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Development of a Probabilistic Forecasting and History Matching Model for Coalbed Methane Reservoirs

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ABSTRACT

In recent years, coalbed methane (CBM) has become an essential component of the United States energy market. However, due to their heterogeneity, the productivity of CBM reservoirs depends upon an inter-related set of reservoir, completion and production parameters. Even though many powerful reservoir simulators are currently available to the industry, their sophistication coupled to the reservoir complexity tends to result in a large outlay of man-hours for a single reservoir study. Recognizing that stochastic (Monte Carlo) simulation techniques are well-known and have been used in a wide variety of applications to aid in the understanding of complex reservoir problems, particularly parametric studies, a stochastic modeling tool has been coupled to a reservoir simulator to address this workflow gap. Through this process, thousands of simulations can be automatically run to explore combinations of unknown parameters across their range of uncertainty. When historical data are available, a least square error function can be run between the simulation data and the historical data. In many cases, the results of this stochastic-based simulation methodology has provided more than one history match to a simulation problem, showing the non-uniqueness of the process and adding insight into the range of parameters that impact the production response of the CBM reservoir being investigated. Already applied to several projects, this approach has shown its efficiency and rapidity in solving complex reservoir simulation problems.

INTRODUCTION

Monte Carlo (or stochastic) modeling techniques have long been used for exploring the impact of uncertainty on oil and gas project performance worldwide. In its purest sense, Monte Carlo simulation employs a mathematical model that interjects randomness between limits to determine a probabilistic or likely outcome. Typically, this result is in the form of a probability distribution, the shape of which lends insight into what is likely to occur if the modeled course of action is pursued.

From a coalbed methane reservoir modeling standpoint, the implementation of a simulation project is in many ways similar to using Monte Carlo techniques, particularly when historical data is available for comparison to model output. Multiple executions of the simulation are typically required to converge on a solution that approximates reality (historical data). Depending on the complexity of the problem being modeled, the time to reach this convergence could range from hours to months of simulation time.

Many authors have seen the promise that these stochastic techniques hold with regard to simulation as well as its use in history match optimization[1-8]. In this work, a fractured reservoir simulator, *COMET3* [9-10], has been coupled to a commercially-available Monte Carlo simulation software, in order to automatically generate tens, hundreds or thousands of simulation cases for probabilistic forecasting and, if available, for comparison to historical data. While this number of simulation runs can generate voluminous data, the program has the capability to illustrate only those cases that meet pre-set statistical cut-offs. Through this process, the authors hope to show the utility of such a process as well as the functionality of automation, which ultimately provides the user a powerful complement to traditional reservoir simulation.

PROCEDURE

Creating the simulation input file

The first step of the process is to create the simulation input file. Once created, modifications to the reservoir properties, wells description, production and injection profiles are established.

Available options

The following are typical variable for the Monte-Carlo approach:

- For single well cases, well spacing can be adjusted at each iteration. Formulas have been implemented to compute the length of each grid block based on the length of the grid block in which the well is located (middle block) and an increment factor necessary to compute the length of each consecutive grid block.

- Another option allows varying the reservoir initial pressure versus depth. A very simple linear equation can be used as shown in equation (1) where P_i refers to the reservoir initial pressure in psia and P_{iFunct} is the pressure gradient in psi per foot. The model being highly flexible in that it may incorporate alternative pressure relationships. The range of possible values for the initial pressure corresponding to a specific probability distribution of this variable parameter is illustrated on Figure 1.

$$P_i = P_{iFunct} \times Depth \qquad (1)$$

- Desorption pressure can be computed versus initial reservoir pressure as shown in equation (2) where P_d refers to the desorption pressure in psia, P_{dFunct} is the variable parameter and P_i is the initial reservoir pressure in psia. In order to not violate the initial water saturation condition criteria, if the desorption pressure is less than the initial pressure (creating an undersaturated condition); the initial water saturation is automatically set to 100%. One may also establish a probability distribution around the initial gas saturation for cases where $P_d = P_i$

$$P_d = P_{dFunct} \times P_i \qquad (2)$$

- Absolute permeability is another parameter that can be varied versus depth. A preferred approach is to derive basin-specific permeability versus depth functions as shown on Figure 2. Equation (3) is an example of a possible function, where K refers to permeability.

