Modeling analysis of CO_2 Sequestration in Saline Formation Using Artificial Intelligence Technology

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Abstract

One of the most domineering environmental issues is the increase in atmospheric carbon dioxide (CO_2) concentration ensuing from anthropogenic sources. Sequestration in geological formations is one of the proposed solutions for removing greenhouse emissions from the atmosphere.

Since aquifers are considered to be most widely available, there is high potential to find a suitable aquifer with large capacity or close to CO_2 source. The structure and the interconnection of the pores provide flow of gases or fluids through the bed and all these factors make aquifers the second largest, naturally occurring potential store for CO_2.

Numerical reservoir simulators are conventionally used to build models of the CO_2 Sequestration process. The sequestration project deals with a wide range of uncertainties. Any comprehensive study or uncertainty analysis of the representative numerical reservoir models would be tedious and time consuming requiring high computational costs. Therefore, comprehensive analysis of such models is quite impractical.

This work presents a new artificial intelligence base technique known as Surrogate Reservoir Model (SRM) that can mimic the behavior of the commercial reservoir model with high accuracy in fractions of a second. Application of SRM to Mattoon field, located in the eastern three quarters of section 8 of Mattoon Township, Coles County, IL, is presented in this article.

Upon validation of SRM Key Performance Indicators (KPIs) of the simulation model are identified to help reservoir engineers concentrate on the most influential parameters on the model's output when studying the reservoir and performing uncertainty analysis. These indicators can be used so as to build a spatiotemporal model which can deliver dynamic properties such as pressure, water saturation and CO_2 mole fraction at each particular location of the reservoir in a specific time.

Unlike conventional geo-statistical techniques that require hundreds of runs to build a response surface or a proxy model,

Background

Mattoon field is located in the eastern three quarters of section 8 of Mattoon Township, Coles County, IL. The CO_2 injection well is close to the center of the Mattoon site. The field has an area of 444.2 acres. The location of the injection well will be at latitude 39.5 N and longitude 88.4 W .

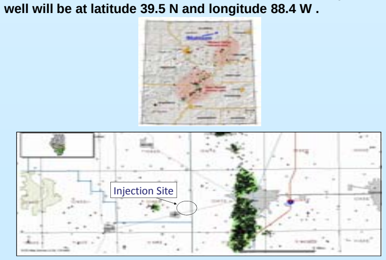

Figure 1 - Matton Oil field and Mattoon FutureGen CO_2 Injection site .

Methodology

Given that there is no wells penetrating the Mt. Simon depth at Mattoon site, information from a near well is used and mapped to help the modeling process of Mattoon site. Information available from a log in Weaber-Horn well located in Louden field close to Mattoon is used to build a reservoir model for Mattoon with porosity and thicknesses taken from this log. Permeability is calculated based on its correlation with porosity.

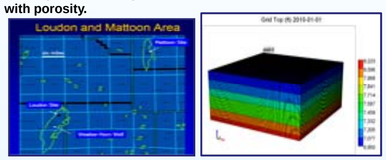

Figure 2 –A) Louden and Mattoon site with Weaber-Horn well in Louden. B) Dynamic model for the Mattoon CO_2 injection site.

Table 1-Reservoir Properties for 6 Layers – Based on Weaber Horn well data

Layer	Thickness (ft)	Porosity	Permeability I(mD)	Permeability J(mD)	Permeability K(mD)
1	214.97	0.09	1.59	1.59	0.16
2	289.67	0.14	42.05	42.05	4.21
3	247.22	0.09	2.12	2.12	0.21
4	311.17	0.12	17.79	17.79	1.78
5	248.83	0.16	140.61	140.61	14.06
6	88.14	0.15	73.83	73.83	7.38

The first and foremost step in developing a surrogate reservoir model is generating a spatiotemporal dataset, which can capture all the aspects of the reservoir.

Different injection scenarios have been designed to include the upper and lower injection margins. From five different simulation runs only three of them (Scenarios 1, 2 and 5) have been used in dataset generation. The other two scenarios (Scenarios 3 and 4) are going to be used as the blind cases for testing the SRM validity.

