**Microcracking Indicators Predict Critical Failure in Berea Sandstone Analog: 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 document the location, mode and stress associated with emergent tensile and shear microcracks during biaxial experiments under confining pressures of 0-45 MPa. 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. Pre-failure microcracking in Berea Sandstone is characterized by: 1) increase in microcracking variance of one to two orders of magnitude, 2)peak shear microcrack fraction ranging from 0.15 to 0.95, 3) a decline in fractal dimension of microcracks from 1.65–1.85 to 1.35–1.55 at critical point, 4) increase in acoustic energy variance of an order of magnitude, and 5) a decline in b-values from 1.4–2.3 to 0.8–1.3 at 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 (R2=0.94) and strain-to-failure (R2=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. Thus, we develop an integrated analysis of microcracking indicators to understand pre-failure and post-failure signatures of critical point and combine them with machine learning to predict failure in granular rock.

1. **Introduction**

Before and after relatively large earthquakes, seismic activity surrounding the source area exhibits generally higher activity than the long-term average. Seismologists have tried to improve earthquake prediction techniques by statistical analysis of observed foreshocks and aftershock sequences associated with these large earthquakes. Statistical variations in seismic event rate, seismic energy and moment magnitude preceding large earthquakes are observed widely but not systematically [Buochon et al., 2013; Wyss, 1997; Mignan 2014; Cicerone et al. 2009]. Since earthquakes have been suggested as scale-independent, self-organized critical phenomenon [Main, 1996; Scholz, 1968], rock deformation experiments have been employed to understand the statistical variation in seismicity during slip along faults. Precursory variations in microcracking and acoustic energy are routinely observed prior to catastrophic rock failure during laboratory stick-slip and biaxial experiments [Rouet-Leduc et al., 2017; Ojala et al., 2004; Lockner 1993]. Several studies have analyzed individual precursory indicators to predict time-to-failure during rock deformation experiments [Rouet-Leduc et al., 2017; Lubbers et al., 2018]. However, an integrated analysis of independent precursors to failure can help improve critical failure and earthquake prediction techniques.

Recent advances in laboratory experiments using acoustic emissions (AE’s) have improved our understanding of observed seismic variations by providing a spatio-temporal understanding of microcracking precursors to critical failure. Experimental analyses to show that macroscopic shear fracture growth in brittle materials is preceded by pervasive evolution of microcrack rate, spatial distribution, acoustic energy and seismic moment. Biaxial experiments reveal accelerated pre-failure microcracking rate across several crystalline rock types [Lei et al., 2007; Baud et al., 2004; Stanchits et al., 2006]. Additionally, biaxial and stick slip experiments conducted on non-cohesive granular rocks show exponential pre-failure AE energy release prior to catastrophic failure [Rouet-Leduc et al., 2017; Johnson et al., 2013]. Biaxial deformation experiments also reveal that pre-failure damage evolution prior to catastrophic failure in crystalline rocks is characterized by localization of microcracking, resulting in a decline in fractal dimension of observed AE hypocenters [Lei et al., 2000; Lei et al., 2004; Lockner, 1993]. Laboratory stick-slip experiments reveal an increase in range of seismic moments observed from AE and a corresponding decline in b-values prior to catastrophic failure [Rivière et al., 2018; Goebel et al., 2017]. While experimental observations have helped identify spatio-temporal indicators of catastrophic failure, they are largely applicable to non-cohesive granular media and crystalline rocks. The constraints over precursory signatures of critical failure in sedimentary rocks of widespread interest such as sandstone remain unexplored.

Shear fracture growth in sandstone is a complex process of coalescence between tensile and shear microcracks [Fortin et al., 2009], and their relative abundance is primarily controlled by confining pressure [Menendez et al., 1996]. The variation in abundance of tensile and shear microcracks with confining pressure alters fracture mechanisms and associated energy [Vora and Morgan, 2019]. While fracture mechanisms in sandstones have been analyzed by experimental and numerical studies, the effect of confining pressure on microcracking mode and observed deformation indicators of microcracking rate, energy and moment remain unexplored. Additionally, the accurate quantification of experimental precursory AE deformation signatures in sandstone remains challenging due to difficulty in recognizing microcrack mode [Modiriasari et al., 2017] and seismic attenuation [Toksöz et al., 1979]. Thus, there is need for a numerical micromechanical study, complementing laboratory AE observations, to analyze precursory deformation signatures in sandstone.

Several studies combine documented deformation indicators with machine learning techniques to predict time-to-critical failure. Rouet-Leduc et al., 2017 show that stick-slip behavior in granular media can be predicted using observations of AE energy using random forests. Zhou et al., 2018 use signal processing techniques with deep learning to predict lab-quakes with 80% accuracy. Florido et al., 2015 employ the temporal variations in observed seismic b-values to predict time to earthquake greater than magnitude 7 in Chile using artificial neural networks. While several studies have tried to predict critical failure in laboratory samples and in the earth’s crust, they do not employ the entire range of observable precursory signatures in their models. An integrated study of independent deformation indicators accounting for microcracking rate, mode and spatial distribution, AE energy release and seismic moment can improve current failure prediction techniques by improving constraints on critical failure.

Numerical methods provide the ability to monitor stresses and displacement of grains on a micro-scale, complementing the deformation indicators observed from microstructural and AE analyses. Discrete numerical methods are attractive to study brittle fracturing because, much like real rocks, the numerical materials are composed of assemblages of grains [Vora and Morgan, 2019]. The grains are bonded to impart cohesion and simulate rock properties. Bond breakage, in response to applied boundary conditions, simulates emergent microcracking allowing us to study the distribution and mode of individual microcracks and associated elastic energy release. In this study, we use the Discrete Element Method [Cundall and Strack, 1979] to examine the behavior of calibrated models of Berea Sandstone during confined biaxial experiments in which cracks and fractures form spontaneously and release elastic energy analogous to acoustic emissions. By monitoring microcracking activity, we seek to constrain precursory signatures of rock deformation during shear fracture nucleation and rupture. We then employ machine learning techniques and use the calculated temporal deformation indicators to predict critical failure.

1. **The Discrete Element Method**

The discrete element method is a particle-based numerical technique that employs a time stepping, finite difference approach to solve Newton’s equations of motion for every particle in a system. The method first solves for forces imposed on the surfaces of each particle by neighboring particles or boundaries and then calculates a displacement based on the acceleration caused by sum of the forces. Particle motions are induced by external forces prescribed by stress or strain rate boundary conditions, and by forces resolved at interparticle contacts. The disequilibrium of forces drives particle displacements. The Discrete Element Method (DEM) has been employed to simulate rock deformation from laboratory scale experiments to large scale geodynamic processes, including formation of deformation bands in sandstones [Wang et al., 2008], analyze changes in porosity and stress during biaxial experiments [Longjohn et al., 2018], calculate energy budgets during deformation experiments [Vora and Morgan, 2019], and deformation of fold and thrust belts [Morgan and Boettcher, 1999]. The numerical code used is RICEBAL, based on open-source code TRUBAL [Cundall and Strack, 1979]. RICEBAL resembles a numerical sandbox but offers added value by allowing material properties and mechanical states to be monitored throughout simulations and be correlated with deformation behavior and structure. The interparticle mechanics of RICEBAL are described in detail in supplementary Text S1 and Fig. S1.

