



Rapid Topology Optimization using Reduced-Order Models

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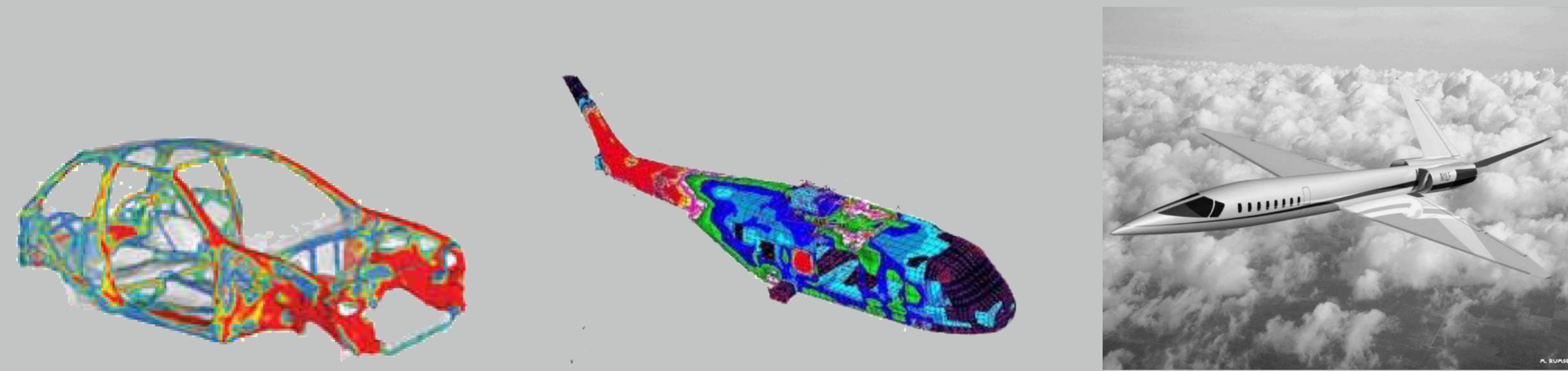
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Motivation

- For industry-scale problems, topology optimization is a beneficial tool that is *time and resource intensive*
 - Large number of calls to structural solver usually required
 - Each structural call is expensive, especially for nonlinear 3D High-Dimensional Models (HDM)
- We introduce a Reduced-Order Model (ROM) as a surrogate for the structural model in a material topology optimization loop
 - Large speedups attained by leveraging cubic structure of the nonlinear equations (large deformations of specific materials)
 - ROM necessitates low-dimensional approx. to material distribution
 - Avoid online computations that scale with HDM
 - Small vector controlling material distribution, to be used as optimization variables



0-1 Material Topology Optimization

$$\begin{aligned} & \text{minimize}_{\chi \in \mathbb{R}^{n_{el}}} \mathcal{L}(\mathbf{u}(\chi), \chi) \\ & \text{subject to } \mathbf{c}(\mathbf{u}(\chi), \chi) \leq \mathbf{0} \end{aligned}$$

- \mathbf{u} is implicitly defined as a function of χ through the HDM equation

$$\mathbf{f}^{int}(\mathbf{u}) = \mathbf{f}^{ext}$$

$$\mathbb{C}^e = \mathbb{C}_0^e \chi_e \quad \rho^e = \rho_0^e \chi_e \quad \chi_e = \begin{cases} 0, & e \notin \Omega^* \\ 1, & e \in \Omega^* \end{cases}$$

- Assume geometric *nonlinearity* and linearity in the constitutive law

Reduced-Order Model

- Model Order Reduction (MOR) assumption
 - State vector lies in low-dimensional subspace defined by Φ

$$\mathbf{u} \approx \Phi \mathbf{y}$$

- Galerkin projection

$$\Phi^T \mathbf{f}^{int}(\Phi \mathbf{y}) = \Phi^T \mathbf{f}^{ext}$$

ROM Optimization Formulation

$$\begin{aligned} & \text{minimize}_{\alpha_r \in \mathbb{R}^{n_\alpha}} \mathcal{L}(\mathbf{y}(\alpha_r), \alpha_r) \\ & \text{subject to } \mathbf{c}(\mathbf{y}(\alpha_r), \alpha_r) \leq \mathbf{0} \end{aligned}$$

