Microcracking Indicators predict Shear Failure in Berea Sandstone

Insights using the Discrete Element Method and Machine Learning

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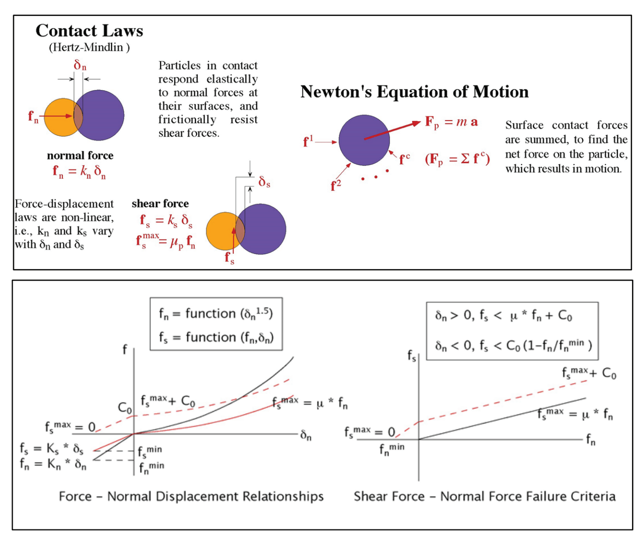
Abstract

We employ the Discrete Element Method to analyze indicators of critical failure during shear fracture growth in calibrated models of Berea sandstone. We calculate strain-dependent statistics including microcracking variance, shear microcrack fraction, fractal dimension, acoustic energy variance and seismic b-value. Each parameter is a function of strain-to-failure and can be treated as an indicator of critical point. We employ the five microcracking indicators and confining pressure as inputs for an artificial neural network (ANN) to predict critical failure. Over confining pressures of 0-45 MPa, our ANN architecture exhibits good prediction capability for stress-to-failure (R^2=0.94) and strain-to-failure (R^2=0.91) in Berea sandstone. Our machine learning approach reveals that microcracking variance, seismic b-value and fractal dimension are the most important damage indicators to predict critical failure.

Discrete Element Method

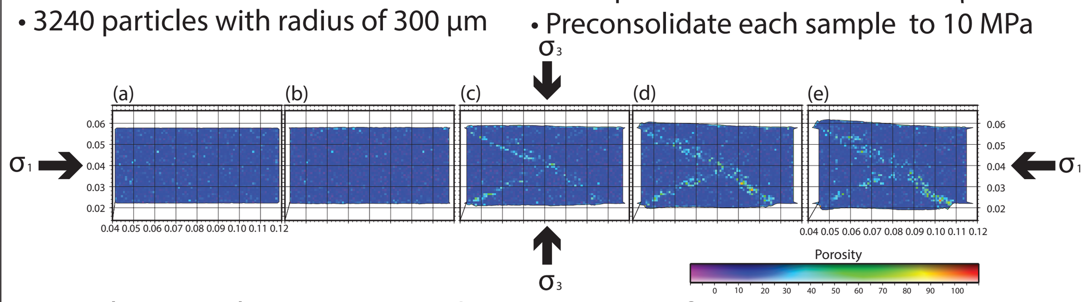
- Construct geologic medium as assemblage of simple particles – disks or spheres
- Apply physical properties to particles: Contact friction, elastic properties
- Implement interparticle bonds to simulate cohesion, which can fail under normal, shear, and rotational stresses
- Resolve forces onto particles and track resultant motion



Model Setup and Methods

1. Setup biaxial experimental setup

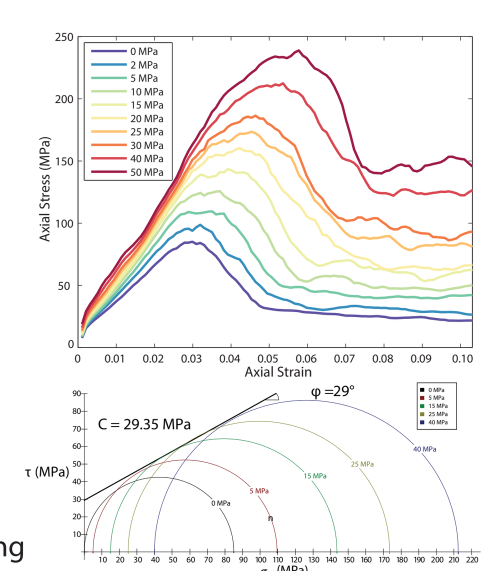
- Domain size: 0.12m x 0.06 m
- 3240 particles with radius of 300 μm
- 2700 particles with radius of 400 μm
- Preconsolidate each sample to 10 MPa



