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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, building an SRM only requires a few simulation runs, which saves a lot of man hour time and computational costs.

Introduction

The increase in atmospheric carbon dioxide (CO_2) concentration resulting from anthropogenic sources is an important environmental issue. Sequestration in geological formations is one the proposed solutions for removing greenhouse emissions from the atmosphere and in most of the cases CO_2 forms a considerable percentage of these greenhouse gases (1).

The geologic carbon storage comprehends capture, transportation and geologic storage. It is a quite recent concept. Its technologies are, in general, well known to the crude oil industry. Nevertheless, carbon capture and geological storage (CCGS) is becoming strategic due to its contribution to more sustainable processes and to the climatic changes mitigation. (2)

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 (1). An aquifer is suited for underground storage of gases or liquids since it is a reservoir with porosity, permeability and a sealing cap rock (3).

Without raising aquifer pressure to a large extent, CO_2 can be injected to aquifers with large volumes. After the injection, CO_2 will dissolve in the brine and cause brine/ CO_2 mixture denser than the brine alone. Dissolving furthermore, fresh brine is brought in contact with the CO_2 phase. It is estimated that hundreds to thousands of years will be required to dissolve all the CO_2, trapping much of the CO_2 (4).

In this study we are using a new technology called Surrogate Reservoir Model (SRM). Classified as an AI-based Reservoir Model (5), the Surrogate Reservoir Model (SRM) is defined as an accurate replica of a reservoir simulation model that runs in real-time. SRMs are ensemble of multiple, interconnected neuro-fuzzy systems that are trained to adaptively learn the reservoir physics and fluid flow behavior from a multi-well, multilayer reservoir simulation model, such that they can reproduce results similar to those of the reservoir simulation model (with high accuracy) in real-time. Sometimes this question rises regarding the necessity of having a SRM while the numerical reservoir model is available. Stipulation of SRM has to do with the fact that massive potential of the existing numerical reservoir simulation models go unrealized because it takes a long time to make a single run. Numerical models that are built to simulate complex reservoirs require considerable run-time, even running parallel on a cluster of CPUs. Thorough and ample evaluation of the solution space for designing field development strategies as well as the quantification of uncertainties associated with the static model are the type of analyses that require a large number of simulation runs to provide meaningful and usable results (6).

In fact, SRM is a customized model that mimics reservoir simulation results by using Artificial Intelligent & Data Mining techniques with a very low computational cost. It consists of one or several neural networks which are trained, calibrated and verified using very small portion of data. SRM can be constructed as well-based or grid-based. Well-based SRM is able to make predictions for the well parameters such as rate of oil, gas and water production (7; 8)and the grid-based SRM will return the grid level parameters such as pressure and liquid/gas phase saturation (9).

Design and development of Grid-based SRM is not trifling and trivial. It necessitates a reasonably deep insight into data mining, machine learning, reservoir modeling and reservoir engineering. The process of developing Grid-based SRM can be summarized as using data from a numerical reservoir simulation model to teach reservoir engineering to a machine, or for now, to a computer program (10).

Field 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 (11).

