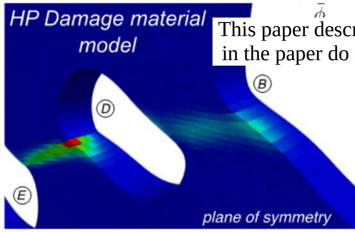
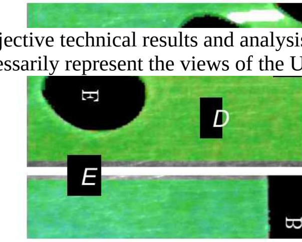
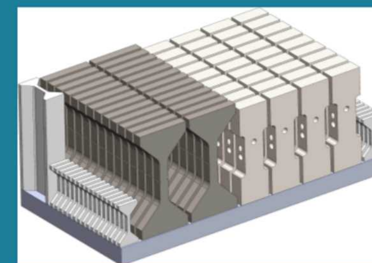
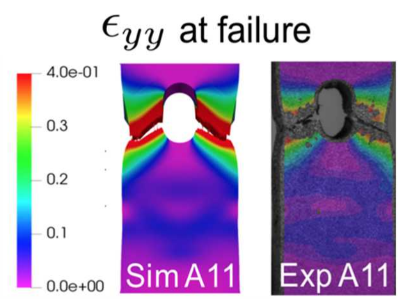


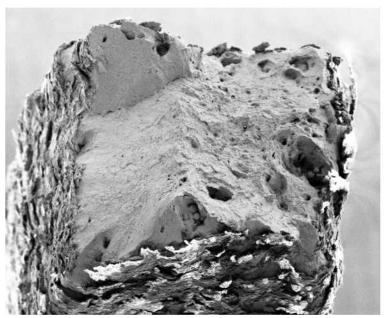


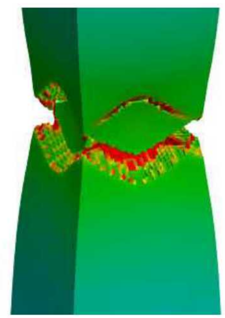
SAND2018-13109C

Exploration of Anisotropic Plasticity Models









PRESENTED BY

C. Alleman, J. Foulk, K. Karlson, K. Manktelow,
J. Ostien, M. Stender, A. Stershic, M. Veilleux, A. Brown

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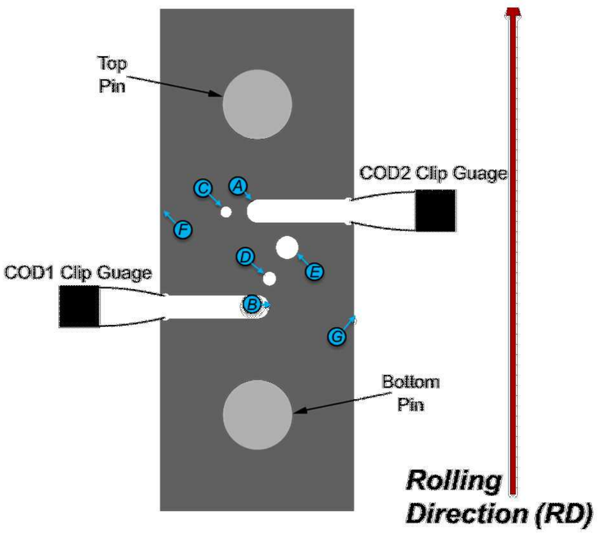
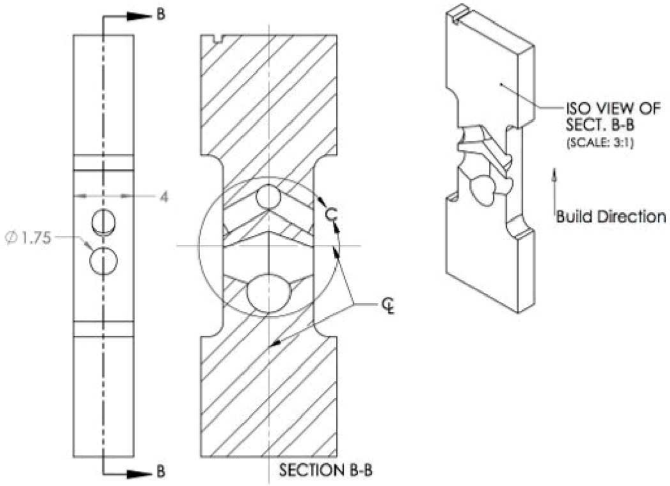
Motivation

- Structural alloy used in engineering applications come in various product forms
  - Rolled plate
  - Forged
  - Sheet
  - Additively Manufactured (AM)
- Worked alloys result in anisotropic plastic response and can have significant performance departures from isotropic and/or annealed material
  - Particularly in terms of localization and failure
  - Creates calibration challenges
- This work is an exploration of the relative importance of using anisotropic yield strength for two structural alloys
  - Case study 1: Ti-6Al-4V – quastistatic and dynamic loading (SFC2)
  - Case study 2: AM SS317L – quasistatic loading (SFC3)

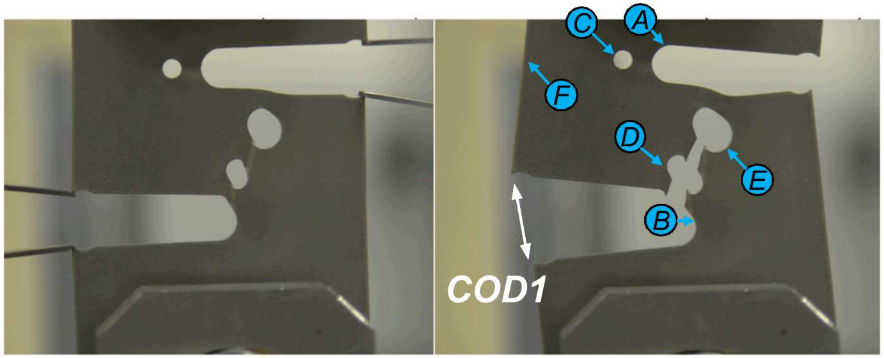
SFC2 - Ti-6Al-4V





SFC3 - AM 316L

Case Study: Sandia Fracture Challenge 2



A single specimen failed with Path A-C-F

All others failed B-D-E-A

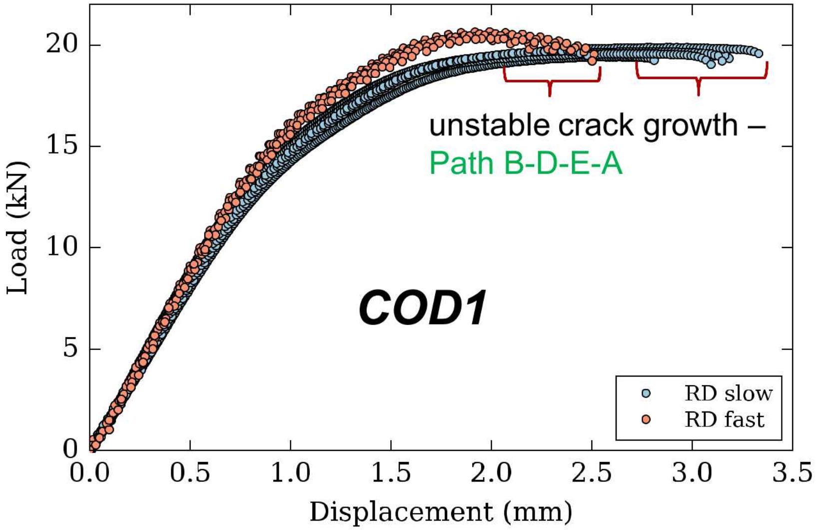
Caused by sample defects.
Out-of-plane warpage.

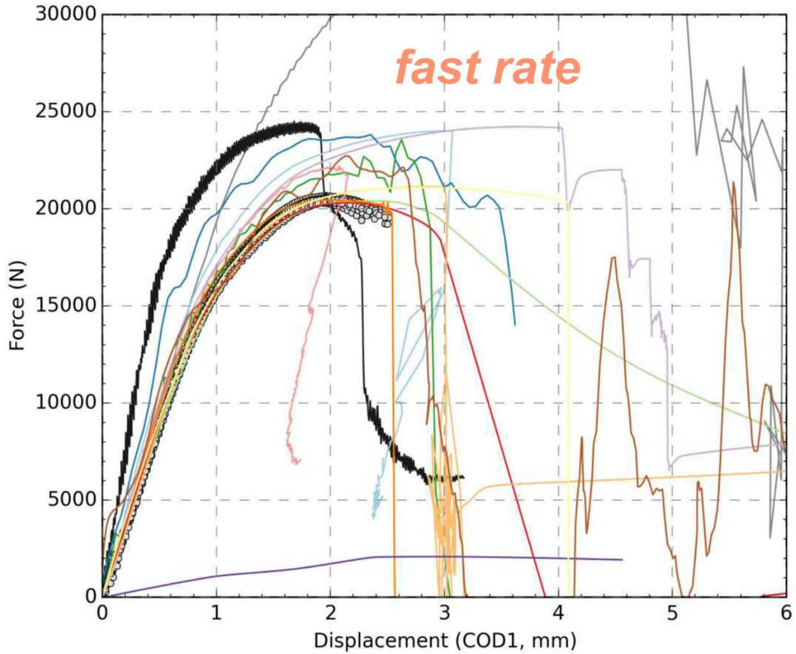
Where will the failure occur?

- *2 teams predicted wrong failure path or could not decide*
- *4 teams predicted B-D-E-A or A-C-F as possible failure paths*
- *9 teams predicted B-D-E-A as only failure path*

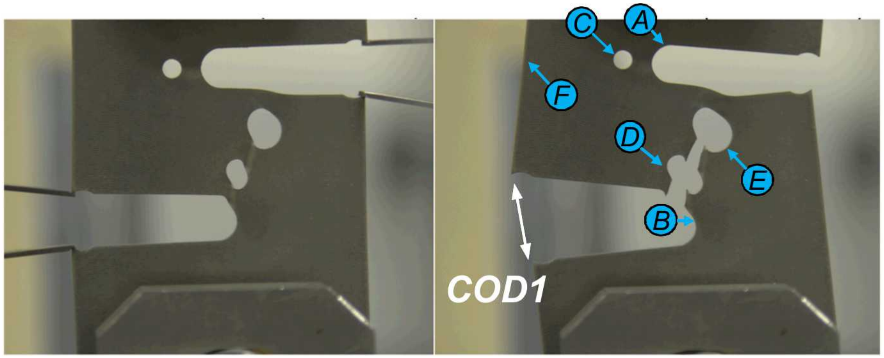
How did it fail?

- *Most teams predict unstable crack growth*
- *2 did not*





Case Study: Sandia Fracture Challenge 2



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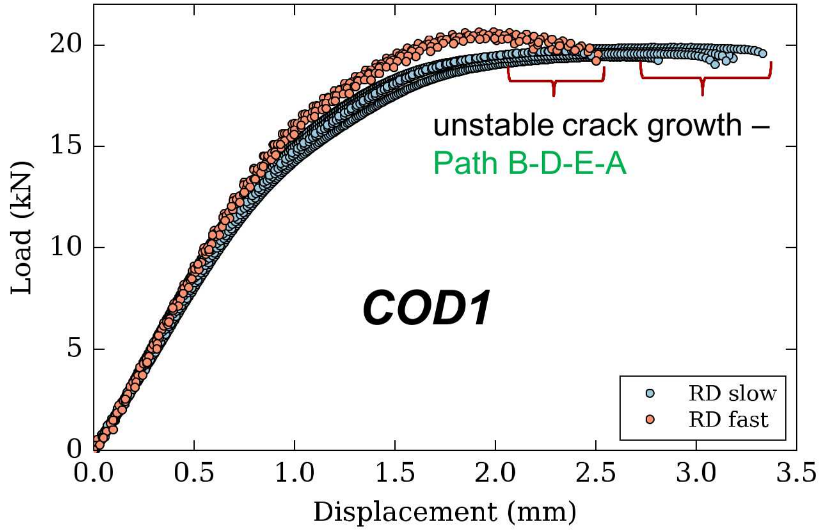
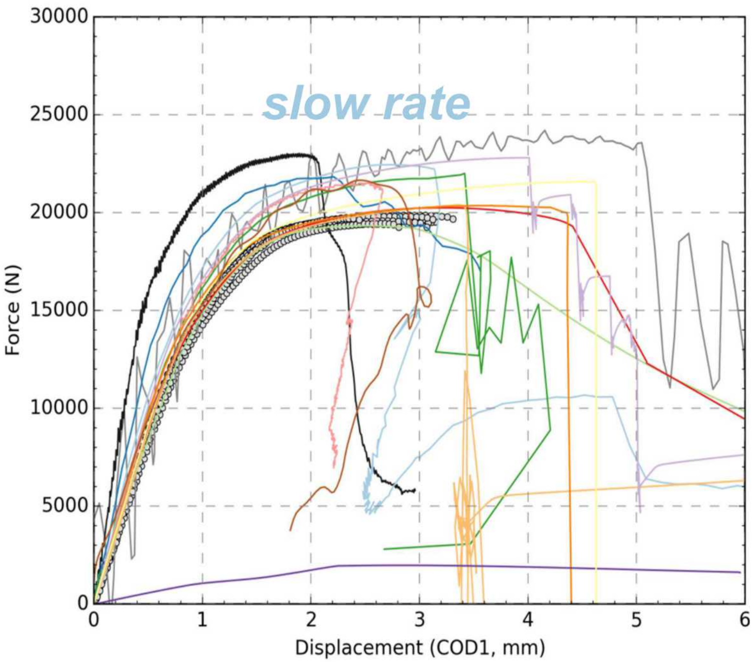
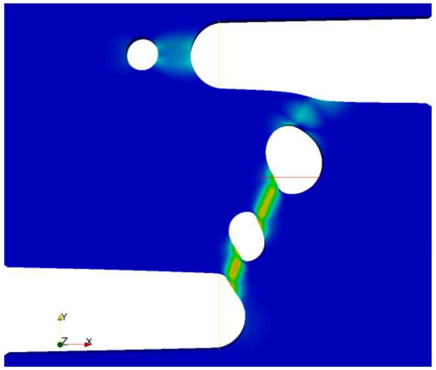
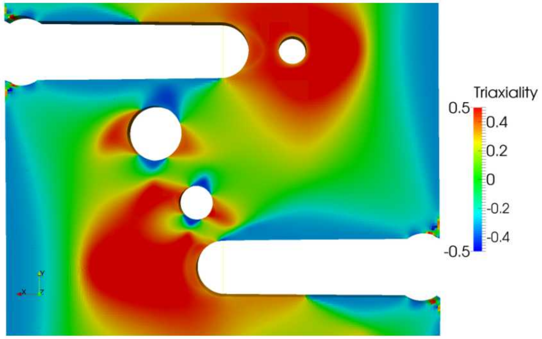


