Using AE based Machine Learning Approaches to Forecast Rupture during Rock Deformation Laboratory Experiments

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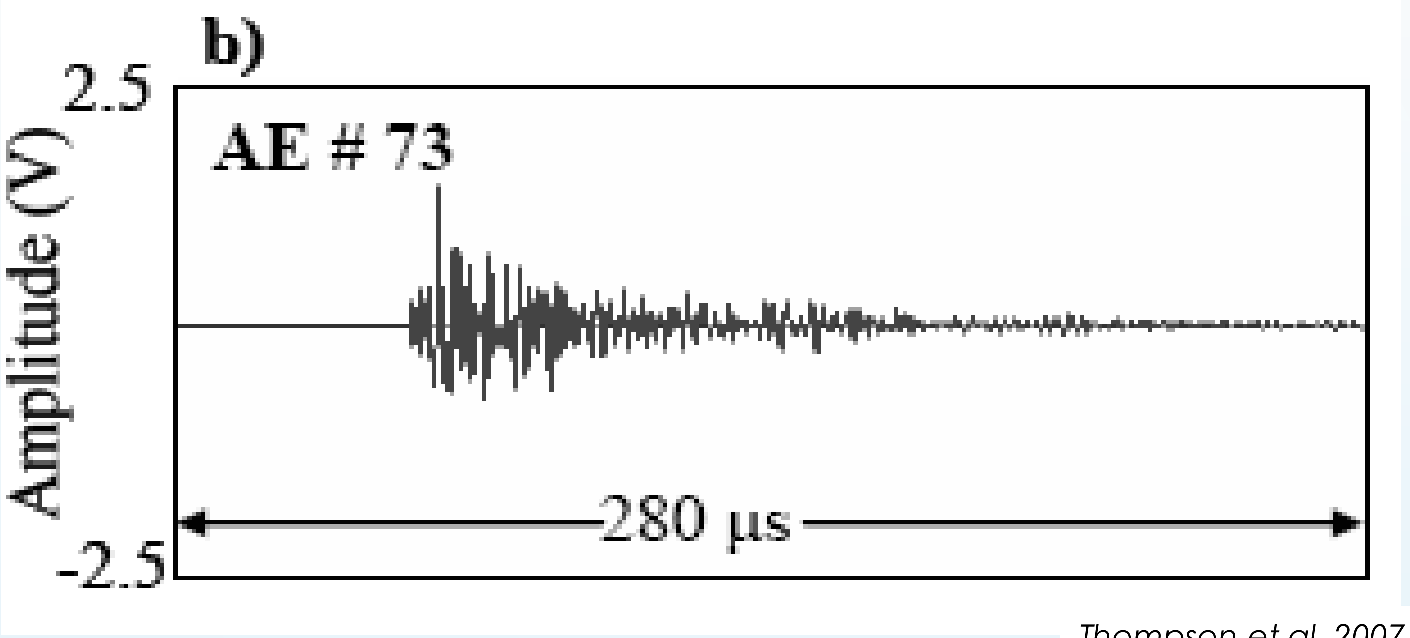
What's an ACOUSTIC EMISSION (AE) and what can it tell us ?



Thompson et al. 2007

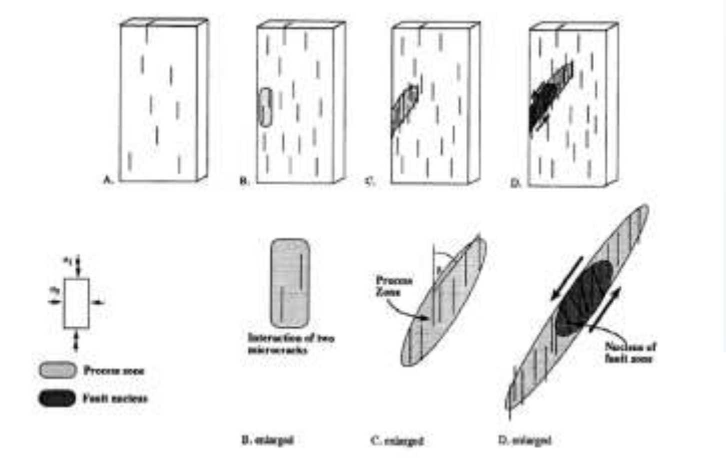
An acoustic emission corresponds to:

- the HF radiated acoustic waves emitted by a fast propagating crack
- average magnitudes Mw : -8 to -4, ie femto to nano earthquakes
- Corner frequency 1MHz ~ crack is only a few mm long (if Vr ~ Vrayleigh)
- Displacement ~ few tens of microns

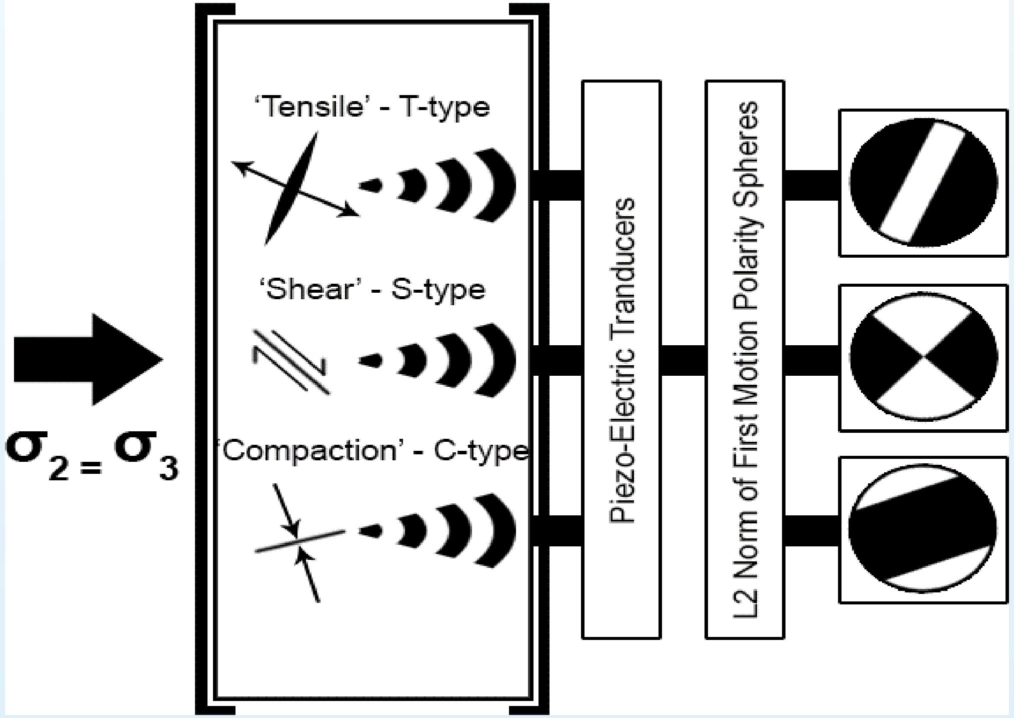
An acoustic emission does not correspond necessarily to a macroscopic slip event, but rather to off fault micromechanical damage

Motivation and aim

- As crack damage nucleates, grows and coalesces into a fault zone, AE-derived properties suggest that strain localization is repeatable and forecastable. However, due to the inherent **heterogeneity** of rocks and the range of **effective pressures**, finding a full prediction of rupture mechanisms from AE analysis over different experimental conditions is still an open goal;
- The objective of this work is to **quantitatively classify phases of deformation/fracturing** on physico-mechanical parameters and develop a model that functions over a range of confining pressures
- We consider the **AE rates, amplitudes** and the derived **source mechanisms** to constraint the stress-strain regime and the **seismic scattering** and **average velocity structure** to define the **evolving medium state** over time as the most important attributes for the neural network model to learn.