2. Simulate Biaxial Experiments under 0 - 50 MPa Confining Pressure
3. Calibrate Bulk Geomechanical Properties of Berea Sandstone

- Unconfined Compressive Strength = 85 MPa
- Young's Modulus = 6.1 GPa
- Mohr-Coulomb Cohesion = 29.3 MPa
- Mohr-Coulomb Slope = 29 °

Young's Modulus of Bonds	5 x 10^9 Pa
Shear Modulus of Bonds	5 x 10^9 Pa
Tensile Strength of Bonds	9 x 10^6 Pa
Cohesion of Bonds	9 x 10^7 Pa
Poissons Ratio of Particles	0.33



4. Quantify Fracture Energy From Microcracking

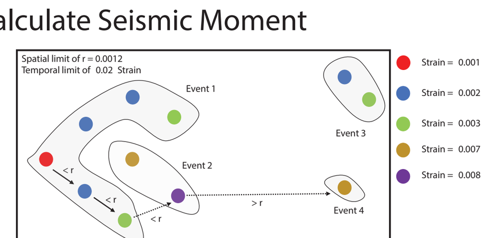
$$E_f = (½)*(\sigma_{cf}^2 v_f / C_f)$$

E_f : Energy of microcrack
C_f : Elastic Modulus of interparticle bond
σ_{cf} : Failure Stress of interparticle bond
v_f : Volume of Microcrack

