SPE 169573

Production Analysis of a Niobrara Field Using Intelligent Top-Down Modeling

S. Alireza Haghighat, Shahab D. Mohaghegh, Vida Gholami, David Moreno, West Virginia University

This paper was prepared for presentation at the SPE Western North American and Rocky Mountain Joint Regional Meeting held in Denver, Colorado, USA, 16–18 April 2014.

Abstract

Unconventional hydrocarbon resources are going to play an important role in the US energy strategy. Conventional tools and techniques that are used for analysis of unconventional resources include decline curve analysis, type curve matching and sometimes (in the case of prolific assets) reservoir simulation. These methods have not been completely successful due to the fact that fluid flow in unconventional reservoirs does not follow the same physical principles that supports mentioned analytical and numerical methods. Application of an innovative technology, Top-Down Modeling (TDM), is proposed for the analyses of unconventional resources. This technology is completely data-driven, incorporating field measurements (drilling data, well logs, cores, well tests, production history, etc.) to build comprehensive full field reservoir models.

In this study, a Top-Down Model (TDM) was developed for a field in Weld County, Colorado, producing from Niobrara. The TDM was built using data from more than 145 wells. Well logs, production history, well design parameters and dynamic production constrains are the main data attributes that were used to perform data driven analysis. The workflow for Top-Down Modeling included generating a high-level geological model followed by reservoir delineation based on regional productivity, reserve and recovery estimation, field wide pattern recognition (based on fuzzy set theory), Key Performance Indicator (KPI) analysis (which estimates the degree of influence of each parameter on the field production), and finally history matching the production data from individual wells and production forecasting. The results of production analysis by Top-Down Modeling can provide insightful guidelines for better planning and decision making.

Introduction

The standard and conventional routine of reservoir modeling in the industry is to develop a numerical reservoir model using available static and dynamic properties. This flow model is based on the geological model. Considering the fact that the geo-cellular model is built using the geological and geophysical data, and then the upscaling process is performed and the flow model is developed using the well-known engineering fluid flow principles followed by the history matching process, it can be asserted that it is “Bottom-Up” process.

The principal assumption that should be made in the traditional reservoir simulation is that all the complexities of the reservoir are known and can be modeled in terms of the available mathematical equations. However any engineer working in this industry believes that this is not the case in reality. It never can be claimed that all the aspects and complications of the geological layers are known no matter how thorough the data acquisition process is; neither can be claimed that all the phenomena happening in the reservoir in terms of fluid flow and interactions of rock and fluid is well represented in terms of mathematical models and formulas available. This problem is even more challenging while dealing with unconventional reservoirs such as Shale. Many engineers believe it would be far from reality when it comes to modeling the physics of what happens in the Shale reservoirs and assert that, the mere reason to use the available models is simply because there is no alternative.

In opposed to “Bottom-Up” process there is another process called “Top-Down Modeling (TDM)”, taking a totally different tactic for the full- field reservoir simulation. In this state-of-the-art technique, reservoir engineering, statistical analysis, advanced data-driven analytics and machine learning are integrated to build a reservoir model as an alternative or complement to the traditional reservoir modeling approaches [6].

In the TDM process although the reservoir engineering concepts are strongly adhered to, the formulation is not imposed to the reservoir model. Instead of imposing the physics to the model this technique let the model learn the behavior from the “Data”. However, one of the most significant differences between TDM and conventional numerical reservoir modeling is in the amount of data needed. The data acquisition process is costly and might not be economical in many cases specifically for the small and mid-sized asset holders and companies. Also, in many brown fields the history of the wells goes back to the time that not much attention was paid to the attainment and recording of the data. In most cases the only available data is production, which will not meet the basic requirements for building a numerical reservoir model. TDM will be the best alternative in these situations, as it will be able to provide the necessary reservoir management equipment and getting help from data driven modeling techniques [7].

Generally the major differences of numerical reservoir models with the TDM technique goes back the small footprints of TDM in development, running and history matching process, ability to provide the full field models that can be used in making the management decisions using the minimum available data and tackling the cost issue for building the geological and flow models. TDM has been used in multiple works [2, 4, 5, 6, and 7] and has proved to be a reliable alternative in cases that traditional reservoir models cannot be developed, due to the limitation in data, or because of the complex physics of the reservoir or the process of model development is too costly or time consuming.

In this study, an asset of 145 wells (the data was available publicly [1]) located in the Weld County, Colorado is to be analyzed using various data driven techniques. Fuzzy pattern recognition was implemented to provide best producing locations as well as under-performing wells. Also, an AI-based history matched model was developed and validated which can be used for predictive practices, sensitivity analysis, infill drilling locations and other reservoir management purposes.

