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Coalbed Methane Reservoir Simulation and Uncertainty Analysis with Artificial Neural Networks

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Abstract. *This paper presents the utilization of a newly developed technique for development of a proxy model in reservoir simulation studies to be used in uncertainty analysis on a Coalbed Methane (CBM) reservoir. This technique uses Artificial Neural Networks (ANN) in order to build a Surrogate Reservoir Model (SRM). An SRM is a replica of the full-field reservoir model that mimics the behavior of the reservoir. A small number of realizations of the reservoir are required to develop the SRM. This is a key difference between the SRM technique and other techniques in the literature, such as developing a Response Surface Model using Experimental Design technique or using Reduced Models. Once trained, SRMs can make thousands of simulation runs in a matter of seconds. The high speed of the SRM enables the engineer to exhaustively explore the solution space and perform uncertainty analysis. During the development process of SRM, Key Performance Indicators (KPIs) are identified. KPIs are the reservoir parameters that have the most influence on the desired objective of the simulation study.*

Keywords: *Surrogate reservoir model; Artificial neural network; Coalbed methane; Reservoir simulation; Uncertainty analysis.*

INTRODUCTION

Reservoir simulation provides information on the behavior of the modeled reservoir under various production and/or injection conditions. Reservoir engineers and managers use reservoir simulators to better understand the reservoir, and to perform future performance predictions and uncertainty analyses. Because of the non-uniqueness of simulation models and uncertainty in reservoir parameters, uncertainty analysis is an important task that is required in order to quantify the uncertainties associated with reservoir parameters.

Different techniques are used to quantify the uncertainties associated with reservoir parameters. Monte Carlo Simulation (MCS) is a technique that is widely used in the oil and gas industry for the purpose of uncertainty analysis. MCS requires thousands of reservoir realizations in order to provide a meaningful conclusion on the reservoir's future performance uncertainties.

Generating thousands of simulation models, especially in the case of large and complex models that require a long time to make a single simulation run, could be impractical. For this purpose, proxy models are built for the reservoir that can mimic the behavior of the model accurately and, at the same time, provide the results in a shorter time when compared to the actual reservoir simulation model. One of the steps in developing these proxy models is to build several realizations of the model and fit the proxy model to the simulation data. Attempts have been made to perform uncertainty analysis with the least number of realizations possible. Common techniques that have gained popularity in the oil and gas industry are the Experimental Design technique and Reduced Models. Response Surfaces Models are generated in order to analyze the results obtained from Experimental Design.

Experimental Design has been used in reservoir simulation since the 1990s. It is used to get maximum information at the lowest experimental cost by changing all the uncertain parameters simultaneously. The aim of experimental design is to provide maximum in-

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formation about the reservoir from the least number of experiments. It is essentially an equation derived from all the multiple regressions of all the main parameters that affect the reservoir's response [1].

Reduced Models are approximations of full, three dimensional, numerical simulation models that approach an analytical model for tractability [2].

Although there has been a lot of progress in the areas needed for reservoir modeling in terms of software and hardware equipment, the availability of computing resources is still taken into account as a restriction when reservoir simulation is considered. This limitation has raised the need for proxy models that reduce the computational loads of simulation studies [3].

The proxy models themselves are expensive to build, since they are based on repeated experiments with the simulations, which are computationally expensive. The substitution of detailed simulations with simplified approximate simulations will result in sacrificing accuracy [4].

The "proxy model" is sometimes referred to as "response surface model", "meta-model" and "surrogate model".

Typical application areas in reservoir simulation include: sensitivity analysis of uncertainty variables, probabilistic forecasting and risk analysis, conditioning of a simulation model to historically observed data (history matching), field development planning and production optimization.

Common methods for creating proxy models include response surface modeling [5] and Kriging [6-8]. Chen has presented the application of these techniques with examples in his paper [9]. However, wide varieties of techniques are available [10]. In addition to the choice of the meta-modeling method, the accuracy of a proxy model is determined by the experimental design used to select data points, size of the design space, range of explored values of design variables, accuracy of the simulation at each data point and the number of data points available to develop the proxy model.

Zubarev investigated the effect of using proxy-modeling methods instead of the common reservoir simulation techniques. His study has compared the results of these different approaches on history matching, production optimization and forecasting. The results have proved that all techniques are dependent on model complexity, input data quality and dimension of design space, while they are almost independent of the type of proxy model [3].

The Kriging method results in a better outcome when dealing with non-linear response surfaces, but computationally it is more difficult to construct. Artificial Neural Networks and polynomial regression techniques are also used as a proxy model. However, these techniques tend to reduce the precision of their predictions due to smoothing out the response surfaces. Thin-Plate Spline models (TPS) are more subject to error for smaller surfaces but they have the advantage of simplicity to construct.

METHODOLOGY

In this section, Surrogate Reservoir Modeling is introduced and the procedure for developing an SRM is explained. Interested readers are encouraged to review other published papers by the authors to learn more about SRMs [11-15].

SURROGATE RESERVOIR MODELS

Surrogate Reservoir Models are essentially Artificial Neural Networks that behave like a reservoir simulation model. Once trained, the SRM can be used to run thousands of simulation runs in a matter of seconds. Also, the number of reservoir realizations required to develop the SRM is significantly small when compared to other traditional techniques. The reason SRMs can be developed with a small number of realizations is due to the way a single reservoir model is presented to the SRM.