Reches and Lockner, JGR 99, 1994.



Materials investigated

King et al., 2021

- **Alzo granite (AG)** is typical of the white granites found in North-Western Italy. It is a medium-grained, plutonic rock comprising quartz, feldspar, and a high biotite content. Crystal sizes range between 2.5 and 6 mm for the biotite and 4–9 mm for the quartz and feldspars. Porosity values are characteristically low at less then 1%.
- **Darley Dale Sandstone (DDS)** comes from a quarry in Derbyshire, UK is a brown-yellow, feldspathic sandstone with a modal composition of quartz (69%), feldspars (26%), clay (3%), and mica (2%). Grain sizes varying from 100 to 800 μm. Porosity of 13-14%

Experimental conditions

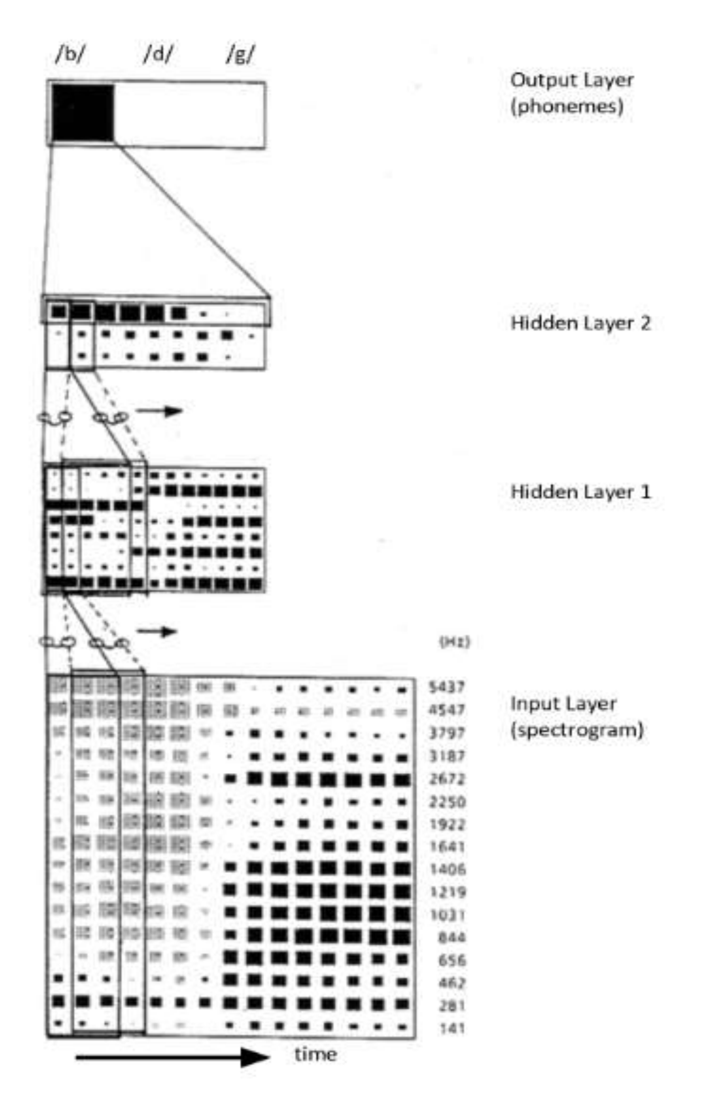
4x10cm samples; 12 AE sensors

Confining pressures = 5, 10, 20 and 40 MPa

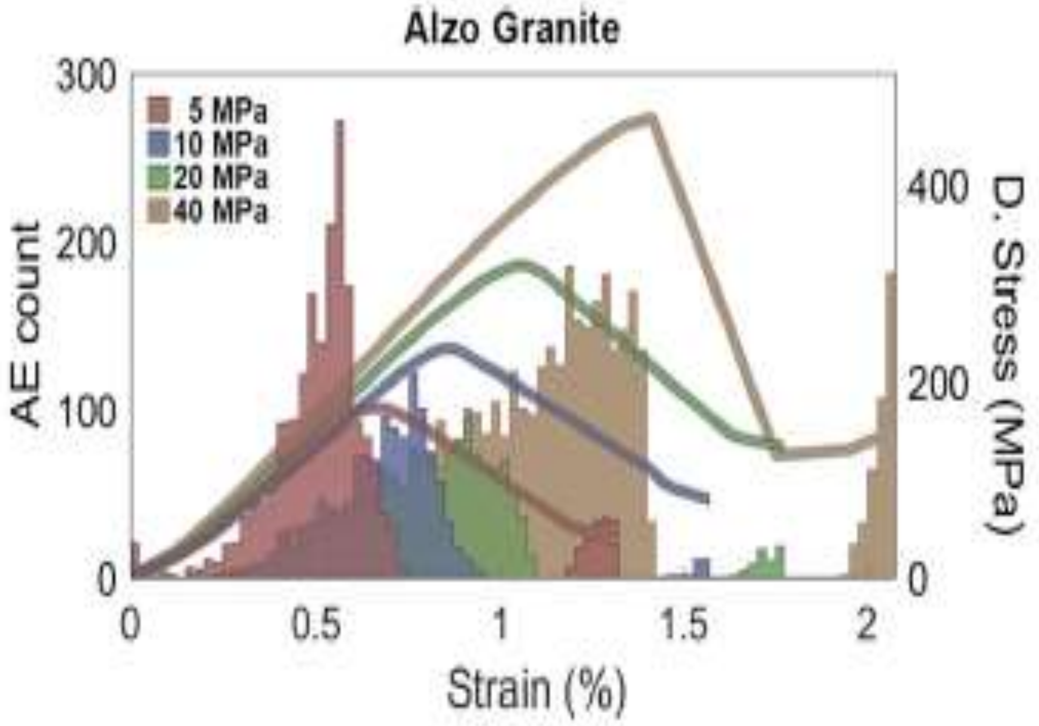
Strain rate = 3.6mm/h

Networks Parametrisation and Analysis Method

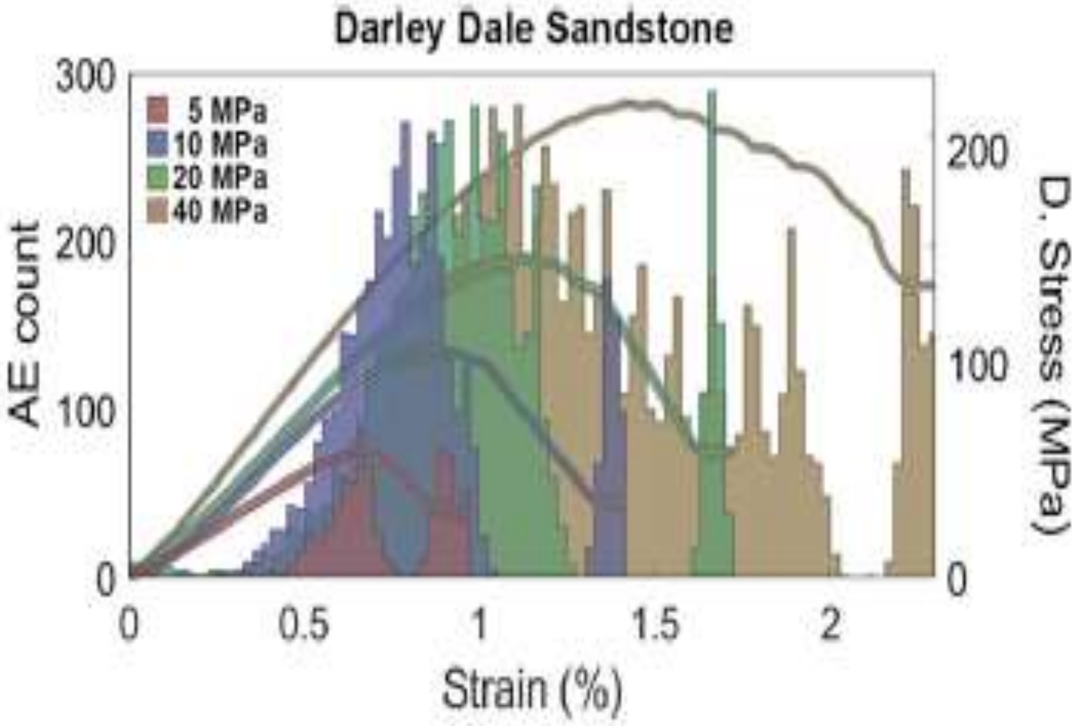
- Time delay neural networks (TDNNs) are *automated signal classification techniques* that are designed with the purpose of identifying patterns and trends in shift-invariant timeseries data without explicitly knowing the beginning or the end of a signal;
- TDNNs are a form of *recurrent neural network (RNN)* that models the propagation characteristics of timeseries data;
- By constructing models of the key elements of audio, or elastic vibrations in the case of seismology, they have already been used to *recognise signal onsets in AE data* (King et al., SRL, 2020).
- As training parameters for the TDNN, we selected 5 key parameters 1) AE event rate, 2) AE amplitude, 3) AE source mechanism, 4) seismic scattering and 5) seismic velocity.
- Discrete parameters are resampled onto a common timeseries and high-pass filtered to simplify the data for the modelling. These timeseries are then classified by the TDNN as variations in stress and strain (target parameters).