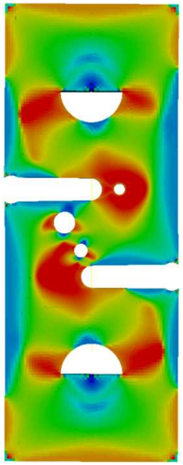


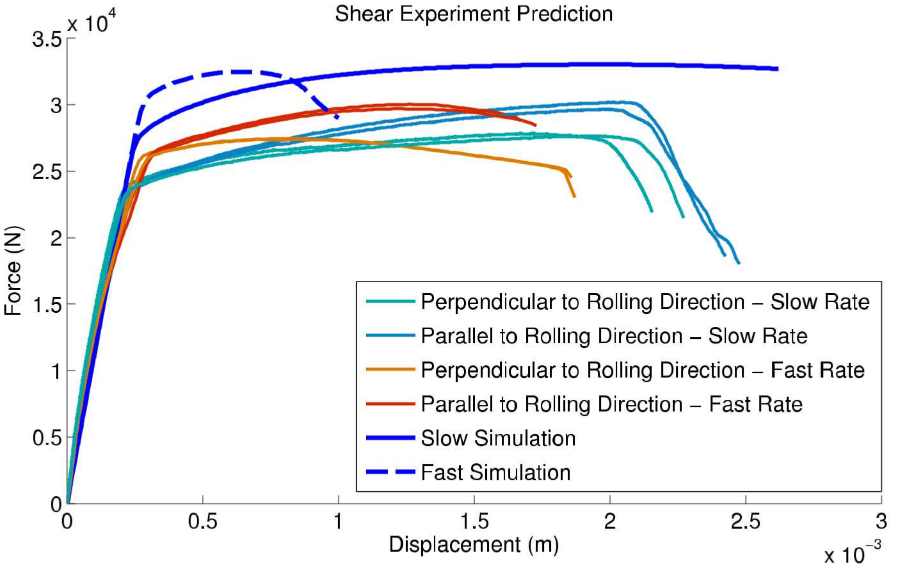
Case Study: Sandia Fracture Challenge 2

- Including anisotropy
- Shear data is not captured by isotropic yield surface
- ~13% overprediction
- Lacking an anisotropic model a region experiencing shear used a lower strength

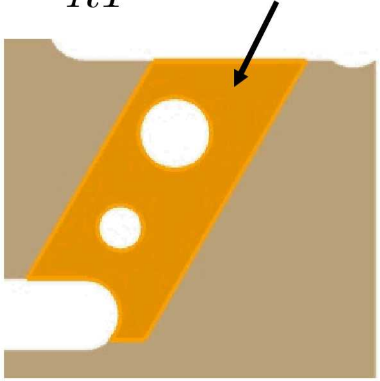


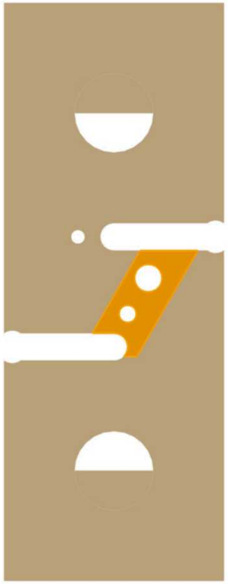






$$Y^{s*}_{RT} = 441 \text{ MPa}$$





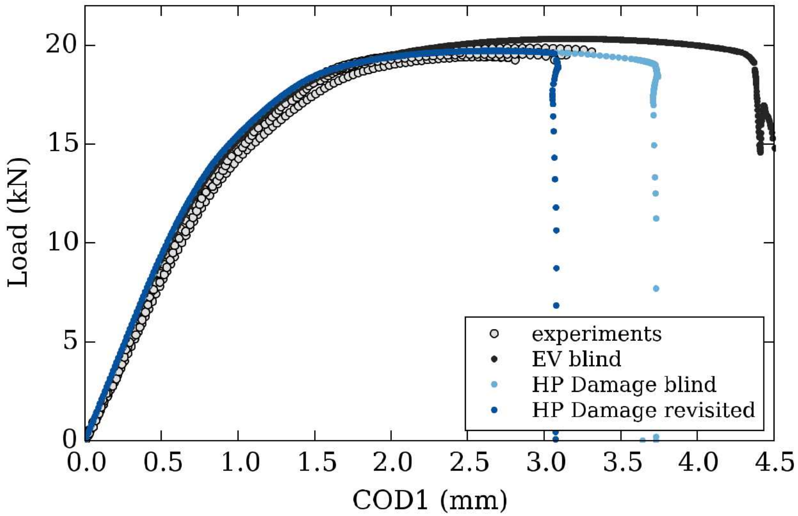
Case Study: Sandia Fracture Challenge 2

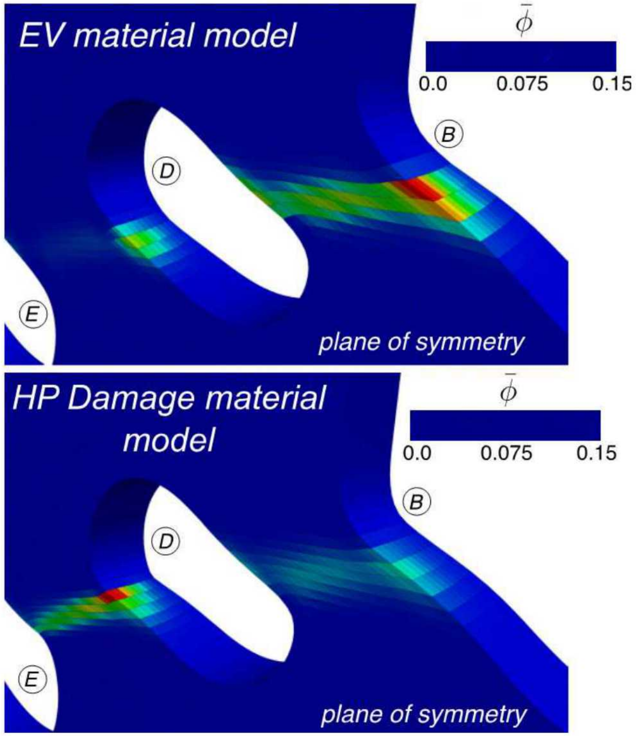
EV damage model + **_Hill yield surface_** → **_HP Damage material model_**

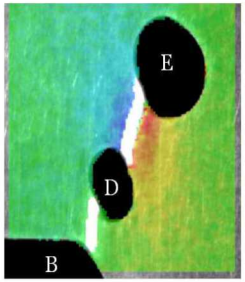
$$\dot{\phi} = \sqrt{\frac{3}{2}}\dot{\epsilon}_p \frac{1-(1-\phi)^{m+1}}{(1-\phi)^m} \sinh\left[\frac{2(2m-1)}{2m+1}\frac{\langle \frac{I_1}{3} \rangle}{\sqrt{3J_2}}\right]$$

$$\dot{\eta} = \eta\dot{\epsilon}_p N_1 \left[\frac{4}{27} - \frac{J_3^2}{J_2^3}\right]$$

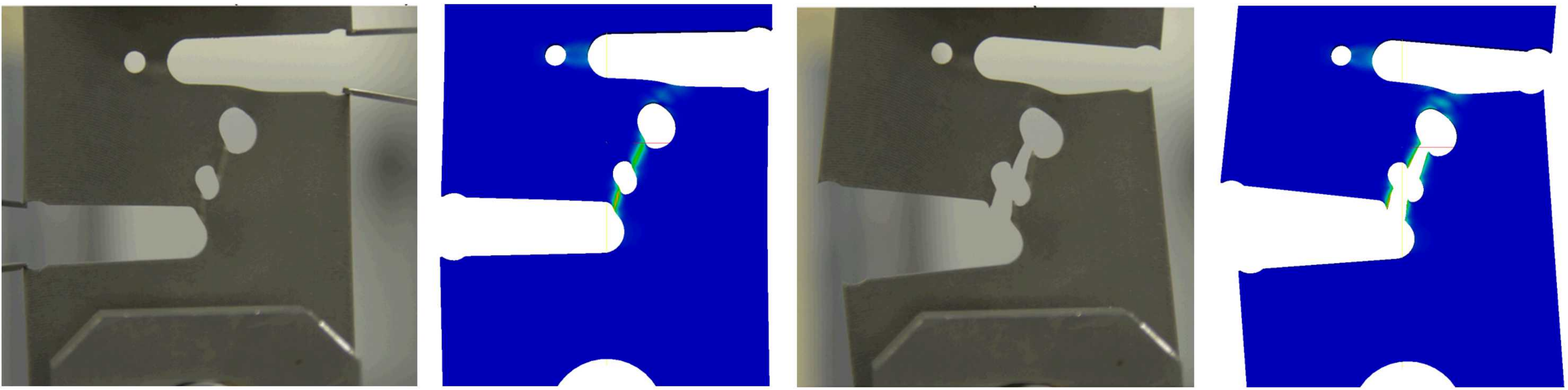
$$f_Y^2(\sigma_{ij}) \equiv F(\sigma_{22}-\sigma_{33})^2 + G(\sigma_{33}-\sigma_{11})^2 + H(\sigma_{11}-\sigma_{22})^2 + 2L\sigma_{23}^2 + 2M\sigma_{31}^2 + 2N\sigma_{12}^2 = \bar{\sigma}_e^2(\epsilon_p)$$

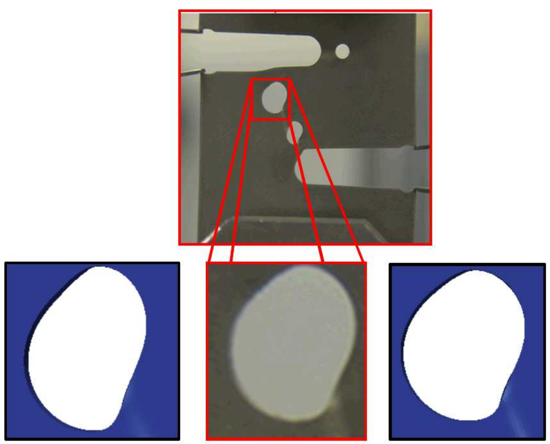






Case Study: Sandia Fracture Challenge 2





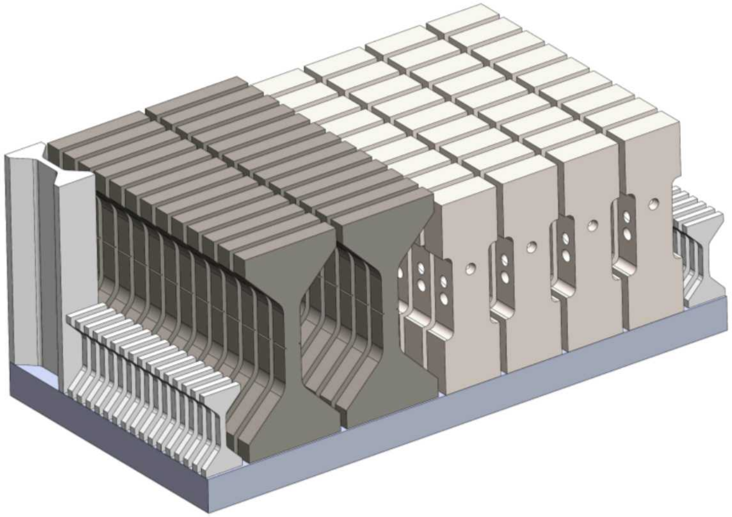
J_2 model

HP Damage model

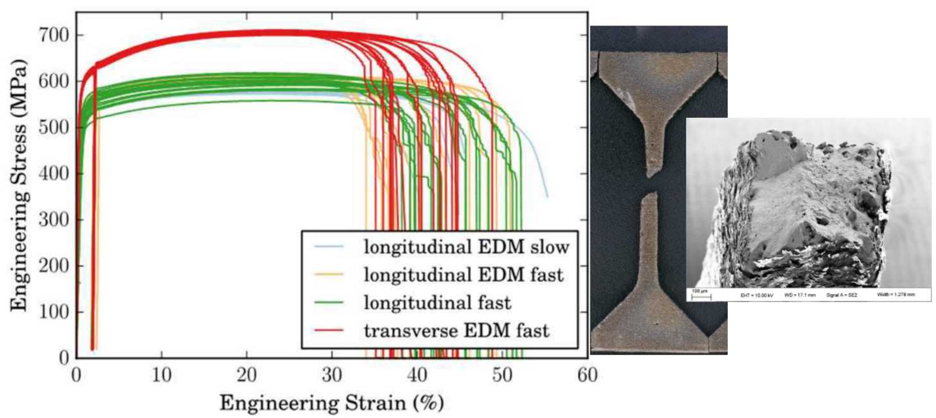
- Lessons learned from this modeling exercise
  - Isotropic yield, even with rate and temperature dependence produced an incorrect fracture path
  - Looking at rate and temperature independent anisotropic yield (Hill) improved localization location predictions
  - Sensitivity studies demonstrate importance of temperature, damage models
  - *Need anisotropy AND rate dependence AND damage AND temperature dependence!!*