Let us assume that the reservoir we are going to model contains 10 operating wells. Wells can be looked at as a communication path between the operator (reservoir engineers) and the reservoir. Each well is telling a story about a specific area of the reservoir by providing production rate and pressure data in response to the operating conditions that are imposed. We can look at the volume in the reservoir that is impacted the most by the well production and name it the "Estimated Ultimate Drainage Area (EUDA). Therefore, a reservoir can be divided into several sub-reservoirs (the number of EUDAs) that are different in their production behavior and reservoir characteristics. With this observation, we can see that one simulation model can be seen as several models (in this example, one simulation model can be seen as 10 potential models).

Given the fact that production in each well is impacted by the production from neighboring wells and in turn impacts the production from those wells (interference), appropriate measures must be implemented in order to take interference between wells into account. In SRM development, well interference is taken into account by providing the static and dynamic behavior of offset wells during the model development. So, if we generate 10 simulation models, we will end up having 100 models (10 models $\times$ the number of EUDAs). In addition, the SRM technique fits more appropriately within the system theory [16] rather than the approach that is commonly used in our industry, which is based on geo-statistics [14]. When using SRMs, changes in input data directly (and in real-time) influence the output of the system, since the SRM is acting as the reservoir simulator.

The objective of the project should be defined as the very first step in developing an SRM. The reader is reminded that it is not possible to develop a global SRM that can predict all the possible outputs of a reservoir model. This is not necessarily a limitation of SRMs since, in most cases, reservoir models are built to study a very limited number of phenomena (such as the effect of water flooding on hydrocarbon recovery or the effect of in-fill drilling location on the total field production, etc.). It is possible, however, to develop several SRMs for the same reservoir where each SRM can be used to study a certain reservoir behavior.

In this study, a Coalbed Methane (CBM) reservoir is being modeled. The CBM reservoir includes 13 pinnate pattern wells (wells with branching laterals, also known as fishbone). All the wells start producing at the same time and will continue production for 15 years at a constant Bottom-Hole Pressure (BHP). The developed SRM was responsible for predicting the cumulative methane production (CH_4-CUM) due to changes in the well's BHP constraint. Figure 1 shows the structure of the CBM reservoir and the locations of the thirteen wells.

As Figure 1 shows, the reservoir is an irregular structure with heterogeneous porosity and permeability characteristics. All 13 pinnate pattern wells have a main lateral and three branches on each side. The lengths of the main lateral and branches are different from one well to another.

In the design phase, realizations were generated such that the effect of changing BHP was shown to

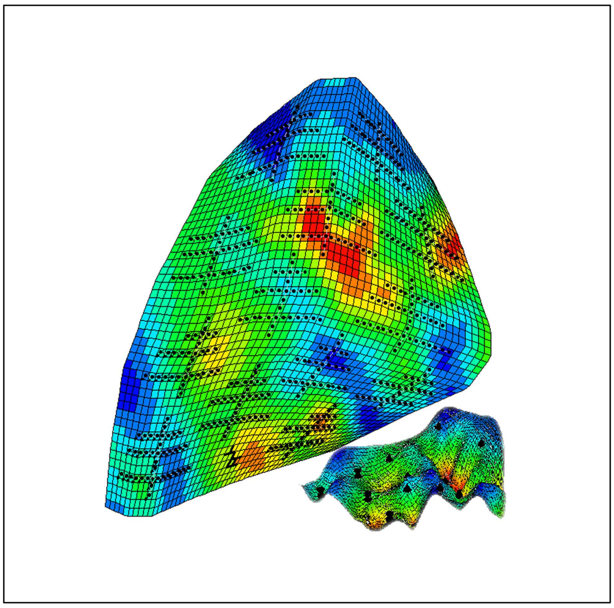

Figure 1. CBM reservoir structure. The black cones in the 3D view are the well-heads. (Source: CMG-Builder.)

the network. It was assumed that all the wells in a model were producing at the same constant BHP value. BHP values of 50, 100, 150 and 200 psia were selected for different models. Also, three different geologic realizations were used for the models. This would provide more information on the effect of porosity and permeability heterogeneity on the reservoir's performance.

Prior to building the SRM, uncertain reservoir parameters need to be identified. These parameters could be either reservoir characteristics, such as overall reservoir permeability (or permeability multiplier), initial water saturation, initial gas content etc., or operational parameters, such as producing bottom-hole pressure or the number or location of injection wells. Minimum, maximum and/or most likely values for each uncertain parameter should be identified. The minimum and maximum values for each parameter are identified through geologic interpretations and reservoir characterization and they are the extreme values possible for the property of the reservoir under study. In other words, the range of each parameter represents the amount of uncertainty associated with that parameter. Once the SRM is built, it can predict the behavior of the reservoir by changing each uncertain parameter in the range specified and it cannot extrapolate beyond the specified range. This is not necessarily a limitation for the SRM if a proper and reasonable range for each parameter were identified during the design of the SRM.

Once all the models are run, geologic information, well configuration and well production are extracted and prepared for SRM development. Twelve realizations (four different BHP cases for three different geologic realizations) were generated and results were exported. To develop the SRM, Intelligent Data Evaluation & Analysis (IDEA) [17] was used. The software provided multiple Neural Network algorithms from which the Back-Propagation algorithm (BP) [18] with one hidden layer was used.

A Back-Propagation algorithm is one of the most popular algorithms in Artificial Neural Networks. It is an easy to understand algorithm with applications in pattern-recognition and, with some minor modifications, it can be implemented to model time-series problems. The BP algorithm looks for the minimum of the error function in weight space using the method of gradient descent. The combination of weights that minimizes the error function is considered to be a solution of the learning problem. A Sigmoid activation function is used for BP networks, which is a popular function since it is continuous and differentiable. Figure 2 shows the structure of a BP network with one hidden layer as an example.

