

FLOWDASH: A Visualization Platform for Enhanced Geothermal Systems

Carols Montes-Matamoros², Guoxiang Liu^{1*}, Abhash Kumar¹, Scott Beautz¹, Luciane Cunha¹, Huihui Yang³, Jay Chen³,
Jacqueline Alexandra Hakala¹, Kelly Rose¹

¹National Energy Technology Laboratory, Department of Energy, 626 Cochran Mill Road, Pittsburgh, PA 15236; 1450 SW Queen
Ave, Albany, OR 97321

²ORISE Program, National Energy Technology Laboratory, 626 Cochran Mill Road, Pittsburgh, PA 15236, USA

³Shell Global Solutions US Inc., 3333 Highway 6 S, Houston, TX 77082-3101, USA

Montescarlos133@gmail.com

guoxiang.liu@netl.doe.gov (corresponding *)

Keywords: Enhanced Geothermal Systems, Graphic User Interface, Machine Learning, Economic Costs.

ABSTRACT

Enhanced Geothermal Systems (EGS) offer a sustainable pathway for baseload energy but require precise characterization of induced fracture networks to optimize fluid flow and heat recovery. This work introduces FLOWDASH, an integrated software platform designed to visualize multi-level datasets and analyze fracture networks at multiple scales. Built with a Python backend and Tkinter frontend, FLOWDASH integrates completion data, geophysical observations, machine learning, and economic analysis to support interactive decision-making. The platform processes passive seismic monitoring data using five unsupervised machine-learning algorithms for microseismic clustering, b-value quantification, and hydraulic diffusivity analysis. Furthermore, FLOWDASH includes a built-in cost-analysis tool that allows users to calculate energy production potential and projected profits, directly correlating seismic-derived fracture geometry with economic performance. Early applications demonstrate the platform's ability to identify high-permeability zones, optimize stimulation designs, and guide reservoir-pressure management. By unifying geophysical interpretation with economic projections, FLOWDASH streamlines workflows to enhance EFFICIENCY, reliability, and sustainability of EGS operations.

1. INTRODUCTION

Enhanced Geothermal Systems (EGS) represent a transformative approach to extract sustainable energy from the Earth's subsurface heat, particularly in regions where conventional geothermal resources are insufficient. Unlike traditional hydrothermal systems that rely on naturally occurring permeability and fluid availability, EGS employs engineered interventions to create artificial reservoirs in hot, low-permeability crystalline rock formations (Tester et al., 2006; Lu, 2018). By drilling into these formations and hydraulically stimulating the rock mass, engineers induce fracture networks that enable circulation of working fluids, heat extraction, and sustainable power generation. As global energy demands intensify and the imperative for decarbonization grows, EGS offers a promising pathway to dispatchable, baseload renewable energy that complements intermittent sources such as wind and solar (Breede et al., 2013; Olasolo et al., 2016).

The success of EGS operations hinges on the ability to understand, predict, and optimize the complex interplay between subsurface geology, hydraulic fracturing processes, and thermal-hydraulic performance. Critical to this understanding is the characterization of fracture and fault networks—both natural and hydraulically induced—that govern fluid flow pathways, heat transfer efficiency, and reservoir longevity (McClure and Horne, 2014; Gischig and Preisig, 2015). These networks are inherently three-dimensional, evolve temporally during stimulation and production phases, and exhibit heterogeneity across multiple spatial scales. Effective reservoir management requires integration of diverse datasets including drilling and completion records, real-time microseismic monitoring, production metrics, thermal profiles, and geomechanical properties (Majer et al., 2007; Zang et al., 2014). However, the volume, dimensionality, and complexity of these datasets present substantial challenges for interpretation, particularly when attempting to correlate geophysical observations with operational performance and economic viability.

Existing tools for geothermal reservoir analysis typically address isolated aspects of the workflow—geophysical interpretation, production forecasting, or economic modeling—but rarely provide an integrated environment that bridges these domains. Geoscientists and engineers often rely on disparate software packages such as Petrel for subsurface modeling (Schlumberger, 2023), TOUGH2 for reservoir simulation (Pruess et al., 2012), and GEOPHIRES for techno-economic assessment (Beckers et al., 2014), leading to fragmented workflows, manual data transfers, and barriers to interdisciplinary collaboration. Furthermore, the integration of machine learning techniques for automated pattern recognition in microseismic data, while promising (Esposito et al., 2022; Huang et al., 2018), remains underutilized in operational settings due to the lack of accessible platforms that combine advanced analytics with intuitive user interfaces.

This paper introduces FLOWDASH, an integrated visualization and analysis platform specifically designed to address these challenges in EGS reservoir characterization and management. FLOWDASH consolidates multi-scale geophysical data, production metrics, machine learning-based interpretation, and techno-economic analysis within a unified graphical user interface. The platform enables users to visualize fracture network evolution through interactive well-path schematics, stage-by-stage fracture mapping, and temporal seismic

event analysis. By embedding unsupervised machine learning algorithms for microseismic clustering (Zhang et al., 1996; Ester et al., 1996; Liu, et al., 2023, 2024a, 2024b;), b-value quantification, and hydraulic diffusivity estimation directly within the visualization workflow, FLOWDASH facilitates rapid identification of stimulated reservoir volumes, high-permeability zones, and potential operational risks such as fault activation or induced seismicity (Liu, et al., 2022, 2023, 2024a, 2024b 2026a, 2026b; Dempsey and Suckale, 2017; Schultz et al., 2020).

