

Optimization Under Uncertainty for Predicting Properties and Performance

Jim Stewart

Senior Manager, *Comp. Sciences and Math*
Sandia National Laboratories

**Uncertainty Quantification in Computational Solid
and Structural Materials Modeling**

January 17, 2019
Baltimore, MD



Sandia National Laboratories is a multi-mission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525. SAND?????????

Acknowledgements

Miguel Aquilo

Stephen Bond

Brett Clark

Drew Kouri

Jon Madison

John Mitchell

Steve Plimpton

Josh Robbins

Theron Rodgers

Jason Sanchez

Aidan Thompson

Veena Tikare

Tom Voth

Context: Topology Optimization

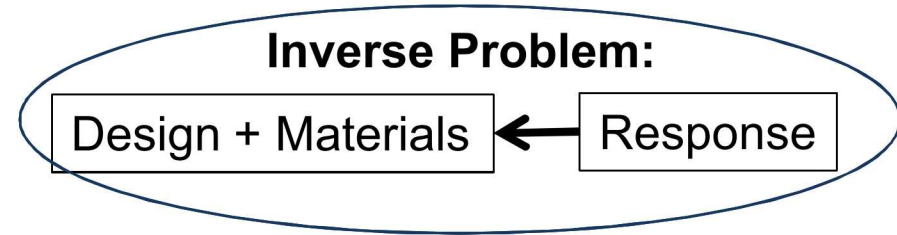
Design Tools to Leverage Additive Manufacturing

Objective: Provide a *design environment* that can leverage existing simulation tools and emerging HPC architectures.

Forward Problem:



Inverse Problem:



Approach: Use *topology optimization* to let performance objectives dictate the design

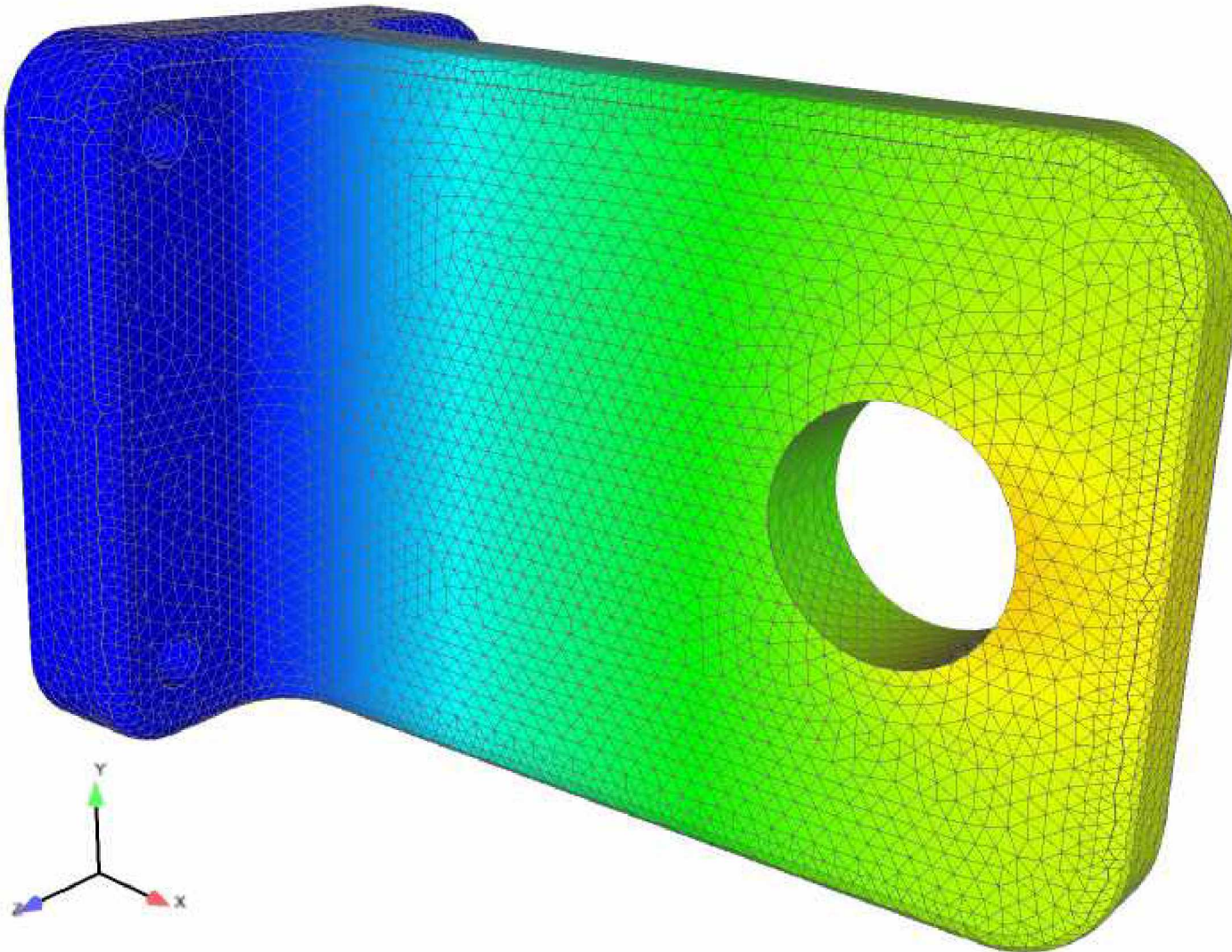
$$\text{Objective: } \min_{\mathbf{z}, \mathbf{x}} \sum_i \alpha_i f_i(\mathbf{u}_i, \mathbf{z}, \mathbf{x})$$

$$\text{PDE Constraint: } \mathbf{g}_i(\mathbf{u}_i, \mathbf{z}, \mathbf{x}) = 0$$

$$\text{Inequality Constraint: } h(\mathbf{u}, \mathbf{z}, \mathbf{x}) \leq 0$$

WATCHING DESIGNS EVOLVE THROUGH SIMULATION

Real time multi-physics design

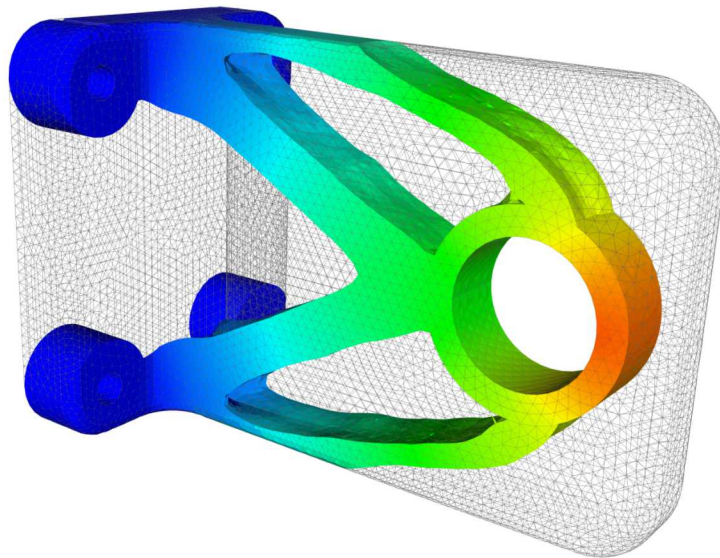


- GPU enabled solver package
- Optimized for stiffness and thermal conductivity
- Video is time is the real time to optimize the design

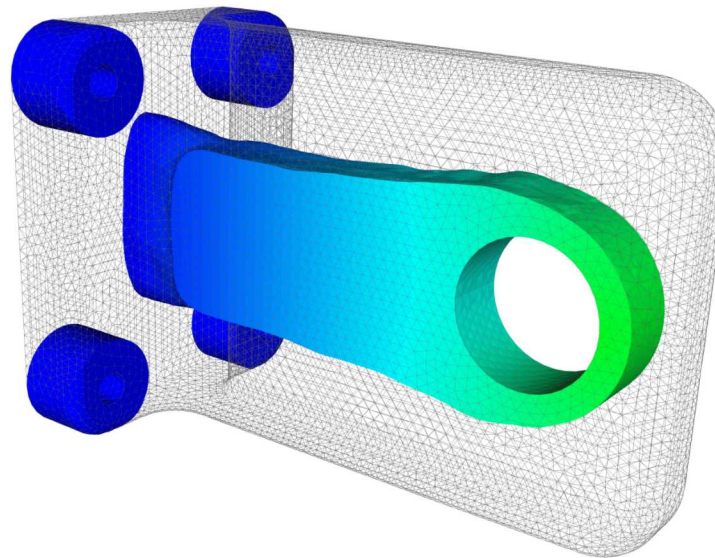
DIFFERENT PERFORMANCE OBJECTIVES LEADS TO DIFFERENT DESIGNS

Important to incorporate as much of the relevant physics as possible

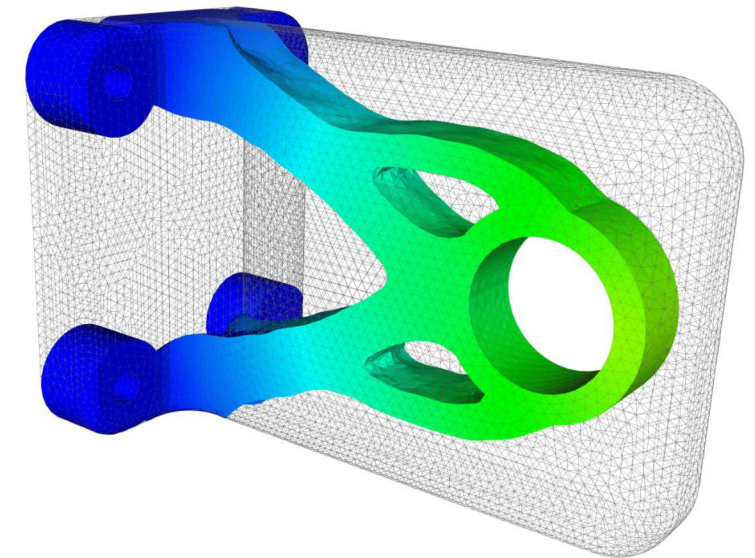
Mechanical compliance
minimization



Thermal compliance
minimization



Mechanical and thermal
compliance minimization



Constraint: *Equal
mass in each design*

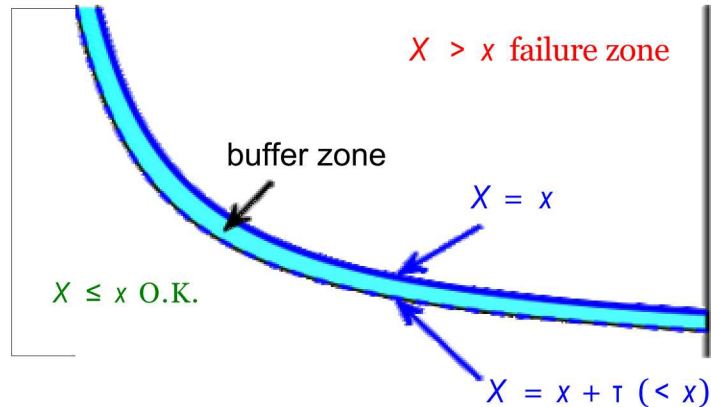
Note: Structure is disconnected from
the mounts – no consideration was
given to mechanical stiffness!

