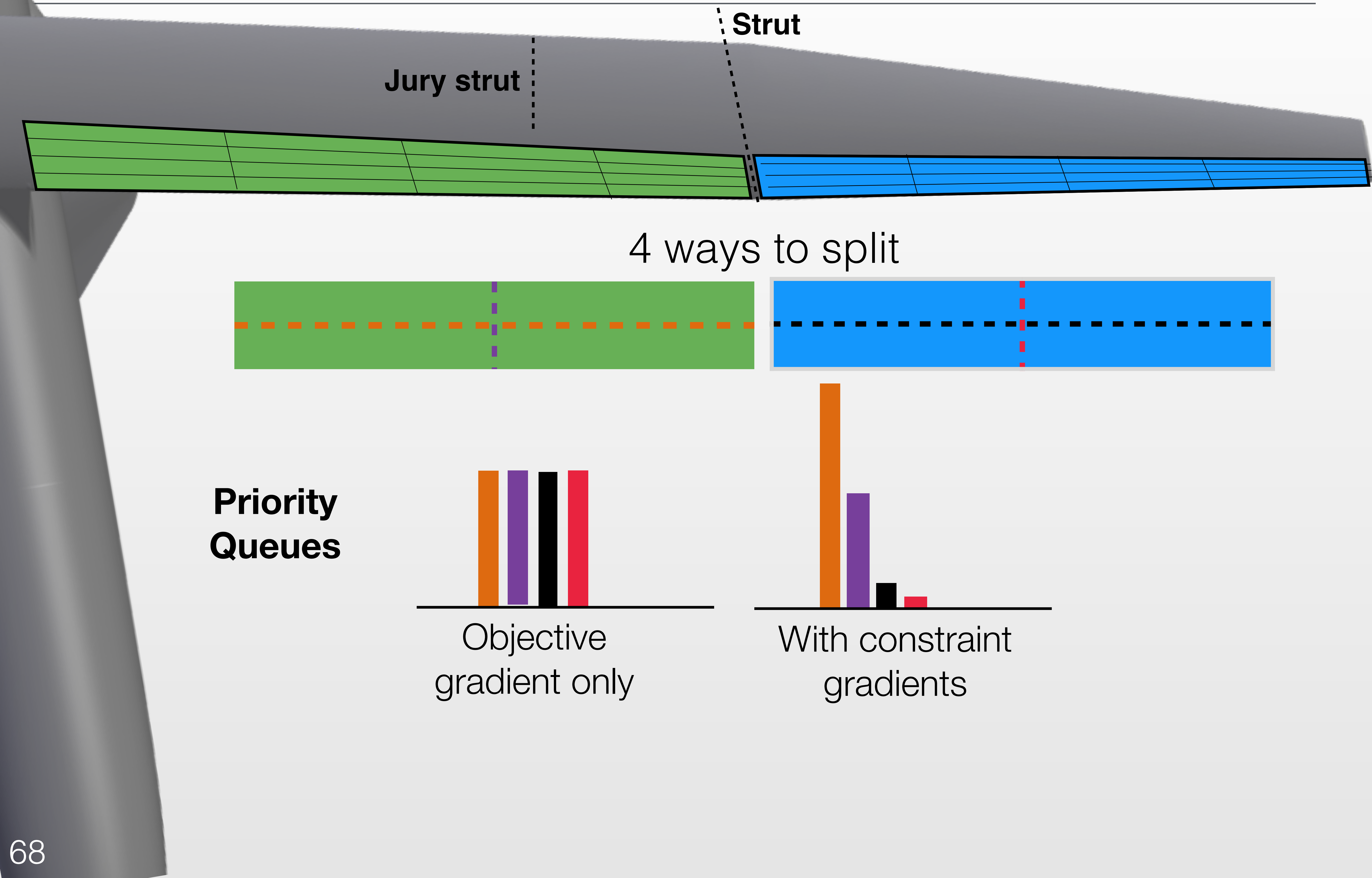
Initially two monolithic flaps, can be subdivided…

span-wise or **stream**-wise



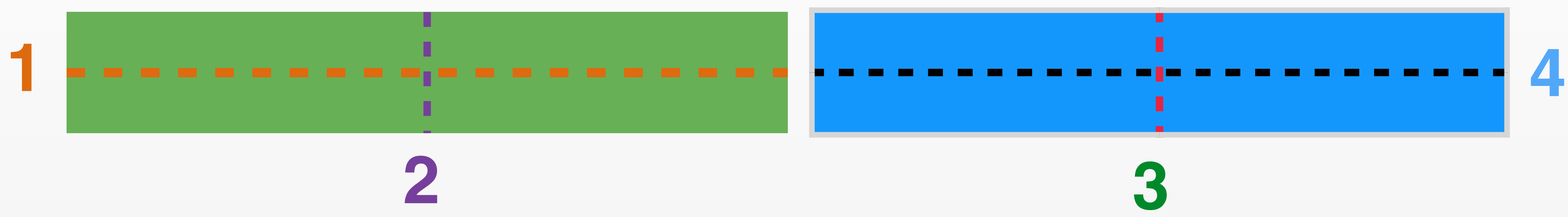
uniformly or **adaptively**

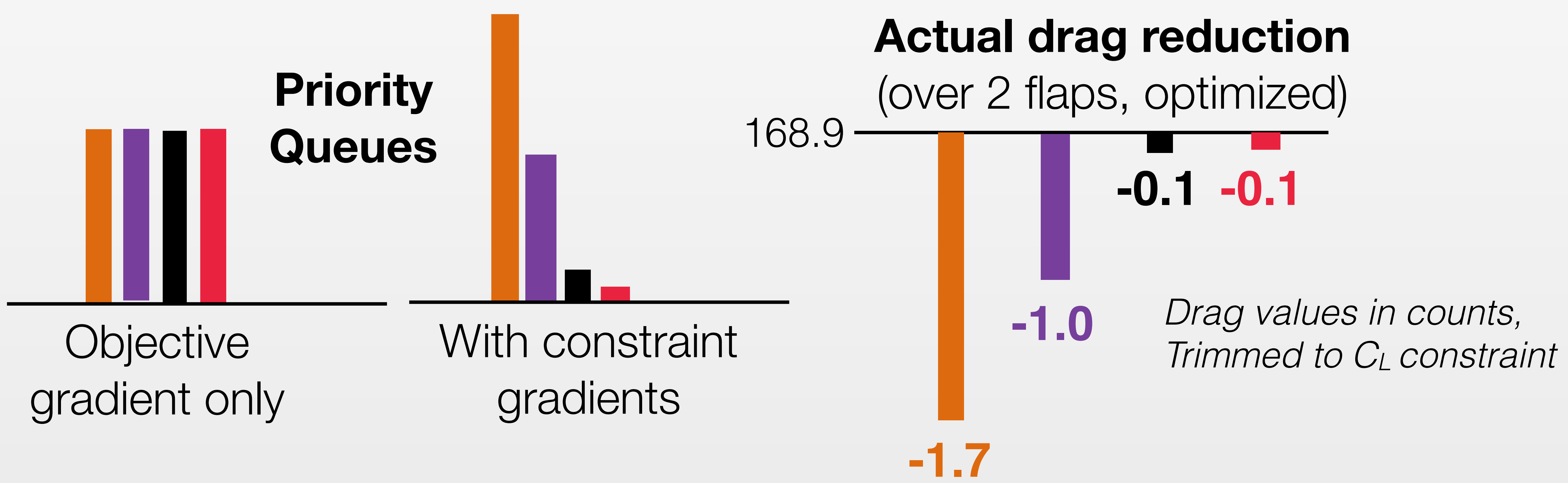
First Step



Strut
Jury strut
4 ways to split
Priority Queues
Objective gradient only
With constraint gradients

