SMART-OG Initiative

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

TASK 6: Real-Time Visualization: Faults and Fracture Networks

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August 23, 2021

U.S. DEPARTMENT OF ENERGY

SMART Task 6 – Team Organization

Experienced team with diverse, complementary backgrounds

EERC
UND UNIVERSITY OF NORTH DAKOTA

(Lead Organization)

Lawrence Livermore National Laboratory

(Co-Lead Organization)

FACT

Los Alamos NATIONAL LABORATORY

BERKELEY LAB

NETL NATIONAL ENERGY TECHNOLOGY LABORATORY

ATM

SMART Task 6 – Overview

Motivation, vision, and Phase I goals

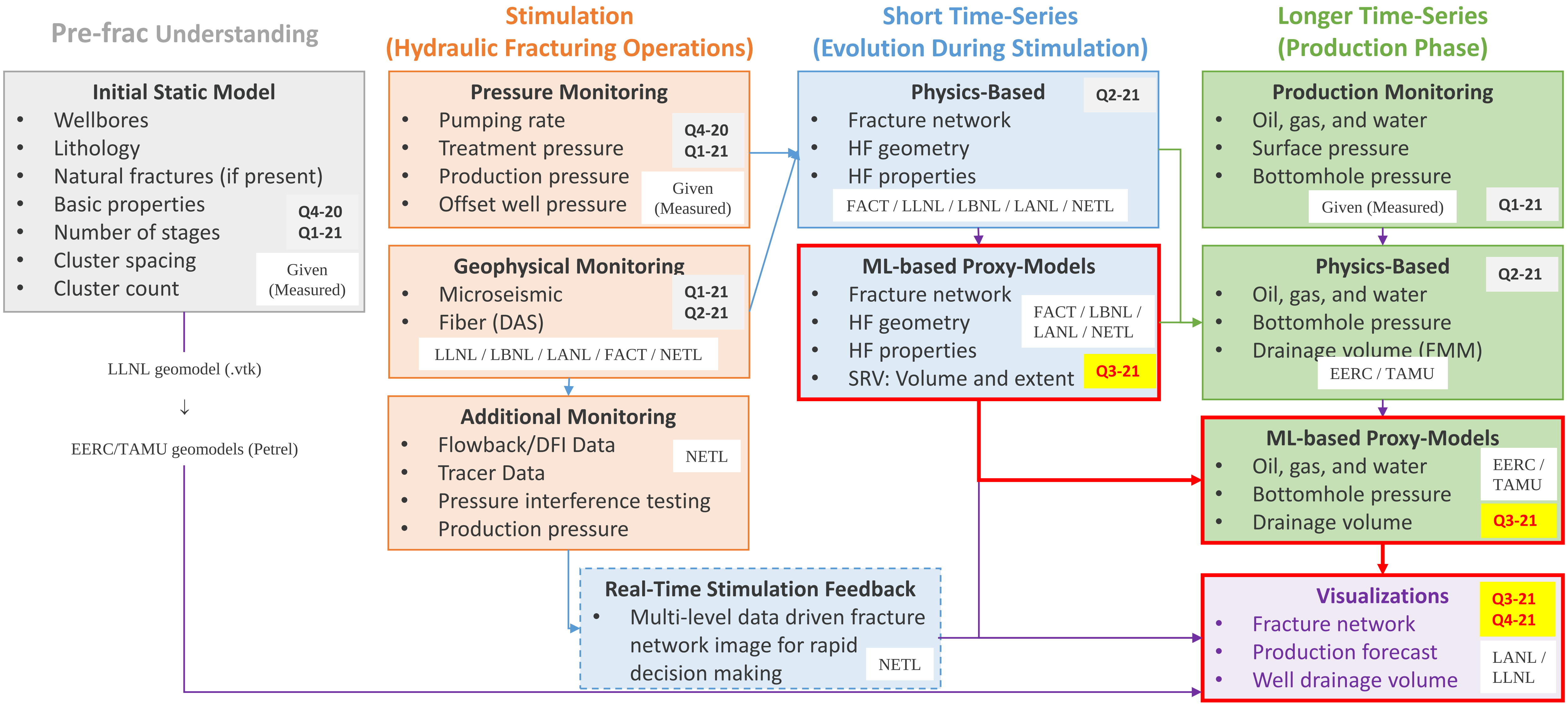
Motivation and Vision

- Strategic advancement in unconventional reservoir development
- Fundamentally change how we visualize and control fractures and faults with initial application to stimulation and production
- Leverage data (measurements), physics-based models, and machine learning (ML) to visualize fracture networks and concomitant fluid flow
- Seamless integration from stimulation to production to inform well, drill-spacing unit (DSU), and field management decisions

Phase I Goals

- Use the Hydraulic Fracturing Test Site (HFTS-1) as our test case
- Generate physics-based datasets for microseismic, distributed acoustic sensing (DAS), and production (oil, gas, and water rates)
- Create ML-based proxy-models to rapidly estimate the fracture network and generate the production forecast
- Integrate proxy-models into powerful visualizations that inform operational decision-making

SMART Task 6 – Workflow



Pre-frac Understanding

Initial Static Model
- Wellbores
- Lithology
- Natural fractures (if present)
- Basic properties
- Number of stages
- Cluster spacing
- Cluster count

Q4-20
Q1-21

Given
(Measured)

LLNL geomodel (.vtk)

↓

EERC/TAMU geomodels (Petrel)

Stimulation
(Hydraulic Fracturing Operations)

Pressure Monitoring
- Pumping rate
- Treatment pressure
- Production pressure
- Offset well pressure

Q4-20
Q1-21

Given
(Measured)

Geophysical Monitoring
- Microseismic
- Fiber (DAS)

Q1-21
Q2-21

LLNL / LBNL / LANL / FACT / NETL

Additional Monitoring
- Flowback/DFI Data
- Tracer Data
- Pressure interference testing
- Production pressure

NETL

Real-Time Stimulation Feedback
- Multi-level data driven fracture network image for rapid decision making

NETL

Short Time-Series
(Evolution During Stimulation)

Physics-Based

Q2-21
- Fracture network
- HF geometry
- HF properties

FACT / LLNL / LBNL / LANL / NETL

ML-based Proxy-Models
- Fracture network
- HF geometry
- HF properties
- SRV: Volume and extent

FACT / LBNL /
LANL / NETL

Q3-21

Longer Time-Series
(Production Phase)

Production Monitoring
- Oil, gas, and water
- Surface pressure
- Bottomhole pressure

Given (Measured)

Q1-21

Physics-Based

Q2-21
- Oil, gas, and water
- Bottomhole pressure
- Drainage volume (FMM)

EERC / TAMU

ML-based Proxy-Models
- Oil, gas, and water
- Bottomhole pressure
- Drainage volume

