Machine-Learning Assisted Reservoir Evaluation for CO_2 Plume Geothermal (CPG) Applications

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Summary

The Cambro-Ordovician hypersaline Deadwood and Winnipeg Formations in southeastern Saskatchewan host geothermal (Deep Earth) and CO_2 storage (Aquistore) operations, within 20 km of each other. This study leverages data from both sites to assess the feasibility of CO_2 plume geothermal (CPG) system, where supercritical CO_2 serves as the circulating fluid to extract heat. Various machine learning applications were used to analyze the combined dataset, assessing the potential for integrating CO_2 storage and geothermal energy production and highlights potential geomechanical challenges, enhancing understanding of reservoir behavior and system feasibility.

A detailed geological and Mechanical Model was developed to represent the DEEP region, performing history matching with geothermal LOOP tests. The 2D model is based on the GAMLS petrophysical model (Vaisblat et al., 2022), which applies a maximum likelihood adaptive neural system to well log data from 17 wells to establish a regional stratigraphic framework. The petrophysical model, validated through core descriptions, identified seven electrofacies (rock-type endmembers) within the Cambro-Ordovician section, and guided core analysis.

Based on the petrophysical model, a regional ~200 m thick, 23 × 48 km Petrel model was constructed with 19 distinct layers and a cell size of 100 × 100 m, resulting in approximately 2 million cells. Vertical upscaling of electrofacies was performed using the "most of" technique within each layer. Variograms were generated for the upscaled electrofacies both along and perpendicular to the primary sediment transport direction (northeast to southwest) and were subsequently used as input for electrofacies distribution within the 3D model via sequential indicator simulation. A key challenge in modeling electrofacies distribution was the limited availability of well data, with only 11 wells across the large study area.

All cells of the model needed to be populated with porosity and permeability values. Porosity was calculated as an average of the density and neutron porosity, which best matched core analysis results. Porosity - permeability correlations did not show a clear trend and were deemed unsatisfactory, but permeability calculated from the NMR log of the two Aquistore wells seemed to be in good agreement with laboratory measurements. None of the other wells, however, had

NMR logs, and thus permeability for these wells was estimated using a machine learning model, composed of 7 input variables (well logs), with a total of 6356 datapoints that were fitted to recreate the NMR permeability curve. A 20:80 testing-training split was applied and the k-fold cross validation technique with 5 folds was implemented for model validation. We use the Scikit-learn library for our predictive modeling. The R-squared metric was chosen to measure the performance of the trained models. The developed model showed high accuracy, achieving 0.9 on test dataset. This model was then used to predict permeability for all other wells in the 3D model and showed good match with core data. Porosity and permeability were upscaled from well log resolution to the grid block scale using arithmetic averaging. Grid cells were populated using gaussian random function simulation technique, guided by the electrofacies distribution.

Next, a section of the regional model, focusing on the Deep Earth site was cut out of the regional model and a finer grid of 50 x 50 m was created, with variable heights for each of the 19 layers. The total area of the focused model which contains ~900,000 cells is 11.5X 10.5 km. Porosity and permeability values were populated in the focused model in a similar fashion as the regional model (Figure 1).

A 1D mechanical Earth model (MEM) was developed to evaluate the geomechanical behavior of the reservoir and both the overlaying and underlaying formations during the geothermal operations. The MEM for Well 1 was built using empirical correlations and validated with laboratory and field data. Wireline logs were used to calculate mechanical properties such as Young's modulus, Poisson's ratio and rock strength which were corrected using lab tests. Pore pressure was assumed hydrostatic and corrected using well tests. Vertical In-situ stress was calculated using overburden and horizontal stresses were derived from poro-elastic models considering strain, tectonic forces and Poisson's ratio. Field leak off test (LOT) was used to correct in-situ stresses. Mechanical properties are assumed constant across geological layers in the 3D model.

Schlumberger INTERSECT was used in this study to run simulations for the DEEP model. At this stage only hydraulic simulation and history matching were performed. Modeled pressure and fluid rates were matched with data from two open geothermal LOOP tests, mostly through adjusting permeability values. For all wells, the flow rates were fixed, and bottom hole pressure was matched. Future work includes coupled Thermal-hydro-mechanical simulations and will eventually progress to simulations using CO_2 as the circulating geothermal fluid.

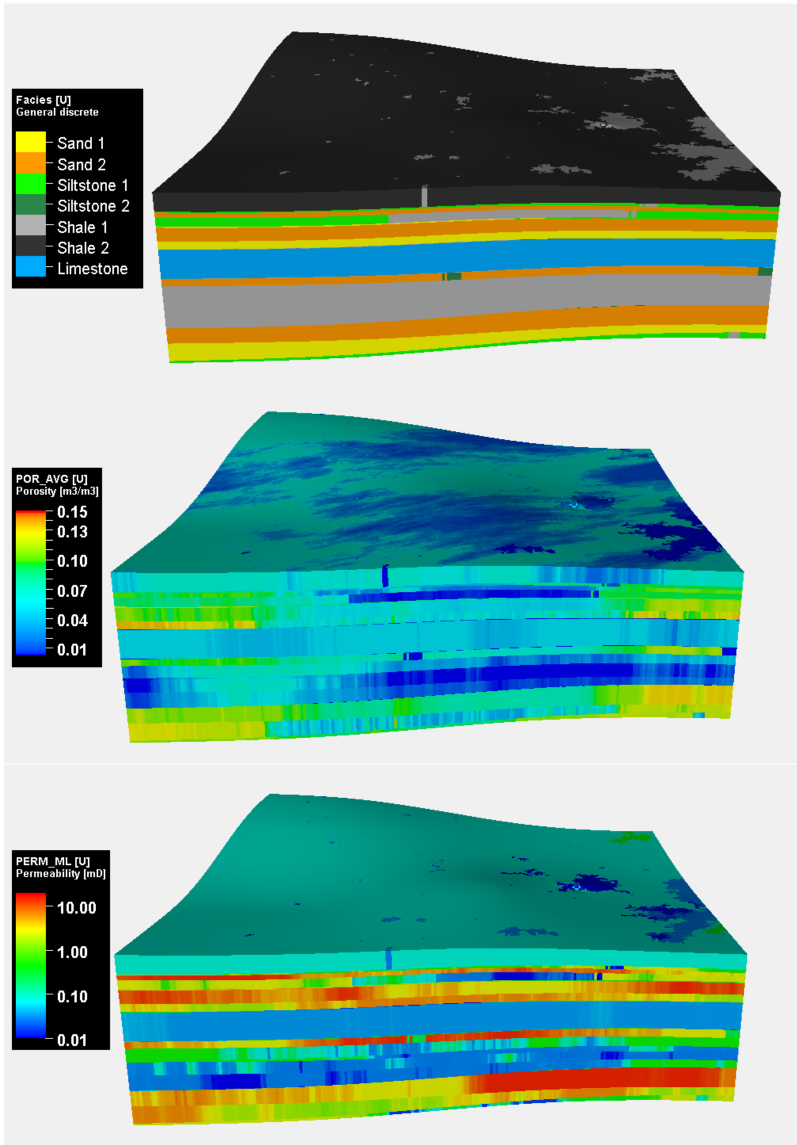

Figure 1: DEEP electrofacies (top) porosity (middle) and permeability (bottom) model.

References:

Vaisblat, N., Deisman, N., & Chalaturnyk, R. J. (2022, October). Petrophysical and Thermo-Hydro-Mechanical Study of a deep hypersaline CO2 reservoir. In *Proceedings of the 16th Greenhouse Gas Control Technologies Conference (GHGT-16)* (pp. 23-24).

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