$$K = 75{,}000 \times Depth^{-1.2} \qquad (3)$$

- Another option is also available regarding relative permeability curves. Two phase relative permeability curves can be approximated using the Corey equations. Equation (4) gives the relative permeability to water and equation (5) the relative permeability to gas where S*w* is the water saturation, S*wr* the irreducible water saturation, S*gr* the irreducible gas saturation, K*rwmax* the maximum water relative permeability, K*rgmax* the maximum gas relative permeability, m the Corey water exponent and n the Corey gas exponent.

$$Krw = K_{rw\max}\left(\frac{Sw - Swr}{1 - Swr - Sgr}\right)^{m} \qquad (4)$$

$$Krg = K_{rg\max}\left(\frac{1 - Sw - Sgr}{1 - Swr - Sgr}\right)^{n} \qquad (5)$$

These parameters have been added to the simulation input file so that a probability distribution can be defined, which generates new relative permeability curves at each iteration.

Defining uncertainties

- Uncertain parameters are then assigned distribution types and ranges. These functions simply represent a range of different possible values that a parameter could take instead of limiting it to just one value. Figure 1, for example depicts a normally distributed function. Other types that may be used are uniform, triangular, exponential, lognormal, Poisson and many more. There is no limitation to the number of parameters that can be varied.

- Most other simulator input parameters can also be probabilistically varied, such as porosity, gas content, isotherm properties, etc.

Defining outputs

Output parameters can also be defined, such as the cumulative gas production and/or the cumulative water production, for subsequent analysis. The program will automatically record the corresponding values from the output file back to the input file at the end of each simulation so that frequency and sensitivity charts (Tornado plots) can later be generated. The parameters that impact the production response of the reservoir investigated can therefore be determined.

Running the simulations

When all the assumptions have been made on the desired parameters and all outputs have been defined, the process is ready to be started. The workflow is outlined in Figure 3.

Following is a detailed description of the automated processes taking place after the number of simulations to be run has been input by the user:

- The Monte-Carlo simulator is started and generates random values for each uncertain parameter from the prescribed probability distribution functions.

- The *COMET3* input file is saved.

- The simulation run is executed.

- At the end of the run, all input/output data is saved.

- The Monte-Carlo simulator generates new random values and the next simulation starts.

Sensitivity charts

At the end of all the simulations, a sensitivity chart (also called Tornado plot) can be created that ranks the uncertain parameters according to the impact they have on the outputs. An example of a sensitivity chart is shown in Figure 4. Note that the most sensitive parameters, or variables impacting target output the most, are at the top of the chart. The shape of which is funnel-like, resulting in the name "Tornado chart". These tornado charts can be invaluable for identifying the impact of unknown or uncertain parameters upon the desired simulation output.

Analyzing the results: plots and error function

When historical data are available, a least square error function can be run between the simulation data and the historical data, bringing forth those simulation cases that yield the best statistical matches. The error function R^2 is computed using equation (6) where ActualData is the value at each time step of the historical data for the selected output parameter, SimData the value at the same time step of the simulation data and Mean the average value of the actual data.

$$R^2 = 1 - \frac{\sum (ActualData - SimData)^2}{\sum (SimData - Mean)^2} \qquad (6)$$

With

$$Mean = \frac{\sum ActualData}{NumberofData} \qquad (7)$$

A summary table is provided containing the input values for each parameter for each trial as well as the corresponding computed error function. The best acceptable match (or matches) can be identified (cases with the value of the error function R^2 closest to 1.0).

CASE STUDY 1

Problem Description

This analysis was performed for a property evaluation in Oklahoma. The work performed involved reservoir simulation history-matching of about 300 wells on 400,000 net acres. To simplify the work, three type wells were created based on geologic setting and production characteristics.

Set Up

The simulation input file for each type well was built based on existing reservoir parameters such as coal depth, coal thickness and isotherm data (Langmuir pressure, Langmuir volume and gas content). Likely ranges were established for 9 unknown parameters (permeability, porosity, pore compressibility, matrix compressibility, Corey water exponent, Corey gas exponent, initial water saturation, skin factor and desorption pressure function Pd/Pi). Table 1 summarizes for each uncertain parameter the type of probability distribution applied as well as the range selected. One thousand simulations were run using a producing bottomhole pressure constraint for each type well. The results were tabulated by computing the gas production rate error function.

