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Forecasting, Sensitivity and Economic Analysis of Hydrocarbon Production from Shale Plays Using Artificial Intelligence & Data Mining

S. Esmaili, A. Kalantari-Dahaghi, SPE,West Virginia University, S.D. Mohaghegh, SPE, Intelligent Solution, Inc. & West Virginia University

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Abstract

Our understanding of the complexities of the flow mechanism in Shale plays has not kept up with our industry's interest in these prolific and hydrocarbon rich formations. Furthermore, massive multi-cluster, multi-stage hydraulic fractures, that have proven to be essential for economic recovery from Shale plays, have significantly increased the complexity of the flow behavior and consequently have made the modeling efforts more challenging.

In this paper, the application of a recently developed AI (Artificial Intelligence)-based reservoir modeling approach on Marcellus Shale is presented. In this approach, data mining and pattern recognition techniques were used to initiate modeling of the hydrocarbon production (dray gas and condensate) from Marcellus Shale. Instead of imposing our understanding of flow and transport in shale gas media, which is a very complex and non-linear system, we allow the production history, reservoir characteristics, and hydraulic fracturing data and operational constraint to force their will on our model and determine its behavior.

In this work, the full-field history matching process was performed on a Marcellus shale asset including 135 wells with multiple pads and different landing targets. The full field AI-based Marcellus Shale model then used for forecasting the future well/reservoir performance to assist in planning field development strategies. The goodness of match quality is self-evident, thereby validating this modeling approach. Nevertheless, to examine the model validity in the forecasting mode, the field data was partially matched and then attempted forecasting. Taking validation one-step further, the production performance of a recently drilled well, which was completely blind to the model (was not involved during training and initial validation), was predicted and compared with actual field measurement.

Furthermore, sensitivity and economic analysis are performed in order to identify the impact of different reservoir descriptions (e.g. different reservoir characteristics, stimulation and completion factors) and rank the impact of above-mentioned parameters on the Net Present Value (NPV) of investing on gas wells producing from Marcellus Shale.

Introduction

Shale gas has attracted attention throughout the world. As a result, there has been a lot of research on the shale gas reservoirs focusing toward improving the understanding of the flow mechanism especially in pore scale, adsorbed gas, lithofacies and mineralogy identification and finally upsacling the physics to macro scale that can be used in numerical simulation model.

On the other hand, hydraulic fracture initiation and propagation, which is essential in productivity of shale plays, is subject of many researches. Different studies have been done trying to incorporate the stimulation zone in flows simulation (e.g. by wing longitudinal fracture and Stimulated reservoir volume).Still there is a debate on what' happinening to the more than 60 to 70% trapped injected water. Are they really act as a proppant (C.A Economides, 2011) or they cause formation damage?

As stated by Swami and Settari, 2012, the equations and mathematical models developed for conventional sandstone and carbonate hydrocarbon reservoirs (pore size range 1- 100 micron) are not applicable for shale with pores at nanoscale. For that reason modifying the reservoir and/or stimulated reservoir volume (SRV) parameters (without much physical support) to match production data may not be correct way of simulating the behavior of these complex resources.

It seems that in history matching and generally shale gas simulation, as in so many other things (George S Wattley, SPE TIG-Simulation): As we know, there are known knowns. There are things we know we know. We also know there are known unknowns. That is to say, we know there are some things we do not know. But there are also unknown unknowns, the ones we don't know we don't know."(Donald Rumsfeld Feb. 12, 2002 Department of Defense news briefing)

Having said that, there are a lot of potential for research in these areas and many questions needed to be answered. With no doubt, further understanding of physics from molecular to macro scale should be implemented in numerical simulation in order to make it as a powerful tools in modeling and simulation of shale gas reservoir.

Here we will not prescribing a final solution to the problem, instead we are trying to give a hand to the shale modeler by introducing an alternative approach which is based on pattern recognition of Artificial Intelligence. The authors believe that the coupled numerical and artificial intelligence approach can be an effective way to model shale gas production behavior, since they are looking at the same problem but from different angle.

AI-based Shale gas modeling- This approach is a formalized, comprehensive and very first full-field empirical shale model using patter recognition of Artificial Intelligence. The main step in development of AI-based model includes Spatio-temporal database development, Simultaneous training and history matching of the reservoir model, Sensitivity analysis and quantification of uncertainties and finally Deployment of the model in predictive mode.

During the AI-based shale model development and history matching, the static model is not modified. Lack of such modifications may present a weakness of this technology, knowing the fact that the static model includes inherent uncertainties. To address this, the AI-based Reservoir Modeling workflow includes a comprehensive set of sensitivity and uncertainty analyses.