EERC /
TAMU

Q3-21

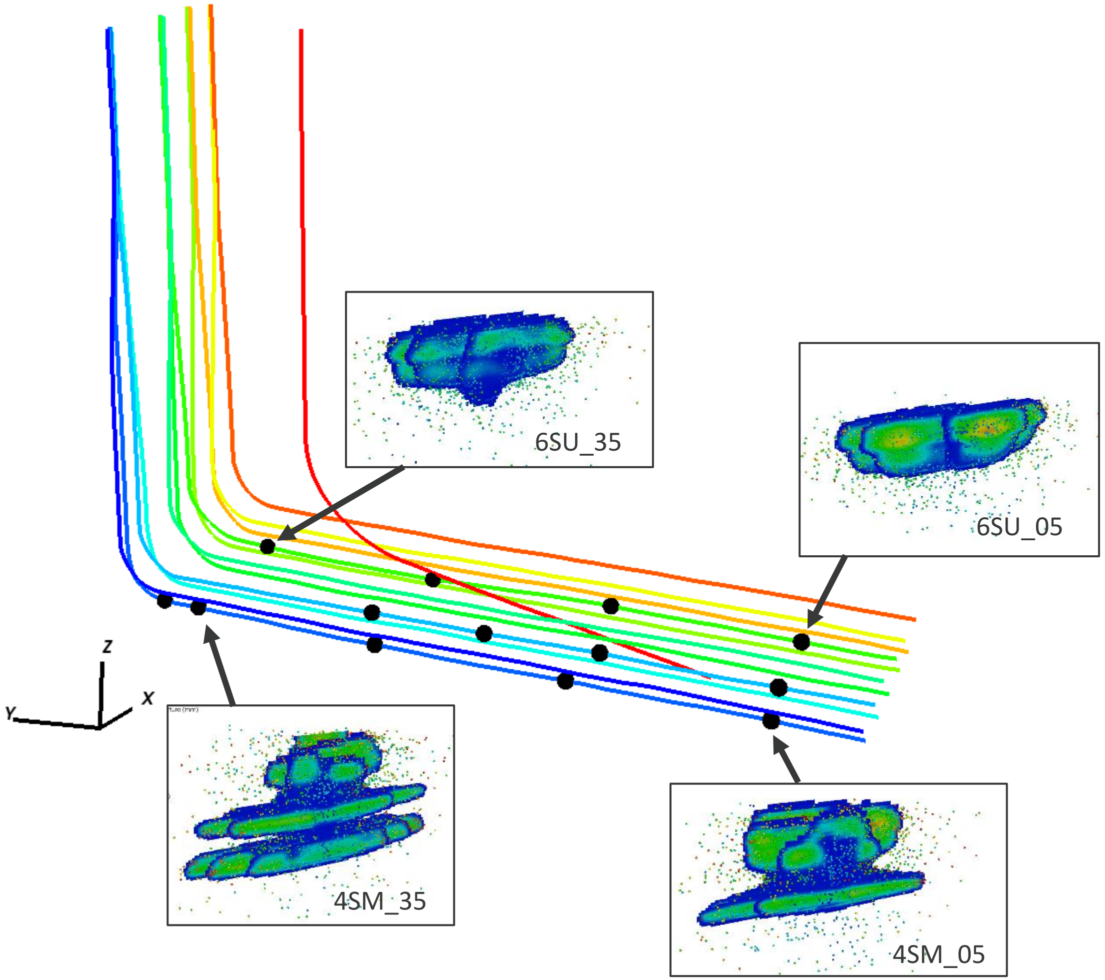
Visualizations
- Fracture network
- Production forecast
- Well drainage volume

Q3-21
Q4-21

LANL /
LLNL

Synthetic Microseismic Models

Training and testing data for ML-based fracture network modeling



Details	Status
4SM_05	☑
4SM_15	☑
4SM_25	☑
4SM_35	☑
4SM_47 (curving, 45/90 fault offset 200m)	☑
6SU_05	☑
6SU_15	☑
6SU_25	☑

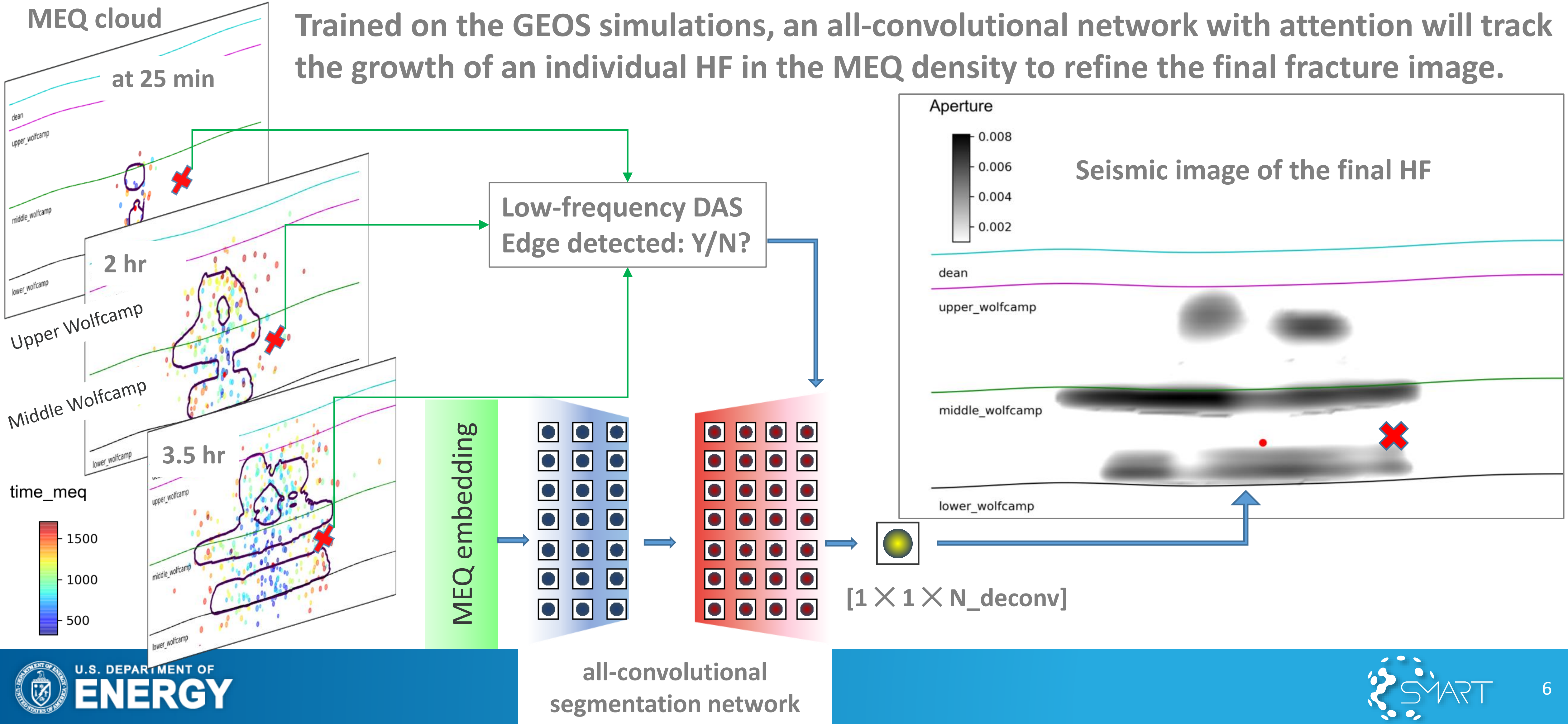
Details	Status
6SU_35	☑
4SU_05	☑
4SU_15	☑
4SU_25	☑
4SU_35	☑
4SM_37 (curving)	🛠
4SM_37 (45/90 fault offset 200m)	🛠

- A growing database of synthetic data
- Supplements real field data from HFTS-1
- Current focus is upon transferring data to ML practitioners to support ML training

Rapid Visualization of Hydraulic Fractures

Microseismic constrained by low-frequency DAS and 4D cross-hole seismic

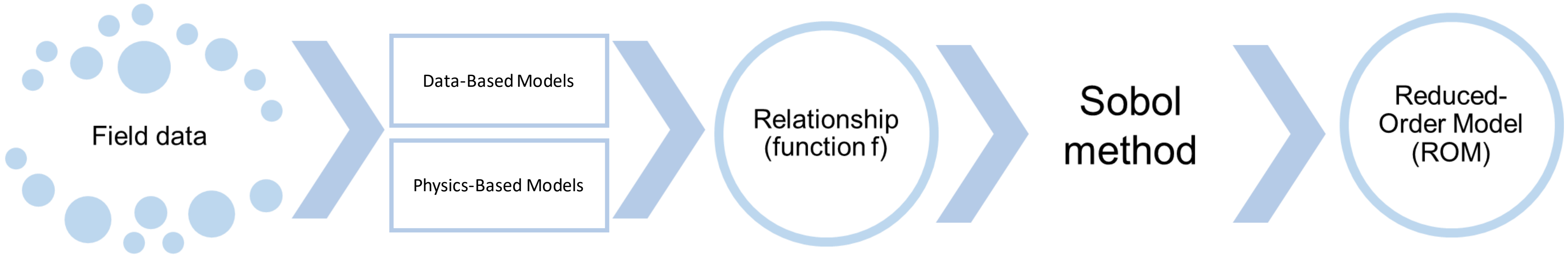
Trained on the GEOS simulations, an all-convolutional network with attention will track the growth of an individual HF in the MEQ density to refine the final fracture image.