5. Implement Spatio-Temporal Clustering to calculate Seismic Moment

$$M_e = (⅔)\log_{10}E_f - 2.9$$

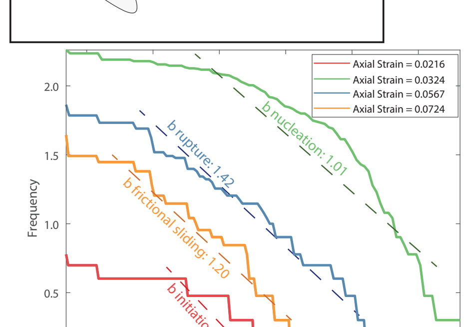
M_e : Seismic moment



$$\log N (M_e) = a - bM$$

N : Number of events with magnitude greater than M

b : Slope of Frequency-Magnitude curve

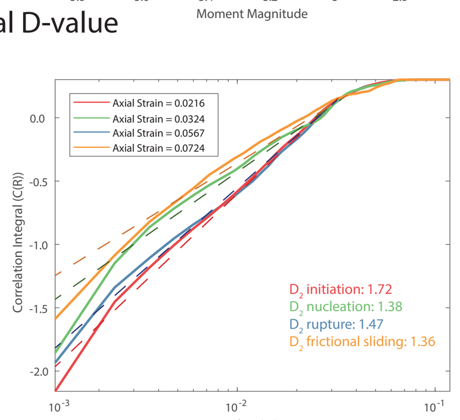


6. Quantify Microcrack distribution using Fractal D-value

$$C (R) = 2 N_{(r<R)} / N(N-1)$$
$$C (R) \alpha R^D$$

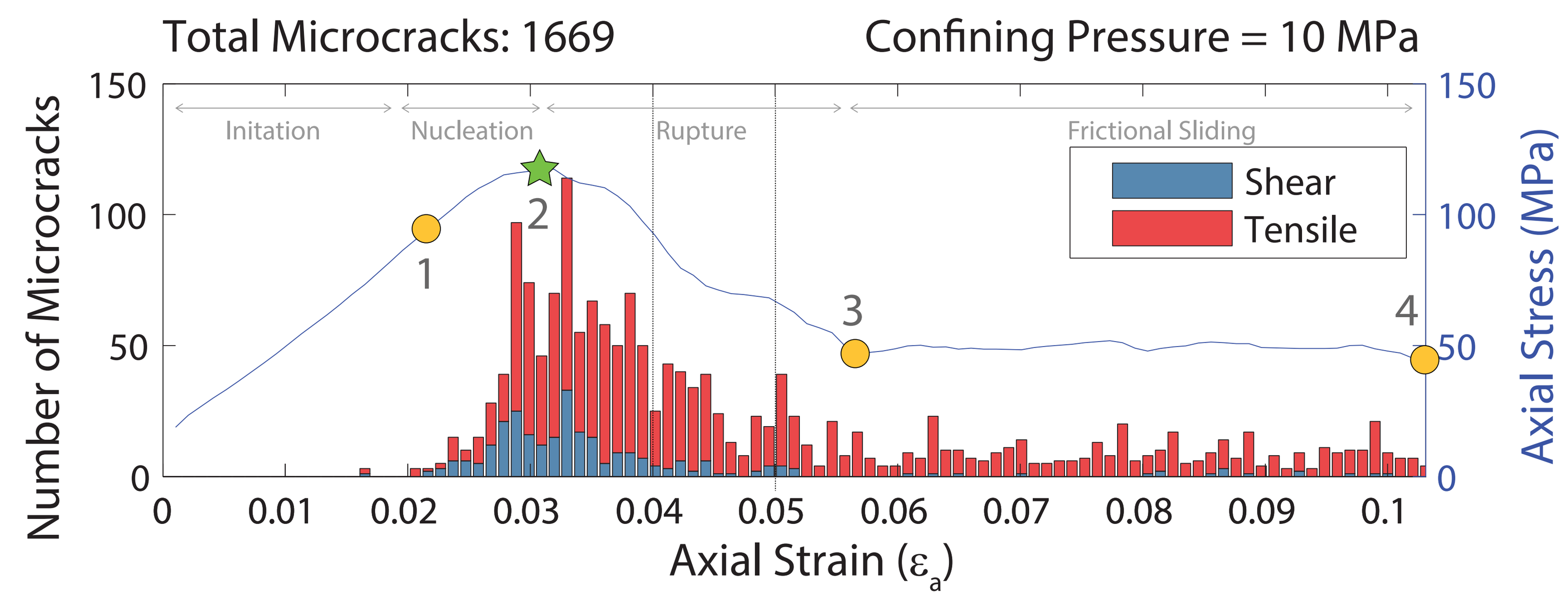
D : Fractal Dimension
N : Number of microcrack pairs
R : Radial distance (m)