In this step, the developed and history matched model is thoroughly examined against a wide range of changes in reservoir characteristics and/or operational constraints. The changes in pressure or production rate at each well are examined against potential modification of any and all the parameters that have been involved in the modeling process. These sensitivity and uncertainty analyses include single- and combinatorial-parameter sensitivity analyses, quantification of uncertainties using Monte Carlo simulation methods and finally development of type curves. All these analyses can be performed on individual wells, groups of wells or for the entire field.

Finally, similar to any other reservoir simulation model, the trained, history matched and validated AI-based shale reservoir model is deployed in predictive mode in order to be used for performing reservoir management and decision making purposes.

History Matching and Forecasting -Application to Marcellus Shale

135 Marcellus shale wells with multiple pads, different landing targets, well length and reservoir properties in Southwestern Pennsylvania were used in this study. In this process, all available data including static, dynamic, completion, hydraulic fracturing, and operational constraint etc. was used for neural network training and validation of the model. After optimizing the number of input parameters and considering different flow regimes, well type and inner –outer distance of target well to its offset, a fullfield Marcellus shale history matched model was achieved.

Table 1 shows the input parameters for history matched model. (For further information about the history matching process of Marcellus shale please refer to SPE 161184 from the same authors and due to confidentiality the monthly gas rates were not shown in the figures)

Acceptable history matching result for entire field and for individual wells were achieved and are shown in Figure 1.The left one represent the fullfield history matching result while the right graphs shows the example of good(top) and bad(bottom) result for selected wells.

In this graph, the orange dots represent the actual monthly rate for the entire field while the green solid line shows the AI-based model results. The orange shadow represents the actual cumulative production (normalized) while the green one is corresponding to cumulative production output (normalized) by AI-based model. The red bar chart at the bottom of the plots shows the number of active Marcellus wells as a function of time.

The model is a multilayer neural network that is trained using a back-propagation technique. Data were partitioned with a

80% training fraction, 20% for calibration and verification (10% for each). The crossplot for predicted and actual values of monthly flow rate(Mscf/m) are shown in Figure 2 .These plots show that the trained network also work very well for the blind data.

Table 1- List of the input parameters in history matched model

Easting (Main Well and its Offset) Northing (Main Well and its Offset) MD (Main Well)	Group1	Well Location	Breakdown Pressure (Main Well and Its Offset) total Slurry volume per well (bbl)(Main Well and Its Offset) Total Proppant pumped (lb) (Main Well) Total Number of Clusters (Main Well)	Group 4	Hydraulic Farcturing
Porosity% (Main Well and its Offset) Net Thickness(ft)(Main Well and its Offset) Water Saturation(%)(Main Well and its Offset) TOC %(Main Well and its Offset)	Group 2	Static - Marcellus	Monthly rich gas production (MScf/m)(dry gas +Equivalent condensate) Flowing well head pressure(psia) No.of days of production	Group 5	Production & opertaional constraint
Comp-Stimulated Lateral Length (ft) (Main Well and its Offset)	Group 3	Completion	Flow Regimes (Main Well and its Offset) Inside and Outside Distances (Main Well) Well Type (Main Well and its Offset)	Group 6	Additional Parametres