Asset Overview-Wattenberg Field in Niobrara

Wattenberg field was discovered in 1970. It is located in the north east of Colorado, and extends approximately 50 to 70 miles in north-south direction (covering 50 townships). Hydrocarbon production in Wattenberg field is from multiple pay zones such as Dakota-Lakota, J Sand, D Sand, Codell, Niobrara (A, B, C), Shannon and Sussex [11] as it is shown in Figure 1. Niobrara, which is considered as an unconventional reservoir, mainly consists of inter-bedded organic-rich shale, calcareous shale, and marl. The formation can be found at the depth of 6200 to 7800 ft with a thickness ranging from 300 to 400 ft [11]. This over-pressured reservoir has low permeability of 0.01 to 0.1 md and total organic content (TOC) of 0.85 to 2.75(weight percent).

Since 1981, more than 10,000 wells have been drilled and completed in Codel and Niobrara. The current oil and gas production amount from these wells in Niobrara is about 20,000 BOPD and 180MMCFGD respectively. The equivalent oil as recoverable reserve in Niobrara formation is estimated to be 2 to 4 billion barrels [11]. The Middle branches of Niobrara (B) are mainly targeted by horizontal drilling [11] with various completion designs such as slick water fracture treatment and multi stage fracturing with 12 to 35 stages [9]. The initial well spacing units was approved to be 320-acre,but the discovery of Codel and Niobrara formations resulted in 80 acre spacing permissions[9].