Low D-values: Localizaed microcracking
High D-value: Distributed microcracking

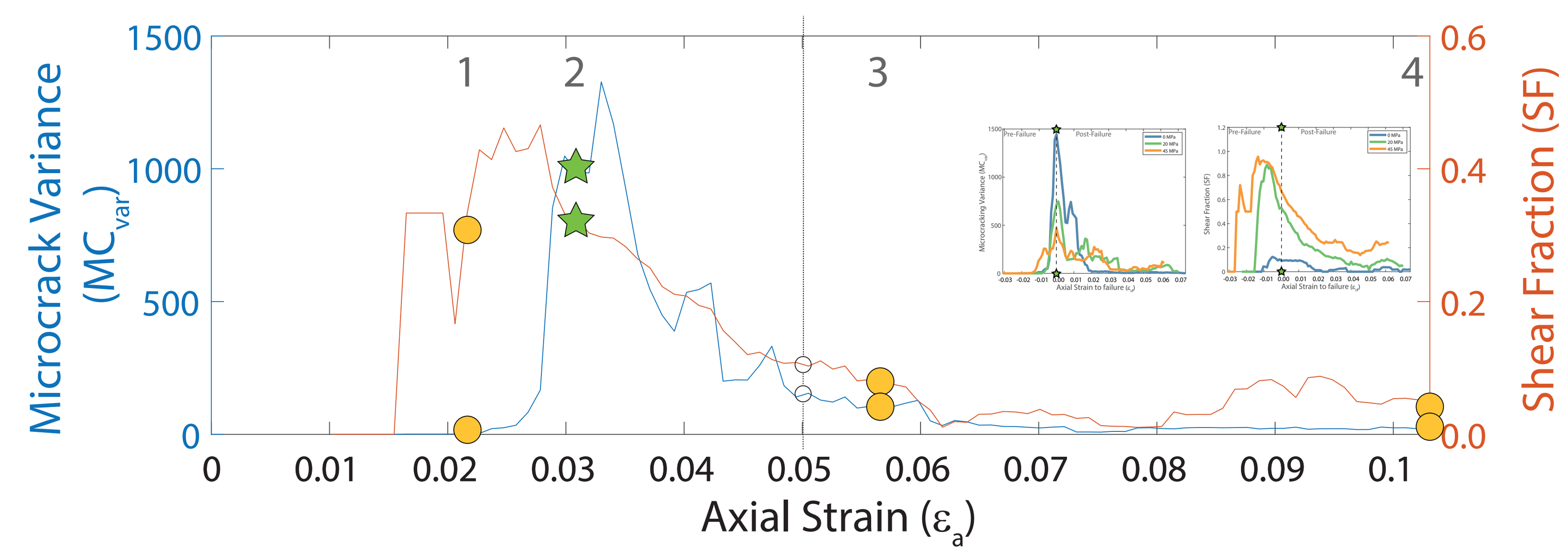


Shear Fracture Growth in Berea Sandstone

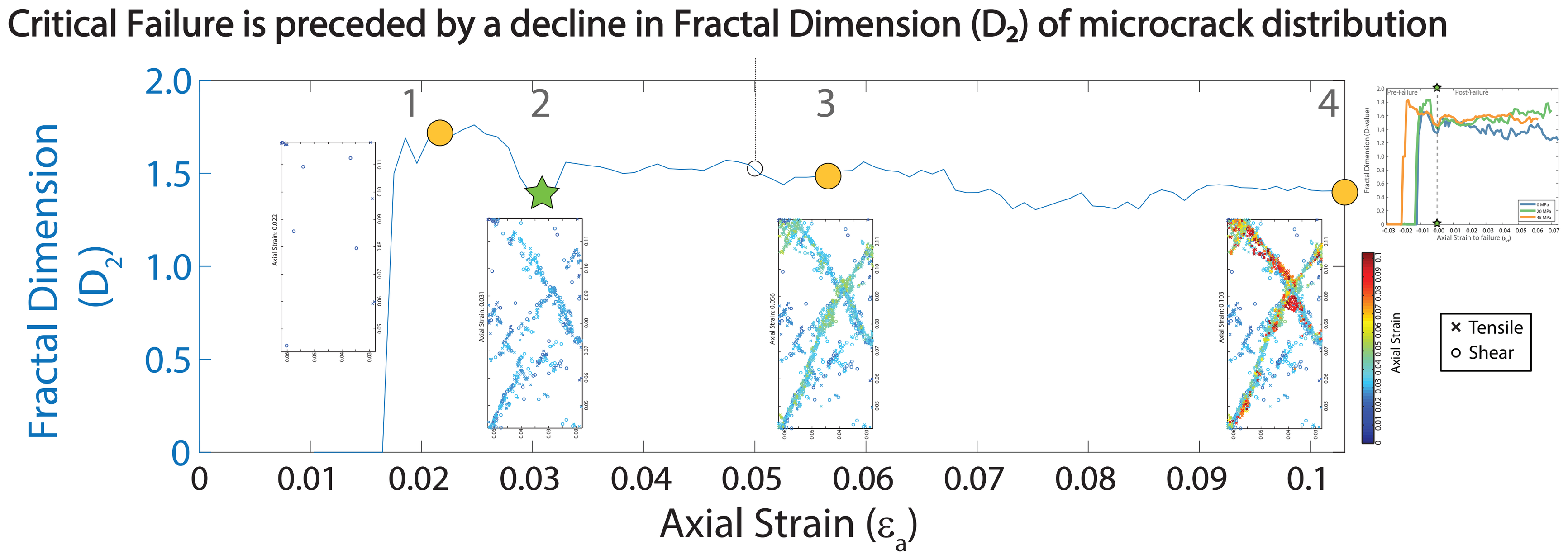
We analyze indicators of critical failure through statistical variations in microcrack growth