Incorporating Uncertainty

- **Probabilistic optimization**
 - Risk measures
 - Buffered probabilities
- **Material-aware optimization**
 - Continuum material anisotropy
 - Microstructure anisotropy due to additive manufacturing

Buffered Probabilities

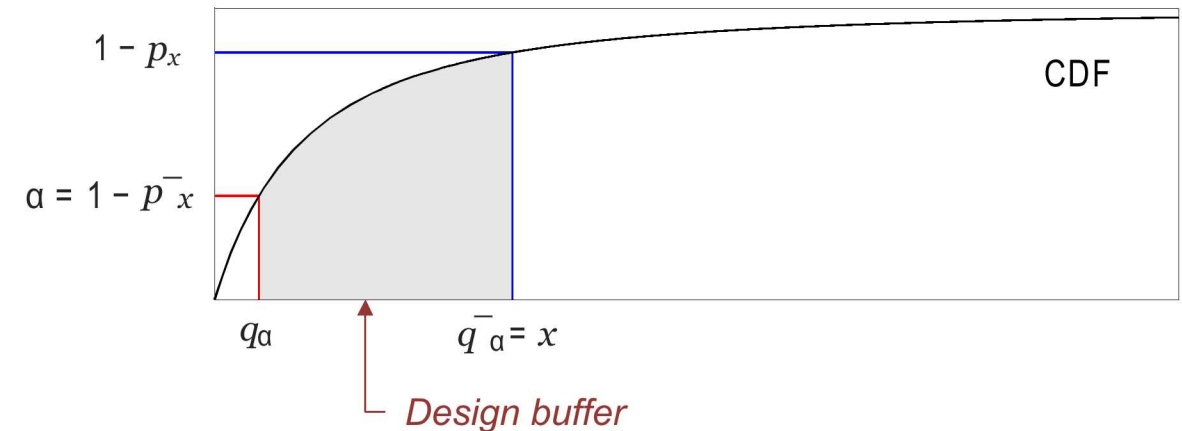
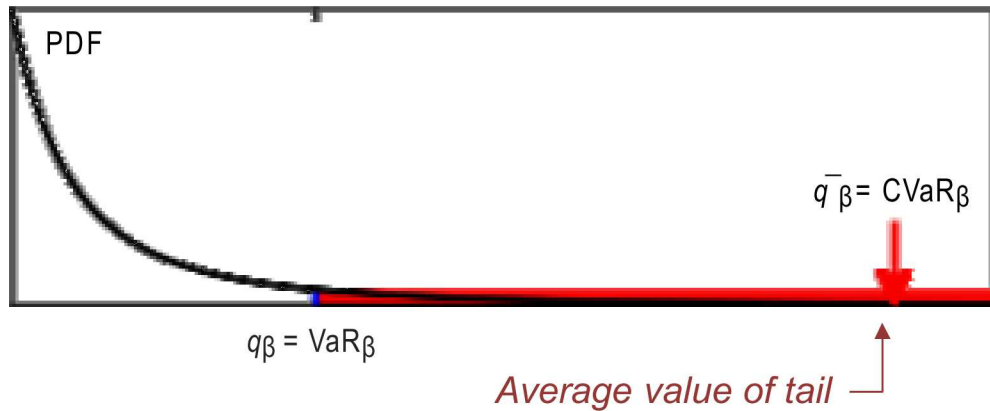
Incorporates conservatism due to large tail values



Buffered probability of exceedance: $R(X) = \bar{p}_x(X) = P(X > \tau(x))$
 where $\tau(x)$ is determined by $\text{CVaR}_{(1-\bar{p}_x(X))}(X) = E[X | X > \tau(x)] = x$

$$\text{bPOE}_x[X] = 1 - \alpha \text{ where } \alpha \text{ solves } \text{CVaR}_\alpha[X] = x$$

Conditional Value-at-Risk



Example: 3D Topology Optimization with Buffered Probability

Given compliance tolerance c_o , probability $p_o \in (0, 1)$, order $q \geq 1$,

$$\min_{0 \leq z \leq 1} \int_D z \, dx =: \text{vol}(z) \quad \text{subject to} \quad \text{bPOE}_{q, c_o} \left(\int_D \mathbf{F} \cdot \mathbf{S}(z) \, dx \right) \leq 1 - p_o$$

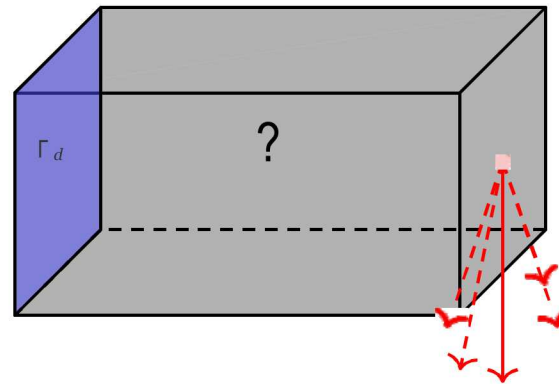
where $\mathbf{S}(z) = \mathbf{u}$ solves the **linear elasticity equations**

$$-\nabla \cdot (\mathbf{E}(z) : \varepsilon \mathbf{u}) = \mathbf{F}, \quad \text{in } D$$

$$\varepsilon \mathbf{u} = \frac{1}{2} (\nabla \mathbf{u} + \nabla \mathbf{u}^T), \quad \text{in } D$$

$$\mathbf{u} = \mathbf{0}, \quad \text{on } \Gamma_D$$

$$\varepsilon \mathbf{u} : \mathbf{n} = 0, \quad \text{on } \partial D \setminus \Gamma_D$$



- \mathbf{F} : Three uncertain parameters
- Magnitude
 - Polar and azimuthal angles

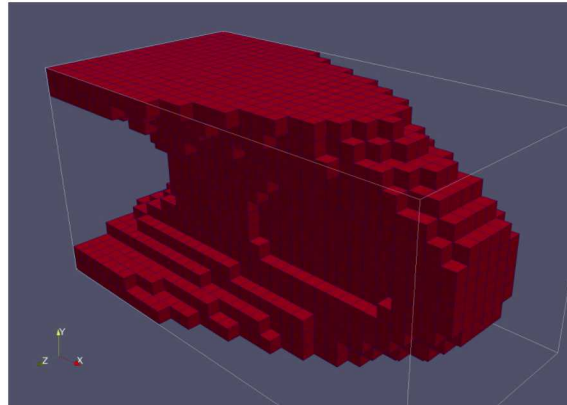
Numerical Results

Spatial Discretization: Q1 FEM on a uniform $32 \times 16 \times 16$ mesh

Stochastic Discretization: $Q = 120$ Monte Carlo samples

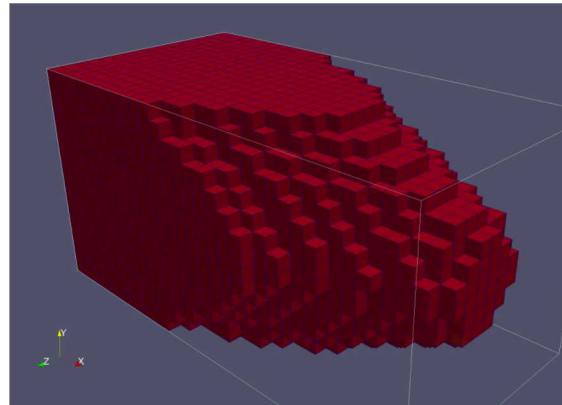
Problem Data: $p_0 = 0.75$ and $c_0 = 2E \left[\int_D \mathbf{F} : \mathbf{S}(\mathbf{1}) dx \right]$

Mean Value



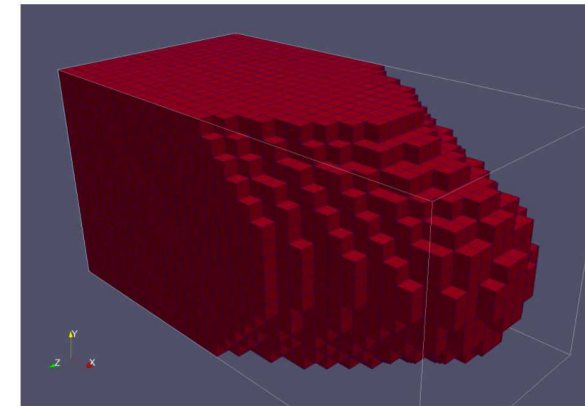
Deterministic

Risk Neutral



Constraint on average compliance

bPOE



Constraint on average of largest 25%

	Mean Value	Risk Neutral	bPOE
Volume Fraction	49.1%	47.6%	67.2%

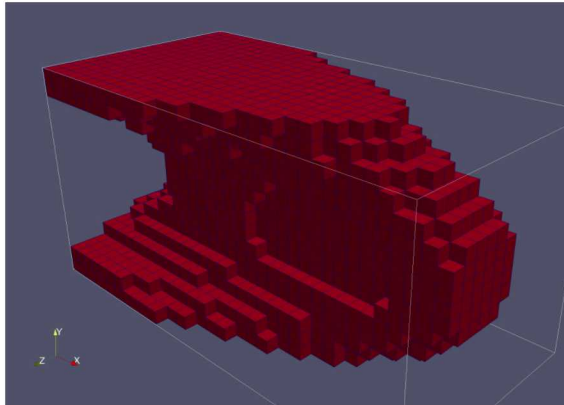
Numerical Results

Spatial Discretization: Q1 FEM on a uniform $32 \times 16 \times 16$ mesh

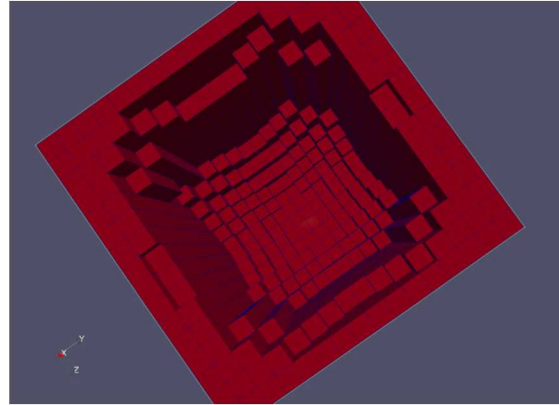
Stochastic Discretization: $Q = 120$ Monte Carlo samples

Problem Data: $p_0 = 0.75$ and $c_0 = 2E \left[\int_D \mathbf{F} : \mathbf{S}(\mathbf{1}) dx \right]$

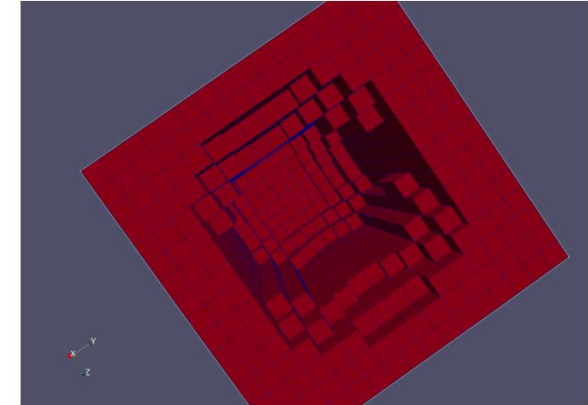
Mean Value



Risk Neutral



bPOE



Note: Topology changes from beam to shell!

