Fracture Network Prediction Using Physics-Based Machine Learning Algorithms

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Introduction

- Mapping fracture and fault networks is crucial for the safety, security, and environmental sustainability of CO₂ sequestration projects. It ensures that potential risks are identified and mitigated effectively.
- Accurate mapping of fracture networks enables the identification of preferential flow paths for CO₂ migration. This understanding helps optimize injection strategies and predict CO₂ movement within the reservoir, enhancing the efficiency and reliability of sequestration efforts.
- In the ongoing SMART Phase II efforts, a suite of machine learning algorithms has been employed to quantify the temporal and spatial distributions of fracture networks at the CO₂ injection site for the Illinois Basin – Decatur Project (IBDP). These advanced techniques provide detailed insights into the evolving fracture systems.



Figure 1. Map showing the location of IBDP site (red dot) within the Illinois Basin (green shaded region).

Data & Site Details

- The IBDP is a carbon capture and storage (CCS) initiative undertaken by the Midwest geological sequestration consortium. It is located in east-central Illinois within the north-central region of the Illinois Basin.
- Approximately 1 million tonnes of super critical CO₂ were injected into the lower Mt. Simon Sandstone at the IBDP site over a period of three years, from November 2011 until November 2014.
- For this study, the microseismic catalog recorded by subsurface arrays from three separate wells at the IBDP site has been utilized, providing critical data for fracture network quantification.
- The preliminary microseismic catalog was comprised of 5,397 events, which were subsequently relocated utilizing a modified version of HypoDD, resulting in the successful relocation of 4,293 events.
- In addition to microseismic, the study also incorporates injection-related data, such as bottomhole pressure and CO_2 flow rate, to provide a comprehensive analysis of the reservoir engineering parameters.



Figure 2. Configuration of borehole and seismic monitoring network at the IBDP site.



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Methods

- The magnitude of completeness and seismogenic b-value are calculated for the microseismic catalog. These parameters help infer the dominant stress regime and failure mode of the recorded seismic events.
- Discrete microseismic time windows are determined based on variations in bottomhole pressure recordings. • The concept of hydraulic diffusivity is employed to identify discrete microseismic triggering fronts within
- each time window.
- A suite of unsupervised machine learning algorithms is tested to identify spatial clusters of microseismic events within each triggering front of individual time windows.
- Two-sigma standard deviational ellipsoids are fitted to individual microseismic clusters, capturing the spatial variation of event distribution in each cluster.
- The eigenvectors corresponding to the largest eigen value of each standard deviational ellipsoid are extracted. These eigenvectors represent the trace of 3D distribution of fracture planes around the injection well.



Figure 3. Plots showing the comparison of cumulative pumping rate with (a) event count, (b) seismic energy, (c) seismic moment, and (d) joint variation of seismic moment and daily pumping rate (green bars).



Figure 4. Plots showing the variation in average downhole pressure. Nineteen microseismic time windows (shaded boxes) marked by extended period of bottomhole pressure changes.



Figure 5. Discrete triggering fronts (shaded rectangles) identified within each microseismic time window.







<u>Science-informed</u> <u>Machine Learning to</u> <u>Accelerate</u> <u>Real</u> <u>Time</u> (SMART) Decisions in Subsurface Applications



Figure 7. Identified clusters of microseismic events within each triggering front of time window 17 (center plot).



Figure 8. 3D distribution of fracture ellipsoids (red ellipsoids) and fracture planes around the injection well (red line) for time windows 16 (a, b) and 17 (c, d).



(d) Hierarchical.



Figure 10. (A) Previously identified fault plane solutions (green lines) for the microseismic clusters. (B) 3D distribution of fracture network (green lines) around the injection well as determined using machine learning techniques in the current study.

Conclusions

- We developed a machine learning based tool and successfully mapped the complex network of fractures around the injection well at the IBDP site using this tool.
- Our fracture network model is in complete unison with the pre-existing geomechanical stress conditions around the IBDP site. **Acknowledgements**

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