* 1. **Biaxial Experiments and Geomechanical Calibration of Berea Sandstone using RICEBAL**

Detailed descriptions of biaxial setup and bulk calibration of numerical analogs can be found in Vora and Morgan, 2019. We simulate samples as granular assemblage of ~6,000 particles with particle radii of 10-40 µm within an initial spatial domain of 0.04 m x 0.03 m. To prepare cohesive samples for biaxial experiments, we preconsolidate our samples to a confining pressure of 10 MPa. The two horizontal confining walls, constructed of rows of particles, are moved inward between rigid vertical walls of particles until preconsolidation stress of 10 MPa is achieved. After consolidation, sample dimensions are 0.0775 m x 0.038 m. We assume plane strain conditions, and out of plane stresses are zero. Following preconsolidation, we reset the particles along horizontal walls to move independently in the vertical direction, while maintaining their constant confining stress, thus acting as a “membrane” that confines the sample during biaxial experiments. Porosity of all samples after preconsolidation is 17.6%. At this stage, we introduce interparticle bonds to simulate cohesive rock material. Axial compression is conducted by moving vertical platens inward at a constant velocity. As the lateral platens move inwards, local differential stresses increase, which causes failure of interparticle bonds, generating microcracks (Fig. 1a-1c). With increasing deformation, the induced asperities coalesce to form one or more shear fractures, ultimately resulting in the failure of the sample (Fig. 1d). Biaxial experiments are run under confining pressures of 0, 5, 10, 15, 20, 25, 30, 35, 40 and 45 MPa. Macromechanical properties of the sample are collected at increments of 2000 cycles, associated with axial strain increments of 0.001 corresponding to incremental platen displacements of 0.008 mm. All simulations of biaxial experiments are conducted up to axial strain of 10.3%.

In our study, we simulate Berea Sandstone, defined by the micromechanical properties of the discrete particles and bonds within the assemblage. The micromechanical model properties are adjusted, and the bulk behavior of our model materials is calibrated to replicate experimental laboratory data for Berea Sandstone [Bobich, 2005; Schellart, 2000]. To capture the range of geomechanical rock behavior under both unconfined and confined conditions, we sought to reproduce to experimental datasets for Unconfined Compressive Strength (*UCS*), Young’s modulus (*E*), Mohr-Coulomb cohesion (*C*), and internal friction coefficient (*µ*). The pertinent input microparameters include (1) mechanical properties of the particles - Shear modulus of particles (*Gp*), Poisson’s ratio of particles (*νp*), (2) mechanical properties of interparticle bonds - Young’s and shear moduli of bonds (*Eb* and *Gb*), tensile strength and cohesion of bonds (*Tb* and *Cb*), and (3) interparticle friction (*µp*). The selected values of input microparameters that best reproduce the bulk properties of the Berea Sandstone are presented in Table 1. The calibration of numerical samples to experimental datasets is explained in detail in supporting Text S2 and supporting Fig. S2 and Fig. S3. The bulk behavior of numerical samples under confined and unconfined conditions is shown in Table 2, replicating the experimental geomechanical character of Berea Sandstone.

1. **Methods: Microcracking Indicators of Deformation**

Each bond breakage event is assumed to be a microcrack in the during biaxial tests on modeled rock samples. As axial stress is applied to the platens during the numerical biaxial experiments, fractures grow by the coalescence of emergent microcracks. During each simulated biaxial experiment, we track microcrack growth at axial strain (*εa*) intervals of 0.001 and calculate the corresponding AE energy and seismic moment. Our goal is to record indicators of deformation derived from microcracking events, using local, moving time windows of the modeled microcracking and associated AE data. We employ continuous, moving axial strain windows of 0.01, corresponding to ten axial strain steps (*ASwindow*=10). The microcrack data and modeled AE data are employed to calculate five characteristic independent deformation indicators: (1) Microcrack Variance, (2) Shear microcrack fraction, (3) Fractal dimension (4) AE energy Variance, and (5) Seismic b-value. We employ these five independent deformation indicators as they (1) have been utilized individually to analyze fracture growth in other lithologies, (2) can be derived from laboratory AE and field-scale seismic datasets, and (3) are scale-independent parameters.

**3. 1.** **Mode and Rate of Microcracking**

Interparticle bonds can fail in either tension or shear [Text S1]. A tensile microcrack forms when interparticle normal stress exceeds the tensile strength of the bond, resulting in a mode 1 microcrack. Similarly, a shear microcrack results when local shear stress exceeds the shear strength of the bond in compression, resulting in a mode 2 microcrack. During our biaxial tests, we document the mode of each microcrack generated in association with the applied axial stress [Fig. 2a]. To normalize the effect of increasing microcracking rate with confining pressure on rock [Fortin et al., 2009; Vora and Morgan, 2019], we calculate the variance of microcracking rate to develop a standardized deformation indicator. The variance of microcracking allows for temporal analysis of microcracking rate and shows a strong correlation with critical failure [Rouet-Leduc et al., 2017]. We use the number of microcracking events per unit strain (*Ni*) to compute microcracking variance (*MCvar*) as:

(Eq. 1)

Where *μMC* is the mean of number of microcracks per unit strain calculated as:

(Eq. 2)

The evolution of *MCvar* with axial strain provides a temporal understanding of variations in microcracking rate during shear fracture growth [Fig. 2b].

The source mechanism of acoustic emissions and earthquake sequences exhibit temporal variations, functioning as time-to-failure indicators [Fortin et al., 2009; Lei et al., 2004; Meredith et al., 1990]. To analyze the temporal changes in shear and tensile microcrack abundance during shear fracture growth, we compute the fraction of microcracks in shear mode (*SF*) within each strain window as:

(Eq. 3)

The evolution of *SF* with axial strain provides a temporal understanding of variations in AE source mechanisms during shear fracture growth [Fig. 2b].