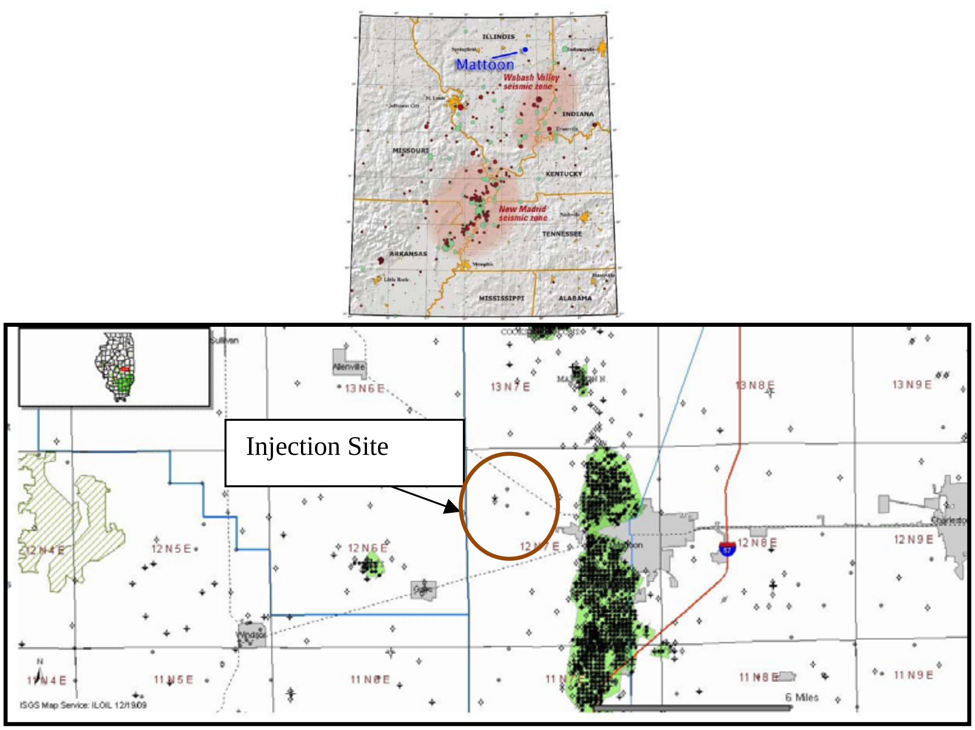

Figure 1 - Matton Oil field and Mattoon FutureGen CO_2 Injection site (11)

Geological Description

Primary saline formation in Mattoon is Mt. Simon. There exists a thick regional seal above the primary saline formation (primary target), the Mt. Simon. This seal is 500-700ft thick and consists of low permeability siltstones and shales of the Eau Claire Formation, underlain by Precambrian granite basement. Beyond the regional seal are two secondary seals. Pennsylvanian cyclic shales, limestones and sandstones provide almost 3000ft of protective barrier between the uppermost secondary seal and the deepest underground sources of drinking water. Currently there is no oil or gas production in the Mt. Simon.

The Mt. Simon sandstone is of Cambrian-age, and is the most widespread in the Illinois basin. It is at a depth of 6500-6950ft with a thickness of 1300-1400ft, with porosity's ranging from 5-15 percent and an effective porosity of 585ft. The salinities of this formation are expected to be 130,000ppm, with base temperatures at 145F. The expected hydrostatic pressure is 3590 psi. Stratigraphy of the proposed injection site is shown in Figure 1.

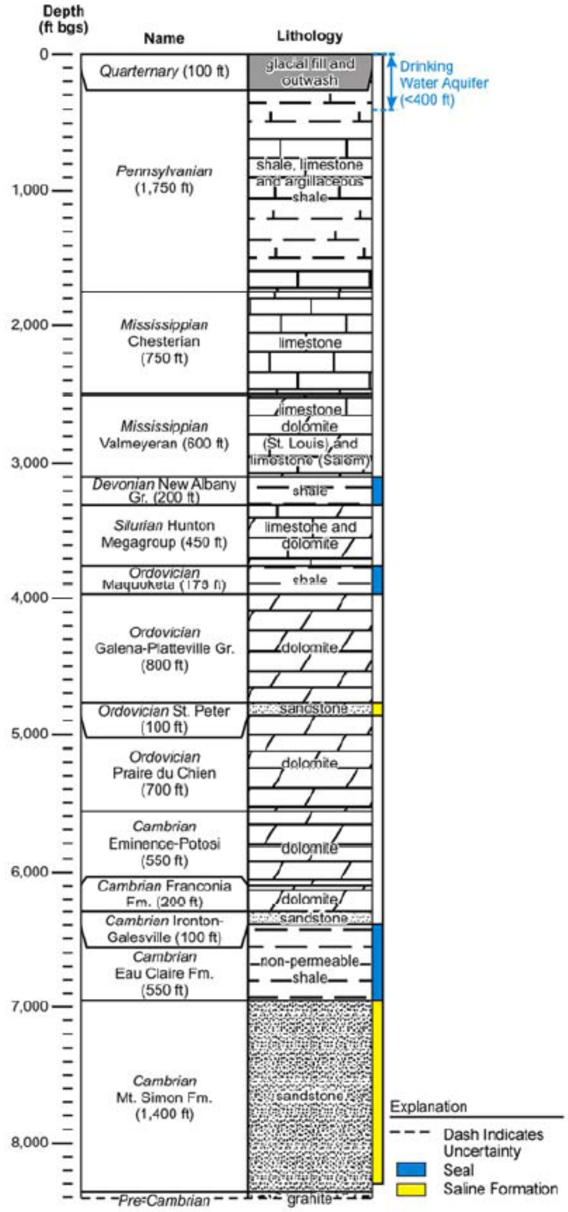

Figure 2.Stratigraphy of Mattoon Injection Site (12)

Tectonic Setting and Stability of the Seals

The location of the Mt. Simon is in a seismically stable area of the Illinois Basin. The near surface rocks are of late Pennsylvanian age and lie close to the horizontal, with the closest earthquake on record being in 1990, 12 miles east of the site, with a magnitude under 3.0. The site is located in a very gentle syncline, immediately east of a series of north-south anticlinal folds that act as traps for oil reservoirs above the Mt. Simon. Although no faults are mapped in this area, many of the anticlines are thought to cover thrust faults in the Precambrian basement. The greatest and least principal horizontal stresses are oriented west-Southwest to east-northeast and south-southeast to north-northwest respectively. Faults and fractures oriented in the direction of the least principal stress (south-southeast to north-northwest) may be less likely to be transmissive. The geologic features of the reservoir provide a very robust setting for CO_2 sequestration. The major sources of leakage are;