Verification of Ranking





Flap Deflection History

Final flap topology

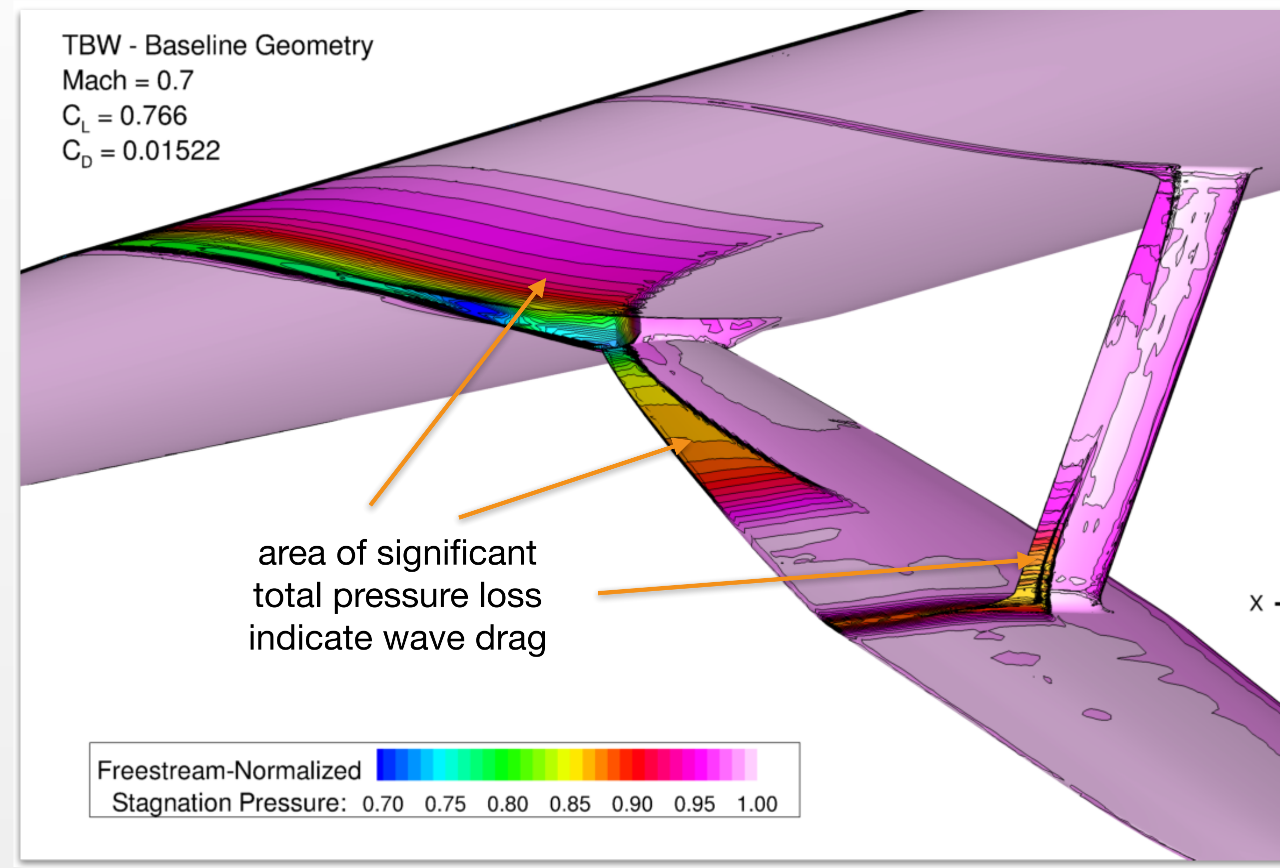
Inboard | Outboard

-1.15° **-1.65°** -0.6° -0.4°

Final deflections

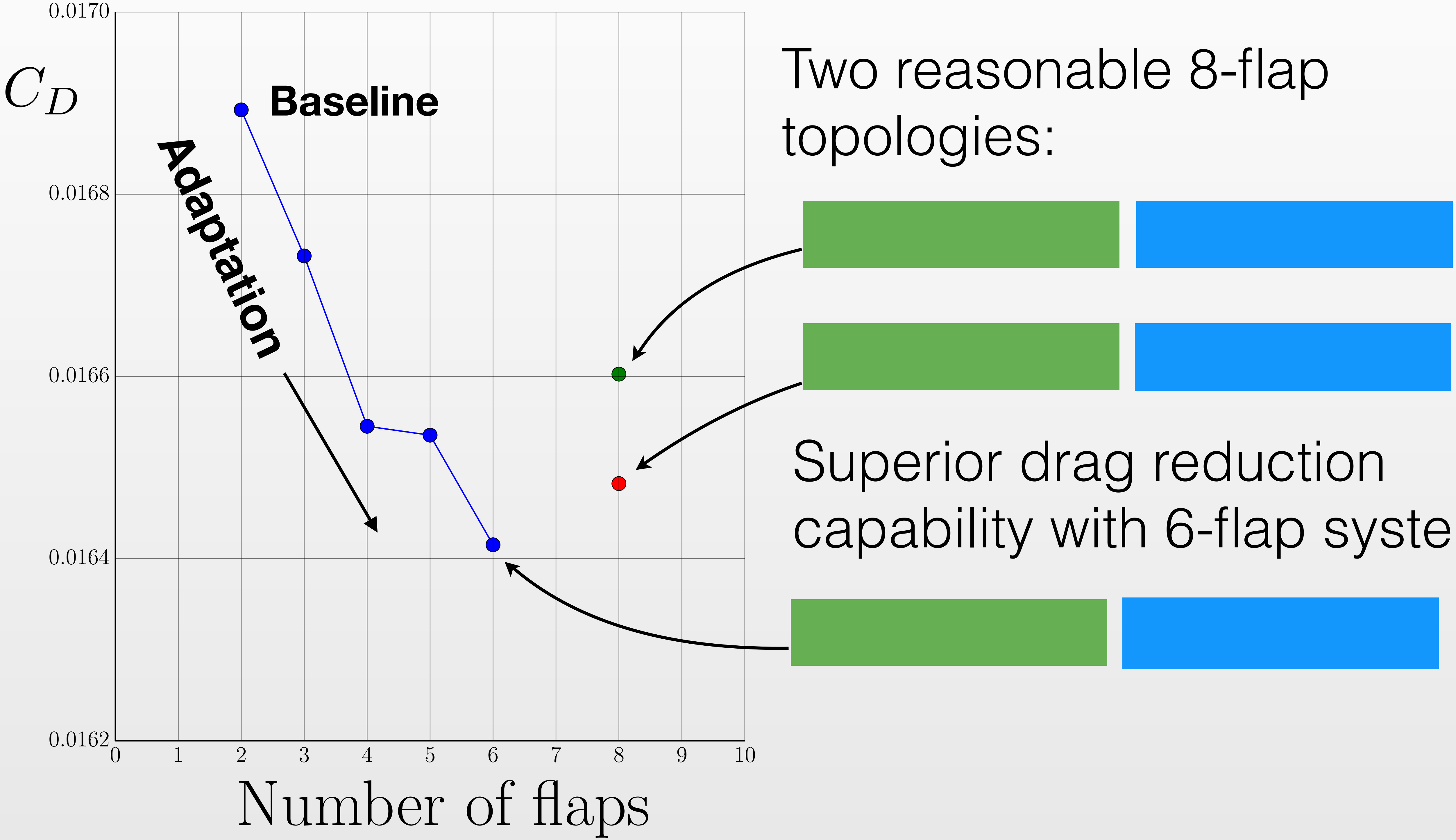
(cumulative deflection at TE)

Negative deflection downward.
Alpha lowered to compensate lift.