- \mathbf{y} is implicitly defined as a function of α_r through the ROM equation

$$\Phi^T \mathbf{f}^{int}(\Phi \mathbf{y}) = \Phi^T \mathbf{f}^{ext}$$

Internal Force - Cubic Polynomial in Displacements

The expression for the internal force is

$$\begin{aligned} \mathbf{f}_{jL}^{int} &= \int_{\Omega_0} \mathbf{P}_{ij} \frac{\partial \mathbf{N}_I}{\partial \mathbf{X}_i} d\mathbf{X} \\ &= \bar{\mathbf{A}}_{jIL} \mathbf{u}_{tI} + \bar{\mathbf{B}}_{LI} \mathbf{u}_{jI} + \\ &\quad \bar{\mathbf{C}}_{LIJ} \mathbf{u}_{kI} \mathbf{u}_{kJ} + \bar{\mathbf{C}}_{ILQ} \mathbf{u}_{jQ} \mathbf{u}_{tI} + \bar{\mathbf{D}}_{IJQL} \mathbf{u}_{kI} \mathbf{u}_{kJ} \mathbf{u}_{jQ} \end{aligned}$$

where $\mathbf{N}_I(\mathbf{X})$ is the shape function corresponding to node I .

Then

$$\begin{aligned} \bar{\mathbf{A}} &= \bar{\mathbf{A}}(\Omega, \lambda(\mathbf{X})) & \bar{\mathbf{B}} &= \bar{\mathbf{B}}(\Omega, \mu(\mathbf{X})) \\ \bar{\mathbf{C}} &= \bar{\mathbf{C}}(\Omega, \lambda(\mathbf{X}), \mu(\mathbf{X})) & \hat{\mathbf{C}} &= \hat{\mathbf{C}}(\Omega, \lambda(\mathbf{X}), \mu(\mathbf{X})) \\ \bar{\mathbf{D}} &= \bar{\mathbf{D}}(\Omega, \lambda(\mathbf{X}), \mu(\mathbf{X})) \end{aligned}$$

Material Distribution Representation

Let material distributions be represented with the basis functions:

$$\begin{aligned} \lambda(\mathbf{X}) &= \phi_i^\lambda(\mathbf{X}) \alpha_i^r, & i &= 1, 2, \dots, n_\alpha \\ \mu(\mathbf{X}) &= \phi_i^\mu(\mathbf{X}) \alpha_i^r, & i &= 1, 2, \dots, n_\alpha \\ \rho(\mathbf{X}) &= \phi_i^\rho(\mathbf{X}) \alpha_i^r, & i &= 1, 2, \dots, n_\alpha \end{aligned}$$

Then

$$\begin{aligned} \bar{\mathbf{A}} &= \bar{\mathbf{A}}(\Omega, \phi_i^\lambda) \alpha_i^r & \bar{\mathbf{B}} &= \bar{\mathbf{B}}(\Omega, \phi_i^\mu) \alpha_i^r \\ \bar{\mathbf{C}} &= \bar{\mathbf{C}}(\Omega, \phi_i^\lambda, \phi_i^\mu) \alpha_i^r & \hat{\mathbf{C}} &= \hat{\mathbf{C}}(\Omega, \phi_i^\lambda, \phi_i^\mu) \alpha_i^r \\ \bar{\mathbf{D}} &= \bar{\mathbf{D}}(\Omega, \phi_i^\lambda, \phi_i^\mu) \alpha_i^r \end{aligned}$$