Mechanical data and AE time occurrence



King et al., 2021



King et al., 2021

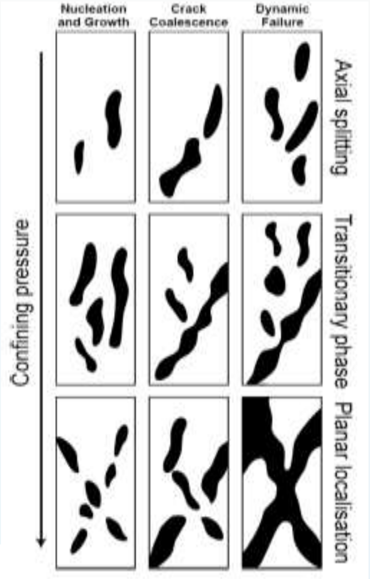
Source Mechanism Percentages vs increasing Strain

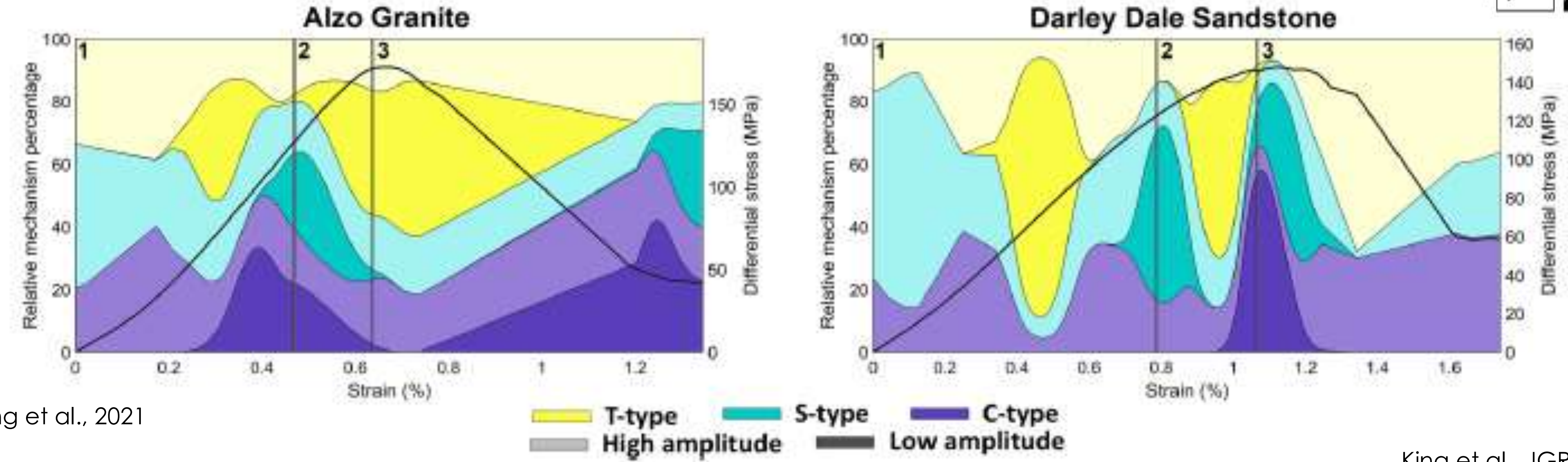
1 - *Single or multi-periodic* fracturing related to initial patchiness of dilatant regions. Cycles begin as dominance of C- and S-type fracturing;

2 - *Transitioning* to bursts of T-type events and crack coalescence;

3 - Single/Multiple episodes of *crack growth* and dynamic failure.

4 – *Low amplitude* C and S-type prior to bursts of T-type events well represent foreschocks

