Development of a Framework for Data Integration, Assimilation, and Learning for Geological Carbon Sequestration (DIAL-GCS)

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National Energy Technology Laboratory
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Developing a multi-tiered, intelligent monitoring system (IMS) for automating CCS modeling/monitoring tasks.
Program Overview

– Funding
  • Federal $1.23 M, Cost Share $346k

– Overall Project Performance Dates
  • Oct 1, 2015–March 31, 2021

– Project Participants
  • Bureau of Economic Geology
  • Texas Advanced Computing Center
  • Graduate students and postdocs
A. Technical Approach/Project Scope

This project includes a number of meaningful and necessary tasks to transform the human domain knowledge into machine-interpretable rules for automating knowledge extraction and discovery in GCS.

a. Major project tasks and schedule

- Task 2: Sensor data schema development and provisioning (Y1)
- Task 3: Development of CEP, machine learning (Y1-3)
- Task 4: Coupled modeling, UQ, and data assimilation (Y1-5)
- Task 5: System integration and demonstration (Y1-6)
b. Project success criteria
   • A meaningful set of use cases are identified and the corresponding methods are developed
   • A suite of computational tools are developed for expediting optimization, uncertainty quantification, and predictive analytics
   • The developed tools are integrated and demonstrated over realistic datasets

c. Significant project risks
   • Web implementation and integration
Progress and Current Status of Project
Key Capabilities of DIAL-GCS

• Real-time sensing and anomaly detection
  – Cranfield controlled release data
  – Surface gas controlled leak data
  – Forge distributed acoustic sensing data

• Tools for optimizing GCS monitoring and project planning
  – Multiobjective optimization under uncertainty
  – Reinforcement learning
DIAL-GCS Cranfield Use Case

- Demonstrated real-time sensing
- Complex event processing
- Flexible framework

Sun et al., 2019
DIAL-GCS Cranfield Use Case

Design 2.0:
- Kafka-based
- Flexible
DIAL-GCS Leakage Cost Estimation Use Case

- A web-based tool for project planning & risk assessment
- Illustrated reduced-order modeling and uncertainty quantification on the web

Types of metamodels currently supported:
- Gaussian process regression
- Sparse grid
Objective Function

Well cost = CAPEX($/well) + OPEX($/well/day) + Intervention($/well)

Leakage cost = Brine($/ton) + CO₂($/ton)

Optimization toolbox

Binary Integer Programming
- Linear problem
- Convex

Optimize monitoring network

Constraints

# of monitoring wells ≤ N_max

CO₂ leakage ≤ M% of total injected CO₂

ΔP at t_leakage detection ≥ ΔP_threshold

Our tool maximizes NPV by considering
- High uncertainty in geologic models
- Monitoring budget
- Leakage damage cost
- 45Q carbon tax credit
Optimal GCS Reservoir Management Use Case

- Multi-period planning horizon
- The operator wants to maximize total CO2 storage while minimizing risks
- Very expensive optimization problem
- We combined deep reinforcement learning and surrogate modeling to expedite the process
Use surrogate model to handle variable injection rate

Injector

Monitoring wells
Joint Fluid-Seismic Inversion Use Case

Reservoir Model (Perm, Poro)

Simulation

Prediction

Cycle

Residual

4D Elastic Project (Al, Amplitude)

Zhong et al., JGR, 2020
Web Implementation of ML-assisted reservoir state prediction
Web implementation of gas leakage detection system
DAS data stream anomaly detection
Accomplishments to Date

• Task 2: Data management
  • Developed data schema and data adaptors for storing, exchanging information, and visualizing information

• Task 3: Complex event processing using machine learning (ML)
  • Implemented predictive models on different test datasets
  • Continued to update the existing platform

• Task 4: Coupled modeling / data assimilation
  • Implemented workflow for automating data assimilation. Focused on ML and DL tool development

• Task 5: Integration and demonstration
  • Experimented with a large number of web-based technologies for making the system more user friendly
Lessons Learned

• Combining machine learning with domain knowledge may significantly improve efficacy of GCS management and risk mitigation
  • Time series anomaly detection can be automated effectively with current technologies
  • High-dimensional cases (e.g., distributed acoustic sensing) present more challenges

• All anomalies are different and no single method works for all cases

• The community needs a functional spec for intelligent monitoring system for GCS
Summary Slide

Project Summary
a. We developed a suite of tools for automating monitoring and anomaly detection in geological carbon sequestration projects.
b. Combined machine learning with domain knowledge, implemented a web-based platform, and demonstrated over real and synthetic data.
c. Results suggest that combining modern instrumentation with integrated, off-the-shelf platforms can significantly improve monitoring effectiveness.

Future plans
a. Finish implementing and integrated Web-based tools
b. Complete the final project report
Appendix

- These slides will not be discussed during the presentation, but are mandatory.
Organization Chart

Ken Wisian
BEG
Associate Director

Hovorka

Sun
(PI)

Romanak
(Co-PI)

TACC

Postdoc (Hoonyoung Jeong, Zhi Zhong)

Fomel

Graduate Students
Bibliography

– Peer-Review Manuscripts


Table 1. Revised Project Gantt chart
(Numbers in table rows indicate milestones).

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