**3.2. Spatial Distribution of Microcracks**

We document the location of each microcrack during simulated biaxial tests as a function of axial strain at the time of failure [Fig. 1]. The hypocenters of seismicity recorded from acoustic emissions and earthquake sequences exhibit localized microcracking during fracture nucleation and rupture, exhibiting time-to-failure characteristics [Lei et al., 2006; Hirata et al., 1987a]. From each axial strain window, we compute the fractal dimension of microcrack location to quantify microcrack distribution during shear fracture growth. We use the number of microcrack pairs (*Np*) within a radius *R*, to calculate the fractal dimension (*D2*) [Hirata et. al, 1987a] within each strain window as:

(Eq. 4)

(Eq. 5)

Where *C(R)* is known as the correlation integral. The value of *D2* within a strain window is calculated from slope of log(*C(R)*) vs *R* [Fig. S4]. A low value of *D2* (~1) indicates localized microcracking in sample; whereas, a high *D2* (~2) indicates distributed microcracking. The evolution of *D2* with axial strain provides a scale-independent understanding of temporal variations in distribution of microcrack locations [Fig. 2c].

**3.3. Energy of Acoustic Emissions from Microcracking**

As axial stress is applied to the platens, interparticle bonds become distorted prior to failure, accumulating elastic strain energy. Bond failure that accompanies microcrack formation releases this energy instantly, emitting an elastic signal analogous to seismic energy. The fracture energy associated with each microcracking event is calculated using the following equation [Tang and Kaiser, 1998]:

(Eq. 6)  
Where *Wfrac* is the energy associated with an individual micro-fracture, *Cf* is the elastic modulus of the bond broken, *σcf* is the peak strength of the failed element and *vf* is the volume of microcrack. RICEBAL provides us with the ability to monitor stress associated with each broken bond *σcf*. Volume of a microcrack (*vf*) is taken as the sum of the areas of the two particles bounding the broken bond. If the microcrack fails in shear, *Cf* takes the value of shear modulus of the bond (*Gb*); if the microcrack fails in tension, *Cf* takes the value of Young’s modulus of the bond (*Eb*). During our biaxial tests, we calculate the acoustic energy (*AEenergy*) released during formation of each microcrack as 10% of released elastic fracture energy, in accordance with estimated energy budgets from laboratory and experimental studies [Madden and Cooke, 2017; Cooke and Murphy, 2004]. The calculated *AEenergy* is documented as a function of axial strain [Fig. 2d]. Total acoustic energy released is calculated as the sum of acoustic energy from all microcracking events during a biaxial experiment, up to an axial strain of 0.103. To normalize the effect of increasing acoustic energy with confining pressure on rock [Vora and Morgan, 2019], we calculate the variance of microcracking energy rate to develop a standardized deformation indicator. Acoustic energy and its associated variance show temporal variations, exhibiting time-to-failure characteristics [Amitrano et al., 2005; Rouet-Leduc et al., 2017]. We use the acoustic energy released per unit strain (*AEi*) to compute the variance of acoustic emissions released (*AEvar*) within each strain window as:

(Eq. 7)

Where *μAE* is the mean of acoustic energy per unit strain calculated as:

(Eq. 8)

The evolution of *AEvar* with axial strain provides a normalized temporal understanding of variations in acoustic energy during shear fracture growth [Fig. 2e].

**3.4. Seismic Moment and b-value from Microcracking**

Microcracks in real rocks defines a broad range of seismic moments, showing strong spatial and temporal correlation [Main et al., 1989]. Due to the narrow range of grain size distribution in our models, the energy associated with microcrack formation, corresponding to individual bond breakage events, also falls into a narrow range. To correct for the limitations of the discrete element approach, we implement a spatial and temporal clustering algorithm developed by Hazzard and Young, 2000 [Text S3; Fig. S5]. We calculate the moment magnitude (*M*) associated with the energy of each clustered event (*Ec*) using the relationship defined by Kanamori, 1983 as:

(Eq. 9)

The AE moment distribution during fracturing experiments has been shown to obey a power law relationship expressed by the Gutenberg-Richter law as [Richter, 1958]:

(Eq. 10)

where *N* is the number of microcrack clusters with moment greater than M, and *a* and *b* are the intercept and the slope of the frequency-magnitude relationship respectively [Fig. S6]. The dimensionless *b-value* shows strong temporal correlation to time-to-failure and has been used widely to predict failure from laboratory scale experiments to large earthquakes [Lei et al., 2007; Meredith et al., 1990]. We employ the seismic moments from clustered microcracks (*M*) and re-arrange the Gutenberg-Richter law to calculate seismic b-value within each strain window as:

(Eq. 11)

The evolution of *b* with axial strain provides a normalized temporal understanding of variations in seismic moment observed during shear fracture growth [Fig. 2e].

1. **Results**

Experimental and numerical analyses show that the damage process in characterized by four distinct phases of microcracking activity: Initiation, Nucleation, Rupture and Frictional Sliding [Amitrano, 2003; Lei et al., 2006; Renard et al., 2017; Vora and Morgan, 2019]. The initiation phase reflects initial distributed microcracking and rupture of pre-existing asperities [Fig. 1a]. The nucleation phase involves sub-critical growth of the microcrack population [Fig. 1b]. The rupture phase corresponds to accelerated growth of the accelerated growth of the ultimate fracture along one or more incipient fracture planes [Fig. 1c]. The frictional sliding phase represents the sliding of fractured blocks along the developed fracture planes and associated microcracking in gouge [Fig. 1d]. In terms of critical point concepts, failure occurs at peak stress during biaxial tests, represented by the end of the nucleation phase. We identify precursory signatures of critical failure by analyzing variations in calculated deformation indicators in the nucleation phase. The evolution of damage indicators in the rupture phase and frictional sliding phase allows for analysis of post-failure characteristics in comparison to precursory signatures.

* 1. **Evolution of Deformation Indicators in Berea Sandstone at 10 MPa Confining Pressure**

As a first demonstration of our simulation results, we examine the growth of fractures in Berea Sandstone under a confining pressure of 10 MPa. Critical failure of the sample occurs at a peak stress of 117.72 MPa, occurring at *εa*=0.031 during the biaxial experiment [Fig. 2a]. Stage 1 (initiation) corresponding to *εa*=0-0.022 is characterized by increasing rock strength from 9.79 MPa to 94.67 MPa and a linear stress-strain curve [Fig. 2a]. This initial stage of the biaxial experiment is characterized by very low microcracking activity; we document a total of 14 microcracks in this phase of this experiment. The low microcracking rate with respect to axial strain results in small values of microcracking variance ranging from 0 to 2.1 [Fig. 2b]. Six of the total 14 microcracks generated during fracture initiation occur in shear mode, resulting in a shear fraction ranging from zero to 0.33 [Fig. 2b] . While initiation stage corresponds to low microcracking activity, the microcracks generated are distributed widely through the sample [Fig. 1a], resulting in relatively high values of fractal dimension of microcracks increasing from zero to 1.73 [Fig. 2c]. We calculate that cumulative AE energy released during fracture initiation is 1.86 J [Fig. 2d], and the associated AE energy variance ranges from zero to 0.024 [Fig. 2e]. Seismic b-values calculated from clustered microcracks exhibit high values ranging from zero to 1.58 in the initiation phase of the experiment [Fig. 2e].