Reduced-Order Model via Precomputations

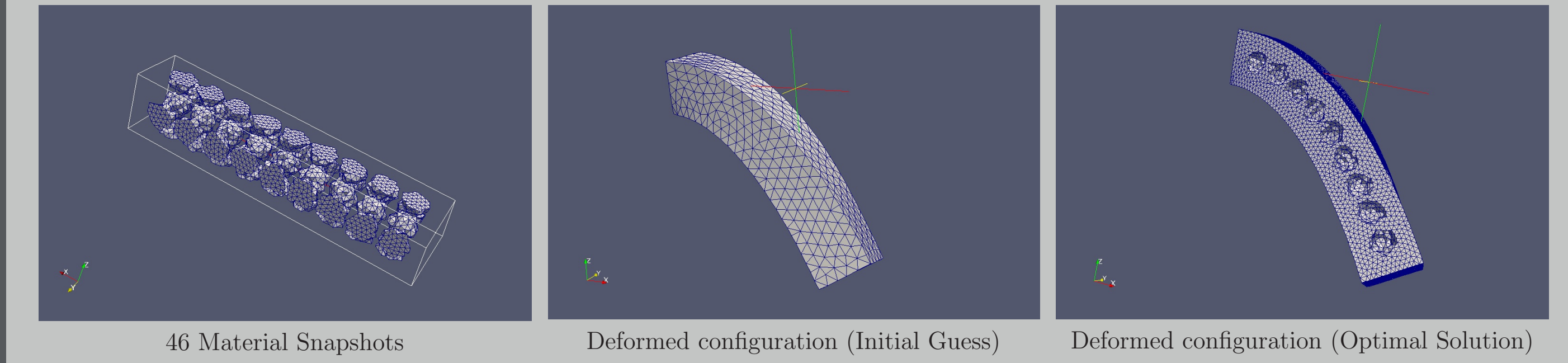
$$\Phi^T \mathbf{f}^{int}(\Phi \mathbf{y}) = \Phi^T \mathbf{f}^{ext}$$

$$\begin{aligned} & \Phi^T \left(\Phi \mathbf{y} \right) = \mathbf{f}_r^{int} \\ & \frac{\partial \mathbf{f}^{int}}{\partial \mathbf{u}}(\Phi \mathbf{y}) \Phi = \mathbf{K}_r \end{aligned}$$

$$[\Phi^T \mathbf{f}^{int}(\Phi \mathbf{y})]_r = \beta_{rp}(\alpha_r) y_p + \gamma_{rpq}(\alpha_r) y_p y_q + \omega_{rpqt}(\alpha_r) y_p y_q y_t$$

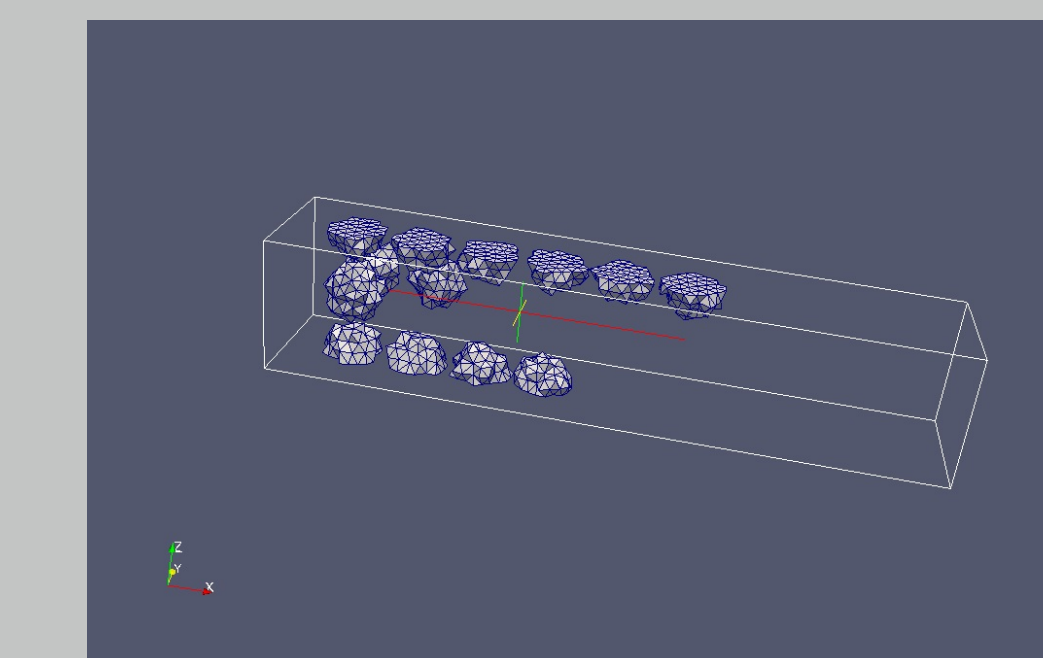
- Amenable to material topology optimization
 - α^r provide control over material distribution
 - α^r optimization variables in 0-1 topology optimization
 - Vary material distribution only in the column space of $\Phi^\lambda, \Phi^\mu, \Phi^\rho$
- Large speedups possible without hyperreduction, $\mathcal{O}(10^3)$
- Currently limited to StVK material, *Lagrangian* elements
- Cost/storage scales poorly with k_u (ROM size)
 - Offline cost scales as $\mathcal{O}(n_\alpha \cdot n_{el} \cdot k_u^4)$
 - Offline storage scales as $\mathcal{O}(n_\alpha \cdot k_u^4)$
 - Online storage scales as $\mathcal{O}(k_u^4)$