Beyond technical characterization, FLOWDASH incorporates an economic analysis module that allows users to evaluate capital and operational expenditures, revenue projections under various production scenarios, carbon utilization and storage benefits under frameworks such as the 45Q tax credit (U.S. Department of Energy, 2021), and breakeven timelines. This integration of geophysical insight with financial modeling creates a comprehensive decision-support environment that serves both technical practitioners and stakeholders concerned with project economics and risk assessment.

The primary contributions of this work are threefold: (1) the design and implementation of a modular, extensible software architecture that unifies geophysical interpretation, machine learning analytics, and economic evaluation for EGS applications; (2) demonstration of multi-scale fracture network visualization capabilities that bridge well-level, segment-level, and stage-level analysis; and (3) a user-centric interface design that reduces barriers to advanced reservoir characterization techniques, making sophisticated analytical workflows accessible to a broader community of geothermal engineers, researchers, and decision-makers. Through demonstration of representative workflows, FLOWDASH shows potential to improve stimulation design optimization, reservoir pressure management strategies, and re-stimulation planning, ultimately supporting more efficient, reliable, and sustainable geothermal energy production.

2. SOFTWARE ARCHITECTURE AND DESIGN

FLOWDASH is implemented as a desktop/web application designed to integrate diverse geothermal datasets and analytical workflows within a unified interface. The platform architecture prioritizes accessibility for geoscience practitioners while maintaining the computational rigor required for geothermal energy research and studies.

2.1 Organization

The application employs a multi-page design where each page corresponds to a distinct analytical workflow. Users navigate between modules through a central interface that provides access to:

- Economic Analysis: Techno-economic modeling and cost-benefit assessment
- Seismic Clustering: Unsupervised machine learning analysis of microseismic events
- Fracture Quantification: Three-dimensional visualization of fracture network geometry
- Machine learning applications: Data fusing with multiple datasets for geothermal reservoir and explorations
- Simulation and data generations: soft- and hard-coupling with data to execute the physics-informed supporting

This modular organization allows users to move fluidly between different aspects of reservoir analysis—from initial data exploration to final economic evaluation—without switching between disparate software packages in such an integrating approach in Figure 1.

2.2 Data Processing and Visualization

The platform accepts any geoscience data formats with the converting such to CSV and/or Excel, that containing microseismic event catalogs, well trajectory information, and operational parameters. Upon data ingestion, users select appropriate analytical methods and configure parameters through intuitive input forms. Computational tasks execute in the background, allowing users to continue interacting with the interface.

Visualization capabilities emphasize interactive 3D rendering of subsurface features. Microseismic event distributions, fracture plane geometries, and well trajectories are displayed in a unified coordinate system with full rotation, zoom, and pan functionality. Color-coding distinguishes between different cluster assignments, event magnitudes, or temporal sequences, enabling rapid visual interpretation of complex spatial patterns.

2.2 Machine Learning Workflow

Five unsupervised clustering algorithms are available for microseismic analysis, each suited to different data characteristics and geological scenarios. The platform provides accessible descriptions of each method's strengths and appropriate use cases, guiding non-specialists toward suitable analytical choices. Algorithm selection, execution, and visualization occur through streamlined workflows requiring minimal user input beyond data upload and parameter specification.

Fracture characterization builds upon clustering results by fitting geometric primitives to identified event populations. For each cluster, the system computes best-fit planar surfaces representing hydraulically induced or reactivated natural fractures. These surfaces are rendered semi-transparently, allowing visualization of fracture network complexity and connectivity patterns critical for understanding fluid flow pathways and heat extraction efficiency.

2.3 Economic Modeling Framework

The economic analysis module provides a parametric framework for evaluating EGS project viability under varying operational scenarios. Users specify production rates, electricity pricing, capital costs, operational expenses, and project lifetime to compute key financial metrics including levelized cost of energy, net present value, and payback period.