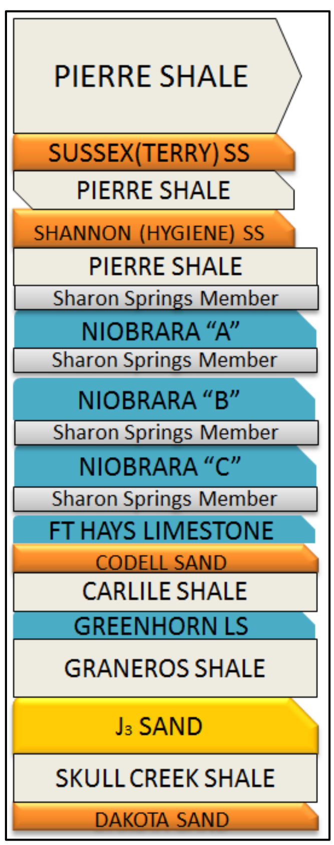


Figure 1: Wattenberg stratigraphic column

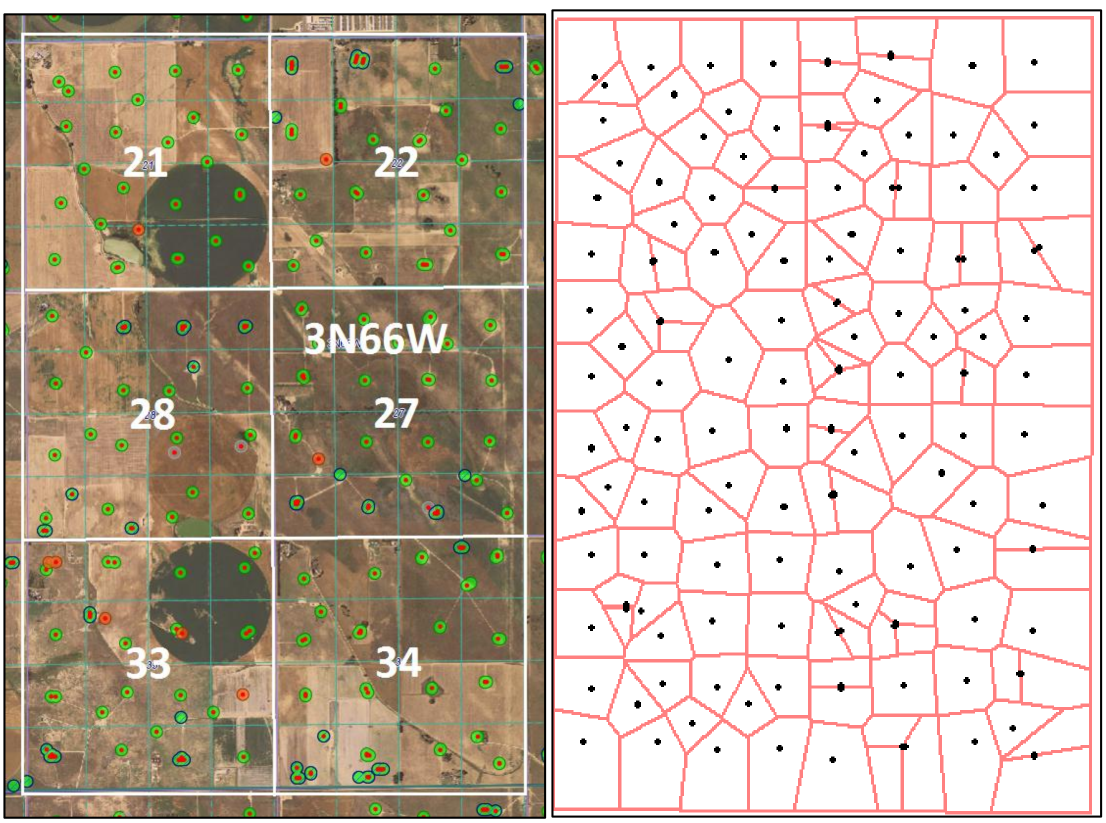
Data Analysis

The area of review in this study consists of 6 sections (21, 22, 27, 28, 33, 34) that are located in Range 66W and Township 3N (Figure 2a).All data for this study was acquired from COGCC website [1]. In this area, there were 222 wells that had production from Codell, Niobrara and J Sand formations. Excluding the wells that produced from only Codell or J Sand formations, resulted in having total of 145 wells in six sections with production from Niobrara formation, or comingled production from Niobrara-Codel. In order to allocate the approximate production to each formation, production ratio was used based on the porositys, formation thicknesses and water saturations obtained from the logs for each well (Equation 1):

$$Production\ Ratio = \frac{q_{Niobrara}}{q_{Codel}} = \frac{h_{Niobrara} \times \varphi_{Niobrara} \times (1 - Sw_{Niobrara})}{h_{Codel} \times \varphi_{Codel} \times (1 - Sw_{Codel})} \quad Equation\ 1$$

Well logs for more than 60 wells were analyzed to obtain the petro-physical data over the area of review. Formation thickness, porosity and water saturation were the most important parameters that were determined from the well logs. Additionally, production history and well completion details (e.g. perforation thickness, volume of total injected fluid and total injected proppant) were acquired to be used in the data driven analysis. Completion reports and well logs were used to find top and thickness of Niobrara formation. Once the thickness was found, average porosity was obtained using "Neutron" and "Density- Porosity" logs in the formation interval. Having the porosity, "Archie" equation was used to calculate water saturation considering resistivity values from the "Induction" logs.

Once all the data was extracted (reservoir, well design parameters and production), spatio-temporal database which can be a representative of the fluid flow in the reservoir, was prepared and processed to be in an appropriate format for pattern recognition technology. This database consisted of static (reservoir properties and well completion specifications) and dynamic (production and days of production in a month) data for each well. In order to make static models and delineate the reservoir, outer boundary was set and drainage area for each well was estimated by Voronoi technique (Figure 2b). The reservoir properties were populated throughout the area of review using geo-statistical methods in order to generate geo-cellular model. Geo-statistical distribution maps were generated for all the available reservoir properties, which were collected from well logs. Volumetric reserves were calculated based on geo-cellular properties and well drainage areas.



(a) (b)

Figure 2: Location of the wells in range 66W and Township 3N (b): Reservoir delineation and drainage area for each well

Field Wide Pattern Recognition

One of the practical implementations of data driven analysis is Field Wide Pattern Recognition which depicts the areas representing high to low production history and remaining reserves. Fuzzy Pattern Recognition was used to determine different sections of the reservoir with varying levels of contribution to the production during a specified time interval. This method can be used in order to assign different indices to each part of the reservoir based on their Relative Reservoir Quality (RRQ). Fuzzy Pattern Recognition results for distribution of the first six months and three years of cumulative oil production are shown in Figure 3. The darker colors represent areas with higher cumulative production (Excellent RRQ) during the specified time interval. It is worth mentioning that RRQ is a good indicator of anticipated cumulative production (during a time interval) for a new drilled well in a specific area of the reservoir. Additionally, it is possible to determine Production Indicator (PI) for each well and compare it with the RRQ of the area that the well is located in. If the PI is less than RRQ, the well can be considered as under-performing well which could be a good candidate for re-stimulation. Figure 3(c) shows under-performing wells for three years of cumulative production (wells in blue color).