Stage 2 (nucleation) corresponding to *εa*=0.022-0.031 is characterized by increasing rock strength from 94.67 MPa to 117.72 MPa and a non-linear stress-strain curve [Fig. 2a]. The nucleation stage is characterized by very high microcracking activity; we document a total of 394 microcracks in this phase of this experiment. The high microcracking rate with respect to axial strain results in large values of microcracking variance, which increase from 3.6 to 1047.9 [Fig. 2b]. 118 of the total 394 microcracks are generated during the nucleation phase are in shear mode. We calculate a shear fraction ranging from 0.30 to 0.46, with peak shear fraction occurring at *εa*=0.028 prior to critical failure at *εa*=0.031. The microcracking activity in the nucleation phase is localized, resulting in the formation of the primary shear fracture [Fig. 1b]. As a result of localized microcracking, we calculate a decline in the fractal dimension of microcracks from 1.76 to 1.38 [Fig. 2c], with the minimum values occurring at critical failure at *εa*=0.031. We calculate that cumulative AE energy released during fracture nucleation is 48.38 J [Fig. 2d], and the associated AE energy variance shows an increasing trend, with values ranging from 0.1 to 14.64 [Fig. 2e]. Seismic b-values calculated from clustered microcracks exhibit a decline in values from 1.55 to 0.97 in the nucleation phase of the experiment [Fig. 2e]. The minimum value of *b* occurs at critical failure, corresponding to *εa*=0.031 [Fig. 2e].

Stage 3 (rupture) corresponding to *εa*=0.031 to 0.056 is characterized by declining rock strength from 117.72 MPa to 47.61 MPa [Fig. 2a]. The rupture stage is characterized by high but declining microcracking activity; we document a total of 863 microcracks in this phase of this experiment. The high but declining microcracking rate with respect to axial strain results in values of microcracking variance ranging from 98.93 to 1327.3 [Fig. 2b]. The peak microcracking variance occurs at *εa*=0.033 occurring shortly after critical failure (*εa*=0.031). 131 of the total 863 microcracks are generated during the rupture phase are in shear mode. We calculate a steady decline in shear fraction from 0.30 at *εa*=0.031 to 0.07 at *εa*=0.056 [Fig. 2b]. The microcracking activity in the rupture phase is localized around the emergent shear fracture and associated conjugate fractures [Fig. 1c]. As a result of increased gouge deformation around primary fracture and the formation of conjugate fractures, we observe an increase in fractal deformation from the nucleation phase between *εa*=0.031 – 0.034. We calculate relatively constant values of fractal dimension of microcracks ranging from 1.44 to 1.57 in the rupture phase [Fig. 2c]. We calculate that cumulative AE energy released during fracture initiation is 84.98 J [Fig. 2d], and the associated AE energy variance ranges from 0.71 to 19.99 [Fig. 2e]. AE energy variance shows a systematic decline after attaining peak value of 19.99 at *εa*=0.033, coinciding with the peak microcracking variance and preceded by critical failure point at *εa*=0.031.Seismic b-values calculated from clustered microcracks range from 1.07 to 1.57, exhibiting larger magnitudes than the suppressed values calculated at critical point [Fig. 2e].

Stage 4 (frictional sliding) corresponding to *εa*=0.057-0.103 is characterized by relatively constant residual stress ranging from 45.22 MPa to 51.85 MPa [Fig. 2a]. The frictional sliding stage is characterized by low and constant microcracking activity; we document a total of 398 microcracks in this phase of this experiment. The low microcracking rate with respect to axial strain results in slow decay in microcracking variance from 128.1 to 8.49 [Fig. 2b]. 17 of the total 381 microcracks are generated during the frictional sliding phase are in shear mode, resulting in a shear fraction ranging from 0.01 to 0.08 [Fig. 2b]. The microcracking activity in the frictional sliding phase is localized around the fully developed fractures [Fig. 1d]. As a result of localized gouge deformation around the developed fractures, we observe an increase in fractal deformation from the rupture phase. We calculate relatively constant values of fractal dimension of microcracks ranging from 1.30 to 1.56 in the frictional sliding phase [Fig. 2c]. We calculate that cumulative AE energy released during fractional sliding is 26.58 J [Fig. 2d], and the associated AE energy variance ranges from 0.04 to 0.88 [Fig. 2e], exhibiting a declining trend with axial strain. Seismic b-values calculated from clustered microcracks range from 0.98 to 1.54, exhibiting a relatively noisy pattern in the frictional sliding phase of the experiment [Fig. 2e].

The documented damage indicators demonstrate distinct strain-to-failure characteristics over the biaxial experiment on Berea Sandstone analog under 10 MPa confining pressure. The calculated microcracking variance (*MCvar*) trend exhibits a sharp increase pre-failure from 2.1 at *εa*=0.022 to 984.54 at *εa*=0.031, attains maximum value of 1327.3 at *εa*=0.033 immediately after critical point, and declines steadily post-failure to values ranging from 10.71 to 52.04 [Fig. 2b]. The calculated shear fraction trend exhibits a peak value of 0.46 at *εa*=0.024 preceding critical point and declines steadily post-failure to low values of 0.01 – 0.08 [Fig. 2b]. The calculated fractal dimension trend exhibits high values of 1.53 – 1.72 pre-failure, a sharp decline to 1.39 at critical point (*εa*=0.031), and rebounds to relatively steady values of 1.41 – 1.51 [Fig. 2c]. The calculated energy variance trend exhibits a sharp increase pre-failure from 0.024 at *εa*=0.022 to 12.26 at *εa*=0.031, attains maximum value of 19.89 at *εa*=0.033 immediately after critical point, and declines steadily post-failure to values ranging from 0.11 to 0.87 [Fig. 2e]. The calculated seismic b-value trend exhibits high pre-failure values ranging from 1.01 to 1.58 , attains a minimum value of 0.97 at critical point (*εa*=0.031) and rebounds to higher values ranging from 1.07 to 1.54 post-failure [Fig. 2e].

* 1. **Effect of Confining Pressure on Deformation Indicators**

To evaluate the effect of confining pressure, we examine calculated deformation indicators during biaxial tests under confining pressures of 0, 20 and 45 MPa. To normalize the varying critical point character of Berea sandstone with confining pressure, we calculate the deformation indicators as functions of axial strain to critical failure. Axial strain to critical failure (*εcf*) is a continuous function calculated as

(12)

where *εamax* is the axial strain corresponding to the peak axial stress during an individual biaxial experiment. Thus, negative values of *εcf* correspond to pre-failure stages (initiation and nucleation), positive values of *εcf* indicate post-failure stages (rupture and frictional sliding) and *εcf*=0 corresponds to critical failure.