ML-based ROM for Estimating the SRV from Microseismic

Data-driven reduced-order models (ROMs) for monitoring the effectiveness of hydraulic fracturing

F A C T



Field data

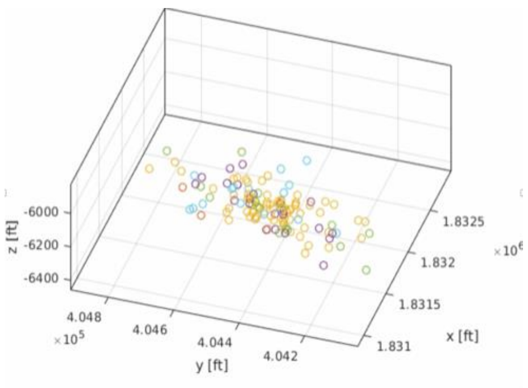
Data-Based Models

Physics-Based Models

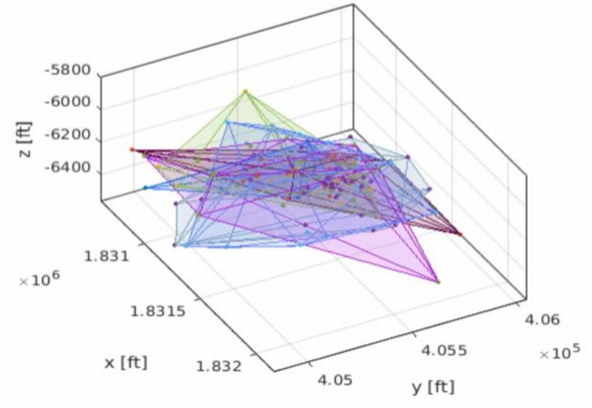
Relationship (function f)

Sobol method

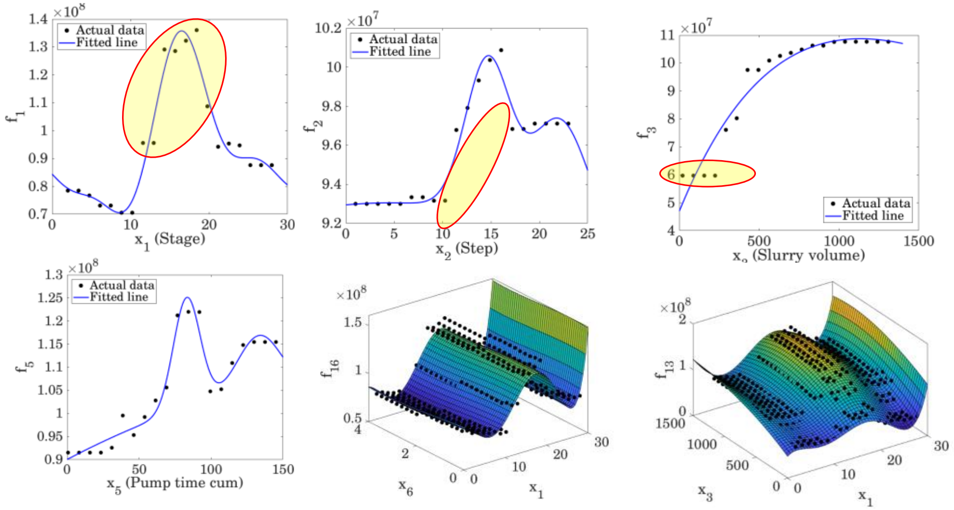
Reduced-Order Model (ROM)



Microseismic



SRV



SRV = f(Stage, Step, Slurry Volume, Pump time cum., S13, S16)

Combining Fast Marching (FM) and ML

Rapid visualization and performance predictions

- Leverage speed of Fast Marching (FM)-based flow simulation for rapid history-matching (2-3 orders of magnitude faster than commercial numerical simulators) and generate training data in high contrast/fractured media
- Use Deep Learning and Image Compression for visualizing evolution of well drainage volumes and hydraulic/natural fracture interactions
- Near real-time performance prediction of selected metrics (e.g., production and pressure response) using machine learning