Once the outputs are generated by the network and an error is generated by comparing the network's

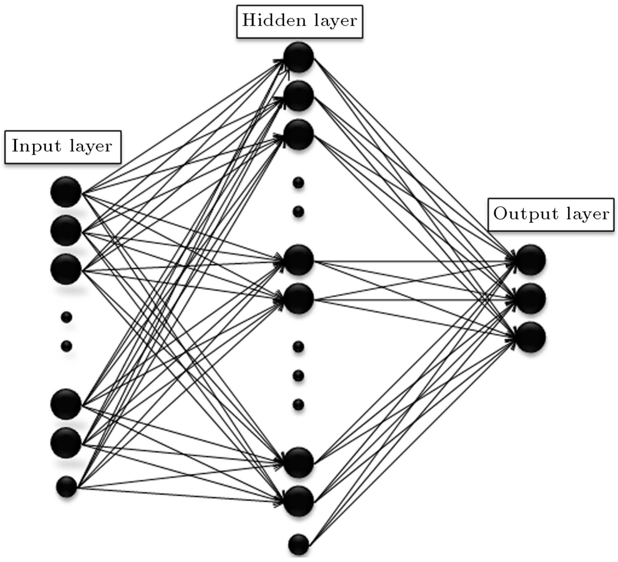

Figure 2. Structure of a Back-Propagation Neural Network with one hidden layer.

output with the actual outputs, the weights are adjusted based on the generated error starting from the weights connecting the hidden neurons to the output neurons in a back-propagating fashion.

Monte Carlo Simulation is used to quantify uncertainties associated with the uncertain reservoir parameters and measure their effect on the reservoir behavior. The MCS technique requires running the simulation model thousands of times in order to provide a meaningful conclusion on the uncertain parameters' influence on the reservoir behavior. In the case of a large complex reservoir for which a single simulation run could take hours or days, performing thousands of simulation runs is not affordable considering the time constraint. Therefore, proxy models of the reservoir model are created which can run much faster than the actual reservoir model and provide results with good accuracy. In this study, the SRM is the proxy model that is used to perform MCS.

RESULTS

For the purpose of this, 12 realizations were generated using a commercial reservoir simulator. These models were different in their porosity and permeability maps and BHP values at the production wells. Table 1 shows the permeability and porosity ranges for these models.

A Gaussian Geostatistical Simulation method was used to generate the three realizations. Thirteen control points were used (ranges shown in Table 1) to generate the porosity and permeability maps.

An elemental volume was defined for the models. An Estimated Ultimate Drainage Area (EUDA) was identified for each well using the Voronoi graph theory [19]. Then, the EUDA was divided into four segments, hence, a total of 52 segments for the entire reservoir. Static and dynamic properties were then averaged for these segments. The SRM dataset can be divided into two major categories: cell-based and well-based data. Cell-based data are the reservoir properties, such as depth, thickness, porosity, permeability etc. Well-based data include well location, well configuration information, and well production data. Tables 2 and 3 show the list of cell-based and well-based data used in this study, respectively.

Three reference points were selected in this study and some of the reservoir properties were evaluated at these reference points (times during simulation). The three reference points were 1/1/2000 (start date of simulation), 1/1/2002 and 1/1/2005. The values of matrix adsorbed gas, fracture gas saturation, fracture

Table 1. General information on the realizations generated for SRM development.

Model ID	Geologic Realization	Porosity %	Permeability mD	Well's BHP psia
1	1	5-12	10-50	50
2	1	5-12	10-50	100
3	1	5-12	10-50	150
4	1	5-12	10-50	200
5	2	5-12	10-50	50
6	2	5-12	10-50	100
7	2	5-12	10-50	150
8	2	5-12	10-50	200
9	3	5-12	10-50	50
10	3	5-12	10-50	100
11	3	5-12	10-50	150
12	3	5-12	10-50	200

Table 2. Cell-based data used for SRM development.

Cell-Based Data Used for the SRM Development	
Depth to top	Thickness
Gross block volume	Fracture gas saturation @ reference point
Fracture water saturation @ reference point	Fracture pressure @ reference point
Matrix adsorbed gas @ reference point	

Table 3. Well-based data used for SRM development.

Well-Based Data Used for the SRM Development	
Location-X	Location-Y
Main leg length	First branch length
Distance of first branch from wellbore	Second branch length
Distance of second branch from wellbore	Third branch length
Distance of third branch from wellbore	Total well length
Well initial bottom-hole pressure	

water saturation and fracture pressure were recorded for each grid cell in these times and were introduced to the SRM. The reason for this is to show the network the way the reservoir produces each fluid. It was assumed that the reservoir simulation model was history matched using the first five years of the production data.

During the process of SRM design, Key Performance Indicators (KPI) can be identified and ranked based on the degree of their influence on the model's output (Figure 3).

This is an important part of the modeling especially when the number of input parameters to the system is relatively high and the engineer needs to identify, use only the most influential parameters and discard the less influential parameters. It should be noted that the engineer's expertise is very important since some parameters need to be included in model development even if they are ranked low in the KPI identification process.

Rank	Feature	% Degree of Influence
1	Seg2_Gross Block Volume_ft3	100
2	Seg3_Gross Block Volume_ft3	99
3	Seg2_Thickness_ft	99
4	Q2_t-1	98
5	Seg3_Thickness_ft	98
6	Seg1_Thickness_ft	97
7	X-COORD	96
8	Seg1_Gross Block Volume_ft3	96
9	Seg4_Gross Block Volume_ft3	96
10	Seg4_Thickness_ft	95
11	SecondLeg	94
12	Total_length	94
13	ThirdLegDis.	94
14	SecondLegDis.	93
15	FirstLeg	92
16	MainLeg	92
17	Y-COORD	91
18	FirstLegDis.	91
19	ThirdLeg	90
20	Seg2_GasSaturationFracture_2000	90
21	D1	89
22	D3	89
23	Seg3_PayDepth_ft	88
24	Seg2_PayDepth_ft	88
25	Seg2_GasSaturationFracture_2000	88

Figure 3. Key performance indicators ranked based on cumulative gas production as the target parameter.