1. Slow or Sudden failure of the Cap rock and seal.
2. Leakage along well bores.

The mineralogy and permeability of the seals of the Mattoon site indicate a strong potential for the containment of permeation. The permeability of the Eau Claire Cap rock ranges from 0.00004md to 0.0006md. A comparison of the fluids in the Eau Claire and its overlying rock shows no fluid transmissions.

The secondary seals, the Maquoketa and New Albany are predominantly marine shales, with vertical permeabilities to water of 0.001 or less. The mineralogy and heterogeneity of the sandstones of the Mt. Simon make upward migration of CO_2 highly unlikely. Although there are five oil fields with anticlinal closure within a 10-mile radius of the Mt Simon, none of the wells drilled in any of those fields penetrates the primary seal of the Eau Claire thus eliminating the risk of CO_2 leakage from wellbores (11).

Methodology

Reservoir Modeling

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.

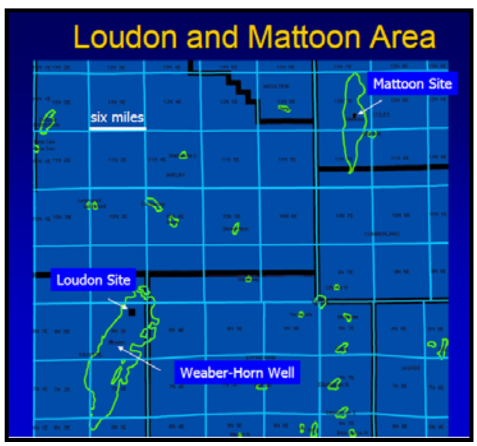

Figure 3 - Louden and Mattoon site with Weaber-Horn well in Louden

In order to model the sequestration process and determine if the reservoir has the necessary capacity to sequester the gas, a base model was built based on the parameters gathered from the DOE's FutureGen program (11). Using the information in these documents a numerical model was built using a commercial reservoir simulator (12).

Since the injection well is located in the center of the reservoir, taking advantage of the symmetry, the reservoir was divided into 4 sections. One of the sections was modeled having the injection well at the top left corner. A schematic of the reservoir model is shown in Figure 4.

The top of the formation is considered to be at 6950ft.The reservoir model has 6 different layers. The injection is taking place only in layers 2, 4, 5 and 6. There are 150 grid blocks in each i and j direction. Other static parameters are listed in Table 1.

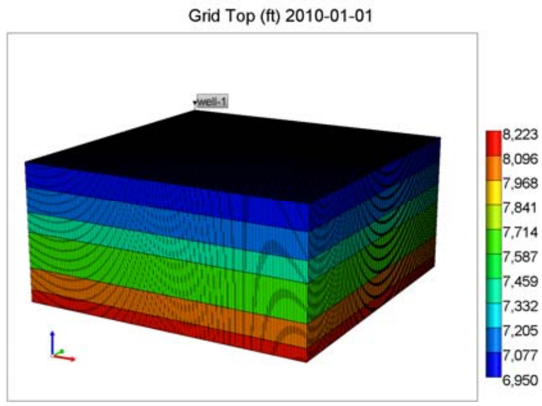

Figure 4. Dynamic model for the Mattoon CO_2 injection site

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

Due to lack of data, porosity and permeability have been considered laterally homogenous in each layer. Thus, it has made it so complicated to develop a surrogate reservoir model for this reservoir. This will be explained more in the following sections.

SRM Development

Dataset Generation

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. Generating this dataset is of high importance because this is going to be used to teach the physics of the reservoir and fluid flow through the porous media to the network.

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. These scenarios are demonstrated in Table 2 and Figure 5.

Table 2. Cumulative Injection after 10 years in Different Injection Scenarios

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

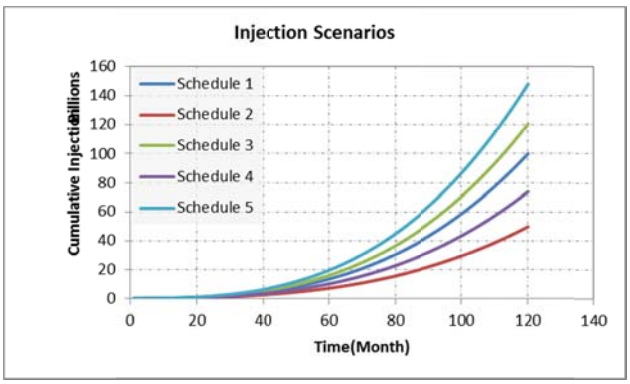

Figure 5. Cumulative Injection after 10 years in Different Injection Scenarios

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 tier system definition is depending on the type of project and alters according to having production, injection, type of injecting fluid, etc. In this case due to the shape of the CO2 plume movement three different type of tiers have been defined. Tier 1 is the planar tier including the properties of the main grid blocks and its surrounding blocks. Tier 2 and Tier 3 consist of the grid blocks in direct contact with the main block from above and below correspondingly.