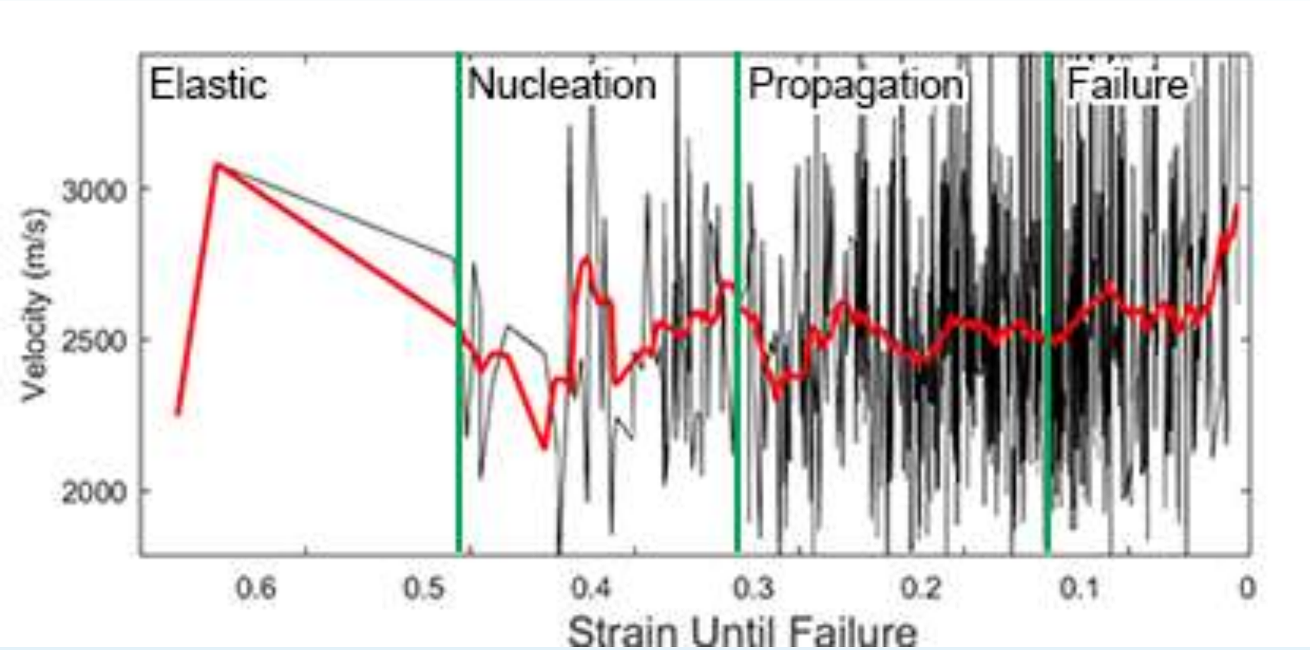




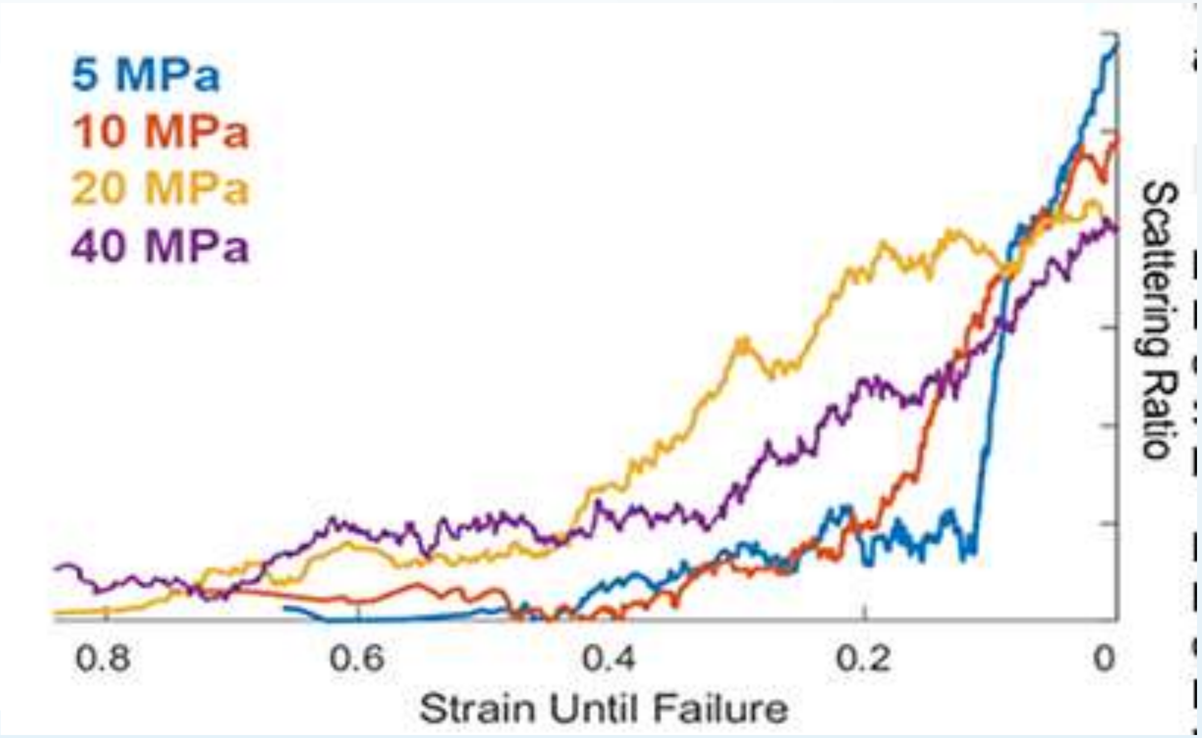
King et al., 2021

King et al., JGR, 2021

Velocity structure and Scattering vs. incremental strain



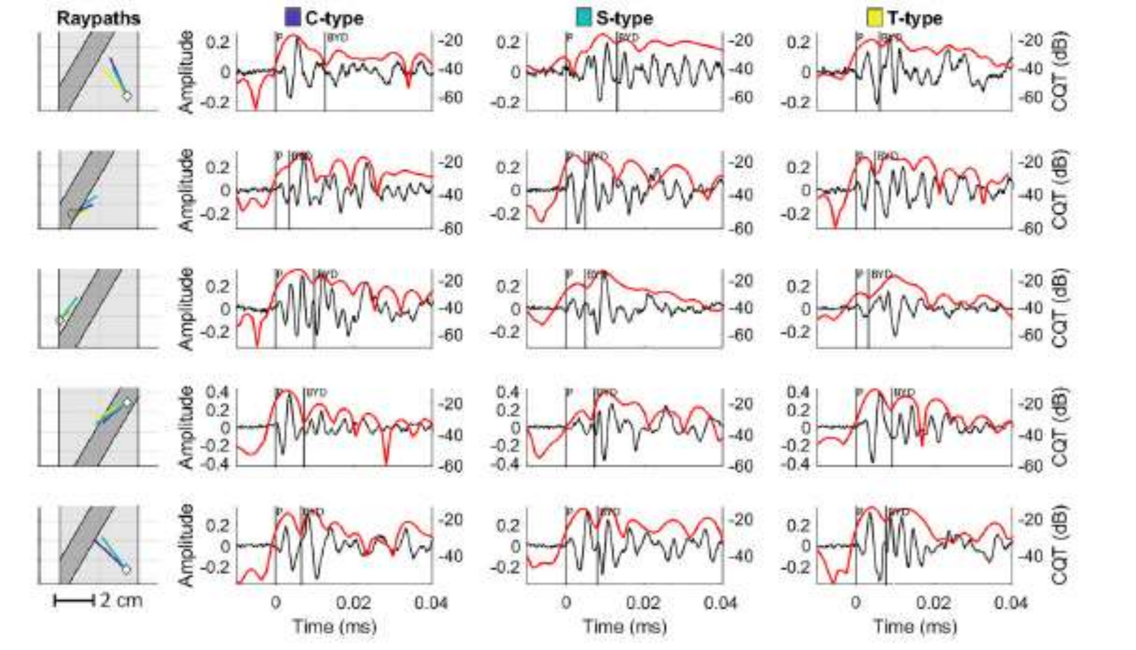
Vinciguerra et al., 2021



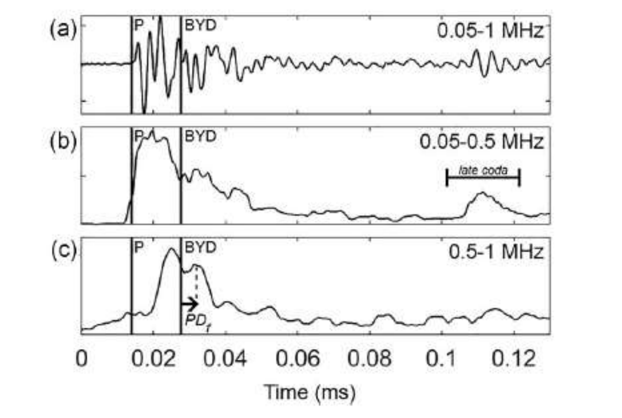
Key additional parameters for deformation vs. incremental strain:

- Velocity structure is derived from the AE arrival time and hypocentral distance
- Scattering ratio is the ratio of low frequency energy to high frequency content in the AE coda