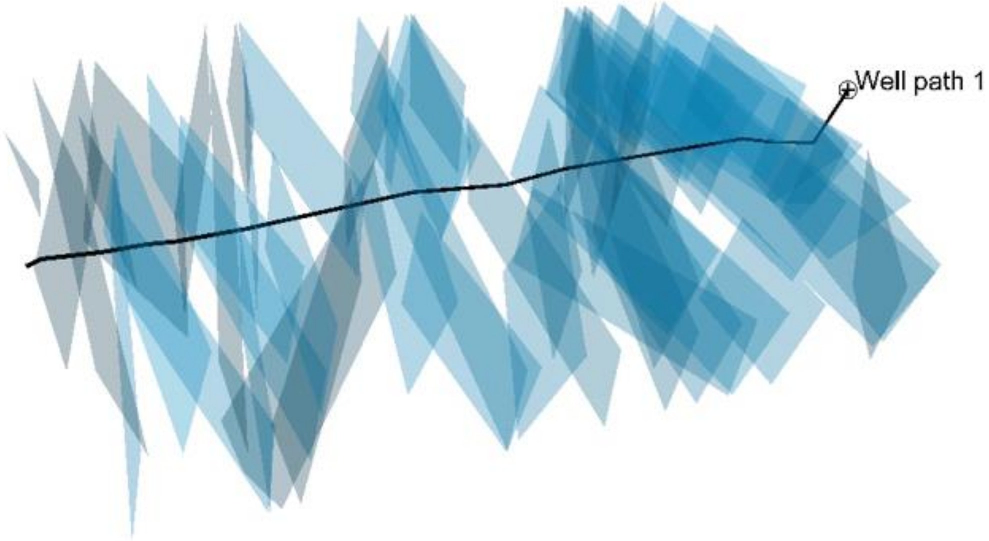
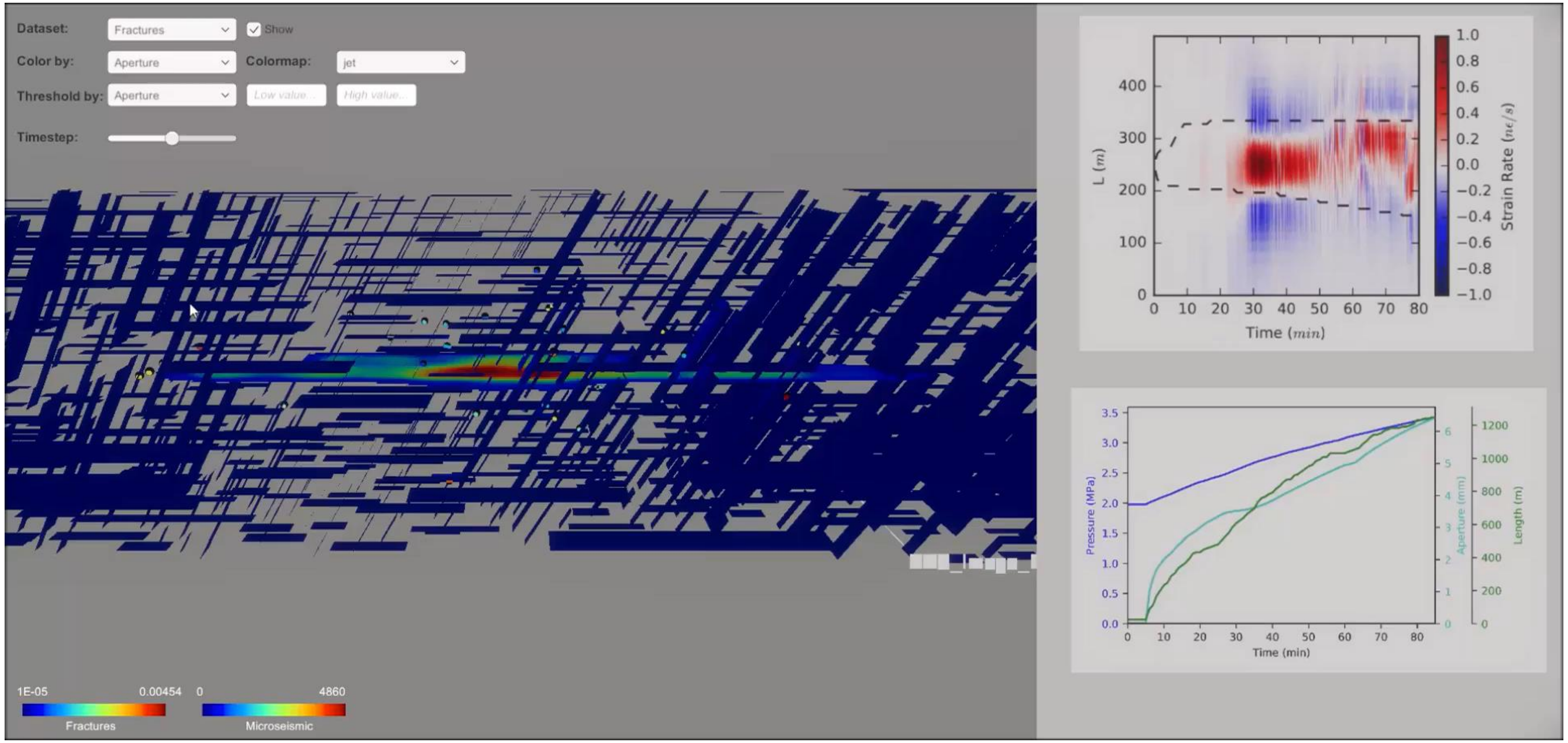


Illustration of drainage volume visualization in the presence of hydraulic and natural fractures using FM-based flow simulation.

Unity Visualization Interface Prototype

- LLNL implemented the necessary features to include subsurface data in the Unity gaming engine
- Exploring new ways to visualize data that leverage the engine
- Next steps will be to plan for accommodating ML outputs



Dataset: Fractures ☑ Show

Color by: Aperture Colormap: jet

Threshold by: Aperture Low value... High value...

Timestep:

The prototype developed by Task 6 will explore novel visualizations and demonstrate near-real-time workflows that utilize ML.

SMART Task 6 – Summary

Key accomplishments and December 2021 targets

Key accomplishments

- Assimilated HFTS-1 datasets into a single Task 6 resource
- Conducted physics-based modeling of stimulation and production to create training/testing datasets for ML-based proxy-models
- Generated preliminary ML-based proxy-models that show potential for rapidly visualizing the SRV, fracture network properties, and associated production
- Created exploratory visualizations in Unity for the proof-of-concept platform

December 2021 targets

- Finalize ML-based proxy-models for the fracture network and production
- Finalize visualizations in Unity and input/output data needs
- Integrate the proxy-models into the visualization platform and test the system

SMART Task 6 – Phase II

Linkages to other activities under the Carbon Storage Program

- Our visualization prototype can inform novel methods for Task 1:
  - Fracture visualization for Carbon Storage and other subsurface applications
  - Communicating real-time microseismic, including uncertainties
  - Exploring how to clearly communicate timely positive and negative projected outcomes
    - Long-term production projections
    - Risk of fault activation or fracturing out of zone
- ML workflows for real-time interpretation of microseismic can be integrated with other capabilities under Phase II with relevance to Carbon Storage

SMART Task 6 – Phase II (cont.)

High-level, long-term objectives

- Identify one or more projects to test the Phase I system using field data
- Engage the field site operator(s) and execute data sharing agreements and other necessary contracts
- Plan and execute data acquisition for the field test site and evaluate the performance of the Phase I system
- Document the field performance and make recommendations
- Additional objectives will be developed during the Phase II planning meeting with the Task 6 team and SMART Advisory Board (August 13, 2021)

Questions?

Thank you!

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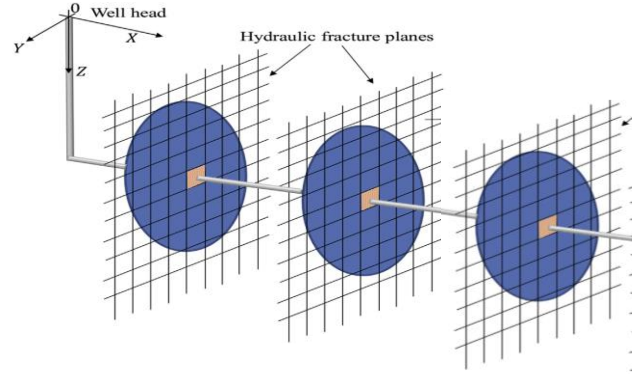
Supplemental Slides

- The supplemental slides highlight additional work conducted by the Task 6 organizations over the preceding quarter that were not included in the main presentation (due to time constraints).
- Please consult the slide notes for additional details about where to find more information about each slide.

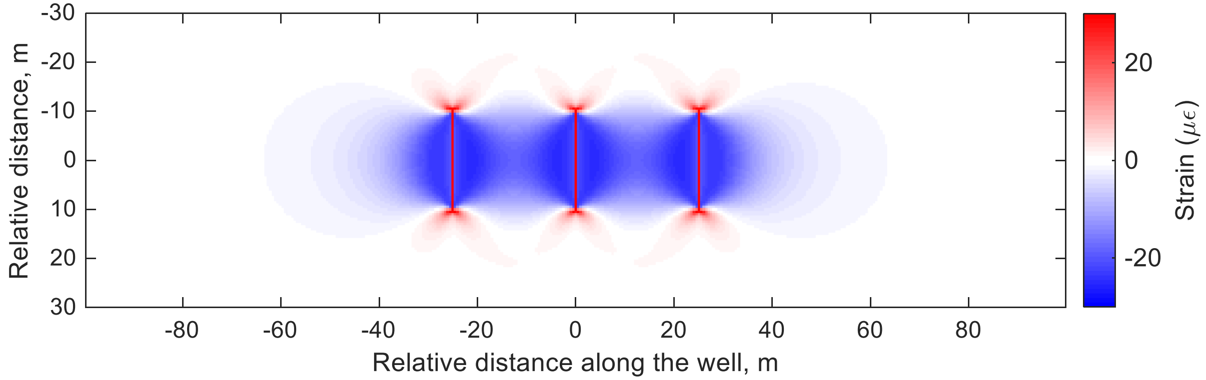
Low Frequency Fiber Optics for Fracture Properties