Cantilever - Weight Minimization

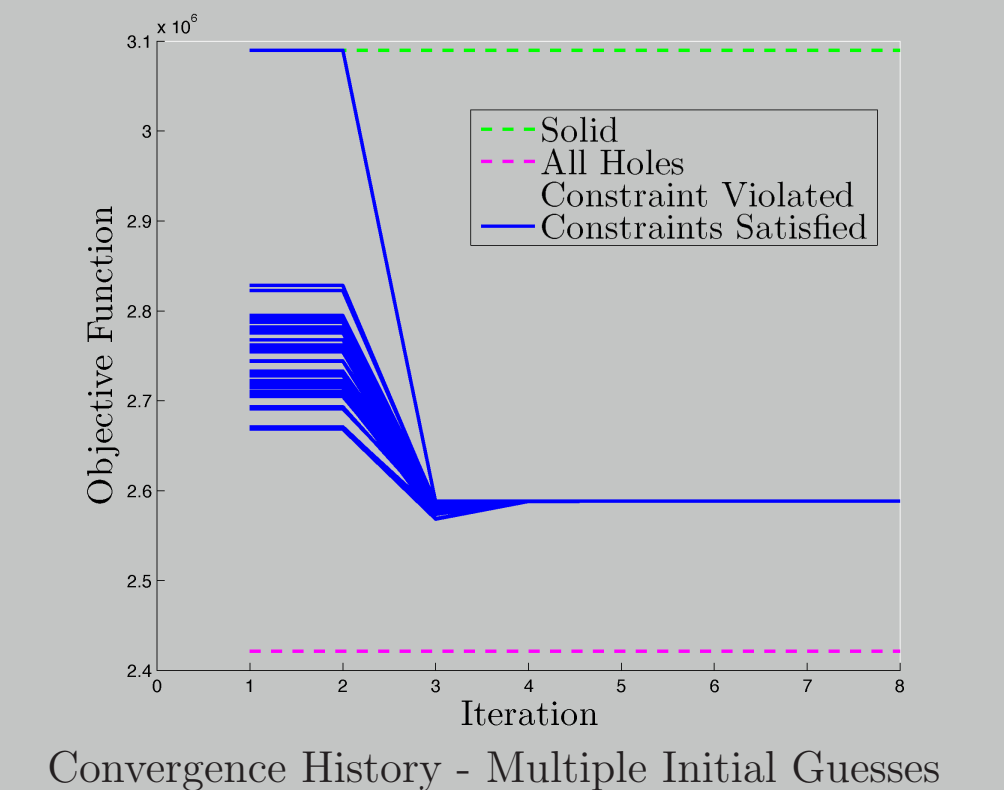


- α^r determines existence of voids
- Vertical displacement bounds
- 38,664 dof
- Loads: bending, twisting, self-weight
- ROM size: $k_u = 5$