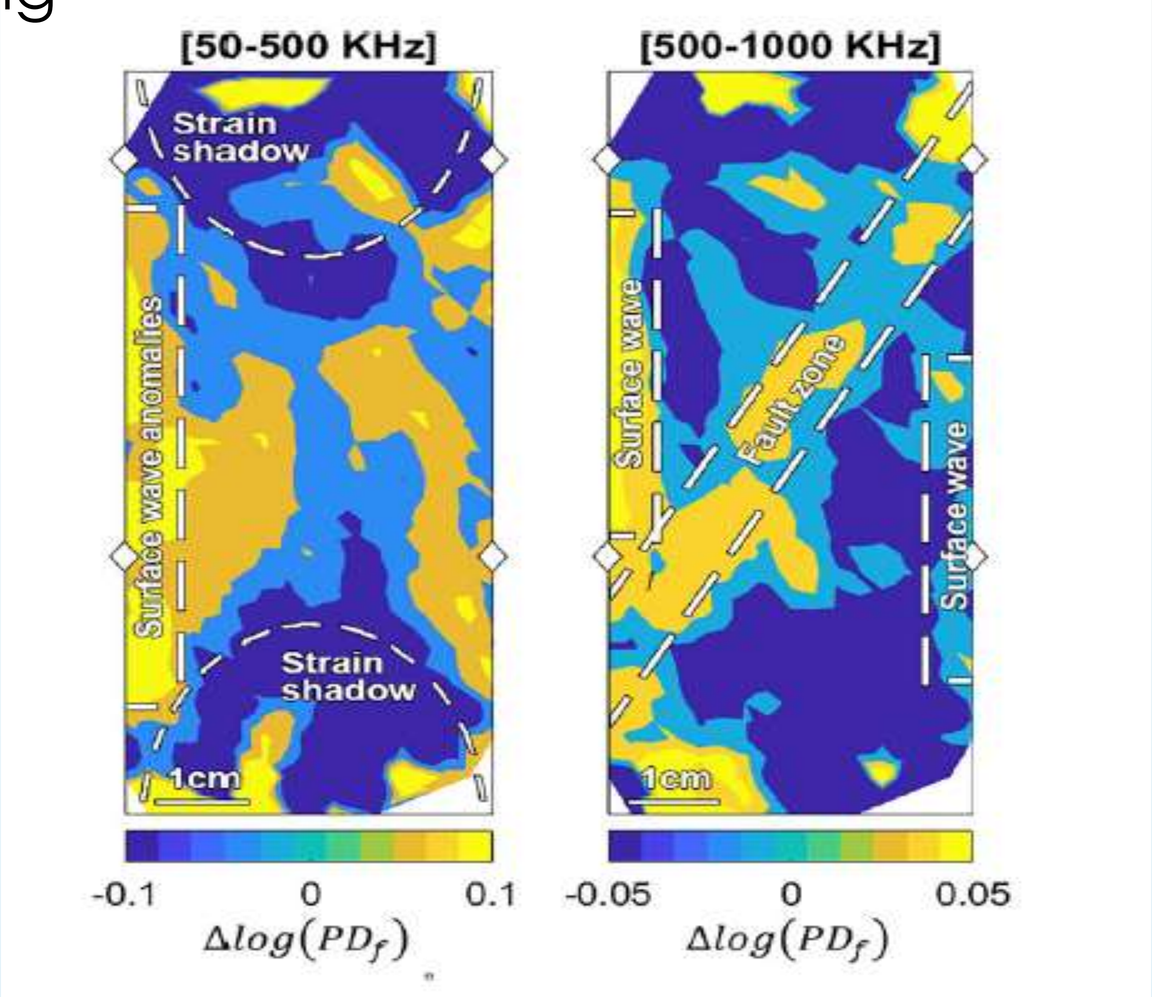
Seismic Scattering



Waveform per type of mechanism



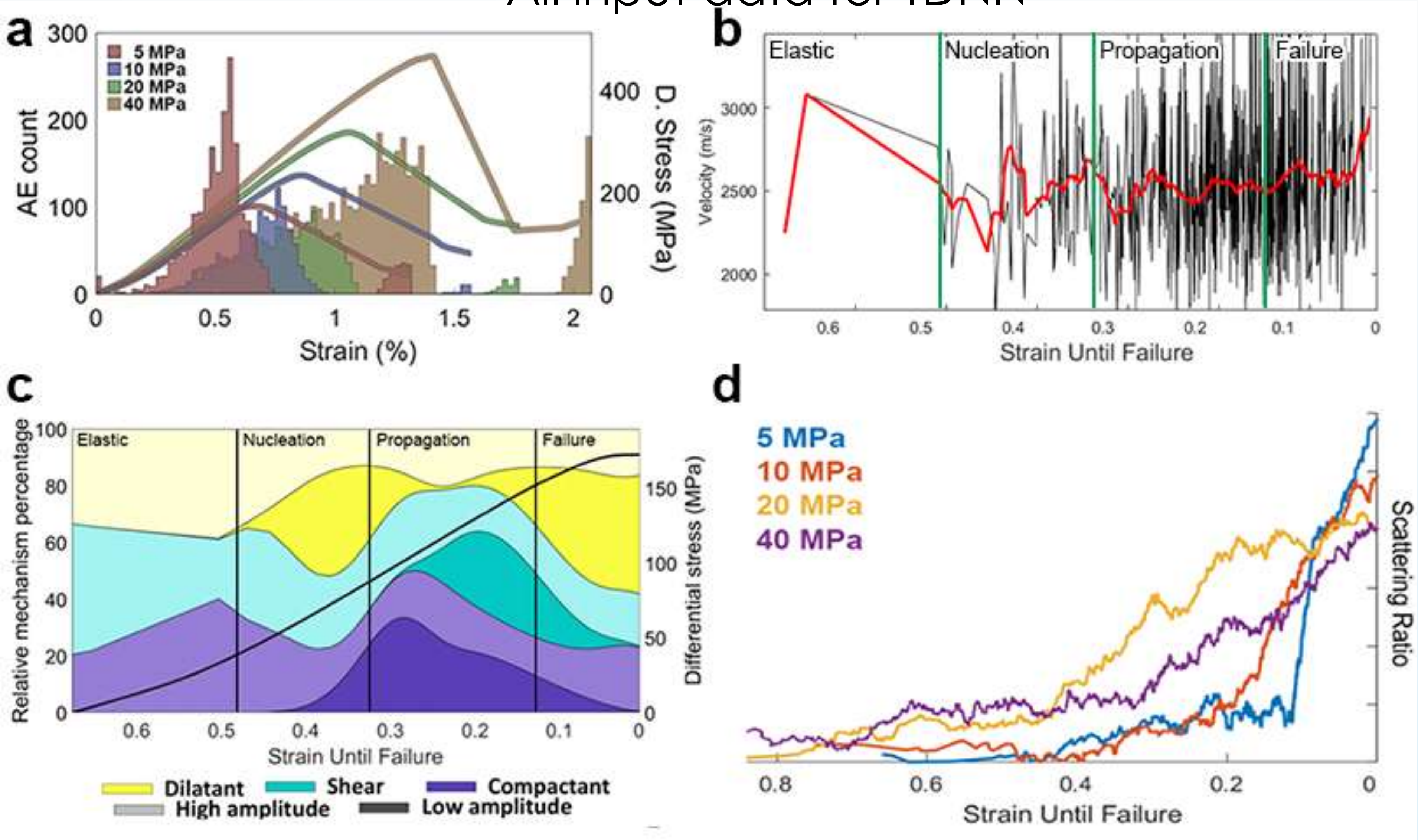
P wave and Beyond the Direct Wave (BYD) at different frequencies



