SMART-CS Initiative

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

Progress and Accomplishments in the Use of Machine Learning for Real-Time Carbon Storage Reservoir Simulation History Matching and Forward Forecasting

Thomas McGuire
Catherine Yonkofski

SMART Task 4

August 6, 2021

U.S. DEPARTMENT OF ENERGY

SMART Task 4 Team

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UND NORTH DAKOTA

Pacific Northwest
NATIONAL LABORATORY

- Thomas McGuire (EERC) – Lead
- Catherine Yonkofski (PNNL) – Co-Lead

Associated Storage (EOR) Team

NATIONAL ENERGY TECHNOLOGY LABORATORY

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Dedicated Storage (saline) Team

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OAK RIDGE National Laboratory

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Carnegie Mellon University

Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Full Team

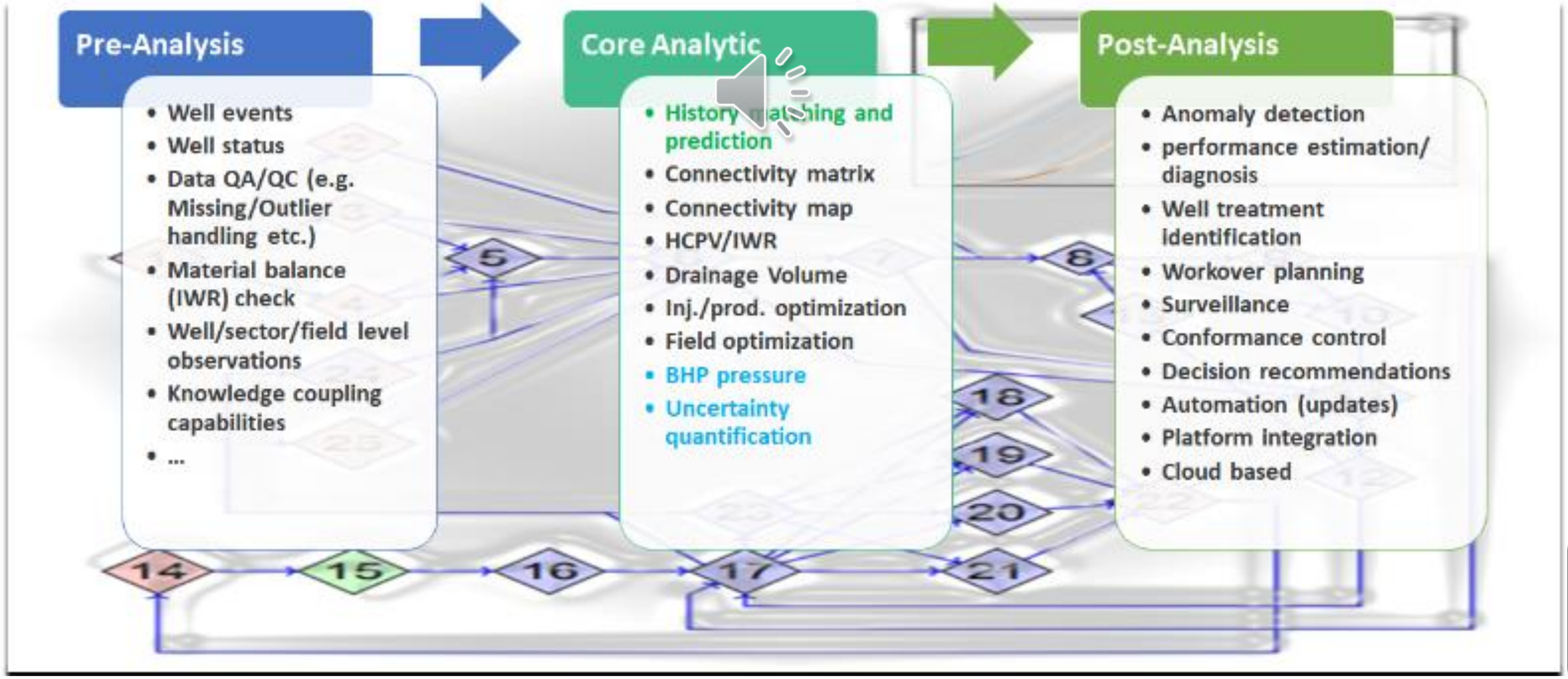
- **Motivation:** The SME oversight and computational resources required for disparate data interpretation, assimilation, and inverse modeling used by conventional history-matching methodologies results in a time-consuming process which is infeasible for rapid, real-time forecast updating or decision support.
- **Task 4 (T4) Objective:** The objective of the T4 team is to develop software tools that employ machine learning (ML) methods to integrate monitoring data into subsurface forecasts more rapidly than current physics-based history-matching workflows allow.
- **Vision:** Resultant forecast-updating methodologies will be incorporated into a software platform which will be deployed for autonomous use by site operators, providing them with decision support and generating real-time performance metrics of dedicated or associated CO_2 storage.

Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Associated Storage (enhanced oil recovery [EOR]) Team: NETL, UU, WVU

— **Phase 1 (December 2021) Goal:** Demonstrate fully functional framework with CO_2 EOR workflow that incorporates simulated real-time monitoring data (well pressures and well injection or production fluid rates [oil, CO_2, and water]) to update a history match and forward forecast for the SACROC CO_2 EOR (associated CO_2 storage) site.