Baseline geometry has substantial **wave drag** through truss

Cost vs. Flap Count



Two reasonable 8-flap topologies:

Superior drag reduction capability with 6-flap system

Conclusions

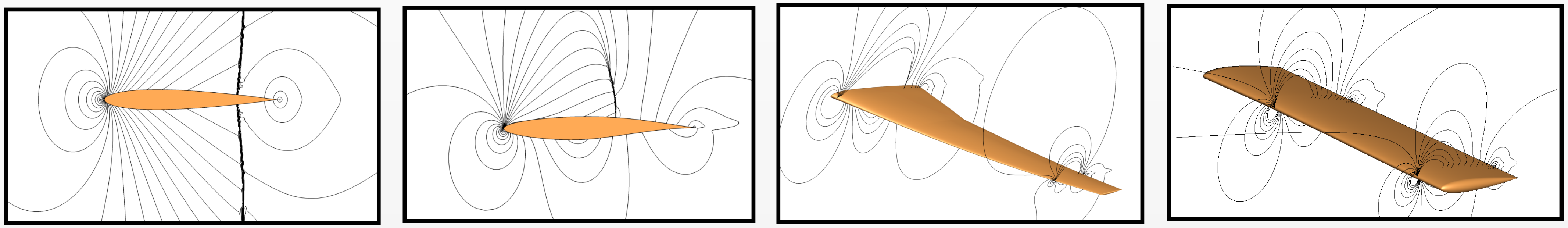
- Demonstrated **adaptive shape parameterization** system for automated, high-fidelity aerodynamic optimization.
    - Enables hands-off design **exploration** for unfamiliar problems.
    - Provides **feedback** about the design problem.
- Verification studies confirm that robust **convergence** to continuous optimum is possible.
- A careful adaptive strategy makes the approach substantially **more efficient** both in terms of design variables and computational time.

New Techniques

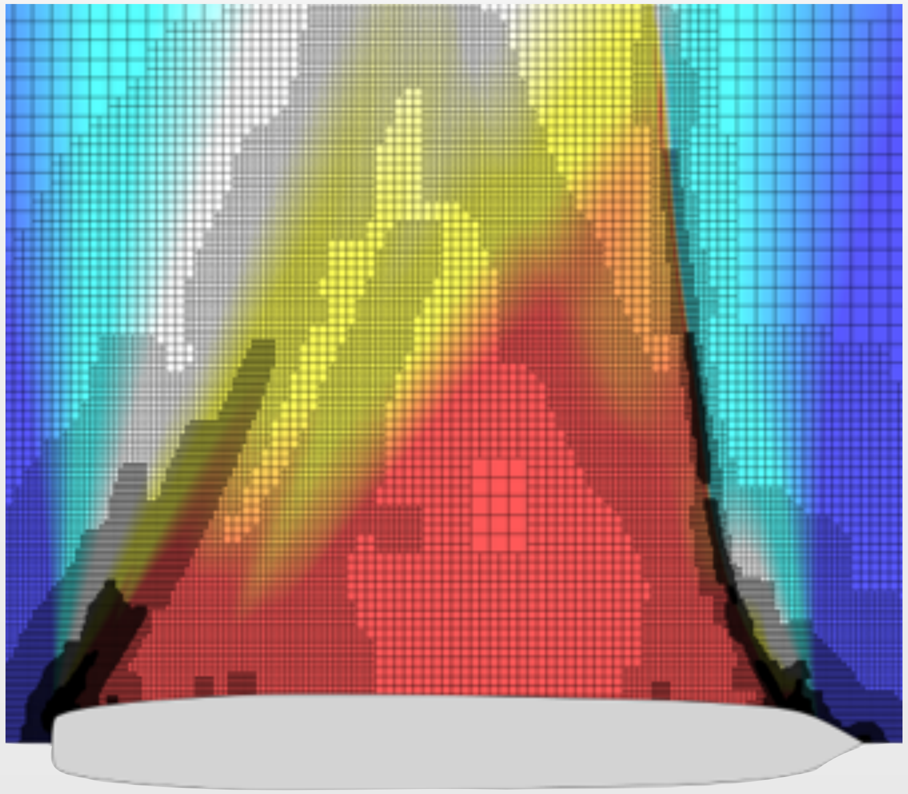
- Goal-oriented **refinement indicator** targeting high potential shape parameters.
  - Substantially improves results over previous best indicator, appropriate for general classes of problems.
  - Leverages information already available during optimization — no *a priori* knowledge required.
- Approximate **Hessian estimation** (prolongation operator)
  - Could also be used to accelerate design in finer design spaces.
- Constructive algorithm to efficiently find an approximate solution to the combinatorial adaptation problem.
- Cost-benefit approaches to automatically determine how many parameters to add and when to trigger refinement.

Optimization Benchmarks

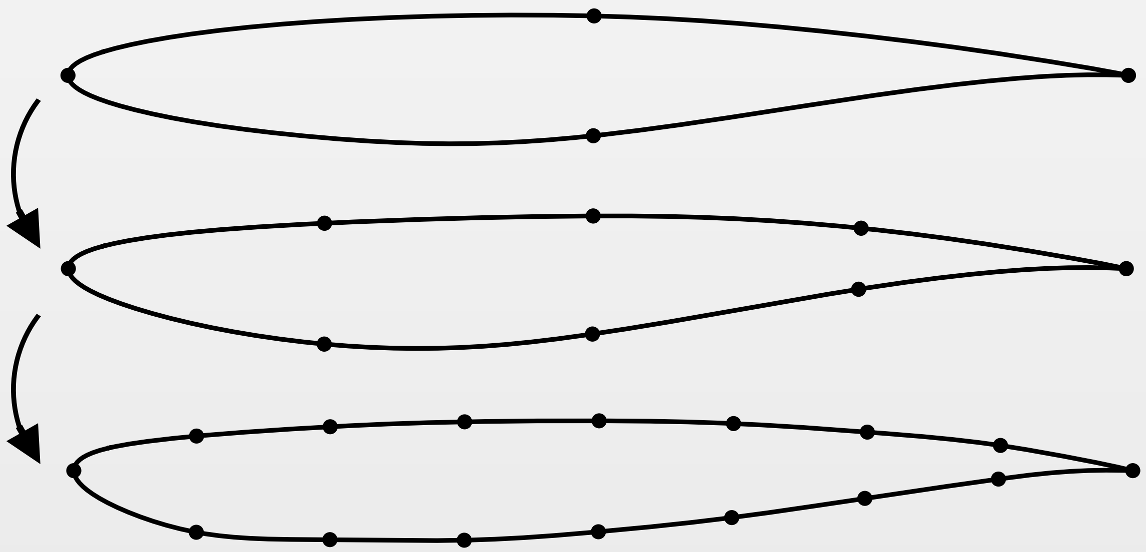
Transonic wing and airfoil design benchmarks



- Combined two **automated, adaptive** elements:



Adaptive mesh refinement



Progressive parameterization

† (2015) **Anderson**, *Nemec, Aftosmis. "Aerodynamic Shape Optimization Benchmarks with Error Control and Automatic Parameterization." AIAA 2015-1719*

Publications

1. **Anderson** and Aftosmis, "**Parametric Deformation of Discrete Geometry for Aerodynamic Shape Design**". *AIAA Paper 2012-0965, 50th AIAA ASM Meeting and Exhibit, Nashville, TN, January 2012.*

2. **Anderson**, Aftosmis, Nemec, "**Constraint-based Shape Parameterization for Aerodynamic Design**". *ICCFD7 Paper-2001. Seventh International Conference on Computational Fluid Dynamics (ICCFD7), Big Island, HI, July 2012.*

3. **Anderson** and Aftosmis, "**Adaptive shape parameterization for aerodynamic design.**" *NASA Technical Memorandum, May 2015.*

4. Rodriguez, Aftosmis, Nemec, **Anderson**, "**Optimized off-design performance of flexible wings with continuous trailing-edge flaps.**" *AIAA Paper 2015–1409, AIAA SciTech 2015, Kissimmee, FL, http://dx.doi.org/10.2514/6.2014-1409, January 2015.*

5. **Anderson**, Nemec, Aftosmis, "**Aerodynamic shape optimization benchmarks with error control and automatic parameterization.**" *AIAA Paper 2015-1719, Kissimmee, FL, http://dx.doi.org/10.2514/6.2015-1719, January 2015.*