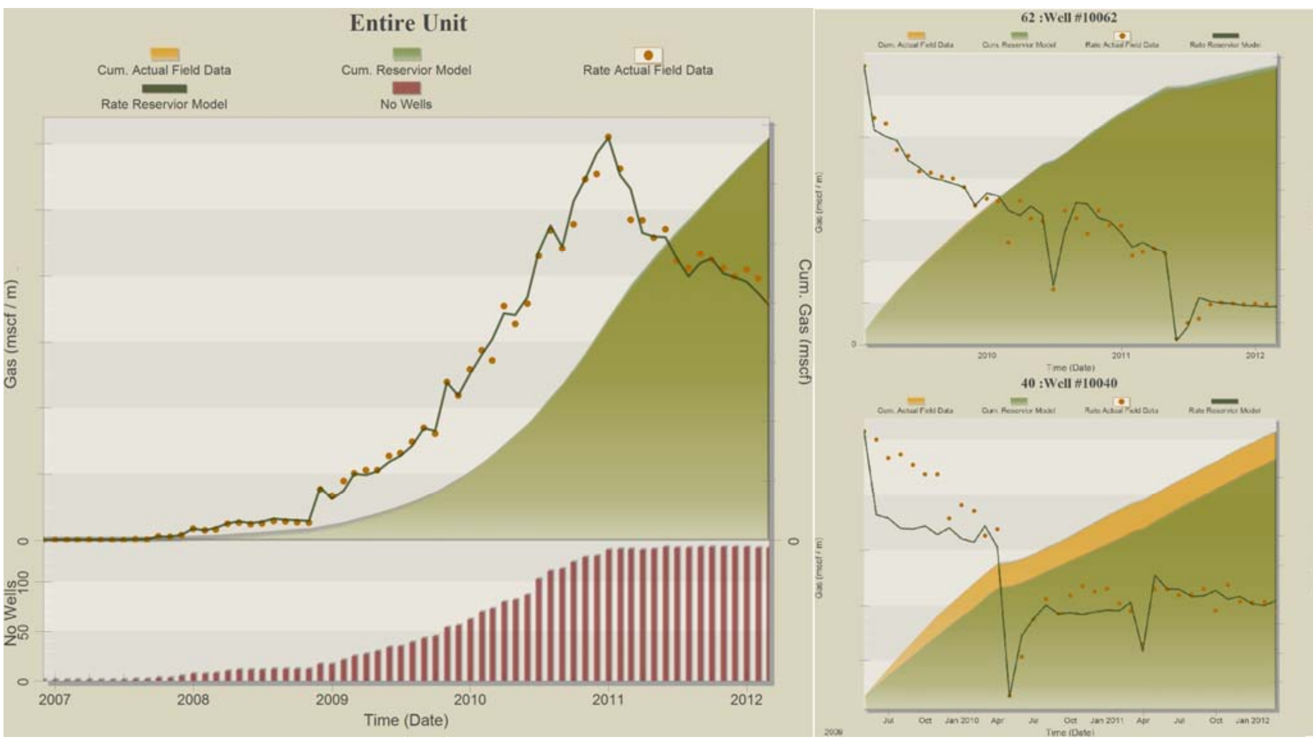

Figure 1.History matching result for entire field (left), good (top right) and bad (bottom right) well

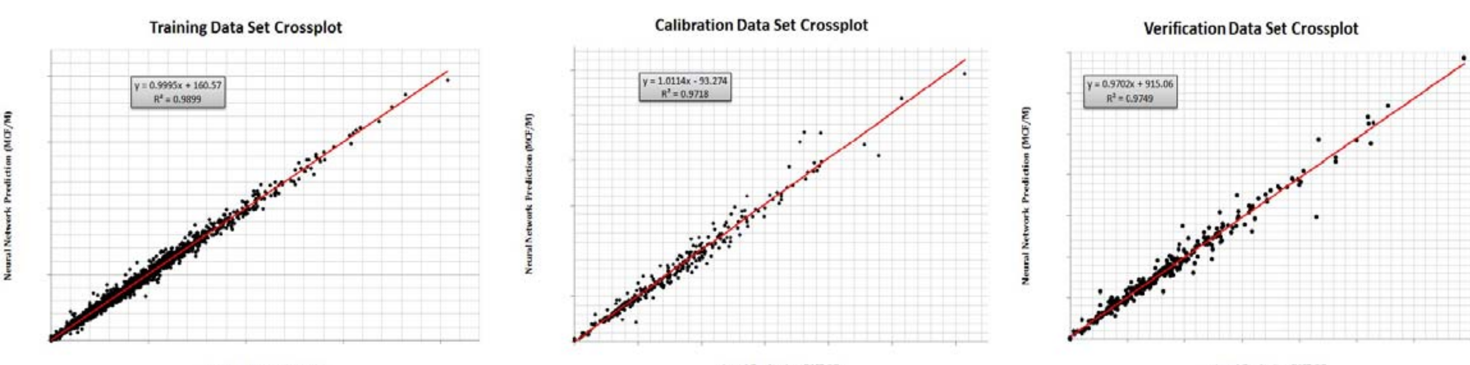

Figure 2.NN training, calibration, and verification results-(R^2 of 0.99, 0.97, and 0.975 respectively)

Forecasting Production Behavior

The goodness of match quality is self-evident, thereby validating this modeling approach. Nevertheless, to examine the model validity in the forecasting mode, the well and field data were partially matched and then attempted forecasting (Step 1). Taking validation one-step further,/ the production performance of a recently drilled well, which was completely blind to the model (was not involved during training and initial validation), was predicted and compared with actual field measurement (Step 2).

In the first step, 20% of last production history was removed from the training data set. Since the length of production for 135 wells is varying between 16 and 67 months, therefore last 4 to 14 months of production were removed to examine the forecasting ability of the model (Blind history match). Additionally, the AI-based model was run to forecast additional 12 months.

For blind history matching of last 4 to 14 months, the number of days of production for that period was included in the training set. The averaged flowing wellhead pressure for the last three months was used as a constraint for the blind history matching forecasting period (4 to 14 months and an additional year).

Figure 3 shows the blind history matching and additional one year forecasting results for two wells with 27 and 36 months of production history correspondingly as an example. In this graph, the orange dots represent the actual monthly rate (normalized) while the green solid line shows the AI-based model results. The black dots show the actual production data that was removed from the training and tried to be predicted by model. Last six and eight months of production were removed from training (20% of total month of production) and AI-based model could predict the production behavior of those periods with acceptable accuracy.