Results

These one thousand simulations ran in approximately two hours, with an additional hour to compute the error function. A plot of the gas production rate for all the simulations for one type-well is shown on

Figure 5. After running the error function on the gas production rate and restricting the results to the simulation runs with $R^2>0.9$, only 15 out of the 1000 simulations were judged to be acceptable. The plot of gas production rate for those selected runs is shown on Figure 6.

The results of this stochastic-based simulation methodology applied to this particular case provided more than one reasonable (statistically) history match, showing the non-uniqueness of the process and adding insight into those parameters that impact the production response of the gas reservoir investigated. The final match parameters for the 15 highly ranked cases are provided in table 2. An average value and an acceptable range of values can be determined for each uncertain parameter.

Generating a Tornado plot on the cumulative gas production identified 6 performance drivers out of the 9 initially unknown parameters as shown on Figure 7. In order to improve this history match, the model could be run a second time, only defining probability distributions on the 6 identified parameters having the greatest impact on production and narrowing the range of uncertainty to the minimum and maximum values from the 15 acceptable simulation cases. However, this was not justified at the time due to the scoping-level nature of the exercise.

CASE STUDY 2

Problem Description

This analysis was performed in support of a possible asset acquisition in Texas. The work performed involved reservoir simulation history-matching of two existing production pilots, one with three wells and one with five wells. Each pilot had about three months of production data.

Set Up

Available reservoir data included coal depth, thickness and the Langmuir isotherm. A multi-well simulation model was built for each pilot, estimating bottom hole producing pressures over time for each well based on available surface pressure and fluid level data. Both models were run on pressure while computing gas and water production.

The variable parameters for history matching included permeability, relative permeability, compressibility (pore and matrix), initial water saturation, porosity, Pd/Pi (i.e., gas content), sorption time, cleat spacing, total model area (i.e., average well spacing), and skin factors for the wells.

Results

Even given the very short-term nature of the production data, reasonable history matches were achieved for each pilot. The gas and water rate matches for each pilot are provided in Figures 8 and 9. The final match parameters are provided in Table 3. The values determined for each unknown parameter were found to be very close between the two pilots.

DISCUSSION

What is clear from our experience with this approach is that simulation problems that would normally require considerable manpower to solve can now be accomplished much more effectively and efficiently by utilizing Monte-Carlo simulation, on automated procedure, and raw computing power. Further, the number and range of variables can be quite large, thus enabling the exploration of a large solution space. Sometimes this has yielded multiple acceptable solutions, demonstrating the non-uniqueness of each case. This has yielded results that would not have been obvious from the outset, and most likely overlooked in a normal process. Thus this approach, we believe, significantly reduces the time, improves the results, and expands the capability of CBM reservoir simulation.

CONCLUSIONS

- A means of probabilistic forecasting and automatic history matching has been created through the use of a coupled stochastic model and reservoir simulator for characterization of CBM reservoirs. These techniques provide the flexibility to run nearly unlimited simulation cases as specified by the user, whereupon completion, automatically high-grade cases of interest.

- Being an effectively automated model, the staff time devoted to the characterization is greatly minimized. Further, as the overall run results can be statistically ranked and compared to actual data, this one can focus only on those results of most interest.

- In several projects, the stochastic-based simulation model provided more than one set of parameters judged to be favorably comparable to the historical data, showing the non-uniqueness of the process and adding insight into the range of parameters that impact the production response of the CBM reservoir investigated.

NOMENCLATURE

Depth = reservoir depth, ft
K = reservoir absolute permeability, md
K_{rg} = relative permeability to gas
K_{rgmax} = maximum relative permeability to gas @ $S_w = S_{wr}$
K_{rw} = relative permeability to water
K_{rwmax} = maximum relative permeability to water @ $S_w = 1 - S_{gr}$
m = Corey water relative permeability exponent
n = Corey gas relative permeability exponent
P_d = desorption pressure, psia
P_{dFunct} = desorption pressure over initial pressure, fraction
P_i = reservoir initial pressure, psia
P_{iFunct} = reservoir pressure gradient, psi/ft
R^2 = error function
S_{gr} = irreducible gas saturation
S_w = water saturation
S_{wr} = irreducible water saturation

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Table 1: Case study 1 probability distribution functions.

