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DEPARTMENT OF ENERGY AND MINERAL ENGINEERING

ANALYSIS OF THE EFFICACY OF CARBON DIOXIDE SEQUESTRATION IN DEPLETED COALBED METHANE RESERVOIRS

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ABSTRACT

In this study, the viability of Carbon Dioxide (CO_2) sequestration in depleted Coalbed reservoirs is investigated using Computer Modeling Group LTD's (CMG) Compositional & Unconventional Simulator (GEM). This simulator features dual-porosity and dual-permeability functions, and thus best suits the needs of the model intended. In order to imitate a stimulation fracture network around the horizontal well, a Stimulated Reservoir Volume (SRV) approach was implemented. Three different models with varied grid size, matrix properties, production rates, and injection rates were investigated in order to determine proper variable ranges for the Monte Carlo Simulation and the Artificial Neural Network (ANN) study, presented in the later part of the study.

With low permeability and porosity, Coalbed methane cannot be easily produced, nor can CO_2 be easily injected, without the implementation of fracture stimulation techniques. The SRV approach significantly improved case performances of both CH_4 production and CO_2 injection [1]. With varied production sand face pressure, production rates for each of the cases will be different. However, producers will be shut-in at a uniform minimum production rate of 300 MSCFD, followed by the opening of injectors at the same well location. Injection performances will be evaluated in this study.

During the final stage of this study, three Artificial Neural Network tools were developed in order to predict various sets of data using combinations of input variables. The first tool can predict production and injection profiles of a given system with error very close or less than 20%. The second tool can predict wellbore design parameters and fracture characteristics with error less than 20%. The third tool can predict formation characteristics with error less than 20%, with the exception of one variable having larger error, yet within acceptable range.

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Chapter 1

Introduction

As the world's demand of energy continues to rise, CO_2 generation also rises. However, effective CO_2 disposal methods are yet to be discovered. Among the few methods that exist, CO_2 sequestration in rock matrix is being constantly investigated and sheds light in the future of effective CO_2 treatment, especially in coal bed reservoirs. The storage mechanism of gas particles in coal bed reservoirs is adsorption, in which gas particles adsorb onto the surface of the coal. According to the DOE [2], the adsorption rate of CO_2 in coal bed is approximately double that of methane, giving it the potential to efficiently displace methane and to remain stored in the bed. CO_2 sequestration in coal bed not only provides a possible solution to CO_2 disposal, but also adds economical value due to possible enhanced methane production.

In this study, the viability of Carbon Dioxide (CO_2) sequestration in depleted Coalbed reservoirs is investigated using Computer Modeling Group LTD's (CMG) Compositional & Unconventional Simulator (GEM). This simulator features dual-porosity and dual-permeability functions, and thus best suits the needs of the model intended. This well-developed simulator will also consider water presence in the matrix, rock compressibility, and adsorption of gas. These three considerations add more accuracy to the study and make the study more practical. Well parameters and matrix properties are entered into the simulator to closely examine every system. Among many rock properties, porosity, permeability, and Langmuir adsorption values are the key factors to the viability of a successful CO_2 sequestration plan. The Stimulated Reservoir Volume (SRV) approach will be implemented in this study to imitate a crushed zone around the horizontal wellbore [1]. All of the well models that will be investigated in this study assume 100% presence of methane in the reservoir prior to the injection of CO_2.

In Chapter 2 of this study, investigations of CO_2 sequestration possibilities through case studies of different systems of different well parameters and matrix properties will be conducted. The purpose of conducting such investigations is to understand the holistic picture of the viability of CO_2 sequestration at moderate and extreme variable settings and determine proper variable ranges for the Monte Carlo Simulation and Artificial Neural Network development in the later part of this study.

A Monte Carlo Simulation will be carried out in Chapter 3 to assess the data distributions of Original Gas In Place (OGIP) of 1,000 systems, each with randomly generated variable values within the range determined in the previous chapter. P90, P50, and P10 values will also be calculated.

At the final stage of this study, three Artificial Neural Network tools will be developed to predict desired production data, well design parameters, and matrix properties with different combinations of input variables under various conditions. The first ANN tool is a forward tool and it will be capable of predicting total production time, total injection time, production rates and injection pressures, with given reservoir properties. The second and third ANN tools are backward tools. The second ANN tool will be capable of predicting well design parameters with given reservoir properties and production data. Finally, the third ANN tool will be capable of predicting matrix properties with given well design parameters and production data.

Chapter 2

Case Study with SRV Approach

The GEM simulator developed by CMG is capable of constructing dual-porosity and dual-permeability models. However, the SRV approach needs to be implemented when stimulation operations are implemented. The unique rock mechanics properties and natural fracture networks of coal beds will always lead to the generation of fracture networks around wells [3]. It is necessary to represent these natural fracture networks, along with hydraulically stimulated fracture networks, in the systems that will be studied. The SRV approach defines the volume of the reservoir that contains the above described fracture networks as a parameter that can be entered into the simulator for accurate representations.

Coal beds are ultralow-permeability reservoirs, and thus require large fracture networks to maximize well performance. Study has shown that larger SRV around the wellbore will result in higher gas production [4]. This is also true for CO_2 injection.

For all of the case study models that will be investigated in this chapter, horizontal wells are constructed in the center of the reservoir. The horizontal wells are fractured, represented by the color red in the grid maps. Producer wells, located at the indicated grid blocks, will produce until a preset minimum production rate is met. The producer wells will then convert to injector wells at the same location and start to inject at a rate specified in each of the studies. System performances will be evaluated at the end of each case study. The purpose of conducting case studies is to conduct preliminary experiments on the actual viability of CO_2 sequestration in different settings. If case studies show no promising results, then such cases should not be considered for later studies.

The three cases are named Low, Mid, and High case respectively, because they each assess the well performance with reservoir property and well design parameters values that are at the lower end, middle level, and higher end of the proposed parameter ranges. All of the three cases implement a grid pattern of 17 by 17 grid blocks. However, the individual grid block sizes vary. The Low case employs a grid block size of 200 ft by 160 ft, which means 200 ft in the X direction and 160 ft in the Y direction. Whereas the Mid case and High case implement grid block sizes of 320 ft by 320 ft and 400 ft by 400 ft respectively. Detailed variable values that are utilized in each case are shown in Table 1. Injection of CO_2 starts immediately after shut-in of producer for all three cases. All injections stop when bottom-hole pressure reaches initial reservoir pressure, which is 2500 psi. Keeping the maximum bottom-hole pressure in alignment with the initial reservoir pressure prevents the injection processes from creating any undesirable fractures.

Table 1 Reservoir properties and wellbore design parameters for the three cases

Parameter	Low	Mid	High	Unit
Thickness (h)	10	15	20	ft
Depth (D)	3000	3000	3000	ft
Matrix Porosity (φ-m)	7	10	14	%
Fracture Porosity (φ-f)	0.5	2	3	%
Matrix Permeability (k-m)	0.0001	0.0003	0.0005	md
Fracture Permeability (k-f)	0.1	0.5	1	md
Fracture spacing (Δx-s)	1.5	2	2.5	in
Reservoir Temperature (T-i)	100	100	100	F
Reservoir Pressure (P-i)	2500	2500	2500	psi
Water Saturation in Matrix (S-wm)	6	9	11	%
Water Saturation in Fracture (S-wf)	0.1	0.1	0.1	%
Langmuir Volume of CH4 (VL-CH_4)	380	515	650	scf/ton
Langmuir Pressure of CH4 (PL-CH_4)	300	500	700	psi
Langmuir Volume of CO2 (VL-CO_2)	570	935	1300	scf/ton
Langmuir Pressure of CO2 (PL-CO_2)	200	350	500	psi
Production P_{sf} (P_{sf}-prod)	0.1* P-i	0.3* P-i	0.5* P-i	psi
SRV Fracture Porosity (SRV-φ-f)	1	7	15	%
SRV Fracture Permeability (SRV-k-f)	0.2	1.25	3	md
SRV Fracture Spacing (SRV-Δx-s)	0.6	1.2	2	ft

2.1 Low Case

The following figures show the holistic views of the SRV-φ-f and the SRV-k-f. The well blocks that are red represent the stimulated reservoir sections. The line with dots in the figures represents horizontal well, with surface reference layer located as shown.

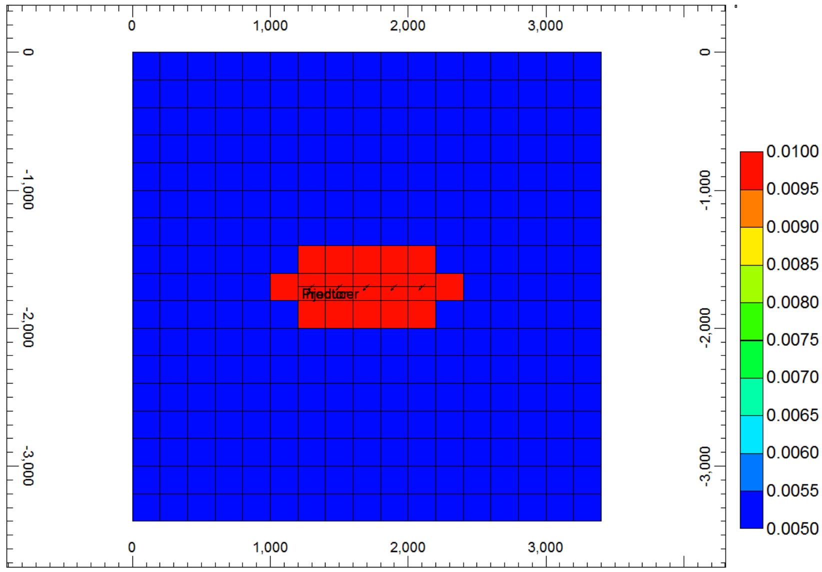


Figure 1 Fracture porosity distribution for low case

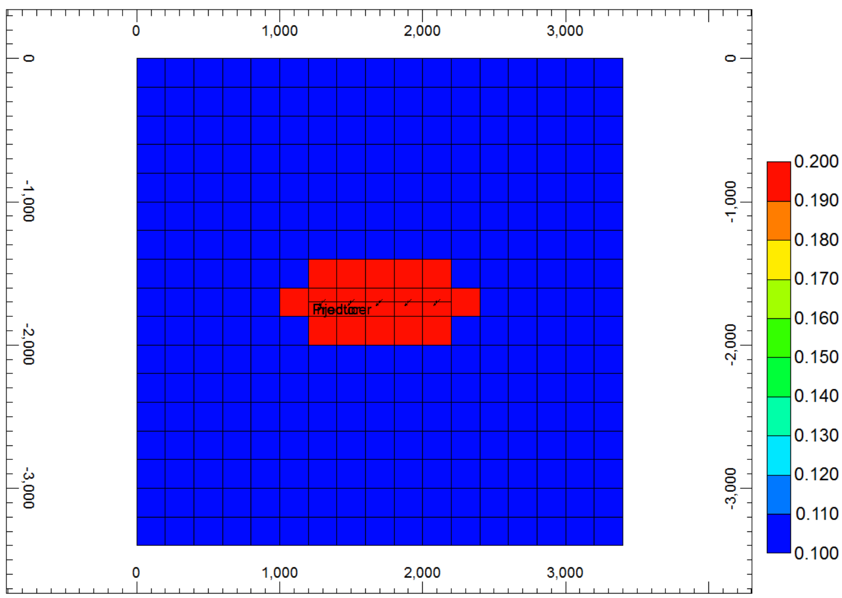


Figure 2 Fracture permeability distribution for low case

The initial production in this case is 1.55MMSCFD. P_{sf} is set to be 0.1* P-i, which is equal to 250 psi. The producer is shut-in when production rate drops to the constraint of 100 MSCFD, and the total production time is 11 years. CO_2 injection potential is then investigated for the Low case. Injection of CO_2 starts at the end of year 11 after initial production and lasts for 18 years with a constant injection rate of 100 MSCFD. The injection process stops at the end of the 18th year of injection because the stopping criteria is met.

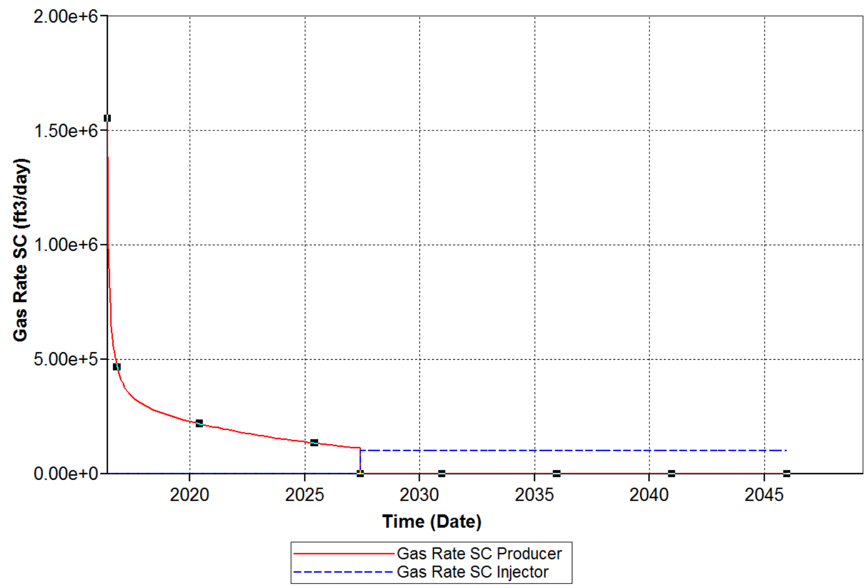


Figure 3 Daily gas production and injection for low case

Total amount of CO_2 injected can be calculated by multiplying injection rate with total injection time. Cumulative CO_2 sequestered is calculated to be 657 MMSCF.