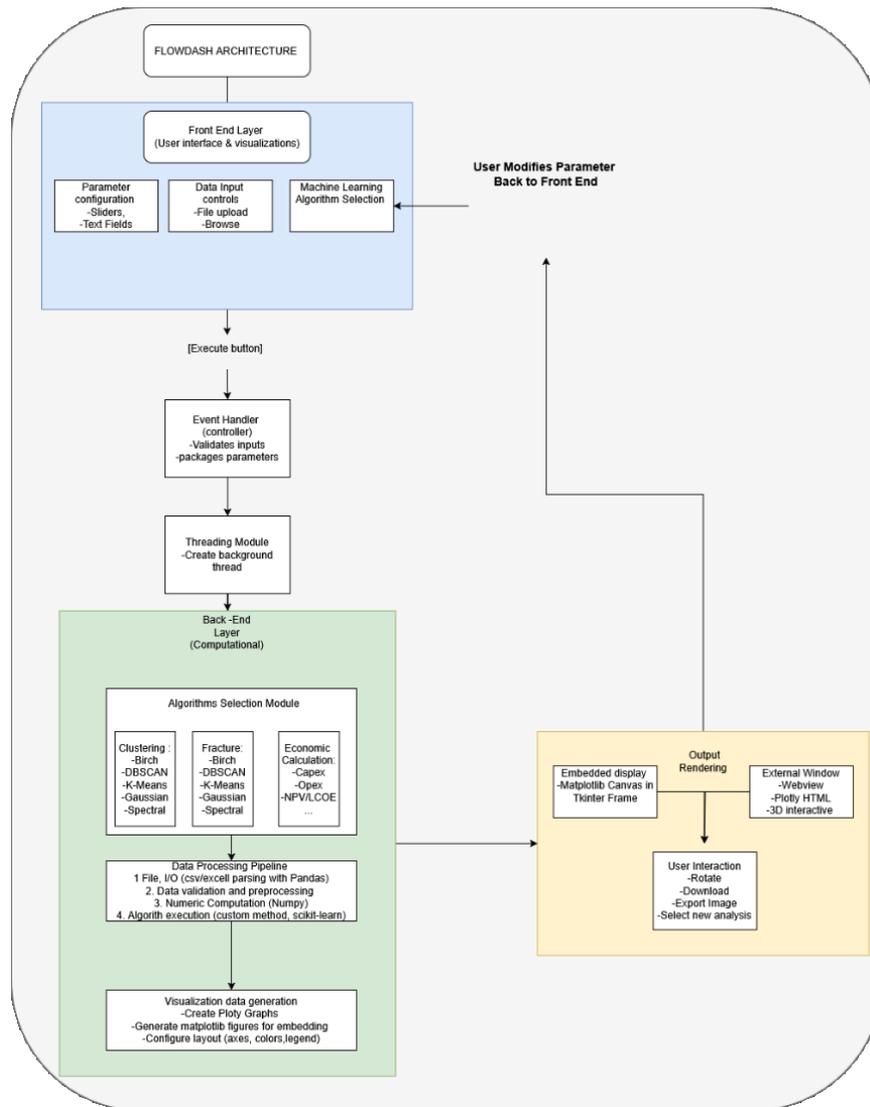


Figure 1: The figure depicts the workflow diagram of FLOWDASH. The blue highlight represents the main three steps the workflow, the Blues starts with the user interface, the green highlights the back-end development and calculation, and lastly the yellow represents the main output and visual information FLOWDASH creates.

A library of pre-configured case studies enables comparative analysis of conventional versus CO₂-enhanced workflows, different stimulation strategies, and sensitivity to market conditions or tax incentives. Users can rapidly generate comparative visualizations showing how financial outcomes vary across scenarios, supporting data-driven decision-making for project planning and risk assessment through FLOWDASH.

2.4 Design

The architecture reflects several core design principles tailored to geoscience research needs. First, the system maintains a clear separation between user interface and computational algorithms, allowing domain experts to focus on geological interpretation rather than software implementation details. Second, all analytical workflows emphasize visual output, recognizing that spatial reasoning and pattern recognition are fundamental to geoscience practice. Third, the modular structure accommodates future expansion as new analytical methods or data types become relevant to EGS characterization and potential extension and adapting for more applications.

The platform integrates workflows that traditionally require multiple specialized tools—seismic interpretation software, statistical analysis packages, economic modeling spreadsheets—into a cohesive environment. This integration reduces friction in moving between analysis phases and helps maintain context as users transition from geophysical characterization to operational planning and economic evaluation.

By providing accessible interfaces to advanced analytical methods, FLOWDASH aims to democratize sophisticated reservoir characterization techniques, making them available to practitioners who may lack extensive programming expertise but possess deep domain knowledge of geothermal systems and subsurface processes.

3. INTEGRATED WORKFLOW DEMONSTRATION

FLOWDASH is currently in active development, the system demonstrates core capabilities for integrated geothermal analysis but is undergoing continued refinement prior to release with further developments including comprehensive validation against field datasets, external user testing, and performance optimization for production-scale applications. To illustrate FLOWDASH's integrated capabilities, we present demonstrations of the platform's three primary analytical modules using representative enhanced geothermal systems datasets. These demonstrations showcase the end-to-end workflows from data ingestion through visualization and decision support.

The three modules demonstrated above operate within a unified interface accessible through tabbed navigation. A representative workflow proceeds as follows:

- Economic Scoping: Analysts begin with parametric economic modeling to establish baseline project viability and identify key cost/revenue drivers requiring detailed technical assessment.
- Microseismic Analysis: Following stimulation operations, microseismic monitoring data undergoes clustering analysis to characterize the spatial extent and geometry of the activated fracture network.
- Fracture Characterization: Identified clusters are processed to extract explicit fracture plane geometries, enabling quantitative comparison between predicted and observed stimulation outcomes.