Variables	Range	Distribution Type
Permeability	10 - 60 mD	Uniform
Porosity	0.5 - 3 %	Uniform
Pore Compressibility	100E-06 - 300E-06 psi^{-1}	Uniform
Matrix Compressibility	5E-07 – 2.5E-06 psi^{-1}	Uniform
Corey Water Exponent	1 - 6	Uniform
Corey Gas Exponent	1 - 6	Uniform
Acreage	80 - 160 acres	Uniform
Initial Water Saturation	0.6 – 1.0	Uniform
Desorption Pressure Function	0.6 – 1.0	Uniform

Table 2: Case study 1 final matches parameters.

Simulation	K	Phi	Pd/Pi	Swi	Skin	Cp	Cm	KrwExp	KrgExp	R2
320	25.5	0.018	0.99	1.00	0.68	1.85E-04	2.1E-06	6.70	1.06	0.95
445	35.5	0.019	0.86	1.00	-0.62	2.27E-04	1.9E-06	5.54	1.19	0.92
451	43.4	0.025	0.77	1.00	-1.70	2.49E-04	1.2E-06	5.27	1.46	0.94
547	56.8	0.030	0.70	1.00	-1.89	2.76E-04	7.5E-07	3.56	1.44	0.90
647	24.6	0.008	0.79	1.00	0.39	2.85E-04	2.0E-06	2.75	1.06	0.93
688	23.6	0.028	0.63	1.00	-2.84	1.31E-04	2.1E-06	1.39	1.10	0.90
733	38.4	0.022	0.62	1.00	-1.95	1.10E-04	7.6E-07	2.70	1.43	0.90
758	49.6	0.021	0.71	1.00	-1.38	1.93E-04	1.5E-06	4.10	1.54	0.92
769	30.6	0.007	0.72	1.00	0.85	2.02E-04	1.9E-06	2.86	1.47	0.93
785	31.4	0.027	0.82	1.00	-1.29	1.22E-04	1.4E-06	3.79	1.17	0.93
799	32.4	0.017	0.68	1.00	0.32	2.79E-04	6.7E-07	1.03	1.05	0.93
843	20.7	0.015	0.80	1.00	-2.42	1.23E-04	6.2E-07	4.74	1.31	0.91
888	34.8	0.023	0.71	1.00	-1.45	2.27E-04	1.6E-06	2.79	1.04	0.92
910	25.6	0.015	0.92	1.00	0.93	1.12E-04	1.2E-06	4.24	1.05	0.93
911	37.9	0.009	0.65	1.00	-0.93	1.56E-04	1.5E-06	5.32	1.06	0.91
970	28.7	0.012	0.71	1.00	-2.87	1.13E-04	1.3E-06	4.87	1.64	0.92
Min	20.7	0.007	0.62	1.00	-2.87	1.10E-04	6.2E-07	1.03	1.04	
Max	56.8	0.030	0.99	1.00	0.93	2.85E-04	2.1E-06	5.70	1.64	
Average	33.7	0.018	0.75	1.00	-1.01	1.87E-04	1.4E-06	3.79	1.26	

Table 3: Case study 2 final match parameters.

	Pilot 1	Pilot 2
Spacing	478 acres/well	420 acres/well
Permeability	30 mD	30 mD
Porosity	0.10%	0.10%
Tau	7 days	7.8 days
Fracture Spacing	2.7 in	2.9 in
Pd/Pi	0.66	0.67
Cp	250E-6 psi-1	250E-6 psi-1
Cm	1E-6 psi-1	1E-6 psi-1
Skin	-2.9	-2.9
Swi	1	1
Swirr	0.26	0.24
KrwExp	5.69	5.93
KrgExp	5.65	5.94
Alpha (Corey Exp)	0.91	0.95

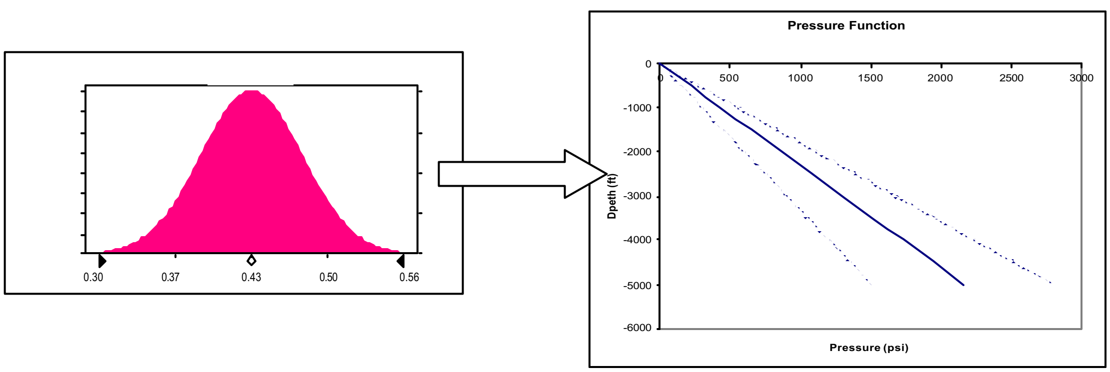


Figure 1: Possible range for the initial pressure
given a specific probability distribution for the pressure gradient.