A second study of CO_2 injection potential is conducted. In this study, CO_2 injection starts at the end of year 11 after production with an injection rate of 200 MSCFD, until bottom-hole pressure reaches stopping constraint of 2500 psi. Finally, the well is again put on production. The purpose of this study is to assess the possibility of sequestering CO_2 while improving methane production. In order to clearly observe the change of gas production due to CO_2 injection, a comparison is made between the well that is shut in then put on production and a well that is shut in, injected, and then put on production.

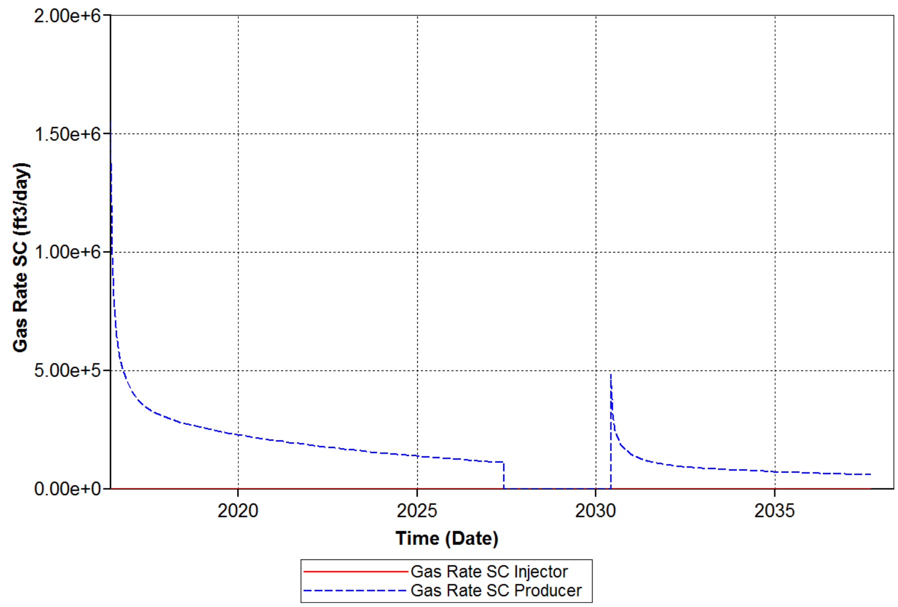


Figure 4 Production change due to shut-in for low case

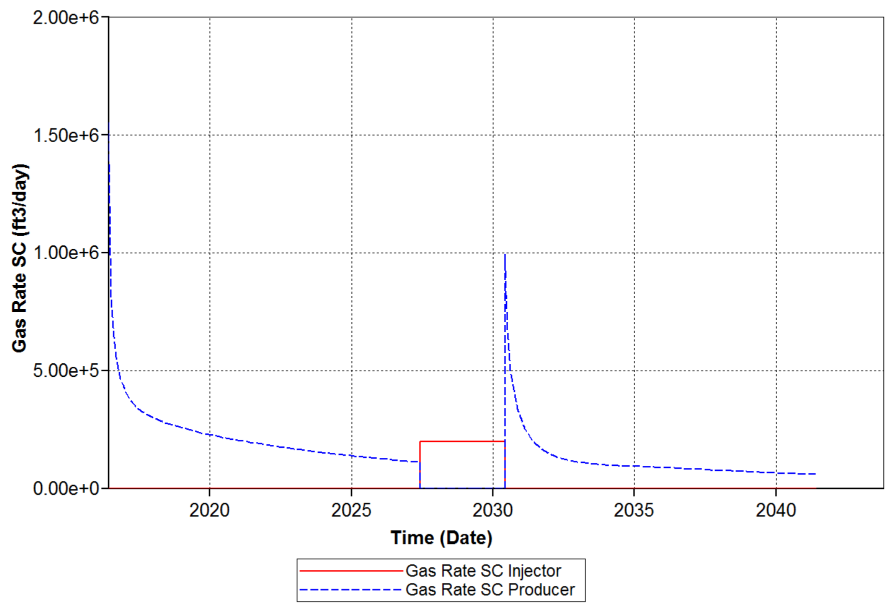


Figure 5 Production change due to CO_2 for low case

Through the above comparison, it can be observed that after 3 years of CO_2 injection, the well is able to produce at an initial rate of 1 MMSCFD, compared to 500 MSCFD without CO_2 injection. An increase of 100% in initial production rate is observed.

Finally, a graph of total CO_2 produced vs. injected is made when the well reaches the second stopping constraint, which is when production rate drops to 50 MSCFD, to assess the CO_2 sequestration possibility in this specific study. Using conversion factor of (1 gmol) CO_2 = (0.84622428 SCF) CO_2, cumulative CO_2 sequestered is calculated to be 29.79 MMSCF.

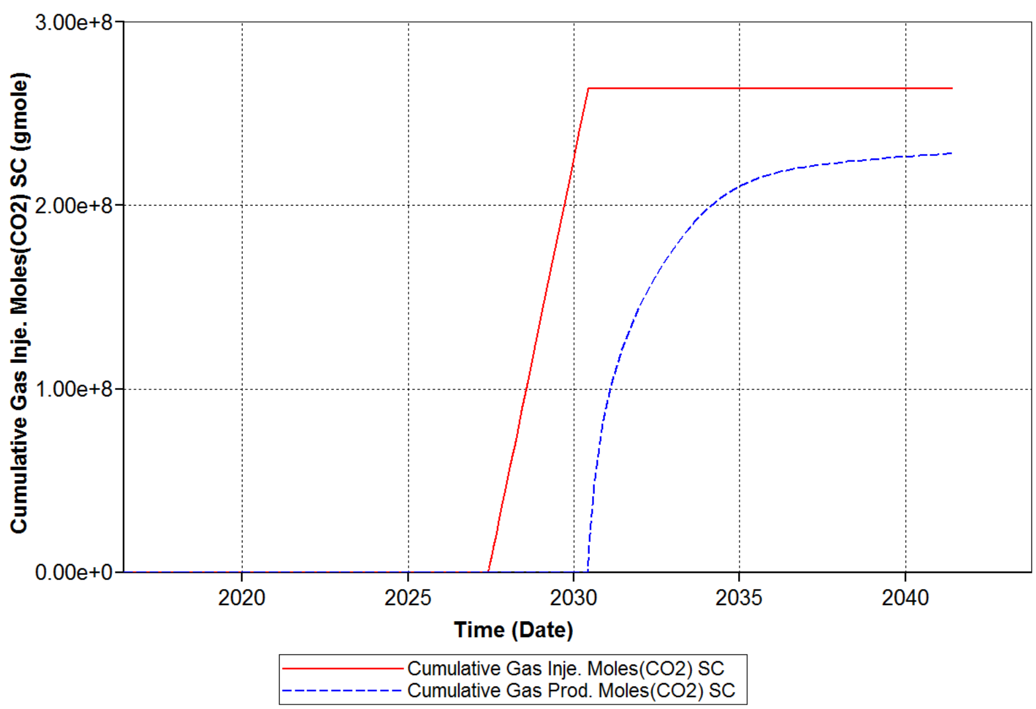


Figure 6 Total CO_2 sequestered after resumed production for low case

2.2 Mid Case

This case is designed to observe differences in well performance, when compared to the previous case, that result from utilizing mid-level parameter values

As shown in the following figures of the holistic views of the SRV-φ-f and the SRV-k-f, this case study incorporates a SRV region that is larger than that of the Low case, as a result of larger grid block sizes. The horizontal well in this case is also longer.

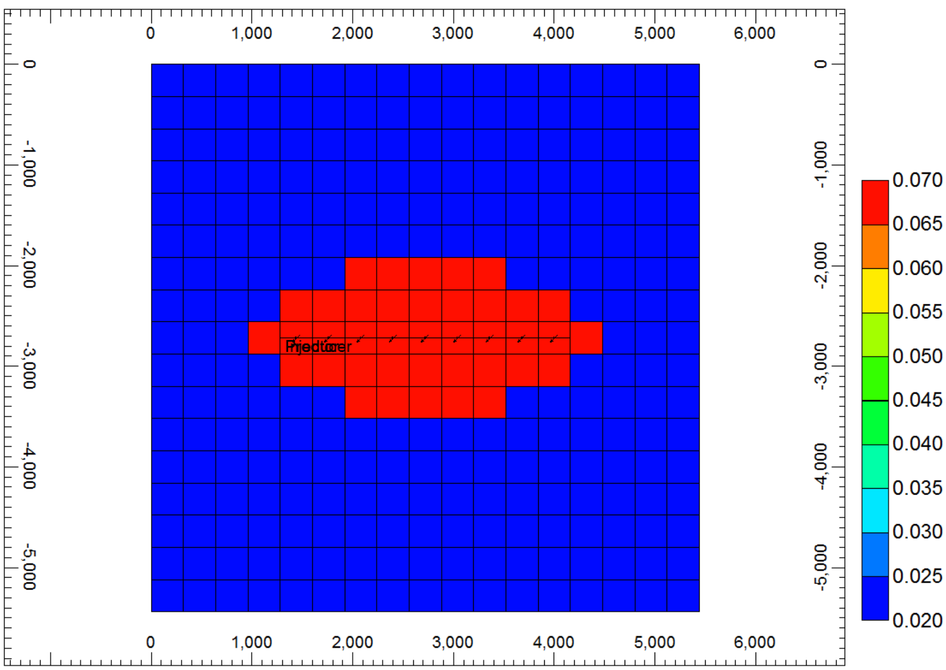


Figure 7 Fracture porosity distribution for mid case

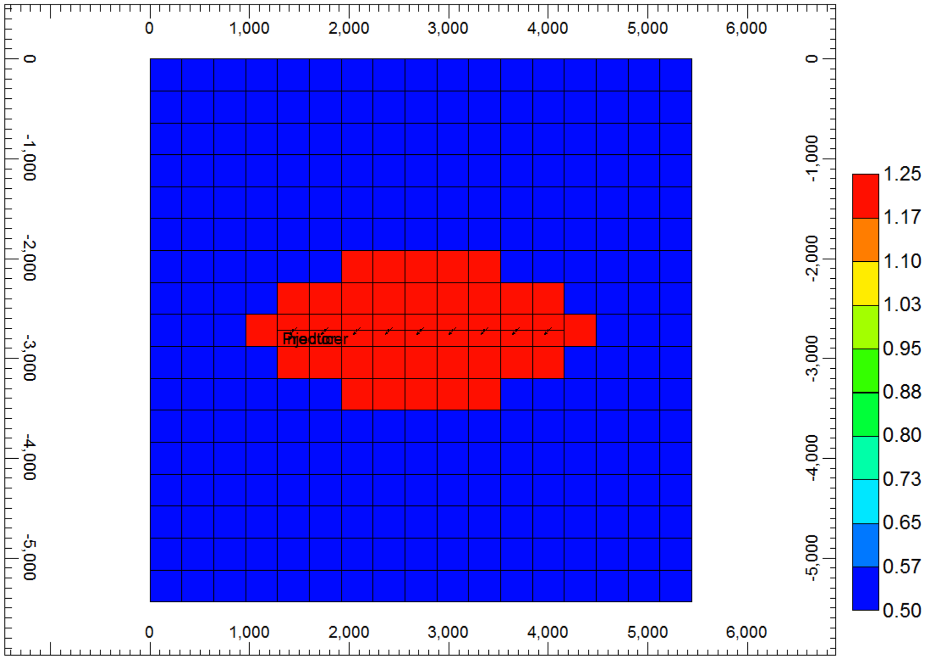


Figure 8 Fracture permeability distribution for mid case

Initial production is observed to be 14.7 MMSCFD as a result of setting P_{sf} to be 750 psi. Injection of CO_2 starts at the end of year 13 after initial production, after the producer is shut-in, when production rate drops to the constraint of 200 MSCFD. The injection process continued for 20 years with a constant injection rate of 1 MMSCFD and stops when bottom-hole pressure reaches 2500 psi. Total amount of CO_2 injected in this case is calculated to be 7.3 BSCF.