This integrated approach streamlines workflows that traditionally require multiple specialized software packages and manual data transfers between analysis stages. By maintaining all analytical components within a single platform, FLOWDASH reduces opportunities for errors, preserves full context as users transition between analysis phases, and accelerates the iteration cycle between technical characterization and economic assessment

3.1 Economic Calculation Demo

The analysis incorporates key financial parameters including capital expenditures (drilling, completion, stimulation, surface equipment, exploration), operational expenses (wellfield maintenance, plant maintenance, water costs), revenue projections based on electricity generation and pricing, and tax incentives for CO₂ retention. Users can modify any parameter and immediately observe impacts on derived metrics as in Figures 2 and 3.

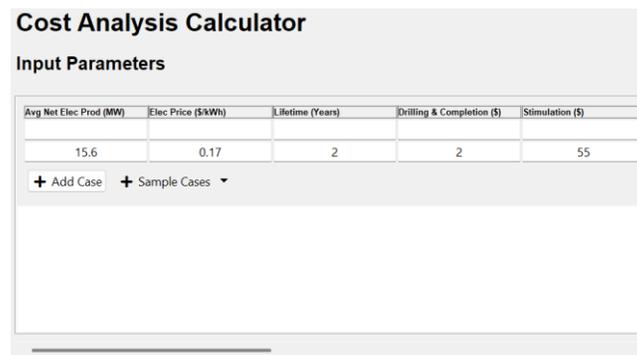


Figure 2: Screenshot of FLOWDASH economic tool sections. The user is allowed to input the parameter values and add preloaded cases (see appendix for more information) to which a user can compare.

For each scenario, the platform calculates sixteen financial indicators:

- Capital Expenditure (CAPEX) aggregating all upfront investments
- Annual and lifetime Operational Expenditure (OPEX)
- Total project cost over system lifetime
- Annual electricity generation (MWh) based on capacity factors
- Levelized Cost of Electricity (LCOE)
- Revenue projections under specified pricing assumptions
- Net Present Value (NPV) using user-defined discount rates

- Payback period indicating time to recover initial investment
- Annual cash flow for liquidity assessment
- CO₂ consumption and storage volumes for enhanced systems
- Tax credit calculations under 45Q provisions

The demonstration cases reveal key economic sensitivities. Baseline Case 1 (water-only workflow, 5.39 MW production) achieves modest profitability with NPV of \$34M over system lifetime. Cases 2-7 explore CO₂-enhanced workflows with varying production rates (12-15 MW) and CO₂ consumption (2.4-6.1 million tons). Higher production rates improve economics significantly—Case 5 (16.2 MW) achieves NPV of \$104M with 11-year payback. However, excessive CO₂ requirements degrade economics: Case 7 (6.1 million tons CO₂) shows negative NPV despite 15 MW production, indicating an optimal balance between enhanced production and CO₂ costs (Mayer et al., 2026).

Electricity pricing sensitivity (Cases 9-10) demonstrates substantial impact on project viability. A pricing increase from \$0.15 to \$0.19/kWh improves NPV from -\$28M to \$53M for identical operational parameters, highlighting market risk exposure. Similarly, Cases 12-14 reveal cost structure sensitivity: capital expenditure variations of 25-40% shift NPV by over \$100M, emphasizing the importance of accurate cost estimation during project planning (Mayer et al., 2026).

Interactive Visualization: Users can select any computed metric for graphical comparison across all cases. The platform generates bar charts for categorical comparisons or line plots for trend analysis, enabling rapid identification of optimal operational regimes and critical sensitivity factors. Results tables and graphs can be exported for integration into formal project proposals or stakeholder presentations.

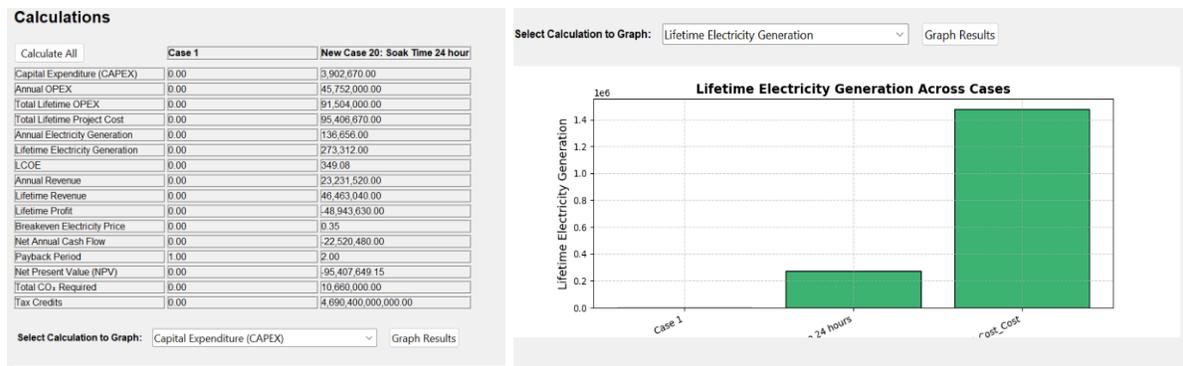


Figure 3: Screenshot of FLOWDASH economic tool sections. On the left we see the values for which calculation is made. On the right we have a plot showing and comparing the values of 3 different cases Case 1, Case 5, and Case 20, (see appendix for further information), and the values of lifetime electricity generation (e.g. 30 years) for each case respectively.