	Mean Value	Risk Neutral	bPOE
Volume Fraction	49.1%	47.6%	67.2%

Incorporating Uncertainty

- **Probabilistic optimization**
 - Risk measures
 - Buffered probabilities
- **Material-aware optimization**
 - **Continuum material anisotropy**
 - Microstructure anisotropy due to additive manufacturing

Material-aware stress minimization

Example: Barlat model w/ anisotropic yield surface

$$\text{Objective: } \min_{\mathbf{z}, \mathbf{x}} f(\mathbf{u}, \mathbf{z}, \mathbf{x})$$

$$\text{PDE Constraint: } \mathbf{g}(\mathbf{u}, \mathbf{z}, \mathbf{x}) = \mathbf{0}$$

$$\text{Inequality Constraint: } h(\mathbf{u}, \mathbf{z}, \mathbf{x}) \leq 0$$

$$f = \left[\frac{1}{V} \int_{\Omega} \left(\frac{\bar{\sigma}}{\sigma_y} \right)^p dV \right]^{1/p}$$

Yield function

$$\phi = \sum_{i=1}^3 \sum_{j=1}^3 \|S'_i - S'''_j\|^a$$

$$\bar{\sigma} = \left(\frac{\phi(\mathbf{S}', \mathbf{S}''')}{4} \right)^{1/a}$$

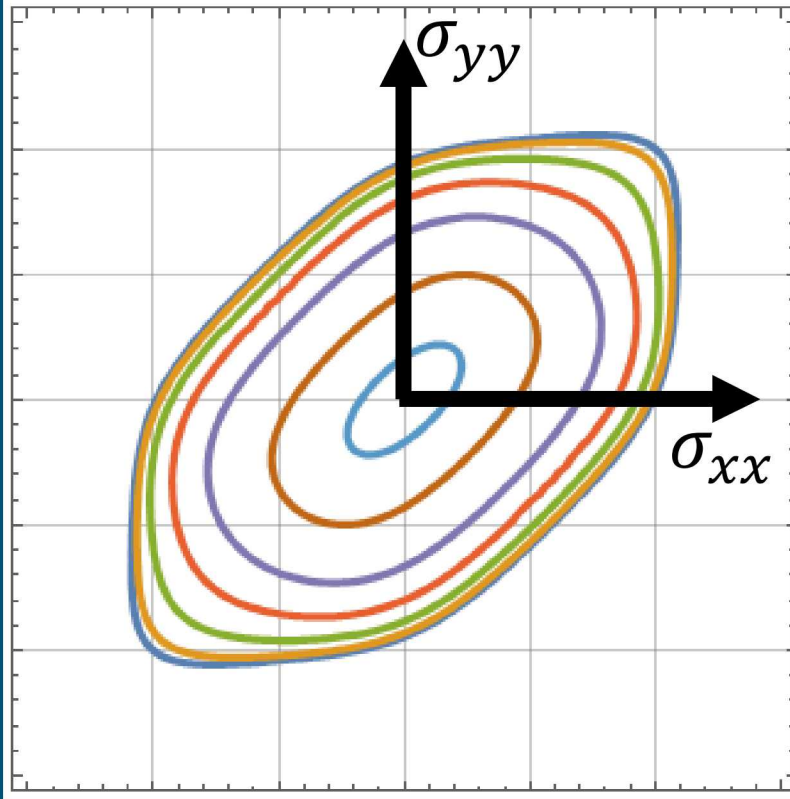
$$\mathbf{s}' = \mathbf{C}' \mathbf{s}$$

$$\mathbf{s}''' = \mathbf{C}''' \mathbf{s}$$

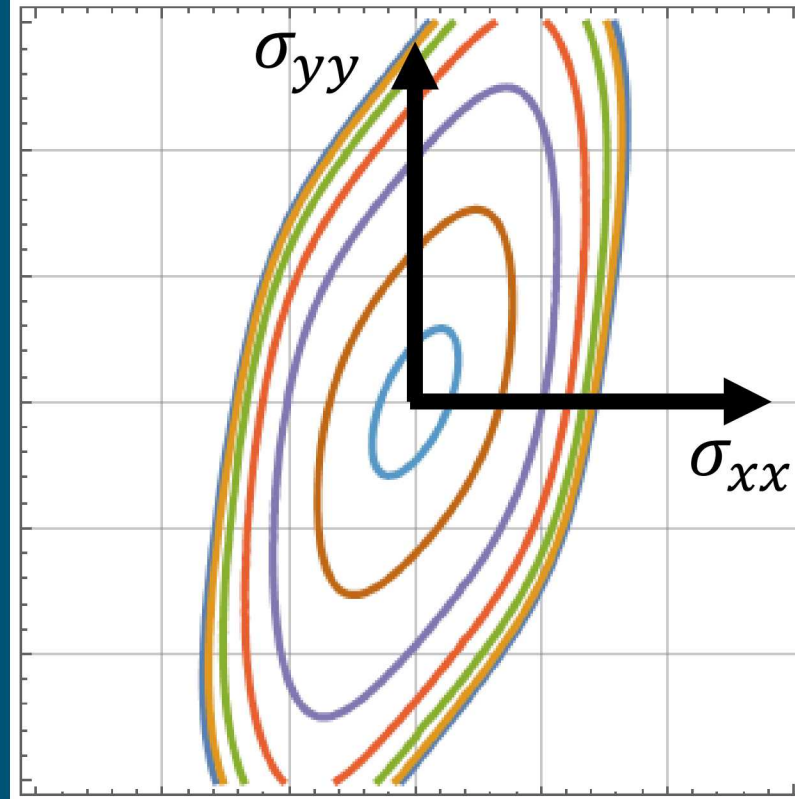
Material constants: \mathbf{C}' \mathbf{C}''' a σ_y

Barlat et al. (2005), Int. J. Plasticity

Yield Surfaces



6111-T4 (Barlat, IJP, 2005)



Hypothetical material

Superposed Shear

$$\begin{aligned}\sigma_{xy} &= 0.0 \\ \sigma_{xy} &= 0.1 \\ \sigma_{xy} &= 0.2 \\ \sigma_{xy} &= 0.3 \\ \sigma_{xy} &= 0.4 \\ \sigma_{xy} &= 0.5 \\ \sigma_{xy} &= 0.55\end{aligned}$$

Example: Material-aware compliance minimization

Thermal and mechanical compliance minimization

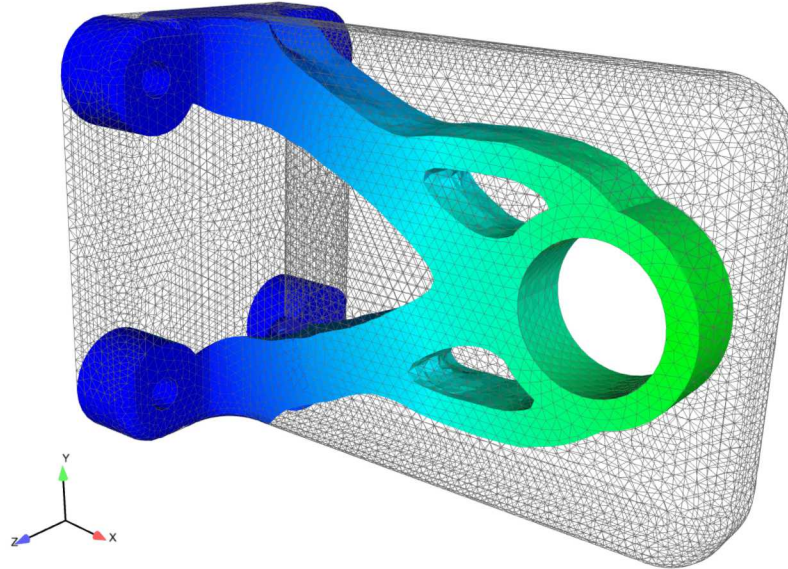
Mechanical and thermal load cases. 2 GPUs.