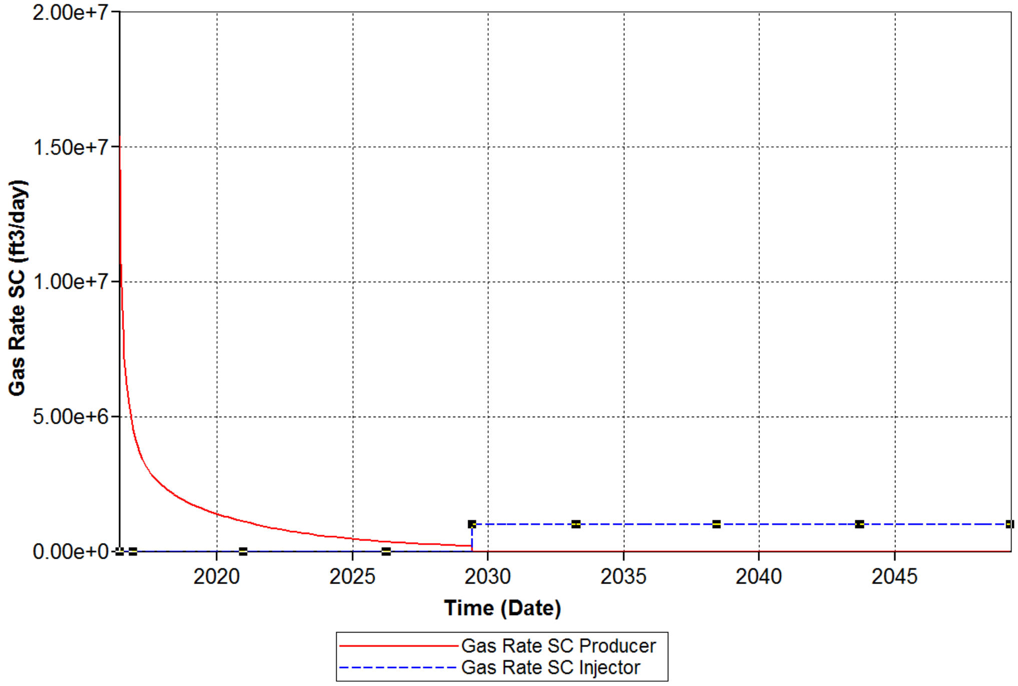


Figure 9 Daily gas production and injection for mid case

For the second investigation, CO_2 injection starts at year 13 after production, with an injection rate of 2 MMSCFD, until bottom-hole pressure reaches stopping constraint of 2500 psi. The well is later again put on production to assess the production performance after injection. A comparison is shown between Figure 10 and Figure 11 to observe the improvement in production due to CO_2 injection.

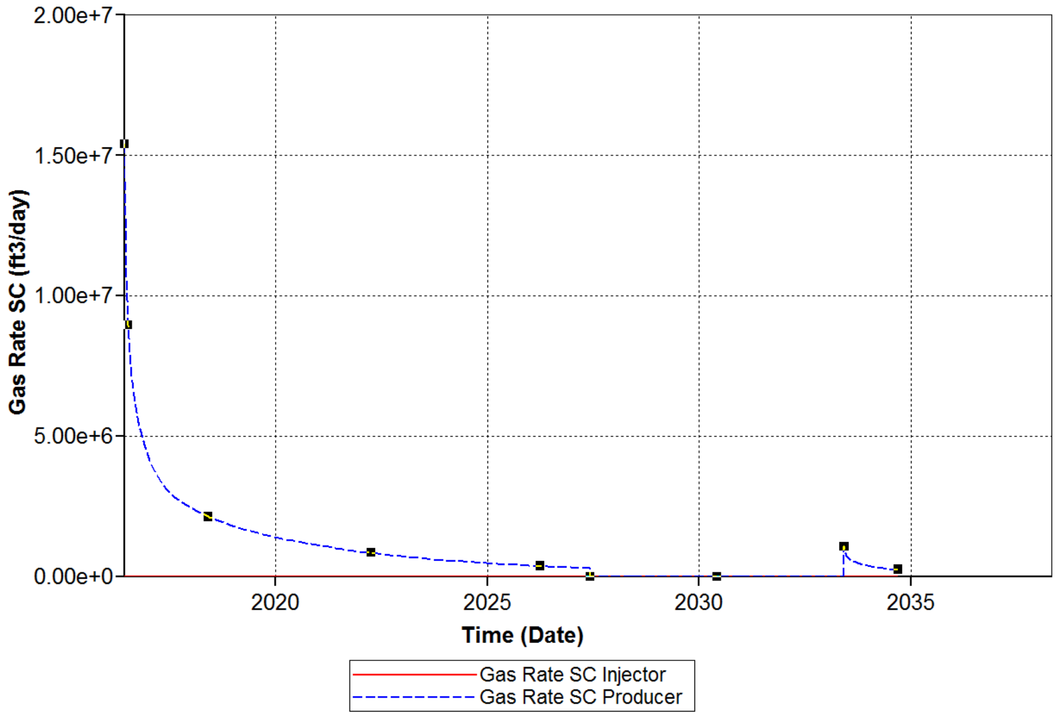


Figure 10 Production change due to shut-in for mid case

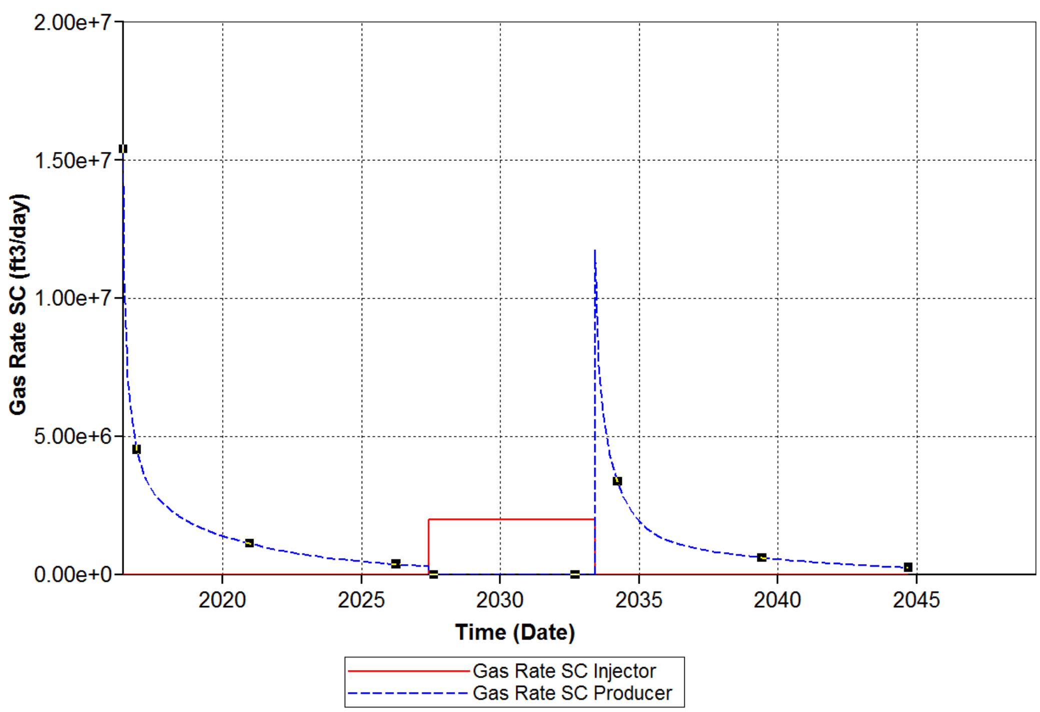


Figure 11 Production change due to CO_2 injection for mid case

It can be observed apparently that by injecting CO_2 at a constant rate of 2 MMSCFD for 6 years, the well is able to produce at a rate that is almost 12 times that of the case without injection, at 12.3 MMSCFD. Improvement in production rate is significant in this case. Cumulative CO_2 sequestered is calculated to be 626.2 MMSCF, based on the information provided by Figure 12.

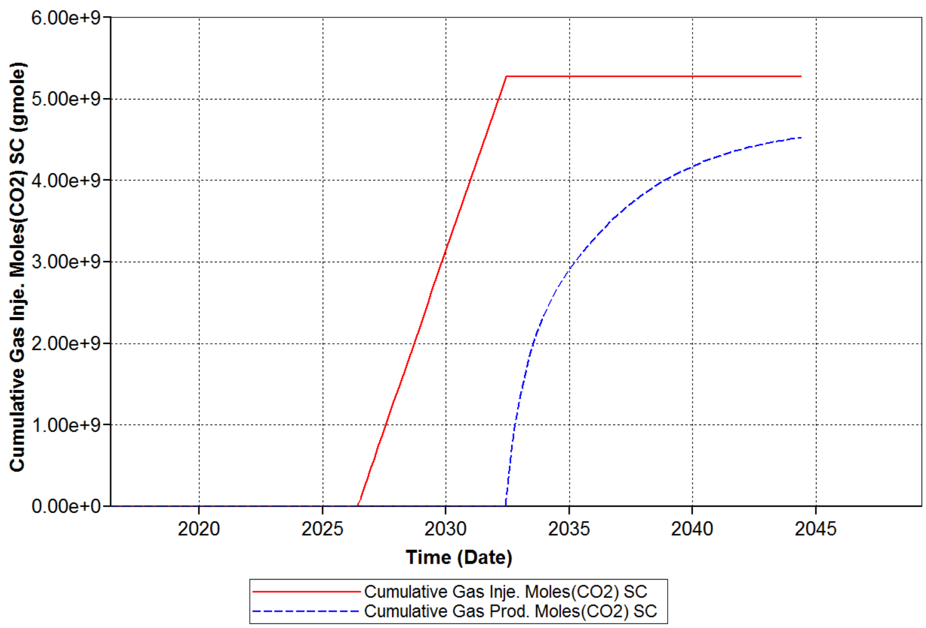


Figure 12 Total CO_2 sequestered after resumed production for Mid case

2.3 High Case

In this final case study, maximum allowable matrix parameter values are accommodated to examine the performance of the best possible system. Larger grid block sizes, larger SRV volume, and longer horizontal wells, when compared to those of the Mid case, are incorporated in this study, as shown by Figure 13 and Figure 14.

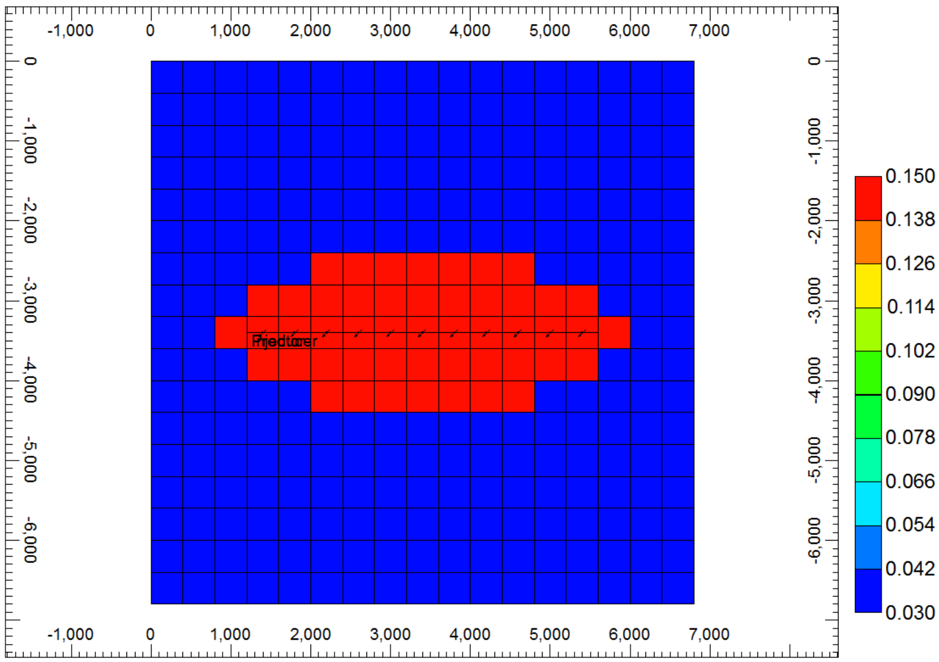


Figure 13 Fracture porosity distribution for high case

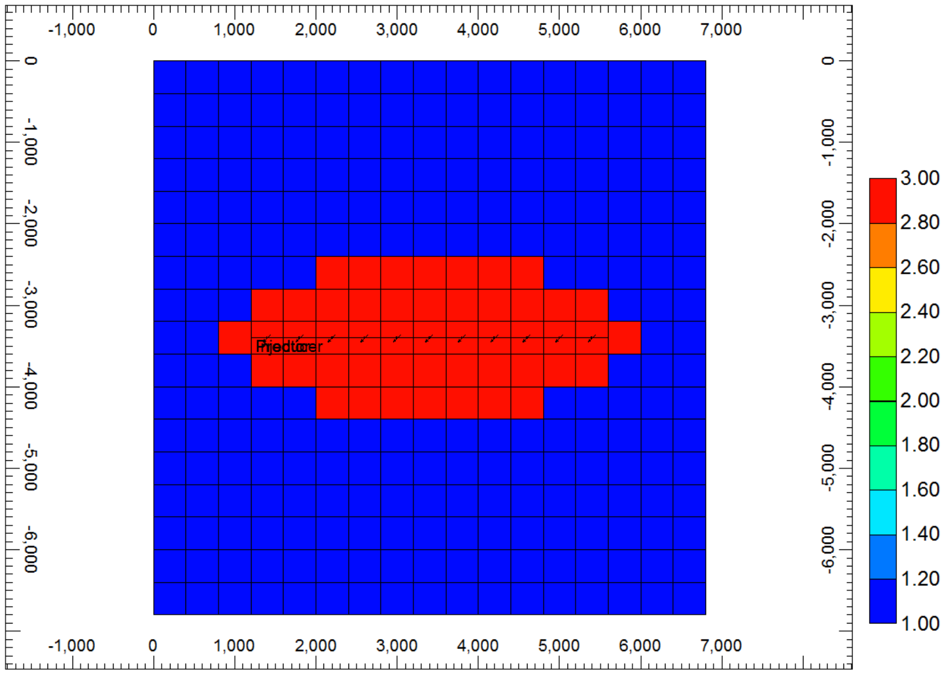


Figure 14 Fracture permeability distribution for high case

Observed initial production is 40 MMSCFD and P_{sf} is 1250 psi. The production period continues for 24 years. The production stopping constraint in this case is when production rate drops to the constraint of 300 MSCFD. Injection of CO_2 immediately follows the shut-in of producer, with an injection rate of 5 MMSCFD and total injection time of 18 years. Cumulative CO_2 sequestered is calculated to be 32.85 BSCF.