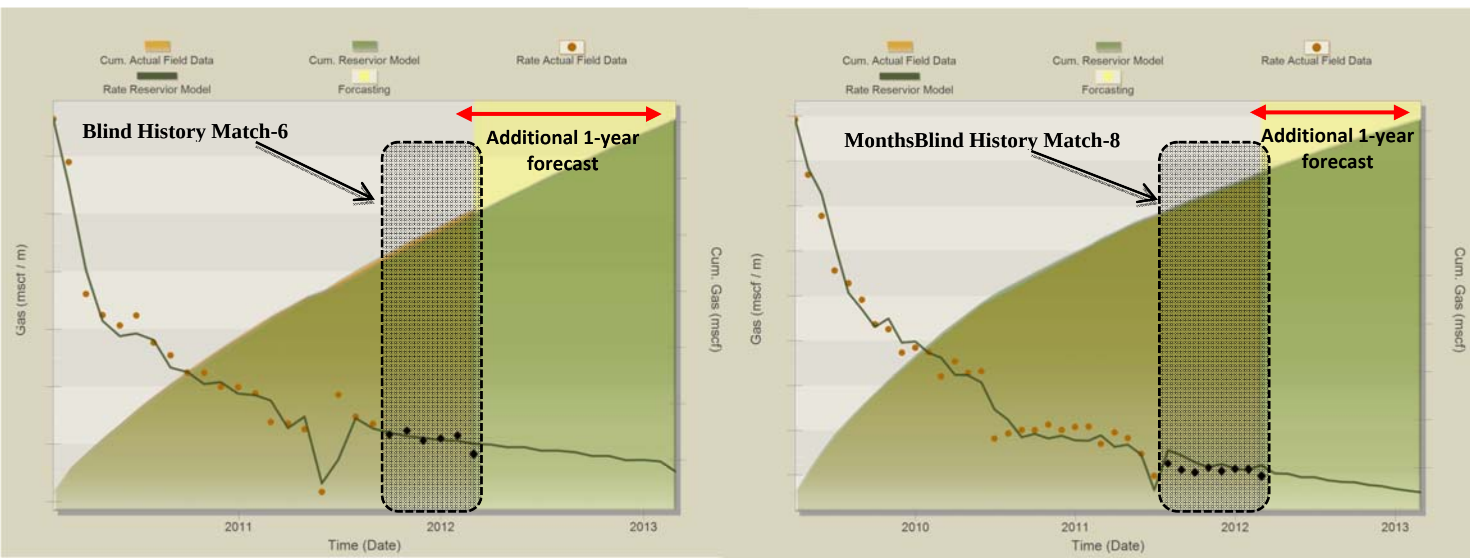

Figure 3. Blind history matching and additional forecasting for two well with 27 and 36 months of production history respectively (left to right)

As a complement to step one of validation process, last four months of production were consistently removed for all the wells and tried to predict the production rate for those months.

Figure **4** shows the blind history matching results as well as forecasting for additional year. By looking at actual production for the last four months, a sudden increase in rate at second month can be clearly observed, that might be because of high demand of natural gas over the winter, then the production followed its natural declining behavior at forth month. Therefore, the model could predict total production rate for the first and fourth month good enough but it underestimate the total rate for second and third months.

The error for predicting the production rate of those four months is varying from 1.4 to 9.2%, for each individual, which shows the capability of model in prediction mode.