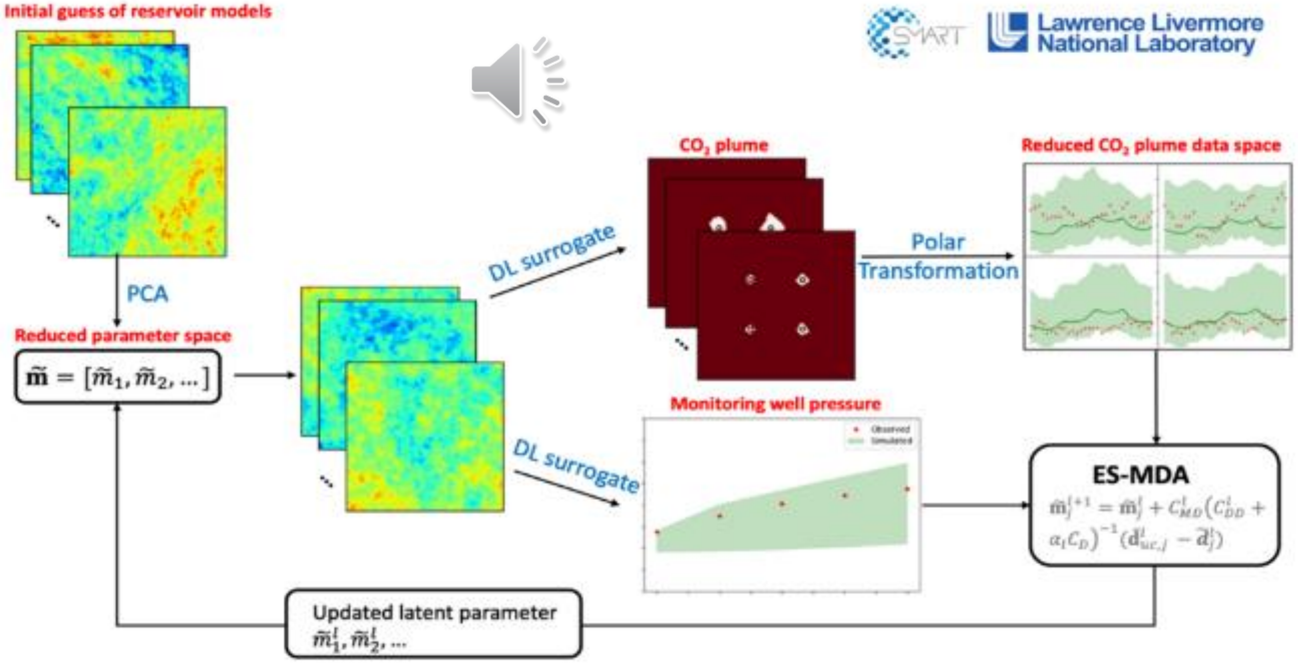


Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Dedicated Saline Storage Team: EERC, PNNL, LLNL, LANL, LBNL, SNL, ORNL, UI, CMU, WVU

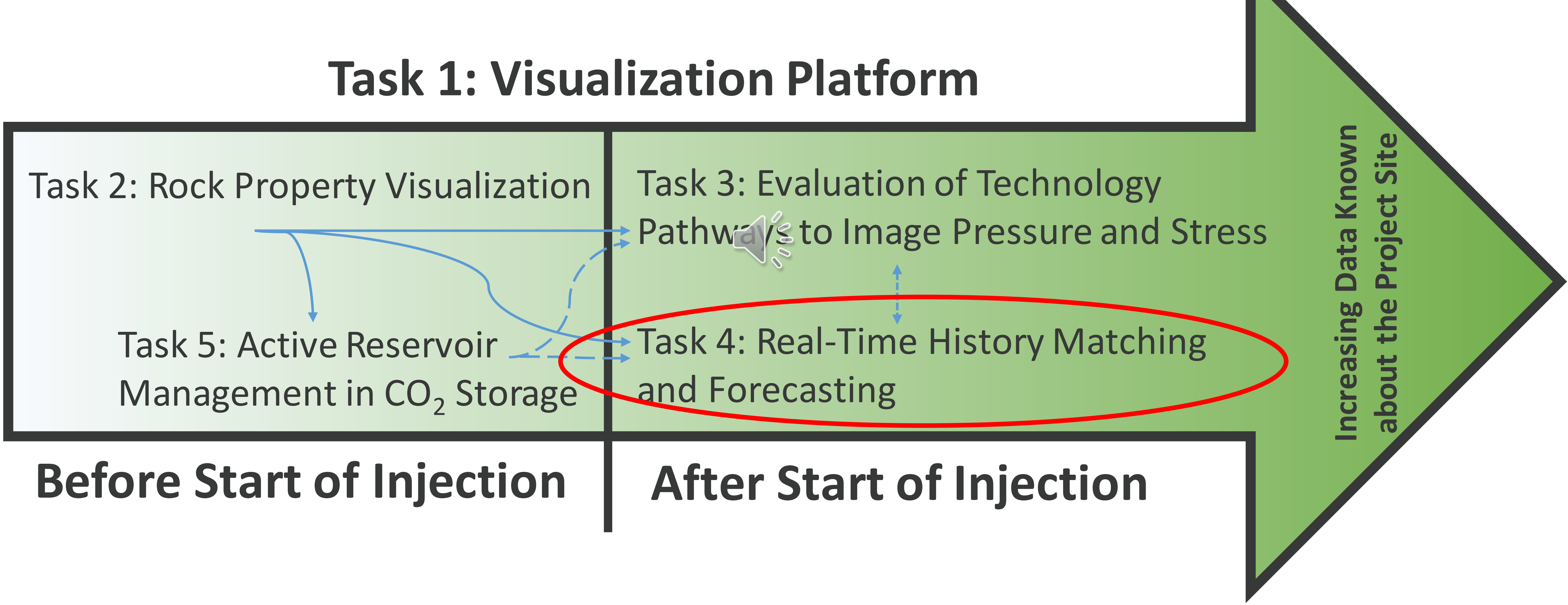
— **Phase 1 (December 2021) Goal:** Demonstrate an integrated software framework with ML methods trained using observations of a synthetic CO_2 storage operation to update forward forecasts of CO_2 and pressure plumes over time as injection into a saline formation occurs.



Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Links to Other SMART-CS Tasks:



Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Overall Task-Level Workflow – Refer to Milestone 4.4.2

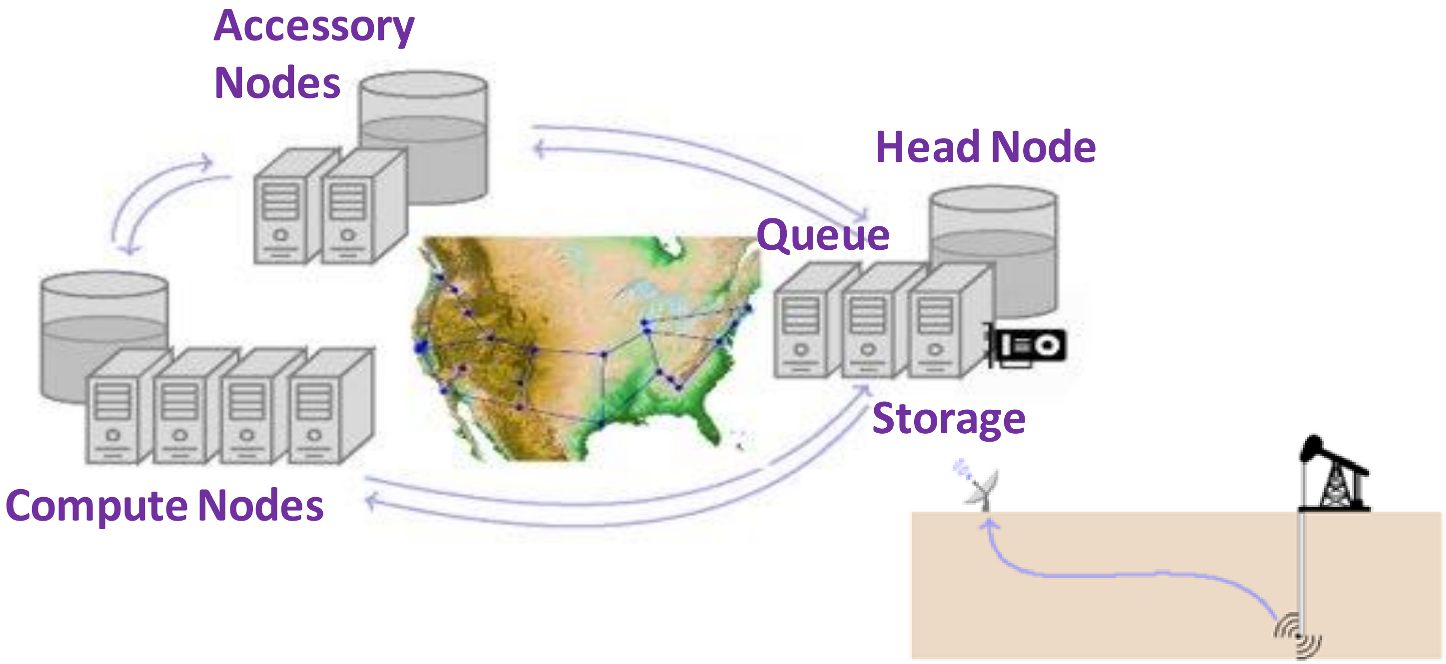
Milestone / Deliverable	Date Due	Description	Status
Milestone 4.1	3/31/2020	Path Forward for Training Data Sets Confirmed	Complete
Milestone 4.3.1 Deliverable 4.3.1	8/31/2020	Design Basis for ML Algorithm Selection, Application, and Testing	Complete
Milestone 4.3.2	10/30/2020	Preliminary ML Algorithm Testing Complete	Complete
Milestone 4.4.1	3/31/2021	Preliminary T4 Framework Integration Complete. Team integration point: go/no-go decision for one or more Phase 1 ML algorithms.	Complete
Milestone 4.4.2	**6/30/21**	**ML Workflows and Proof-of-Concepts Complete**	**Complete**
Milestone 4.5.1 Deliverable 4.5.1	12/31/2021	SMART Initiative Phase 1 Task 4 Final Report Complete	In Progress

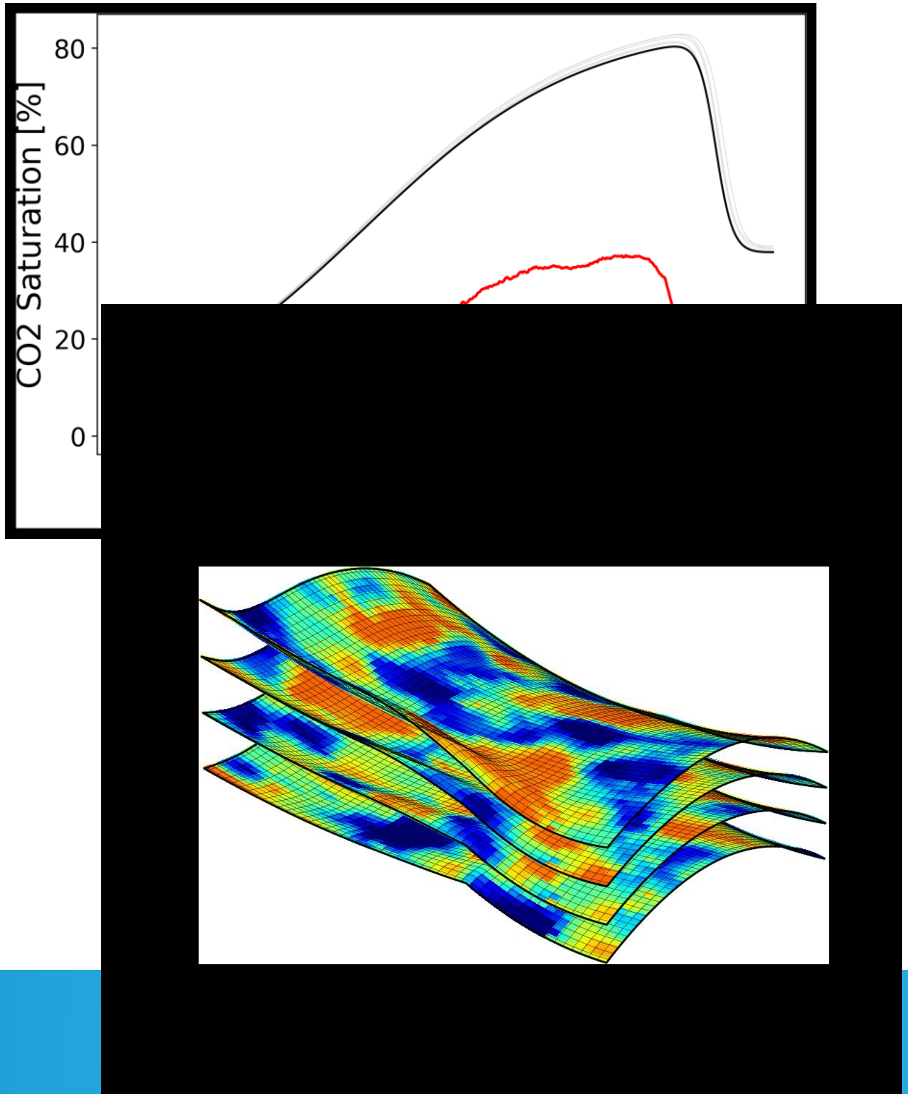
Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Milestone 4.4.2 (June 30, 2021): ML workflows and proof-of-concepts complete.