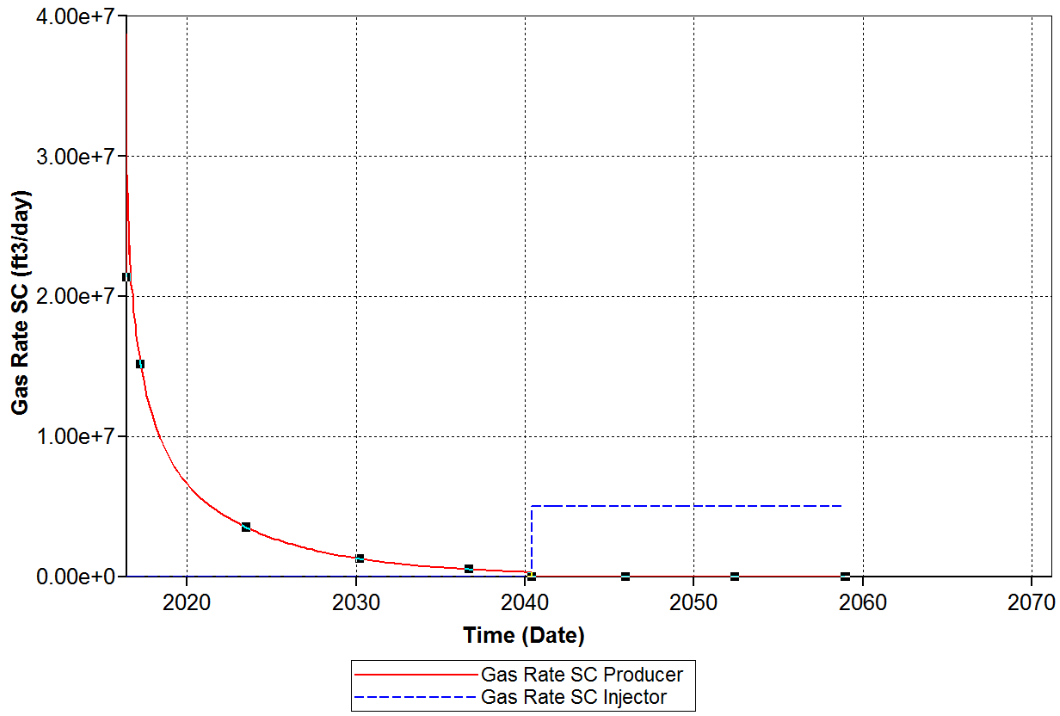


Figure 15 Daily gas production and injection for high case

In the second study, CO_2 injection starts at year 24 after production with an injection rate of 7 MMSCFD, until bottom-hole pressure reaches stopping constraint of 2500 psi. The well is re-opened to observe any possible changes to production performance. Increase in production rate can be observed by comparing Figure 16 and Figure 17.

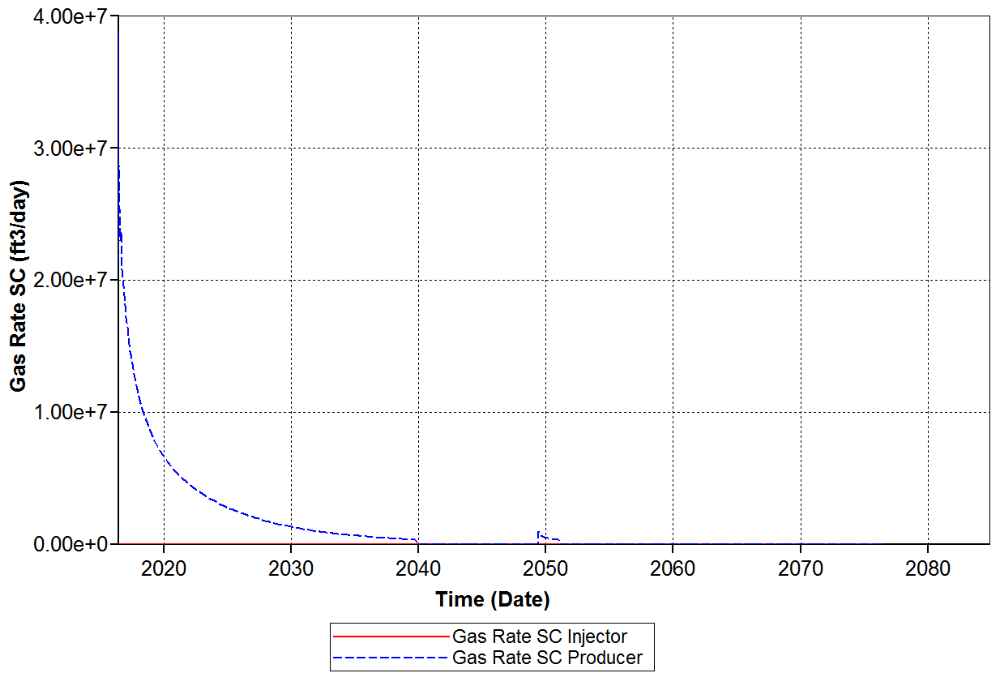


Figure 16 Production change due to shut-in for high case

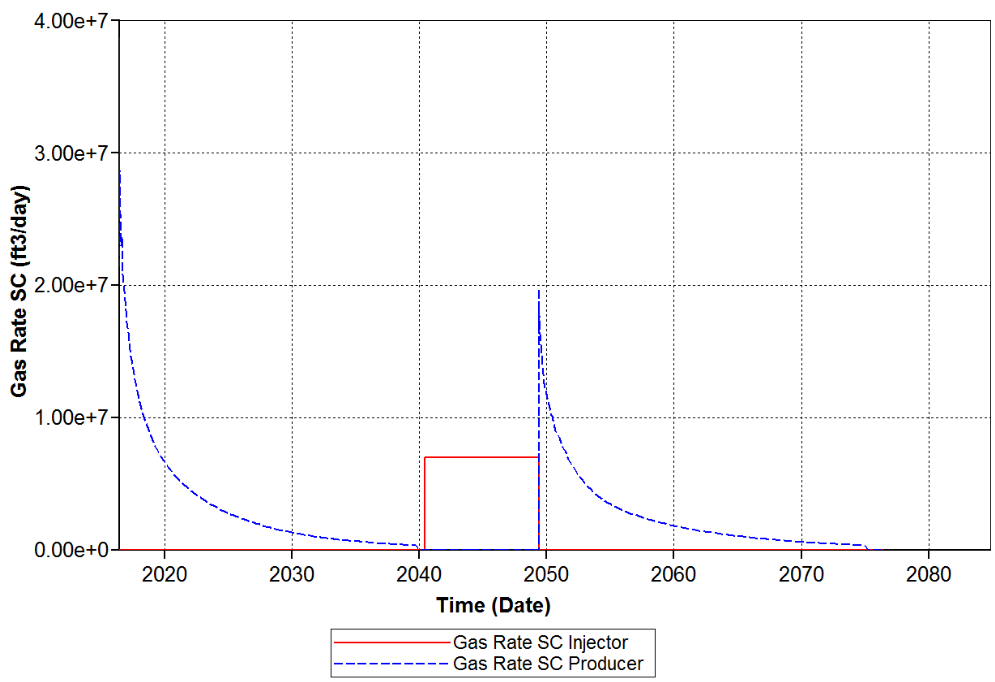


Figure 17 Production change due to CO_2 injection for high case

After 9 years of CO_2 injection, the well is able to increase its production to 20 MMSCFD, instead of 971 MSCFD for the scenario without CO_2 injection. Injection of CO_2 significantly increases production rate.

When production rate drops to 250 MSCFD in the second production period, total CO_2 sequestered is calculated to be 3.49 BSCF.

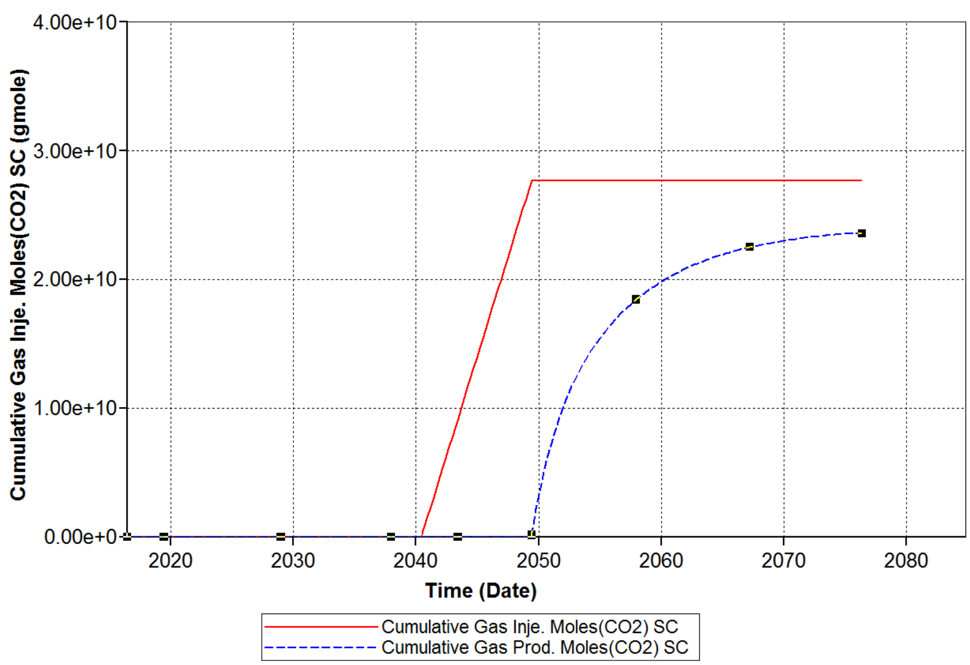


Figure 18 Total CO_2 sequestered after resumed production for High case

Chapter 3

Monte Carlo Simulation

Estimation of petroleum reserves has always been time consuming and, at the same time, vital to the success of every proposed production and storage plan. A Monte Carlo Simulation is conducted, in order to facilitate such complex processes, with a total of 1000 simulation runs that are made with randomly generated thickness, matrix porosity, fracture porosity, matrix permeability, fracture permeability, fracture spacing, water saturation in matrix, Langmuir Volume of CH_4 (VL-CH_4), Langmuir Pressure of CH_4 (PL-CH_4), Langmuir Volume of CO_2 (VL-CO_2), Langmuir Pressure of CO_2 (PL-CO_2), SRV Fracture Porosity (SRV-φ-f), SRV Fracture Permeability (SRV-k-f), and SRV Fracture Spacing (SRV-Δx-s). Grid block pattern is selected to be 17 by 17 grid blocks and size of each grid block is selected to be 250 ft by 250 ft. Grid block pattern and size combinations larger than the one selected yields inaccurate results. Grid block pattern and size combinations smaller than the one selected do not improve accuracy of calculations. In all of the simulation runs, the producer will be shut-in when production rate drops to 300 MSCFD. Varied injection rate within the range of 0.5 to 1 MMSCFD is utilized for each case. Stopping constraint for injection is when bottom-hole pressure reaches 2500 psi. A distribution fit is applied to the histogram of OGIP data, please note that the portion of the fit line that is below zero should not be considered as a part of the valid data set.

