Dimensionally Reduced Model for Rapid and Accurate Prediction of Gas Saturation, Pressure, and Brine Production in a CO₂ Storage Application: Case Study at the SACROC Field

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SMART Task 5 – Motivation and Vision

How can we overcome the lack of relevant experience among CCS stakeholders to ensure rapid and safe deployment of large-scale geologic CO₂ storage?

- The oil and gas industry has learned through doing over decades.
- There is no Commercial-scale CO₂ storage in the US.
- Transformational approach using advances in machine learning: virtual learning environments.

**Vision:** Enable a virtual learning environment (VLE) for exploring and testing strategies to optimize reservoir development, management and monitoring prior to field activities.

- An interactive way to gain an intuitive understanding of CO₂ storage site behavior.

**Study Objective:** Develop a fast, accurate, physics-informed predictive model for reservoir pressure, CO₂ saturation, and water production in a CO₂ storage application (that can be used in a VLE).

https://edx.netl.doe.gov/smart/
SACROC Modeling Domain

Grid dimensions in a 25 x 16 x 34 orientation (13,600 grids total)

Permeability: Three components \((i, j, k)\) per grid

\(k = \text{layer 25 (deepest)}\)

Porosity: One component per grid

\(k = \text{layer 25 (deepest)}\)

Modeling Domain Contains:
- Three (3) \(\mathrm{CO}_2\) injection wells (I1, I2, and I4).
- Two (2) brine production wells (P2 and P3).
- Three (3) permeability and porosity variants (P10, P50, and P90).

<table>
<thead>
<tr>
<th>Geologic Realization</th>
<th>Permeability (i) (mD)</th>
<th>Permeability (j) (mD)</th>
<th>Permeability (k) (mD)</th>
<th>Porosity (decimal)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P10</td>
<td>55.84</td>
<td>179</td>
<td>55.84</td>
<td>17.9</td>
</tr>
<tr>
<td>P50</td>
<td>53.37</td>
<td>183</td>
<td>53.37</td>
<td>18.2</td>
</tr>
<tr>
<td>P90</td>
<td>48.2</td>
<td>195</td>
<td>48.2</td>
<td>19.5</td>
</tr>
</tbody>
</table>
Summary of Training/Testing Data

**CMG-GEM Framework**

- CMG-GEM model to simulate 90 cases of different injection allocation and geology realizations.
- CO₂ Injection / Water Production for 30 years; 50 years of plume stabilization (represented by 963 timesteps).

**Physics-based Realization Library**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Sample Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulated Cases</td>
<td>90</td>
</tr>
<tr>
<td>Geologic Realizations (Porosity and Permeability)</td>
<td>P10, P50, P90</td>
</tr>
<tr>
<td>Total Mass of CO₂ Injection (Million Metric Tons)</td>
<td>22.4, 16.8, 11.2, 8.4, 5.6</td>
</tr>
<tr>
<td>CO₂ Injection Allocation Scenarios (%)</td>
<td></td>
</tr>
<tr>
<td>2 Active Injection Wells</td>
<td></td>
</tr>
<tr>
<td>- 50/50 Split (24)</td>
<td></td>
</tr>
<tr>
<td>- 10/90 Split (13)</td>
<td></td>
</tr>
<tr>
<td>- 90/10 Split (20)</td>
<td></td>
</tr>
<tr>
<td>3 Active Injection Wells Cases</td>
<td></td>
</tr>
<tr>
<td>- 33/33/33 Split (7)</td>
<td></td>
</tr>
<tr>
<td>- 60/20/20 Split (9)</td>
<td></td>
</tr>
<tr>
<td>- 20/60/20 Split (10)</td>
<td></td>
</tr>
<tr>
<td>- 20/20/60 Split (7)</td>
<td></td>
</tr>
</tbody>
</table>
**Autoencoder Overview**

**Goal:** Reduce the dimensionality of the geologic input into a single input array.

```
Input                              | None, 4, 34, 16, 25
Flatten                            | None, 54400
Encode 1                           | None, 256
Encode 2                           | None, 128
Encode 3                           | None, 64
Decode 1                           | None, 128
Decode 2                           | None, 256
Decode 3                           | None, 54400
Reshape                            | None, 4, 34, 16, 25
```

“None” in the model architecture above refers to a tensor that could vary in size. In this case, it is consistent with the three geologic realizations ($P_{10}$, $P_{50}$, and $P_{90}$).