The dataset generation prerequisites a reservoir engineering perception in order to select the most prominent parameters and it can go above and beyond of the abovementioned properties depending on the project. Engaging the reservoir engineering knowledge with some clustering techniques can lead to another set of information called Grid Type. Only some percent of the data will be used for modeling. So data sampling should be performed as the last step of dataset construction.

Key Performance Indicators

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. The input data will be selected based on their influence on the output which is going to be predicted.

With the intention of finding the most influential parameters, KPI (Key performance indicator) is performed for the comprehensive dataset. “Key Performance Indicators (KPI)” analysis is a guide to identify most correlated attribute with the model output. Degree of influence spans between 0 and 100 with 100 showing the most influence of the attribute on the model output. A sample of KPI results for global CO_2 mole fraction has been illustrated in Figure 5.

Rank	Feature	% Degree of Influence
1	Gas_Mole_Time_(t)	100
2	Water_Mole_Time_(t)	100
3	Gas_Mole_Time_(t-1)	71
4	Global_Mole_Time_(t-1)	71
5	Water_Mole_Time_(t-1)	68
6	Tier 1-Water_Saturation_Time_(t-1)	48
7	Tier 1-Water_Saturation_Time_(t)	47
8	Tier 2-Global_Mole_Time_(t)	42
9	Tier 2-Gas_Mole_Time_(t)	42
10	Tier 2-Water_Mole_Time_(t)	39
11	Water_Saturation_Time_(t)	37
12	Tier 2-Water_Mole_Time_(t-1)	31
13	Tier 1-Water_Mole_Time_(t)	30
14	Water_Saturation_Time_(t-1)	29
15	Tier 2-Gas_Mole_Time_(t-1)	28
16	Tier 2-Global_Mole_Time_(t-1)	28
17	Tier 1-Global_Mole_Time_(t)	28
18	Tier 1-Gas_Mole_Time_(t)	27
19	Tier 3-Water_Saturation_Time_(t-1)	21
20	Tier 3-Water_Saturation_Time_(t)	20
21	Tier 1-Global_Mole_Time_(t-1)	19
22	Tier 1-Gas_Mole_Time_(t-1)	18
23	Tier 1-Water_Mole_Time_(t-1)	18
24	Min D to injection	14
25	Tier 3-Water_Mole_Time_(t-1)	12
26	Tier 3-Gas_Mole_Time_(t-1)	12
27	Tier 3-Global_Mole_Time_(t-1)	12
28	Tier 3-Gas_Mole_Time_(t)	11
29	Tier 3-Global_Mole_Time_(t)	11
30	Tier 3-Water_Mole_Time_(t)	10
31	j	5
32	Y	5
33	X	5
34	i	5
35	Min D to boundary	4
36	Tier 3-Pressure__Time_(t)	3
37	Tier 3-Pressure__Time_(t-1)	2
38	k	2
39	Z	2
40	Poro-Tier3(Below)	2
41	Pressure__Time_(t)	2
42	Permeability I	2
43	Avg Perm-Tier1	2
44	Pressure__Time_(t-1)	2
45	Tier 1-Pressure__Time_(t-1)	2
46	Tier 1-Pressure__Time_(t)	2
47	Tier 2-Pressure__Time_(t)	2
48	Tier 2-Pressure__Time_(t-1)	2
49	Avg Poro-Tier1	2
50	Porosity	2
51	Grid Thickness-Tier2	2
52	Perm-Tier3	2
53	Grid Thickness	2
54	Avg Grid Thickness-Tier1	2
55	Grid Thickness-Tier3	2
56	Poro-Tier2(Above)	2
57	Perm-Tier2	2
58	Inj.Rate_(t)	1
59	Time_(t-1)	1
60	Time_(t)	1
61	Inj.Rate_(t-1)	1
62	BHP_(t)	1
63	BHP_(t-1)	1
64	Injection Layer	1
65	Tier 2-Water_Saturation_Time_(t)	1
66	Tier 2-Water_Saturation_Time_(t-1)	1
67	Grid Type	1

Figure 6.KPI for CO2 Mole Fraction Model

Surrogate Reservoir Model

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 algorithm used for training the model is Back Propagation in which error is fed back to the network at the end of each epoch (13).