Figure 4 shows a schematic of well pattern and SRM segments. Cell-based properties are averaged for these segments. The parameters shown in Table 3 can characterize and describe a pinnate pattern well with three branches.

The generated dataset was divided into three subsets: training set calibration set and verification set. Only a training set is directly used for training, calculating errors and adjusting weights. The calibration set is used for cross-validation in order to see the accuracy of the network in predicting outputs of some input data

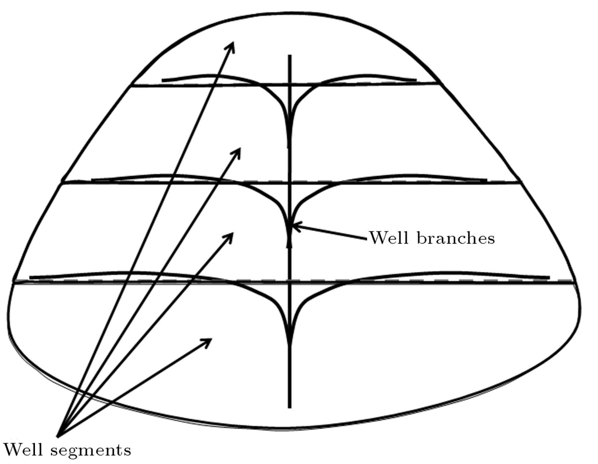

Figure 4. Schematic of well branches and SRM segments.

that the network has not seen before, and to identify a good time to stop the training process. Once training is completed, the network is applied to the verification set and the network's outputs are compared with the actual results in the verification set.

An extra step was taken to test the accuracy of the SRM since the SRM is going to be used to predict the reservoir's behavior with changing well's BHP. A new model was built with a BHP value as a well constraint that was not among those used for training, namely a BHP of 170 psia was used for this extra verification dataset and the results were obtained.

The input data were introduced to the SRM and cumulative methane production for each well in the reservoir for the next 15 years was generated by the SRM. Figures 5 through 8 show the comparison of the results of the SRM and the commercial reservoir simulator for 4 wells in the reservoir. As the results show, the SRM was able to accurately predict the well's performance under the new BHP constraint (170 psia). Table 4 is the summary of SRM's prediction error for all 13 wells.

The advantage of the SRM over the conventional reservoir simulation is that, once the SRM is developed, it can run the model and generate results in a fraction of a second. With SRM, we can make thousands of simulation runs in seconds. This will enable us to exhaustively explore the solution space and find optimum solutions for our problem. We can perform uncertainty analysis (Monte Carlo Simulation) for which thousands of simulation runs are required. This issue becomes very important when we are modeling a large complex reservoir which could involve having a system of millions of grid blocks.

Sensitivity analysis also can be performed on the reservoir properties using the developed SRM. Figure 9 shows the results of the sensitivity analysis performed on well BHP and its effect on cumulative methane production.

MCS on different input parameters can be performed in order to quantify the uncertainties associated with these parameters and study their effect on the model's output. Let us study the effects of one of the inputs, gross block volume of segment 1 (the first segment from bottom in the well, shown in Figure 4), on the model's output which is the cumulative methane production.

Based on the amount of information available on this parameter, different Probability Distribution Functions (PDF) can be assigned to generate values of this parameter in order to perform MCS. A common PDF for an input with a known minimum and maximum is a uniform distribution. A uniform distribution means that any value between (and including) the