- T4 platform has been deployed on AWS.
- Scripts to execute each ML method autonomously complete.
- Video walkthrough located on EDX.





Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Milestone 4.4.2 (June 30, 2021): ML workflows and proof-of-concepts complete.

- PNNL has successfully created a framework to integrate all Task 4 ML approaches, both the EOR (associated storage) and saline (dedicated) storage.
- Framework stored in GitLab SMART group.
- Framework designed to work on servers—current recommendations are through AWS or Open Science Grid.
- Current integration status:
  - ML Approaches Integrated into Framework
    - LANL
    - LLNL
    - ORNL
    - NETL
    - PNNL
    - SNL
    - UU
  - Files Received and Integration in Process
    - LBNL
    - WVU

Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Representative Results/Accomplishments/Findings – Refer to Milestone 4.4.1

Milestone / Deliverable	Date Due	Description	Status
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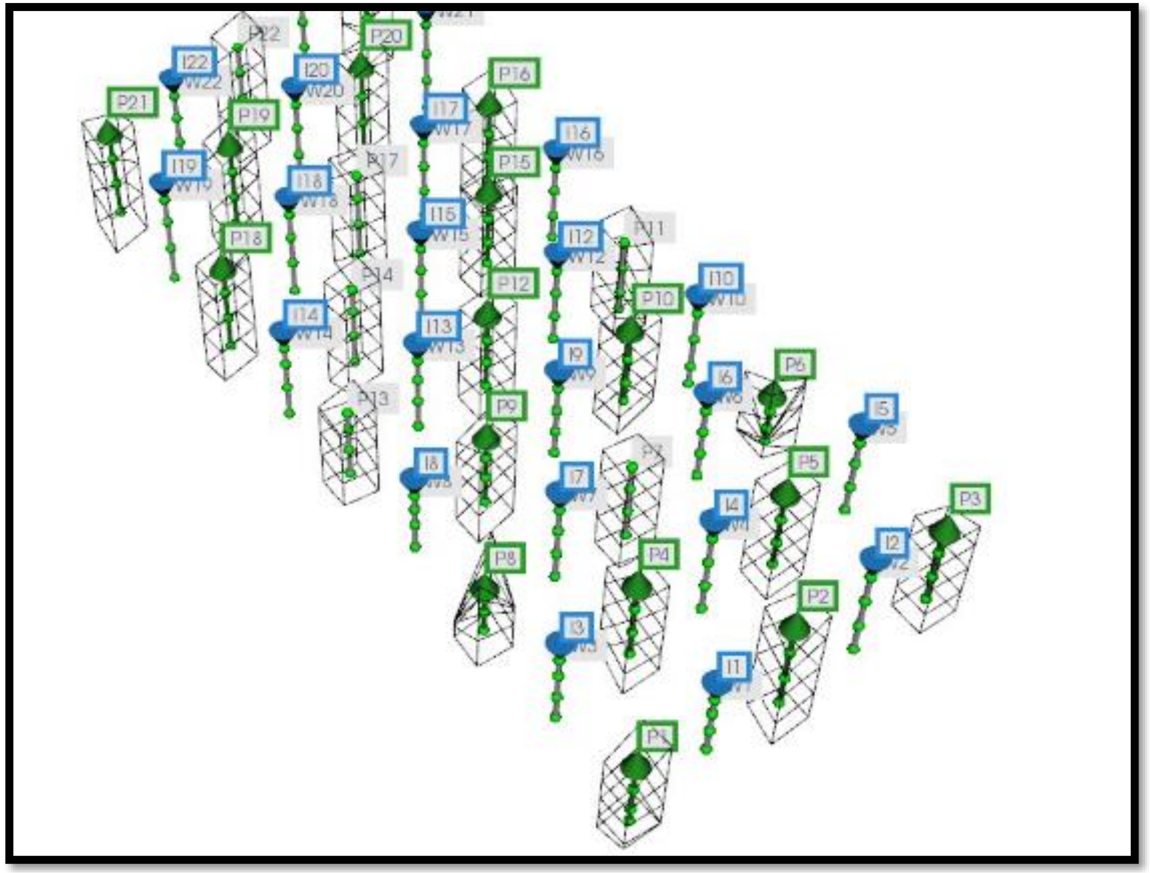
Milestone 4.4.2	6/30/21	ML Workflows and Proof-of-Concepts Complete	Complete
Milestone 4.5.1 Deliverable 4.5.1	12/31/2021	SMART Initiative Phase 1 Task 4 Final Report Complete	In Progress

Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Associated Storage (EOR) Team: Problem Solved

- Utilize 25 years of simulated field production and injection history with the Coarse SACROC model to forecast the next 5 years of simulated field data.
- 23 producer wells and 22 injector wells in a five-spot pattern.
- Phase 1 History Match and Forecasting Focused on
  - Oil Production
  - CO_2 Production
  - Water Production
- Phase 2 History Match and Forecasting will include
  - Reservoir Pressure
  - Reservoir Fluid Saturations
- **Traditional reservoir simulators requires hours to days to calculate the history match and forecast.**
- **ML forecast computation times are on the order of seconds to minutes.**



Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Milestone 4.4.1 (March 31, 2021): Approaches and Results

— In Task 4, EOR history matching and forecasting are achieved and demonstrated using three different ML approaches.