elements: 187k

dofs: 110k

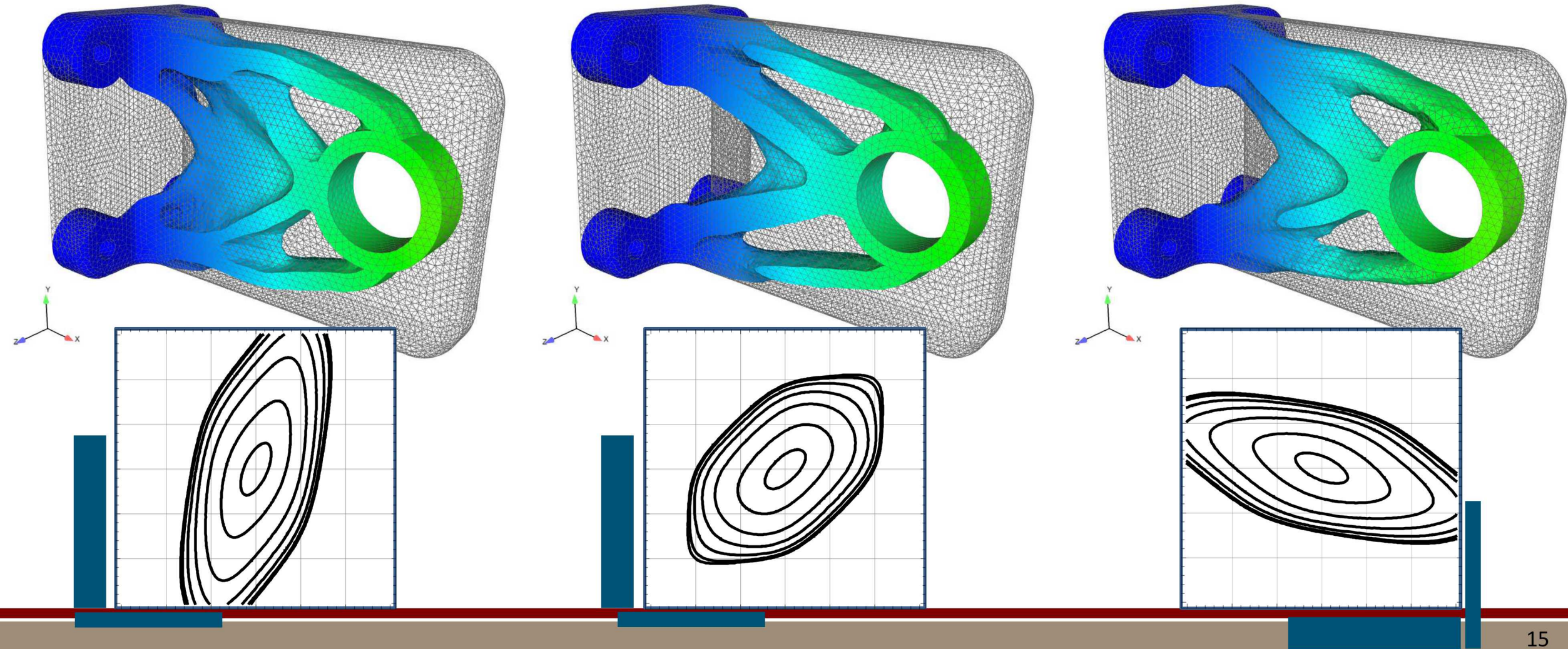
iterations: 26

Run time: 28s



Example: Material-aware compliance minimization

$$V_f: 0.25$$

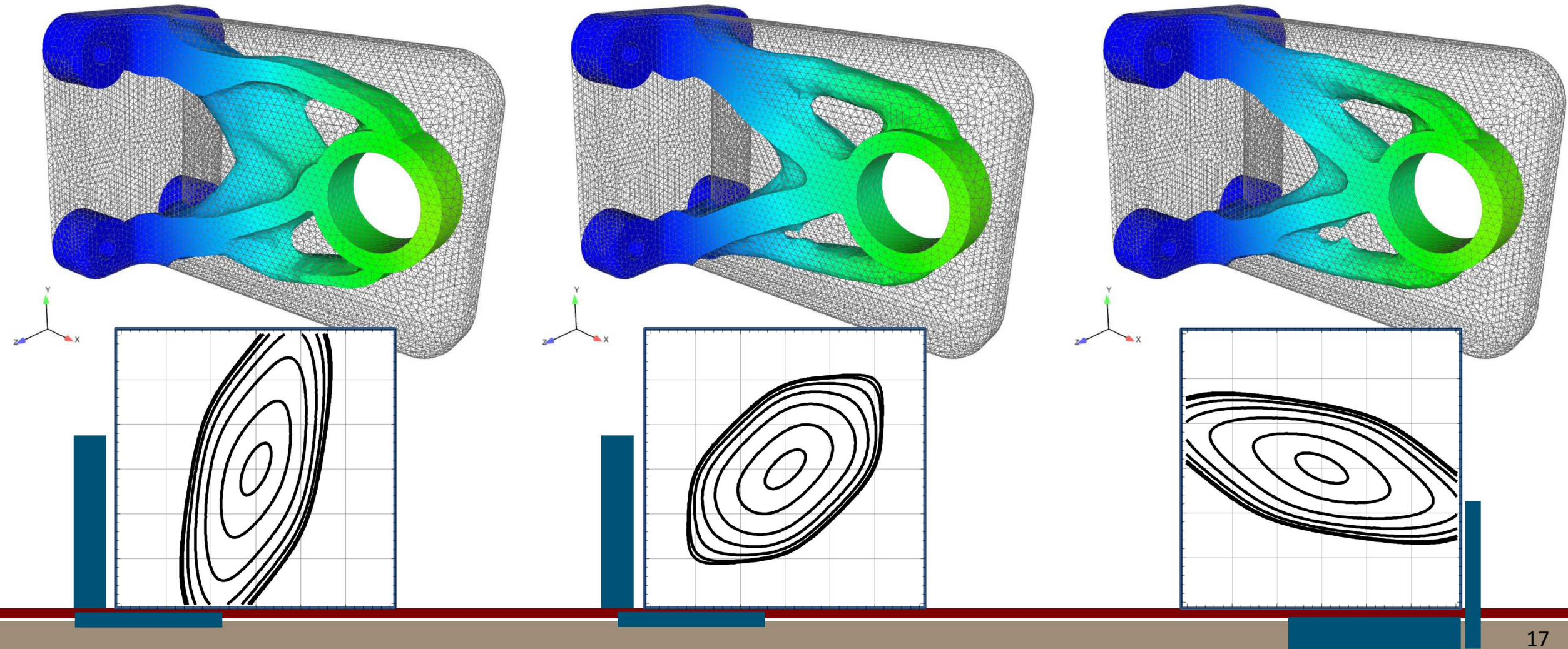


REMARK

In AM, it is common to see anisotropy in the build direction. Therefore, the desired bulk properties might influence choice of build direction.

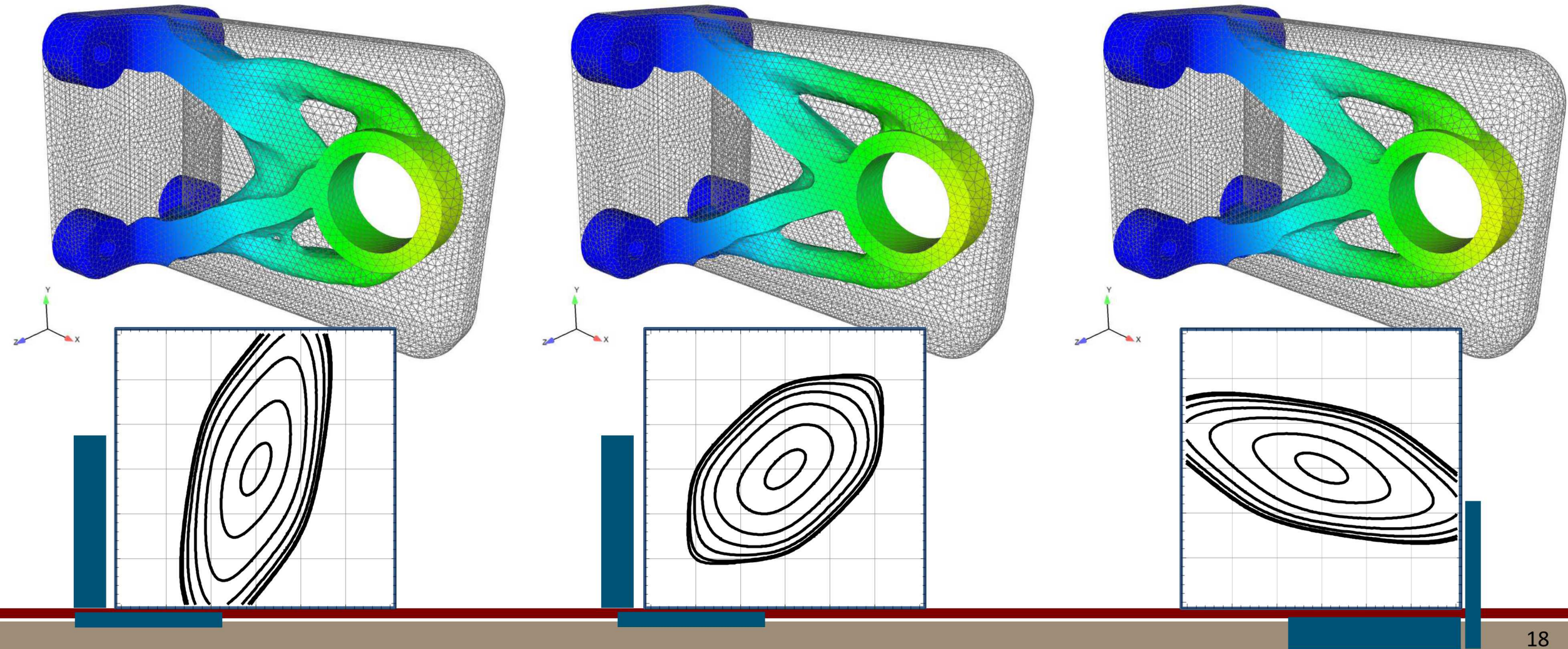
Example: Material-aware compliance minimization

$V_f: 0.20$



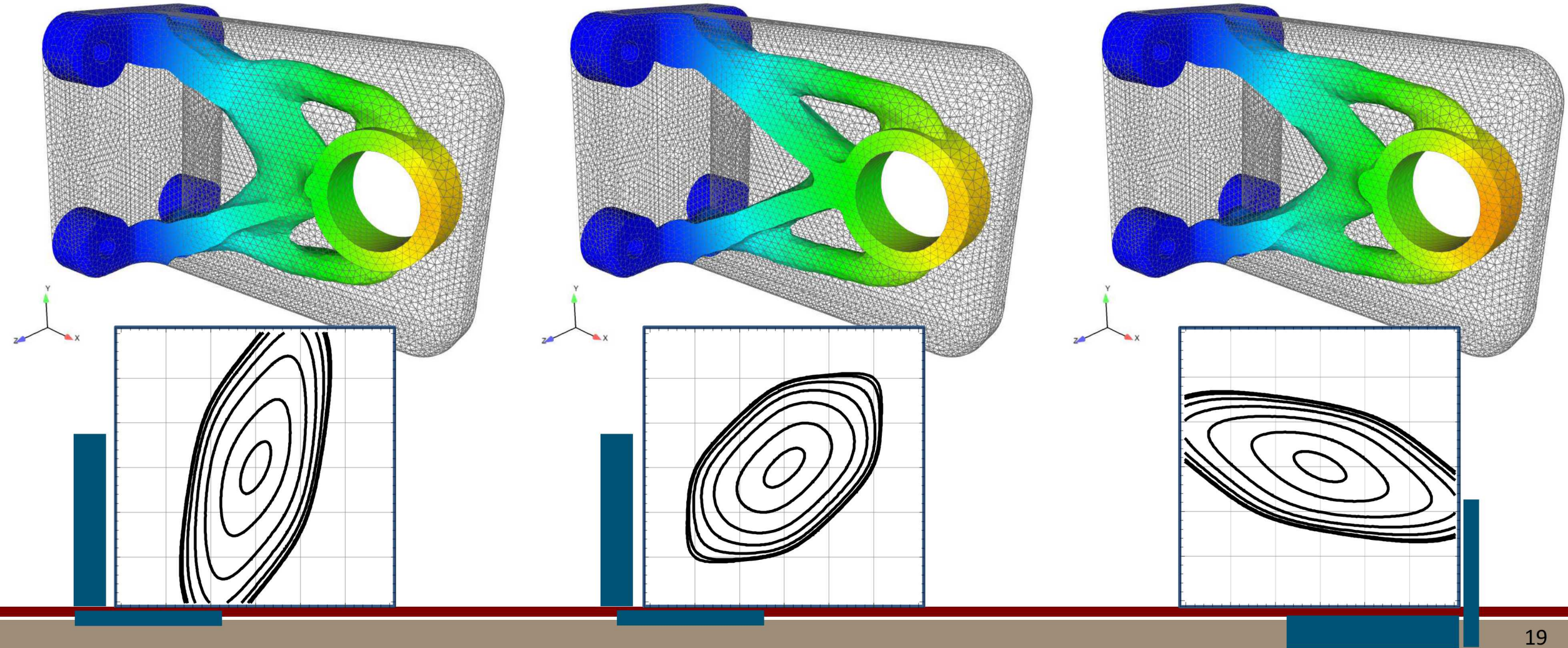
Example: Material-aware compliance minimization

