SPE-189790-MS

Need for Speed: Data Analytics Coupled to Reservoir Characterization Fast Tracks Well Completion Optimization

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This paper was prepared for presentation at the SPE Canada Unconventional Resources Conference held in Calgary, Alberta, Canada, 13-14 March 2018.

Abstract

In today's data-driven economy, operators that integrate vast stores of fundamental reservoir and production data with the high-performance predictive analytics solutions can emerge as winners in the contest of maximizing estimated ultimate recovery (EUR). The scope of this study is to demonstrate a new workflow coupling earth sciences with data analytics to operationalize well completion optimization. The workflow aims to build a robust predictive model that allows users to perform sensitivity analysis on completion designs within a few hours.

Current workflows for well completion and production optimization in unconventional reservoirs require extensive earth modeling, fracture simulation, and production simulations. With considerable effort and wide scale of sensitivity, studies could enable optimized well completion design parameters such as optimal cluster spacing, optimal proppant loading, optimal well spacing, etc. Yet, today, less than 5% of the wells fractured in North America are designed using advanced simulation due to the required level of data, skillset, and long computing times. Breaking these limitations through parallel fracture and reservoir simulations in the cloud and combining such simulation with data analytics and artificial intelligence algorithms helped in the development of a powerful solution that creates models for fast, yet effective, completion design.

As a case study, the approach was executed on Eagle Ford wells. Over 2000 data points were collected with completion sensitivity performed on a multithreaded cluster environment on these wells. Advanced machine learning and data mining algorithms of data analytics such as random forest, gradient boost, linear regression, etc. were applied on the data points to create a proxy model for the fracturing and numerical production simulator. With the gradient boost technique, over 90% accuracy was achieved between the proxy model and the actual results. Hence, the proxy model could predict the wellbore productivity accurately for any given change in completion design. The operators now had a much simpler model, which served as a plug-and-play tool for the completion engineers to evaluate the impact of changes in completion parameters on the future well performance and making fast-tracked economic decisions almost in real time. The approach can be replicated for varying geological and geomechanical properties as operations move from pad to pad. Although the need for heavy computing resource, simulation skillset, and long run times

was eliminated with this new approach, regular QA/QC of the model through manual simulations makes the process more robust and reliable.

The methodology provides an integrated approach to bridge the traditional reservoir understanding and simulation approach to the new big data approach to create proxies, which allows operators to make quicker decisions for completion optimization. The technique presented in this paper can be extended for other domains of wellsite operations such as well drilling, artificial lift, etc. and help operators evaluate the most economical scenario in close to real time.

Introduction

The current volatility and uncertainty in the oil and gas industry is motivating operators to pursue innovative solutions beyond the traditional compensation and headcount methods that lowers operational costs. To optimize the return on investment in field development campaigns for the unconventional basins, operators have started focusing on solutions to questions such as "Is there an optimal hydraulic fracturing design for my well?" and "What would be the hydrocarbon recovery from my hydraulically fractured well?" etc. Answers to these kinds of questions can significantly lower development costs and can potentially improve production and recovery.

In the oil and gas industry, we accumulate massive volumes of data from the wellsite every day. Although in the last few years the rig count in North America has declined considerably, the resilient industry is already showing an upswing as the rig counts have started to rise in the last few quarters (Figure 1).

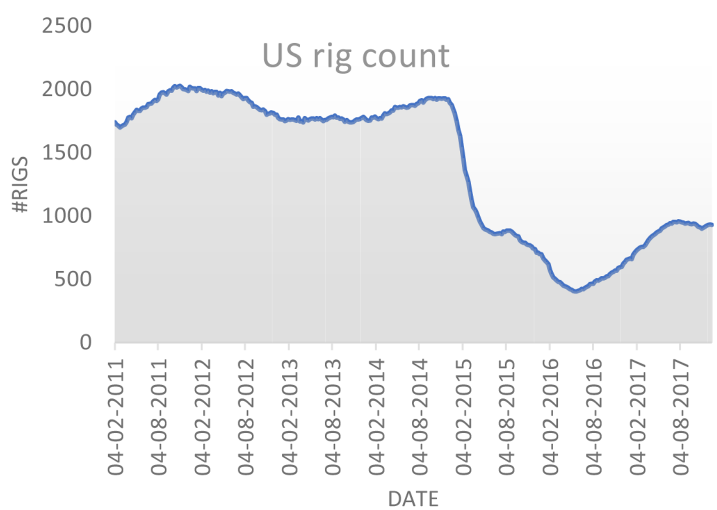


Figure 1—US rig count evolution over time (source Baker Hughes)