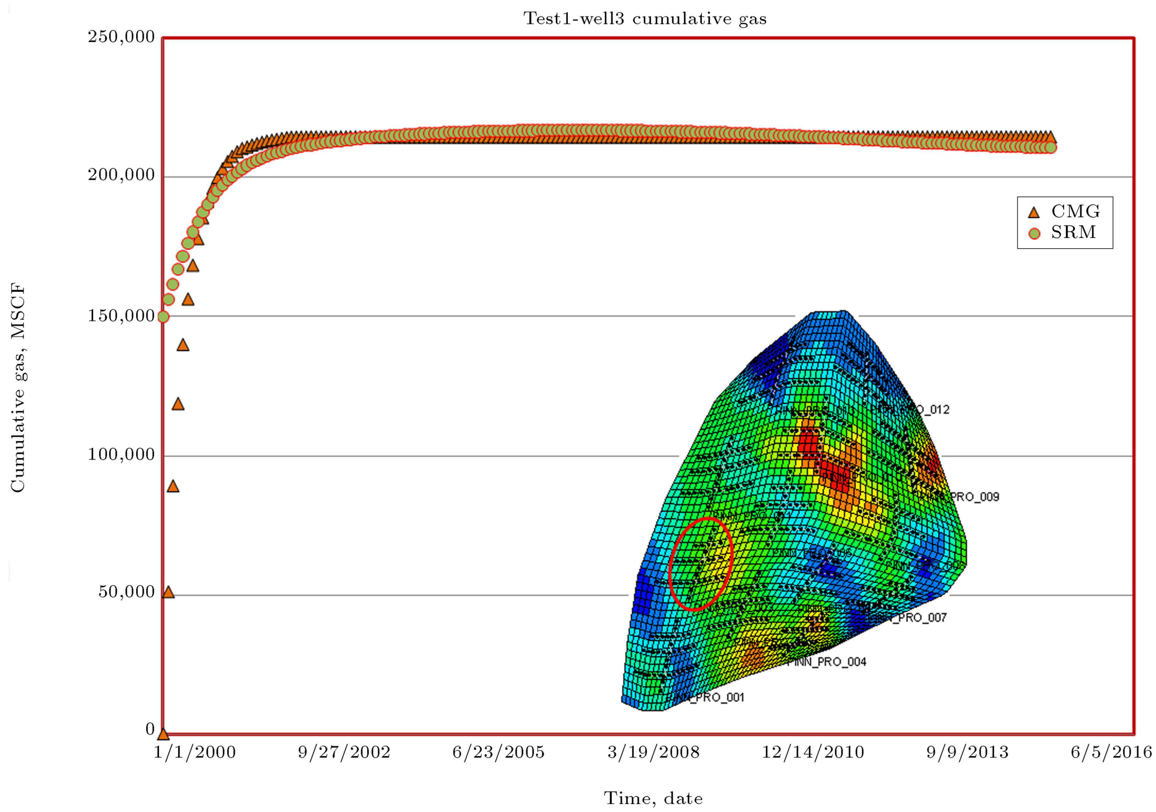

Figure 5. SRM and CMG cumulative methane production for well 3 (BHP = 170 psia).

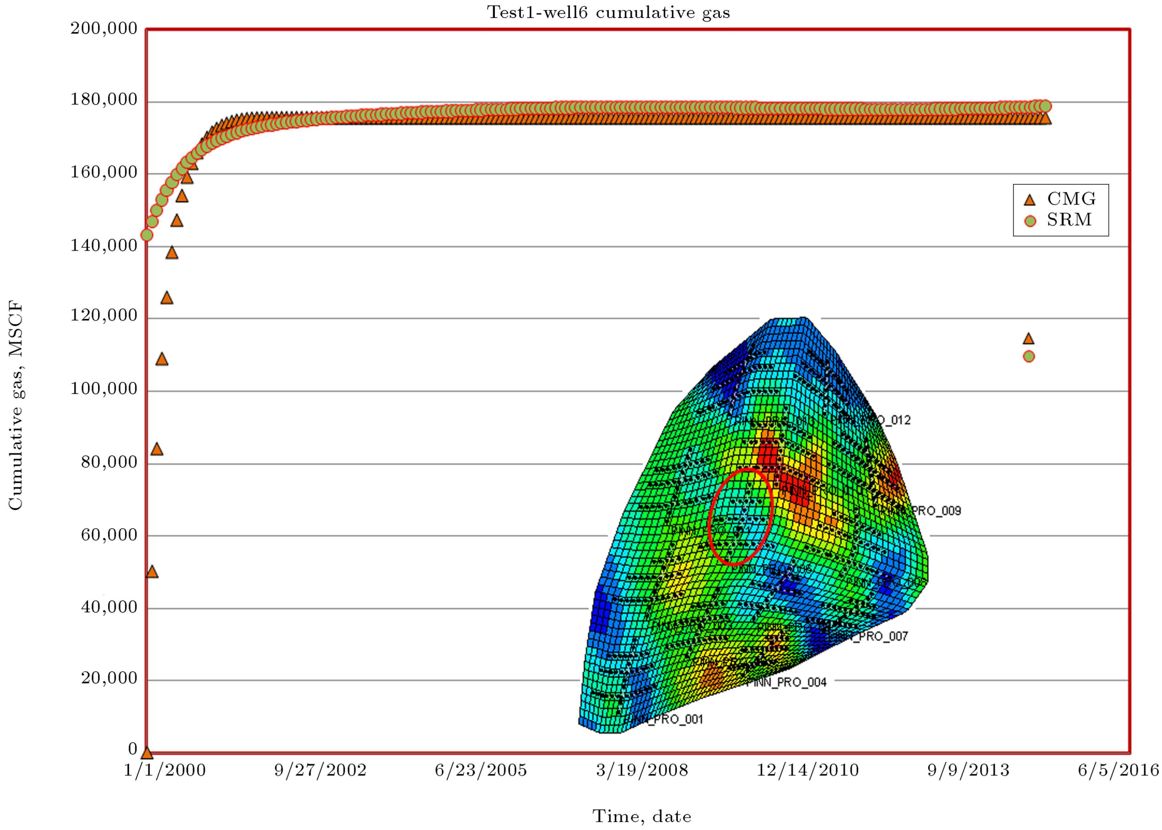

Figure 6. SRM and CMG cumulative methane production for well 6 (BHP = 170 psia).