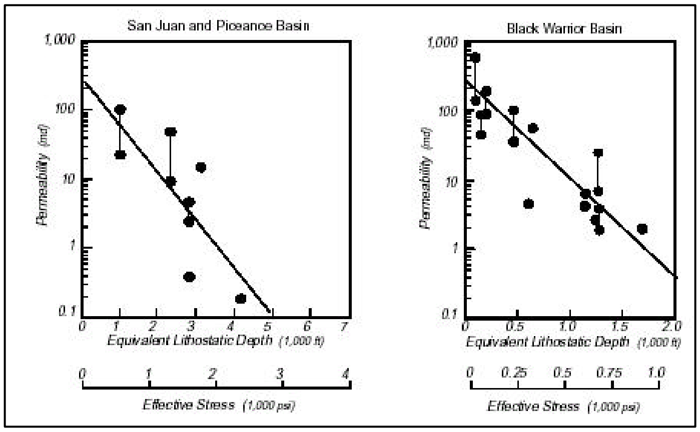


Figure 2: Typical permeability versus depth functions for several CBM basins.

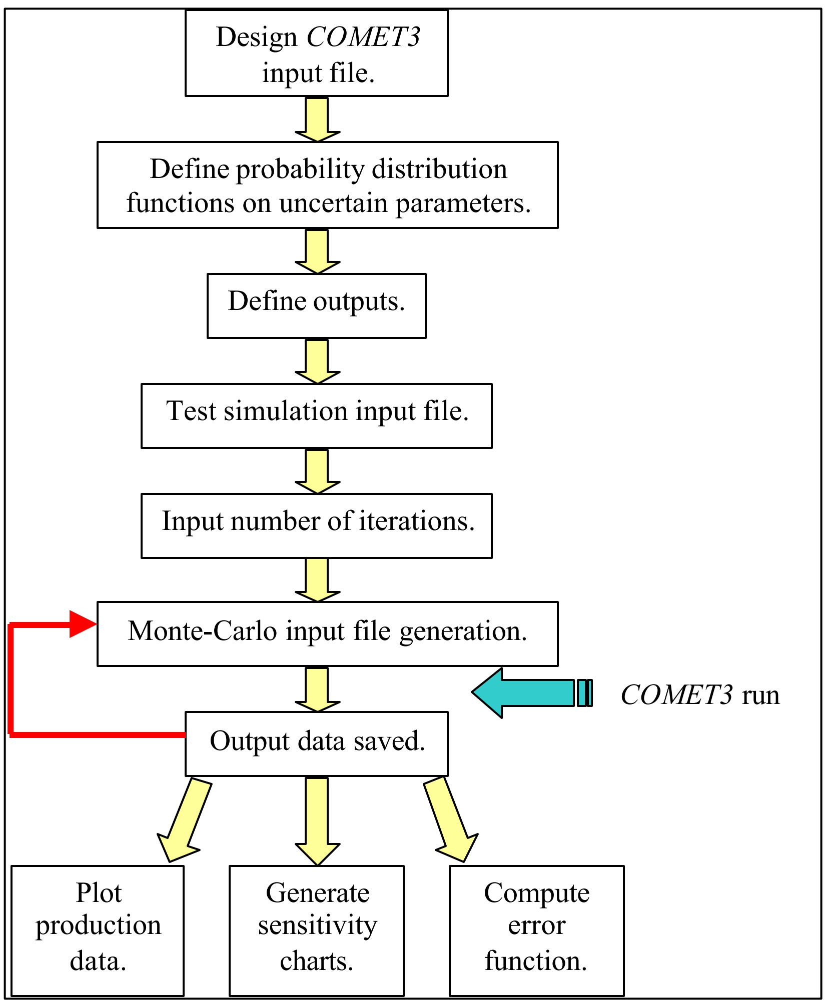


Figure 3: Model flow chart.