**Training Overview**

Trained on the $P_{10}$, $P_{50}$, and $P_{90}$ realizations of porosity and permeability.

**Performance**

Geologic input represented in single 1 x 64 array.
- 850-fold reduction.
- > 99.9% reconstruction accuracy.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Time/RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Time per Epoch (sec)</td>
<td>&lt; 1</td>
</tr>
<tr>
<td>Training Error (normalized)</td>
<td>3.24E-7</td>
</tr>
<tr>
<td>Test Error (Full Dataset - normalized)</td>
<td>1.71E-6</td>
</tr>
<tr>
<td>Porosity (decimal)</td>
<td>4.10E-7</td>
</tr>
<tr>
<td>Permeability - i (mD)</td>
<td>0.0115</td>
</tr>
<tr>
<td>Permeability - j (mD)</td>
<td>0.0115</td>
</tr>
<tr>
<td>Permeability - k (mD)</td>
<td>0.0012</td>
</tr>
</tbody>
</table>
Autoencoder Reconstruction Results

Model Prediction vs. Ground Truth

Porosity
Porosity (i-direction)
Permeability (j-direction)
Permeability (k-direction)

Porosity
Permeability (log10 mD)
Permeability (log10 mD)
Permeability (log10 mD)
Approach: Integrate the autoencoder that reduces geomodel dimensions into a deep learning framework intended for CO₂ saturation, reservoir pressure, and water production prediction. Evaluate the efficacy of the framework’s prediction response time and preservation of performance accuracy.

“None” in the model frameworks refers to a tensor that could vary in size. In this case, it is consistent with 963 timesteps per batch.
Pressure, CO₂ Saturation, Water Production Models

Model Objective

- Predictive capability for pressure and CO₂ saturation over project life at all grid blocks.
- Predictive capability for flow rates over project life from the two water (brine) production wells.

Training Overview

- Trained and validated on 81 simulation realizations (train = 78, validation = 3).
- Early stopping applied to prevent overfitting of training data.
- Tested on all nine test realizations.

Model Performance

- > 99.9 percent accuracy following reconstruction.
- Fast prediction (~ 1 second) for full project (963 time steps).

<table>
<thead>
<tr>
<th>Model / Target Prediction</th>
<th>Training Duration Summary</th>
<th>Prediction Time per Realization</th>
<th>Accuracy on Test Data</th>
<th>Root Mean Squared Error on Test Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Training time per Epoch, Number of Epochs</td>
<td>Total Training Time</td>
<td>System Info.</td>
<td>CPU Time</td>
</tr>
<tr>
<td>Pressure</td>
<td>7 sec., 403 epochs</td>
<td>~ 47 minutes</td>
<td>16 GB NVIDIA P100 GPU</td>
<td>0.84 sec.</td>
</tr>
<tr>
<td>CO₂ Saturation</td>
<td>7 sec., 444 epochs</td>
<td>~ 52 minutes</td>
<td></td>
<td>0.97 sec.</td>
</tr>
<tr>
<td>Water Production</td>
<td>16 sec., 229 epochs</td>
<td>~ 61 minutes</td>
<td>Intel® Core™ i5-6300U CPU @ 2.40GHz</td>
<td>1.56 sec.</td>
</tr>
</tbody>
</table>
99% of the predictions have an error of less than 250 kPa
Saturation Model Performance

84% of the predictions are within 1% of the true value.
Pressure and Saturation Model Performance

Model Prediction vs. Ground Truth (Test Case 1 = Realization 82) for 1 layer at 2 different timesteps

15 years of CO₂ Injection

25 years post-injection
Majority of the predicted water production values fall within a close range of the true water production values.

- More than 83% of the predictions have an error of less than 15 m³/day.
- Approximately 90% of the predictions have an error of less than 25 m³/day.
Findings and Implications

• Integration of encoder into DL model framework offers >99% accuracy in predicting reservoir pressure, CO₂ saturation, and water production in ~1 second.

• Computational resources and model training/prediction time are important in real-time / virtual learning—use of autoencoder to reduce input data dimensions reduces training/prediction time with minimal compromise to accuracy.

• Other neural network formulations were tested with the autoencoder framework, but the bidirectional LSTM model was found to be most efficient for training times and prediction performance.

• Feature engineering and selection helps maintain model accuracy at no cost for additional data acquisition.
  ◦ The use of cumulative injection volumes as input was found to improve model performance compared to test models compiled relying only on instantaneous CO₂ injection rates.
Disclaimer

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