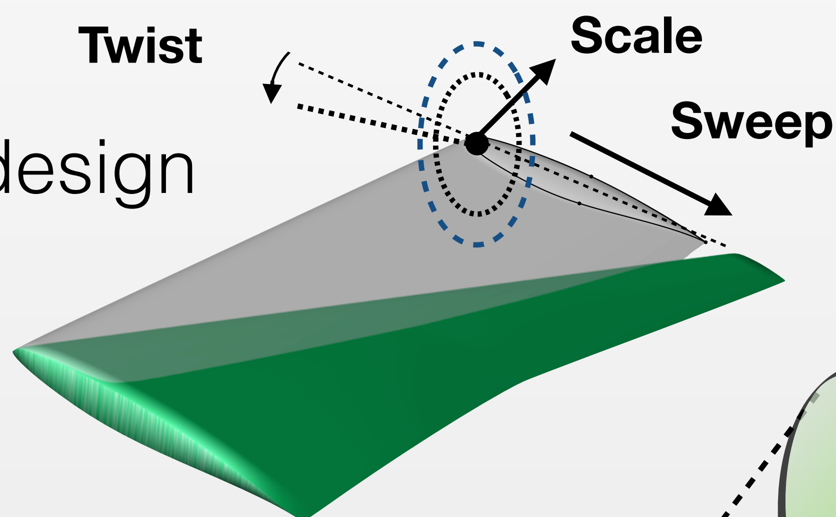
6. **Anderson** and Aftosmis, "**Adaptive shape control for aerodynamic design.**" *AIAA Paper 2015-0398, AIAA SciTech 2015, Kissimmee, FL, http://dx.doi.org/10.2514/6.2015-0398, January 2015.*

Future Work

Major outstanding topic:

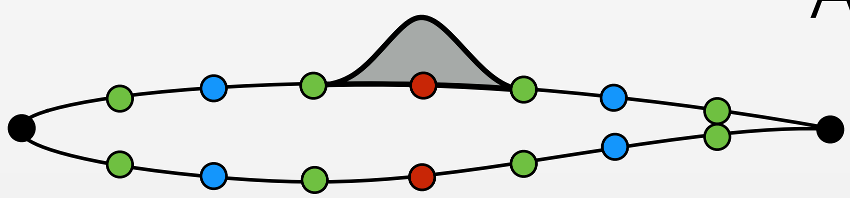
- Discovering effective **classes** of shape control

Wing design

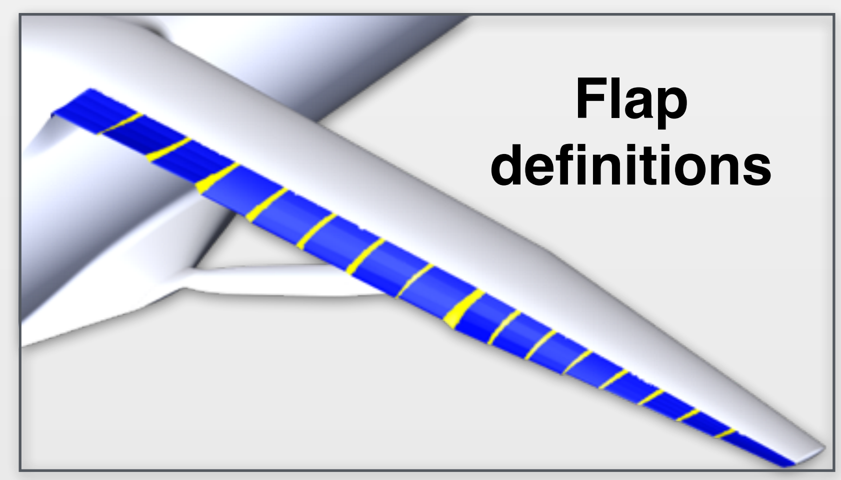


Radial basis functions

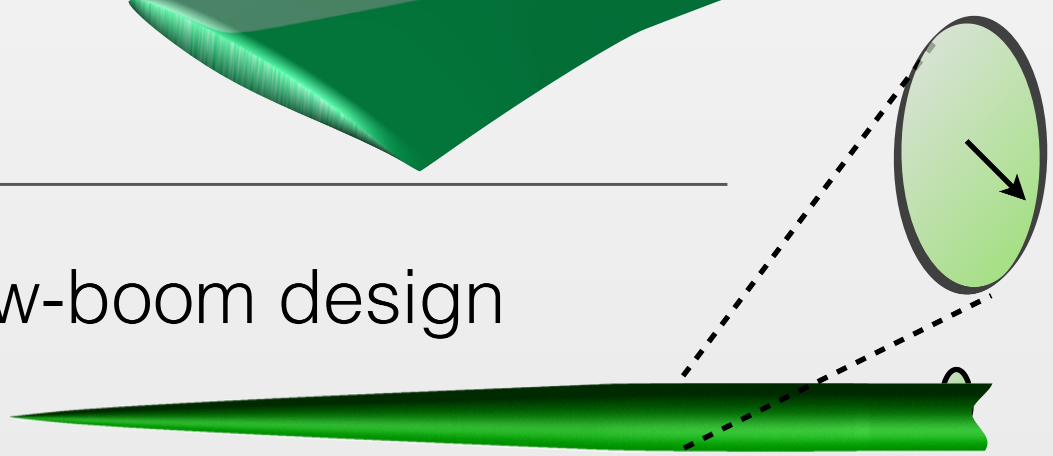
Airfoil design



Flap system design

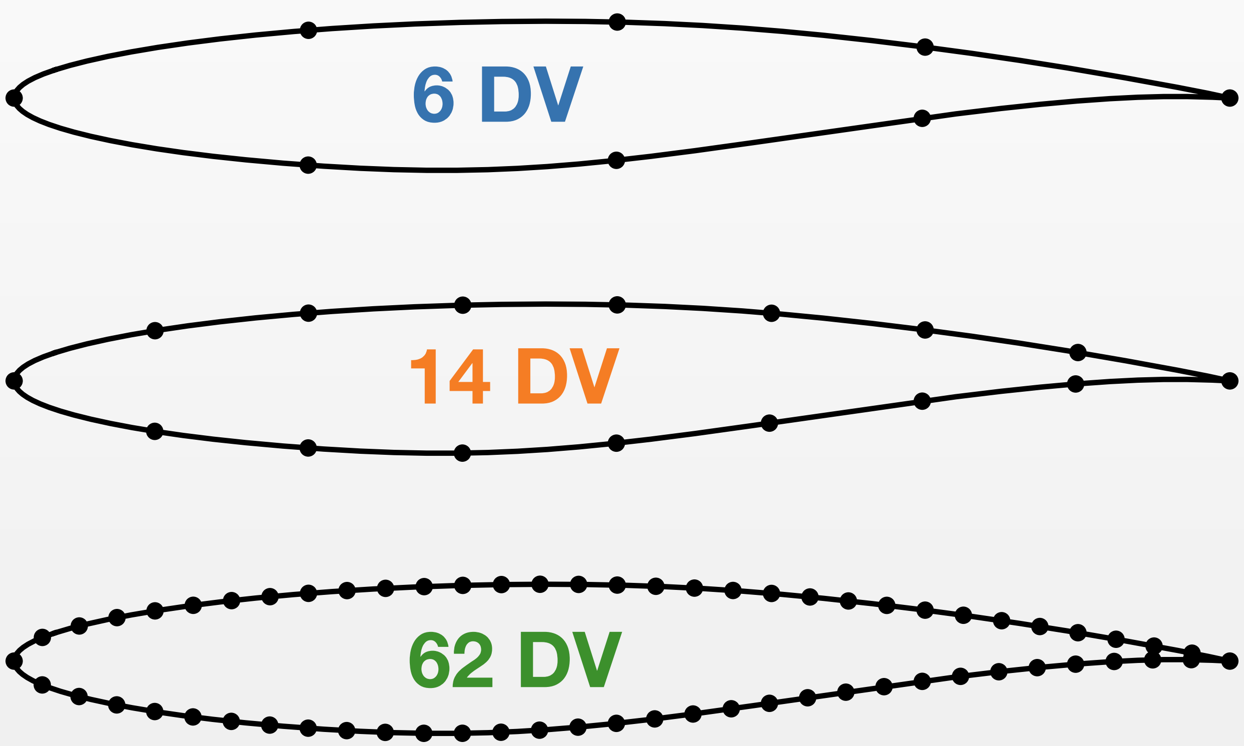


Low-boom design



Backup Slides

But How Fast Is It?