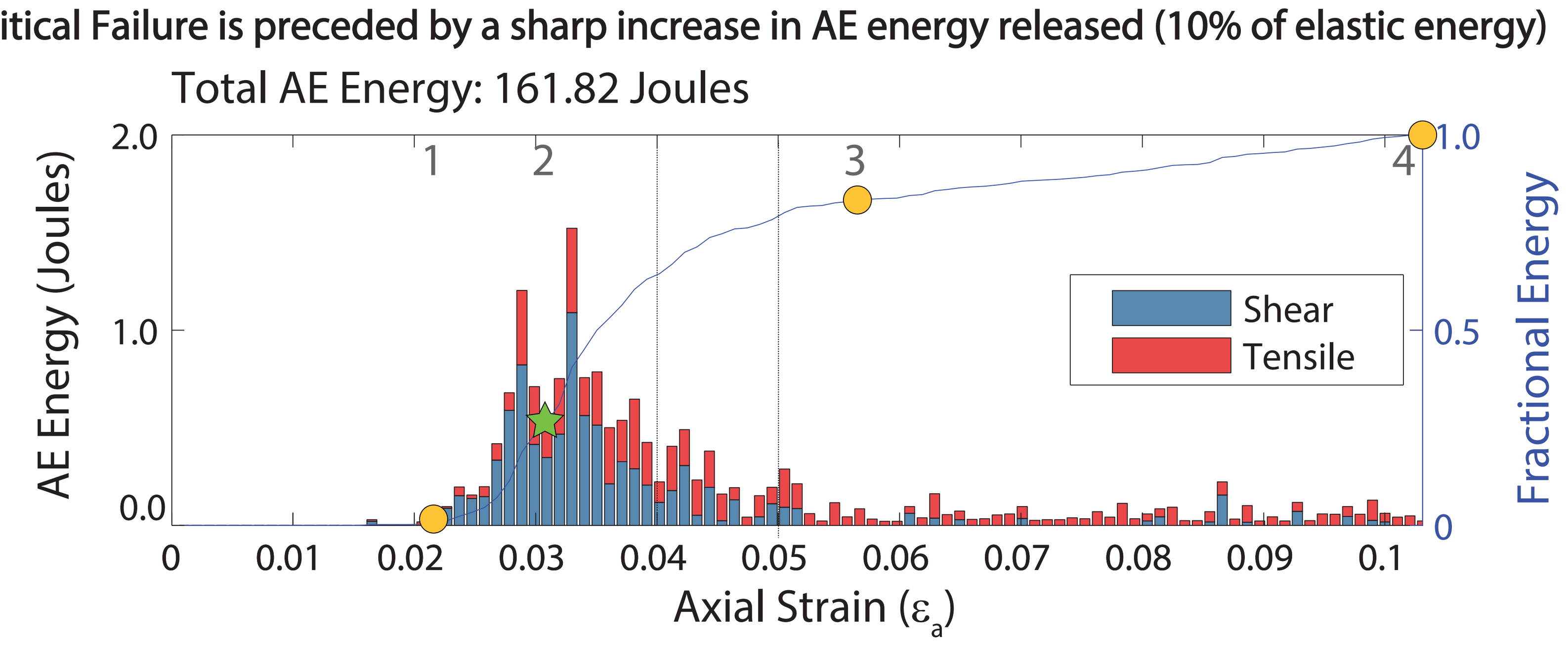
Critical Failure is preceded by sharp increase in microcracking variance and shear fraction