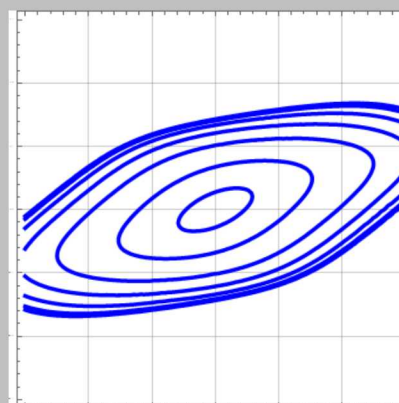
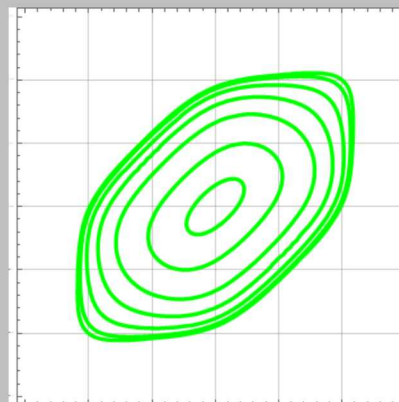
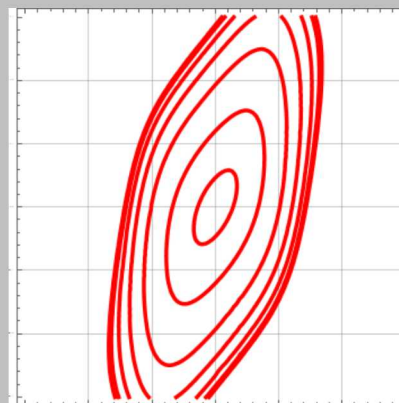
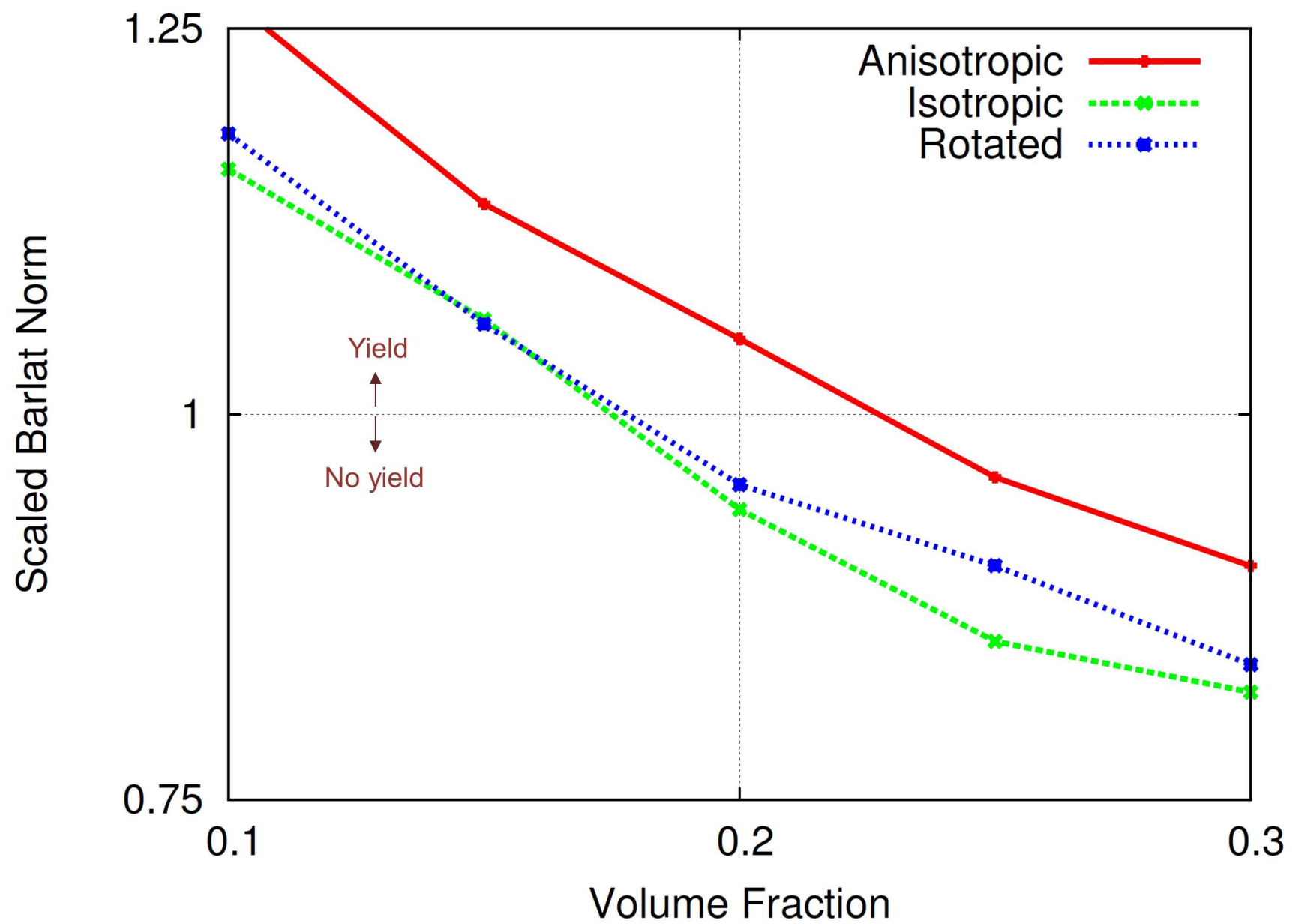
$$V_f: 0.15$$



Example: Material-aware compliance minimization

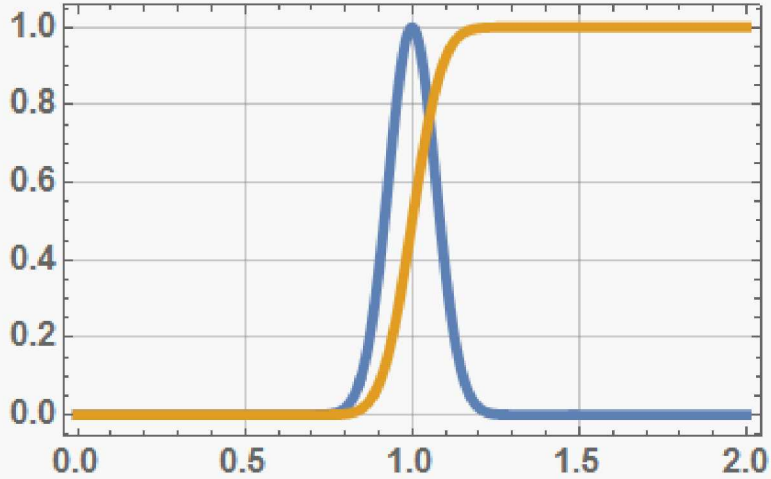
$V_f: 0.10$



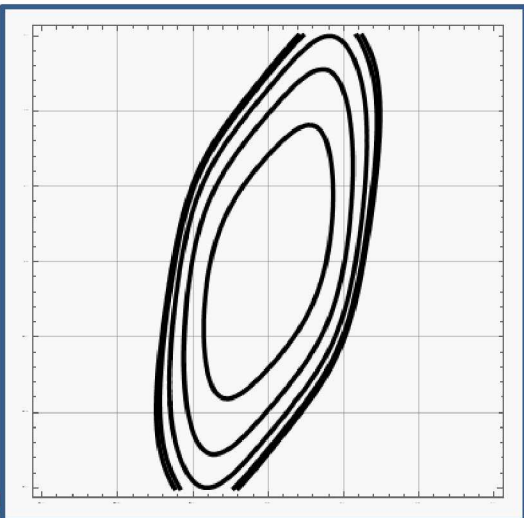


What if Yield Stress is **Uncertain**?