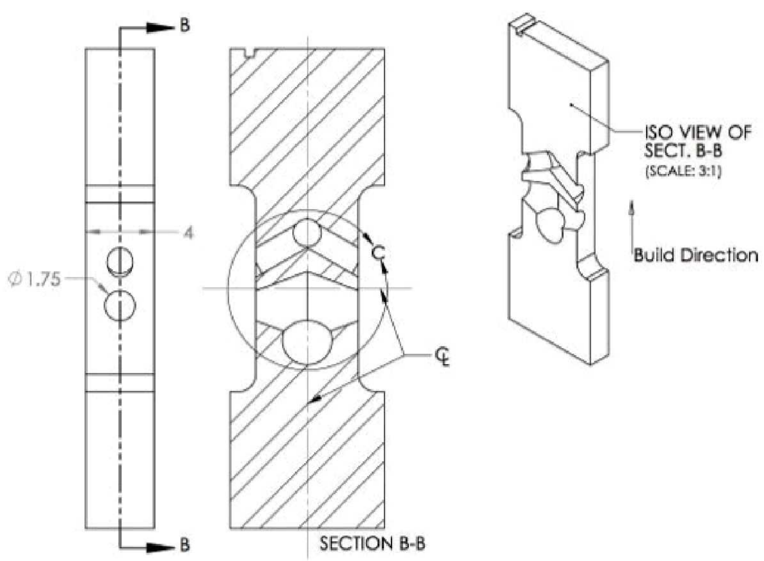
Case Study: Sandia Fracture Challenge 3

- Additively Manufacture 316L

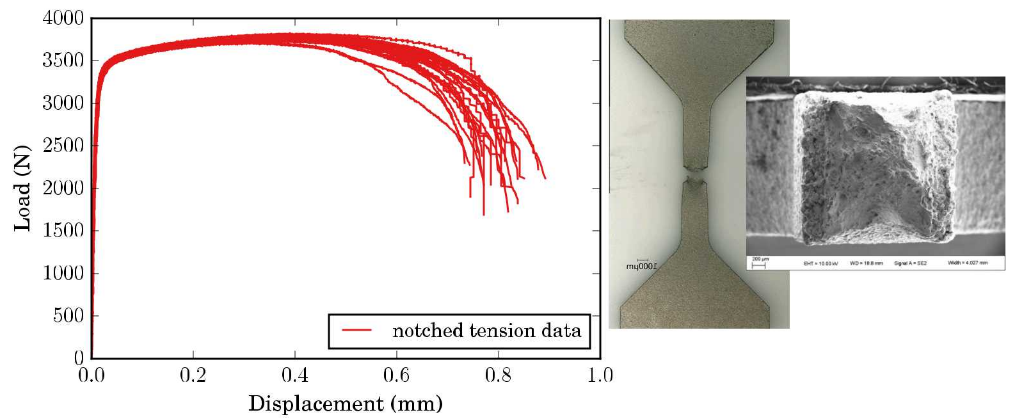


tension tests

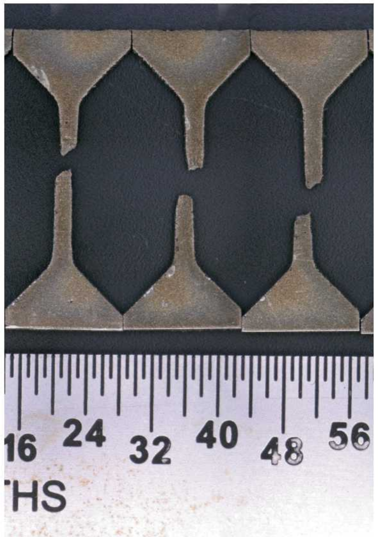


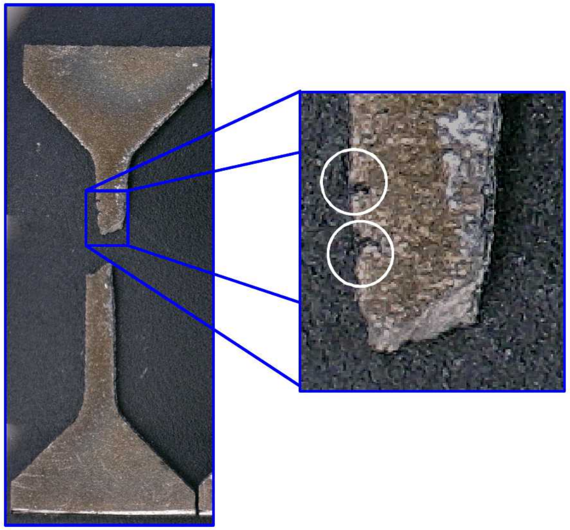


notched tension tests

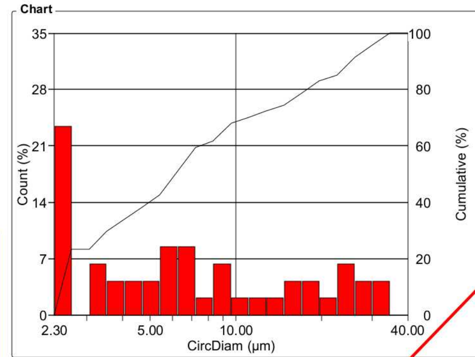


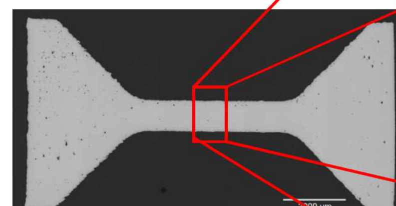
SFC3: Tension data

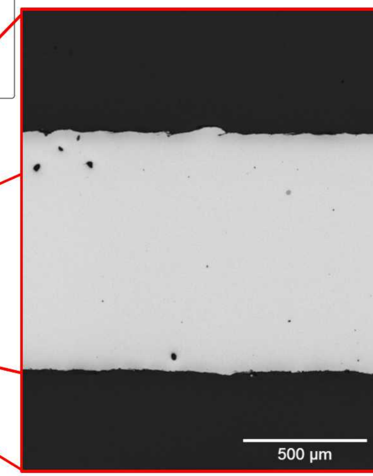




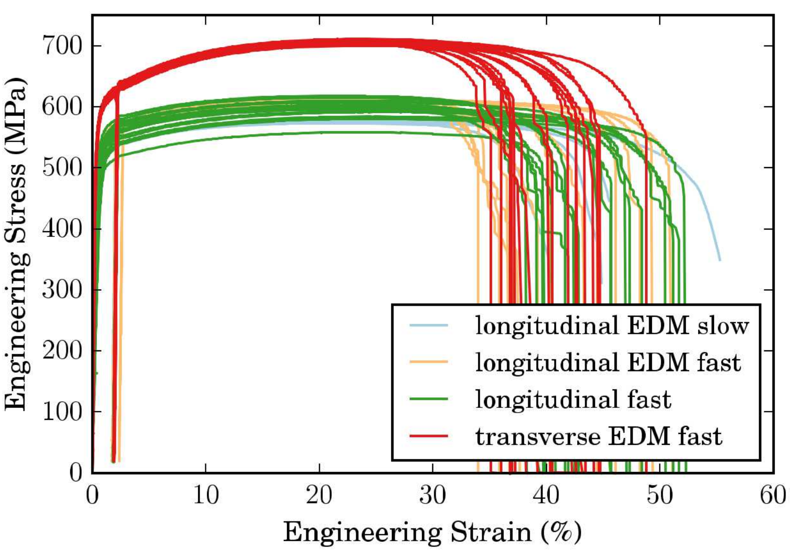
surface defects (cracks)

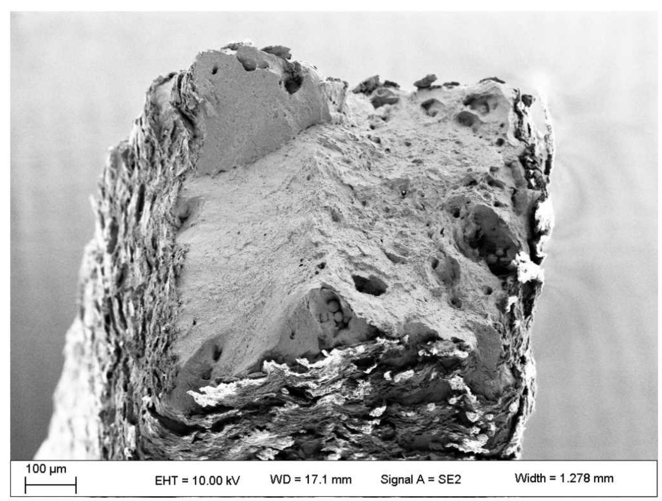


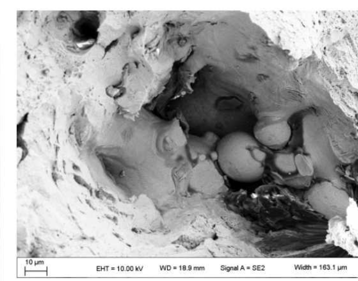


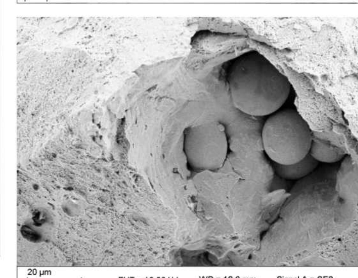


internal defects (voids)