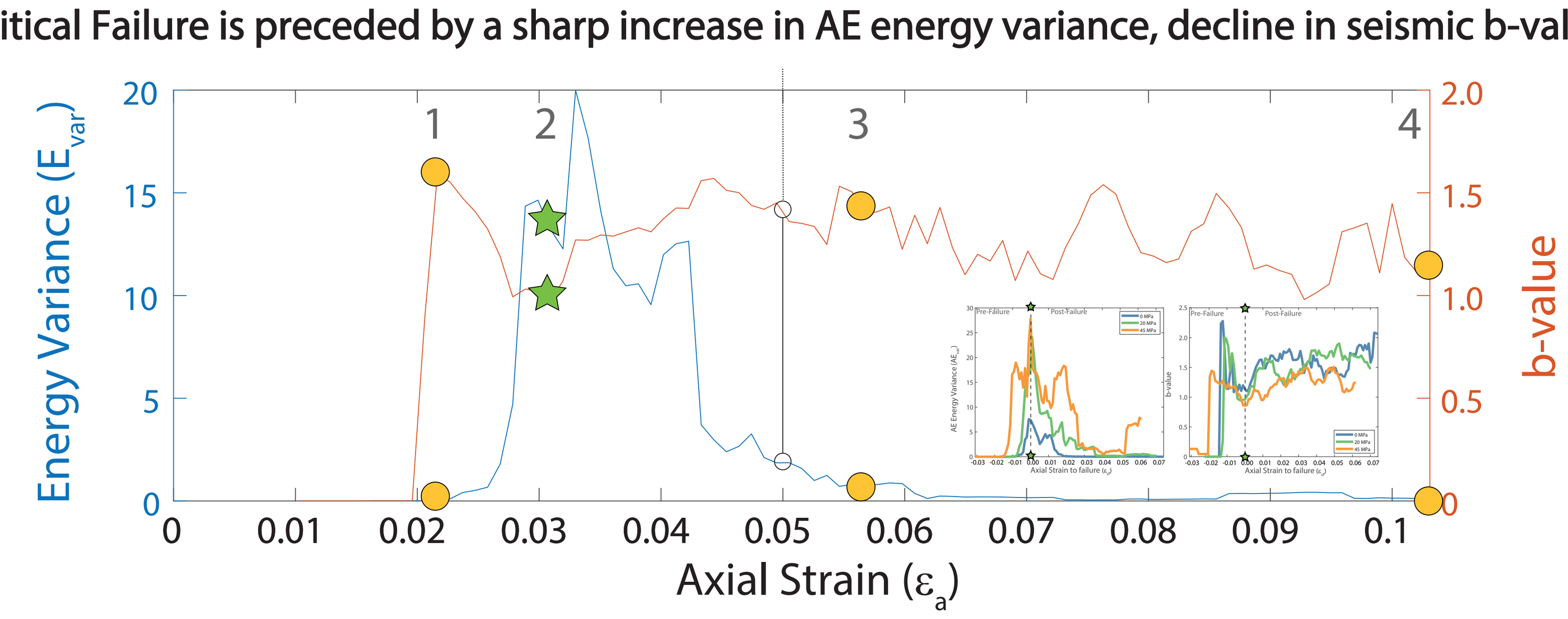
Critical Failure is preceded by a decline in Fractal Dimension (D_2) of microcrack distribution