At each time step the predicted attribute from last time step (t-1) is used as an input so that the same attribute at the present time step (t) is predicted. This process is called cascading through which at each new time step the predicted value of the previous time step is used as the (t-1) value to make the predictions for the dynamic parameters at current time step (t). Therefore, the only value of the dynamic parameter which is used within this process is the initial value of these parameters (9).

This project is an ongoing project. The trained model has used the data for the first year of injection (Monthly data). In the next step the yearly injection up to the tenth year will be used.

The training process can be investigated by observing the correlations, cross plots and corresponding R-Square values. The process of modeling might be repeated in order to find the best set of input values and get the best trained model. A sample of these cross plots for the network, which is predicting pressure in the first six months of injection, is illustrated in Figure 7.

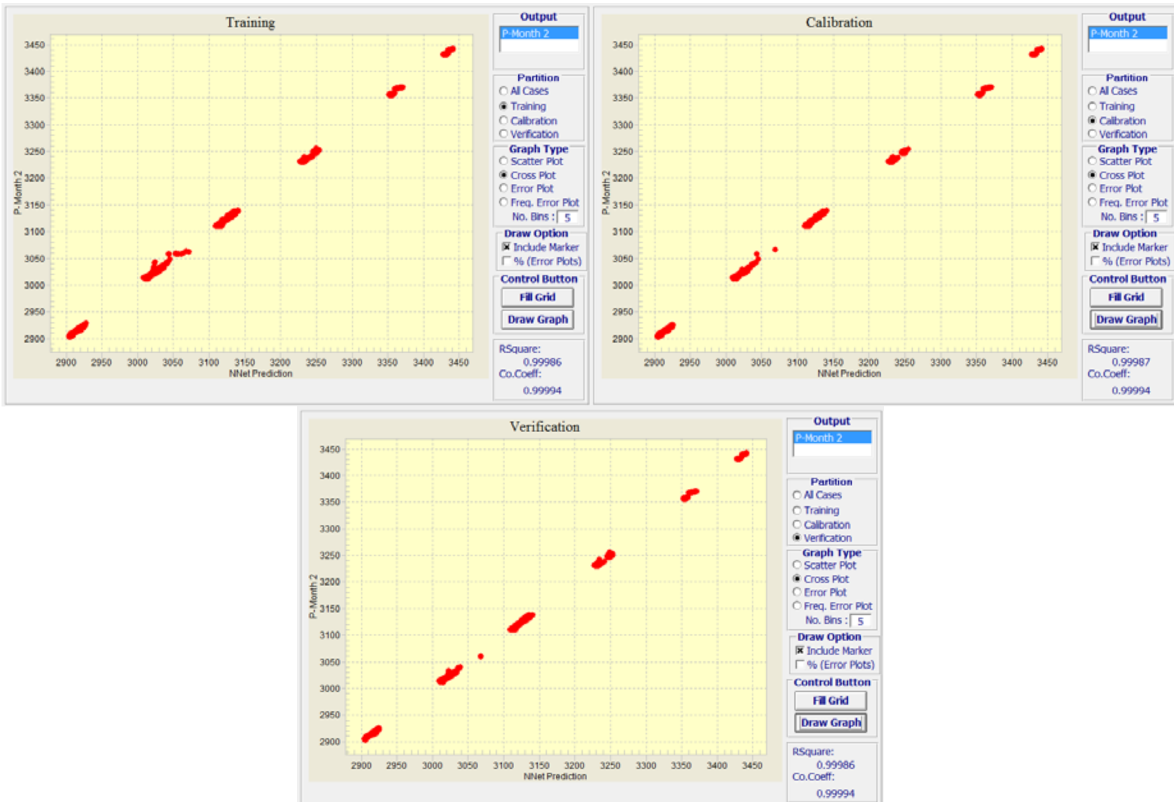

Figure 7. Cross plot of SRM Pressure prediction versus simulation output for training, calibration and validation sets.

Results and Discussion

In order to check the validity of the model, the SRM will be deployed on the blind cases (the scenarios which have not been used in the training process). If the network is able to predict the results on the scenarios that have not been seen by the model before, it can be relied in predicting any other scenarios which are in the trained range.

Since the injection in the first year has been studied and most of the changes during the first year are taking place in grid blocks adjacent the injection well, only 50 by 50 grid blocks area have been shown here.