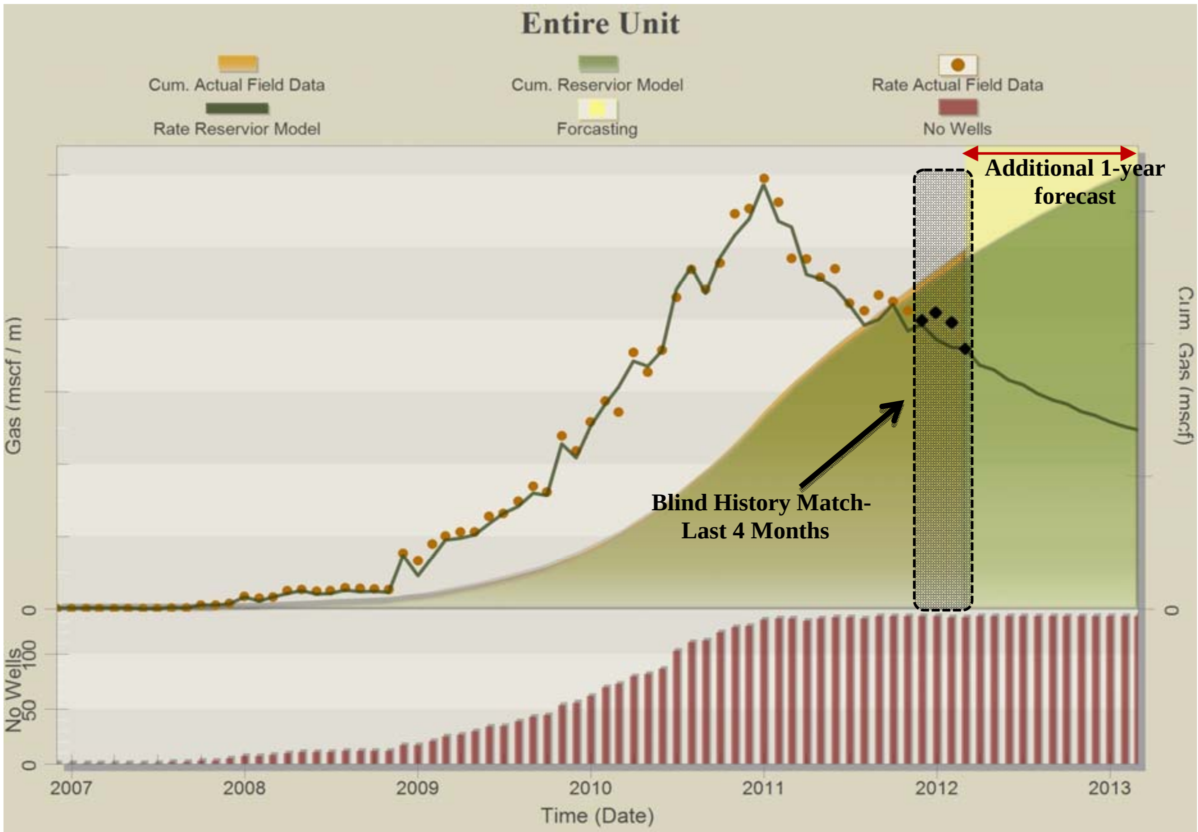

Figure 4. . Blind history matching of last four months and additional year of forecasting for entire field

In second step (final) of testing the capability of model for forecasting the production performance, the operator provided the location of a new pad including five recently drilled wells that are producing for five month in the study area The wellhead pressure for all the wells was kept at 200 psi (based on the closest offset wells).

For the first run, number of days of production was not included in the model and it was assumed that all the wells are producing for whole month. In the second run, the provided number of days of production was included in predictive model. The forecasting results for all five new wells and the location of them in part of area of study are shown in (Figure 5).

In this figure, the red line represents the completely blind forecasted cumulative production without including the no. of days of production while the blue dashed line shows forecasted cumulative production by including the no. of days of production. The black dots are actual cumulative production for five months. Additional seven months of forecasting are identified by a grid dashed box.

Figure 5 shows the range of error for forecasted cumulative production, for those new wells with five months of history, between 8.7 to 21.7%. More than 10% error in the forecast might be attributed to very short production history for those new wells. Nevertheless AI-Based Marcellus Shale model shows its capability on predicting and forecasting of new well/s performance.

It has to be mentioned that the properties of the new wells were not available and neural network used the average static parameter, completion and stimulation data from the nearby wells.

Sensitivity Analysis

Sensitivity analysis is a quantitative method of determining the effect of parameter variation on model results. Single-Parameter sensitivity analysis is performed on a pad. During Single-Parameter sensitivity analysis parameters are selected one at a time to be studied. While all other parameters are kept constant at their original value, the value of the target parameter is varied throughout its range and the model output (3, 12, 21, and 30 months cum. gas production) is calculated (using the predictive model) and plotted for each variation. Figure 6 shows the sensitivity analysis results for selected response parameters after 3, 12, 21 and 30 months of production from a single pad with six horizontal wells.