Table 2 Constant parameters for Monte Carlo simulation

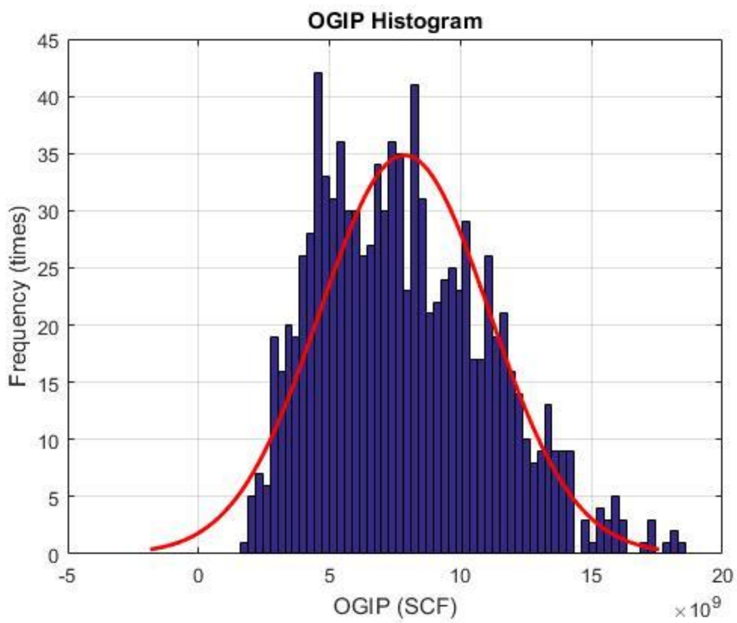
Parameter	Value	Unit
Depth (D)	3000	ft
Reservoir Temperature (T-i)	100	F
Reservoir Pressure (P-i)	2500	psi
Water Saturation in Fracture (S-wf)	0.1	%
Stopping criteria 1(q_prod)	300	MSCFD
Stopping criteria 2(Psf-inj-stop)	2500	psi

Table 3 Variable ranges for Monte Carlo simulation

Parameter	Min	Max	Unit
Thickness (h)	5	20	ft
Matrix Porosity (φ-m)	7	14	%
Fracture Porosity (φ-f)	0.5	3	%
Matrix Permeability (k-m)	0.0001	0.0005	md
Fracture Permeability (k-f)	0.1	1	md
Fracture spacing (Δx-s)	1.5	2.5	in
Water Saturation in Matrix (S-wm)	6	11	%
Langmuir Volume of CH4 (VL-CH_4)	380	650	scf/ton
Langmuir Pressure of CH4 (PL-CH_4)	300	700	psi
Langmuir Volume of CO2 (VL-CO_2)	1.5*VL-CH_4	2*VL-CH_4	scf/ton
Langmuir Pressure of CO2 (PL-CO_2)	200	500	psi
SRV Fracture Porosity (SRV-φ-f)	2*φ-f	5*φ-f	%
SRV Fracture Permeability (SRV-k-f)	2*k-f	3*k-f	md
SRV Fracture Spacing (SRV-Δx-s)	0.4*Δx-s	0.8*Δx-s	in
Production constraint (P_{sf}-prod)	0.1*2500	0.5*2500	psi
Injection constraint(q-inj)	0.5	1.5	MMSCFD

The result of the Monte Carlo simulation for a varied production sand face pressure, ranging from 0.1 to 0.5 of the initial reservoir pressure, indicates the uncertainty of OGIP is large. OGIP distribution has the range of 1.61 BCF to 18.57 BSCF, as shown in the following histogram. The histogram shows a lognormal fit of data sets, as plotted with the following histogram. A figure of the probability distribution for OGIP is shown below. This figure indicates that P90, P50, and P10 values are 3.91, 7.53, and 12.25 BSCF for OGIP.

Figure 19 OGIP histogram for fixed injection rate



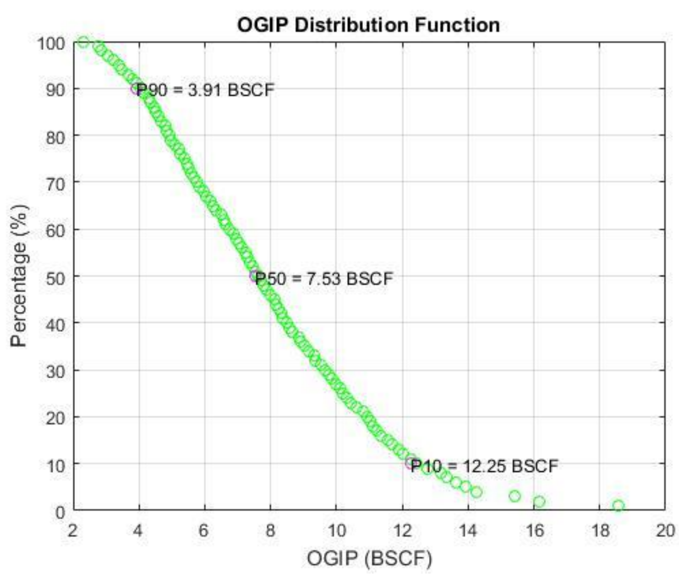


Figure 20 OGIP distribution function for fixed injection rate

Chapter 4

Development of Artificial Neural Network Tools

In order to optimize operations to achieve highest gas production and highest amount of CO_2 sequestered, different combinations of reservoir properties and wellbore design parameters need to be investigated under sensitivity analysis and ultimately reach on a desired plan. Manually changing each parameter that will have an effect on the final performance of the system is extremely inefficient, especially when the number of systems that need to be evaluated is large. The implementation of ANN will facilitate such tasks with great ease and accuracy.

ANN learns to correlate the inputs and outputs through complex calculations and iterations conducted by the artificial neurons in each of the layers of the network. In adjusting the number of total layers and neurons, the network can correlate data within desired accuracy and ultimately "learn" from the correlations and establish relationships ready for use when new data is being implemented.

The powerful calculation and correlation capability of ANN allows it to produce tools for this specific study. Three ANN tools will be developed, which are one forward tool and two backward tools. For the forward tool, the objective will be to obtain the total production time (t_prod), total injection time (t_inj), 11 production rates (q_prod1~11) each at time step equals to [0.1, 0.2, 0.3….,1] * [t_prod] , and 11 injection pressures (p_inj1~11) each at time step equals to [0.1, 0.2, 0.3….,1] * [t_inj]. Choosing time steps at the above spots ensures the proportionality of the data that will be predicted. The input parameters for this tool will be thickness (h), matrix porosity (φ-m), fracture porosity (φ-f), matrix permeability (k-m), fracture permeability (k-f), fracture spacing (Δx-s), matrix water saturation (S-wm), Langmuir volumes and pressures for both CH_4 and CO_2 (VL-CH_4,PL-CH_4,VL-CO_2,PL-CO_2), SRV fracture porosity (SRV-φ-f), SRV fracture permeability (SRV-k-f), SRV fracture spacing (SRV-Δx-s), production sand face pressure (P_{sf}-prod), and injection rate (q-inj). Functional links will also be employed to help the neural network learn in the direction that is desired.

The objective for the first backward tool is to predict well design parameters, namely SRV fracture porosity (SRV-φ-f), SRV fracture permeability (SRV-k-f), SRV fracture spacing (SRV-Δx-s), and production sand face pressure (P_{sf}-prod). The inputs for this tool will be total production time (t_prod), total injection time (t_inj), thickness (h), matrix porosity (φ-m), fracture porosity (φ-f), matrix permeability (k-m), fracture permeability (k-f), fracture spacing (Δx-s), matrix water saturation (S-wm), Langmuir volumes and pressures for both CH_4 and CO_2 (VL-CH_4,PL-CH_4,VL-CO_2,PL-CO_2), injection rate (q-inj), 11 production rates (q_prod1~11), and 11 injection pressures (p_inj1~11).

The goal of the second backward tool is to predict reservoir properties, which are thickness (h), matrix porosity (φ-m), fracture porosity (φ-f), matrix permeability (k-m), fracture permeability (k-f), fracture spacing (Δx-s), and matrix water saturation (S-wm). The inputs for this tool will be Langmuir volumes and pressures for both CH_4 and CO_2 (VL-CH_4,PL-CH_4,VL-CO_2,PL-CO_2), SRV fracture porosity (SRV-φ-f), SRV fracture permeability (SRV-k-f), SRV fracture spacing (SRV-Δx-s), production sand face pressure (Psf-prod), injection rate (q-inj), total production time (t_prod), total injection time (t_inj), 11 production rates (q_prod1~11), and 11 injection pressures (p_inj1~11).

The development of an ANN usually involves data cleansing and changing the architecture. When error rates are outside of desired range, one should first look at data distributions of the variable that is causing the high error rate. Outliers that have extreme values and cases that are unreasonable should be deleted for the integrity and accuracy of the ANN. For example, a system where injection only lasts for less than a year should not be considered as a case being investigated, because such system will not generate any economical worth and will decrease the overall performance of the ANN. Other methods that should be taken to improve the performance of the ANN include the implementation of functional links and changing the number of hidden layers, number of neurons, activation functions, and transfer functions. 12 functional links are implemented as inputs for the forward tool in order to help the ANN in correlating total injection time with the input parameters. Most of the functional links don't have physical meanings. For example, one of the functional links is the multiplication of fracture porosity and fracture permeability. The meaning of this functional link is to help the ANN in realizing when fracture porosity and fracture permeability are low, injection will quickly reach the preset constraint of 2500 psi, and thus decrease the total injection time.

Error analyses will be conducted for each of the predicted variables of each of the tools. A total of 1000 systems will be randomly generated and investigated using the parameter ranges below with a grid block pattern of 17 by 17 blocks and grid block size of 250 ft by 250 ft.

Table 4 Data ranges for all three tools

Parameter	Min	Max	Unit
Depth (D)	3000	3000	ft
Reservoir Temperature (T-i)	100	100	F
Reservoir Pressure (P-i)	2500	2500	psi
Water Saturation in Fracture (S-wf)	0.1	0.1	%
Thickness (h)	5	20	ft
Matrix Porosity (φ-m)	7	14	%
Fracture Porosity (φ-f)	0.5	3	%
Matrix Permeability (k-m)	0.0001	0.0005	md
Fracture Permeability (k-f)	0.1	1	md
Fracture spacing (Δx-s)	1.5	2.5	in
Water Saturation in Matrix (S-wm)	6	11	%
Langmuir Volume of CH4 (VL-CH_4)	380	650	scf/ton
Langmuir Pressure of CH4 (PL-CH_4)	300	700	psi
Langmuir Volume of CO2 (VL-CO_2)	1.5*VL-CH_4	2*VL-CH_4	scf/ton
Langmuir Pressure of CO2 (PL-CO_2)	200	500	psi
SRV Fracture Porosity (SRV-φ-f)	2*φ-f	5*φ-f	%
SRV Fracture Permeability (SRV-k-f)	2*k-f	3*k-f	md
SRV Fracture Spacing (SRV-Δx-s)	0.4*Δx-s	0.8*Δx-s	in
Production constraint (P_{sf}-prod)	0.1*2500	0.5*2500	psi
Injection constraint(q-sf-inj)	0.5	1.5	MMSCFD
Stopping criteria 1(q_prod)	300	300	MSCFD
Stopping criteria 2(Psf-inj-stop)	2500	2500	psi

4.1 Production-Injection Prediction Tool

The developed tool correlates 16 parameters that define the reservoir under investigation and 12 functional links that helps the ANN in learning to predict accurate total injection times, with 24 output variables. The systems generated operate with randomly generated production sand face pressures and stop at a fixed minimum production constraint of 300 MSCFD. The injection process operates at the same well location as the producer and injects at a constant, a randomly generated rate that is within 0.5 and 1.5 MMSCFD.

It can be observed from design diagram Figure 21 that the forward tool has 28 neurons, 50 neurons, and 24 neurons in the input layer, hidden layer and output layer, respectively. The tool predicts total production time, total injection time, 11 production rates (q_prod1~11), and 11 injection pressures (p_inj1~11).

Out of the 1000 data sets, 800 data sets are used for training and 100 data sets were used for validation. A total of 100 data sets are tested, and results for four predicted data sets are shown below. Average error for total production time is 3.70%. Average error for total injection time is 22.40%. Average error for each of the 11 production rates are 5.67%, 6.33%, 8.22%, 7.98%, 6.27%, 5.46%, 6.13%, 5.85%, 5.56%, 5.39%, and 5.40% respectively. Average error for each of the 11 injection pressures are 4.59%, 3.78%, 4.24%, 1.96%, 1.70%, 1.69%, 1.66%, 1.77%, 1.92%, 1.77%, and 1.82% respectively.

With an average error goal of 20%, the Production-Injection Prediction Tool predicts accurate results for all of the 24 output variables. Average error for total injection time is slightly higher than the desired goal, yet it is within acceptable range.

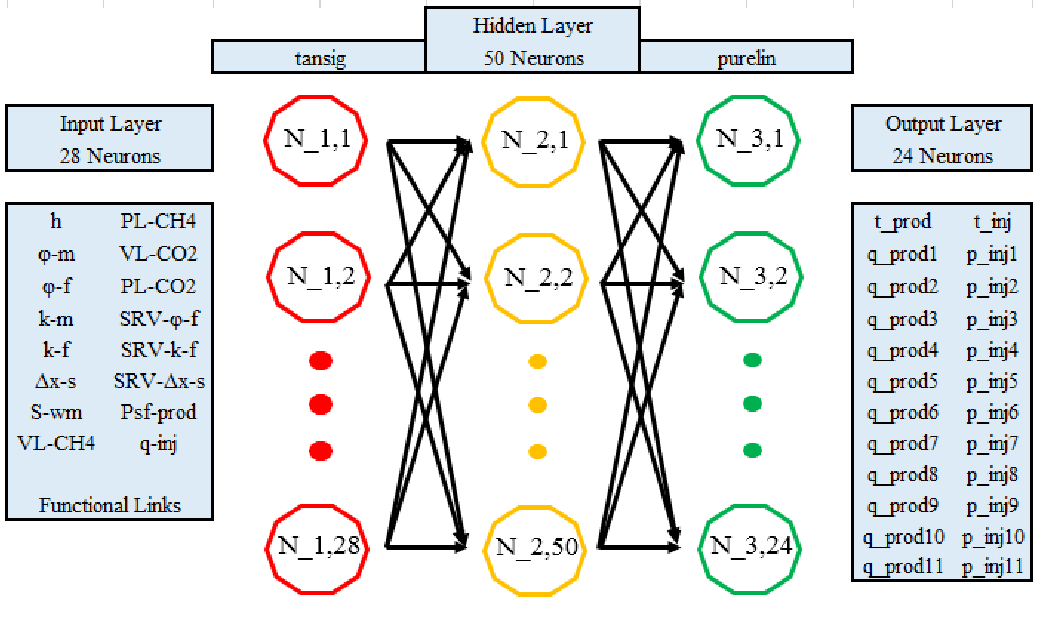


Figure 21 ANN structure for the Production-Injection Prediction Tool

	Case 6	Case 8	Case 17	Case 40
	Days			
total injection time	7239	10792	13349	6509
injection time prediction	8864.347	9055.544	11288.97	7894.948
Error %	22.45264	16.09021	15.43206	21.2928
total production time	4583	3487	6309	5113
production time prediction	4453.719	3315.055	6301.736	5372.494
Error %	2.820871	4.931016	0.115136	5.075184