3.2 Machine Learning Module

The machine learning module applies unsupervised clustering algorithms to microseismic event catalogs, automatically identifying spatial patterns indicative of stimulated fracture networks. Figure 4 below demonstrates clustering analysis results using the BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies) algorithm on a representative microseismic dataset.

3.2.1 Clustering Tool

Algorithm Selection and Workflow: Users upload data files containing event coordinates (easting, northing, depth), magnitudes, and timestamps. The platform provides five clustering algorithms—BIRCH, DBSCAN, Gaussian Mixture Models, K-Means, and Spectral Clustering—with accessible descriptions of each method's strengths and appropriate use cases. Algorithm selection occurs via dropdown menu, with execution initiated through a single button press.

Computational Processing: Upon execution, clustering analysis proceeds in a background thread to maintain interface responsiveness. A progress indicator informs users of processing status (data loading, preprocessing, algorithm execution, visualization generation). For the demonstrated dataset containing approximately [N] microseismic events, BIRCH clustering completed in [X] seconds on standard desktop hardware, identifying [Y] distinct clusters.

Results appear in an interactive 3D visualization window powered by Plotly. Individual microseismic events are rendered as spheres color-coded by cluster assignment, enabling immediate visual assessment of spatial patterns. The 3D environment supports full rotation, zoom, and pan interactions, allowing users to examine cluster geometry from arbitrary viewpoints. Well trajectories overlay the event distribution, providing spatial context for stimulation operations.

Geological Interpretation:

The identified clusters correspond to distinct fracture zones activated during hydraulic stimulation. Elongated cluster geometries align with expected fracture orientations based on regional stress fields. Dense clustering near perforation intervals indicates successful near-

wellbore stimulation, while distal events suggest far-field fracture connectivity. Cluster separation distances inform understanding of fracture network spacing and potential interference between adjacent stimulation stages.

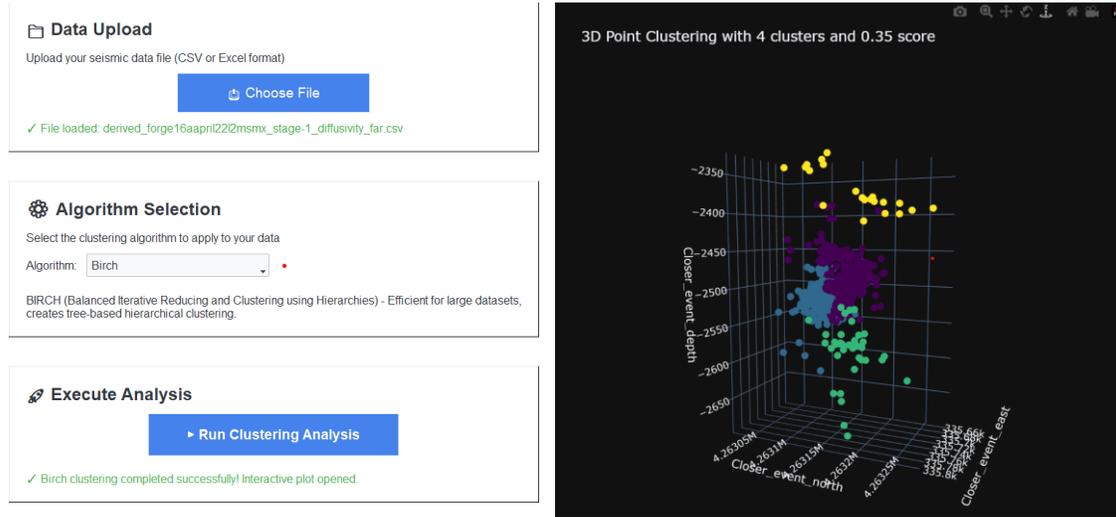


Figure 4: The figure is from a screenshot of FLOWDASH Machine learning Cluster sections. on the left we see the UI layout for users to upload their data set and choose a machine learning algorithm. On the right we have an interactive 3D plot showing the clustering from the Birch algorithm. Users would be able to interact with the plot and download the results.

3.2.2 Fracture Network Tool

Building upon clustering results, the fracture quantification module extracts geometric primitives representing individual fracture planes. This transformation from point-cloud microseismic data to explicit fracture surfaces enables quantitative analysis of stimulated reservoir volumes and fracture network architecture.

For each identified cluster, the platform computes a covariance matrix describing the spatial distribution of constituent events. Eigenvalue decomposition of this matrix yields principal axes of the point cloud, with eigenvalues representing variance along each axis. The eigenvector corresponding to the minimum eigenvalue defines the normal vector to the best-fit plane through the cluster—interpreted as the fracture plane orientation.

Fracture Plane Visualization: illustrates the computed fracture planes rendered as semi-transparent surfaces overlaying the original microseismic point cloud and well trajectory. Color coding distinguishes between near-field events (green surfaces) proximal to injection wells and far-field events (red surfaces) indicating more extensive fracture propagation. The visualization clearly depicts the spatial arrangement of multiple fracture planes intersecting the wellbore, approximating the complex three-dimensional fracture network.