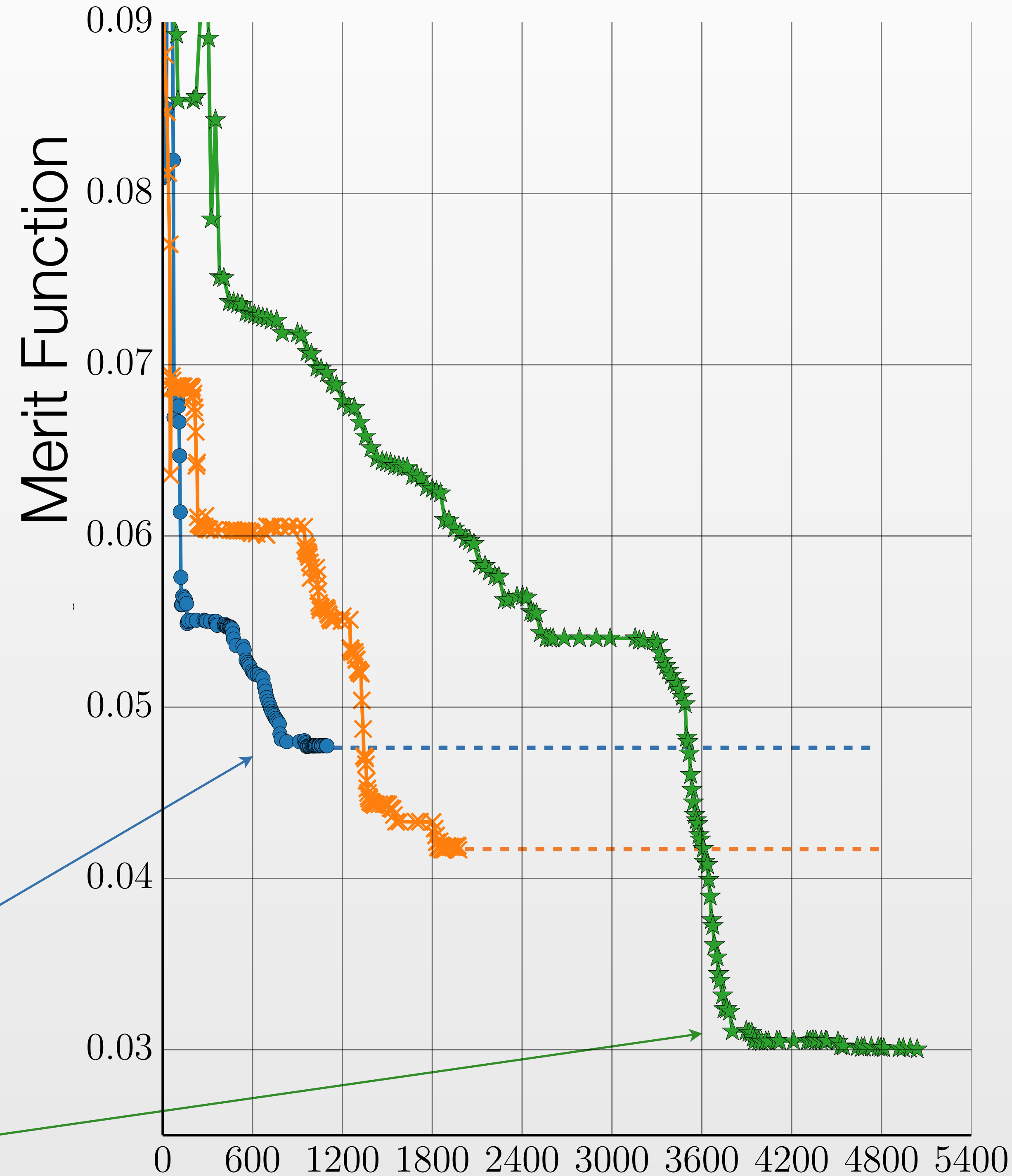


Low resolution:

Faster design improvement

High resolution:

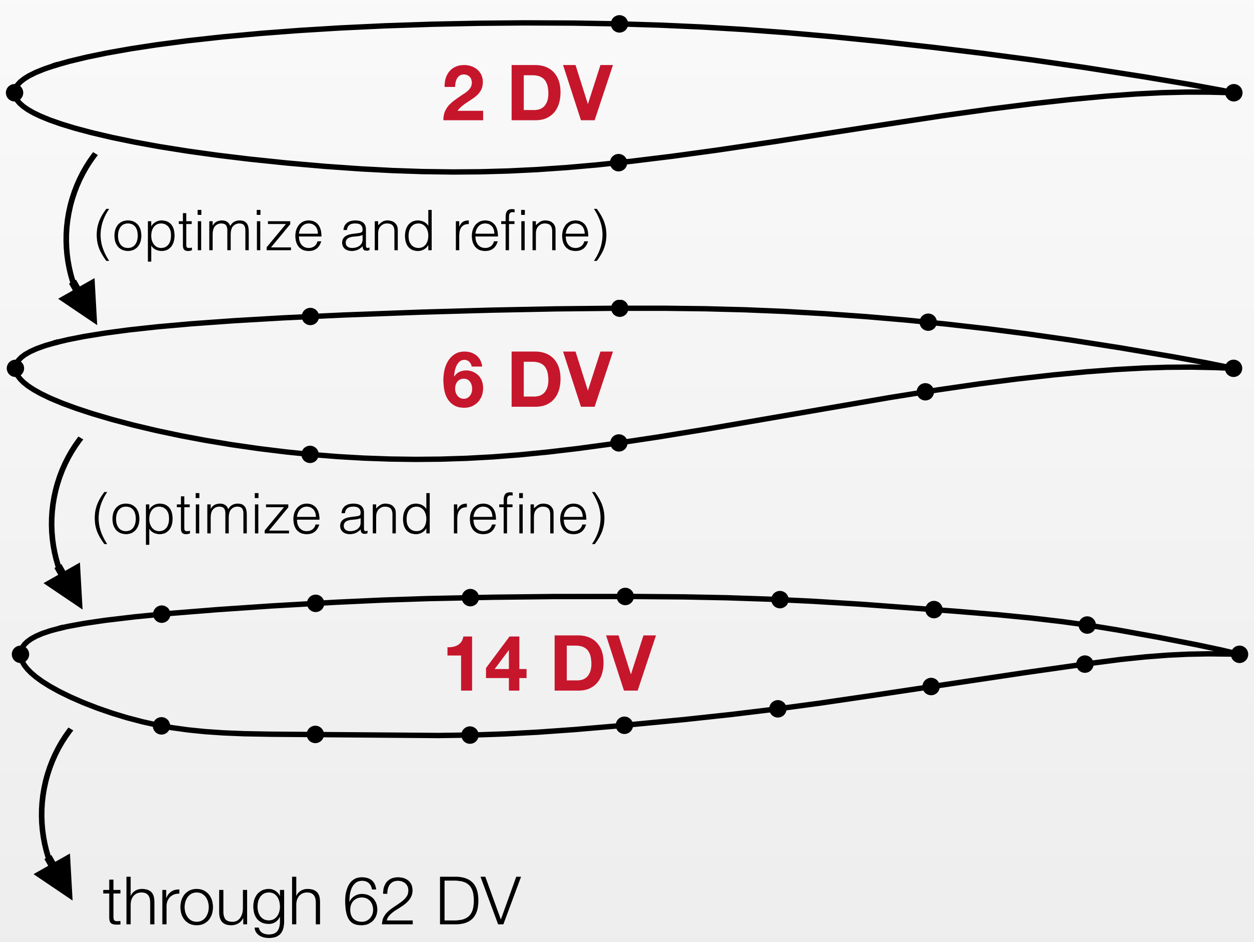
Better designs

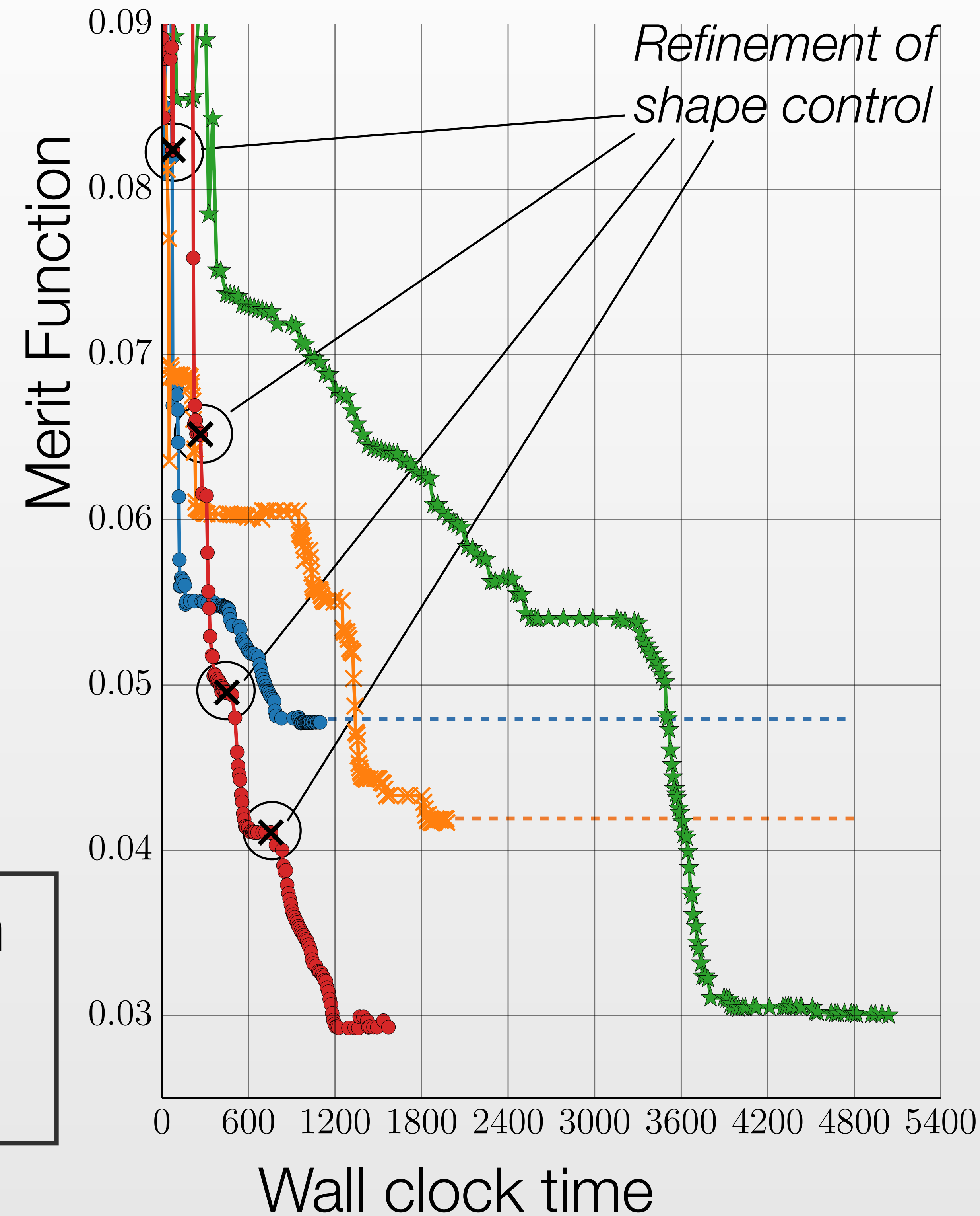


Wall clock time

In minutes, plotted at major search iterations, on 20 Ivybridge cores

Progressive vs. Static





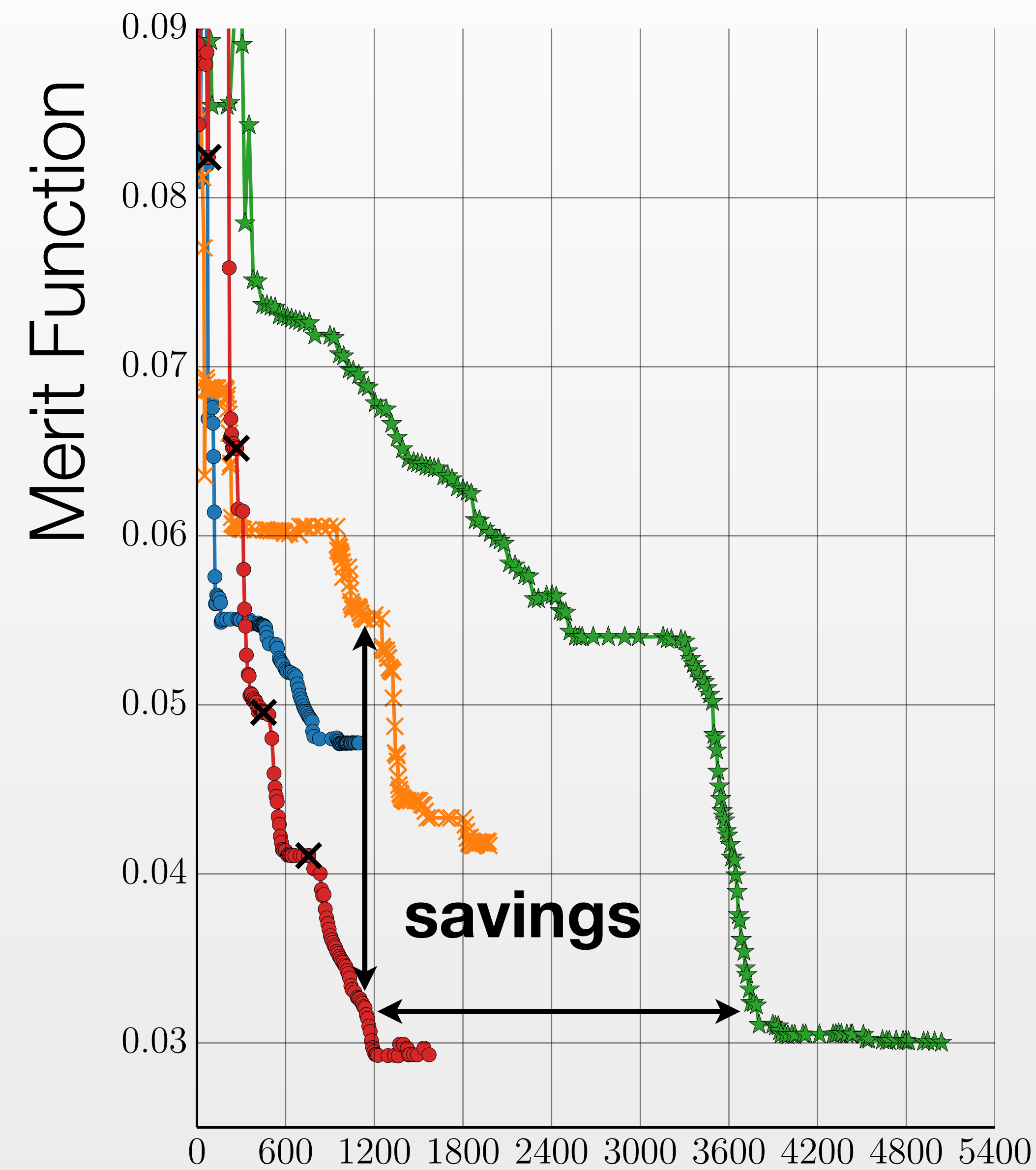
In minutes, plotted at major search iterations, on 20 Ivybridge cores

Fast improvement in coarse search spaces, but ultimately approaching **full design space**.