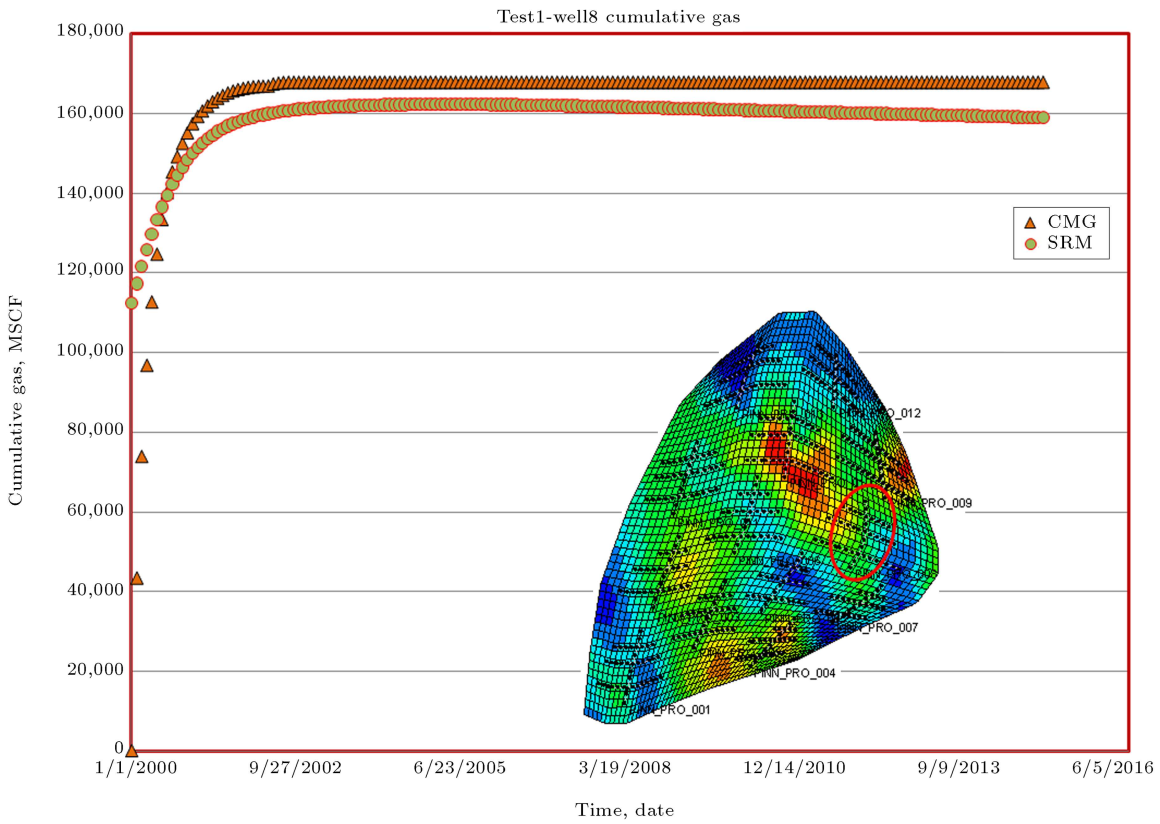

Figure 7. SRM and CMG cumulative methane production for well 8 (BHP = 170 psia).

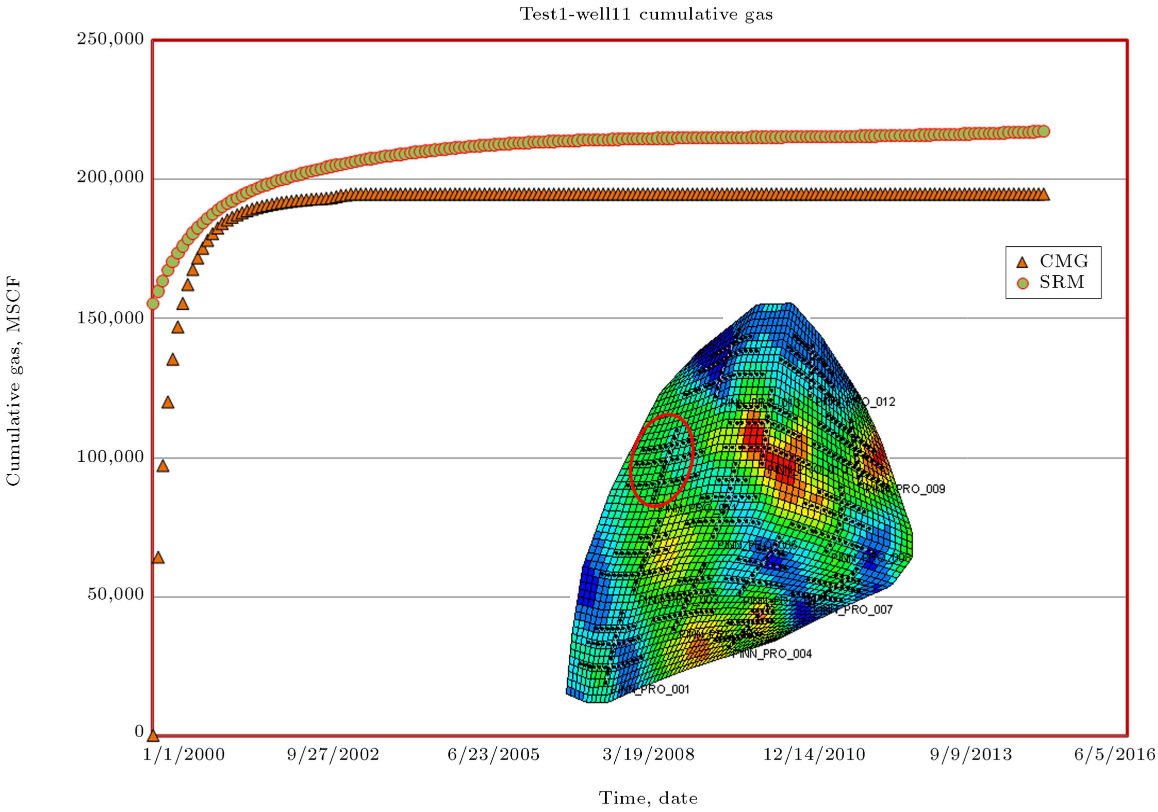

Figure 8. SRM and CMG cumulative methane production for well 11 (BHP = 170 psia).

Table 4. Summary of error in SRM's prediction for all 13 wells.