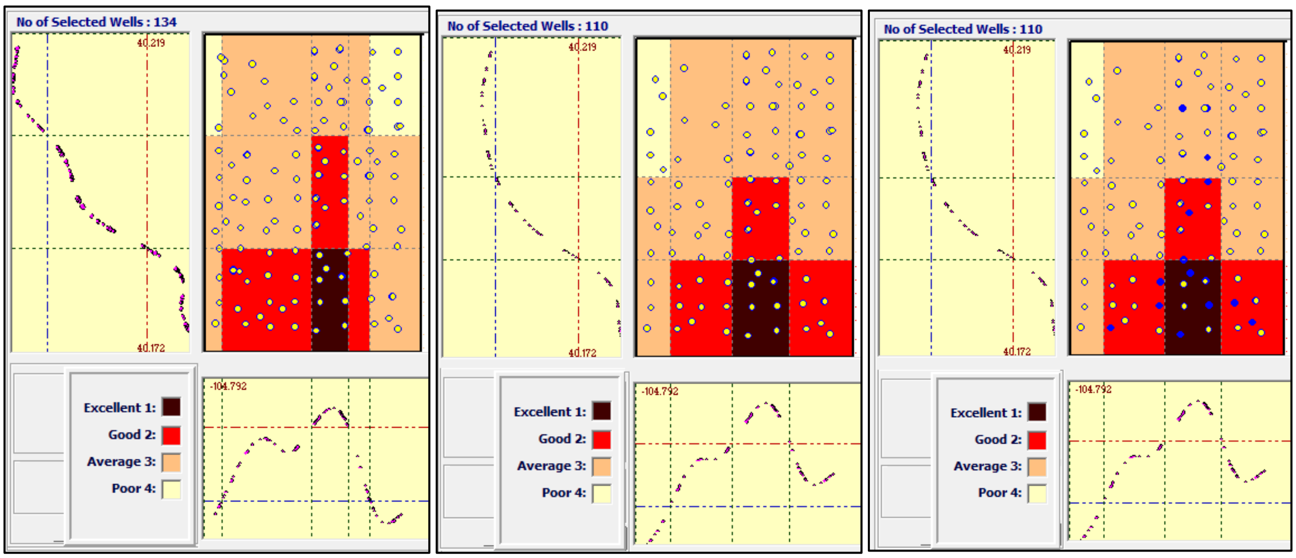


Figure 3(a): Fuzzy pattern recognition analysis for 6 months cumulative production (b) 3 years cumulative production (c) location of underperforming well (blue colors) based on 3 years cumulative production

AI-Based Top-Down Reservoir Modeling

The most important aspect of data driven analysis for the oil production of this asset was developing a time based reservoir model. This model used pattern recognition techniques (e.g. Artificial Intelligence) and honored reservoir engineering practices to regenerate production history and predict the future performance of the existing and new wells. In order to make an AI-based reservoir model, it was necessary to train neural networks, which were able to recognize patterns between production history of the wells and corresponding static (reservoir properties, well completion information) , dynamic data (operational information like days of production per month). Once all possible inputs and outputs were prepared, Key Performance Indicator (KPI) analysis was performed to determine the degree of influence of each static or dynamic property on the production. The results of the KPI analysis and the list of inputs for TDM development are shown in Figure 4 and Table 1.

Rank	Feature	% Degree of Influence
1	Stimulation date	100
2	q(t-1)-Oil	93
3	q(t-2)-Oil	79
4	Perf Thickness	60
5	Weigth of Inj Propant	55
6	Porosity (%)(1P)	49
7	X/Longitude	48
8	Porh(1-sw)(1P)	46
9	Porh(1-sw)-Ave.(1P)	46
10	Water Saturation (%)	46
11	Elevation	42
12	Vol of Total Inj Fluid	42
13	Porh(1-sw)-Ave.	40
14	Time	40
15	Resistivity	38
16	Porosity (%)	37
17	Porosity (%)-Ave.	37
18	Top (ft)	37
19	Distance(1P)	36
20	Days of Production(t)	33
21	Top (ft)(1P)	33
22	Y/Latitude	32

Figure 4: KPI analysis results for relative influence of different inputs on the monthly oil production

Table 1: List of inputs for Top-Down Model development

Top-Down Model Inputs		
Static Data(reservoir properties)	Static Data(well design parameters)	Dynamic Data
Pay Thickness	Well Location	Time
Porosity	Well Drainage Area	No. of Days of Production
Water Saturation	TVD	q-Oil (t-1)
Porosity (offset well)	Perforation Thickness	q-Oil (t-2)
Neutron Porosity (log)	Volume of Total Injected Fluid	Stimulation Date
Formation Top	Weight of Injected Proppant	
	Distance to Offset Well	
	Well Drainage Area (offset well)	

Production data from 145 wells that began in 1986 and continued to December 2012 were used in neural network training. Reasonably good history match results for the entire field and individual wells were achieved (Figure 5). Also, the future productions of the wells were predicted for three years starting from year 2013 (yellow shadow in Figure 5).