- NETL – Capacitance Resistance Model (CRM): Combination of mathematical equations and ML algorithms
- U. Utah – Long Short-Term Memory (LSTM)-Derived Proxy Models: Applying time-dependent approach and developing single model for each well in the field
- WVU – Top-Down Modeling (TDM): Full-field, single-reservoir model with no mathematical equations covering all the wells in field based on both space and time

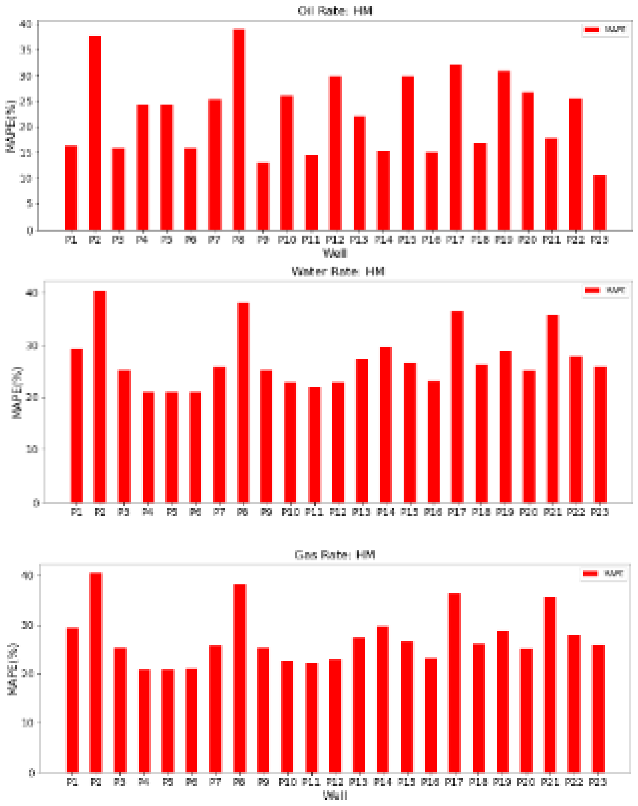
— All three EOR teams demonstrated different approaches that all predict CO_2, oil, and water production from the 23 production wells with similar mean absolute percent error (MAPE), so they were all chosen for integration into the T4 framework.

Task 4: Real-Time History Matching and Forecasting

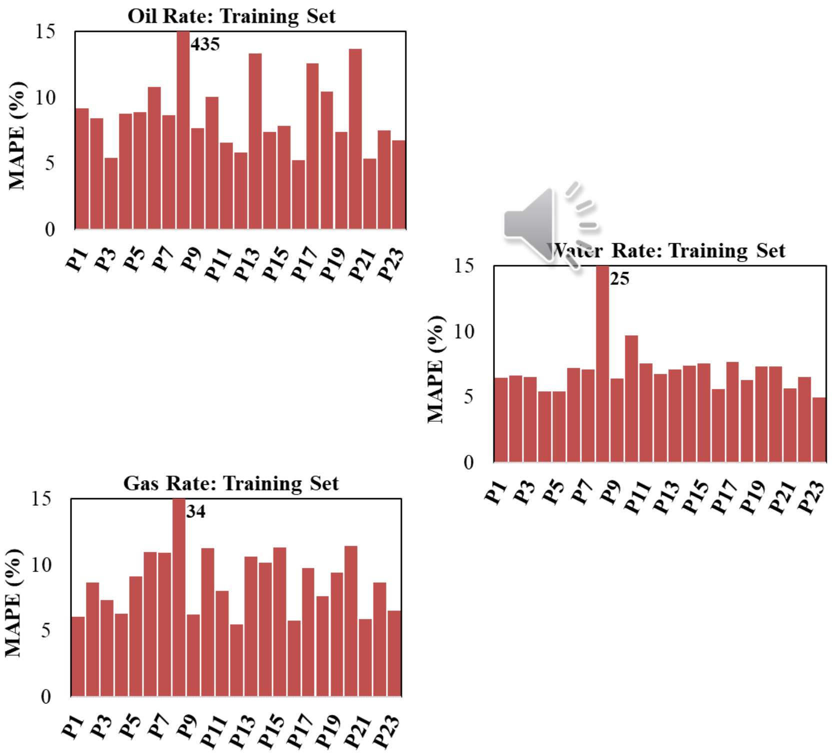
EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Milestone 4.4.1 (March 31, 2021): Results (history match comparison)

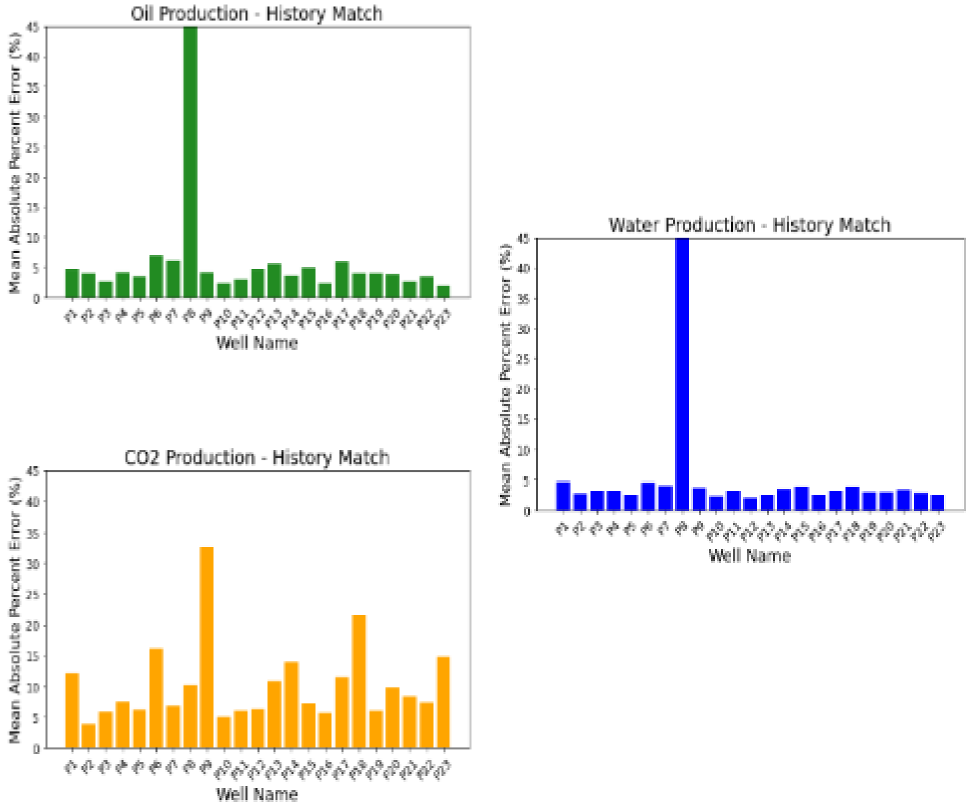
NETL (CRM)