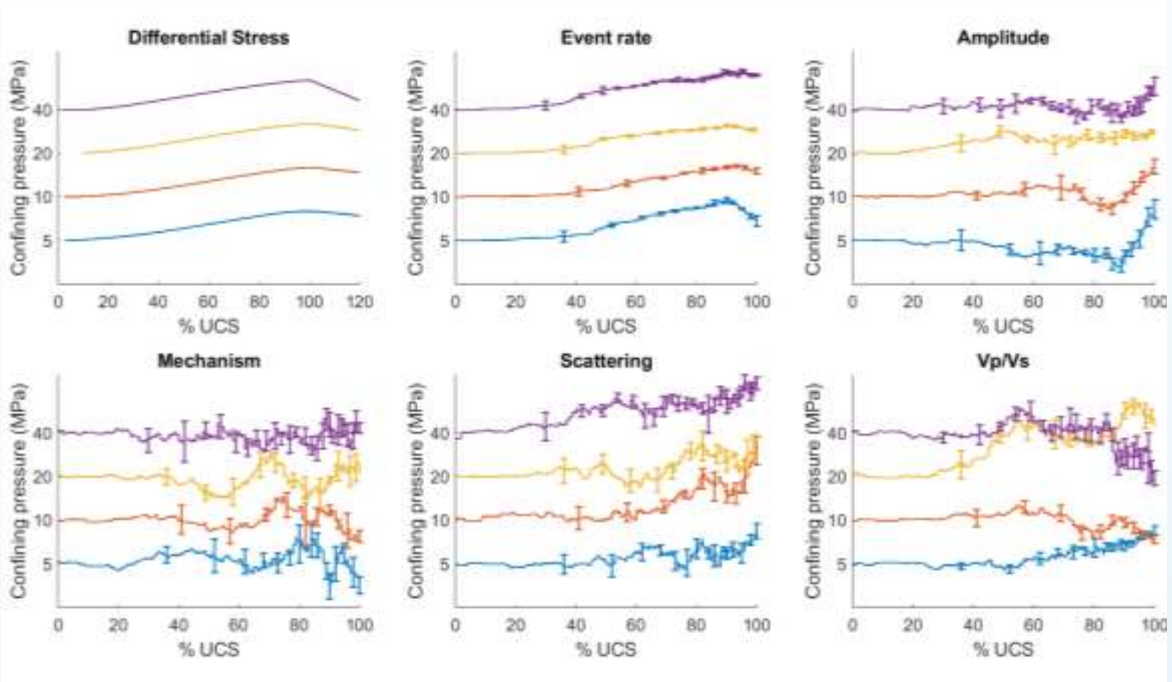
Distribution of logarithmic variations of BYD at low and high frequencies

King et al., GJI, 2022, 2023

All input data for TDNN



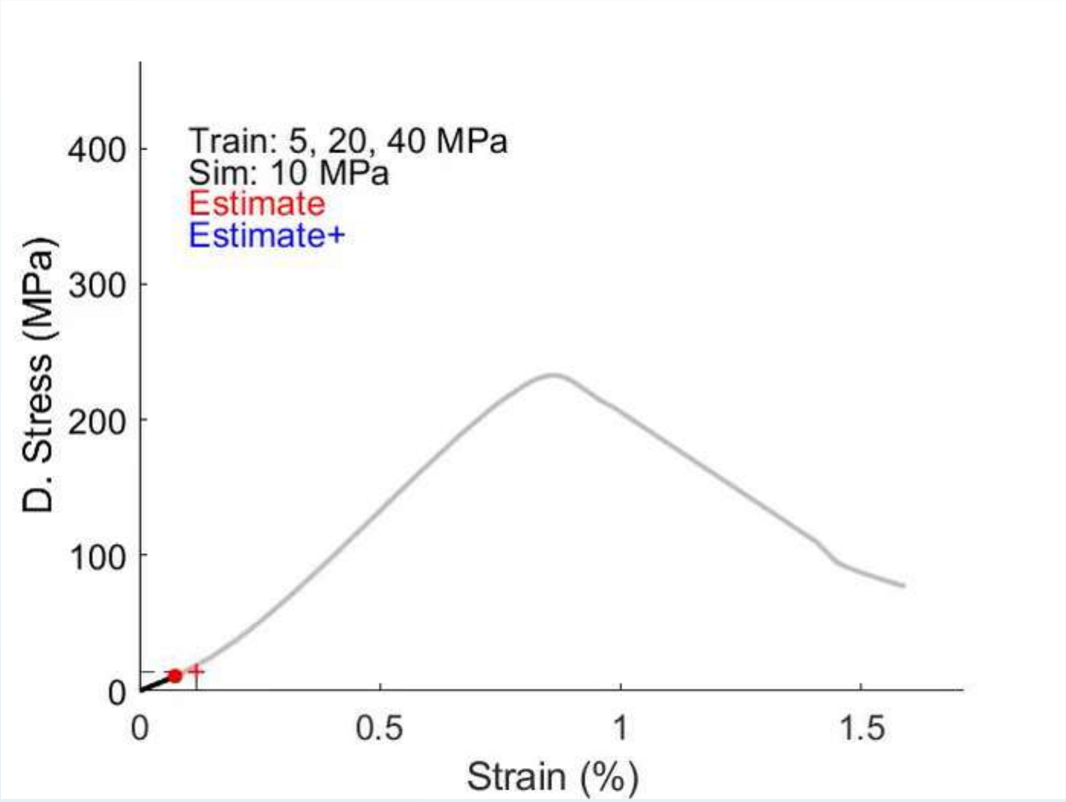
Training Data parameterisation



- Observed stress-strain data are the classification target for the ML model
  - Both are normalized to Ultimate Compressive Strength (UCS)
  - Strain is linear and shows little variation
  - Stress has phases of softening and hardening
    - Can the model resolve more complex target features?

- Parameterised AE data are smoothed in a weighted moving average window (100 events)
  - Weighting is assigned according to amplitudes and to clusters of events
  - Results in a 5-20% improvement in correlations between datasets compared to a simple moving average
    - This is key for data generalization