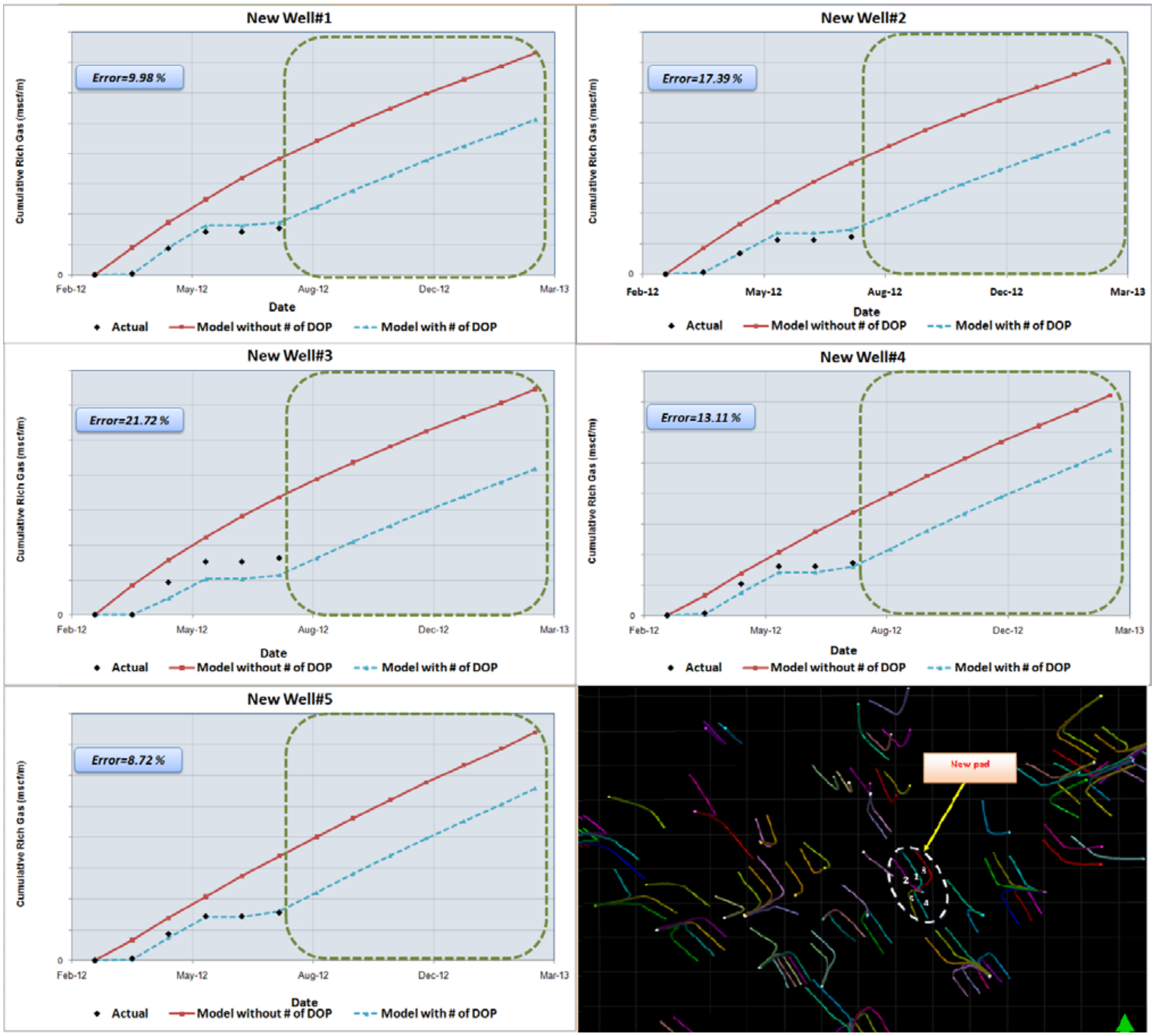

Figure 5.Location of new pad including five wells in a part of study area

By comparing all four-tornado charts, it can be clearly seen that four parameters consistently play significant role in short and long-term cum. production. These parameters are stimulated lateral length, slurry volume, amount of proppant and breakdown pressure (BDP)

It has to be noted that since all the parameters (but the one being analyzed) are kept constant at their original value, these analyses for some of the parameters may look a bit strange from time to time. This is the result of an intuitively linear analysis (single-parameter sensitivity analysis) performed on a highly non-linear system.

Given the fact that gas and condensate production from Marcellus Shale that is the result of massive, multi-stage, multi-cluster hydraulic fracturing that is performed on long lateral wells is anything but linear, such sensitivity analyses may not be telling of the whole story. To examine the simultaneous impact of changes in multiple parameters in a highly non-linear system other techniques such as Monte Carlo Simulation that are statistically sound are required.

Marcellus Shale AI-Based Type Curves

Upon successful development of the AI-based Marcellus shale model, type curves can be generated to assist operators during the decision making process on where to place the next well (or which wells should get priority for drilling) and how to complete and stimulate it. Type curves can be generated for individual wells, for groups of wells and for the entire field. In type curves, the y-axis is the model output (in this case, 365 days cum. gas production). The x-axis should be selected from one of the input parameters and curves represent a third parameter.

Figure 7 shows a set of 365 days cum. production type curves for total amount of injected slurry volume (bbl), total Marcellus porosity (%), total stimulated lateral length (ft) and total amount of proppant (lb) as a function of total number of clusters.