One of the challenges in this project has been the homogeneity of the reservoir. Despite most of technologies in academia or petroleum industry, SRM works better in heterogeneous reservoirs, simply because each simulation run is carrying a lot of information in a heterogeneous reservoir. That is why SRM can deliver fairly accurate results compared to some other methodologies such as response surfaces using remarkably less simulation runs. But unfortunately in some homogenous cases (such as this study) we do not have the privilege of a lot of data in each data record. This deficiency can be overcome by adding more simulation runs to the dataset which still use by far less number of realizations in comparison with response surfaces.

Figure 8 and Figure 9 compare the predicted pressure in the reservoirs with the results obtained from the numerical reservoir simulator (CMG). Injection well is located at the top left corner of the plots. As it can be seen the results from the SRM are fairly close the ones from the reservoir simulator. Since the pressure change in the first year of the reservoir is not outstanding the colors might be misleading. Referring to the plot legend, it can be seen that difference lies within the range of few psi pressure difference. Hence, the best way of investigation the accuracy of the model is probing the percent of error propagated in the reservoir. Up to ten percent error can be tolerated in this work. Figure 10 displays the percent of difference between the SRM prediction and reservoir simulator prediction for pressure attribute in one of the layers at the end of first and sixth month of injection.

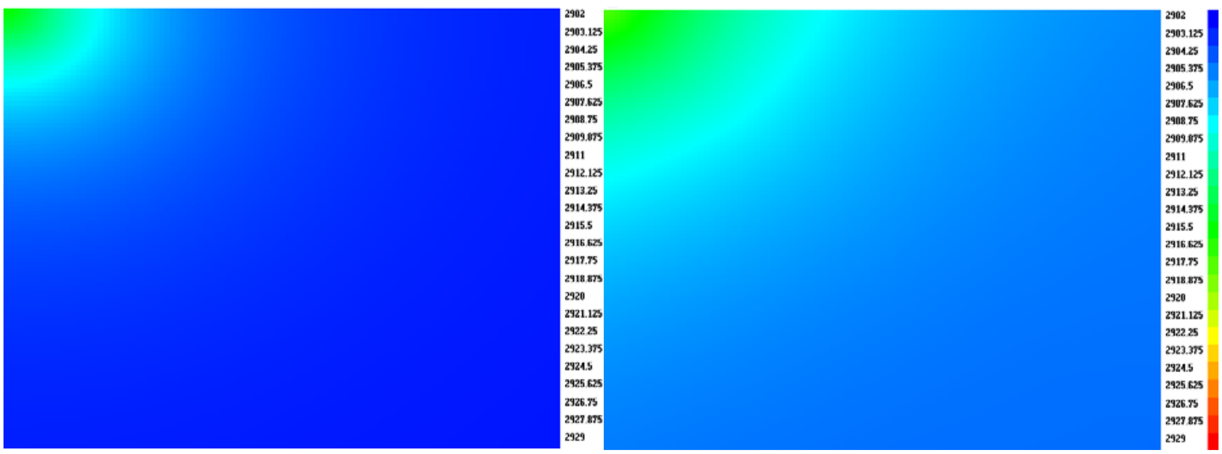

Figure 8.Pressure distribution Layer 1 after 1 month of injection, comparison CMG (Left) , SRM (Right)

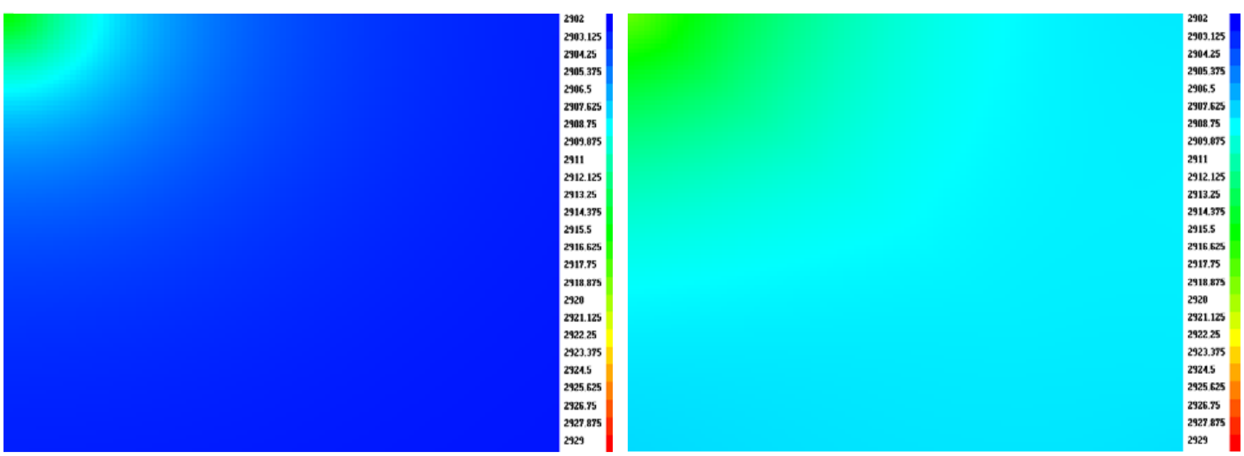

Figure 9.Pressure distribution Layer 1 after 6 months of injection, comparison CMG (Left) , SRM (Right)

