Real-Time Forecasting and Operational Control (RTFO) Module

Ivani Patel[1], Alexander Hanna[1], Ashton Kirol[1], and Maruti Mudunuru[1]
[1]Pacific Northwest National Laboratory, Richland, WA; *ivani.patel@pnnl.gov

PNNL-SA-201590

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

Summary

- **Objective:** Provide advanced, user-friendly tools for real-time decision support in CO_2 injection management.
- **Importance:** Addresses the critical need for accurate simulation and optimization of reservoir conditions for CO_2 sequestration to mitigate climate change.
- **Technology:**
  - Interface: Dynamic, browser based, built with Python and Plotly Dash.
  - Accessibility: Allows users to interact with reservoir simulation tools without needing to install software.
- **Capabilities:**
  - Integration: Combines forward models and history matching algorithms.
  - Data handling: Users can upload monitoring data, choose history matching algorithm, and run simulations.
- **Models:**
  - History Matching (HM): Uses the TAMU's history matching machine learning model for the Illinois Basin Decatur Project (IBDP) dataset.
  - Forecasting: Utilizes the University of Texas at Austin's Bureau of Economic Geology (UTBEG) model.
- **Optimization:** Aims to optimize storage and minimize pressure build-up.
- **Benefits:**
  - Real-Time adjustments: Facilitates real-time modification to operations and monitoring strategies.
  - Efficiency: Enhances the efficiency and effectiveness of CO_2 sequestration projects.

Features

- Provides real-time actionable decision support to improve operation and risk management strategies during geological carbon sequestration operations.
- Integrates history-matching ML models and visualizes them within the modern-looking graphical user interface.
- Forecasts future reservoir performance based on historical monitoring data.
- Optimizes storage efficiency by varying injection strategies.

Results

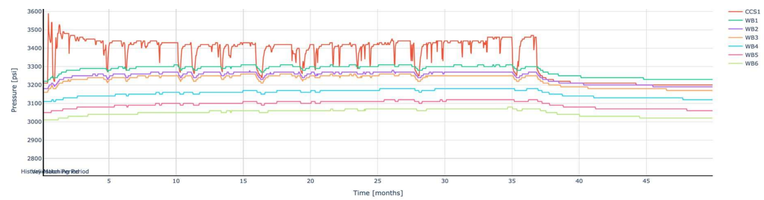

Figure 1. IBDP Bottom Hole Pressure

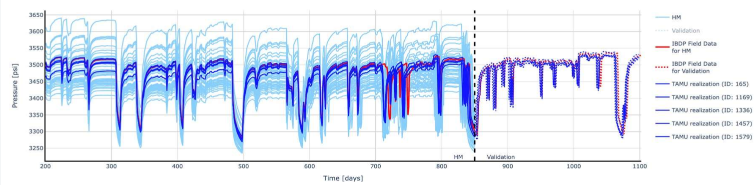

Figure 2. TAMU Pressure History Matching

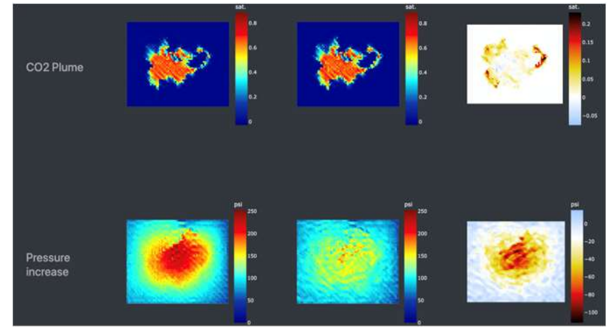

Figure 3: CO_2 saturation and pressure increase predicted by the Texas A&M model for scenarios with a base (left) and optimized (middle) injection rate. The difference between the two scenarios is shown on the right.

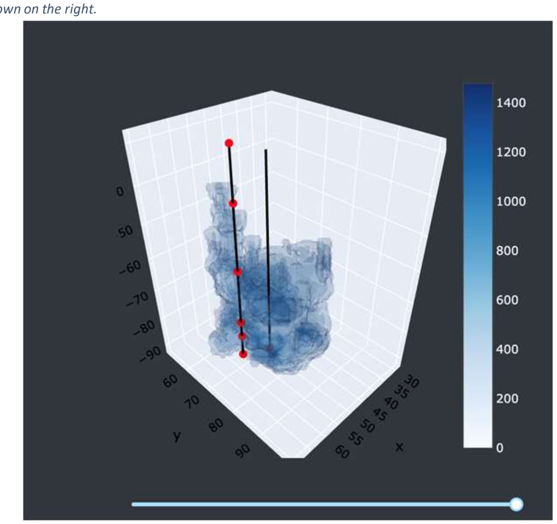

Figure 4: 3D representations of IBDP CO_2 Plume

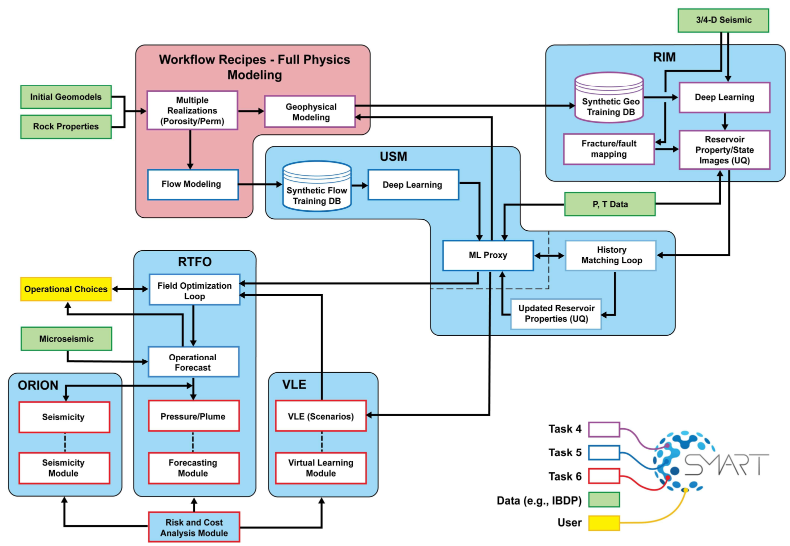

Figure 5: Workflow of SMART Modules

Conclusion

- The RTFO module utilizes machine learning-driven history matching to accurately constrain subsurface parameters, enhancing reservoir model precision.
- It enables the creation of optimized site operation plans despite uncertainties.

Acknowledgement

This work is developed with funding support from the United States Department of Energy's Office of Fossil Energy and Carbon Management (DOE-FECM) through the Science-informed Machine Learning to Accelerate Real-Time (SMART) Decisions in Subsurface Applications Initiative. This support is gratefully acknowledged. Portions of this work were produced under the auspices of the U.S. Department of Energy by Pacific Northwest National Laboratory under Contract DE-AC06-76RLO1830.