Distributed Acoustic Sensing from Fiber Optics – Low Frequency Geomechanical Changes with Precision

1. DDM Modeling Allows Rapid Generation of HF Basis Functions for LF DAS:



DDM Generated Hydraulic Fractures (HF)



Low-Frequency (LF) DAS Response

2. DDM Fracture Database are Used to Train our ML Algorithm & Invert Fracture Properties:

Key LF DAS Fracture ML Inversion Parameters:

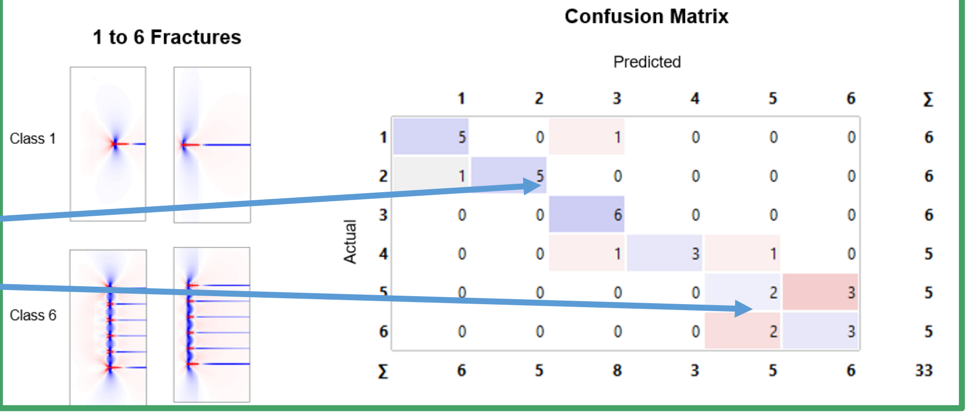
- **Number of fractures**
- **Propagation velocity**
- **Length**
- **Height**
- **Width**
- **Azimuth**

Example ML Inversion for *Number of Fracture Hits*:

1-3 Fractures – Easy

4-6 Fractures – More difficult

Number of Fractures



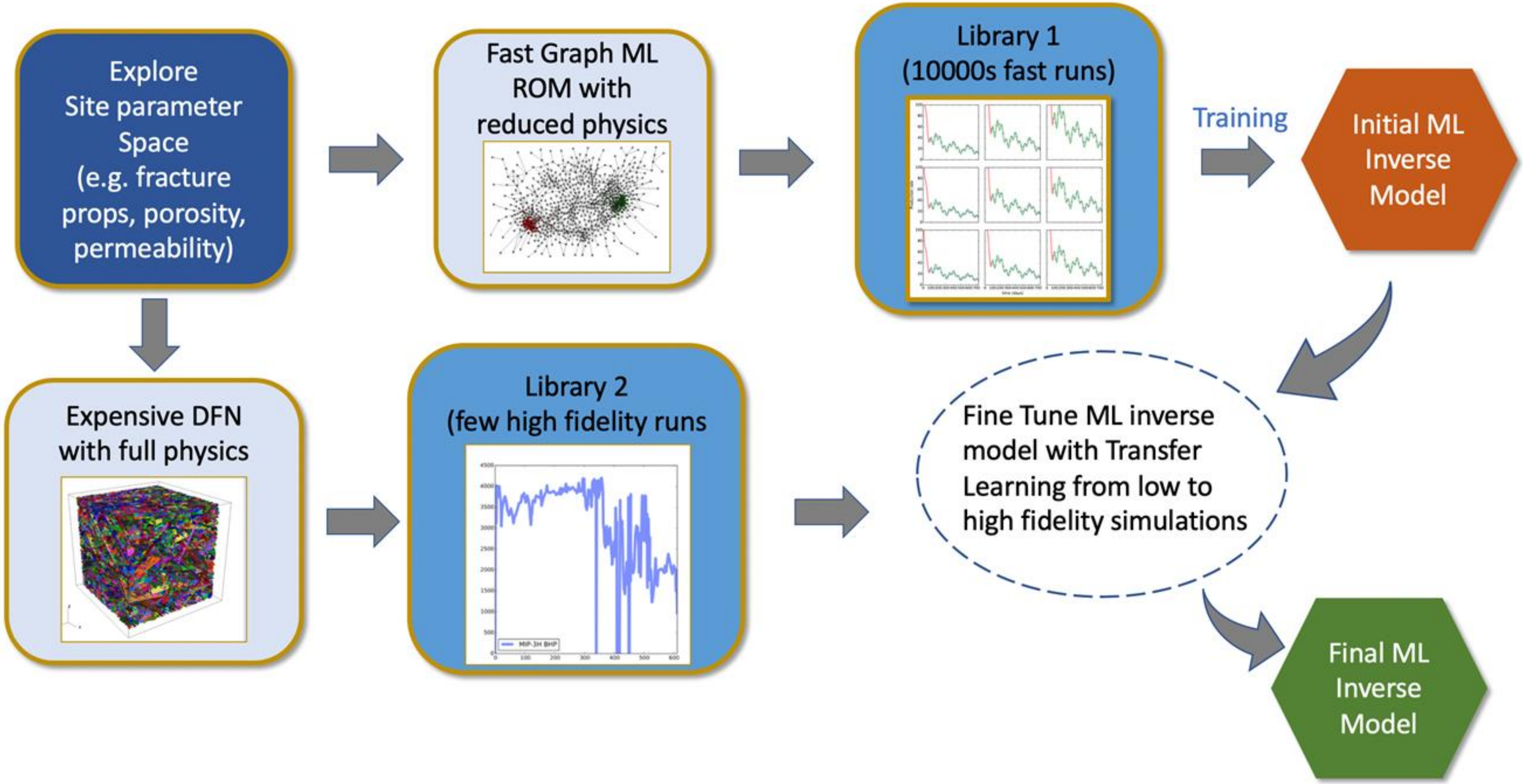
Confusion Matrix

Predicted

Actual	1	2	3	4	5	6	Σ
1	5	0	1	0	0	0	6
2	1	5	0	0	0	0	6
3	0	0	6	0	0	0	6
4	0	0	1	3	1	0	5
5	0	0	0	0	2	3	5
6	0	0	0	0	2	3	5
Σ	6	5	8	3	5	6	33

ANNs to Predict HFTS-1 Site Parameters

Slide 1 of 2



Explore
Site parameter
Space
(e.g. fracture
props, porosity,
permeability)

Fast Graph ML
ROM with
reduced physics

Library 1
(10000s fast runs)

Training

Initial ML
Inverse
Model

Expensive DFN
with full physics

Library 2
(few high fidelity runs

Fine Tune ML inverse
model with Transfer
Learning from low to
high fidelity simulations