Figure 22 Production time and injection time error analysis

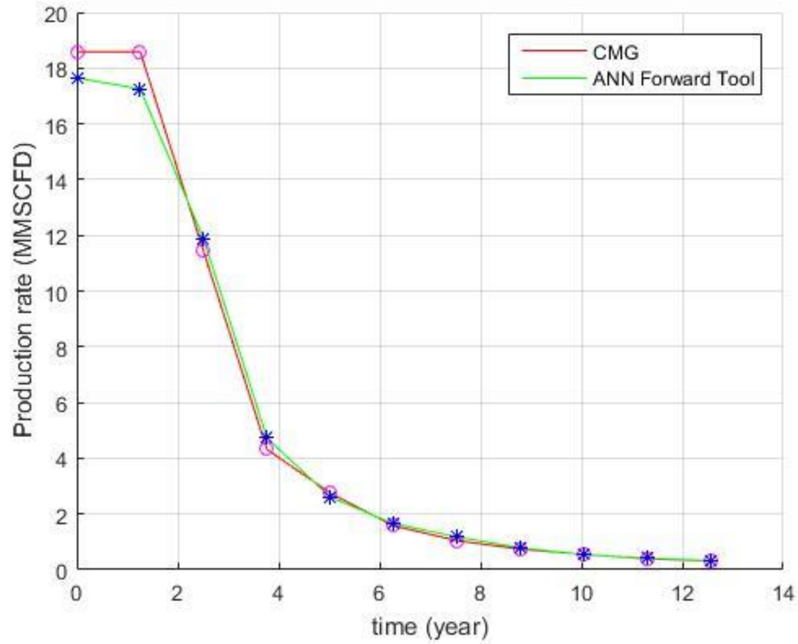


Figure 23 Production rate prediction Case 6

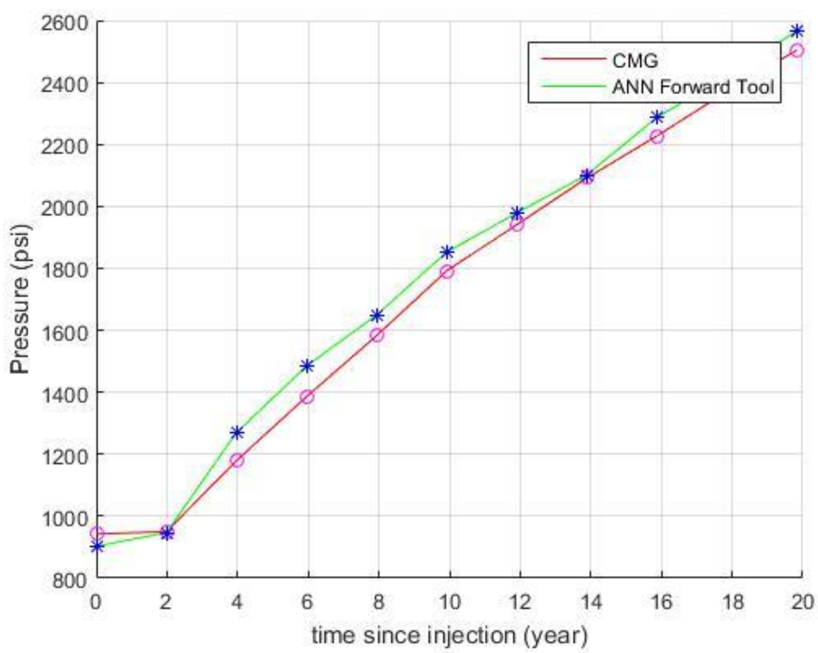


Figure 24 Injection pressure prediction Case 6

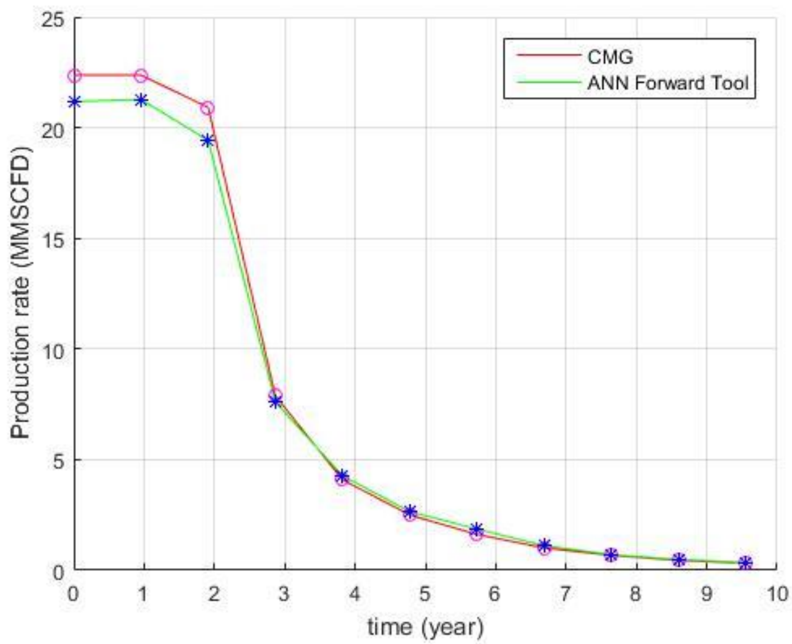


Figure 25 Production rate prediction Case 8

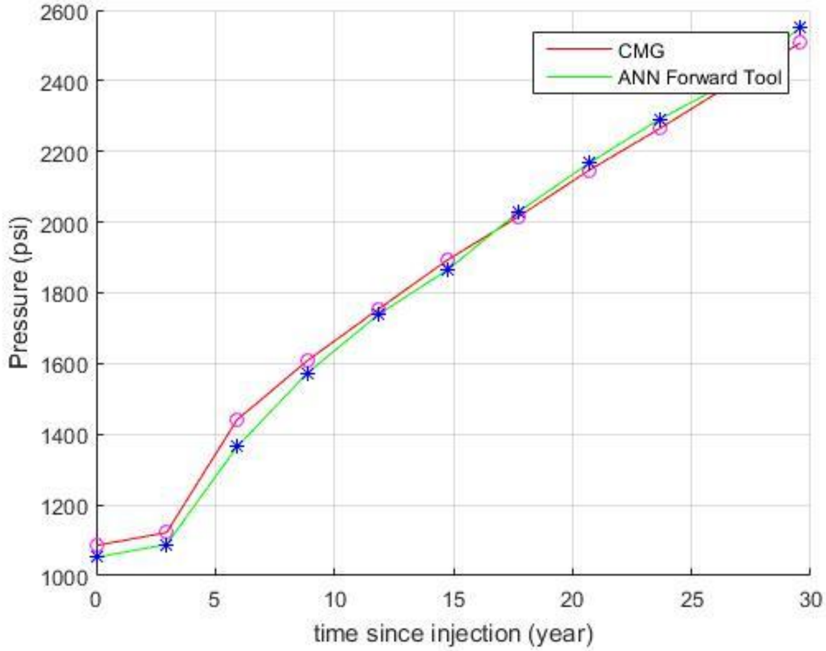


Figure 26 Injection pressure prediction Case 8

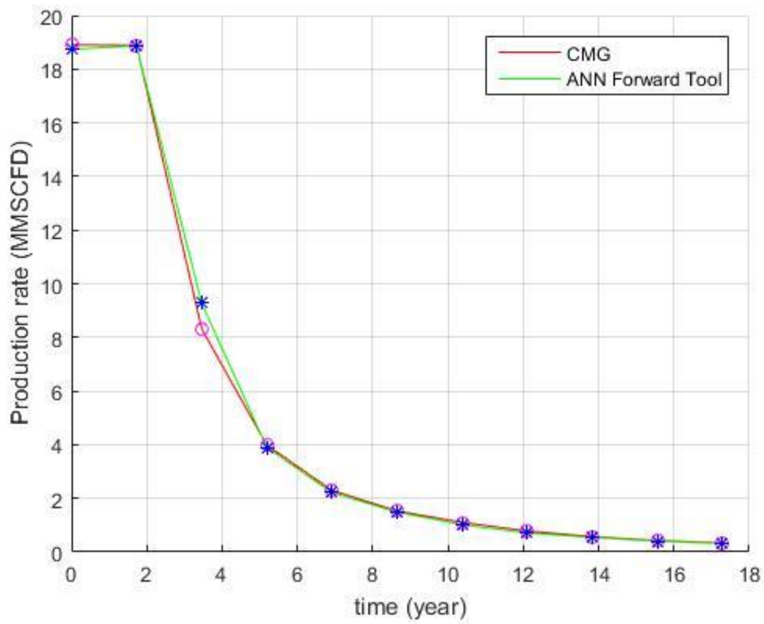


Figure 27 Production rate prediction Case 17

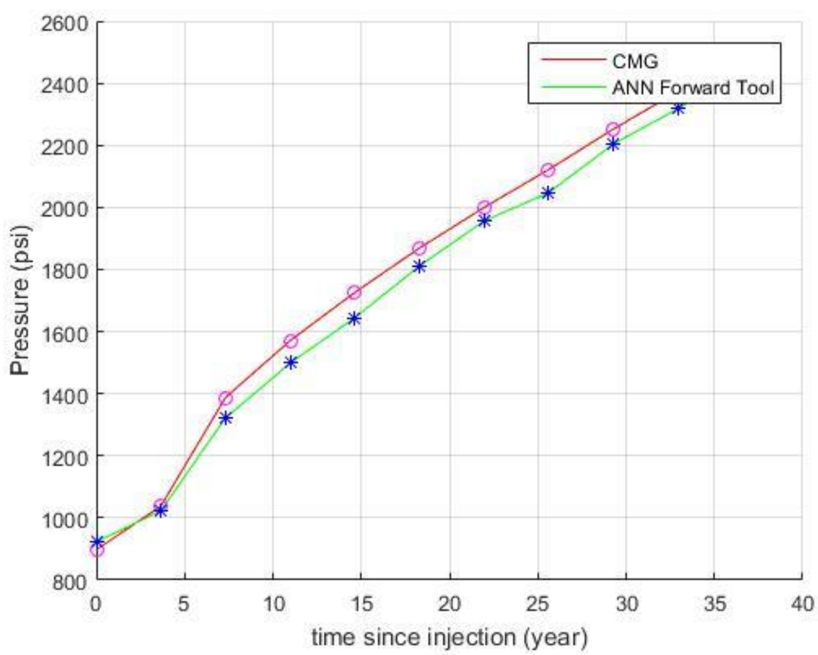


Figure 28 Injection pressure prediction Case 17

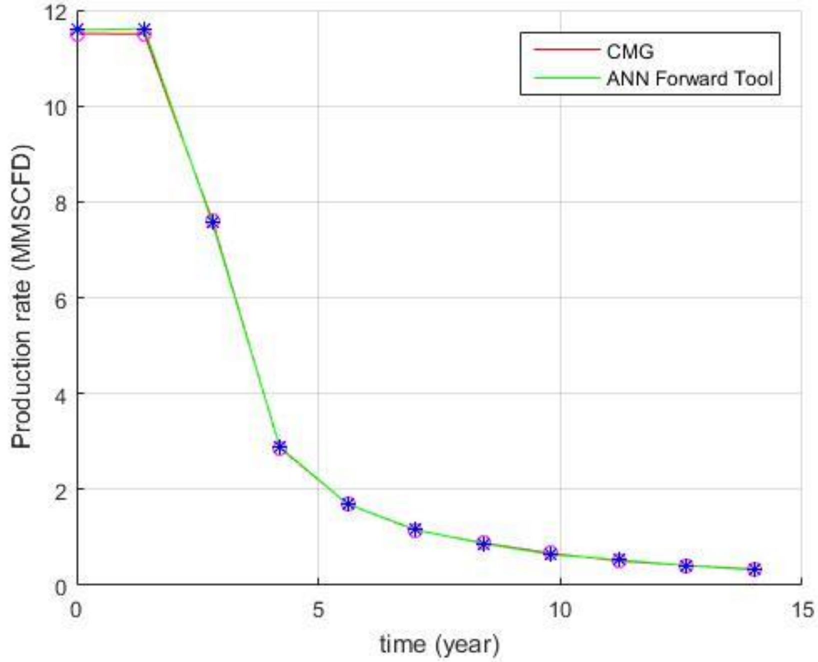


Figure 29 Production rate prediction Case 40

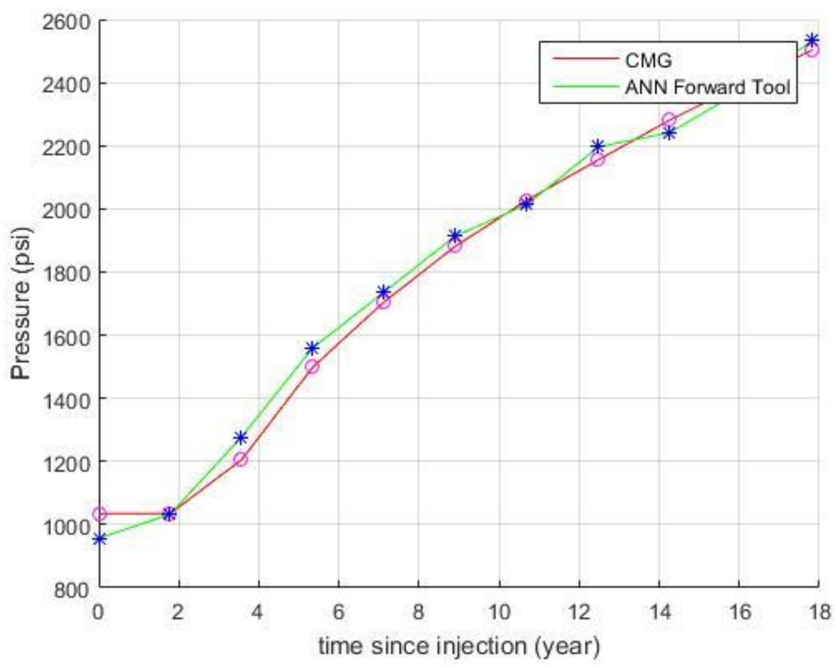


Figure 30 Injection pressure prediction Case 40

4.2 Well Design Parameter Prediction Tool

The first backward tool takes a part of the inputs from the forward tool and combines it with the outputs from the forward tool to form the new input data set. In this tool, 36 parameters are correlated with 4 output variables.