Model Training and Validation

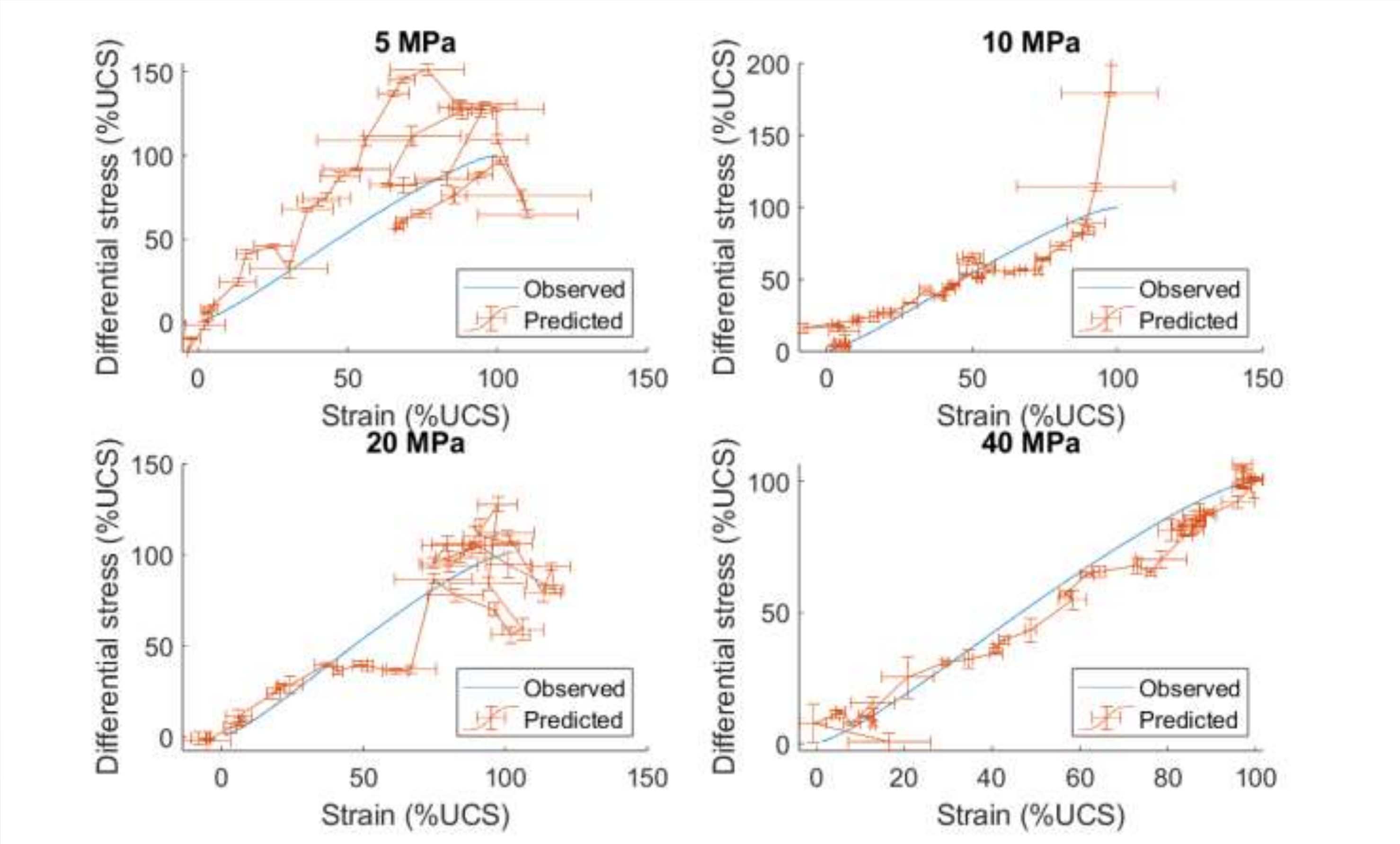


Vinciguerra et al., 2021

Estimate: Moving average
Estimate+: MA for low standard deviations

- Hyperparameters for the neural network are optimised using a **Genetic Algorithm (GA)** by evaluating the misfit between **training target** (mechanical data) and **model output**.
  - Each model is **trained** on a **single dataset** and **validated** on the **others**
- We then investigate **120 configurations** for the training data following a **'leave-one-out'** strategy.
- E.g., a model is trained on 5, 10 and 20 MPa datasets whilst omitting the Event rate parameter. The model is then validated on the 40 MPa dataset.
- **Individual training** runs result in notable differences in the **final output** due to an inherent randomness
  - Therefore, we repeat this whole process multiple times

Model Training and Validation



- Example model output for a **single training run** (orange) on validation datasets demonstrate that the TDNN can **classify AE-derived parameters** as increasing variations in **stress** and **strain** (blue)

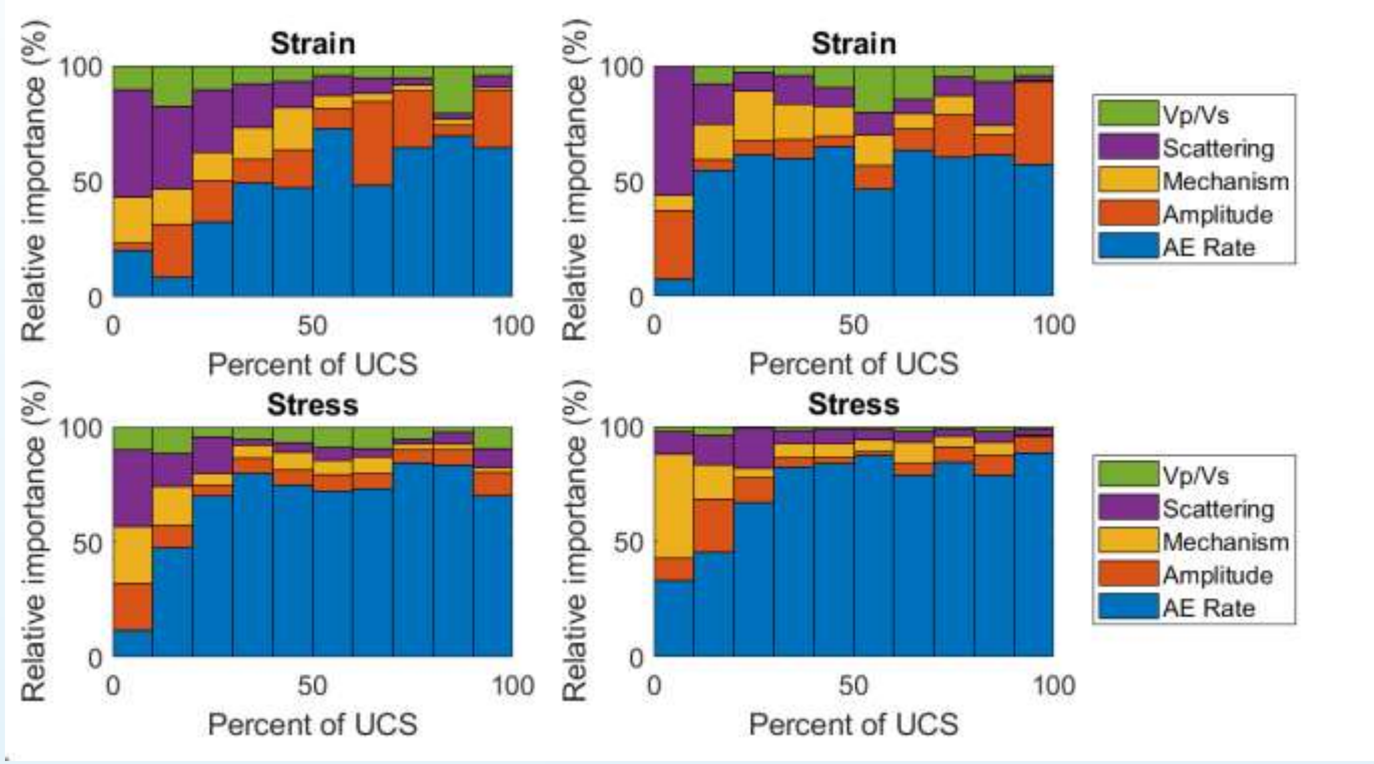
- The hyperparameters for this particular model were optimised for **10** and **40 MPa** datasets that demonstrated better stability compared to the others

Parameter Importance

- By comparing models that include all the training data with models that **omit individual parameters**, we can make estimates on their importance

- Between model runs there remains uncertainty but there are clear trends
    - **AE event rate** dominates the modelling due to less uncertainty in the data and high correlation between training datasets
    - Relative parameter importance not only varies with time but also for target parameter (i.e, stress or strain)