Critical Failure is preceded by a sharp increase in AE energy released (10% of elastic energy)



Critical Failure is preceded by a sharp increase in AE energy variance, decline in seismic b-values



- Critical Point
- Strain Marker
- Example Axial Strain Window
- Derived Damage Indicator

References

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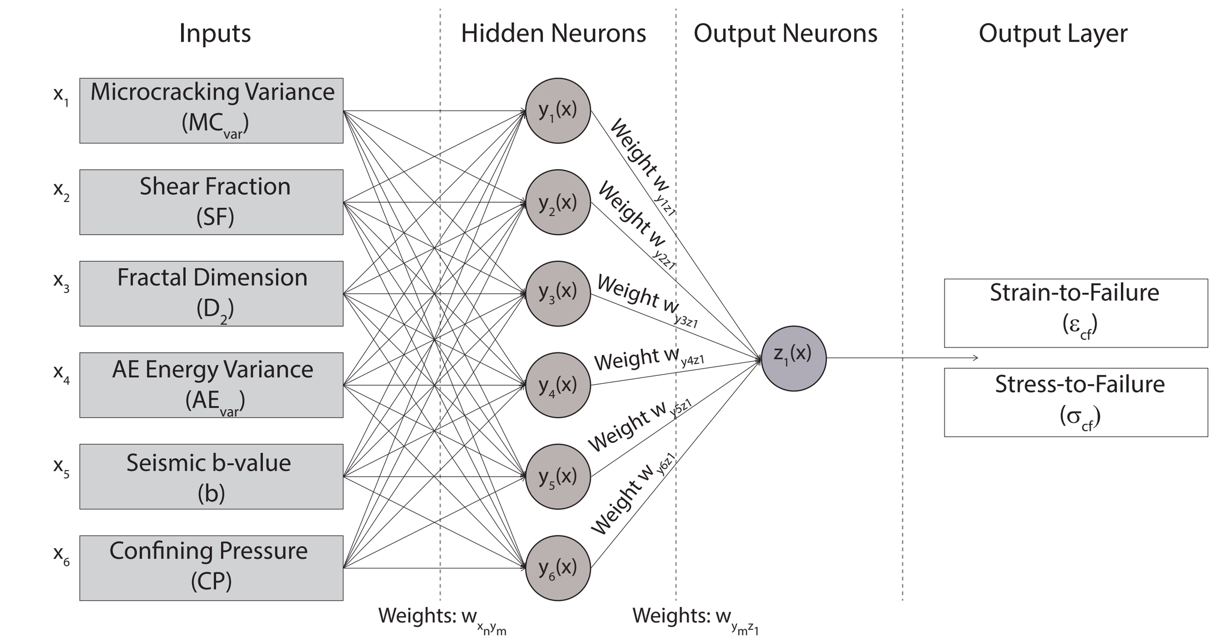
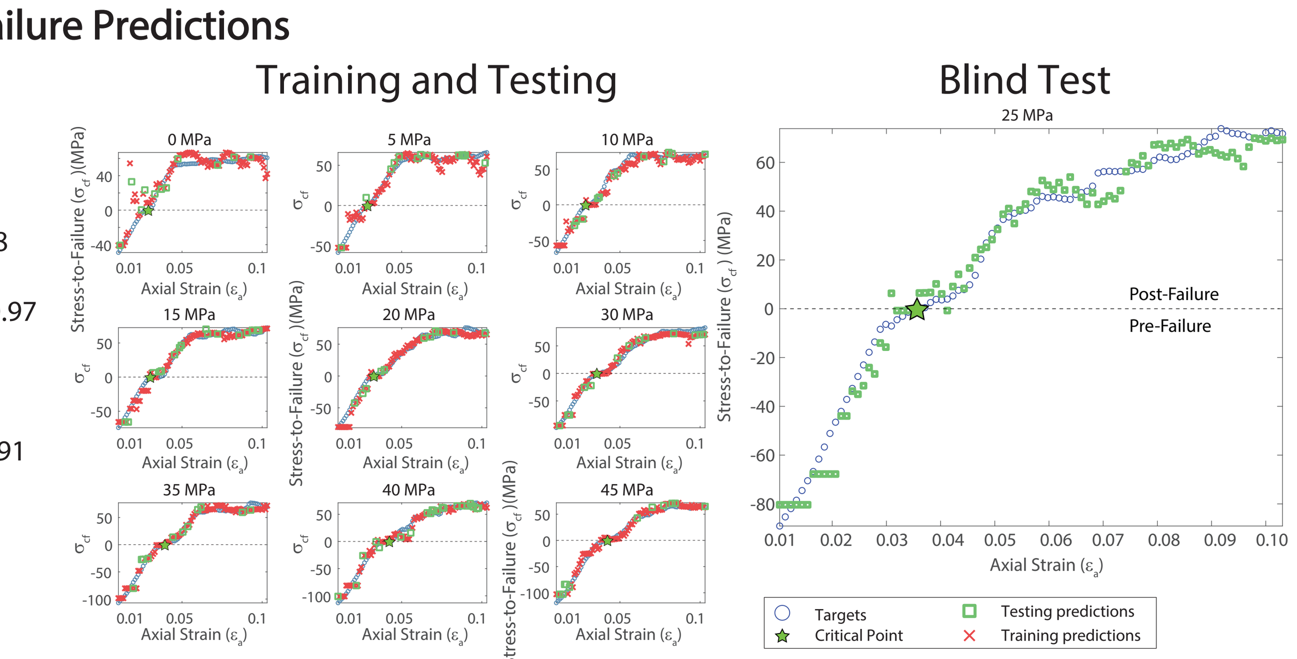
Critical Failure Prediction

We employ the calculated deformation indicators and confining pressure as inputs for an Artificial Neural Network (ANN) to predict stress-to-failure and strain-to-failure