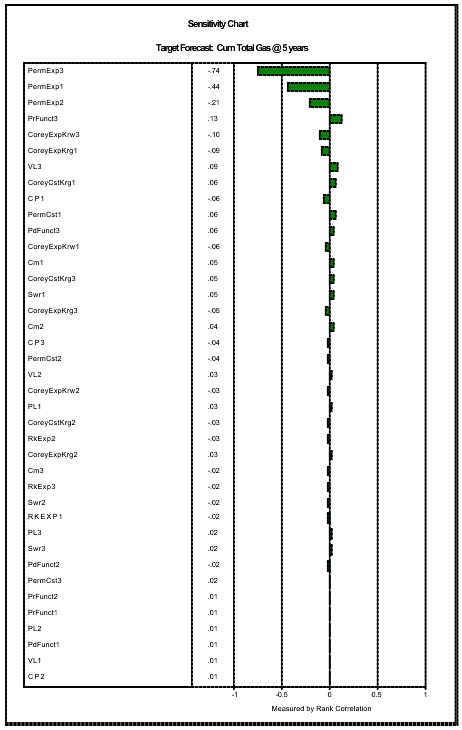


Figure 4: Example of a sensitivity chart.

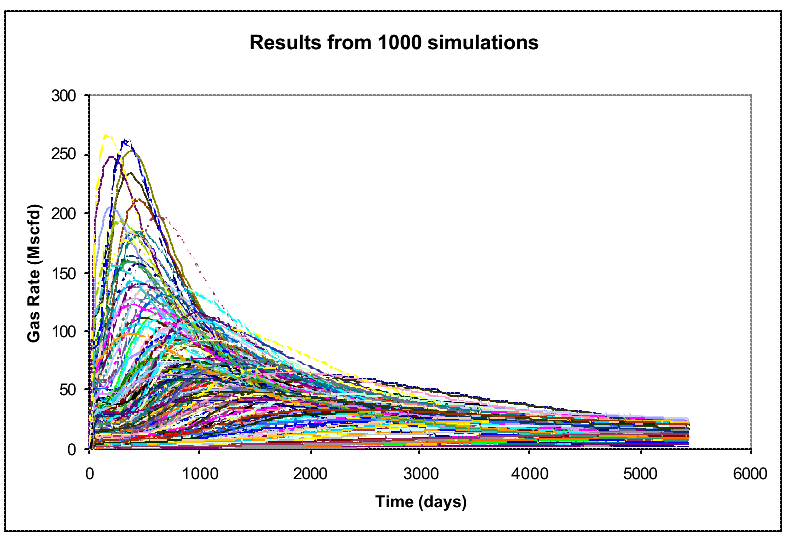


Figure 5: Gas production from 1000 simulations.

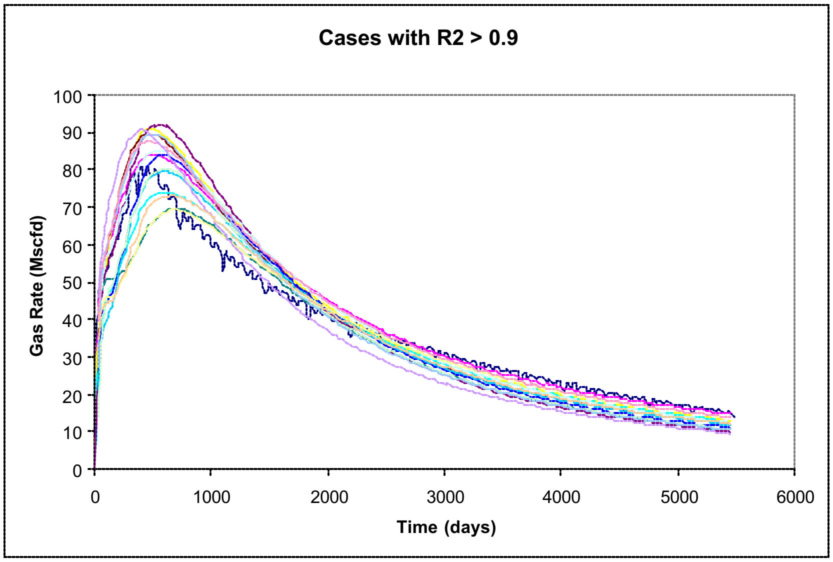


Figure 6: Gas production for simulations with R^2>0.9.

