SMART Initiative

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

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Vision: Transform reservoir management decisions through rapid analysis of real time data to visualize forecasted behavior in an advanced control room “human-in-the-loop” format.

Real time means in seconds to minutes—rapidly enough to inform the decision.
Forecasted behavior means pressure evolution, injection/production rates, hydrocarbon recovery, storage efficiency, etc.

Potential Operational Decisions

- How to adjust production rates and pressures to maximize recovery, sweep efficiency, economics, ...
- How to adjust CO$_2$ injection & brine production in multiple wells to maximize storage and minimize pressure plume
- Where to place infill wells to increase total recovery
- When to inject fluids for managing reservoir pressure to increase total recovery
Vision: Accurate Real-time Forecasting of Fractured Reservoirs

MSEEL DOE Field Site

Real-time Pressure Management Dashboard

Prototype for Real-time Forecasting of Pressure Management Scenarios for MSEEL-I
Phase 1 Goals: Enable real-time forecasting at MSEEL to predict the pressure dependent behavior relative to recovery efficiency.

Natural fractures around a single stage in MIP-3H

Fracture network along entirety of MIP-3H

Initial simulation of drainage along fracture network.
Real-time forecasting demo

What is being controlled

Controls

Real-time predictions
High drawdown (blue) vs low drawdown (red) with no fracture closure

High Drawdown (Low Pressure) vs Low Drawdown (High Pressure)

History Matched to MSEEL MIP3H Prediction

High drawdown produces 25% more gas than Low drawdown if fracture closure due to drawdown is not considered,

But...
High drawdown (blue) vs low drawdown (red) with fracture closure

Lower drawdown can produce more with more complex physics of fracture closure considered
Key Tools Developed in Phase 1 for Phase 2 CO₂ Injection Case

- Cost-efficient machine learning approaches to reservoir imaging and design
- Transfer Learning and Multi-Fidelity Methods
- Site Behavior Libraries
- Graph-based machine learning emulators for fractured systems
- Methods to combine reservoir forecasting and economics forecasting
WVU Characterization ML Tools

Drill string borehole imager and vibration sensor.

Drill String Acceleration Data Analysis

Low Fidelity Approaches
Integrated with
High Fidelity Approaches
to make Smart Decisions

Shmin Fracture
Intensity

Acoustic Waterfall 0-7500Hz
Transfer Learning and Multi-Fidelity Methods

Improve low-fidelity model performance by transfer-learning with high-fidelity data

Reduce uncertainty by combining high-fidelity and lower-fidelity models for improved UQ performance
“Behavior Library” that allows operators to tailor pressure drawdown for optimum recovery.
Workflow for Fractured Systems using Machine Learning and Graphs to Accelerate Physics-Based Reservoir Models

1. Fractured Rock at Field Site
2. High Fidelity DFN
3. Graph Representation
4. Pruned Graph
5. Pruned DFN
6. QOI - Breakthrough
7. Machine Learning / Physics Informed Pruning
8. Physics on Graph
9. UQ / Bias Correction
10. Corrected Breakthrough
Role of Technoeconomic Analysis (TEA) in Evaluating Pressure Drawdown Strategies

- Traditional production of unconventional oil and gas wells is aimed at acquiring high initial production via rapid pressure draw down
  - Rapid drawdown allows the operator to realize returns on investments quickly

- Preliminary modeling has shown that increasing flowing bottom hole pressure by reducing the choke setting at the wellhead can result in a greater of production over time

- Analysis is needed to cross-check the economic viability of the pressure management strategies resulting from the model predictions
  - Facilitates development of optimization schemes that balance
    1. Improving recovery efficiencies of unconventional reservoirs
    2. Attaining desired economic rates of return

Cumulative gas production curves under large and small drawdown cases

Modeling process of technical–economic boundary of FECM/NETL Unconventional Shale Well Economic Model

\[
NPV(x) = \sum_{t=0}^{n} \frac{C_t(x) - C_0(x)}{(1 + i)^t}
\]

- \( NPV(x) \): Net Present Value
- \( C_t(x) \): Cash Flows at time \( t \)
- \( C_0(x) \): Initial Investment
- \( i \): Discount rate (in percent)
- \( n \): Number of time periods (months)
NETL Economic Tools – Unconventional Shale Well Economic Model

Model evaluates economics of unconventional shale wells on a per well and per pad level

The model allows for direct comparison of alternative technologies through multiple profitability indicators

Model Input
- Production data for the life of the well
- Can compare the economics of 700 wells in a single model run

Model Outputs (month or pad basis)
- Net cash flow, NPV, IRR, EBITDA, breakeven price, payout month, and payout year
**NETL Economic Tools – Unconventional Shale Well Economic Model**

NETL is augmenting the existing Task 7 Phase I efforts by leveraging the Unconventional Shale Well Economic within the LANL/WVU workflow to enable a robust TEA analytical capability.

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**Research Approach:**
1. Infuse time-series production data generated from LANL that explore various drawdown strategies.
2. Evaluate and analyze modeling results.
3. Perform sensitivity analyses on economic parameters to assess impact on result outcomes.
Phase 2 Planning: CO$_2$ sequestration in saline aquifer

- Pressure management is equally important for injecting fluid and CO$_2$ sequestration
  - Optimize CO$_2$ without setting off felt seismic events
  - Optimize most gas in without harming reservoir (inverse of O&G)
- How do we transition oil sector to storage sector?
  - Big companies not really doing it (optimize storage but going after product)
  - Will be small independents but they don’t have R&D
- Integrate task 7 tools with tasks 1-6
  - MSEEL WVU tools: 1) leaks we can characterize, 2) seismic hazard characterization, 3) ML to characterize data
  - Transfer learning and multi-fidelity machine learning tools
  - Scenario libraries
  - Graph-based machine learning emulators for fractured systems
  - Economic tools integrated with machine learning workflows is unique
Questions?
Thank you!

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