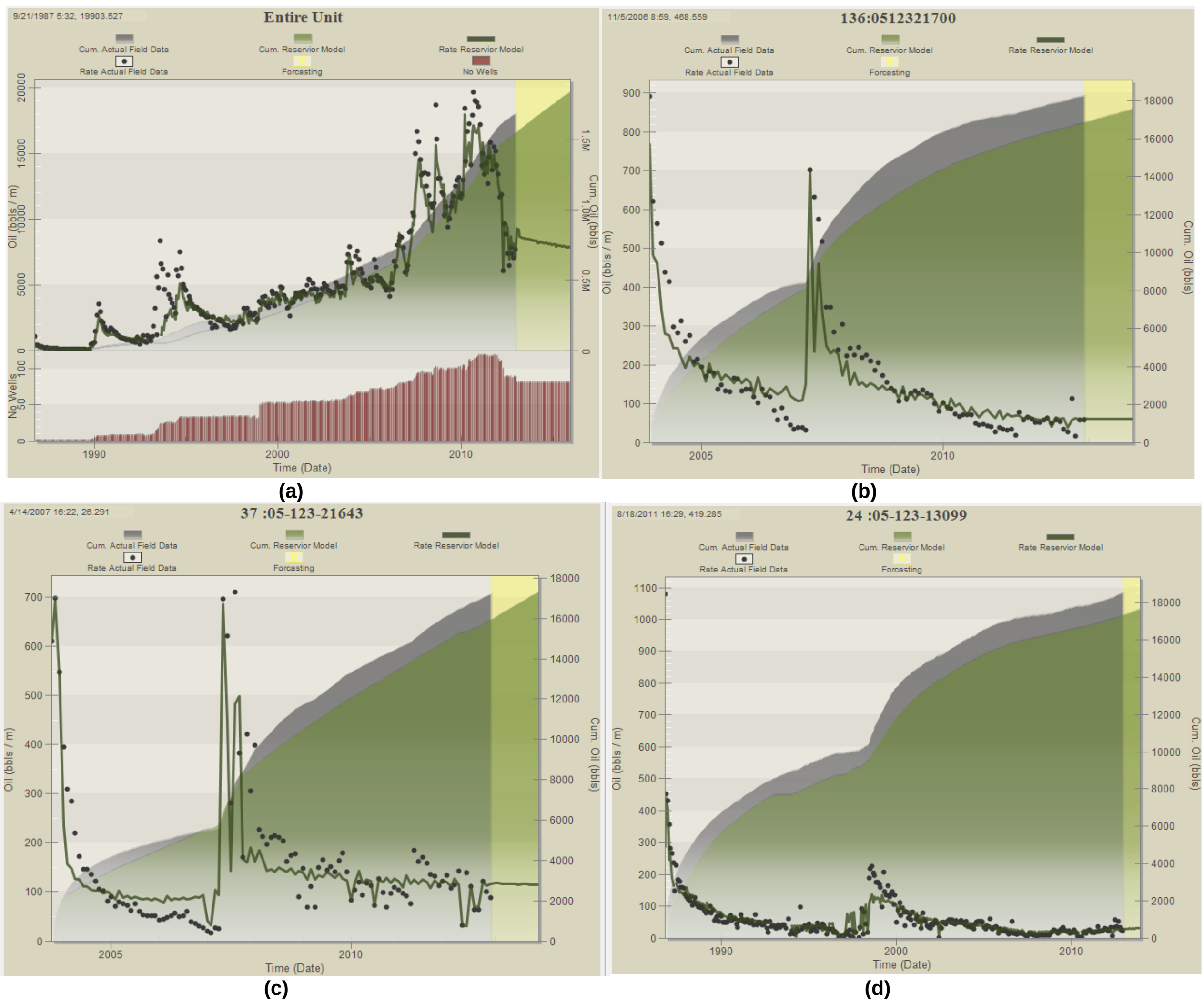


Figure 5: Top-Down Model estimations for production history (from 1986 to 2012) and 3 years future prediction (from 2013 to 2015). Green line represents model's estimation and prediction and dots represent actual data. Cumulative production for actual data and model's prediction are shown by gray and green shaded areas respectively. (a): results for the entire field, (b): results for well 0512321700, (c): results for well 0512321643, (d): results for well 0512313099

In order to validate the model, the production data for the final year was set aside and not used in the training process. The trained and history matched model was used in order to forecast the production data for the final year and the results were compared to the actual available data. As it is shown for two of the wells in Figure 6 and Figure 7 it can be seen that the model is capable of a reasonable forecasting. This validated model can be used for forecasting the future production.