Schedule	Cum. Inj. (BCF)	Cum. Inj. (tonnes)
1	100.00	5,719,842
2	49.81	2,849,077
3	120.54	6,894,722
4	73.88	4,225,981
5	148.24	8,479,287

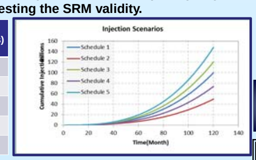

Figure 3 - Cumulative Injection after 10 years in Different Injection Scenarios

The dataset includes static data, dynamic data and operational constraints for all the grid blocks throughout the reservoir. The static data consists of location of each grid block in the reservoir and its location regarding the boundaries and the injection well and reservoir parameters (porosity, permeability, etc.). Since some properties such as the pressure, phase saturation (water or gas) and CO_2 mole fraction (global, in water or gas) at each specific location is a function of time, these properties will be considered as the dynamic data. Operational constrains include the bottom hole pressure or injection rates depending on the case under the study. Apart from the information in each grid blocks some tiers can be defined.

The dataset generated is an all-inclusive source to use for model development. But not all the data are necessarily going to be used in developing the model. KPI (Key performance indicator) is performed on the comprehensive dataset.

The pre-arranged dataset was partitioned. A part of the data (80%) was used for training the model, the second partition was used in order to calibrate the model and the last partition is used for model validation. The trained model has used the data for the first year of injection (Monthly data).

Results

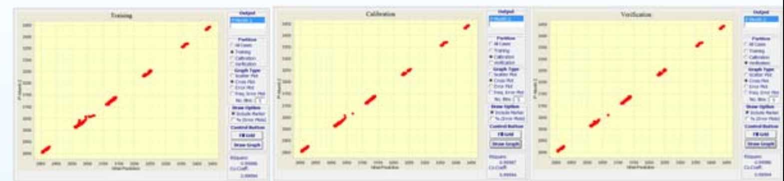

Figure 4 - Cross plot of SRM Pressure prediction versus simulation output for training, calibration and validation sets.

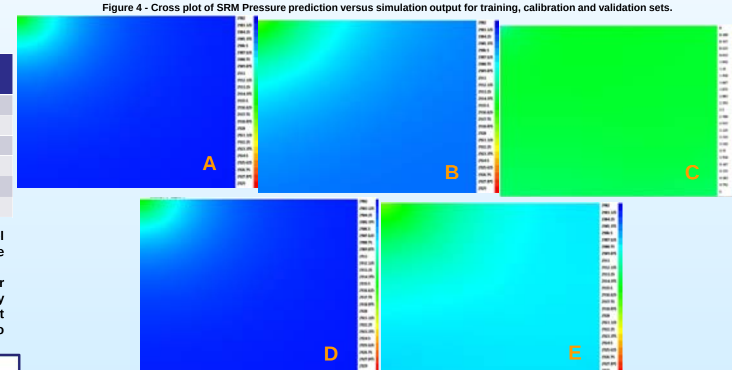

Figure 5 - Pressure distribution in Layer 1 after 1 month of injection, comparison b/w CMG (A) and SRM (B), The percent of error propagation in Layer 2 at the end sixth month of injection (C), Pressure distribution in Layer 1 after 6 months of injection, comparison b/w CMG (D) and SRM (E).

Conclusion

Application of Grid based SRM to a saline formation was studied.

It was shown that the SRM is trained and matched with the results from a commercial numerical reservoir simulation model and was validated using a blind simulation run. As long as there is a reservoir model for an asset, SRM can be built for that model. It can replicate the results from the reservoir simulation model with high accuracy while it can run in fractions of seconds requiring minimal computational cost. It requires by far less number of simulation runs and realizations in comparison with some other methodologies such as response surfaces.

Acknowledgement

Authors wish to acknowledge Computer Modeling Group for providing the reservoir Simulation models CMG-GEM™ for the case study that were conducted at West Virginia University , Intelligent Solutions, Inc. for providing IDEA™ that was used to develop the Grid-based SRM and DOE-NETL for providing the required data.