The microcracking variance (*MCvar*) calculated during biaxial test under 0 MPa confining pressure exhibits pre-failure increase from 0.17 at *εcf*=-0.014 (*εa*= 0.014) to a peak value of 1444.9 at critical failure (*εcf*=0; *εa*=0.029), and a post-failure decline during rupture to 28.18 at *εcf*=0.018 (*εa*=0.047), decaying to a final value of 2.4 at *εcf*=0.074 (*εa*=0.103) [Fig. 3a]. Similarly, *MCvar* calculated during biaxial test under 20 MPa confining pressure exhibits pre-failure increase from 0.1 at *εcf*=-0.014 (*εa*= 0.018) to a peak value of 714.84 at critical failure (*εcf*=0; *εa*=0.033), and a post-failure decline during rupture to 31.56 at *εcf*=0.036 (*εa*=0.069), decaying to a final value of 14.49 at *εcf*=0.074 (*εa*=0.103) [Fig. 3a]. Finally, *MCvar* calculated during biaxial test under 45 MPa confining pressure exhibits pre-failure increase from 0.17 at *εcf*=-0.024 (*εa*= 0.016) to a peak value of 470.23 at critical failure (*εcf*=0; *εa*=0.041), and a post-failure decline during rupture to 43.15 at *εcf*=0.031 (*εa*=0.072), increasing to a final value of 105.83 at *εcf*=0.074 (*εa*=0.103) [Fig. 3a]. Over confining pressures of 0 – 45 MPa, our results show that microcracking variance behaves as a reliable deformation indicator with peak microcracking variance coinciding with the critical point. Our results show that as confining pressure on rock increases, magnitude of calculated microcracking variance declines and post-failure decay to residual values is slower with respect to axial strain.

The shear fraction (*SF*) calculated during biaxial test under 0 MPa confining pressure exhibits pre-failure increase from 0 at *εcf*=-0.014 (*εa*= 0.014) to a peak value of 1.03 prior to critical failure (*εcf*=-0.001; *εa*=0.028) and a post-failure decline during rupture to 0.022 at *εcf*=0.018 (*εa*=0.047), decaying to a final value of 0.019 at *εcf*=0.074 (*εa*=0.103) [Fig. 3b]. Similarly, *SF* calculated during biaxial test under 20 MPa confining pressure exhibits pre-failure increase from 0.24 at *εcf*=-0.014 (*εa*= 0.018) to a peak value of 0.88 prior to critical failure (*εcf*=-0.008; *εa*=0.025) and a post-failure decline during rupture to 0.08 at *εcf*=0.036 (*εa*=0.069), decaying to a final value of 0.05 at *εcf*=0.074 (*εa*=0.103) [Fig. 3b]. Finally, *SF* calculated during biaxial test under 45 MPa confining pressure exhibits pre-failure increase from 0.50 at *εcf*=-0.024 (*εa*= 0.016) to a peak value of 0.96 prior to critical failure (*εcf*=-0.013.; *εa*=0.028) and a post-failure decline during rupture to 0.26 at *εcf*=0.031 (*εa*=0.072), increasing to a final value of 0.24 at *εcf*=0.074 (*εa*=0.103) [Fig. 3b]. Over confining pressures of 0 – 45 MPa, our results show that shear fraction behaves as a consistent deformation indicator with peak shear fraction occurring prior to critical failure. Our results show that as confining pressure on rock increases, peak shear fraction increases and axial strain between peak shear fraction and critical point increases.

The fractal dimension (*D2*) calculated during biaxial test under 0 MPa confining pressure exhibits pre-failure decline from the peak value of 1.66 at *εcf*=-0.006 (*εa*=0.023) to 1.35 at critical failure (*εcf*=0; *εa*=0.029), and relatively constant values of 1.23 – 1.48 post-failure [Fig. 3c]. Similarly, *D2* calculated during biaxial test under 20 MPa confining pressure exhibits pre-failure decline from the peak value of 1.83 at *εcf*=-0.004 (*εa*=0.028) to 1.42 prior at critical failure (*εcf*=0; *εa*=0.035), and relatively steady values of 1.46-1.78 post-failure [Fig. 3c]. Finally, *D2* calculated during biaxial test under 45 MPa confining pressure exhibits pre-failure decline from the peak value of 1.83 at *εcf*=-0.017 (*εa*=0.023) to 1.46 at critical failure (*εcf*=0; *εa*=0.041), and relatively steady values of 1.45-1.63 post-failure [Fig. 3c]. Over confining pressures of 0 – 45 MPa, our results show that *D2* behaves as a consistent deformation indicator with a sharp decline in values of *D2* occurring at critical failure point. Our results show that *D2* values increase with confining pressure on rock.

The AE energy variance (*AEvar*) calculated during biaxial test under 0 MPa confining pressure exhibits pre-failure increase from 0.0005 at *εcf*=-0.014 (*εa*= 0.014) to a peak value of 7.57 prior to critical failure at *εcf*=-0.001 (*εa*=0.028), and a post-failure decline during rupture to 0.13 at *εcf*=0.018 (*εa*=0.047), decaying to a final value of 0.01 at *εcf*=0.074 (*εa*=0.103) [Fig. 3d]. Similarly, *AEvar* calculated during biaxial test under 20 MPa confining pressure exhibits pre-failure increase from 0.004 at *εcf*=-0.014 (*εa*= 0.018) to a peak value of 23.64 at critical failure (*εcf*=0; *εa*=0.033), and a post-failure decline during rupture to 0.69 at *εcf*=0.036 (*εa*=0.069), decaying to a final value of 0.09 at *εcf*=0.074 (*εa*=0.103) [Fig. 3d]. Finally, *AEvar* calculated during biaxial test under 45 MPa confining pressure exhibits pre-failure increase from 0.004 at *εcf*=-0.024 (*εa*= 0.016) to a peak value of 20.79 at critical failure (*εcf*=0; *εa*=0.041), and a post-failure decline during rupture to 1.74 at *εcf*=0.031 (*εa*=0.072), increasing to a final value of 7.62 at *εcf*=0.074 (*εa*=0.103) [Fig. 3d]. Over confining pressures of 0 – 45 MPa, our results show that AE energy variance behaves as a reliable deformation indicator with peak microcracking variance coinciding with the critical point. Our results show that as confining pressure on rock increases, AE energy variance increases and post-failure decay to residual values is slower with respect to axial strain.