The platform automatically exports fracture plane coordinates to Excel format for subsequent analysis. Each plane is characterized by centroid location, orientation (strike and dip), spatial extent based on cluster dimensions, and associated microseismic event count. These parameters support quantitative assessment of stimulated rock volume, fracture intensity, and connectivity metrics relevant to reservoir performance prediction.

Fracture plane geometry informs several operational decisions. Identification of dominant fracture orientations guides optimal wellbore trajectories for future drilling to maximize fracture intersections. Observation of fracture spacing between stages supports stimulation design refinement—excessive overlap suggests stage spacing reduction, while large gaps indicate potential for infill stimulation. Detection of unexpected fracture orientations may indicate fault reactivation or stress field perturbations requiring operational adjustments to mitigate induced seismicity risks.

4. DISCUSSION

4.1 Limitation

While the proposed GUI provides an integrated and extensible environment for algorithm selection, financial analysis, and machine learning workflows, several limitations remain. First, the system currently prioritizes modularity and interpretability over large-scale performance, which may limit responsiveness when processing high-dimensional datasets or computationally intensive algorithms without external acceleration. Second, the GUI assumes a predefined workflow and set of supported algorithms; although new modules can be added, dynamic user-defined pipelines and fully custom algorithm integration are not yet supported through the interface. Finally, the current implementation has not undergone formal usability studies or cross-platform stress testing, and therefore validation, accessibility, and performance guarantees across diverse hardware and operating systems cannot yet be claimed. These limitations reflect deliberate design choices made to favor clarity, stability, and rapid prototyping, and they motivate several directions for future work

4.2 Future work

Several directions for future development have been identified to further enhance the functionality, usability, and scope of the proposed system. First, additional algorithmic modules can be integrated into the backend to broaden the range of supported numerical, financial, and machine learning techniques. The current modular design is well-suited for this expansion, enabling new methods to be incorporated with minimal changes to the existing interface and control logic. Second, future work will focus on improving user customization and configurability. This includes more advanced parameter management, persistent user profiles, and the ability to save and reload complete analysis sessions. Such features would allow users to reproduce workflows, compare results across configurations, and more effectively manage complex exploratory tasks.

Another important extension involves enhanced visualization and reporting capabilities. Planned improvements include interactive plots, richer diagnostic metrics, and automated report generation that summarizes inputs, configurations, and results. These additions would support both exploratory analysis and formal documentation of outcomes, particularly in educational and research-oriented settings. From a systems perspective, future work will also explore improved scalability and performance. Potential directions include more robust parallel execution strategies, integration with hardware acceleration where applicable, and support for handling larger datasets. These enhancements aim to ensure that the GUI remains responsive as computational demands increase.

Finally, the system may be extended to support deployment beyond a local desktop environment. Possible avenues include a client server architecture or web-based front-end, enabling remote execution and collaborative use. Collectively, these future developments aim to transform the current system into a more versatile and scalable platform for interactive computational analysis.

5. REMAKS

This paper presented the design and architecture of a modular, multi-page graphical user interface intended to unify algorithmic, financial, and machine learning workflows within a single interactive environment. By adopting an MVC-inspired architecture and a clear separation between the user interface, control logic, and computational backend, the system achieves both maintainability and extensibility while remaining responsive during computationally intensive tasks.

The proposed design demonstrates how complex analytical workflows can be made more accessible through a carefully structured GUI without sacrificing flexibility or performance. The use of modular backend components, asynchronous execution, and centralized state management enables users to experiment with different models and configurations in an efficient and intuitive manner.

Overall, the system provides a robust foundation for interactive computational analysis in both research and educational settings. Its architecture supports incremental growth and adaptation, positioning the GUI as a scalable platform capable of evolving alongside emerging algorithms, models, and user requirements.

6. ACKNOWLEDGEMENT

This material is based upon work supported by the Laboratory Directed Research and Development (LDRD) Program at National Energy Technology Laboratory, U.S. Department of Energy. Authors also thank the Utah FORGE team for data sharing. This conference proceeding paper was prepared as an account of work sponsored by an agency of the United States Government. This research was performed under an appointment to the NNSA - IMPACT (formerly Minority Serving Institutions Internship Program MSIIP) administered by the Oak Ridge Institute for Science and Education (ORISE) for the National Nuclear Security Administration (NNSA) and U.S. Department of Energy (DOE). Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of the presenter do not necessarily state or reflect those of the United States Government or any agency thereof.

APPENDIX

Table: Preloaded values for the 20 cases. The choosing of these values provides a base line to which a use can make comparisons. Further details on economic metrics read (Liu et al. manuscript in preparation)