Cost

Factors contributing to acceleration:

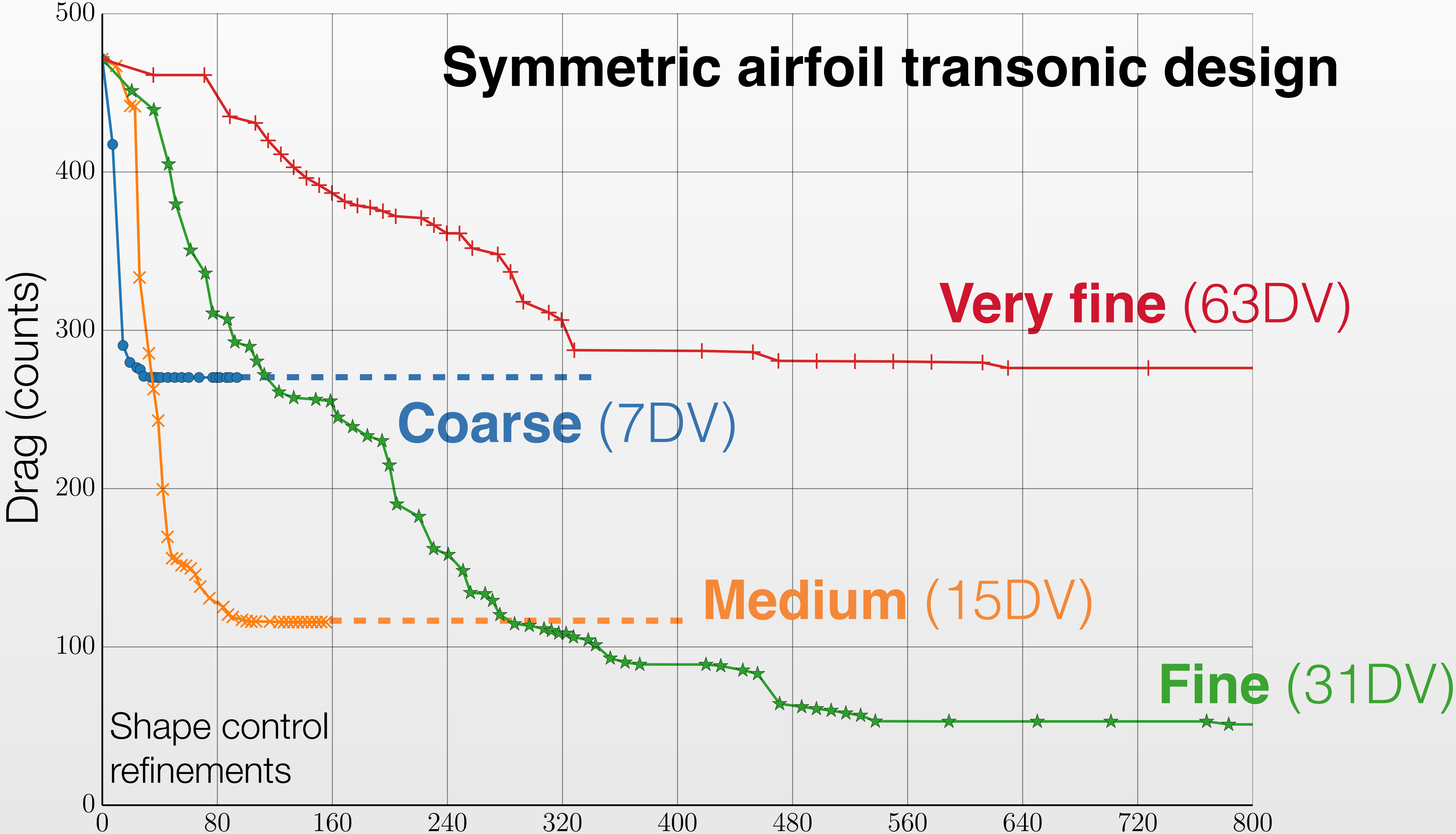
- Early on there are few design variables:
  - Accelerates **BFGS rate of improvement** w.r.t search direction.
  - Reduces # of shape sensitivities and gradient projections.
- Later, more design variables are added, **preventing optimization from stalling.**