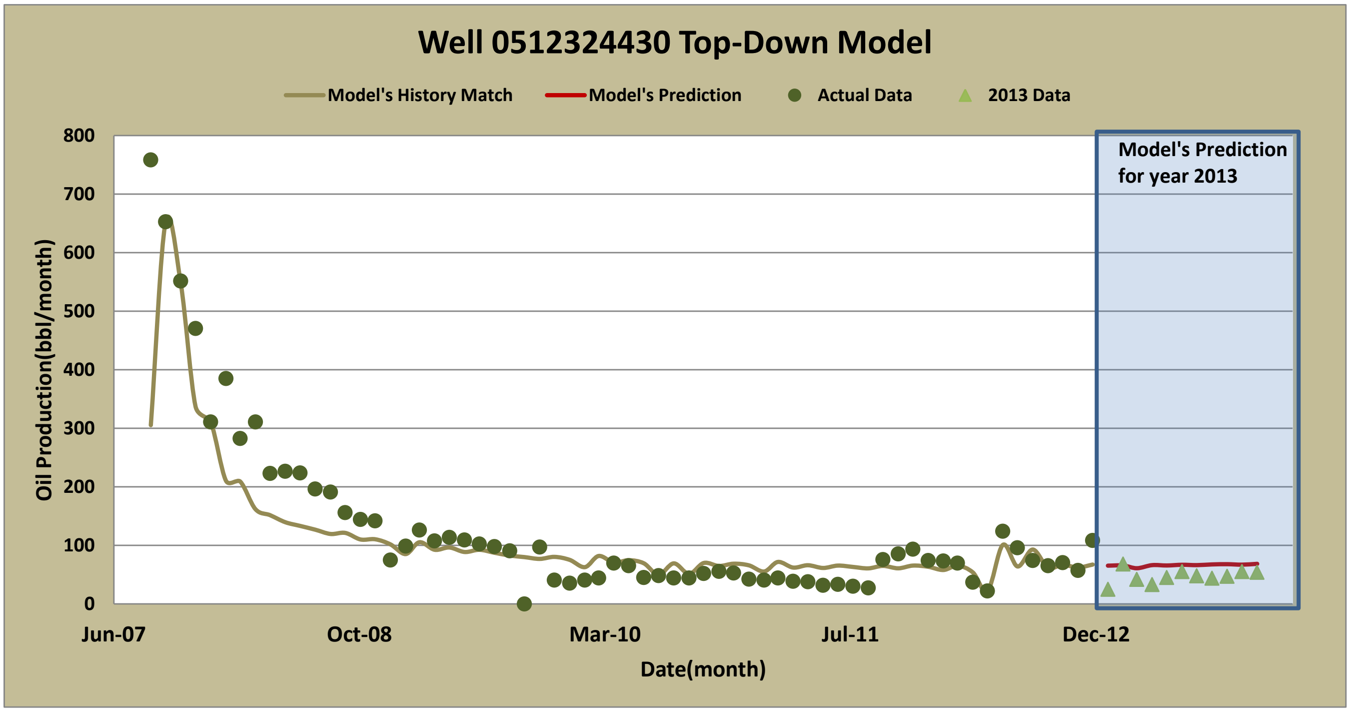


Figure 6: Verification of 11 months production forecast results for well 05112324430- year 2013