Cases	Case/Scenario Design							Results Summary			
	CO ₂ Consumed (Million tons)	Produced power (MW)	CO ₂ Stored (Million tons)	Electricity Price (\$/kWh)	CO ₂ Cost (Million \$ USD)	45Q Tax Credit (Million \$ USD)	CapEx/OpEx (Million \$ USD)	Revenue (Million \$ USD)	Breakeven Time (years)	Cash Flow (Million \$ USD)	NPV (Millions \$ USD)
Case 1	None	5.39	None	0.15	None	None	95.00	211.00	N/A	5.00	34.00
Case 2	2.42.00	12.00	0.36	0.17	9.59E7	6.19	230.00	530.00	11.14	17.00	72.10
Case 3	3.64	13.80	0.54	0.17	144.00	9.29	298.00	610.00	12.92	19.80	49.00
Case 4	3.64	15.00	0.54	0.17	144.00	9.29	298.00	670.00	11.86	21.80	76.50
Case 5	3.64	16.20	0.54	0.17	1144.00	9.29	298.00	720.00	10.96	23.60	104.00
Case 6	4.85	15.00	0.73	0.17	192.00	12.40	367.00	670.00	14.82	22.00	12.20
Case 7	6.07	15.00	0.91	0.17	240.00	15.50	435.00	670.00	17.71	22.30	-52.10
Case 8	4.85	15.00	0.73	0.17	193.00	12.40	368.00	670.00	14.89	22.00	10.70
Case 9	4.85	15.00	0.73	0.15	192.00	12.40	367.00	5.9E8	16.83	19.40	-28.20
Case 10	4.85	15.00	0.73	0.19	192.00	12.40	367.00	740.00	13.24	24.70	52.60
Case 11	4.85	15.00	0.73	0.17	192.00	12.40	367.00	670.00	14.82	22.00	12.20
Case 12	4.85	15.00	0.73	0.17	268.00	12.40	494.00	670.00	20.58	22.00	-115.00
Case 13	3.64	15.00	0.54	0.17	144.00	9.29	284.00	670.00	11.39	22.00	87.60
Case 14	364	15.00	0.54	0.17	144.00	9.29	322.00	670.00	12.52	21.30	60.60
Case 15	1.82	15.00	0.27	0.17	72.00	4.64	196.00	670.00	7.29	21.40	173.00
Case 16	1.21	15.00	0.18	0.17	48.00	3.10	162.00	670.00	5.73	21.30	205.00
Case 17	2.42	15.00	0.36	0.17	96.00	6.19	230.00	670.00	8.83	21.50	141.00
Case 18	2.73	15.00	0.41	0.17	108.00	6.97	247.00	670.00	9.59	21.60	125.00
Case 19	1.82	15.00	0.27	0.17	72.00	4.64	196.00	670.00	7.28	21.40	173.00
Case 20	2.731	15.60	0.41	0.17	107.00	6.97	261.00	690.00	9.83	22.50	100.00