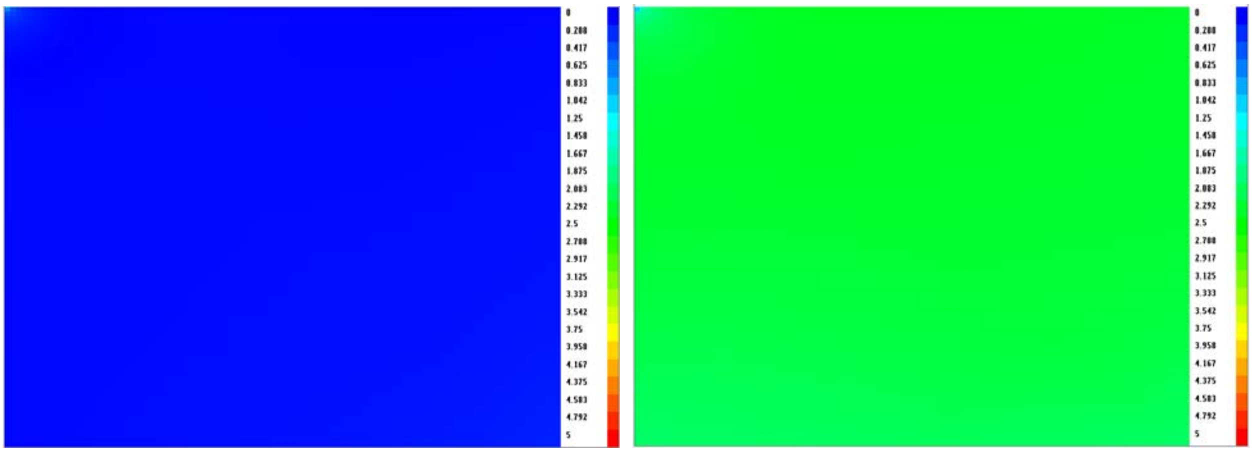

Figure 10.The percent of error propagation in Layer 2 at the end of first (Left) and sixth (Right) month of injection.

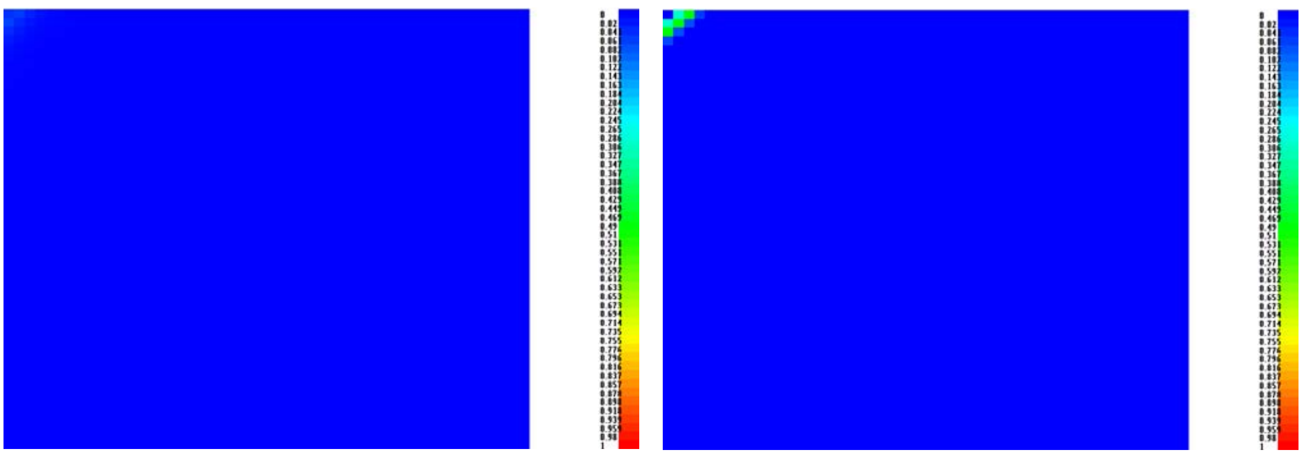

Figure 11. The difference between the S_g predicted by SRM and CMG for layer 2 at the end of first (Left) and sixth (Right) month of injection

Figure 11 illustrates the difference between the SRM prediction and reservoir simulator prediction for gas saturation attribute in one of the layers at the end of first and sixth month of injection. Since the early injection time is under study in this work, most of the changes is happening only adjacent to injector which is located in the top left of the reservoir.