Well	Simulation Gas Cum., MSCF	SRM Gas Cum., MSCF	Error, %
Well 1	259,769	263,490	-1.43
Well 2	107,678	101,003	6.20
Well 3	214,641	210,892	1.75
Well 4	70,210	53,480	23.83
Well 5	99,842	105,351	-5.52
Well 6	175,828	178,974	-1.79
Well 7	50,189	49,302	1.77
Well 8	168,001	158,867	5.44
Well 9	45,752	36,324	20.61
Well 10	105,092	92,774	11.72
Well 11	194,951	217,401	-11.52
Well 12	33,445	30,163	9.81
Well 13	95,147	115,403	-21.29

minimum and maximum are equally likely to occur. Other PDFs can be selected for the input based on how much we know about the input parameter, such as Gaussian, Triangular, Discrete distributions etc.

In our example, a uniform distribution (schematic shown on Figure 10) is selected for the gross block volume of segment 1 of well 1. The gross block volume is essentially the net volume (assuming ash and moisture contents are negligible) of segment 1 (shown in well schematic, Figure 4). The minimum and maximum values selected for this analysis were 20,000 and 120,000 ft^3, respectively. These values are

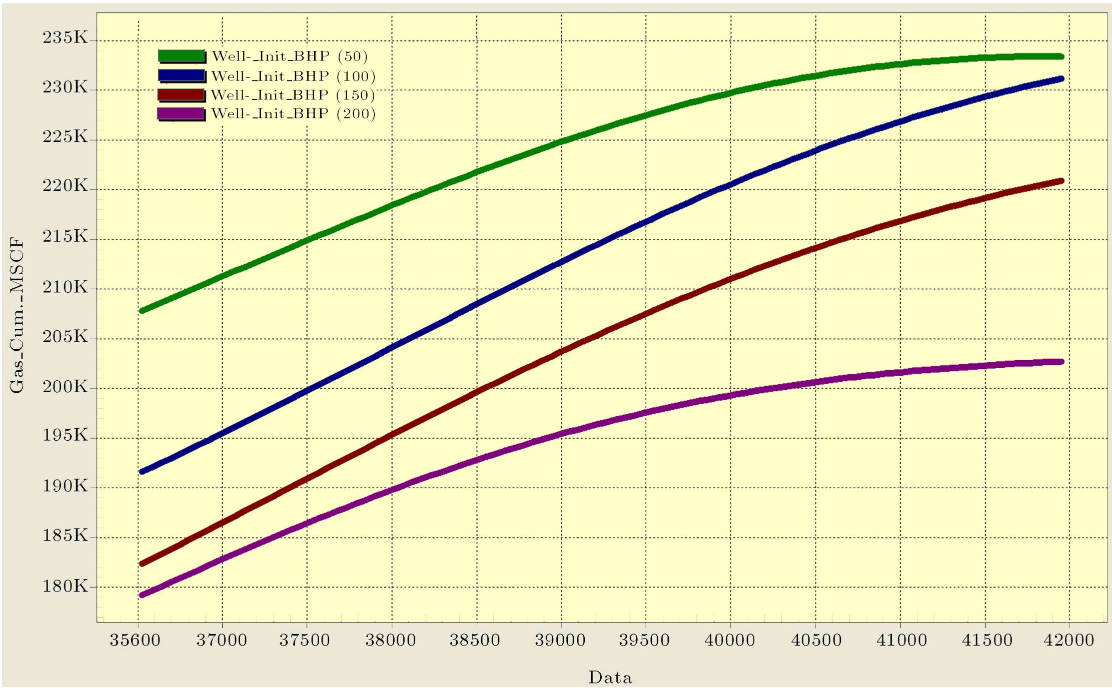

Figure 9. Cumulative methane production for different BHP values.

Figure 10. Schematic of uniform probability distribution used for gross volume uncertainty analysis.

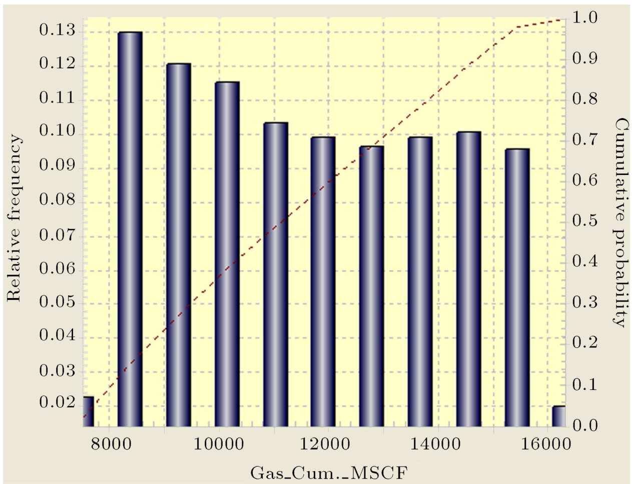

Figure 11. Monte Carlo simulation results for gross volume of segment 1 of well 1 with uniform PDF used for gross volume.

the approximate limits of the gross volume of segment 1 in the entire reservoir. Using this PDF for the gross volume of segment 1, the model was run 5,000 times in less than 10 seconds.

Figure 11 shows the results of the MCS analysis. The change in the gross volume of segment 1 of well 1 shows that cumulative methane production will have a change of about 10,000 MSCF on average.

Figure 12 is the result of a sensitivity analysis on the gross volume of segment 1. As the results show, methane production increases with the increase in gross volume.

In another example, Figure 13 shows the results of uncertainty analysis for the average permeability of segment 1 in well 1. A triangular probability distribution function was selected for permeability with 20, 35, and 50 mD as minimum, most likely, and maximum values, respectively. As Figure 13 shows, methane production has a triangular behavior with a change of permeability in segment 1 with a peak at around 9,500 MSCF as the most likely value. Figure 14 shows the schematic of the triangular probability distribution function used to generate values for permeability.