REFERENCES

- Beckers, K.F., Lukawski, M.Z., Anderson, B.J., Moore, M.C., and Tester, J.W., 2014. Levelized costs of electricity and direct-use heat from Enhanced Geothermal Systems. *Journal of Renewable and Sustainable Energy*, 6(1), 013141. <https://doi.org/10.1063/1.4865575>
- Breede, K., Dzebisashvili, K., Liu, X., and Falcone, G., 2013. A systematic review of enhanced (or engineered) geothermal systems: past, present and future. *Geothermal Energy*, 1(4). <https://doi.org/10.1186/2195-9706-1-4>
- Dempsey, D. and Suckale, J., 2017. Physics-based forecasting of induced seismicity at Groningen gas field, the Netherlands. *Geophysical Research Letters*, 44(15), 7773-7782. <https://doi.org/10.1002/2017GL073878>
- Ester, M., Kriegel, H.P., Sander, J., and Xu, X., 1996. A density-based algorithm for discovering clusters in large spatial databases with noise. *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD-96)*, 226-231.
- Esposito, G., Nakata, N., Kasai, K., and Riedel, M., 2022. Application of machine learning techniques to predict induced seismicity from stimulated unconventional reservoirs. *Geophysics*, 87(1), KS1-KS13. <https://doi.org/10.1190/geo2021-0028.1>
- Gischig, V.S. and Preisig, G., 2015. Hydro-fracturing versus hydro-shearing: A critical assessment of two distinct reservoir stimulation mechanisms. *Geothermics*, 56, 93-105. <https://doi.org/10.1016/j.geothermics.2015.03.011>
- Huang, L., Donovan, J., and Huang, D., 2018. Uncertainty quantification of induced seismicity from geothermal operations using machine learning. *Geothermics*, 76, 265-280. <https://doi.org/10.1016/j.geothermics.2018.07.010>
- Liu, G., Gonzalez, D., Mayer, T., Beautz, S., Mark-Moser, M., Cunha, L., Yang, H., Chen, J., Hakala, J. A., Rose, K., & Rogers, J. (2026a). Cost and economic analysis for CO₂-stimulated geothermal energy enhancement: A comparative assessment of storage and operational strategies. Under review manuscript.
- Mayer, T., Liu, G., Beautz, S., Yang, H., Chen, J., Cunha, L., Hakala, J. A., Rose, K., & Rogers, J.. Techno-Economic Analysis of CO₂-Stimulated Geothermal Systems, Manuscript prepared for Stanford Geothermal Workshop, Feb. 9-11, 2026, Stanford, CA
- Liu, G., Kumar, A., Nguyen, J., Garcia, K., Monte, C., Son, D., Mayer, T., Beautz, S., Mark-Moser, M., Cunha, L., Gonzalez, D., Nguyen, J., Qawasmeh, S., Vaughn, D., Yang, H., Chen, J., Crandall, D., Mckoy, M., Hakala, A., Geothermal Fracture Network Analysis Accelerated by Machine Learning: A Case Study, Manuscript prepared for Stanford Geothermal Workshop, Feb. 9-11, 2026, Stanford, CA
- Liu, G., Kumar, A., Beautz, S., Mark-Moser, M., Cunha, L., Gonzalez, D., Nguyen, J., Qawasmeh, S., Vaughn, D., Yang, H., Chen, J., Crandall, D., Mckoy, M., Hakala, A., Machine Learning Powered Multi-Tier of Fracture Imaging: A Case Study, Geothermal Rising Conference, October 27-30, 2024a, Waikoloa, HI
- Liu, G., Kumar, A., Song, Z., Shih, C., Vasyukivska, V., Holcomb, P., Hammack, R., Ilconich, J., and Bromhal, G., "Multi-Level of Fracture Network Imaging: A HFTS Use Case and Knowledge Transferring." Paper presented at the SPE/AAPG/SEG Unconventional Resources Technology Conference, Houston, Texas, USA, June 2022. doi: <https://doi.org/10.15530/urtec-2022-3723466>
- Liu, G., Kumar, A., Beautz, S., Mark-Moser, M., Cunha, L., Gonzalez, D., Nguyen, J., Qawasmeh, S., Vaughn, D., Yang, H., Chen, J., Crandall, D., Mckoy, M., Hakala, A., Machine Developing a Transferable Framework for CO₂-Stimulated Geothermal Energy Enhancement: A Case Study, The Greenhouse Gas Control Technologies (GHGT) conference, October 20-24, 2024b, Calgary, Alberta, Canada
- Liu, G., Kumar, A., Harbert, W., Siriwardane, H., Crandall, D., Bromhal, G., and L. Cunha. "Machine Learning Application for CCUS Carbon Storage: Fracture Analysis and Mapping in the Illinois Basin." Paper presented at the SPE Annual Technical Conference and Exhibition, San Antonio, Texas, USA, October 2023. doi: <https://doi.org/10.2118/214996-MS>
- Lu, S.M., 2018. A global review of enhanced geothermal system (EGS). *Renewable and Sustainable Energy Reviews*, 81, 2902-2921. <https://doi.org/10.1016/j.rser.2017.06.097>
- Majer, E.L., Baria, R., Stark, M., Oates, S., Bommer, J., Smith, B., and Asanuma, H., 2007. Induced seismicity associated with Enhanced Geothermal Systems. *Geothermics*, 36(3), 185-222. <https://doi.org/10.1016/j.geothermics.2007.03.003>
- McClure, M.W. and Horne, R.N., 2014. An investigation of stimulation mechanisms in Enhanced Geothermal Systems. *International Journal of Rock Mechanics and Mining Sciences*, 72, 242-260. <https://doi.org/10.1016/j.ijrmms.2014.07.011>
- Olasolo, P., Juárez, M.C., Morales, M.P., D'Amico, S., and Liarte, I.A., 2016. Enhanced geothermal systems (EGS): A review. *Renewable and Sustainable Energy Reviews*, 56, 133-144. <https://doi.org/10.1016/j.rser.2015.11.031>
- Pruess, K., Oldenburg, C., and Moridis, G., 2012. TOUGH2 User's Guide, Version 2.1. Lawrence Berkeley National Laboratory Report LBNL-43134. <https://doi.org/10.2172/1003990>
- Schlumberger, 2023. Petrel E&P Software Platform. <https://www.software.slb.com/products/petrel>
- Schultz, R., Skoumal, R.J., Brudzinski, M.R., Eaton, D., Baptie, B., and Ellsworth, W., 2020. Hydraulic fracturing-induced seismicity. *Reviews of Geophysics*, 58(3), e2019RG000695. <https://doi.org/10.1029/2019RG000695>

- Tester, J.W., Anderson, B.J., Batchelor, A.S., Blackwell, D.D., DiPippo, R., Drake, E.M., Garnish, J., Livesay, B., Moore, M.C., Nichols, K., Petty, S., Toksöz, M.N., and Veatch Jr., R.W., 2006. *The Future of Geothermal Energy: Impact of Enhanced Geothermal Systems (EGS) on the United States in the 21st Century*. Massachusetts Institute of Technology, Cambridge, MA.
- U.S. Department of Energy, 2021. 45Q Tax Credit for Carbon Oxide Sequestration. Office of Fossil Energy and Carbon Management. <https://www.energy.gov/fecm/45q-tax-credit-carbon-oxide-sequestration>
- Zang, A., Oye, V., Jousset, P., Deichmann, N., Gritto, R., McGarr, A., Majer, E., and Bruhn, D., 2014. Analysis of induced seismicity in geothermal reservoirs – A review. *Geothermics*, 52, 6-21. <https://doi.org/10.1016/j.geothermics.2014.06.005>
- Zhang, T., Ramakrishnan, R., and Livny, M., 1996. BIRCH: An efficient data clustering method for very large databases. *ACM SIGMOD Record*, 25(2), 103-114. <https://doi.org/10.1145/235968.233324>