Drilling and completing wells in a factory mode has been in the past only focused on well drilling completion efficiency, and little attention was paid to the inefficacy generated in the operations. During the downturn, many operators have realized the need to "get more out of little". Because of this, failure of a treatment or drop of production on a well is no longer looked as a "negative" outcome, but rather as a source of information that is immensely important to diagnose the underlying mechanism of poor performance. Subsurface characterizations, understanding geomechanics, hydraulic fracture simulation, and numerical modeling of the reservoir response have become increasingly popular amongst operators. Unconventional plays possess operating and completion challenges due to the inherent low permeability tight formation, high heterogeneity, and complex fluid-flow mechanisms. With the massive amount of data generated in the last decade or so in unconventional basins, data mining methods could unlock the value and knowledge from the available datasets. Analyzing all the data in real time can reap unparalleled benefits in improving operational efficiency, reducing cost, increasing reliability, and delivering robust forward predictability and forecasting.

However, achieving a platform and infrastructure to create an efficient time-cost-resource planning module through data analytics is a challenging problem for our industry.

Currently, machine learning solutions and artificial intelligence (AI) methods are being tested and implemented in abundance. Earlier examples include predicting density logs from vertical seismic data (Artun et al. 2005), designing drilling fluids using machine learning algorithms (Shadravan et al. 2005), and a top-down modeling approach (Mohaghegh et al. 2011) employing data mining techniques to analyze shale production. Today, we see an exponential increase in the number of techniques to integrate vast amount of high-frequency data and complement physics-based models for decision making. Recent examples, such as classifying hydraulic fractures in the Marcellus shale using machine learning (Anderson et al. 2016), horizontal shale well EUR determination using pattern recognition in the Permian Basin (Gaurav 2017), and data-driven approaches to forecast production from unconventional basins (Cao et al. 2016), are a testimony to that.

The scope of this study covers a unique methodology of applying of data science and machine learning techniques into the world of unconventional reservoir completion modeling. Real-time analysis and prediction of the completion change at the wellsite is only feasible if the completion engineer can work on a fast yet scalable model "proxy" on the wellsite. A model itself is a form of a dataset. A combination of multiple data points—logs, geology, geomechanics, natural fractures, hydraulic fractures, reservoir simulation, finite element simulation, etc. —all lead to create a model. The more data points or simulation results, the better the model is and the more reliable the model becomes to predict the future performance. When such a calibrated model is perturbed in the space of uncertainty of completion parameters, it generates multiple realizations that measure the impact of the variables perturbed. The realizations for a practical field level model can have hundreds and thousands of realizations. If such vast data model and realizations are combined into one single model to measure the impact of change of one variable and predict the resultant objective function, which could be net present value (NPV) or cumulative production, then such single model could be termed a "proxy" model. The use of a proxy model could be multidimensional, starting from extracting quick impact of the completion design change, directionally improving the completion design to get higher production or NPV or even measure the damage to productivity of the wells when the execution on wellsite is compromised and suboptimal design is pumped.

This paper outlines an approach based on data analytics applied on Eagle Ford wells that presents a simple, low data intensive, and exponentially faster predictive proxy model for operationalizing a full-scale numerical simulation.

Machine Learning

Machine learning is a field of study that gives computers the ability to learn without being explicitly programmed (Samuel 1959). It is a branch of AI in which machines learn and adapt through experience, and it can automate analytical model building.

Machine learning algorithms can be broadly classified into supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the algorithm consists of a target / outcome variable, which is to be predicted from a given set of predictors or independent variables. In this process, a function is generated that maps input to desired outputs. The training process is continued until the model achieves a desired level of accuracy on the training data. Some of the examples for supervised learning are regression, decision tree, random forest, and gradient boosting. Because in our approach, we have used supervised learning for model building, we will consider definitions and details of some of the methods here.