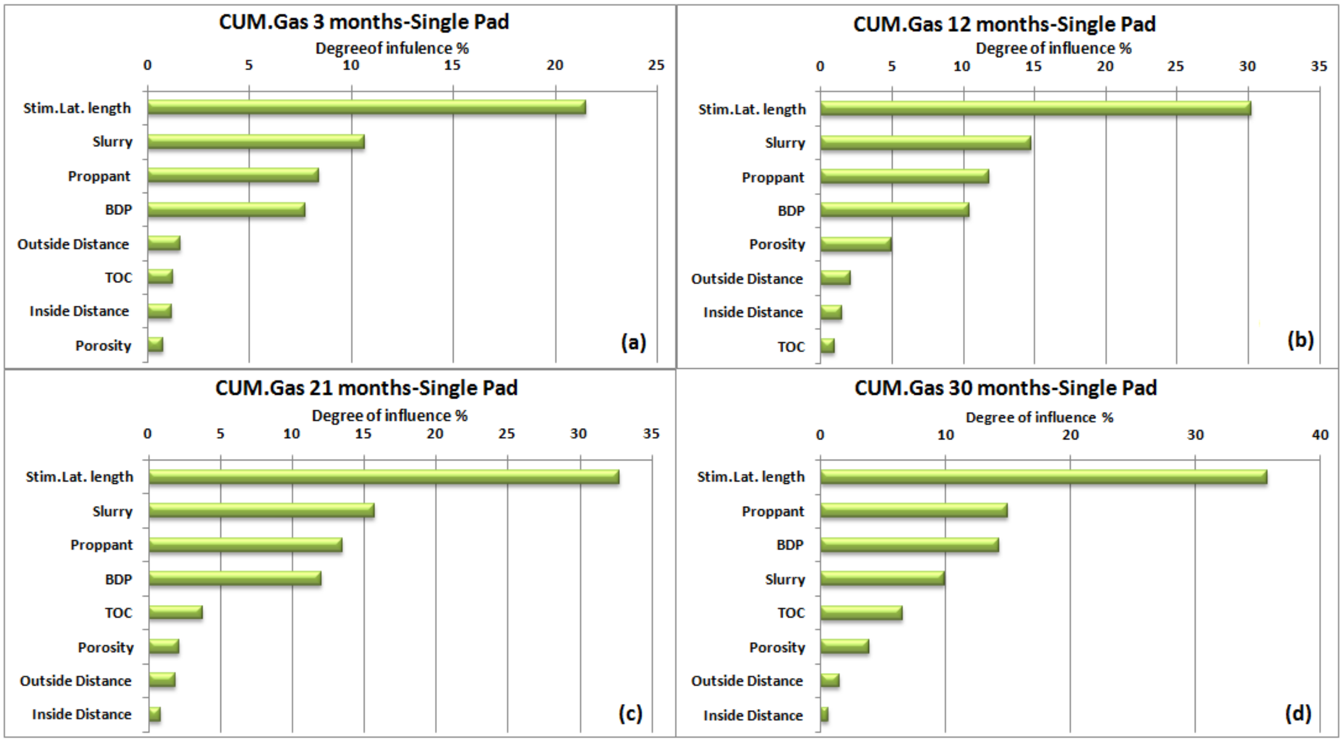

Figure 6.Tornado charts showing the uncertainties affecting different response parameters. (a) After3 months cum. production for a pad, (b) After 12 months cum. production, (c) After 21 months cum. production (d) After 30 months cum. production