1. **Discussions**

We conduct a temporal analysis of microcracking during biaxial tests on Berea sandstone analogs over confining pressures ranging from 0 to 45 MPa. We employ microcracking rate, microcracking mode, spatial distribution of microcracks, acoustic energy from microcracking and range of seismic moments to derive five key deformation indicators. The five independent deformation indicators are scale-independent and can be derived from laboratory AE and datasets of earthquake sequences. Each of the five deformation indicators is a function of strain-to-failure and can be treated as an indicator of the critical point.

The calculated microcracking variance (*MCvar*) and associated acoustic energy variance (*AEvar*) account for the temporal variations in microcracking rate and associated elastic energy released. Our results indicate that *MCvar* and *AEvar* shows sharp pre-failure increase, a peak value at or slightly after critical point, and a slow decay post-failure [Fig. 2, Fig. 3]. This sharp increase in microcracking variance and associated energy around critical point is indicative of the high microcracking rate observed around the critical point in our biaxial experiments [Fig. 2]. The heightened rates of microcracking and associated energy release preceding critical failure have been documented by laboratory AE and numerical studies [Rouet-Leduc et al., 2017; Lei et al., 2004; Lisjak et al., 2013]. Additionally, our results show that the variance of microcracking declines with confining pressure, exhibiting consistent peak at critical point [Fig. 3a]. However, variance of AE energy increases with confining pressure, exhibiting consistent peak at critical point [Fig. 3d].

The shear fraction (*SF*) accounts for the temporal variations in microcracking source mechanisms. *SF* shows sharp pre-failure increase, attaining peak value prior to critical point, and shows systematic decline post-failure [Fig. 2b, Fig. 3b]. The pre-failure peak in shear fraction indicates the localization of differential stress along asperities within the sample, which is released in the form of acoustic emissions upon the formation of a microcrack. The increase in shear microcracking preceding critical failure have been documented by laboratory and numerical studies [Lei et al., 2004; Fortin et al., 2009; Vora and Morgan, 2019]. Additionally, our results show that over confining pressures of 0 to 45 MPa, shear fraction increases with confining pressure and exhibits consistent strain-to-failure characteristics [Fig. 3b]. T

he fractal dimension (*D2*) accounts for the temporal variations in spatial distribution of microcracks. *D2* shows sharp pre-failure increase, and sharp decline at critical point, and relatively constant values post-failure [Fig. 2c, Fig. 3c]. The pre-failure peak in *D2* indicates distributed microcracking during fracture initiation, followed by localization of microcracks along the emergent shear fracture and conjugate fractures [Fig. 1a]. As a result, we calculate a decline in *D* during the nucleation and rupture stages [Fig. 1b, Fig. 1c]. The pre-failure peak during fracture initiation and following decline in *D* at critical failure has been documented from AE hypocenter locations [Lei et al., 2007; Hirata et al., 1987b]. Additionally, our results show that over confining pressures of 0 to 45 MPa, *D* increases with confining pressure and exhibits consistent strain-to-failure characteristics [Fig. 3c].

The b-value accounts for temporal variations in seismic moment of microcracks. *b-value* exhibits and sharp decline at critical point from relatively larger pre-failure magnitudes, and relatively constant values post-failure [Fig. 2e, Fig. 3e]. Goebel et al., 2017 show that the b-value is an inversely correlated with the localization of differential stress in the rock sample. Several other studies [Weimer and Wyss, 1997; Wyss et al., 2004] show that b-values are low when resistance to fault slip is high. Our results suggest b-value attains a peak value prior to failure, indicating distributed stress and microcracking within the sample [Fig 3e; Fig 1a]. We calculate a decline in b-values as we approach critical failure, indicating localization of differential stress along the emergent fault rupture and an increase in resistance to failure [Fig. 3e; Fig. 1b]. b-values rebound to higher magnitudes post-failure indicating a decline in resistance to deformation [Fig. 3e; Fig. 1c]. The decline in b-values prior to critical failure, and an increase in magnitude after rupture has been observed during rock deformation in the laboratory and during earthquake cycles [Rao and Lakshmi, 2005; Lei et al., 2004; Meredith et al., 1990]. Our results indicate that calculated trends of shear fraction (*SF*) and b-value are inversely correlated [Fig. S7]. This indicates that the b-value is a predictor of localization of shear stresses during fracture growth [Fig. 1]. Shear microcracking results in an increase in range of moment magnitudes, especially those of large magnitudes, resulting in lower b-values [Fig. S6]. Our results show that over confining pressures of 0 to 45 MPa, b values decline with confining pressure and exhibit consistent strain-to-failure characteristics [Fig 3e].

While several studies have analyzed individual time-to-failure indicators, we provide an integrated analysis of deformation indicators utilizing microcracking rate, mode, spatial distribution, energy and moment. Additionally, we quantify the effect of confining pressure over the derived deformation indicators to test their strain-to-failure characteristics. We employ the calculated temporal trends of microcracking variance, shear fraction, fractal dimension, AE energy variance and b-value to predict critical failure in Berea Sandstone using machine learning techniques.

1. **Critical Failure Prediction using Artificial Neural Networks**

We use machine learning techniques to predict stress-to-failure (*σcf*) and strain-to-failure (*εcf*) using deformation indicators calculated from microcracking during biaxial tests of Berea sandstone analogs under confining pressures of 0-45 MPa. Axial stress to critical failure (*σcf*) is a continuous function calculated for each time step as

, if εcf > 0 (13)

, if εcf < 0 (14)

where *σamax* is the peak axial stress corresponding to the critical point of a biaxial experiment. Thus, negative values of *σcf* correspond to pre-failure stages (initiation and nucleation), positive values of *σcf* indicate post-failure stages (rupture and frictional sliding) and *σcf*=0 corresponds to critical failure.

Machine learning offers a variety of algorithms suitable for modeling the non-linear relationship between input data (here characterized by features derived from a time window of microcracking indicators) and corresponding output (stress-to-failure and strain-to-failure). Artificial neural networks (ANN) are quantitative pattern recognition functions that are suitable for failure prediction due to their mathematical non-linearity, error tolerance and their ability to incorporate inputs across different physical units and magnitudes. ANN’s have been used by researchers to forecast catastrophic geologic failure in the form of landslides [Dou et al., 2015], rock fracture [Ouenes, 2000] and earthquakes [Panakkat, 2009]. In our study, we use a particular type of ANN model, known as back propagation neural network (BPNN).