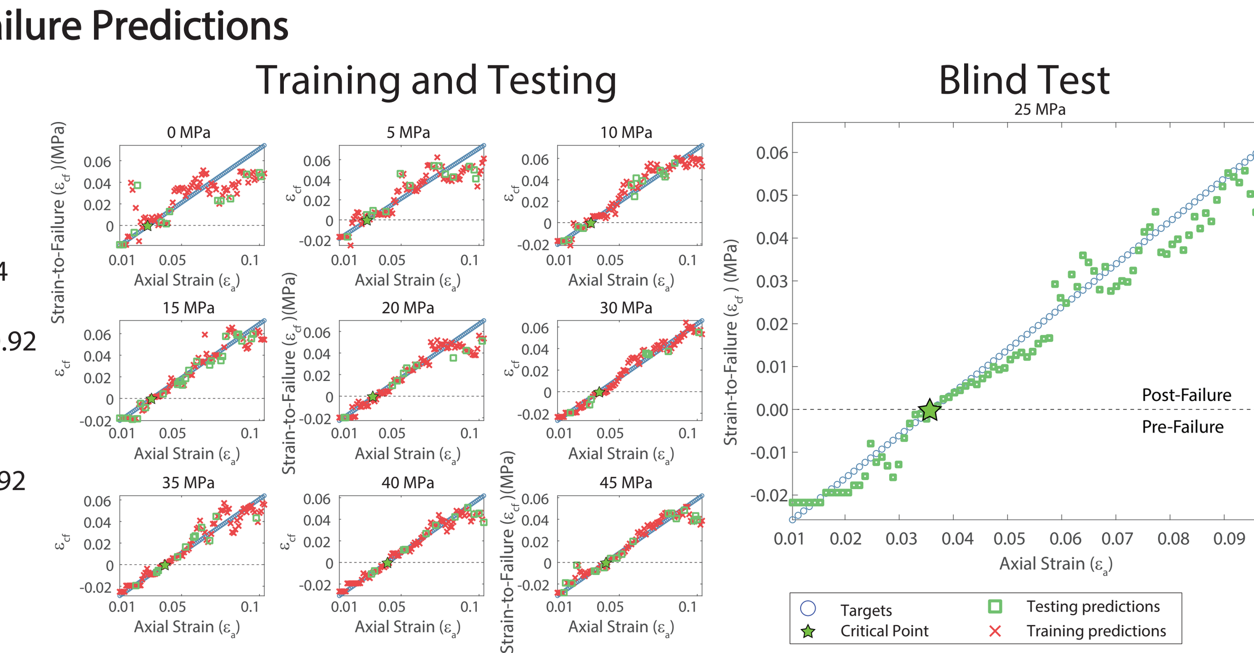
Stress-to-Failure Predictions

Training R^2 = 0.98
Validation R^2 = 0.97
Testing R^2 = 0.96
Blind Test R^2 = 0.91



Strain-to-Failure Predictions

Training R^2 = 0.94
Validation R^2 = 0.92
Testing R^2 = 0.90
Blind Test R^2 = 0.92



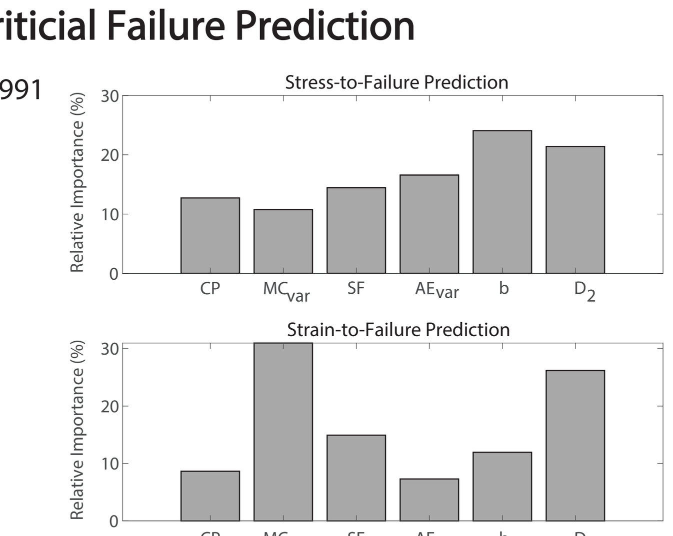
Relative Importance of Deformation Indicators for Critical Failure Prediction

We calculate the relative importance of critical predictors using Garson, 1991

$$I_x = \sum_{x=1}^{n} \frac{|w_{xy} w_{yz}|}{\sum_{y=1}^{m} |w_{xy} w_{yz}|}$$

$$RI_x = \frac{I_x}{\sum_{x=1}^{n} I_x} * 100$$

- b-value and D_2 are most important stress-to-failure prediction
- MC_{var} and D_2 are the most important strain-to-failure predictors
- All inputs contribute towards critical failure predictions, indicating the benefits of an integrated indicator analysis



Conclusions

1. Pre-failure microcracking in Berea Sandstone is characterized by:
   a) increase in microcracking variance of one to two orders of magnitude,
   b)peak shear microcrack fraction ranging from 0.15 to 0.95,
   c) a decline in fractal dimension of microcracks from 1.65–1.85 to 1.35–1.55
   d) increase in acoustic energy variance of an order of magnitude, and
   e) a decline in b-values from 1.4–2.3 to 0.8–1.3 at critical point.
2. The deformation indicators can be combined with machine learning to predict critical failure. Our Artificial Neural Network (ANN) exhibits good prediction capability for stress-to-failure (R^2=0.94) and strain-to-failure (R^2=0.91) in Berea sandstone.
3. Our machine learning approach reveals that microcracking variance, seismic b-value and fractal dimension (D_2) are the most important predictors of critical failure.