The triangular probability distribution function is usually used for parameters that have a most probable value for them, in addition to their minimum and maximum values in the area.

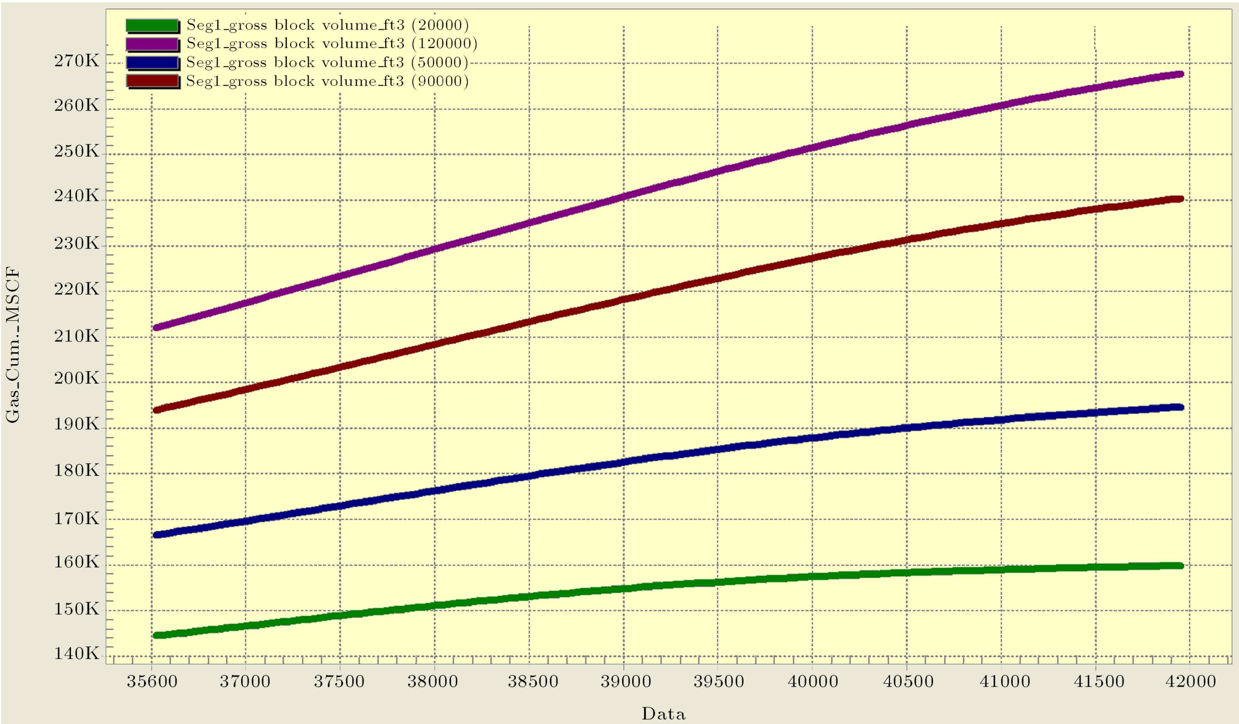

Figure 12. General model behavior for change in gross block volume of segment 1.

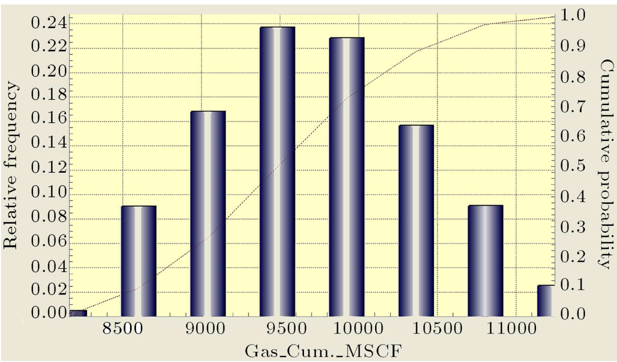

Figure 13. Monte Carlo simulation results for permeability of segment 1 of well 1 with a triangular PDF used for permeability.

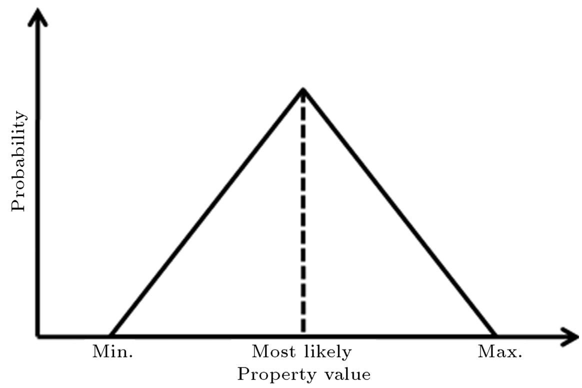

Figure 14. Schematic of triangular probability distribution used for permeability uncertainty analysis.

CONCLUSIONS

A Coalbed Methane reservoir model consisting of 13 pinnate pattern wells in a complex reservoir structure was simulated using a Surrogate Reservoir Model. An SRM is a prototype of a 3-dimensional full reservoir model that is built based on Artificial Neural Networks. The advantage of SRMs when compared to other reservoir simulators is its fast run time and its fast development using only a few realizations of the reservoir. Once the SRM is developed, one can perform Monte Carlo Simulation (that requires running of thousands of simulation runs) and quantify the uncertainties associated with reservoir parameters.

In this study, the objective of the SRM was to predict well's cumulative methane production by changing the well control value (BHP). Utilizing the developed model, the engineer can generate type curves for the modeled reservoir that can provide cumulative methane production for any BHP value in the range that was used to train the SRM.

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BIOGRAPHIES

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