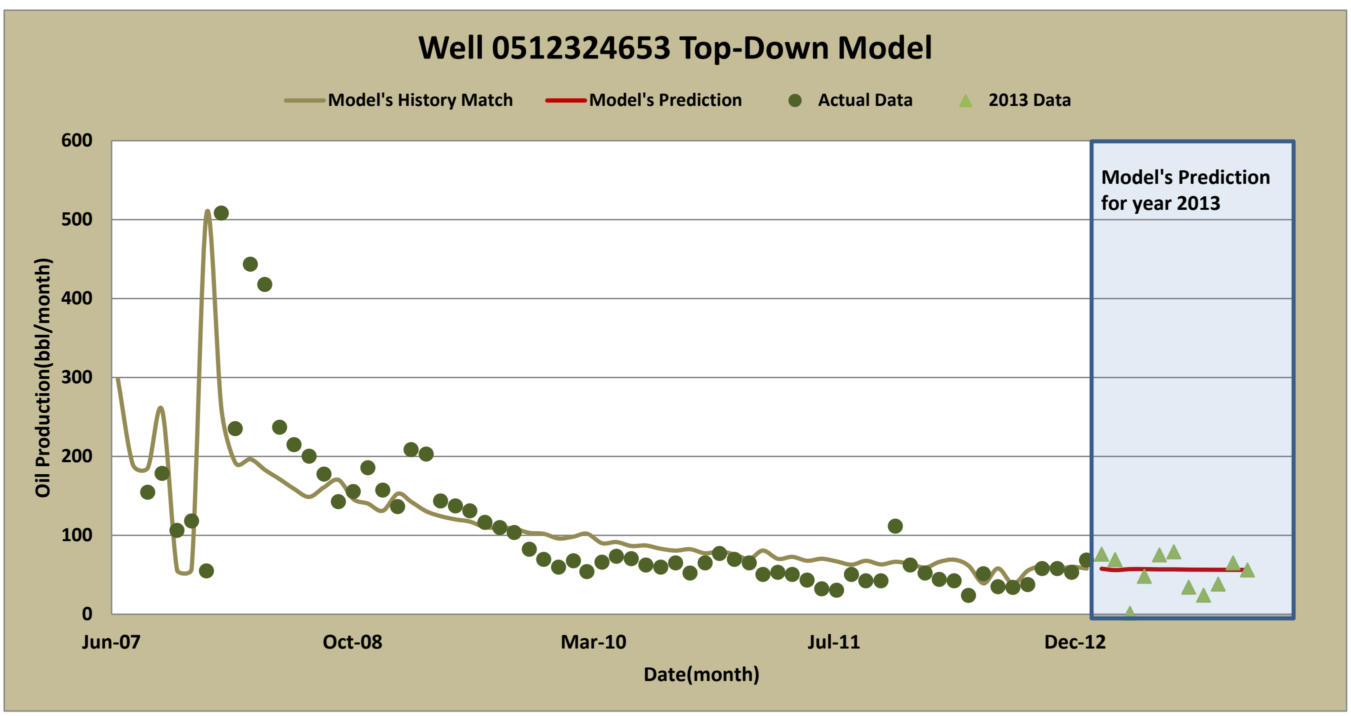


Figure 7: Verification of 11 months production forecast results for well 05112324653- year 2013

The other capability of the TDM is to perform sensitivity analysis. Reservoir and well design properties are uncertain and change in them will definitely have an effect on the production prediction. Using sensitivity analysis, the effect of uncertainty of these parameters on the production forecasting was investigated. Monte-Carlo simulation (a widely practiced method for uncertainty/sensitivity analysis) was used in this study. The advantage of TDM was fast computation time which allowed performing up to thousands production scenarios for Monte-Carlo simulation. Sensitivity of the production forecast to pay thickness value for one well is shown in Figure 8. The Gaussian distribution was considered for pay thickness with mean value of 256 ft and standard deviation of 28ft (maximum and minimum values for this parameter are 385 and 185 ft respectively).