U. Utah (LSTM)



WVU (TDM)

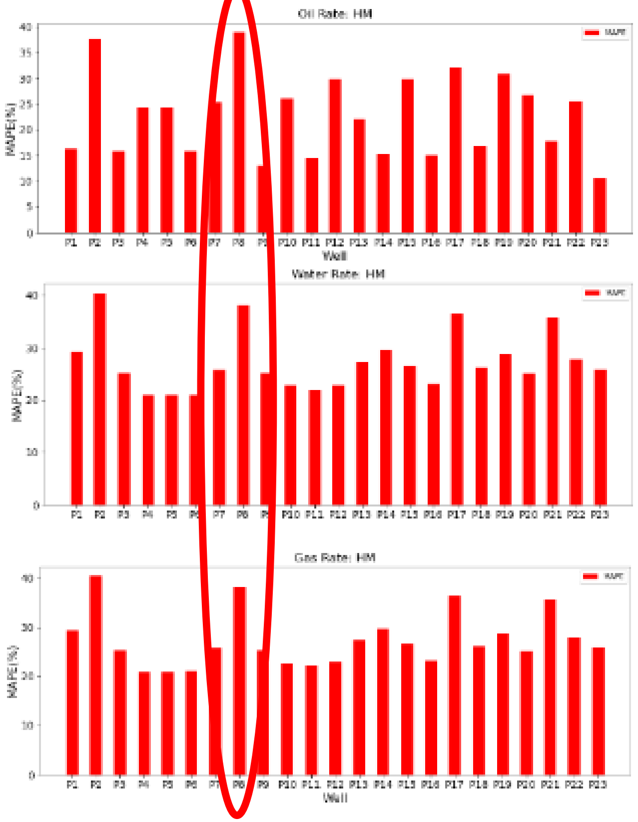


Task 4: Real-Time History Matching and Forecasting

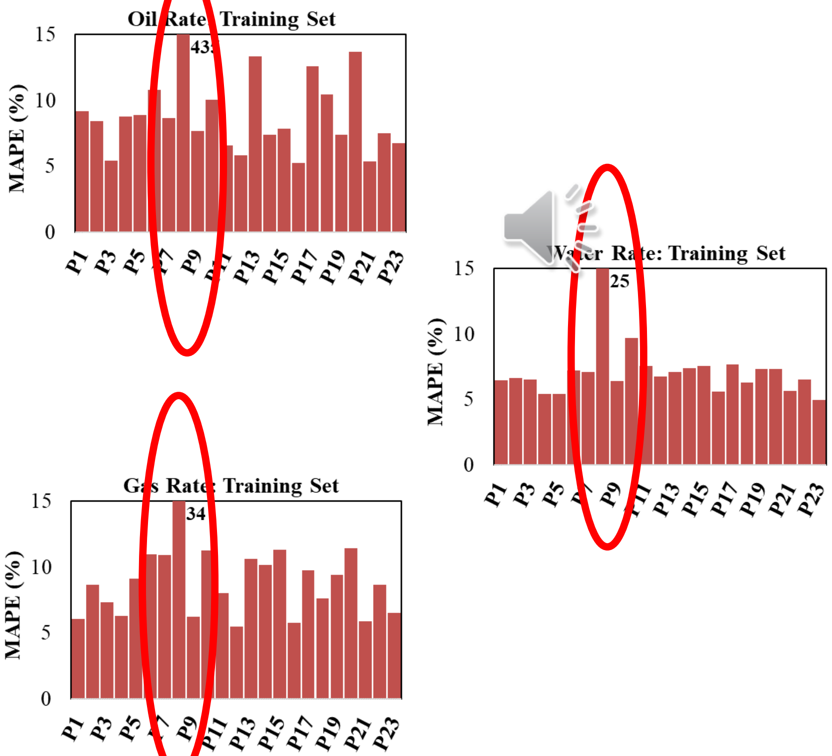
EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Milestone 4.4.1 (March 31, 2021): Results (history match comparison)

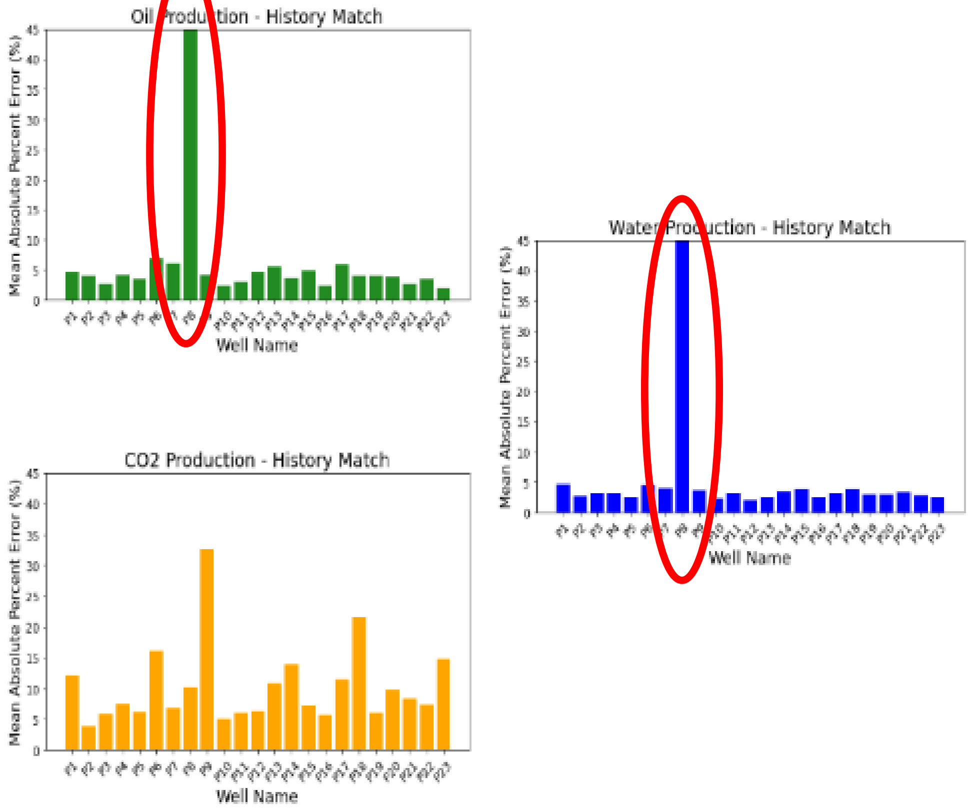
NETL (CRM)