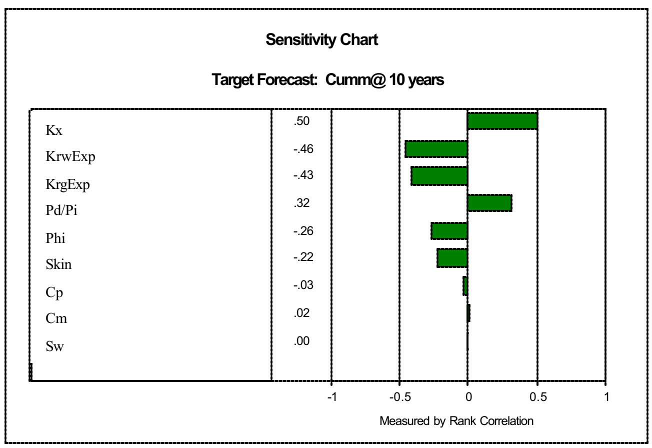


Figure 7: Tornado plot: performance drivers identified.

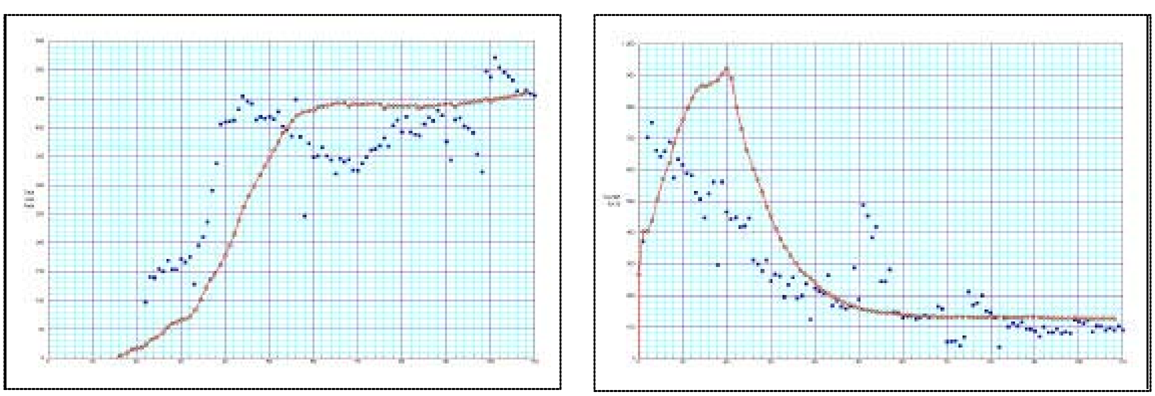
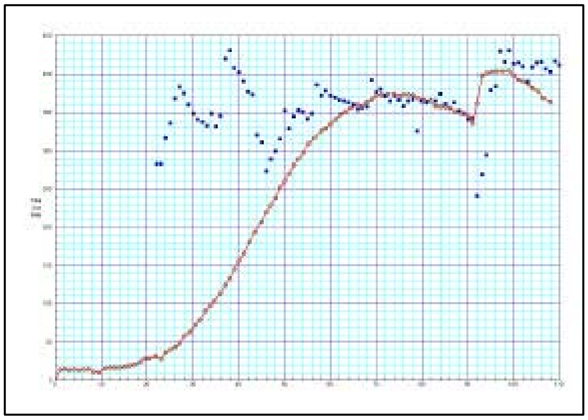


Figure 8: Gas and water production for pilot 1.



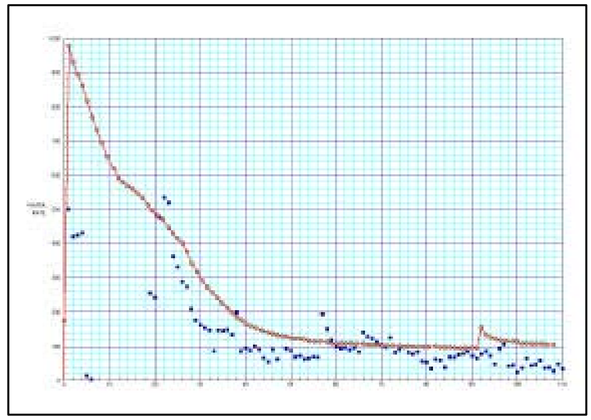


Figure 9: Gas and water production for pilot 2.