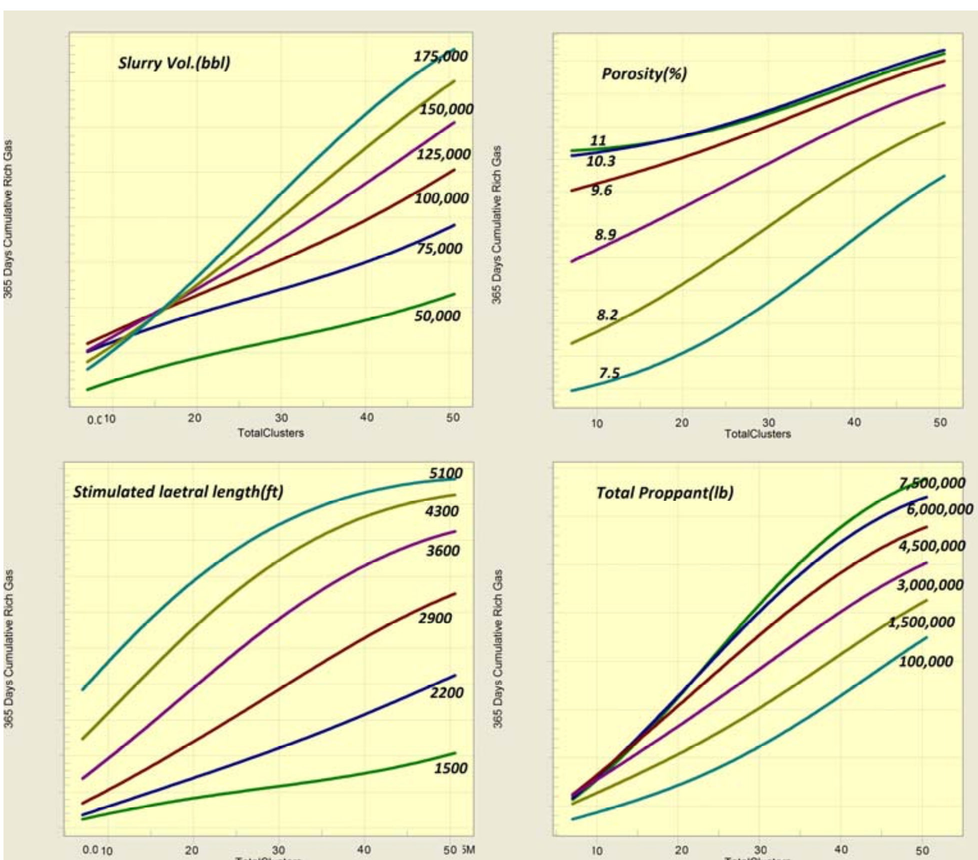

Figure 7. Type Curves for a well showing changes in 365 Days Cum. Gas as a function of Number of Stages and different slurry volume (bbl), porosity (%), Stimulated lateral length (ft) and total proppant (lb)

Economic Analysis

Although the advanced technologies of horizontal drilling and hydraulic fracturing make the extraction of natural gas from extremely tight reservoir such as Marcellus shale feasible, this question is always being asked that if it would be advantageous to do. There are some problems associated with shale gas production based on recent market changes in the natural gas industry that raise concerns about economic viability of this phenomenon.

In order to determine the profitability of Marcellus shale wells in the studied area, an economic analysis by using various cost components and different gas prices was performed. The net present value (NPV) of the cash flows and internal rate of return (IRR) was calculated for each scenario of gas price. Profitability was gauges based on whether the values were positive or negative for the resulting NPV calculations and if the IRR values were greater than the minimum acceptable rate of return of 10 percent (Duman 2012).

Several cost components and assumptions were taken into account for economical calculation, are briefly explained below:

Royalty Costs- The royalty rates in the Marcellus Shale currently range from a minimum of 12.5 percent to 18 percent with the average rate of 17% per gross revenue that is currently being offered in Pennsylvania (Duman 2012).

Lease Acquisition costs -Lease bonus payments in the Marcellus Shale can range from several hundred dollars per acre to over $10,000 per acre with the current average being approximately $3,450 per acre (Duman 2012).

Site Preparation and Permission fees -For a total wellbore length of 10,000 feet, an application fee of $2,600 and a bond amount of $2,500 is required. The approximate costs associated with prepping a site for drilling amount to roughly $400,000 (Duman 2012).

Drilling and Completion Costs -The drilling and completion costs associated with a 10000 ft long well (3000 ft lateral length & 10 stages) in southwestern PA is about 4.0 MM$.

Operating Costs -The operating costs were assumed to remain constant at $0.70 per mcf throughout the life of the well (Duman 2012).

State and Federal Income Taxes -A state corporate tax rate of 9.99 percent and a Federal income tax rate of 34% was utilized to the analysis (Duman 2012).

Economic analysis was performed based on 10 years of forecasted dry gas production for one of the recently drilled wells, which was used for final model validation previously. The annual production of this well is based on the minimum wellhead pressure of 200 Psi. Three different gas prices of four, five and six ($/Mscf) with annual increase of 2% was considered.

The cash flow statement was constructed based on above-mentioned assumptions and the net present value and internal rate of return was calculated in order to determine the overall profitability of the well. Table 2 shows a summary of results of a typical Marcellus shale gas well under the ten-year production.

Table 2: Results for the Cash Flow Statement for a well with 10 years production

Initial Gas Price ($/Mscf)	Cumulative Gas in 10 years (BCF)	Total CAPEX ($)	Total Operating Costs in 10 years	Total Income after Tax ($)	NPV ($)	IRR (%)
4.0	2.8 BCF	3.1 MM	1.9 MM	4.54 MM	0.43 MM	16
5.0	2.8 BCF	3.1 MM	1.9 MM	5.97 MM	1.55 MM	34
6.0	2.8 BCF	3.1 MM	1.9 MM	7.39 MM	2.65 MM	50

Based on the positive NPV and an acceptable IRR (>10%), this new gas well under the assumptions and values used in this analysis was found to be profitable based on ten-years of production.

Conclusions

1. An alternative approach for shale gas modeling based on data mining and pattern recognition technology was proposed and successfully applied to the Marcellus shale asset with multiple wells. Fullfield history matching was achieved with acceptable accuracy. The history-matched model went through a series of verification and validation process to investigate the capability of the developed AI-based model in forecasting the future performance of current wells as well as proposed wells in the area of study by taking out the hidden information which is embedded within the production data.

2. In order to identify the impact of different parameters on production behavior, sensitivity analysis was performed and a series of type curves was developed.

3. Given the assumptions made and input values used for economic analysis shows that the new well with forecasted 10 years of production not only recoup the initial investment but also make profit considerably.

Acknowledgments

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