Wall clock time

In minutes, plotted at major search iterations, on 20 Ivybridge cores

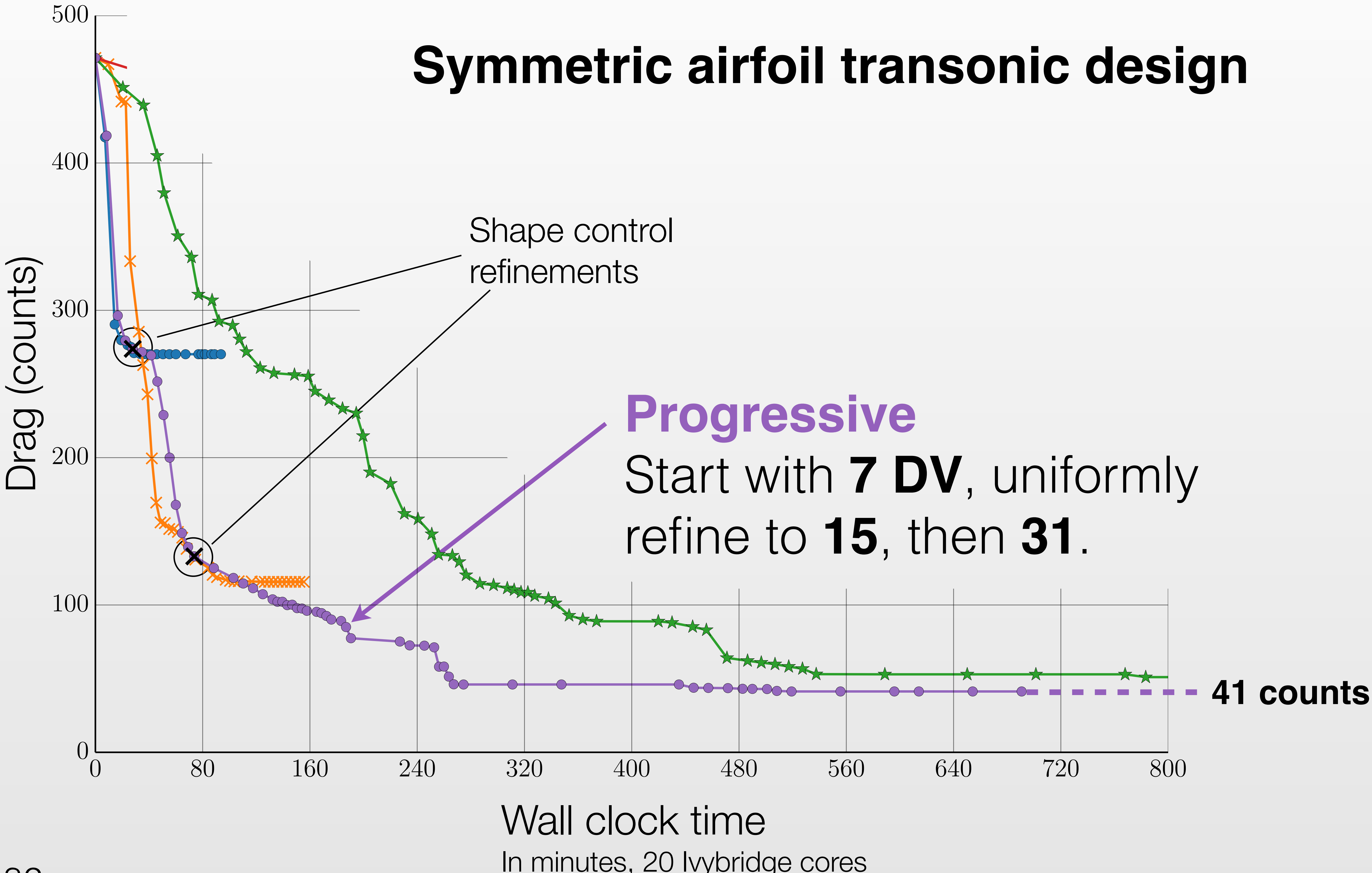
Impact of Parameterization



Wall clock time

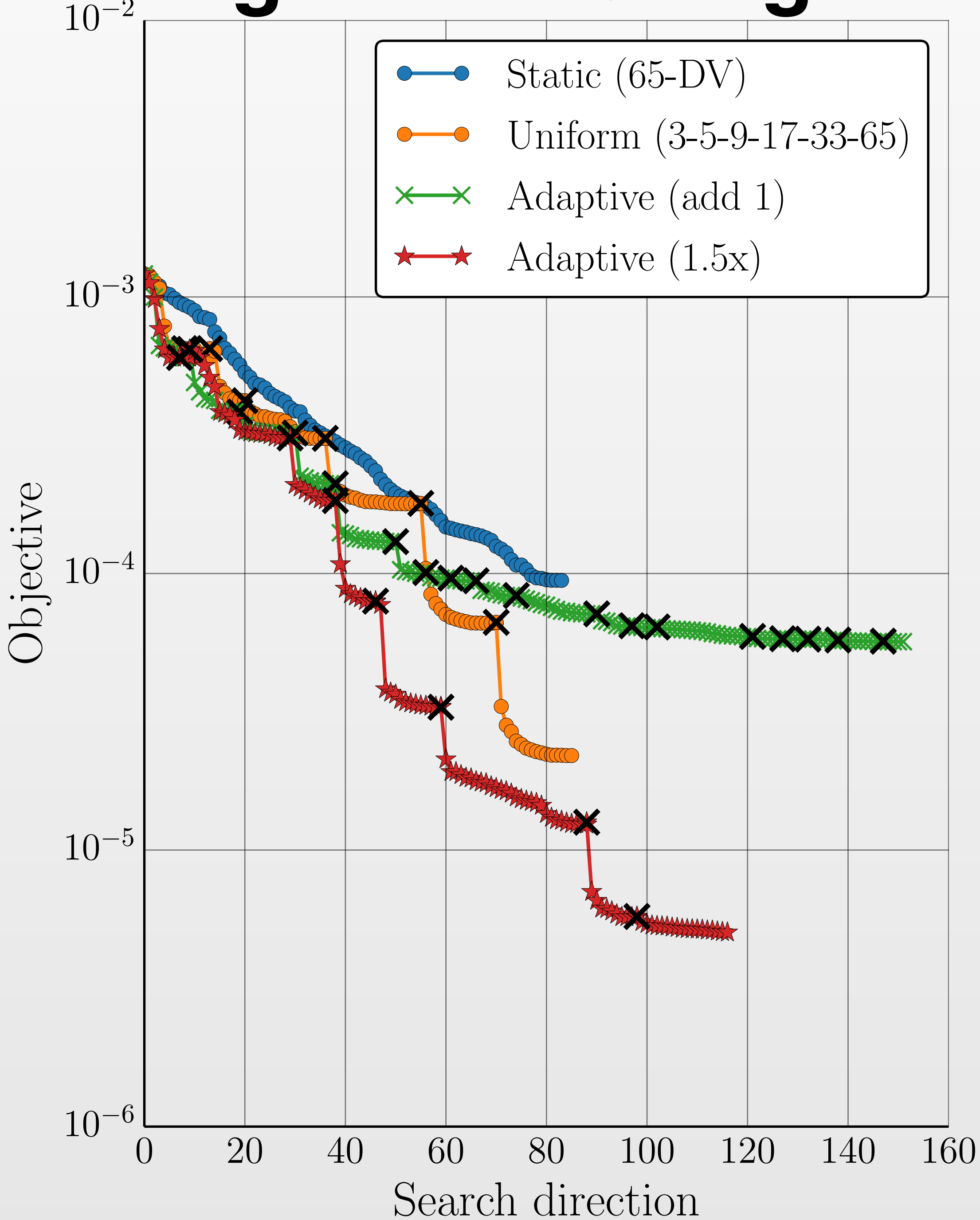
In minutes, plotted at major search iterations, on Ivybridge node — 20 cores

Progressive vs. Static

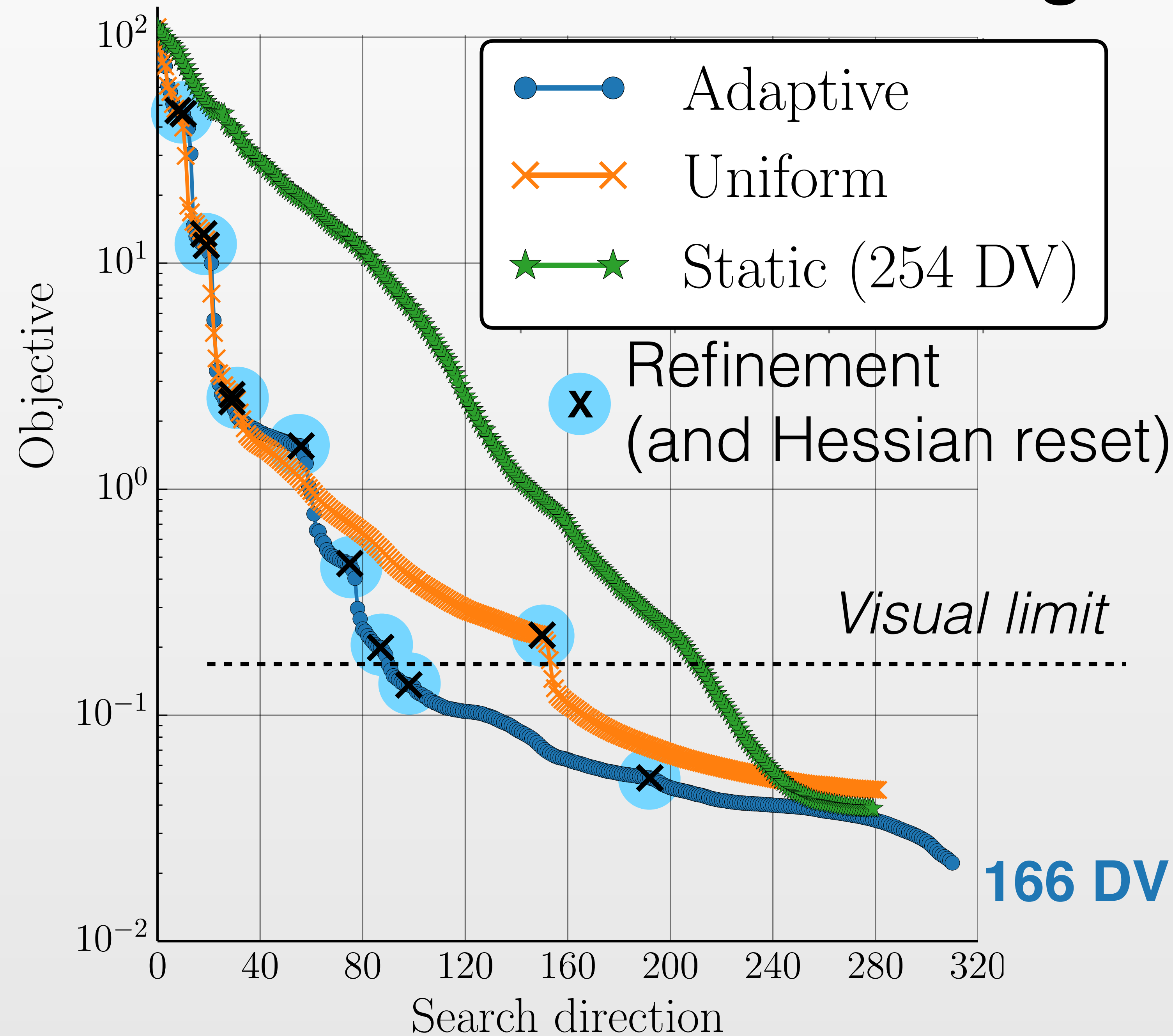


Adaptive vs. Uniform

Supersonic signal-matching



Airfoil Pressure matching



Goals of Adaptation