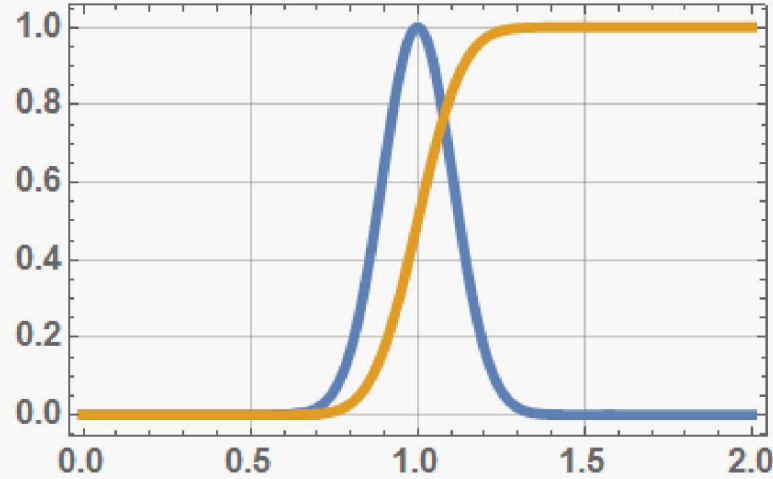
Standard Deviation: 0.1



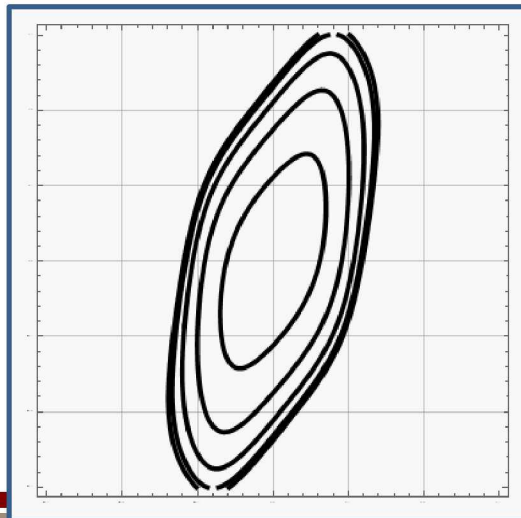
95% Confidence: 0.884



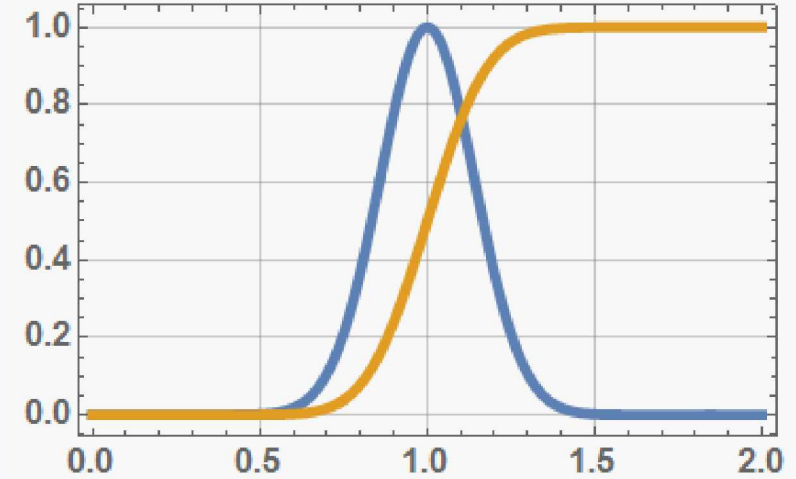
Standard Deviation: 0.15



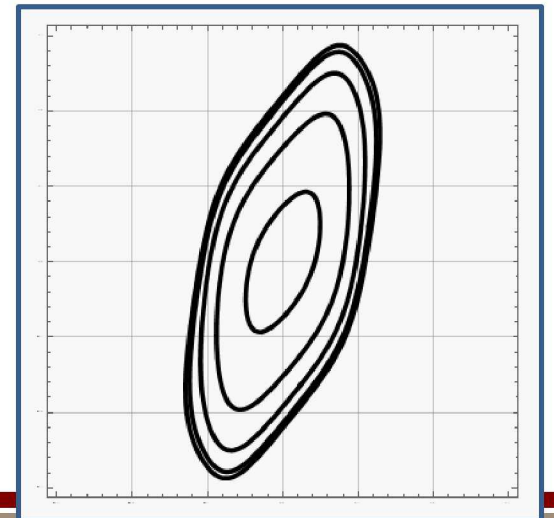
95% Confidence: 0.826

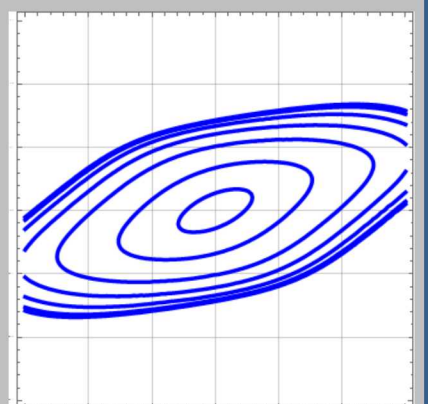
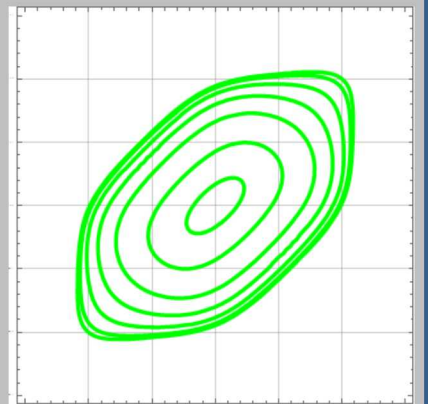
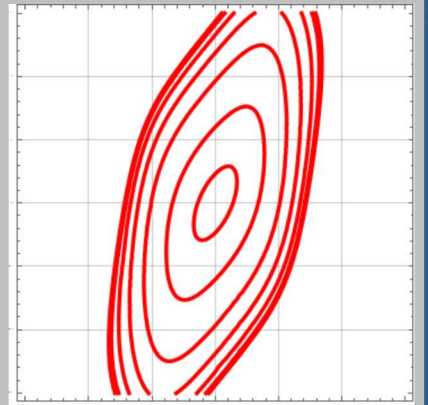
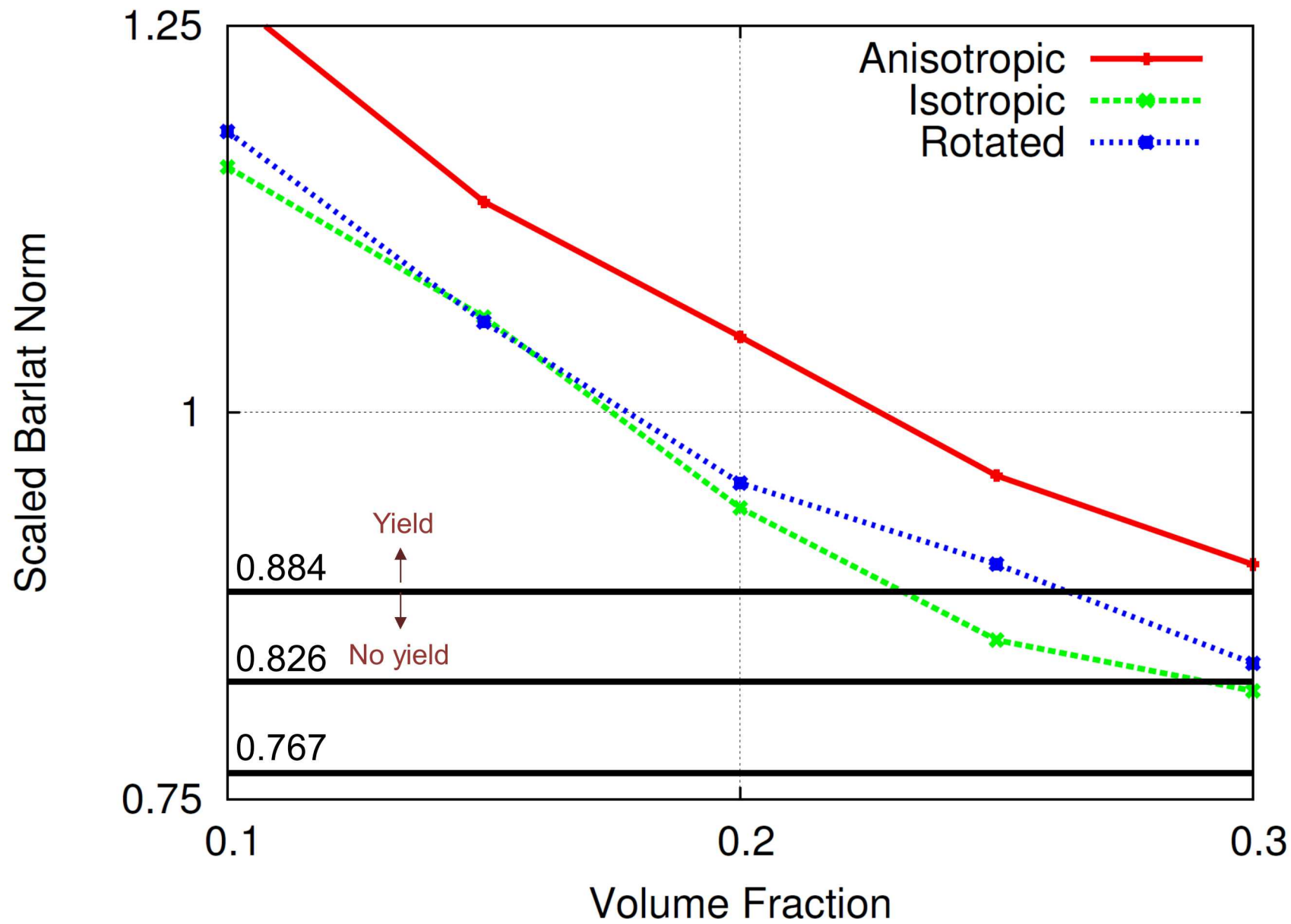


Standard Deviation: 0.2



95% Confidence: 0.767





Incorporating Uncertainty

- **Probabilistic optimization**
 - Risk measures
 - Buffered probabilities
- **Material-aware optimization**
 - Continuum material anisotropy
 - Microstructure anisotropy due to additive manufacturing

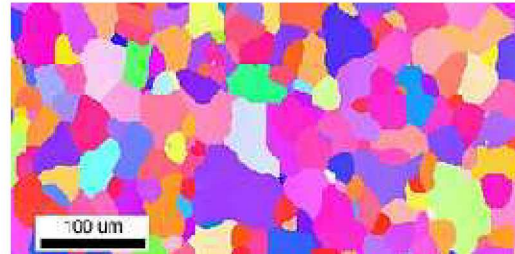
Additive Manufacturing for Metals

What are the issues?