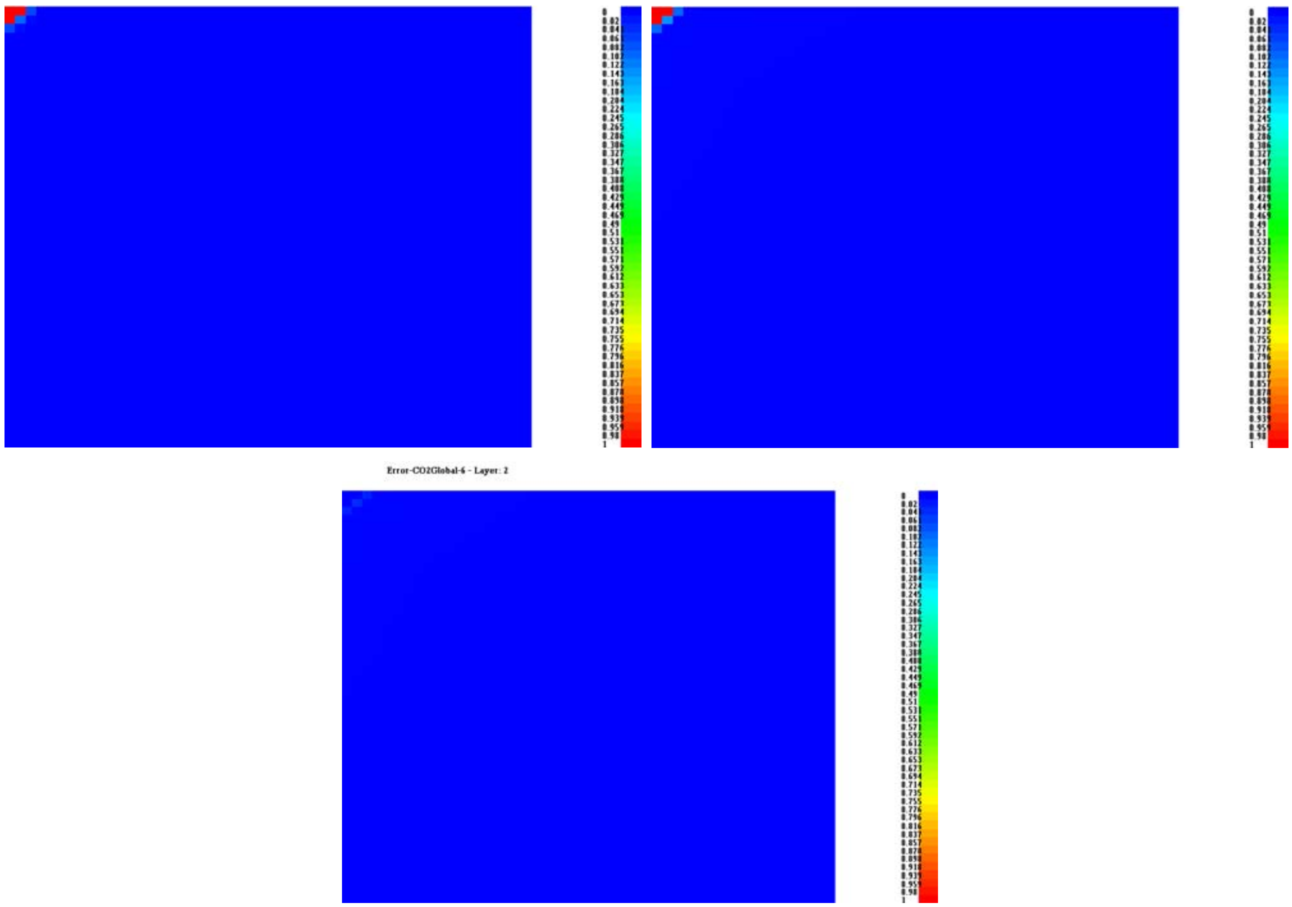

Figure 12. Global CO_2 mole fraction at the end of sixth month of injection in layer 2. CMG results (Top Left), SRM Results (Top Right), and the error propagation (Bottom)

As it can be seen in Figure 12, SRM can predict the CO_2 global mole fraction distribution in the reservoir with a high accuracy.

In order to get even better results, more scenarios can be added to the training dataset. As explained before having a homogenous reservoir (simply due to lack of data) has a negative influence on the SRM development.

Conclusion

Application of Grid based SRM to a saline formation was presented. The process and steps involved in the development of the SRM for this reservoir was explained and discussed. 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.

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