The systems generated operate with randomly generated production sand face pressures and stops at a fixed minimum production constraint of 300 MSCFD. The injection process operates at the same well location as the producer and injects at a constant, randomly generated rate that is within 0.5 and 1.5 MMSCFD.

The tool incorporates 40 neurons in its only hidden layer and predicts SRV fracture porosity (SRV-φ-f), SRV fracture permeability (SRV-k-f), SRV fracture spacing (SRV-Δx-s), and production sand face pressure (P_{sf}-prod).

Out of the 1000 data sets, 80% of the data sets were used for training and 10% of the data sets were used for validation. A total of 100 data sets are tested and results for four predicted data sets are shown below. Average error for SRV fracture porosity (SRV-φ-f), SRV fracture permeability (SRV-k-f), SRV fracture spacing (SRV-Δx-s), and production sand face pressure (P_{sf}-prod) are 9.58%, 7.17%, 19.56%, and 17.34% respectively. All of the average error rates are within target range.

Results for four sample cases are shown below.

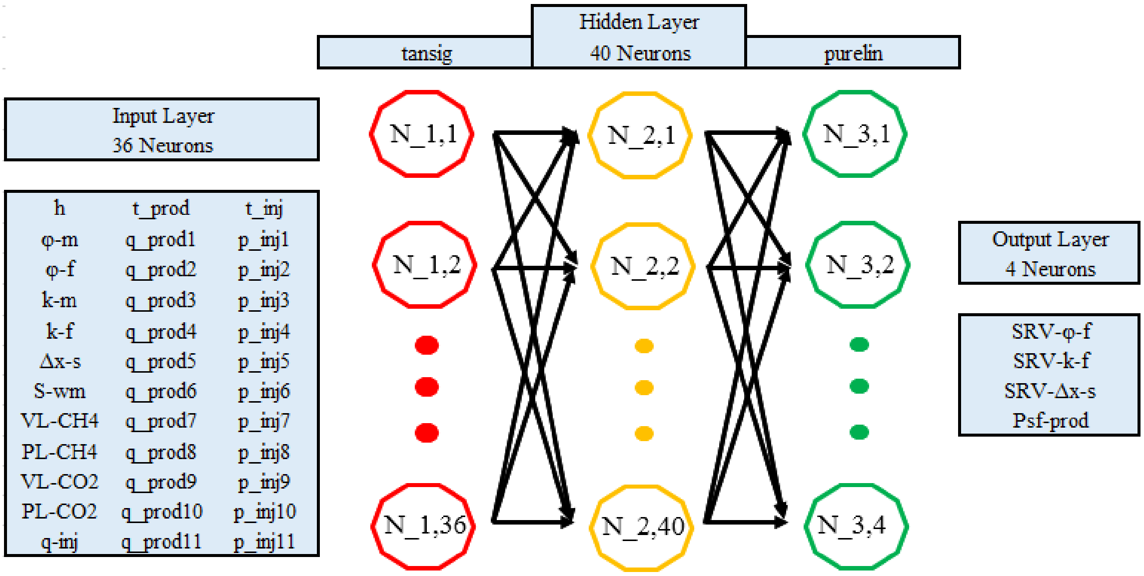


Figure 31 ANN structure for the Well Design Parameter Prediction Tool

Table 5 Result and error analysis for Case 2

		Case 2	Case 2 Prediction	Error %
Psf_prod	psi	754.4385	708.6624778	6.067563
SRV k-f	md	1.584308	1.633796032	3.123642
SRV-φ-f	%	3.131571	3.205080871	2.347394
SRV-Δx-s	ft	0.083792	0.087466665	4.385141

Table 6 Result and error analysis for Case 5

		Case 5	Case 5 Prediction	Error %
Psf_prod	psi	558.1784	529.5774478	5.123976
SRV k-f	md	0.868339	0.821909743	5.346943
SRV-φ-f	%	5.969621	5.797276962	2.887019
SRV-Δx-s	ft	0.111002	0.105287039	5.148608

Table 7 Result and error analysis for Case 7

		Case 7	Case 7 Prediction	Error
				%
Psf_prod	psi	847.7782	770.1460936	9.157125
SRV k-f	md	2.54106	2.552461479	0.448709
SRV-φ-f	%	5.819785	5.721806585	1.683541
SRV-Δx-s	ft	0.115597	0.108995064	5.711501

Table 8 Result and error analysis for Case 18

		Case 18	Case 18 Prediction	Error
				%
Psf_prod	psi	479.1563	447.1952871	6.670271
SRV k-f	md	2.154258	2.049150114	4.879095
SRV-φ-f	%	1.887898	2.008783535	6.403164
SRV-Δx-s	ft	0.102607	0.110889139	8.071402

4.3 Matrix Property Prediction Tool

In this second backward tool, all variables except for matrix properties will be the inputs. The developed tool correlates 33 input variables with 7 output variables. The systems generated are the same as the previous tools and operate with randomly generated production sand face pressures and stops at a fixed minimum production constraint of 300 MSCFD. Injection rates will be randomly generated the range of within 0.5 and 1.5 MMSCFD.

As seen from the design diagram from Figure 32, the tool incorporates 33 neurons, 40 neurons, and 7 neurons in the input layer, hidden layer and output layer, respectively. The tool predicts thickness (h), matrix porosity (φ-m), fracture porosity (φ-f), matrix permeability (k-m), fracture permeability (k-f), fracture spacing (Δx-s), and matrix water saturation (S-wm).

Same division of the total number of 1000 data sets will be employed, with 800 data sets in training, 100 data sets in validation, and 100 data for testing. Average error for thickness (h), matrix porosity (φ-m), fracture porosity (φ-f), matrix permeability (k-m), fracture permeability (k-f), fracture spacing (Δx-s), and matrix water saturation (S-wm) are calculated to be 15.99%, 19.42%, 9.63%, 38.42%, 15.57%, 14.79%, and 15.30% respectively.

6 out of the 7 predicted variables show error rates within the desired range. Note that error for matrix permeability predictions are 38.42%. However, given the very small values of matrix permeability in coalbed reservoirs, this high error will introduce a negligible error to the proposed project.

Results for four sample cases are shown below.

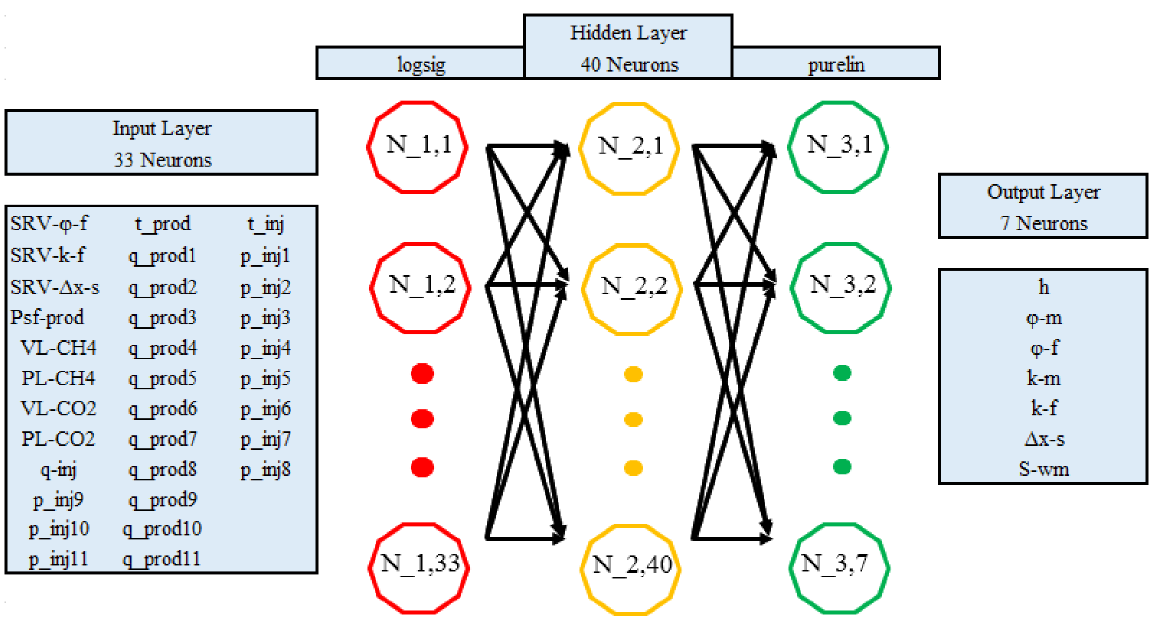


Figure 32 ANN structure for the Matrix Property Prediction Tool

Table 9 Result and error analysis for Case 3

		Case 3	Case 3 Prediction	Error
				%
k-f	md	0.748893	0.683308618	8.757463
φ-f	%	2.024765	1.74112695	14.00842
Δx-s	ft	0.145037	0.170390255	17.48041
k-m	md	0.000375	0.000283132	24.58733
φ-m	%	9.706718	10.11760395	4.233003
S-wm	%	10.56629	8.408811541	20.41852
h	ft	15.13453	16.13452887	6.607408

Table 10 Result and error analysis for Case 27

		Case 27	Case 27 Prediction	Error
				%
k-f	md	0.305375	0.316187316	3.540668
φ-f	%	2.276757	2.124844917	6.672301
Δx-s	ft	0.155906	0.167362908	7.3486
k-m	md	0.000383	0.000295425	22.86554
φ-m	%	9.413898	10.05461518	6.806077
S-wm	%	7.341045	8.204637932	11.7639
h	ft	11.87128	13.49728572	13.69697

Table 11 Result and error analysis for Case 50

		Case 50	Case 50 Prediction	Error
				%
k-f	md	0.472309	0.518313007	9.740159
φ-f	%	1.338935	1.584080234	18.30896
Δx-s	ft	0.171559	0.148226839	13.60004
k-m	md	0.000286	0.000245804	14.00142
φ-m	%	12.63563	10.55067631	16.50057
S-wm	%	6.962031	8.188996438	17.62366
h	ft	11.08941	12.4968082	12.69134

Table 12 Result and error analysis for Case 57

		Case 57	Case 57 Prediction	Error
				%
k-f	md	0.250922	0.227546045	9.316
φ-f	%	1.934865	1.901128443	1.743592
Δx-s	ft	0.194235	0.196388358	1.108398
k-m	md	0.000438	0.000306433	29.97771
φ-m	%	10.76244	11.39188387	5.848562
S-wm	%	9.036471	8.340831889	7.698127
h	ft	15.71673	15.72068652	0.025186

Chapter 5

Discussion and Conclusions

As discussed in the introduction section, this study has three major parts: CH_4 production and CO_2 injection case studies, Monte Carlo Simulation, and development of three ANN prediction tools.

Among the three cases studied, Low case has the lowest initial production rate, CO_2 injection rate, total CO_2 stored, and total production time. Overall performance of the resumed production after injection is not pleasing. It was discovered that if injection rate were to increase by 50%, total injection time significantly reduces. The performance of the system in the Low case is not promising as expected because this case study employs parameters that are at the lower end of the ranges.

The Mid case performance shows improvement when compared to the Low case. The system in this case has a more promising initial production rate and total production time. The system is also capable of sustaining CO_2 injection at a rate that has economical worth while maintaining a relatively long total injection time.

The High case has the best performances in every aspect. However, due to realistic reasons, it is very unlikely that a system will have this combination of good parameters values. As a result, the settings of the High case were not considered for being a base model of the Monte Carlo Simulation and ANN development.

The settings of the Mid case were adopted for later studies. However, slight changes were made to some of the parameters in order for the system to sustain greater variable ranges and would still produce reasonable results, as required by the Monte Carlo Simulation and ANN development.

In the Monte Carlo Simulation, OGIP results distributions show a desired lognormal fit, with P90, P50, and P10 values of 3.91, 7.53, and 12.25 BSCF for OGIP. Large uncertainty for OGIP is observed.

All of the three Artificial Neural Network tools predicted promising results, with mean error of most of the variables within the desired range of 20%. Total injection time in the forward tool yields a mean error of 22.40%, which is slightly higher than the desired range. Matrix permeability in the second backward tool yields a mean error of 38.42%. However, given the very small values of matrix permeability in coalbed reservoirs, this high error will introduce a negligible error to the proposed project. It can be concluded that all three tools will predict reliable results, given input variables within the predetermined range.