Final ML
Inverse
Model

ANNs to Predict HFTS-1 Site Parameters

Slide 2 of 2

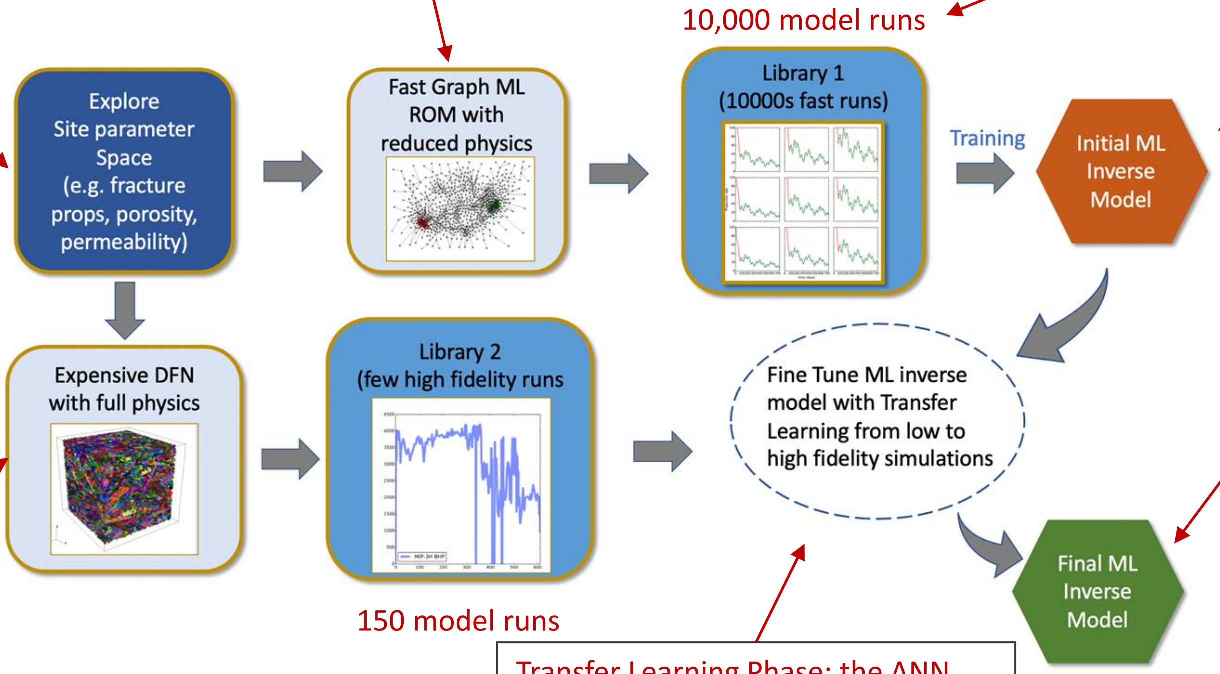
Analyze subsurface data to constrain physical properties of the reservoir (fracture networks and matrix) and transient in situ stress and fluid conditions for model construction.

High fidelity models are generated in dfnWorks using site parameters constrained by subsurface data (fracture density, orientation, height, aperture etc.). Flow simulations are then run upon varying the site parameters in order to generate scenarios in Library 2.

Fast but less accurate reduced order models are created through ML; this can be accomplished through graph theory in combination with other physics-informed models (e.g., analytical model of Patzek et al 2013).

Abundant synthetic data are generated for Library 1, with parameter ranges initially constrained by several high-fidelity simulations. The training data is in the form of historical production as predicted by the ROM.

The ML inverse model is an artificial neural net (ANN) that can predict the site parameters (α , M) based on short term production data.



Explore
Site parameter Space (e.g. fracture props, porosity, permeability)

Fast Graph ML ROM with reduced physics

10,000 model runs

Library 1 (10000s fast runs)

Training

Initial ML Inverse Model

Expensive DFN with full physics

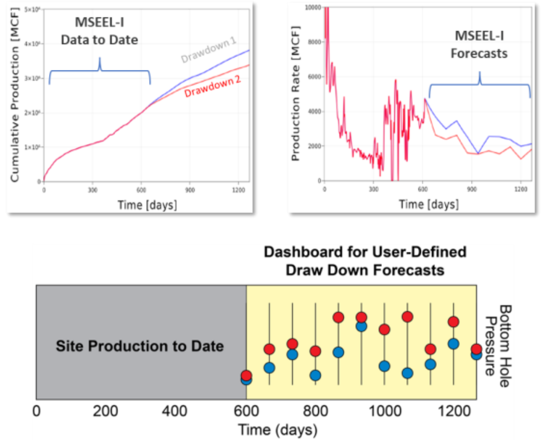
Library 2 (few high fidelity runs

150 model runs

Fine Tune ML inverse model with Transfer Learning from low to high fidelity simulations

Final ML Inverse Model

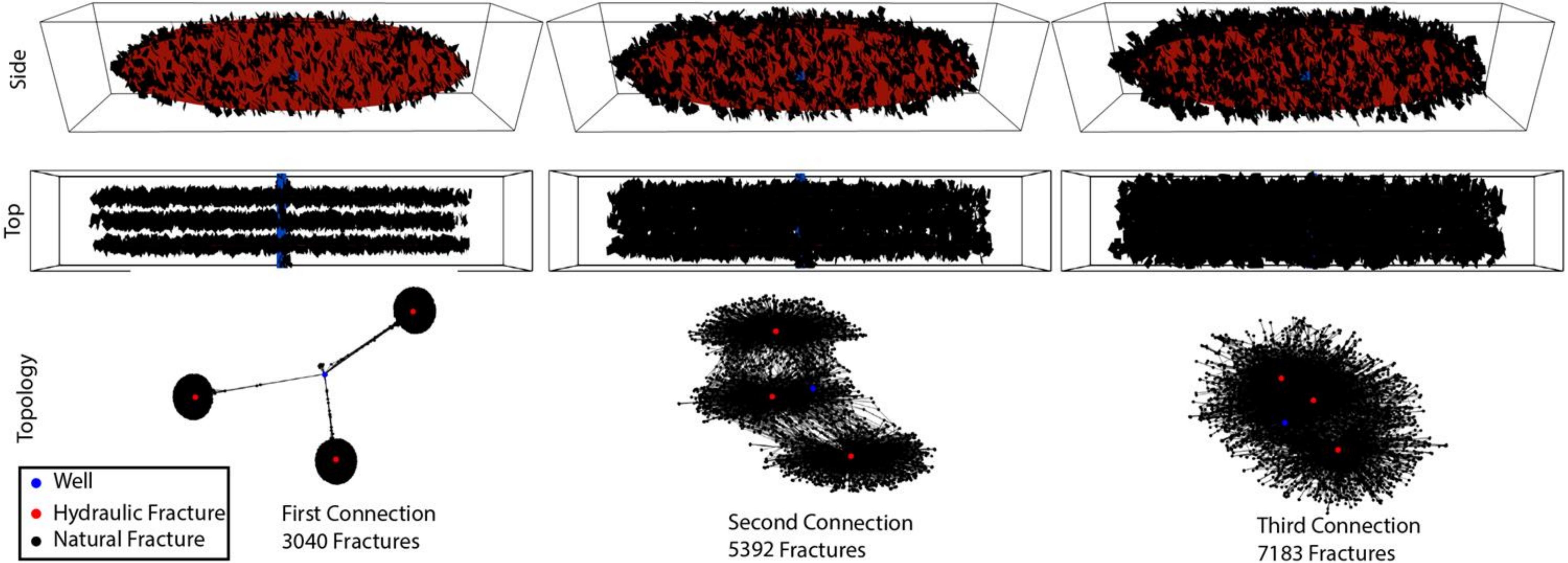
Forward models are generated for predicting site behavior (e.g., long-term production, EUR, reservoir depletion) based on re-training the reduced-order models (Library 1) with the high-fidelity models (Library 2).



Transfer Learning Phase: the ANN trained with synthetic data from low-fidelity models (ROM) is re-trained with synthetic data generated from high-fidelity models.