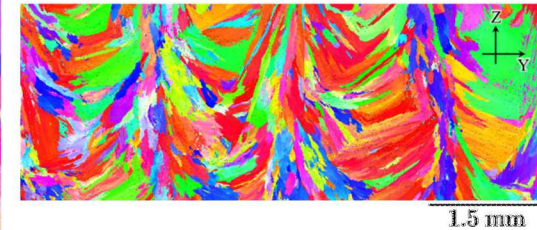
Additive Manufacturing &
Engineering Design

Caveat: not exhaustive

Wrought 304L stainless
steel microstructure



AM 304L stainless steel
microstructure



AM materials exhibit **spatial heterogeneity**

- Heterogeneous textures and morphologies at various length scales
- Residual stresses

Measurements indicate **higher variability** than wrought materials

- Yield stress, ductility, ultimate stress, rate effects

Challenges traditional deterministic modeling and design approaches

- Spatial heterogeneity and length scales

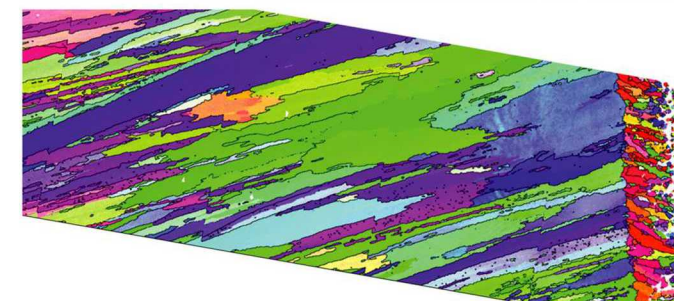
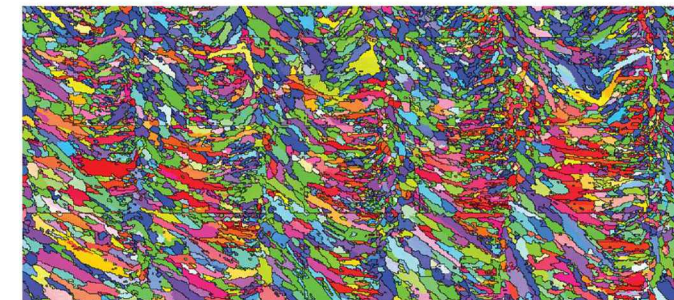
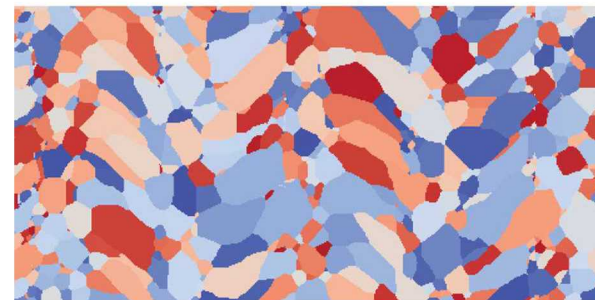
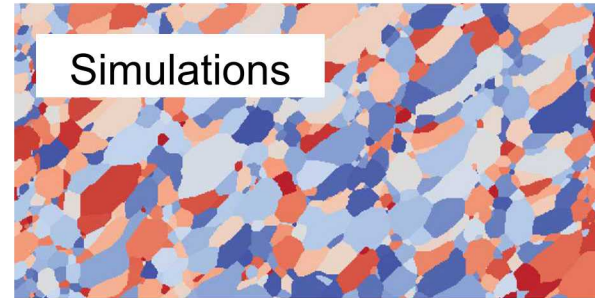
WHY IS A MICROSTRUCTURE SIMULATOR IMPORTANT?

Microstructural variations within and between different components control variation in engineering properties

Simulation of microstructural evolution during fabrication will inform:

- Design of process variables
- Uncertainty quantification in final components produced

SPPARKS: Stochastic Parallel
PARticle Kinetic Simulator
spparks.sandia.gov



Scan direction
↑

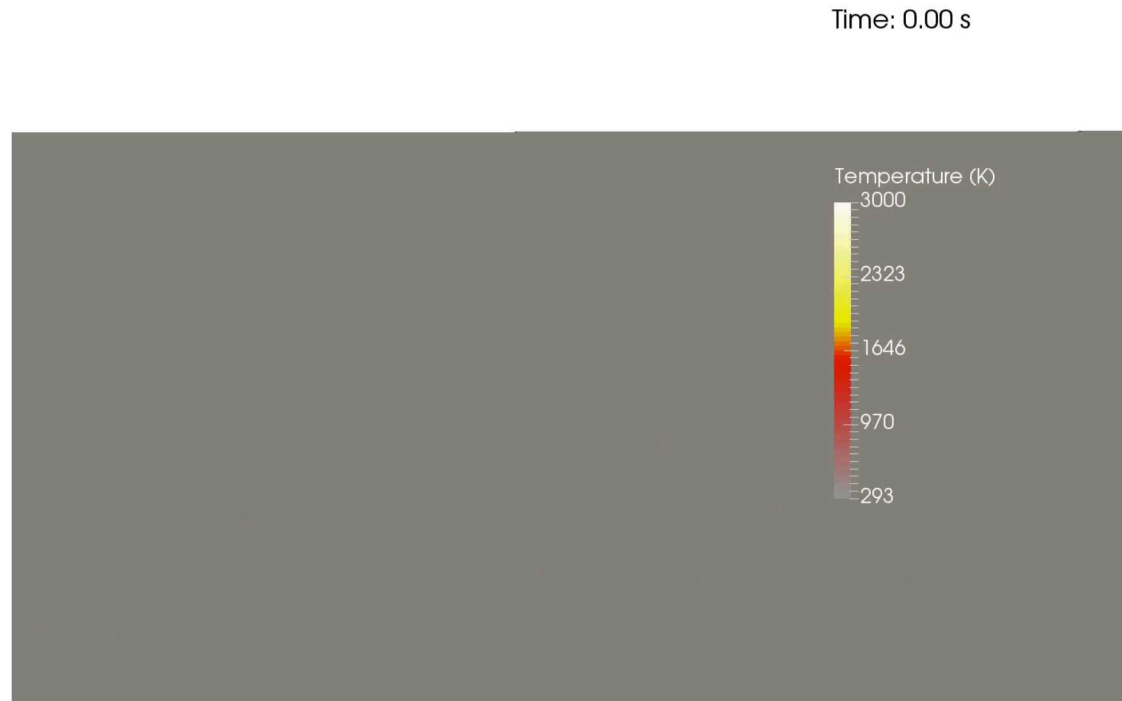
↑
↓

↑
↓

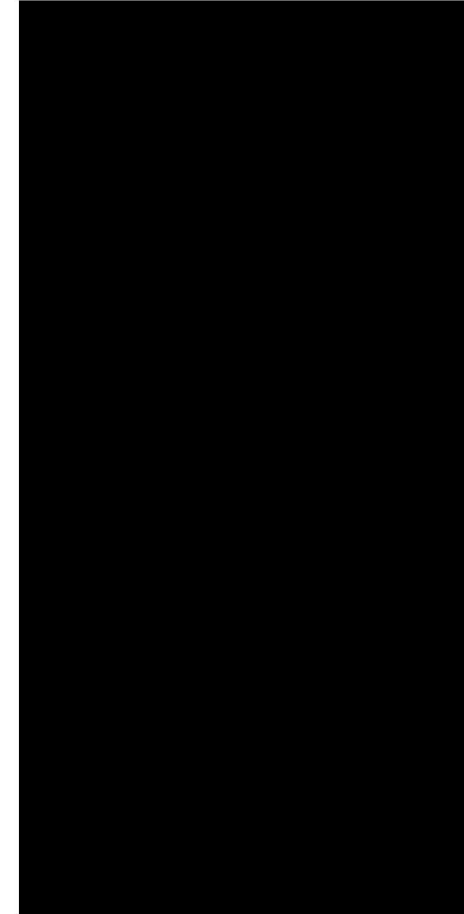
Build direction →

PROCESS PARAMETERS – MICROSTRUCTURE – PERFORMANCE

Process determines structure



Sierra FEA Thermal Model

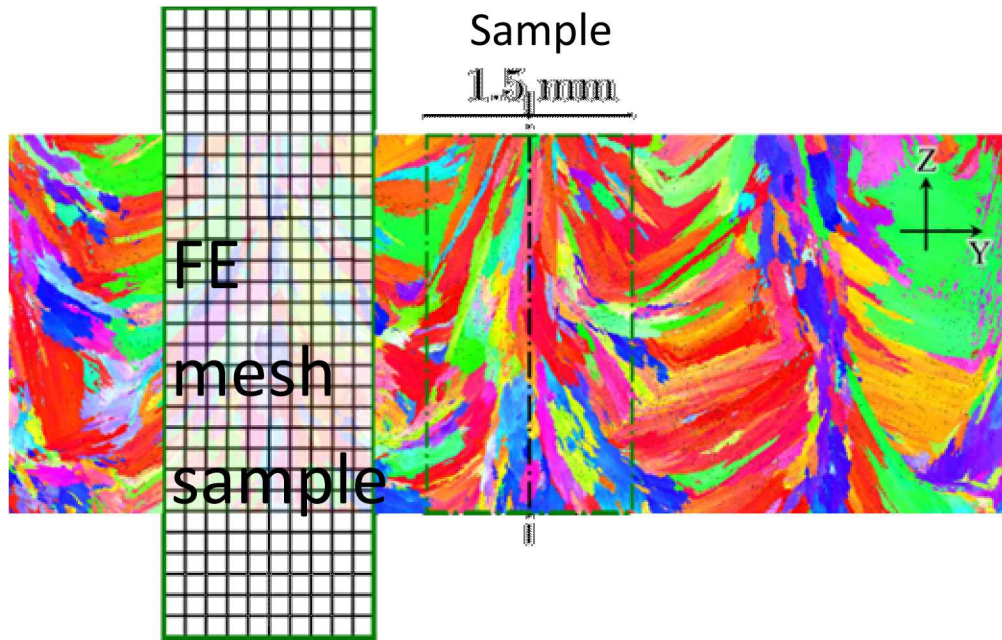


SPPARKS
MC Model

Coupling with
SIERRA thermal
models

How to model this heterogeneity and variability?

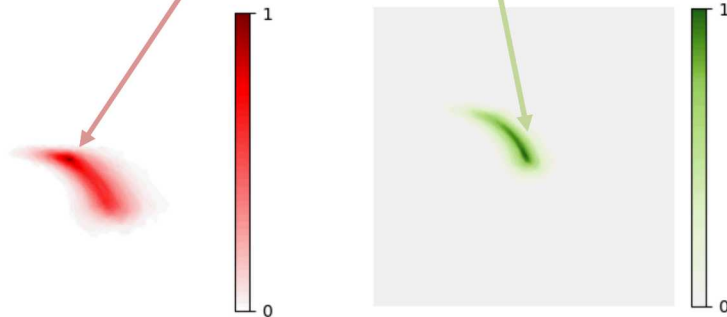
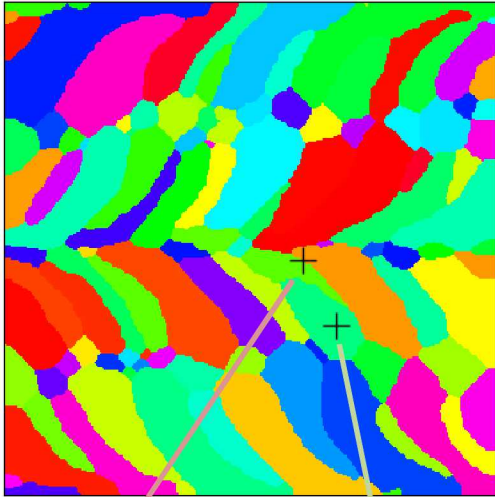
Approach: *Upscale microstructural effects*



- ☐ Avoids vexing problem of meshing material details
- ☐ *Systematically represents properties on coarse continuum model*
- ☐ Respects length scale and microstructure morphologies
- ☐ Reflects microstructure heterogeneity and variability