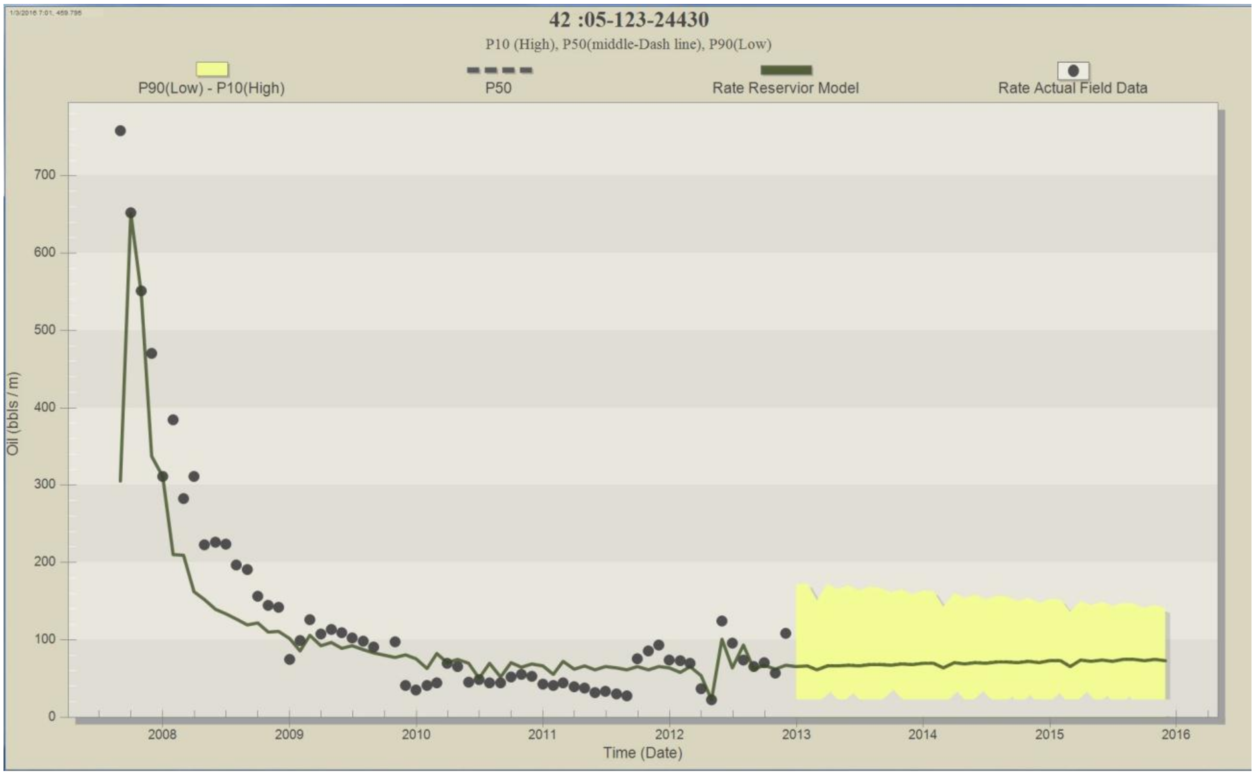


Figure 8: Sensitivity analysis results for well 0512324430 production's forecast subject to uncertainty in pay thickness using Monte-Carlo simulation. The yellow shaded area is the range for the production forecast.

Conclusion

Production behavior of an unconventional asset in Wattenberg Field-Niobrara was analyzed using data mining and pattern recognition technology based on available (public) production history, well design parameters, reservoir properties and operational information. Fuzzy pattern recognition was implemented to categorize reservoir region according to production history. Consequently under-performing wells which could be candidate for re-stimulation operations were identified. Finally a novel approach for the production modelling of all the wells in the asset was introduced .The AI-based model re-generated the production history with acceptable accuracy. This model showed to be a practical tool for production forecast and sensitivity analysis. The outcome of the Top-Down Model (TDM) can provide useful guidelines for reservoir management.

Acknowledgment

Authors would like to acknowledge Intelligent Solutions, Inc. (ISI) for providing the IMAGINE™ software (which was used for data driven analysis) for the case study that were conducted at PEARL group at West Virginia University.

Nomenclature

h = pay thickness, ft
q = oil production, bbl/month
S_w= water saturation. %
φ= porosity, %

References

1. COGCC. 2013. Colorado Oil and Gas Conservation Commission, http://cogcc.state.co.us
2. Esmaili, S., and Mohaghegh, S.D, *Using Data-Driven Analytics to Assess the Impact of Design Parameters on Production from Shale*, SPE 166240, SPE Annual Technical Conference and Exhibition. New Orleans, Louisiana, September 30 - October 2, 2013
3. Finn T.M, Johnson R.C, *Niobrara Total Petroleum System in the Southwestern Wyoming Province*, Chapter 6 of Petroleum Systems and Geologic Assessment of Oil and Gas in the Southwestern Wyoming Province, Wyoming, Colorado, and Utah, By USGS Southwestern Wyoming Province Assessment Team, U.S. Geological Survey Digital Data Series DDS–69–D
4. Khazaeni Y, Mohaghegh, S.D, *Intelligent Production Modeling Using Full Field Pattern Recognition*,SPE Journal of Reservoir Evaluation and Engineering, December 2011
5. Maysami M, Gaskari, R, Mohaghegh, *S.D, Data Driven Analytics in Powder River Basin, WY*, SPE 166111, Annual Technical Conference and Exhibition. New Orleans, Louisiana, September 30 - October 2, 2013
6. Mohaghegh, S.D, *Top Down Intelligent Reservoir Modeling (TDIRM); A new approach in Reservoir Modeling by Integrating Classic Reservoir Engineering With Artificial Intelligence & Data Mining*, Denver Colorado: AAPG Annual Convention 2009
7. Mohaghegh S.D, *Reservoir Simulation and Modeling based on Artificial Intelligence and Data, Mining (AI&DM)*, Journal of Natural Gas Science and Engineering 3 (2011) 697 -705
8. Mohaghegh, S.D, Gruic O,Zargari S, Kalantari A, Bromhal G, *Top Down, Intelligent Reservoir Modeling of Oil and Gas Producing Shale Reservoirs; Case Studies*, International Journal of Oil, Gas and Coal Technology,Vol.5, No .1, 2012
9. Mortiz E.C,Barron N.S, *Wattenberg Field Unconventional Reservoir Case Study*, SPE-152570-MS, Middle East Unconventional Gas Conference and Exhibition, 23-25 January 2012, Abu Dhabi, UAE
10. Paterniti M, Losacano T, *Evaluation of Completion Techniques in the Codell and Niobrara Formations of the Wattenberg Field*, SPE-168771-MS, Unconventional Resources Technology Conference, 12-14 August 2013, Denver, Colorado, USA
11. Sonnenberg S.A, *New Reserves in an Old Field, the Niobrara Resource Play in the Wattenberg Field, Denver Basin, Colorado* , SPE-168682-MS, Unconventional Resources Technology Conference, 12-14 August 2013, Denver, Colorado, USA