	Online (sec)	Speedup
HDM	750	-
ROM	156	4.80
pROM	0.37	2,051

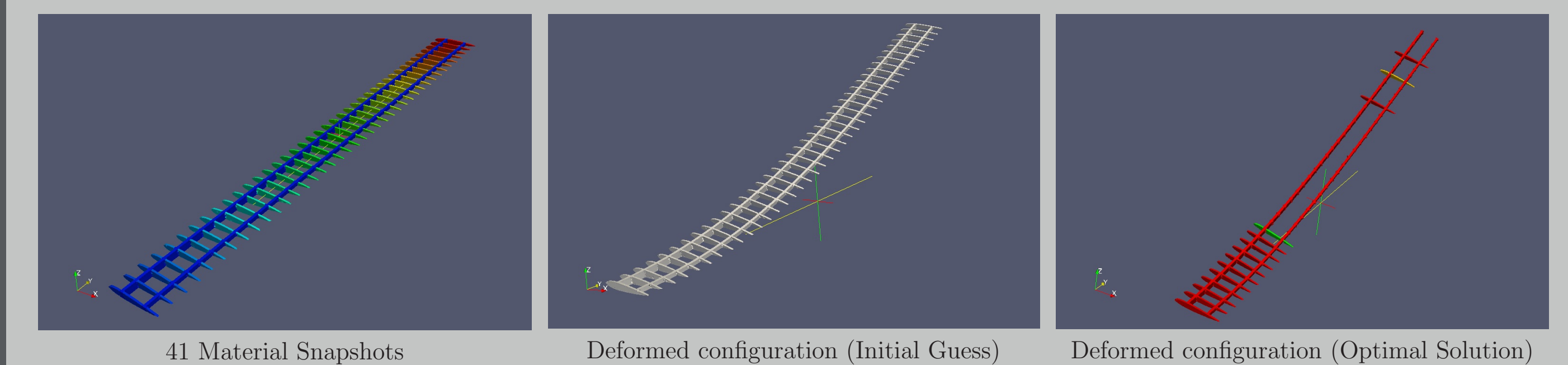


Remaining Material at Optimal Solution (Outer Matrix Removed)



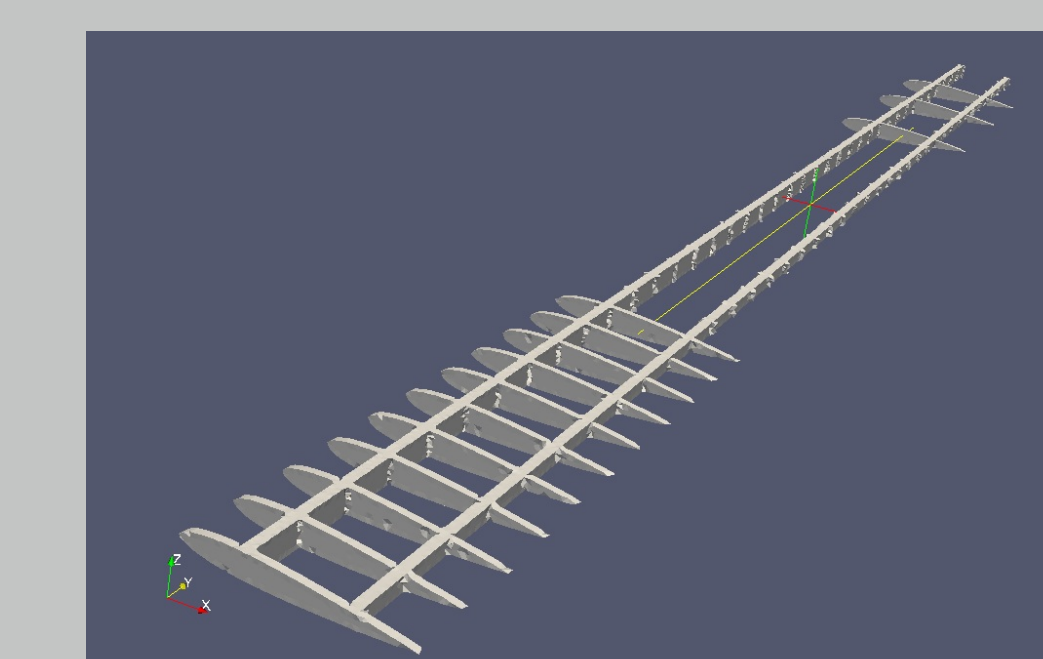
Convergence History - Multiple Initial Guesses