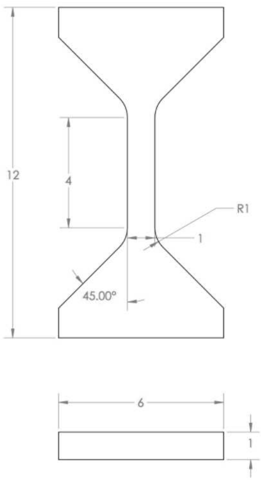


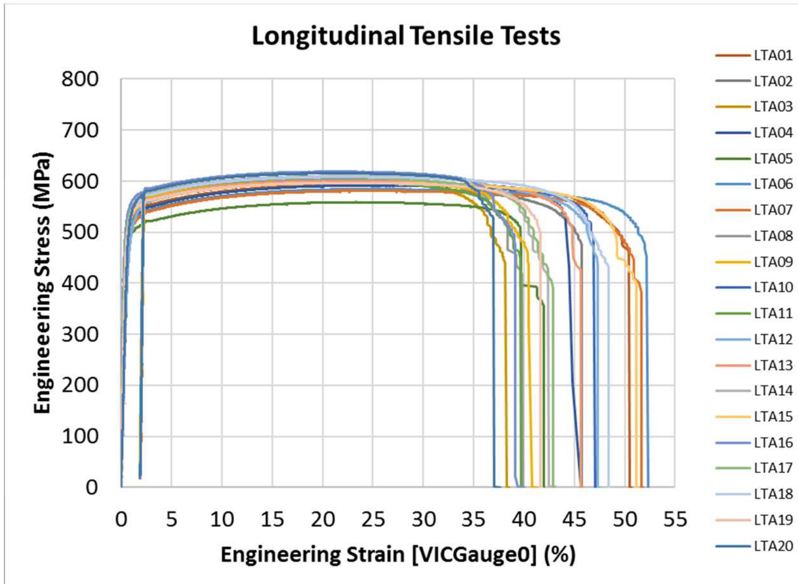






SFC3: Tension data



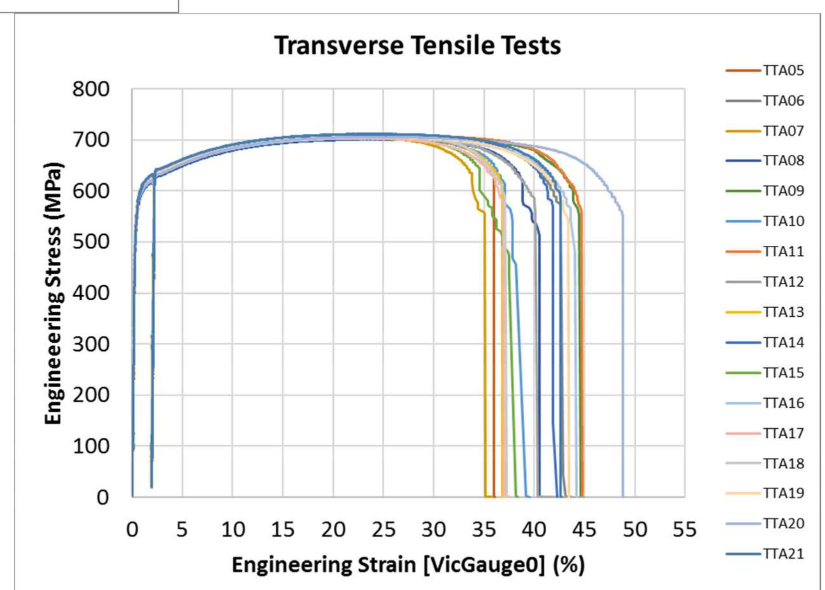


Longitudinal vs. transverse

- Lower yield strength
- More variable strain-to-failure

Hypotheses

- Grain size/morphology
- Texture
- Defect size/morphology
- Residual stresses



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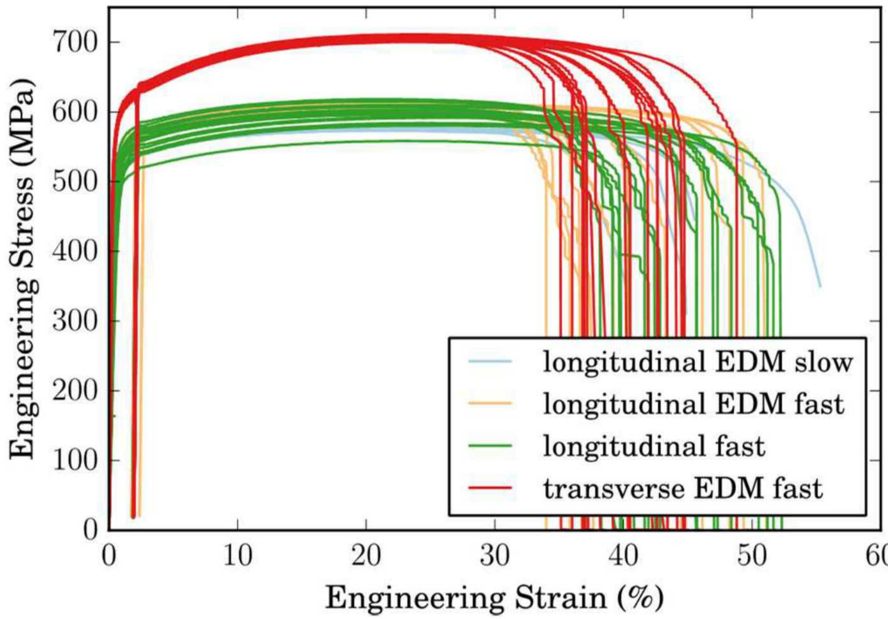
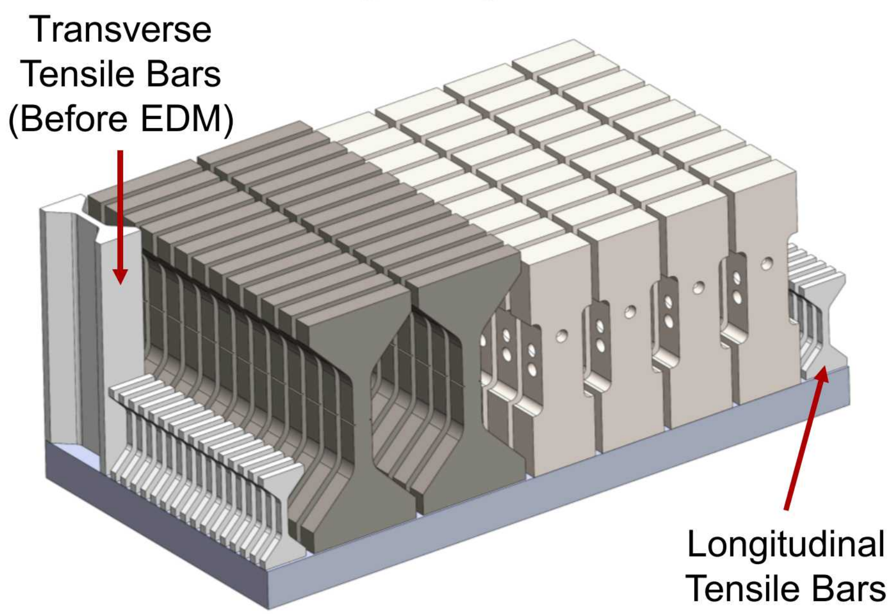
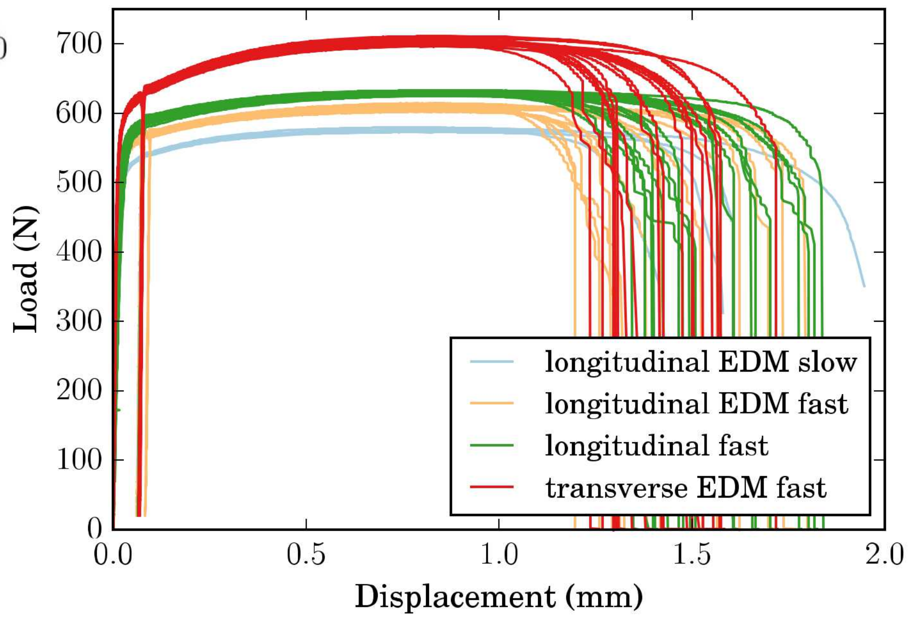
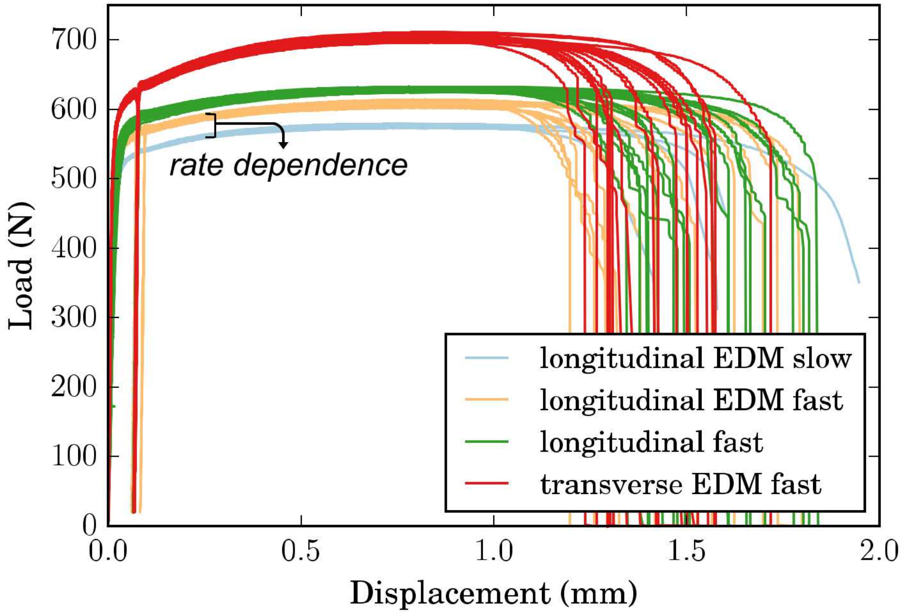


Apparent variability in flow stress for longitudinal (as-printed) specimens does not appear in load data





SFC3: Modeling assumptions and calibration



Modeling methodologies

- Temperature and rate dependent plasticity
- Plastic anisotropy
- Geometric variability, surface defects/voids
  - Explicit representation of geometries
  - Inclusion of surface defects
- Void nucleation, growth

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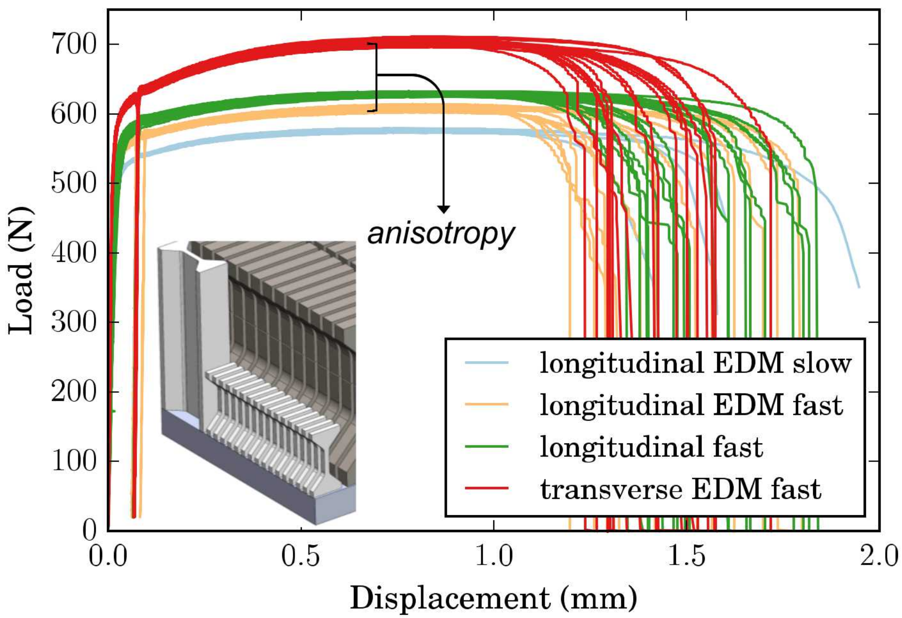

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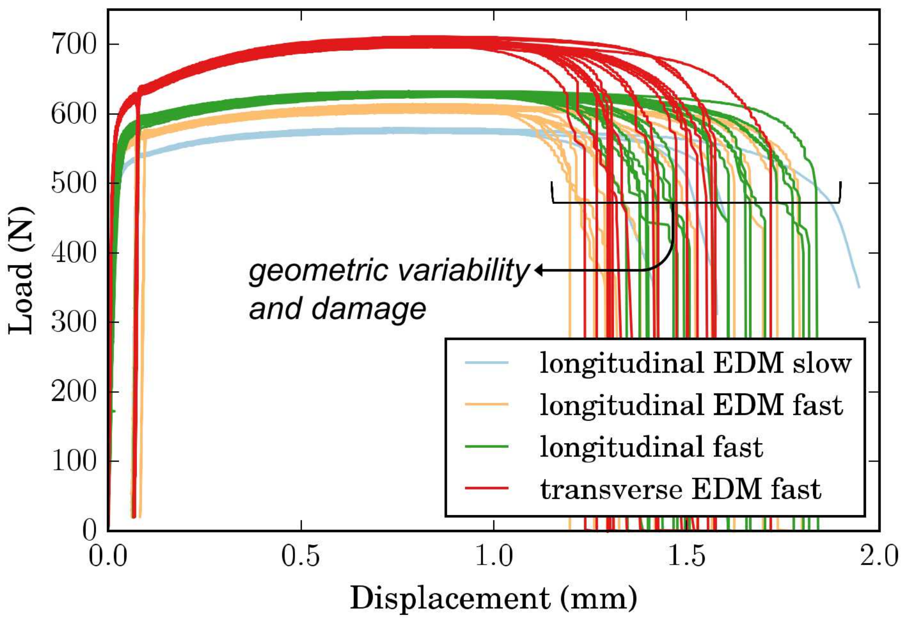

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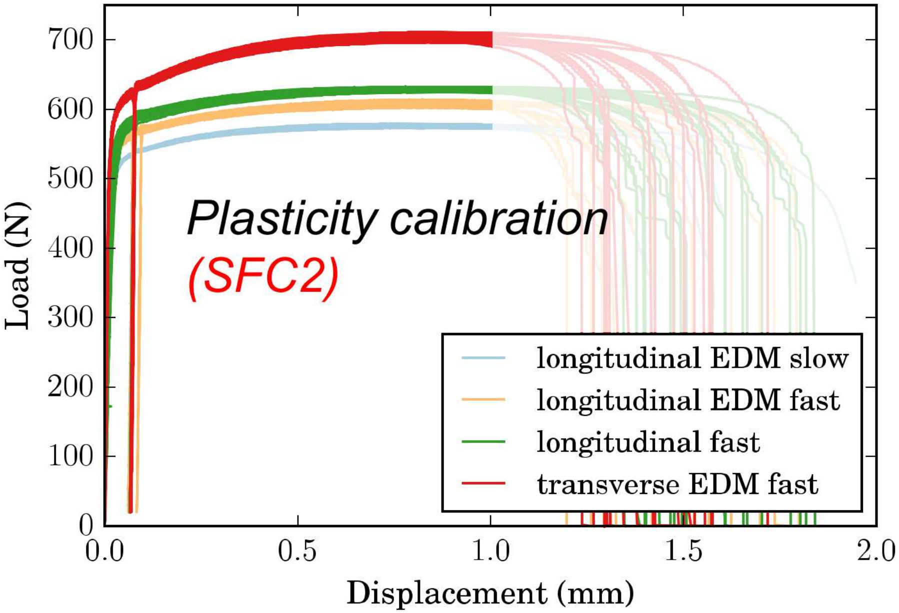

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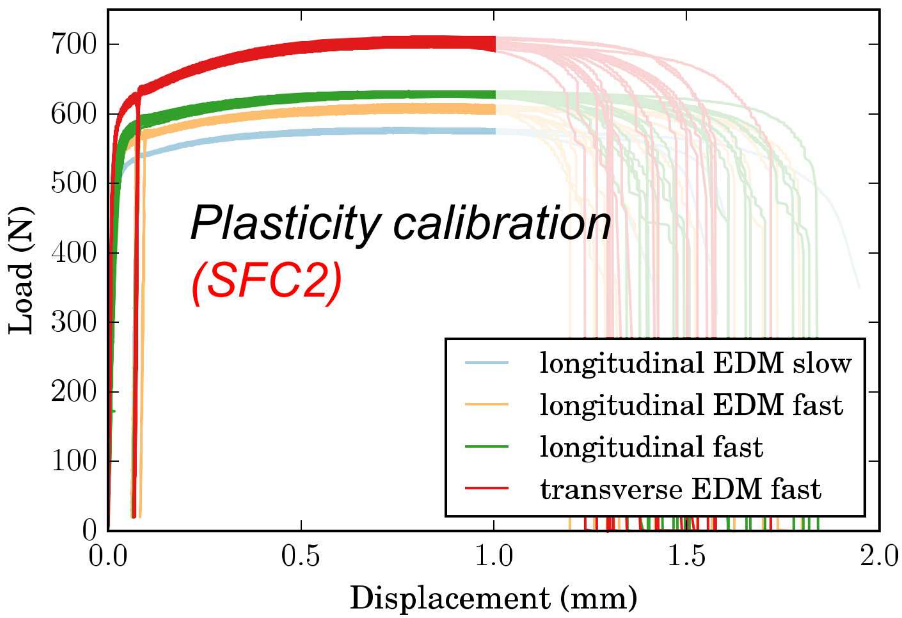

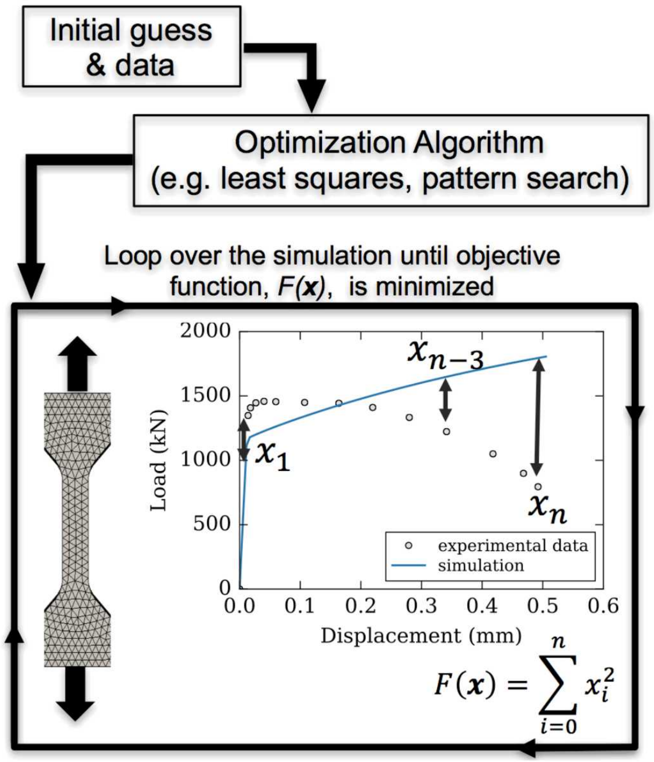

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- *Sierra/SM* for FEA
- *Dakota* for Optimization Algorithm
- *MatCal* for file and model management