It is discovered during the ANN development phase that excess number of hidden layers will increase error rate, a phenomenon known as over fitting. It is also discovered that the total number of neurons that will be employed in a single hidden layer should not exceed the sum of the number of inputs and the number of outputs. Exceeding this sum usually increases error; however, this can only serve as a rule of thumb and should not be taken as a set rule when designing an ANN architecture. Another observation is that when output values are distributed in a relatively large range, pre-normalization of output values should be conducted prior to normalization using MATLAB commands. Pre-normalization, when necessary, reduces error significantly.

Data cleansing and the utilization of functional links significantly improve prediction accuracy. If necessary, data sets that have unreasonably high or low variable values should be completely removed. Functional links should also be utilized when prediction results are not promising. Functional links should include relationships that have physical meaning and expressions that have no physical meaning. The goal of utilization of functional links is to help the ANN in learning in the direction that is desired.

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[2] DOE, ‘CARBON STORAGE R&D’ Washington, DC: U.S. Department of Energy, 2017.

[3] Zhao Yu-long, Zhang Lie-Hui, Feng Guo-Qing, Zhang Bo-Ning, and Kang Bo, “Analysis of the Efficacy of Carbon Dioxide Sequestration In Depleted Shale Gas Reservoirs" Oil Gas Sci. Technol., Volume 71, Number 1, January–February 2016

[4] M. J. Mayerhofer, E. P. Lolon, N. R. Warpinski, C. L. Cipolla, D. Walser, C. M. Rightmire, “What Is Stimulated Reservoir Volume?" Society of Petroleum Engineers. doi:10.2118/119890-PA

Appendix A

Data generation scripts and ANN development scripts

C1. Data Generation

C1.1 .dat file generation

```
%%%The following ANN scripts were developed with the help of Jian Zhang%%%

%% delete existing variables
clear
%% read in pattern file as string
% pattern file name
filename='Monte-Carlo-Pattern-new.dat';
% read pattern file to text string
pattern = fileread(filename);
%% generate random varibles (set)
N = 1000;

prodbhp = genRand(0.1,0.5,N).*2500;
thickness = genRand(5,20,N);
matpor = genRand(0.07,0.14,N);
frcpor = genRand(0.005,0.03,N);
srvfrcpor = genRand(2,5,N).*frcpor;
matperm = genRand(0.0001,0.0005,N);
frcperm = genRand(0.1,1,N);
srvfrcperm = genRand(2, 3, N).*frcperm;
frcspac = genRand (0.125,0.2083, N);
srvfrcspac = genRand(0.4,0.8,N).*frcspac;
matsw = genRand(0.06,0.1100,N);
VlCH4 = genRand(380,650,N);
PlCH4 = genRand(300,700,N);
VlCO2 = genRand(1.5,2,N).*VlCH4;
PlCO2 = genRand(200,500,N);
qinj = genRand(500000,1500000,N);

%% generate dat files
% loop for each random variabel set,
% replace the corresponding words in pattern with the generated variable
values
for i = 1 : N
    newdat = pattern;
    % replace corresponding %%variable%% in the pattern text
    newdat = strrep(newdat,'%%PRODBHP%%',num2str(prodbhp(i)));
    newdat = strrep(newdat,'%%QINJ%%',num2str(qinj(i)));
    newdat = strrep(newdat,'%%THICKNESS%%',num2str(thickness(i)));
    newdat = strrep(newdat,'%%MATPOR%%',num2str(matpor(i)));
    newdat = strrep(newdat,'%%FRCPOR%%',num2str(frcpor(i)));
    newdat = strrep(newdat,'%%SRVFRCPOR%%',num2str(srvfrcpor(i)));
    newdat = strrep(newdat,'%%MATPERM%%',num2str(matperm(i)));
```

```
    newdat = strrep(newdat,'%%FRCPERM%%',num2str(frcperm(i)));
    newdat = strrep(newdat,'%%SRVFRCPERM%%',num2str(srvfrcperm(i)));
    newdat = strrep(newdat,'%%FRCSPAC%%',num2str(frcspac(i)));
    newdat = strrep(newdat,'%%SRVFRCSPAC%%',num2str(srvfrcspac(i)));
    newdat = strrep(newdat,'%%MATSW%%',num2str(matsw(i)));
    [output, adsMax] = langmuir(VlCO2(i), PlCO2(i));
    newdat = strrep(newdat,'%%ADSCO2%%',output);
    newdat = strrep(newdat,'%%ADSCO2MAX%%',num2str(adsMax));
    [output, adsMax] = langmuir(VlCH4(i), PlCH4(i));
    newdat = strrep(newdat,'%%ADSCH4%%',output);
    newdat = strrep(newdat,'%%ADSCH4MAX%%',num2str(adsMax));
    % new file name is to attach number in the back of the pattern filename
    newfilename = strrep(filename,'.dat',['_',num2str(i),'.dat']);
    % write new text to a new file
    writeTextFile(newfilename, newdat);
end
%% save the variables to mat file
save ('generated_input');
```

C1.2 Function for generating random variable values

```
function r = genRand(min, max, N)
% get random vector. each vector is of size of Nx1. min is the
lower limit,
% max is the upper limit, and N is the number of random number
to be
% generated.
r = min + (max - min) * rand(N,1);
end
```

C1.3 Function for calculating Langmuir values at different pressures

```
function [output, Max]=langmuir(Vl,Pl)
pressure = linspace(14.7,6500,20)';
adsorption = 0.000598248 * Vl * pressure ./ (Pl + pressure);
data = [pressure, adsorption];
% transfer data into string
output='';
for i=1:size(data,1)
    output=[output num2str(data(i,:)) sprintf('\n')];
end
% extract the max value
Max = max(adsorption)*1.1;
end
```

C1.4 Function for writing text files

```
function writeTextFile(filename, content)
% open file. 'w' means 'write' mode
fileID = fopen(filename,'w');
% write content to file. '%s' means the content is text string
fprintf(fileID,'%s',content);
% close file
fclose(fileID);
end
```

C2. Data extraction

C2.1 RWD file generation

```
%% delete existing variables
clear
%% read in pattern file as string
% pattern file name
filename='Extract-Pattern.rwd';
% read pattern file to text string
pattern = fileread(filename);
N = 1000;

for i = 1 : N
    newdat = pattern;
    % replace corresponding %%variable%% in the pattern text
    newdat = strrep(newdat,'%%NUMBER%%',num2str(i));

    newfilename=strrep(filename,'.rwd',['_',num2str(i),'.rwd']);
    % write new text to a new file
    writeTextFile(newfilename, newdat);
end
%% save the variables to mat file
Save
```

C2.2.1 Data extraction from .RWO files

```
clear
clc

N = 1000;

tprod_Add2 = zeros();

for i = 1 : N
    k = i;
```

```
    FileName = sprintf('Extract-Pattern_%d.rwo',k);
    fid = fopen(FileName);
    HDRS = textscan(fid, '%s %s %s %s %s ', 11,'delimiter','\t');
    DATA = textscan(fid, '%f %f %f %f %f');
    fclose(fid);
    DATA1 = cell2mat(DATA);
    B=DATA1==0;
    indice=find(B(:,3));
    Locat=indice(1);
    tprod_Add2(i,1) = DATA1(Locat,1);

end
save ('tprod_Add2');
```

C2.2.2 Data extraction from .RWO files

```
clear
clc

N = 1000;

tinj_Add2 = zeros();

for i = 1:N
    k = i;

    FileName = sprintf('Extract-Pattern_%d.rwo',k);
    fid = fopen(FileName);
    HDRS = textscan(fid, '%s %s %s %s %s ', 11,'delimiter','\t');
    DATA = textscan(fid, '%f %f %f %f %f');
    fclose(fid);
    DATA1 = cell2mat(DATA);

    qinj=DATA1(:,5);
    indice1=find(qinj,2);
    time = DATA1(:,1);
    lasttime = time(end,1);


    tinj_Add2(i,1) = lasttime-time(indice1(2),1);


end
```

C3. ANN development

C3.1 ANN Architecture Determination

```
%%%The following ANN scripts were developed with the help of Venkat Putcha%%%

clc
clear all

load('RawData.mat')


anninp=RawInput;
annout=RawOutput;


data=anninp;
OUTPUT_C=annout;
INPUT_C=anninp;


Pn=log10(INPUT_C);
Tn=log10(OUTPUT_C);


[Pn,ps] = mapminmax(Pn,0,1);
[Tn,ts] = mapminmax(Tn,0,1);

[mi,ni] = size(Pn);
[mo,no] = size(Tn);


Ntrial=2;

Nshuffles=2;



MaxNeuron=40;
MinNeuron=40;

MaxLayers=1;
MinLayers=1;


HiddenLayers=cell(Ntrial,1);
TF=cell(Ntrial,1);
ParaInput=cell(Ntrial*Nshuffles,1);
result=ones(Ntrial,1);
```

```
for kk=1:Ntrial

    nLayer=randi([MinLayers, MaxLayers]);
    Architecture=zeros(1,nLayer);
    for i=1:nLayer
        Architecture(i)=randi([MinNeuron, MaxNeuron]);
    end

    TransferFunction=cell(1,nLayer+1);
    TransferFunction{end}='purelin';


    for i=1:nLayer
        Determine=randi([0, 1]);
        if Determine==1
            TransferFunction{i}='logsig';
            TransferFunction{i}='tansig';
    end

    HiddenLayers{kk}=Architecture;
    TF{kk}=TransferFunction;

    for jj=1:Nshuffles
        [Pn_train,Pn_val,Pn_test,trainInd,valInd,testInd] =
dividerand(Pn,0.80,0.10,0.10);
        [Tn_train,Tn_val,Tn_test] = divideind(Tn,trainInd,valInd,testInd);
        ParaInput{Nshuffles*(kk-
1)+jj}={Pn,Tn,ps,ts,Pn_train,Pn_val,Pn_test, ...
            Tn_train,Tn_val,Tn_test,Architecture,TransferFunction,0,1};
    end

end

sched=parcluster();
job = createJob(sched);
tic
t = createTask(job, @ANN_Training_Script, 4, ParaInput);
submit (job); wait (job);
toc
taskoutput=fetchOutputs(job);
[ANNParameters] =ANN_Selection(ParaInput,taskoutput, Nshuffles,Ntrial);


save('ANN_archetecture.mat')
```

C3.2 ANN Iterative Training

```
%%%The following ANN scripts were developed with the help of Venkat Putcha%%%

clc
clear all

 load('RawData.mat')

anninp=RawInput;
annout=RawOutput;


data=anninp;
OUTPUT_C=annout;
INPUT_C=anninp;

inputs1=INPUT_C;
targets1=log10(OUTPUT_C);
[inputs,ps] = mapminmax(inputs1,0,1);
[targets,ts] = mapminmax(targets1,0,1);
clearvars data

counter=1;
counter2=1;
  load ('ANN_archetecture.mat','ANNParameters')

while counter<20


trf=0.8;
valf=0.06;
tesf=0.14;


 [Pn_train,Pn_val,Pn_test,trainInd,valInd,testInd] =
dividerand(inputs,trf,valf,tesf);
 [Tn_train,Tn_val,Tn_test] = divideind(targets,trainInd,valInd,testInd);
val.T = Tn_val;
val.P = Pn_val;
test.T = Tn_test;
test.P = Pn_test;

net=ANNParameters.Selectednet;

net.performFcn = 'msereg';
net.trainParam.goal = 0.0001;
net.trainParam.epochs = 2000;
net.trainParam.show = 1;
net.trainParam.showWindow = true;
net.trainParam.max_fail =10;
net.efficiency.memoryReduction = 60;
```

```
net.trainParam.showWindow=0;
[net,tr] = train(net,Pn_train,Tn_train,[],[],test,val);

Tn_train_ann = sim(net,Pn_train);
Tn_test_ann = sim(net,Pn_test);

prediction=(sim(net,Pn_test));
denormprediction=mapminmax('reverse',prediction,ts);
Pann=10.^denormprediction;
inputs2=mapminmax('reverse',Pn_test,ps);
targets2=10.^(mapminmax('reverse',Tn_test,ts));

  count1=0;
percentbhp=abs(Pann-targets2)*100./targets2;
errorp=max(max(percentbhp))
errorc(counter2)=errorp;
stdp=std(max(percentbhp))
stdc(counter2)=stdp;


if errorp<=min(min(errorc))
        Minerror=errorp
         save('ANN_retrained')
         counter=counter+1
end
counter2=counter2+1
end
```

C3.3 Obtaining ANN Prediction Results

```
%%%The following ANN scripts were developed with the help of Venkat Putcha%%%

clc
clear all

 load('RawData.mat')



anninp=RawInput;
annout=RawOutput;


data=anninp;
OUTPUT_C=annout;
INPUT_C=anninp;


inputs1=INPUT_C;
targets1=log10(OUTPUT_C);
```

```
[inputs,ps] = mapminmax(inputs1,0,1);
[targets,ts] = mapminmax(targets1,0,1);
clearvars data


counter=1;
counter2=1;

load('ANN_retrained_329.mat','net')

prediction=(sim(net,inputs));

denormprediction=mapminmax('reverse',prediction,ts);
Pann=10.^denormprediction;

percentall=abs(Pann-annout)*100./annout;
```

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