Wing Box Design - Weight Minimization

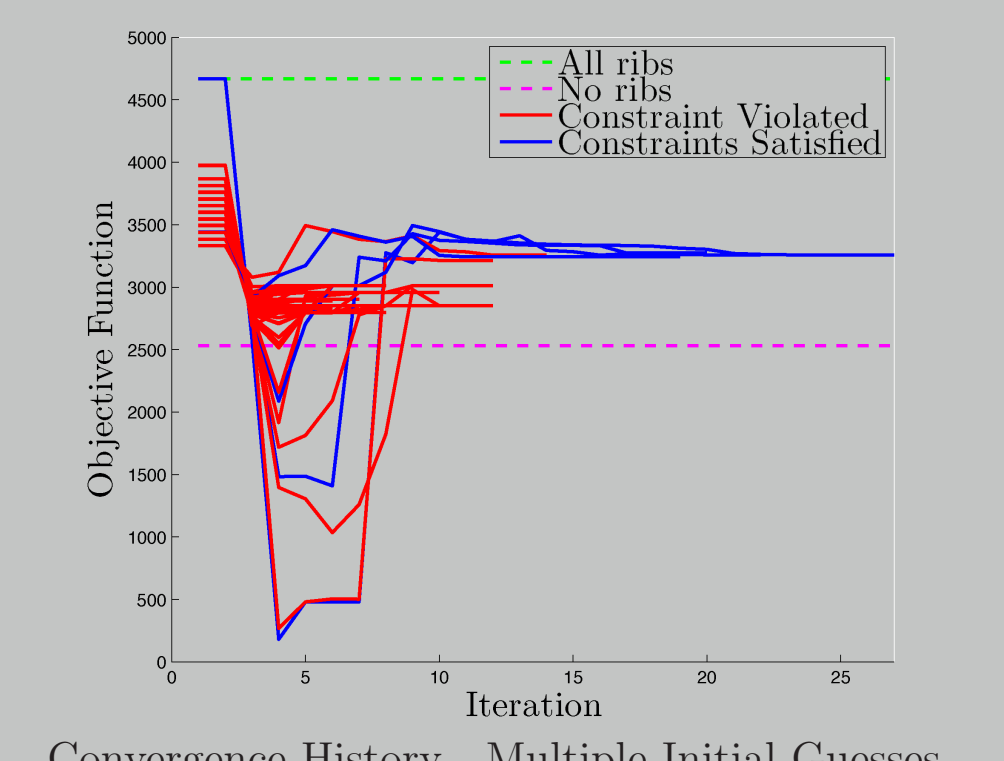


- α^r determines placement of ribs
- Vertical/horizontal disp bounds
- Loads: bending (lift and drag loads), twisting, self-weight
- 86,493 dof
- ROM size: $k_u = 5$

	Online (sec)	Speedup
HDM	811	-
ROM	376	2.16
pROM	1.51	538



Optimal Solution



Convergence History - Multiple Initial Guesses

Conclusion

- New method for material topology optimization using reduced-order models
 - $\mathcal{O}(10^3)$ speedup over HDM
- Potential to address large problems