* 1. **Artificial Neural Network Architecture**

The BPNN algorithm uses the gradient-descent algorithm[Goodfellow et al., 2016] to minimize the total error of predicted targets computed by the neural network with respect to the known targets of stress-to-failure and strain-to-failure. The developed BPNN consists of three layers: input, hidden and output [Fig. S8]. The BPNN is developed using guidelines from Goodfellow et al., 2016. Each layer has its corresponding neurons and weights. The input layer (layer *x*) propagates normalized components of the input matrix after assigning synaptic weights (*wxy*) to each connection between the input and output and the hidden layer (layer *y*) The hidden layer consists of consists of six neurons [Fig. S8]. The hidden layer computes outputs corresponding to these weighted sums through a nonlinear tan-sigmoid activation function [Goodfellow et al., 2016]. The hidden layer predicts the output using synaptic weights (*wyz*) assigned to each connection between the hidden layer and the output layer (layer *z*). The neural network iteratively varies connection weights wxy and wyz to optimize fit to desired targets (*σcf* and *εcf*).

The BPNN input is a two-dimensional array *I*, representing damage indicators from nine biaxial tests under confining pressures of 0, 5,10,15,20,30,35,40 and 45 MPa. The columns of *I* correspond to six input features: microcracking variance, shear fraction, fractal dimension, AE energy variance, b-value and confining pressure. The rows of *I* correspond to 91 axial-strain steps for nine individual biaxial tests(91 x 9 = 819 rows). We allocate 15% of the input dataset for training, 15% for validation and 15% for testing of the neural network using random row-wise distribution. The data calculated from biaxial test at confining pressure of 25 MPa is withheld from the training phase to later conduct a blind test and evaluate test the performance of the neural network.

* 1. **Stress-to-Failure prediction**

Over confining pressures of 0 – 45 MPa, our ANN shows good correlation between multivariate inputs and target stress-to-failure (*σcf*) (training R2= 0.98; validation R2= 0.97; testing R2=0.96). The predicted values *σcf* show good match with the target data, with the predictions improving for biaxial tests conducted at higher confining stresses of 15 - 50 MPa [Fig. 5a]. We conduct a blind test by employing the trained and validated ANN to predict the evolution *σcf* during the 25 MPa biaxial test. The values of *σcf* predicted by the ANN show strong correlation with target values (R2=0.91) [Fig. 5b]. The predictions of *σcf* for blind test on dataset acquired during the 25 MPa test exhibit better predictions with respect to target *σcf* values as we approach critical point during the experiment. Pre-failure *σcf* predictions corresponding to *εa*=0.010-0.025 show weak correlation with the target *σcf* data due to low microcracking activity during fracture initiation resulting in fuzzy values for deformation indicators [Fig. S8]. Thus, precursory microcracking indicators can be used with machine learning to predict stress-to-failure during biaxial tests in granular rocks.

* 1. **Strain-to-Failure prediction**

Over confining pressures of 0 – 45 MPa, our ANN shows good correlation between multivariate inputs and target strain-to-failure (*εcf*) (training R2= 0.94; validation R2= 0.92; testing R2=0.90). The predicted values *εcf* show good match with the target data, with the predictions improving for biaxial tests conducted at higher confining stresses of 15 - 50 MPa [Fig. 6a]. We conduct a blind test of the trained and validated ANN to predict the evolution *εcf* during the 25 MPa biaxial test. The values of *εcf* predicted by the ANN show good correlation with target values (R2=0.92) [Fig. 6b]. The predictions of *εcf* for blind test on dataset acquired during the 25 MPa test exhibit better predictions with respect to target *εcf* values as we approach critical point during the experiment. Pre-failure *σcf* predictions corresponding to *εa*=0.010-0.030 show weak correlation with target *εcf* data due to low microcracking activity during fracture initiation. This results in noisy values for deformation indicators and their changes may be imperceptible to the ANN to predict critical failure [Fig. S8]. Post-failure *σcf* predictions corresponding to *εa*=0.085-0.103 show poor correlation with target *εcf* data due to relatively noisy and indistinguishable trends of deformation indicators during the frictional sliding stage of experiments [Fig. 3].Overall, precursory microcracking indicators can be used with machine learning to predict strain-to-failure during biaxial tests in granular rocks.

* 1. **Relative Importance of Damage Indicators**

The ANN iteratively finds correlations between the input deformation indicators and outputs (*σcf* and *εcf*) by iteratively assigning weights to the set of nodes and connections. The weights assigned to nodes and connections depend on the predictive capability of each of the deformation indicators. Thus, we investigate the weights and to the trained and tested ANN’s to understand the relative importance of each input variable. We employ the methodology presented by Garson [1991] to determine the relative importance of each input variable in the network as

, (15)

, (16)

where *Ix* is the importance of input *x*, *n* is the number of inputs (*n*=6), m is the number of hidden neurons (*m*=6), *Σy=1m* *wxywyz* is the sum of product of the final weights of the connections from input neurons to the hidden neurons (*wxy*) with the connections from the hidden neurons to the output neurons (*wyz*), and *RIx* is the relative importance of input *x* as a percentage.

We calculate a range of 10.75%-24.07% for *RI* of six input parameters into the neural network for stress-to-failure prediction [Fig. 7a; Table S1], indicating that all input parameters contribute to improvement of predictions. Our results show that seismic *b-value* and fractal dimension (*D2*) are the most important parameters for stress-to-failure (*σcf*) predictions, accounting for 24.07% of and 21.40% of connection weights respectively [Fig. 7a; Table S1]. Similarly, we calculate a range of 8.65%-30.96% for *RI* of the six input parameters into the neural network for strain-to-failure prediction [Fig. 7b; Table S2], indicating that all input parameters contribute towards improvement of predictions. Our results show that microcracking variance (*MCvar*) and fractal dimension (*D2*) are the most important parameters for strain-to-failure (*εcf*) predictions, accounting for 30.96% and 26.18% of the connection weights [Fig. 7b; Table S2]. Our results show that *MCvar*, *b* and *D2* are the most important predictors for critical failure prediction. However, the calculated relative importance of other input parameters – confining pressure (*CP*), shear fraction (*SF*) and energy variance (*AEvar*) - lie within the same order of magnitude as the primary predictors, indicating the importance for supplementing primary predictors with other independent predictors for failure predictions. Additionally, our methodology reveals that deformation indicators and machine learning can be used in conjunction to facilitate critical failure prediction. Thus, an integrated analysis of independent deformation indicators employing microcracking rate, mode, energy and seismic moment improves critical failure prediction.

Our numerical study demonstrates that damage creation and catastrophic fracture of faults is characterized by statistical variations in microcracking. Explicit precursory signatures are observed in the nucleation phase preceding the dynamic rupture of heterogenous faults [Fig. 2]. Due to the self-similarity in geological structure, several of the deformation indicators in our study have been utilized individually to predict fault slip and earthquakes. Several studies have shown the decline in b-values of foreshocks in comparison to long-term seismicity of a region [Meredith et al., 1990], and this character has been utilized for earthquake prediction with moderate success [Asencio-Cortès et al., 2016; Florido et al., 2015]. Our results show that there are several independent precursory signatures of critical failure and employing multiple independent deformation indicators as inputs for machine learning algorithms can facilitate improved failure prediction.