With *18 unknown parameters*, calibrate using an iterative approach with increasing complexity :
(1) rate dependence (2) hardening (3) anisotropy (4) damage

SFC3: Calibration Process for Flow

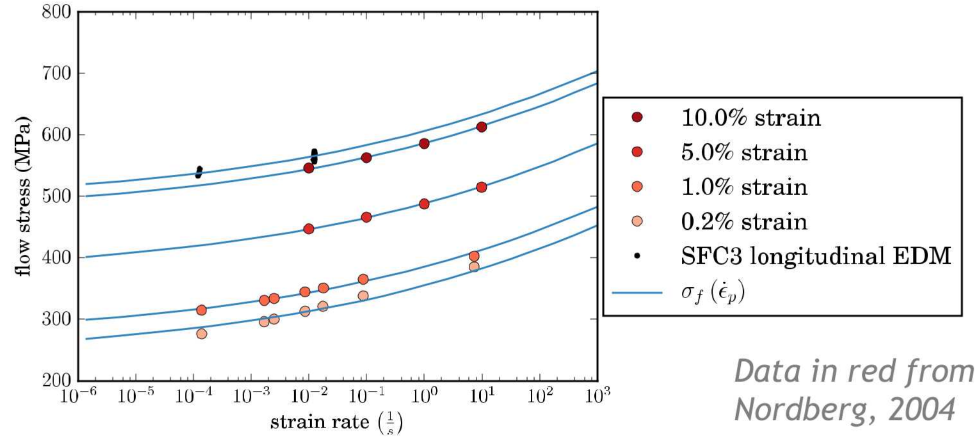
Rate-dependent anisotropic plasticity model with power-law hardening

$$\bar{\sigma}_e = Y_0 \left\{ 1 + \sinh^{-1}\left[\left(\frac{\dot{\epsilon}_p}{f}\right)^{1/n}\right]\right\} + A\langle \epsilon_p \rangle^b + \kappa_m$$

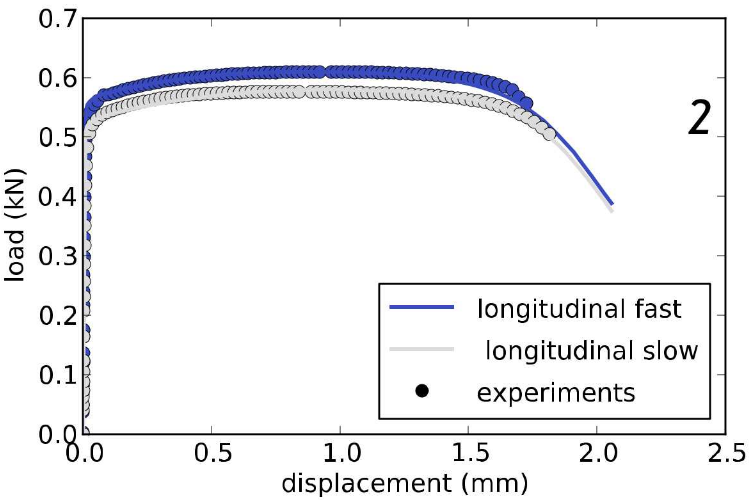
$$f_Y^2(\sigma_{ij}) \equiv F(\sigma_{22}-\sigma_{33})^2 + G(\sigma_{33}-\sigma_{11})^2 + H(\sigma_{11}-\sigma_{22})^2 + 2L\sigma_{23}^2 + 2M\sigma_{31}^2 + 2N\sigma_{12}^2 = \bar{\sigma}_e^2(\epsilon_p)$$

$$R_{ii} = \frac{\sigma_{ii}^y}{Y_0} \qquad R_{ij} = \sqrt{3}\frac{\tau_{ij}^y}{Y_0}$$

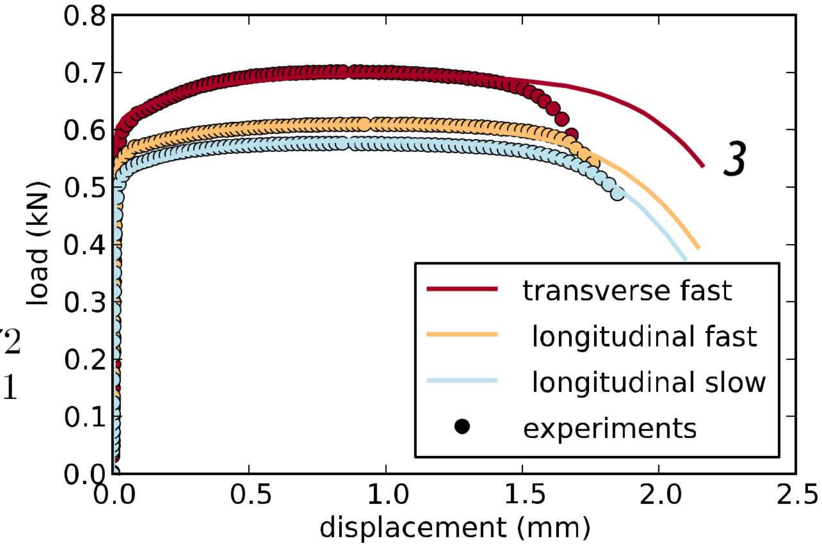
Rate-dependence fit from challenge tests and literature data



Data in red from Nordberg, 2004

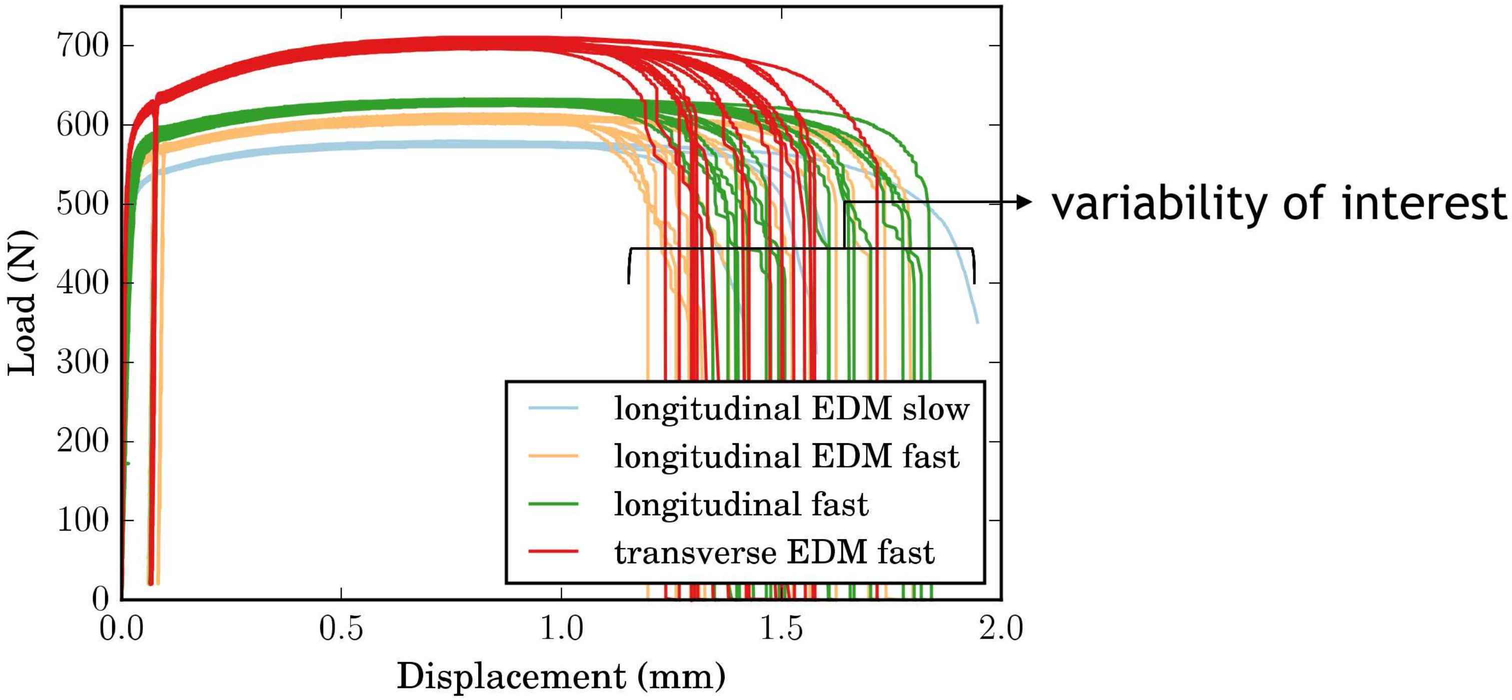


$$Y_0 = 475 \text{ MPa}$$
$$\kappa_m = 0 \text{ MPa}$$
$$f = 26854\left(\frac{1}{s}\right)$$
$$n = 9.15$$
$$A = 753$$
$$b = 0.764$$
$$R_{11} = R_{33} = 1.072$$
$$R_{22} = R_{ij} = 0.961$$



SFC3: Material variability from damage

Significant variability exists in displacement-to-failure. Where does this come from?



Hypothesis 1: constitutive model can account for observed variability

Hypothesis 2: explicit modeling of defects required to accurately capture variability

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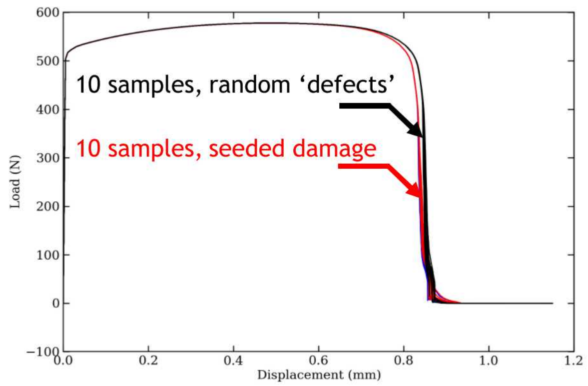

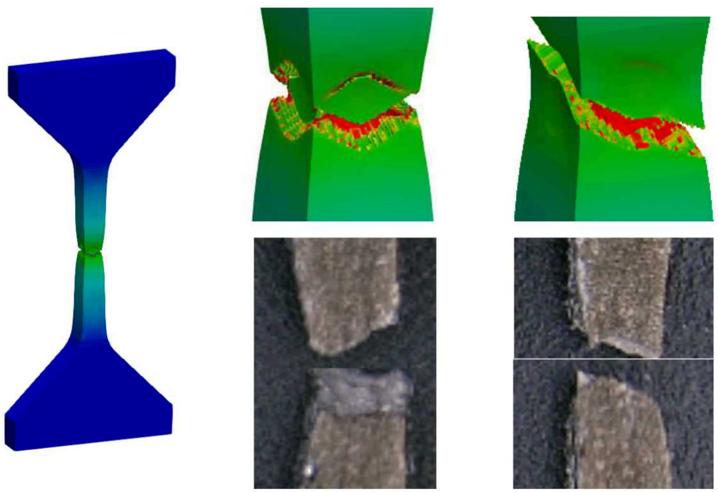

Conclusion: Damage field changes fracture surface, but not displacement-to-failure

SFC3: Material variability form damage

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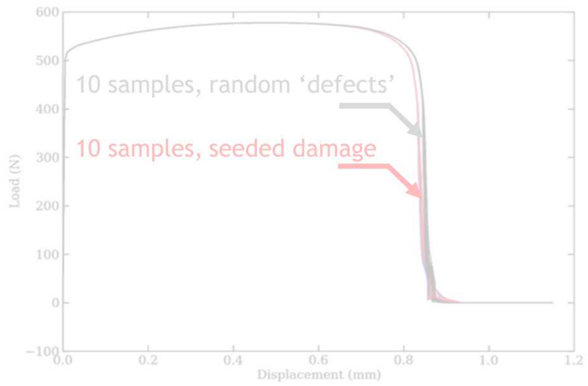
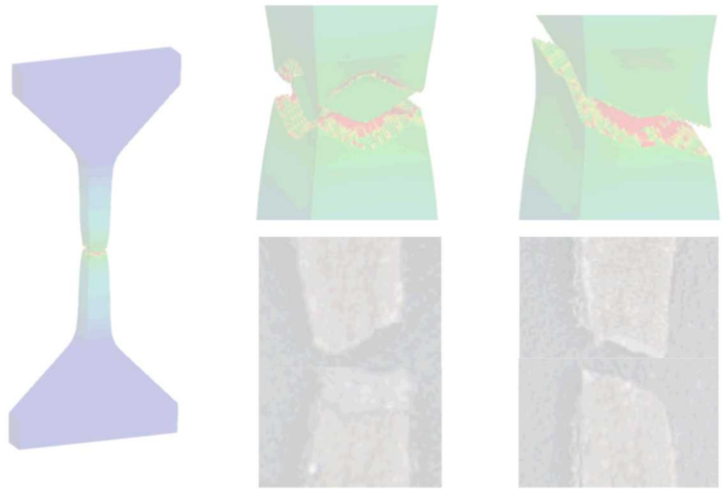
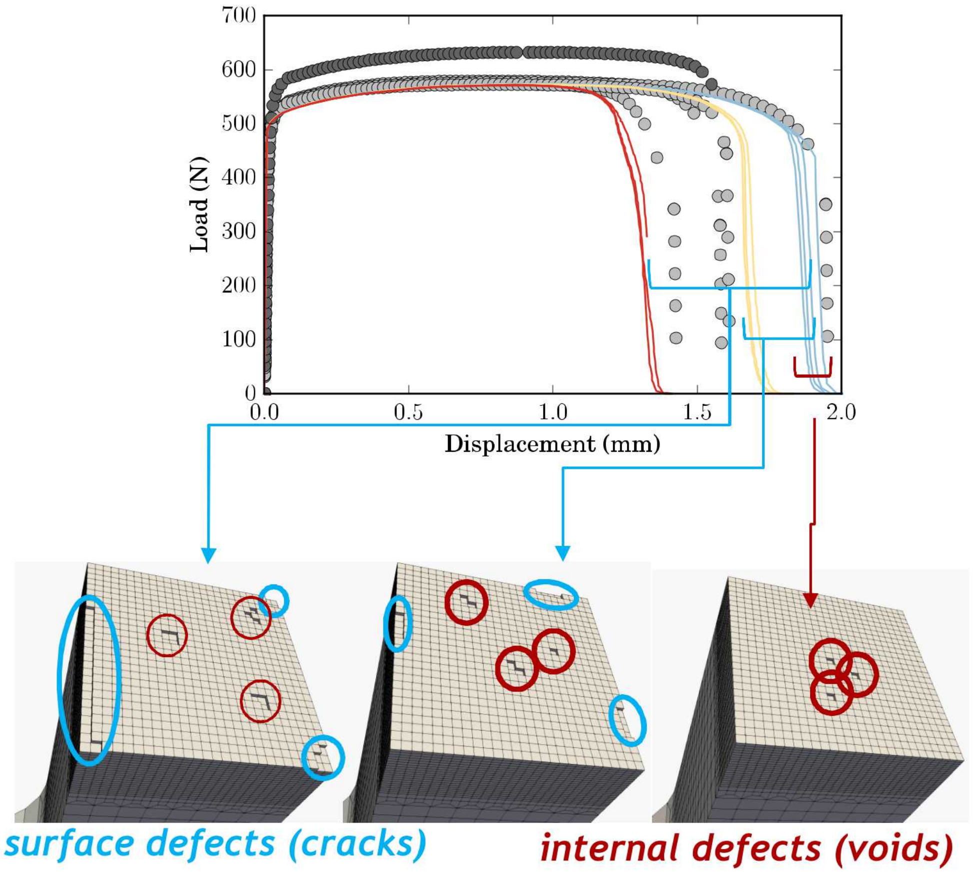