Visualizing Connectivity Between Hydraulic and Natural Fractures

Slide 1 of 2



First Connection
3040 Fractures

Second Connection
5392 Fractures

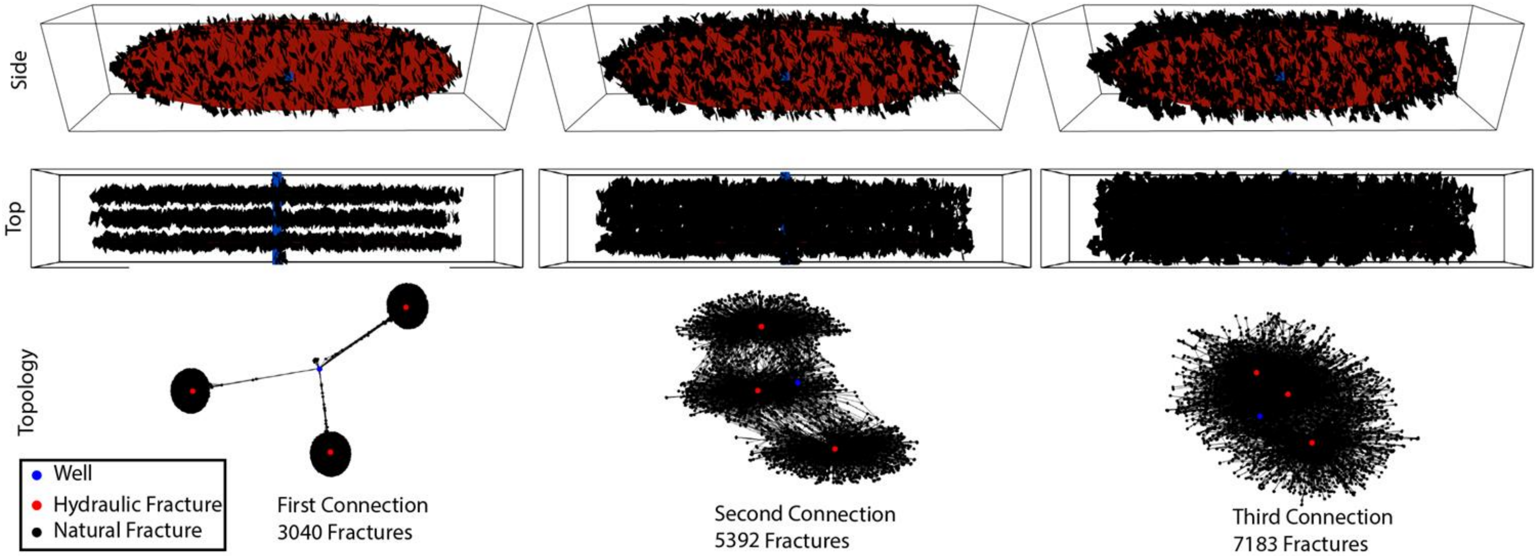
Third Connection
7183 Fractures

Visualizing Connectivity Between Hydraulic and Natural Fractures

Slide 2 of 2

LANL's dfnWorks will explore the connectivity of fracture networks, and its impact on flow and transport through the stimulated rock volume, through graph-based reduced order models (ROMs). This method increases computational efficiency while retaining the accuracy of key quantities of interest (e.g., primary flow channels), thereby allowing for real-time visualizations and decision-making. In the examples below, the topology (connectivity) is captured as vertexes (fractures) and edges (intersections between fractures). The section of the horizontal lateral (blue) contains three hydraulic fractures (red), with the natural fractures in black. The graph-based ROMs can evaluate the connectivity and flow properties of different degrees of connectivity as shown below. The "first connection" only considers those natural fractures that directly intersect the hydraulic fractures. The second connection includes the natural fractures connected to the first connection, and so forth. Through production history matching, this method can estimate the subset of natural fractures that contribute to the active flow network in stimulated reservoirs.

Graph representations



These topological models can be further reduced to display only the "fracture backbones", i.e., the primary flow paths

Natural fractures that directly intersect the hydraulic fractures.

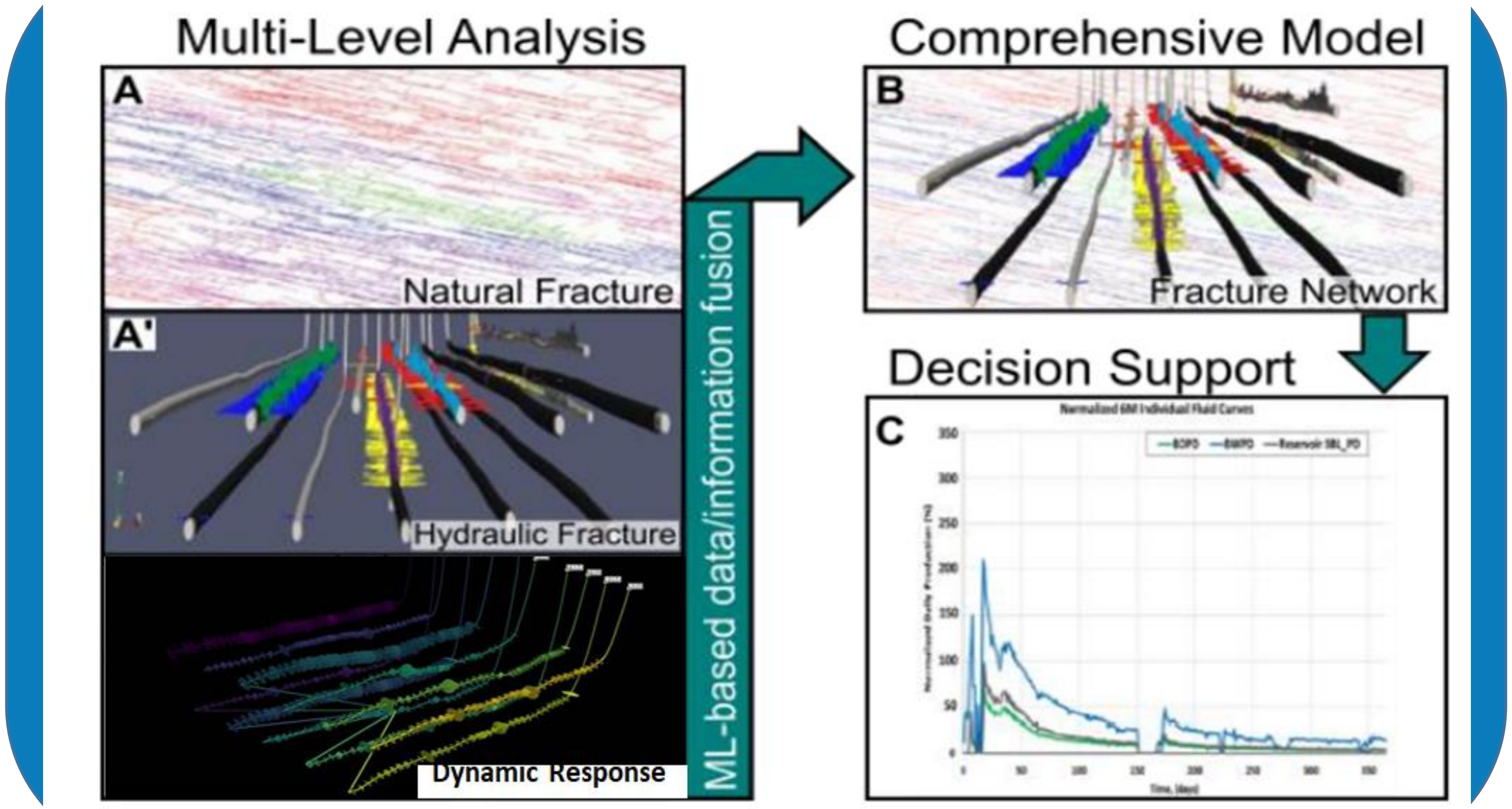
First connection fractures plus natural fractures that intersect the first connection fractures.