U. Utah (LSTM)



WVU (TDM)

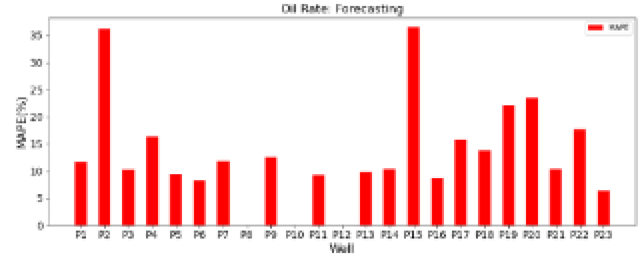


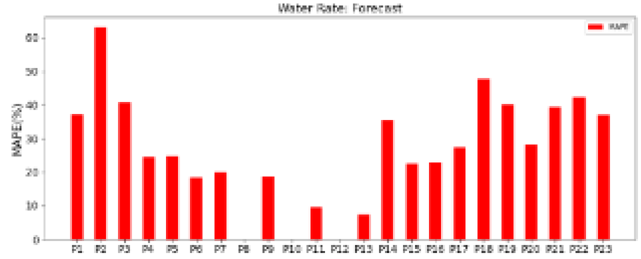
Task 4: Real-Time History Matching and Forecasting

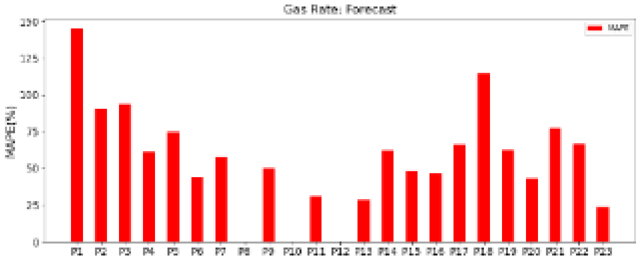
EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Milestone 4.4.1 (March 31, 2021): Results (forecasting accuracy comparison)

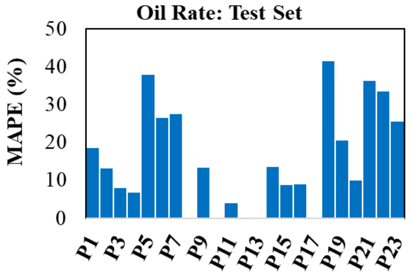
NETL (CRM)

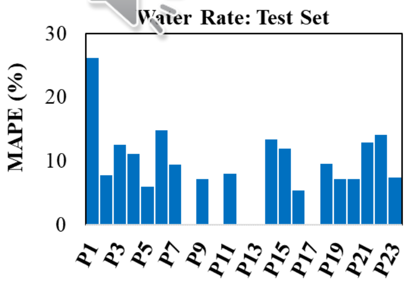


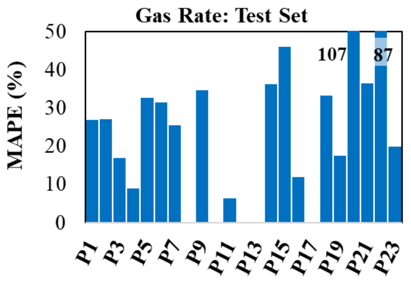




U. Utah (LSTM)







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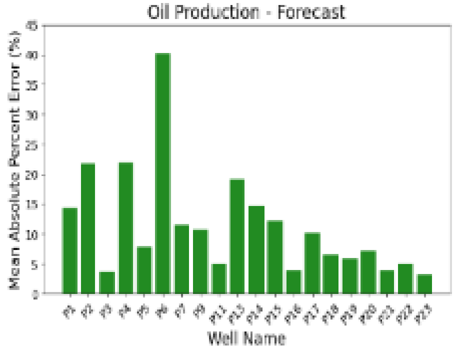
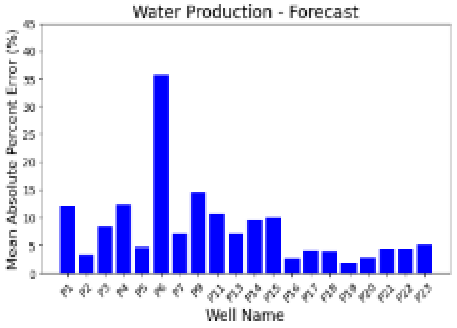
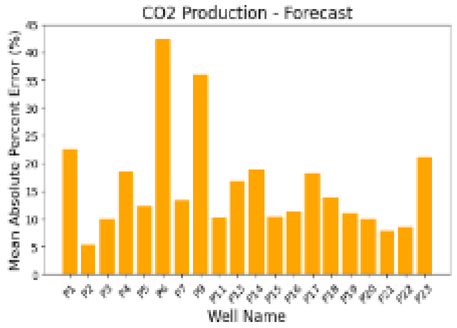