Conclusion: Damage field changes fracture surface, but not displacement-to-failure

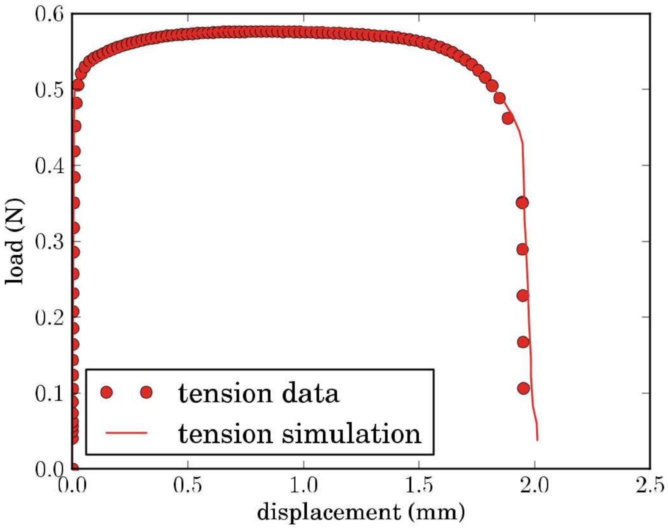
Hypothesis 2: explicit modeling of defects required to accurately capture variability

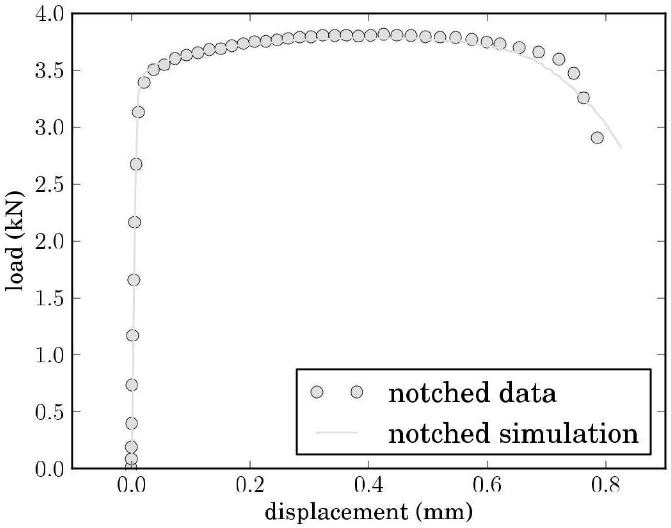


Conclusion: Yes. Internal defects cause marginal change, surface defects dominate

SFC3: Model for damage nucleation/evolution

- Calibrated to uniaxial and notched specimens with largest displacements
- Attributed variability in failure displacements in uniaxial tension tests to surface defects introduced by AM.





$$\dot{\phi} = \sqrt{\frac{2}{3}}\dot{\epsilon}_p \frac{1-(1-\phi)^{m+1}}{(1-\phi)^m} \sinh\left[\frac{2(2m-1)}{2m+1}\frac{\langle p \rangle}{\sigma_e}\right]$$

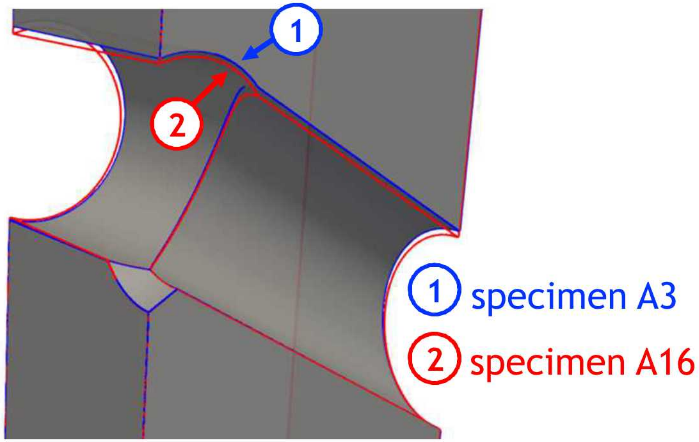
$$\dot{\eta} = \eta\dot{\epsilon}_p\left(N_1\left[\frac{4}{27}-\frac{J_3^2}{J_2^3}\right] + N_3\left[\frac{\langle p \rangle}{\sigma_e}\right]\right)$$

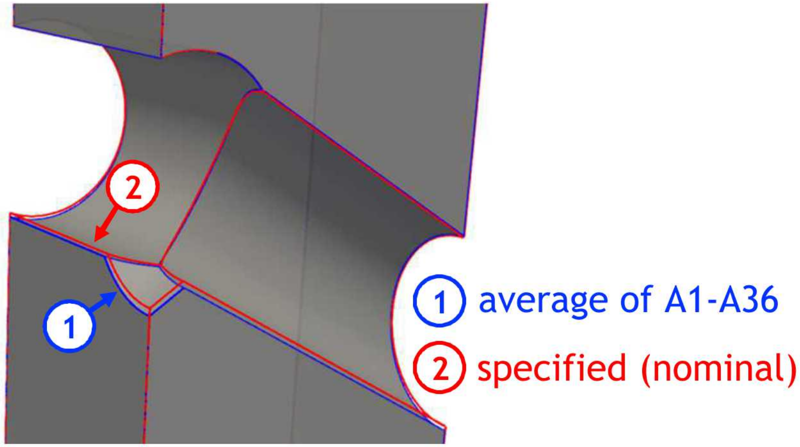
Final parameter values

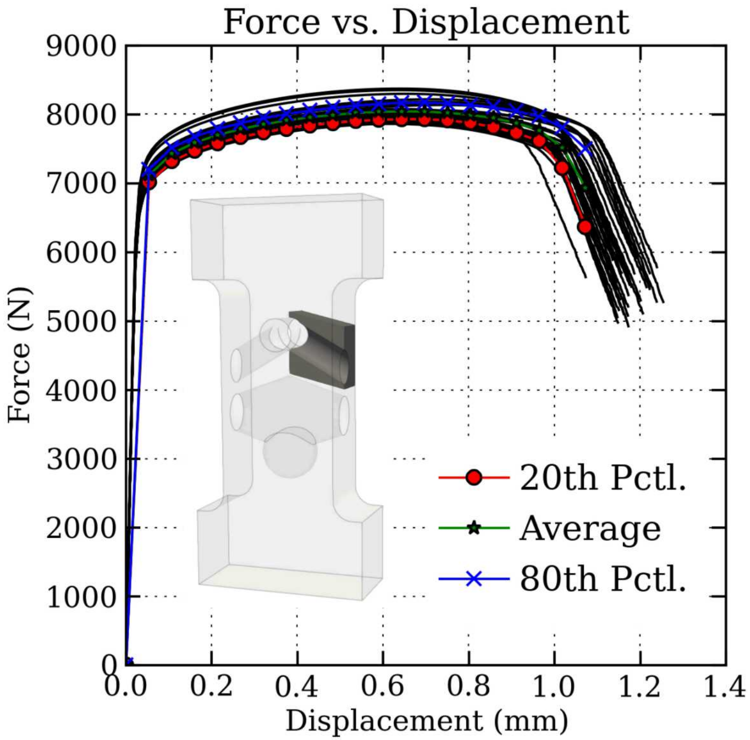
$$Y_0 = 475 \text{ MPa}$$
$$\kappa_m = 0 \text{ MPa}$$
$$f = 26854\left(\frac{1}{s}\right)$$
$$n = 9.15$$
$$A = 753$$
$$b = 0.764$$
$$R_{11} = R_{33} = 1.072$$
$$R_{22} = R_{ij} = 0.961$$
$$m = 2.9$$
$$N_1 = 2.0$$
$$N_3 = 2.5$$
$$\phi_0 = 6.3 \times 10^{-5}$$
$$\eta_0 = 1.59 \times 10^{-5}$$
$$\eta_n = 4$$

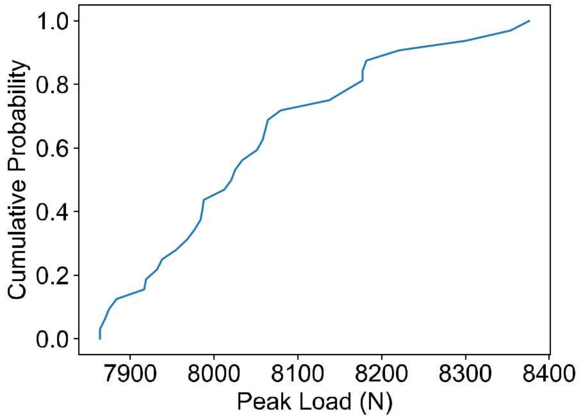
SFC3: Assessing structural variability/uncertainty

Geometric variability plays a significant role in uncertainty in the structural performance

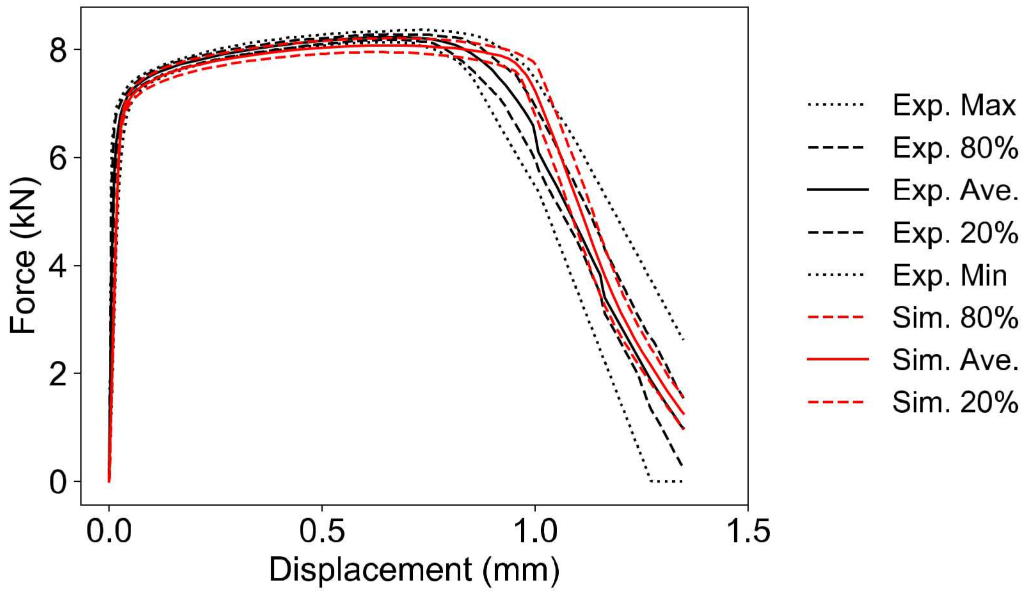






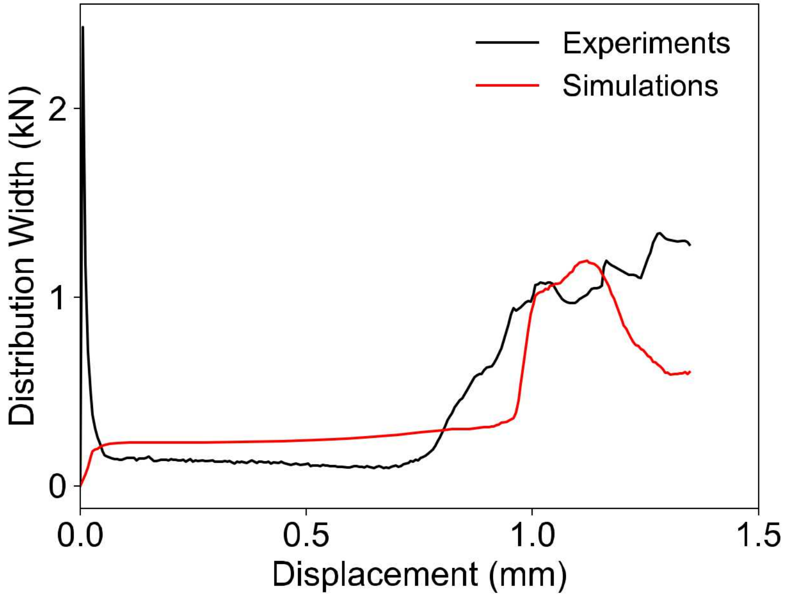


SFC3: Comparison and uncertainty



Global trends in experimental load-displacement results reproduced by models

Variability in experiments also well-captured



Take away message:

- Geometric fluctuations in these AM specimens are a major contributor to variability
- Just as important as material variability (if not more so)
- *Having robust and accurate models of anisotropic behavior facilitate these studies and conclusions*

References

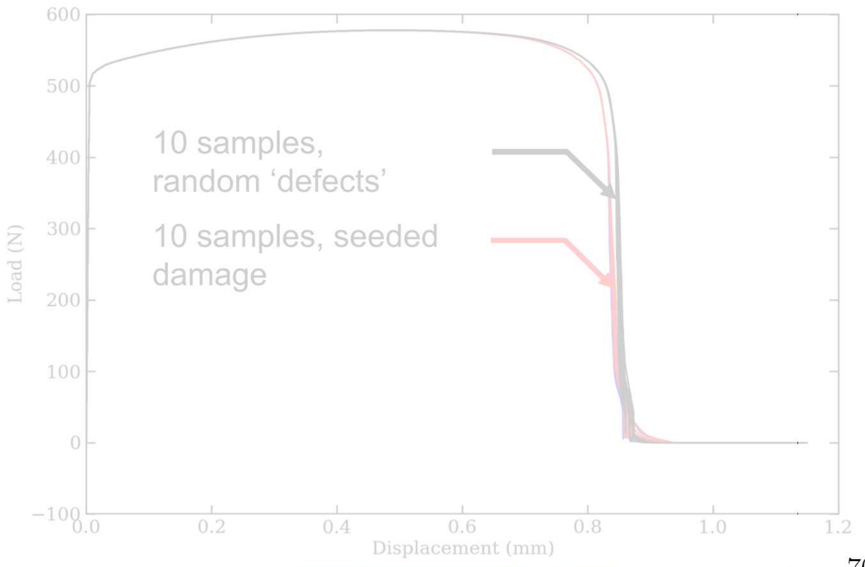
- Boyce, B. L., et al. "The second Sandia Fracture Challenge: predictions of ductile failure under quasi-static and moderate-rate dynamic loading." *International Journal of Fracture* 198.1-2 (2016): 5-100.
- Karlson, Kyle N., et al. "Sandia fracture challenge 2: Sandia California's modeling approach." *International Journal of Fracture* 198.1-2 (2016): 179-195.
- Scherzinger, William M. "A return mapping algorithm for isotropic and anisotropic plasticity models using a line search method." *Computer Methods in Applied Mechanics and Engineering* 317 (2017): 526-553.
- Lester, Brian T., and William M. Scherzinger. "Trust-region based return mapping algorithm for implicit integration of elastic-plastic constitutive models." *International Journal for Numerical Methods in Engineering* 112.3 (2017): 257-282.
- Brown, Arthur A., and Douglas J. Bammann. "Validation of a model for static and dynamic recrystallization in metals." *International Journal of Plasticity* 32 (2012): 17-35.
- SFC3 journal articles *in prep for International Journal of Fracture*

Thank you

Supporting Slides

Material variability: Damage

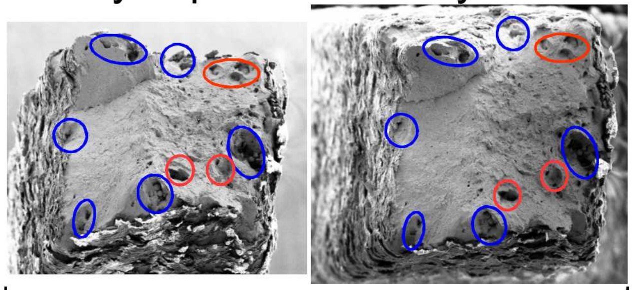
- Hypothesis 1 – constitutive model can account for observed variability



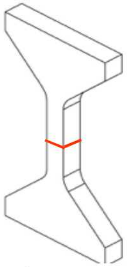
- Hypothesis 2– explicit modeling of defects required to accurately capture variability

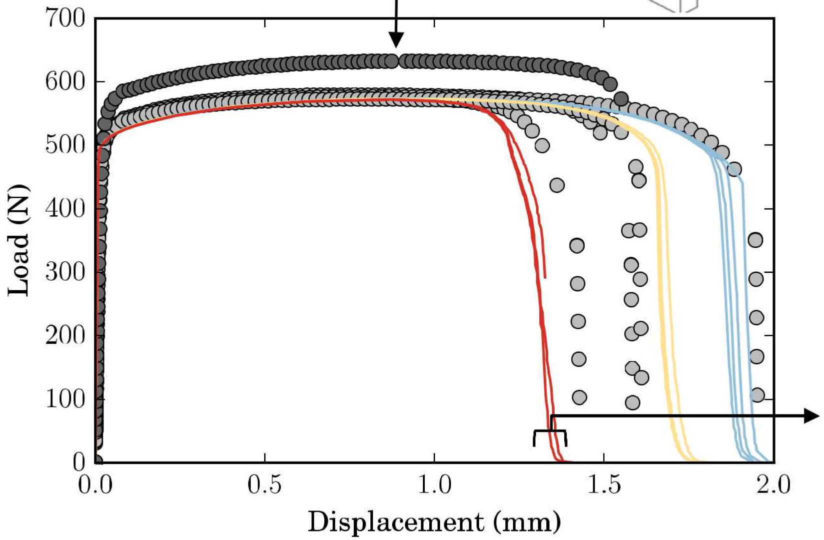
surface defects (cracks)

internal defects (voids)



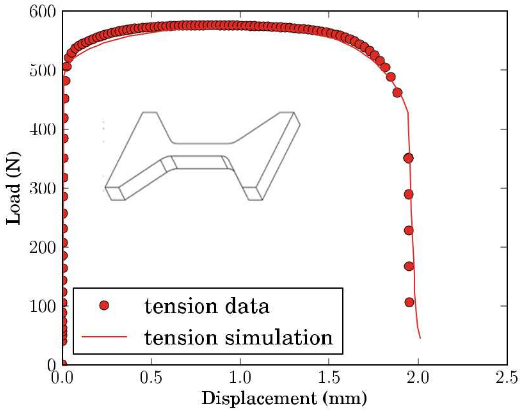
Specimen LTA04

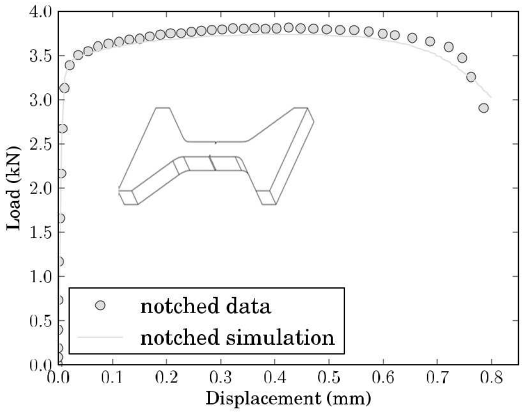




Assessing material variability/uncertainty

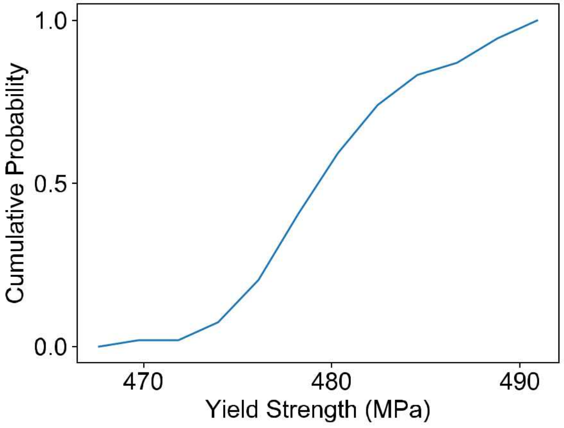
Calibrate material model for each specimen individually to obtain parameter variability

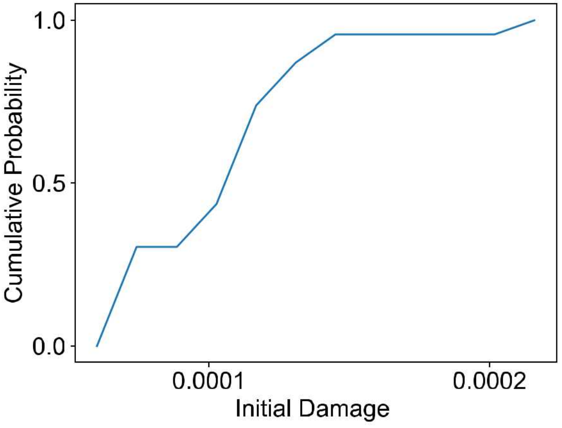




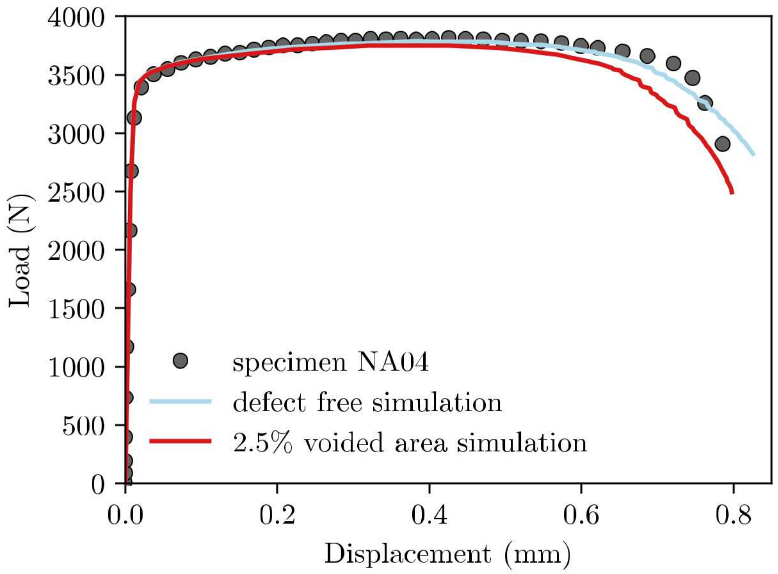
53 calibrations for plasticity

22 calibrations for damage

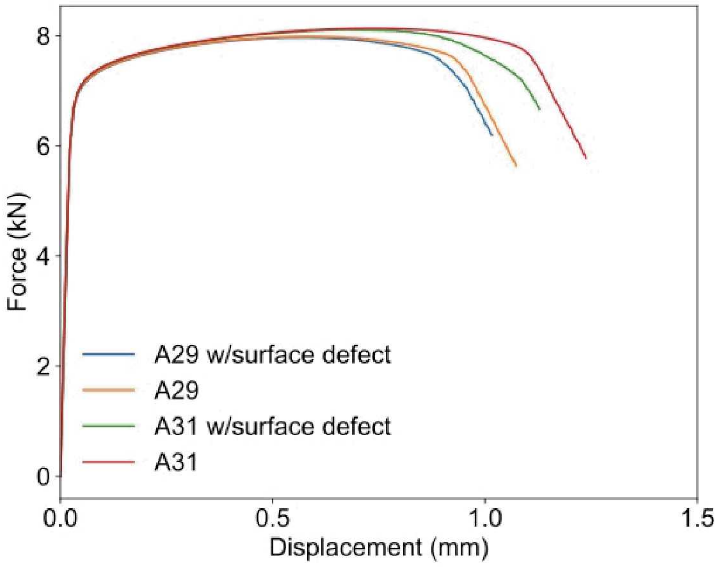


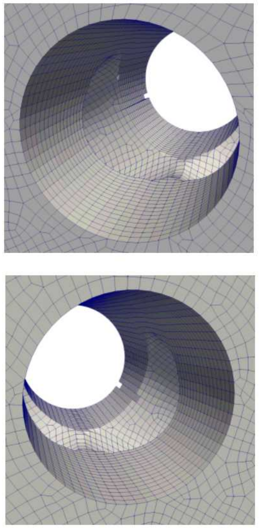


SFC3: Defect effect



Notched tension specimens show a 50% decrease in reduction in displacement-to-failure over smooth tension specimens

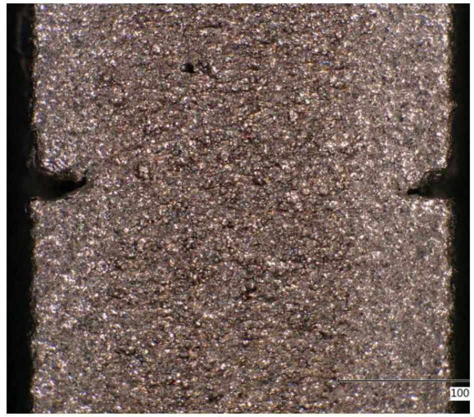


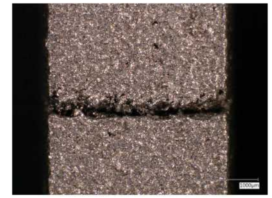


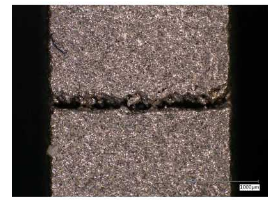
For challenge specimens, worst-case scenario (very large surface defect in region of highest stress concentration) shows some effect; variability in structure geometry dominates

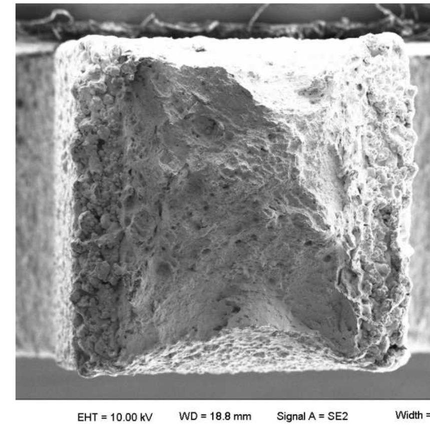
Characterization of AM 316L (Notched tension)

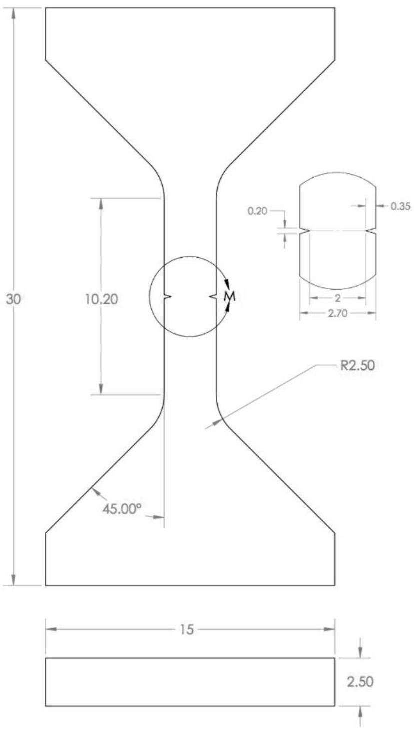
Notched data provided to calibrate crack initiation and propagation. We employed notches to check flow and fit damage evolution.