1. **Conclusions**

We use the Discrete Element Method to analyze the signatures of critical point in Berea sandstone and develop a machine learning tool to predict failure. We document the growth of shear fractures during simulated biaxial tests on calibrated numerical analogs of Berea sandstone under confining pressures of 0 MPa to 45 MPa. We track the abundance, location and energy associated with emergent microcracks during the deformation tests to derive five key scale-independent deformation indicators – variance of microcracking (*MCvar*), shear fraction of microcracks (*SF*), fractal dimension of microcracks (*D2*), acoustic energy variance (*AEvar*) and seismic *b-value*. Over confining pressures of 0 MPa to 45 MPa, each deformation indicators shows typical strain-to-failure characteristics. Pre-failure microcracking in Berea Sandstone is characterized by: 1) increase in microcracking variance of one to two orders of magnitude, 2)peak shear microcrack fraction ranging from 0.15 to 0.95, 3) a decline in fractal dimension of microcracks from 1.65–1.85 to 1.35–1.55 at critical point, 4) increase in acoustic energy variance of an order of magnitude, and 5) a decline in b-values from 1.4–2.3 to 0.8–1.3 at critical point.

We extend our study to develop a predictive tool for critical failure using the derived deformation indicators and machine learning techniques. Temporal trends of the derived deformation indicators and confining pressure are used as input into an artificial neural network (ANN) to predict stress-to-failure and strain-to-failure in Berea Sandstone. Over confining pressures of 0 MPa to 45 MPa, the ANN shows strong predictive capability of stress-to-failure (R2=0.94) and strain-to-failure (R2=0.91). Our results indicate that microcracking variance (*MCvar*), fractal dimension of microcrack distribution (*D2*) and seismic *b-value* are key predictors of critical failure. Additionally, our results document beneficial contribution of AE energy variance (*AEvar*) and confining pressure towards failure prediction, supporting the enhanced value of an integrated analysis of precursory signatures to critical point. Thus, we show that statistical, scale-independent deformation indicators can be combined with machine learning to predict failure across scales – from laboratory deformation experiments to earthquakes.

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**Tables**

Table 1: Microparameters used in DEM modeling of Berea Sandstone.

|  |  |
| --- | --- |
| Micromechanical Parameter | Berea Sandstone |
| Young’s Modulus of Bonds (*Eb*)  *GPa* | 0.2 |
| Shear Modulus of Bonds (G*b*)  *GPa* | 0.5 |
| *σc/σt* | 10 |
| Tensile Strength of Bonds (T*b*)  *MPa* | 30 |
| Cohesion of Bonds (*Cb*)  *MPa* | 300 |
| Shear Modulus of Particles (*Gp*)  *GPa* | 29 |
| Poisson’s Ratio of Particles (*νp*) | 0.33 |
| Interparticle friction (*µp*) | 0.4 |

Table 2: Macromechanical behavior of models calibrated to Berea Sandstone.

|  |  |  |
| --- | --- | --- |
| Macromechanical Property | Model Values for Berea Sandstone | Experimental Values for Berea Sandstone |
| Unconfined Compressive Strength (UCS)  *MPa* | 89.37 | 95.00 |
| Young’s Modulus (*E*)  *GPa* | 6.48 | 8.00 |
| Mohr-Coulomb Cohesion (*C*)  *MPa* | 28.03 | 26.10 |
| Mohr Coulomb Slope (*µ*) | 0.44 | 0.49 |

**Figure Captions**

**Figure 1:** The growth of a primary shear fracture and conjugate fractures in Berea sandstone during biaxial test under a confining pressure of 10 MPa. The growth of fractures occurs through the coalescence of shear and tensile microcracks, exhibited at axial strain of (a) 0.022, (b) 0.031, (c) 0.056, and (d) 0.103. The spatial distributions of microcracks are referenced back to their initial position at the onset of the biaxial test to maintain a consistent framework across biaxial experiments of varying confining pressures.

**Figure 2:** Evolution of microcracking and derived in Berea sandstone during biaxial compression test under confining pressure of 10 MPa. (a) Applied axial stress and microcracking in shear and tensile modes documented as a function of axial strain. Strain markers 1-4 indicate deformation stages (initiation, nucleation, rupture and frictional sliding) and correspond to axial strain of 0.022, 0.031, 0.056 and 0.103, complementing the microcrack distributions in Fig. 1. (b) Deformation indicators microcrack variance (*MCvar*) and shear fraction (*SF*) exhibit an increase in magnitude prior to critical point (c) Deformation indicator fractal dimension (*D2*) derived from moving axial exhibits a decline prior to critical point. (d) Calculated energy of acoustic emissions (AE) from shear and tensile microcracks documented as a function of axial strain. (e) Deformation indicator AE energy variance (*AEvar*) exhibits an increase in magnitude while b-value exhibits a decline prior to critical failure.

**Figure 3:** Temporal evolution of derived deformation indicators as a function of strain-to-failure (εcf) during biaxial tests on Berea sandstone under confining pressures of 0, 20 and 45 MPa. (a) Microcracking variance (*MCvar*) declines with confining pressure and exhibits consistent peak at critical point. (b) Shear fraction (*SF*) increases with confining pressure and exhibits consistent peak prior to critical point. (c) Fractal dimension (*D2*) increases with confining pressure and exhibits consistent decline at critical point. (d) Acoustic Energy variance (*AEvar*) increases with confining pressure and exhibits consistent peak at critical point. (e) Seismic *b-value* declines with confining pressure and exhibits consistent decline at critical point.

**Figure 4:** Stress-to-failure predictions for Berea sandstone using the developed artificial neural network during (a) training and testing phase using deformation indicators derived from biaxial tests under confining pressure of 0,5,10,15,20,30,35,40 and 45 MPa (R2=0.97) (b) blind prediction using deformation indicators derived from biaxial tests under confining pressure of 25 MPa (R2=0.91).

**Figure 4:** Strain-to-failure predictions for Berea sandstone using the developed artificial neural network during (a) training and testing phase using deformation indicators derived from biaxial tests under confining pressure of 0,5,10,15,20,30,35,40 and 45 MPa (R2=0.91) (b) blind prediction using deformation indicators derived from biaxial tests under confining pressure of 25 MPa (R2=0.92).

**Figure 6:** Relative Importance of input parameters of artificial neural network calculated from connection weights of trained neural network. (a) Seismic *b-value* and fractal dimension of microcrack distribution (*D2*) are primary predictors for stress-to-failure prediction, and (b) Microcracking variance (*MCvar*) and fractal dimension of microcrack distribution (*D2*) are primary predictors for strain-to-failure prediction.