Task 4: Real-Time History Matching and Forecasting

Milestone 4.4.1 (March 31, 2021): Improvement on Current Workflows

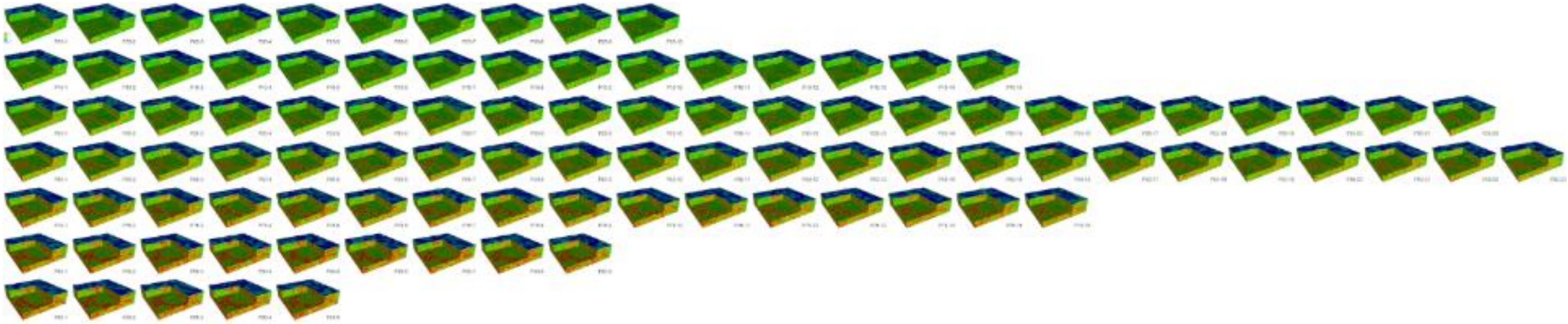
- Traditional reservoir simulators require hours to days to calculate the history match and forecast compared to ML forecast computation times which are on the order of seconds to minutes.
- All ML approaches show similar MAPE when forecasting the oil, CO_2, and water production rates.
- Comparison of reservoir fluid saturation predictions have not been conducted yet.
- **Once reservoir fluid saturation predictions are finalized and compared, this workflow will represent a 1–2 order of magnitude decrease in the time required for the forecast.**
- **This decrease in the time required to run a forecast will allow 10–100 times more sensitivity simulations to be run for each project—decreasing the uncertainty.**

Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Dedicated Storage (saline) Team: Problem Solved

- Utilized an initial set of 100 realizations of the Clastic Shelf geomodel from the EERC
- Four injection wells at fixed (x,y) locations
- 2 MMt CO_2 per year across all four wells
- 10 years of CO_2 injection
- 2 MMt CO_2 per year x 10 years = 20 MMt CO_2 injection target
- 32 output time steps to predict **CO_2 saturation** and **reservoir pressure**:
  - Months 1, 2, …, 24
  - Years 3, 4, …, 10
- Maximum bottomhole pressure (BHP) constraint for each injector was Pf = 0.7 psi/ft.



(Equiprobable) Highly Probable Outcomes

Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Dedicated (saline) Storage: Approaches

— The following ML approaches were explored for history matching and/or forecasting updating by the Task 4 Dedicated (saline) Storage teams:

- Markov Chain Monte Carlo with Proxy Modeling (MCMC-Proxy)
- Variation Autoencoder (VAE)
- Model Reduction and Matrix Factorization (MRMF)
- Differentiable Programming (DP)
- Compressed State Kalman Filter (CSKF) and Smoothing-based CSKF (sCSKF)
- Transient Macroscopic Invasion Percolation (TMIP) and Diffusion-Limited Aggregation (DLA)
- Image-to-Image Mapping with Convolutional Neural Networks (CNNs)
- Learning-based Inversion-free Prediction framework (LIP)
- Ensemble-based data assimilation (EnDA) with the latent space and multiple ML-based models
- Conditional deep convolution-Generative Adversarial Networks (cDC-GAN)
- Extreme Gradient Boosting (XGBoost)

Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Dedicated (saline) Storage: Results and Improvement on Current Workflows

- Comparison of performance of dedicated storage predictions have not been completed yet.
- Traditional reservoir simulator requires hours to days to calculate the history match and forecast compared to ML forecast computation times on the order of seconds and minutes.
- Once performance comparison of dedicated storage approaches is completed, the best-performing approaches are expected to provide a 1–2 order of magnitude decrease in prediction time (enabling greater uncertainty and sensitivity testing) with accuracy comparable to traditional reservoir simulation.

Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Milestones: All of the above information will be captures in the Final Report.

Milestone / Deliverable	Date Due	Description	Status
Milestone 4.1	3/31/2020	Path Forward for Training Data Sets Confirmed	Complete
Milestone 4.3.1 Deliverable 4.3.1	8/31/2020	Design Basis for ML Algorithm Selection, Application, and Testing	Complete
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Milestone 4.5.1 Deliverable 4.5.1	**12/31/2021**	**SMART Initiative Phase 1 Task 4 Final Report Complete**	**In Progress**

Task 4: Real-Time History Matching and Forecasting

EY21–Q1 SMART-CS Quarterly Progress Report, April—June 2021

Lessons Learned in Phase 1 (so far)

- The resolution required for training ML methods to predict pressure plumes and CO_2 plumes are significantly different.
- Experience to date has demonstrated the extreme importance of history matching storage reservoir simulations prior to forecasting CO_2 injection rates.
- Industrial projects typically keep project data confidential, making the development of highly accurate simulations using site-specific data uncommon and difficult.

Task 4: Real-Time History Matching and Forecasting

Task 4 Path to SMART Phase 2

— Phase 2 of SMART will focus on demonstration and deployment of the T4 platform to current and developing CO_2 storage operations.

— The T4 platform should be used in Phase 2 to integrate methods developed across all SMART-CS tasks in Phase 1.

- To prepare for this, alpha testing will continue focused on integrating methods from Tasks 3 and 5.

— Development of the T4 platform will allow *extremely important* integration of site-specific historical data into forecast simulations for storage facility permits (SFPs). Historical (history match) data may include:

- Real-time pressure and rate history matching during Class VI injection to improve forecasts.
- Production or injection history of well(s) in the simulation domain *prior* to Class VI injection.
- Injectivity tests prior to Class VI injection.
- Ability to expand the simulation domain using basic geomodeling parameters and history match using wells outside of the original area of interest.

Questions?

Thank you!

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SMART Initiative

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

Real-Time Visualization
"CT" for the Subsurface

Rapid Prediction
Virtual Learning

Real-Time Forecasting
"Advanced Control Room"

Transforming decisions through **clear vision** of the present and future subsurface.

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