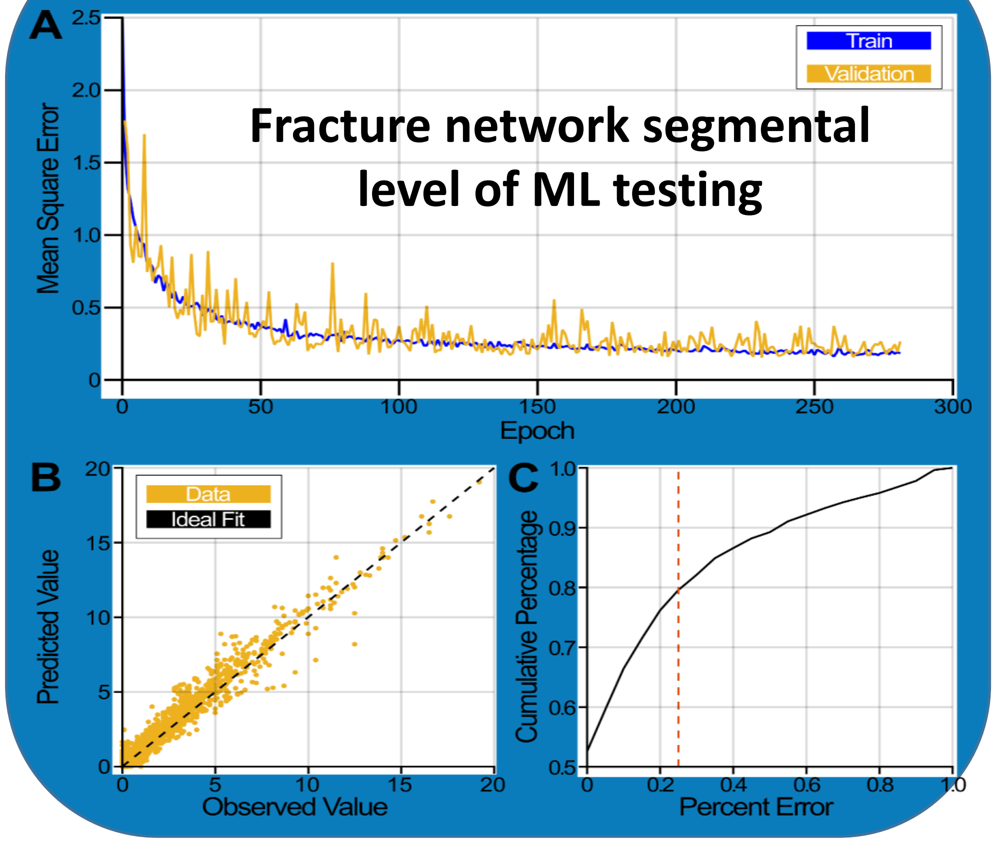
First and second connection fractures plus natural fractures that intersect the first and second connection fractures.

NETL: Multi-Level Data Driven Fracture Network Visualization

HFTS-1 Dataset

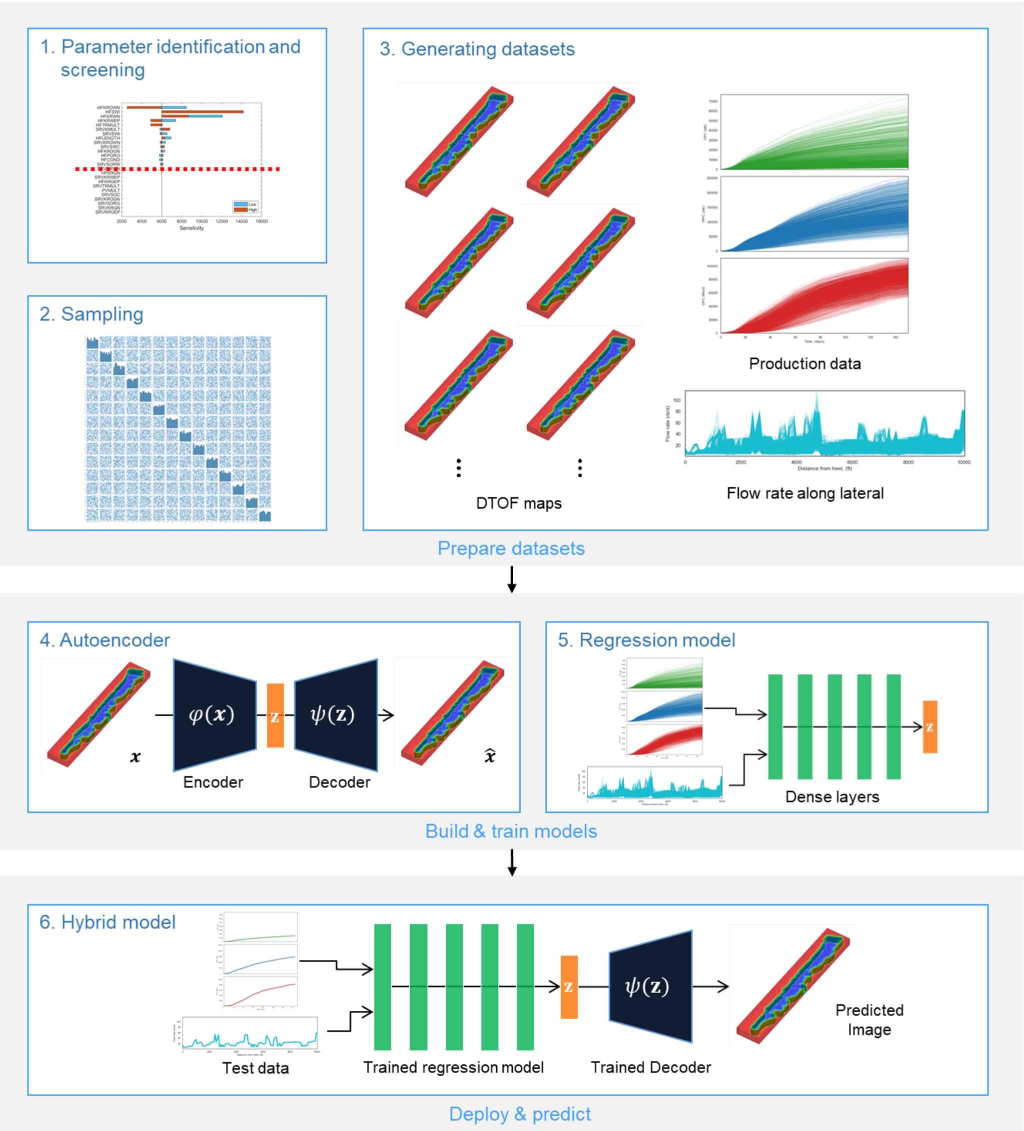
- Microseismic Data Fracking/Pumping Data Flowback/DFI Data Well layout/distance
- Tracer Data Production data Pressure interference testing Log/Core Data




Fracture network segmental level of ML testing

Details were reported in manuscript for URTeC, 2021

Workflow: Drainage Volume Visualization Using Machine Learning and FMM



1. Generate Training Method Data Using Fast Marching
   - Parameter identification, screening, and sampling history-matched models
   - Generating training data using Fast Marching-Based Rapid Simulation
2. Image Compression and Training ML models
   - Autoencoder/Decoder for compression
   - Deep Learning for Regression model
3. Deploy and Predict
   - Given well response, visualize drainage volume evolution
   - Predict future well performance