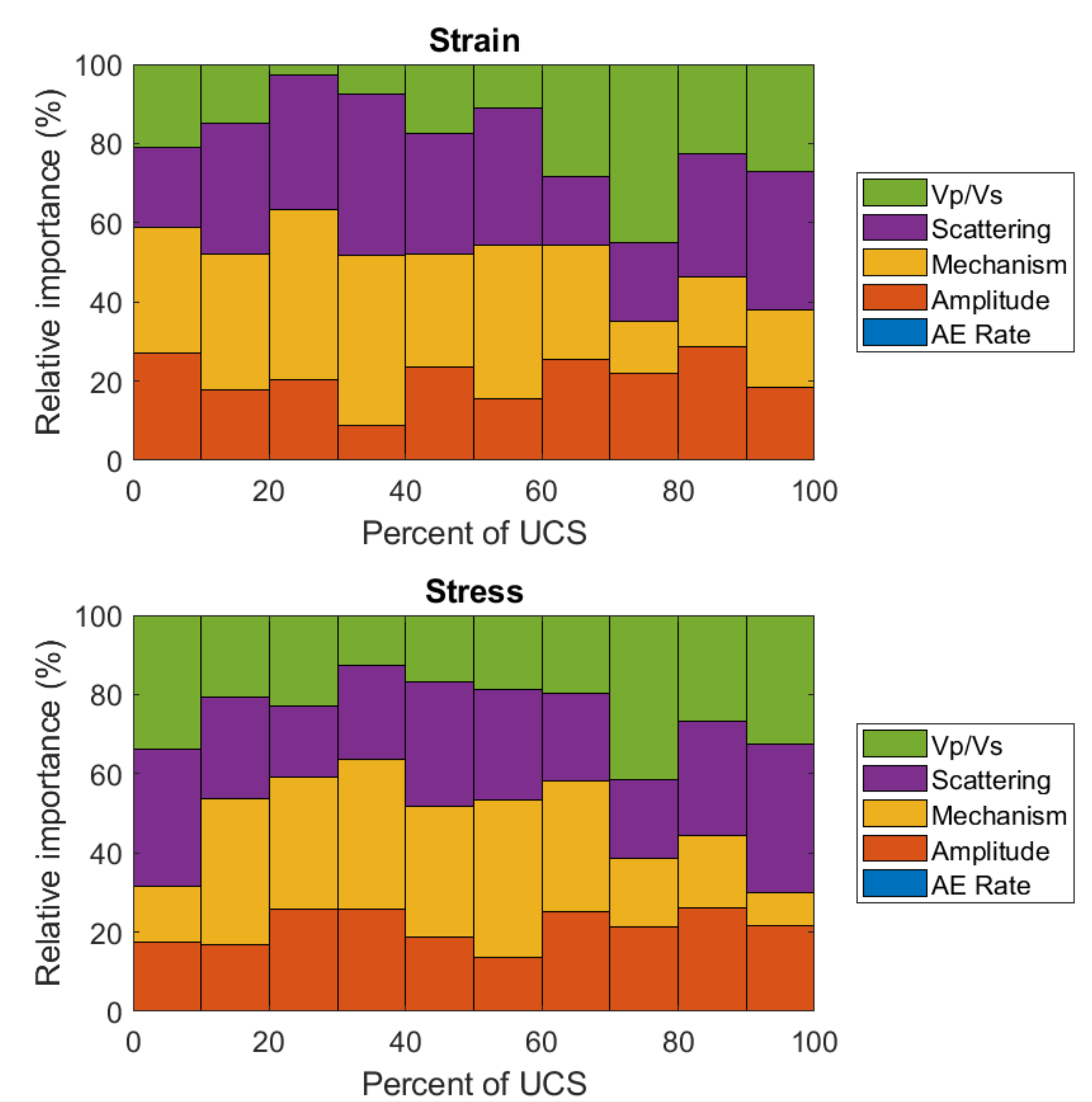
Run 1 Run 2



Parameter Importance

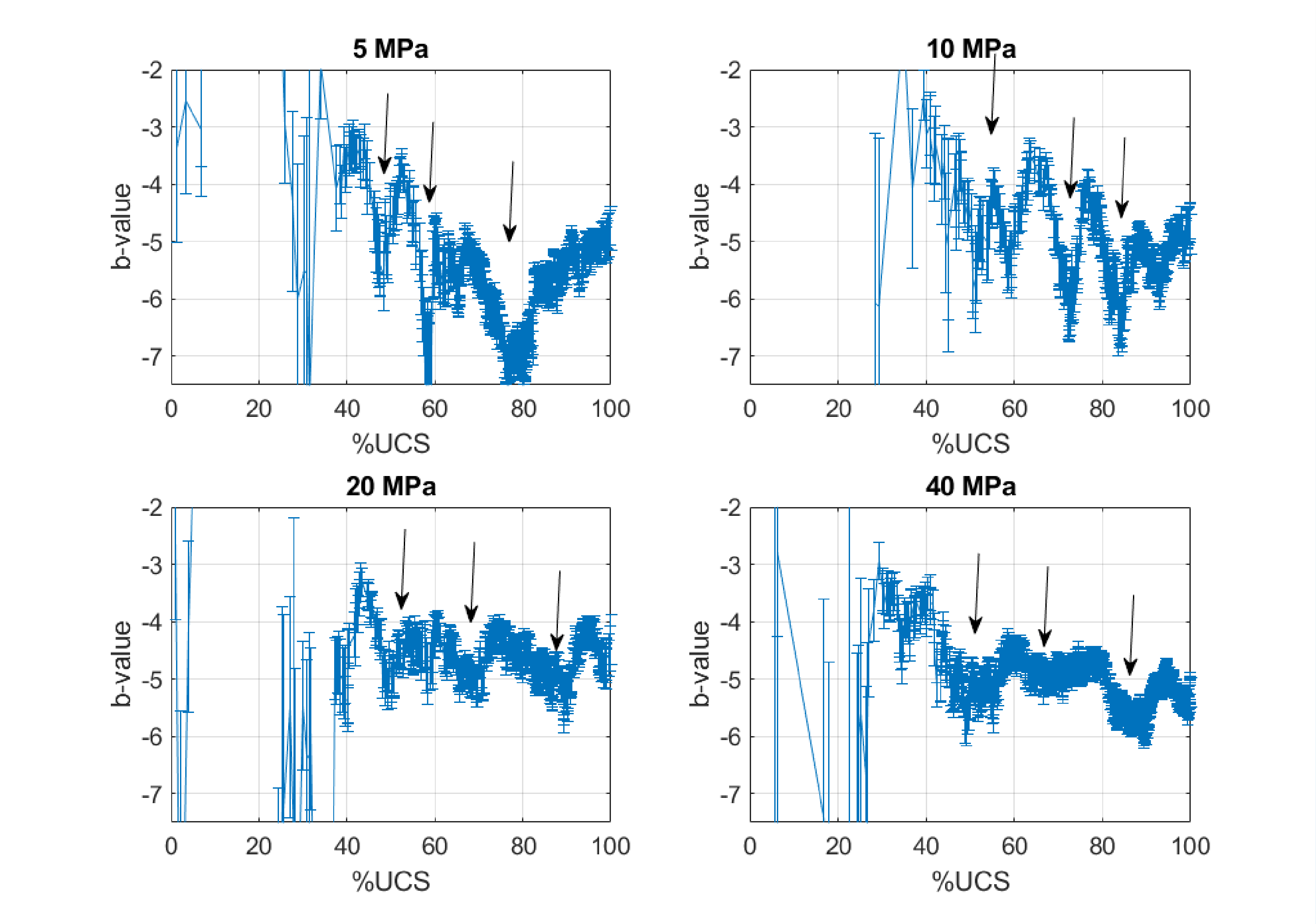
- By comparing models that include all the training data with models that **omit individual parameters**, we can make estimates on their importance

- By **omitting AE event rate**, a clear dominance amongst the other parameters is hard to see
  - However, there is a clear prevalence on the importance of **Vp/Vs** pre-failure



Conclusions

- Neural Networks are complex yet powerful tools for data analysis;
- Key to their use is in understanding what aspects of the training data and methodology they are sensitive to;
- This will allow us to not only optimize their effectiveness in making a valid forecast for new fracture development but also to understand regions where such models may not be used due to limited observations
- Our approach demonstrates that even with **small datasets** and **less training parameters** than other methods, simple Time Delay Neural Network models can be **generalized** between different environmental conditions
  - This is a crucial achievement if we wish to apply such models to field data
  - **The parameter importance** analysis has highlighted that correlations between datasets are key to this
- **Different parameters** are more or less useful to forecasting rupture, but this depends on when in seismic cycle you are and on what you are trying to classify your waveform data as, i.e., stress or strain
  - **AE rate** clearly dominates the modelling with >50% importance
  - Future testing will investigate the **other parameters** in more detail to pull out trends in the parameters more traditionally used in tomography approaches, i.e., *spatial clustering* and *b-value*


5 MPa
10 MPa
20 MPa
40 MPa
b-value
%UCS
-2
-3
-4
-5
-6
-7
0
20
40
60
80
100