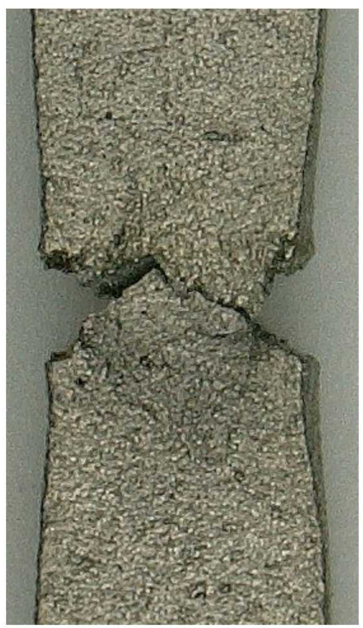


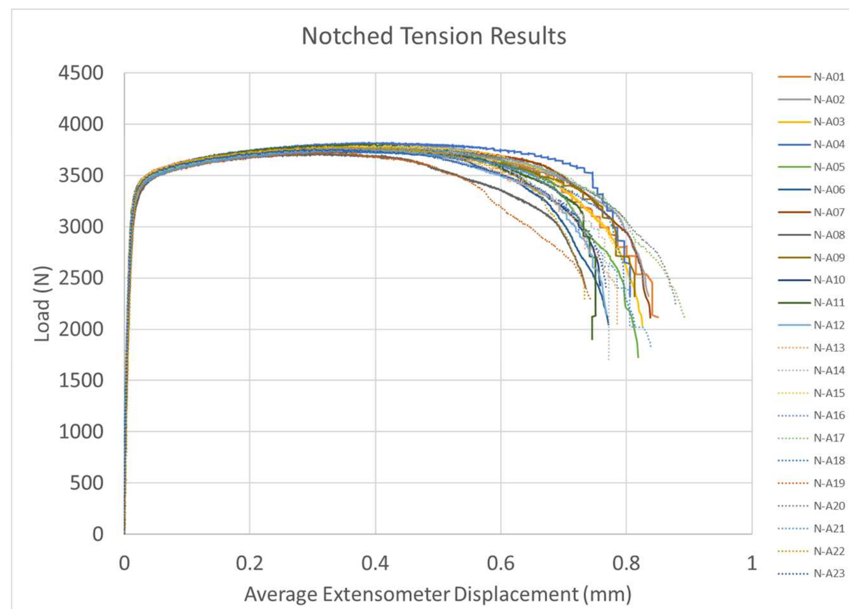










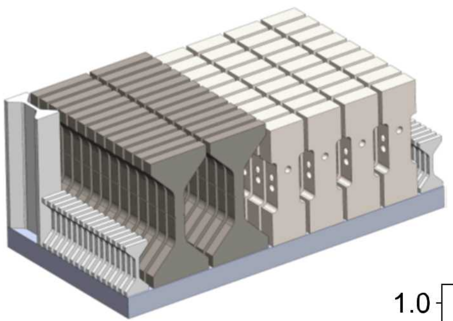


Accounting for material and structural variability

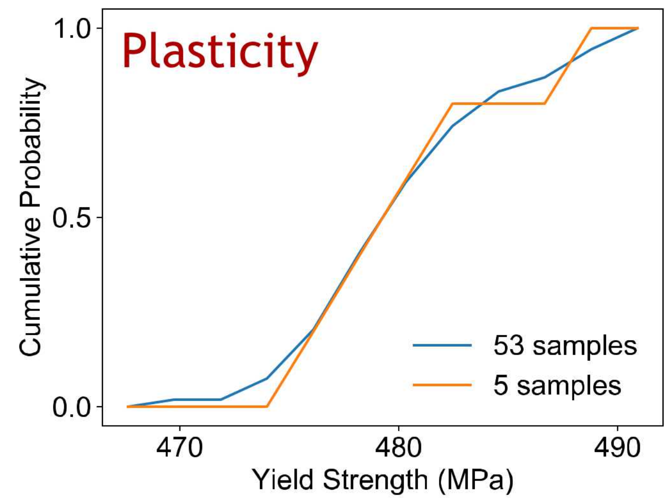
The ***Kolmogorov-Smirnov*** *test statistic was used to obtain optimal downsampled subsets*

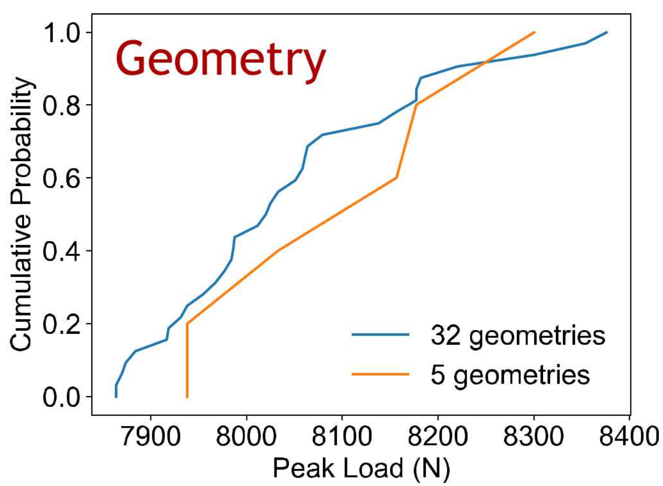
5 parameters selected from each parameter set

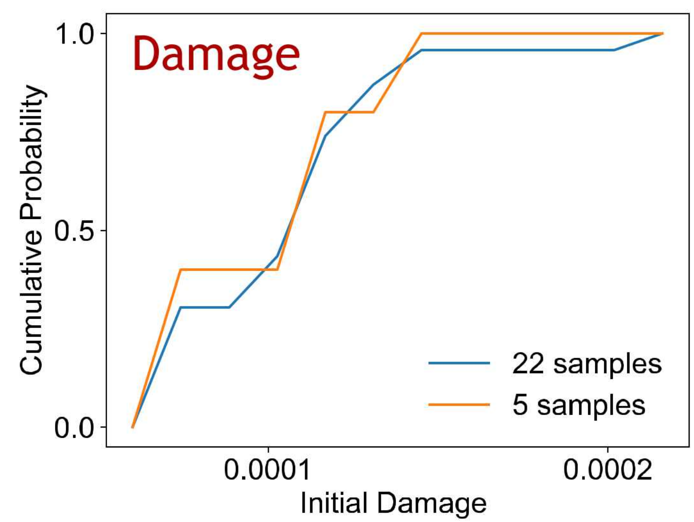
- Yield strengths for each *smooth tension experiment*
- Initial damages for each *notched tension experiment*
- Principal components for each *challenge* geometry



*Reduced ~**42000** simulations to **125** simulations total*







Accounting for Geometric Variability

Significant correlations were found between a number of the quantities of interest. To reduce the data by eliminating redundancy in the sampled specimens, apply principal component analysis to output data

Data matrix $\boldsymbol{X}$ (36 specimens, 21 variables)

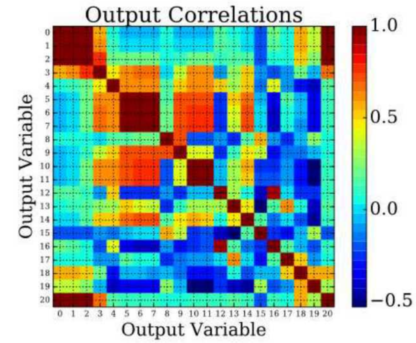
X_{ij}: i-th measurement of j-th variable

Correlation matrix $\boldsymbol{C}$ (21 x 21)

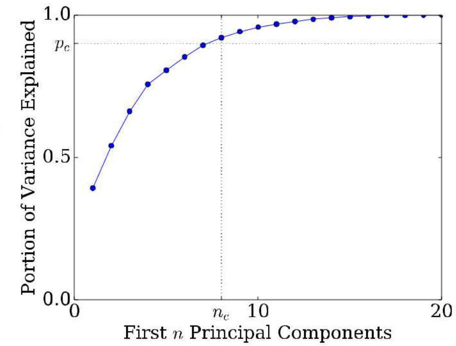
$$\boldsymbol{C} = \frac{1}{n-1}\boldsymbol{X}^{\mathrm{T}} \cdot \boldsymbol{X}$$

Set threshold of p_c, and keep n_c of the largest principal components S_{kk}, such that

$$\sum_{i=1}^{n_c} S_{kk} \geq p_c$$



PCA Cutoff



Downsampled vs Full Sample CDFs

The Kolmogorov-Smirnov test statistic used to obtain an optimal reduced set of specimens

$$D_{n,m} = \sup_x \left| F_{1,n}(x) - F_{2,m}(x) \right|$$

quantifies similarity of $F_{1,n}(x)$ and $F_{2,m}(x)$ of two samples of size n and m, respectively

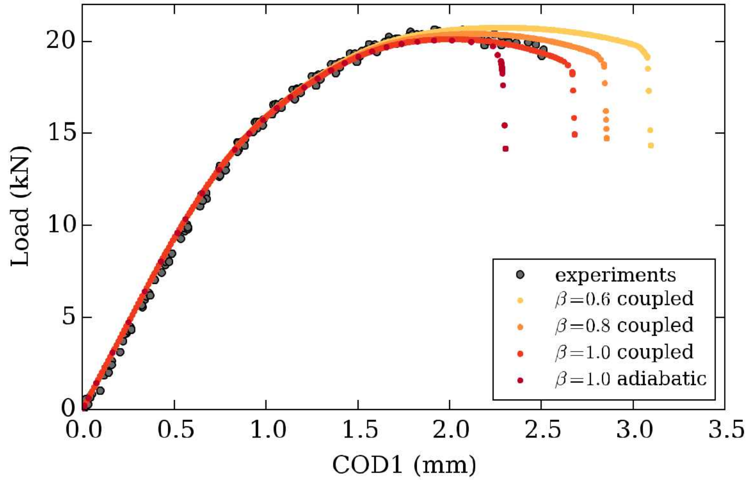
Compute $D^*_{n,m}$ for $m = 5$ and pick a reduced set of inputs that best represent the full sample

A1, A11, A20, A27, A28

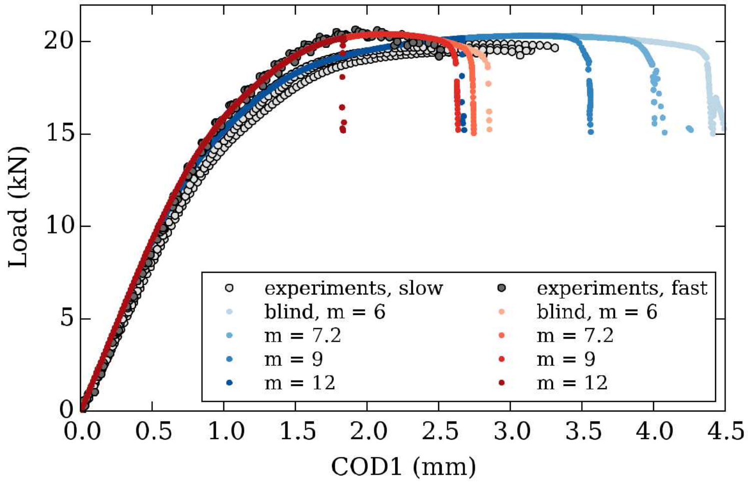
Sandia National Laboratories

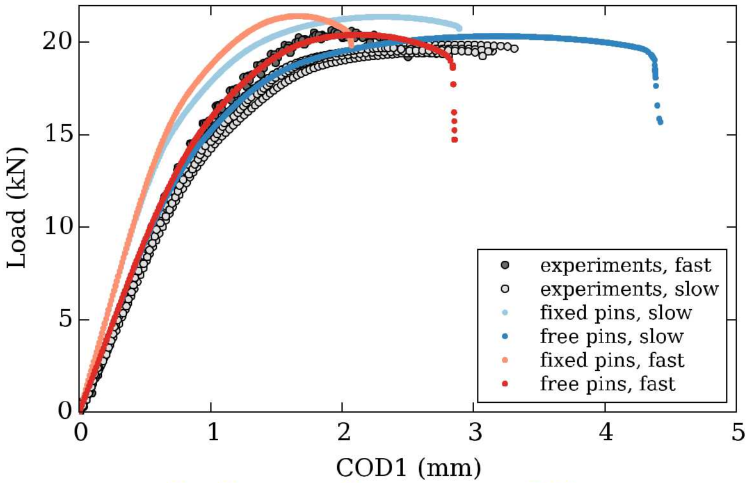
Sensitivity to uncertain parameters

thermal parameter, β

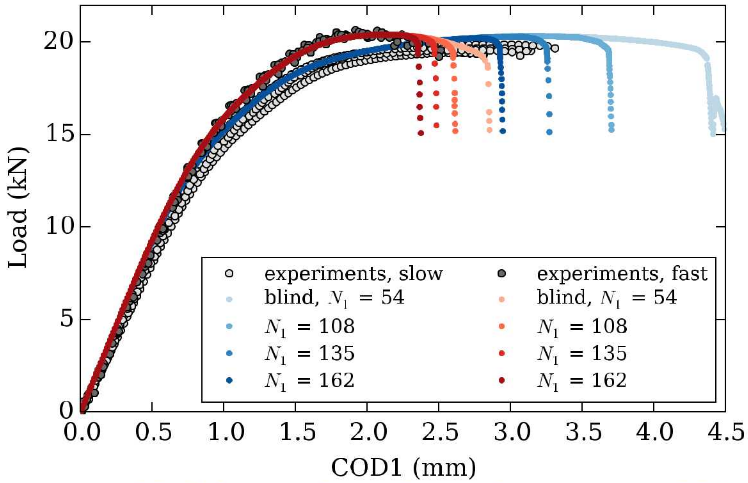


void growth damage, m





pin boundary condition



Void nucleation damage, N1