Upscaling Approach

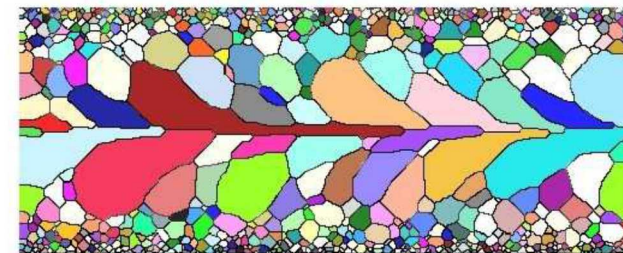
- Use synthetic microstructures via SPPARKS model of AM process



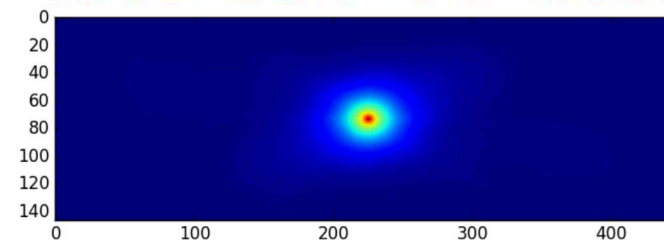
Spatial probability surrounding locations are part of grain +

- Compute spatial statistics for FE quadrature points
(for 150 SPPARKS simulations)
- Apply cluster algorithms from machine learning

Comparison to current state-of-the-art



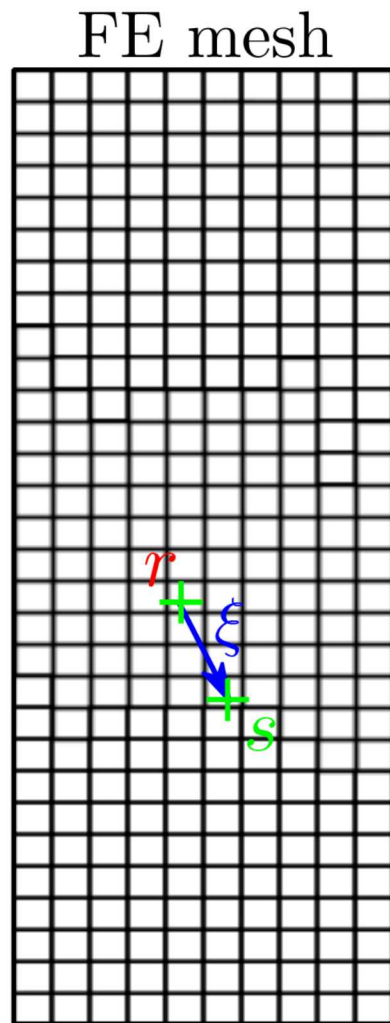
*Sample
Microstructure*



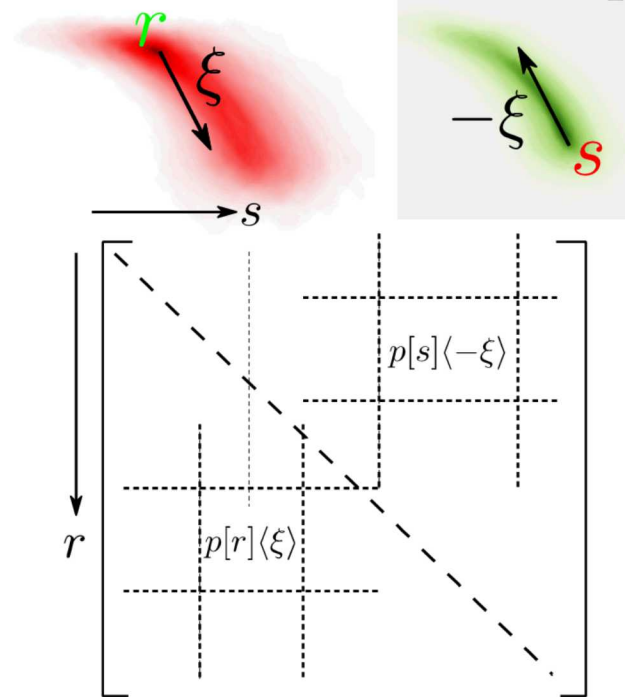
Global S2: *Spatial
heterogeneity lost*

Computing spatial statistics

Identify FE quadrature points as fixed observation points

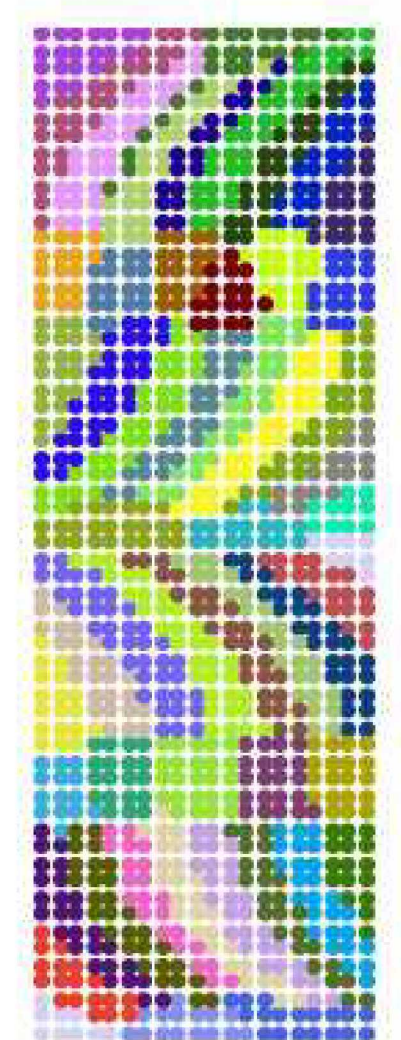


Generalize probabilities
for fixed observation points



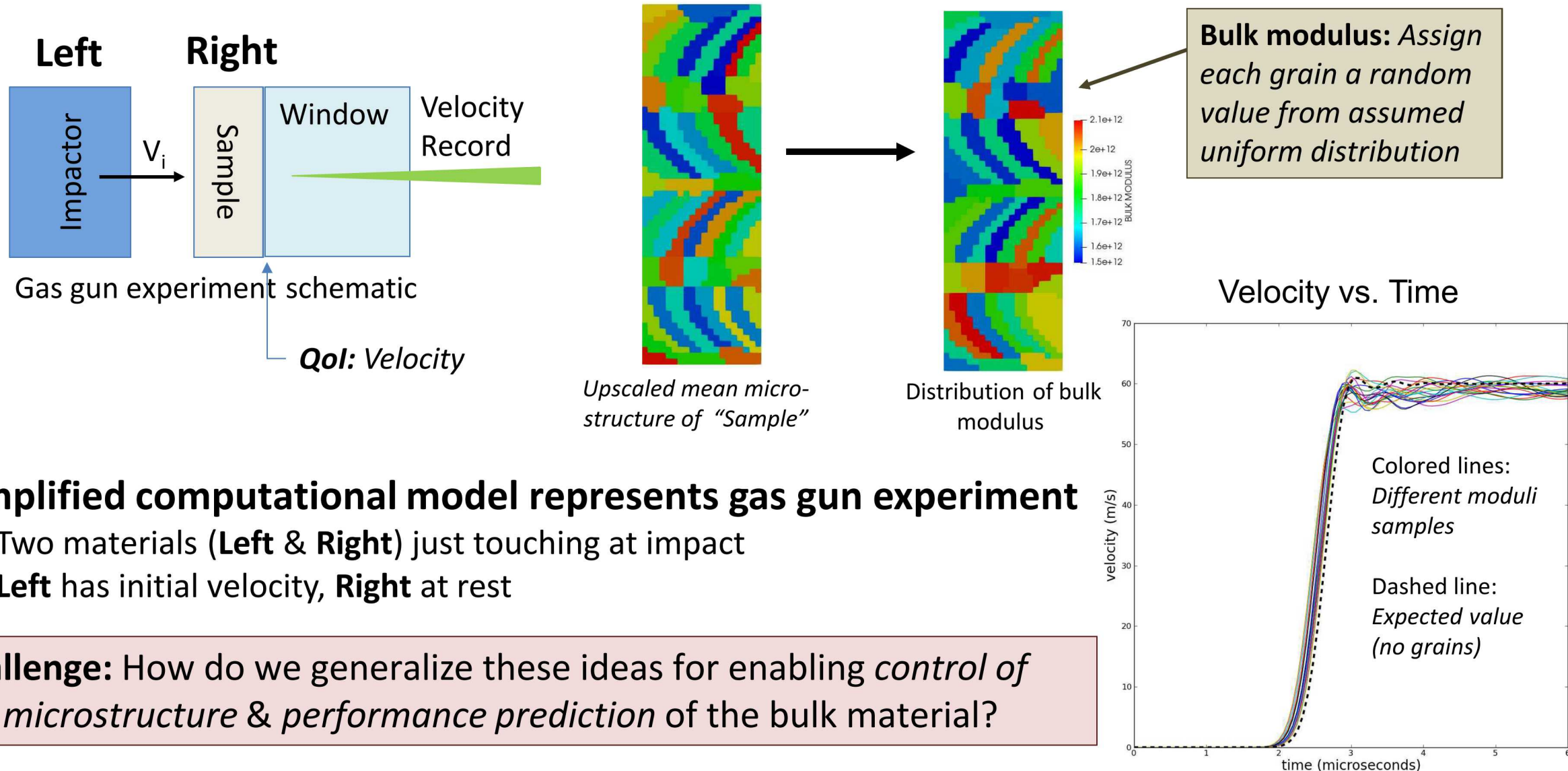
Symmetric affinity matrix

ML Clustering



RESULT: Upscaled “mean” microstructure

Example: Sandia's ALEGRA Shock Physics Code



- **Context:** New designs and materials enabled by *additive manufacturing*
- **New risk measures for topology optimization**
 - Buffered probabilities
- **Importance of accounting for *AM-induced material anisotropy and variability* in design and analysis**
- **Introduced an approach for upscaling the heterogeneous and variable AM microstructure**
 - Leverages SPPARKS stochastic simulator of microstructural evolution

Broader challenges and potential new directions

1. New science of materials

- a) Can we “discover” new materials with desired (and revolutionary) performance properties?

2. Reproducibility and certifiability

- a) Can we reproduce such materials in a predictable and cost-effective way?
- b) Can we confidently “certify” that a particular material will perform as intended in a given application?

3. New models and algorithms

- a) Beyond AM process control -- how do we model the extremely heterogeneous and variable materials at all length scales?
- b) How do we obtain and assimilate potentially *voluminous, uncertain data* into our models?
- c) Digital twins?

4. How do we package our results for human decision-making?

- a) Influencing engineering designs, risk and failure analyses, research funding, etc.