A decision tree algorithm builds models in the form of a tree structure (Figure 2). It is built top-down from the root node and breaks down a dataset into smaller and smaller subsets while, at the same time, an associated decision tree is incrementally developed. The result is a tree with decision nodes and leaf nodes. The branching or splitting of a tree is decided by the cost function which is given by

$$\text{Cost function} = \sum [\text{Actual output(y)} - \text{predicted output(y')}] \quad (1)$$

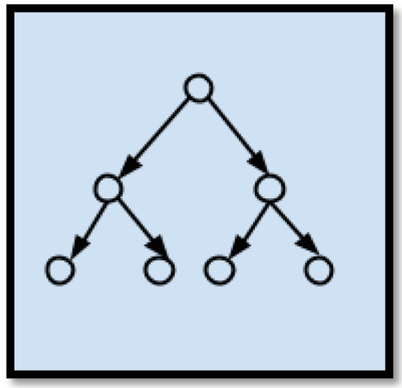


Figure 2—A simple decision tree structure representation

Decision trees are simple to understand, interpret, and visualize. The trees implicitly perform variable screening or feature selection where the root node acts as best predictor.

Decision tree models could come with high variance, which means that small changes in the input training data result in large changes in output. To lower the variance of the models, methods like boosting and bagging are used. Boosting is an ensemble technique in which many weak regressors are grouped to create a strong regressor (Drucker 1997). We have used AdaBoost, also known as adaptive boosting, and gradient boosting methods in our models. In AdaBoost, the training process selects only features known to improve the predictive power of the model, reducing dimensionality and potentially improving execution time. In gradient boosting, it trains many models sequentially where each new model gradually minimizes the prediction error using the gradient descent method, which utilizes an iterative process to find the minimum of a function (Elith et al. 2008). Random forest is another popular decision-tree-based algorithm in which multiple trees are considered rather than using a single tree and an average of outputs is considered. It is useful in dealing with higher dimensionality datasets, and it provides the importance of each variable in the model. We also experimented with linear regression and ordinary least squares method to predict outputs. Neural network models are nonparametric regression methods, which are usually more complex than traditional regression techniques (Shadravan et al. 2015; Cao et al. 2016). Neural network models were also explored in our study and compared with other algorithms.

Methodology

To create a proxy model production prediction, we need to have three key sets of data: a geological earth model, a completion strategy, and a fracture treatment schedule. The goal of the predictive proxy tool is to provide a direct and instantaneous translation of a completion strategy in a simple workflow that is unaffected by the prerequisites of data acquisition, modeling, and recalibration on each well. By exploding the set of completion variables in multiple dimensions and their combinations in one calibrated model, it is feasible to create an envelope for operating parameters as the wellsite operations move from one well to the other. This envelope of results from the sensitivity is encapsulated in a predictive proxy model using advanced analytical tools. Using such predictive proxy model alleviates the need to build numerical models for each well.

The completion parameters sensitized in our model include well spacing, number of stages, clusters per stage, pump schedules (fluid type, proppant type, and proppant size), pump rates, proppant loading, and bottomhole pressure constraints. To build a predictive model for an acreage for the study, a static model must be created for an existing set of well(s) covering the extents and bounds of the drainage area. As a precondition, the static-numerical model must be calibrated for hydraulic fracture geometries in the wellbore and matched to the real production data. After this, a set of sensitivity parameters and their ranges are specified. The sensitivity parameters are then sampled using standard sampling techniques such as Latin hypercube to randomly sample the parametric space within the bounds specified. Advanced sampling algorithms ensure zero duplicacy in sample space for the given number of experiments specified by the user. The number of experiments will depend of the scale of variation for different sensitivity parameters. Typically, if there is large variation in the sample space, then more experiments must be run to capture the entire range of data. A permutation-combination of multiple variables can also be done to include the impact of more than one variable change at a time. The experiments are run using numerical engines and fundamental reservoir engineering platforms on a powerful multithreaded cluster environment in which multiple experiments can run in parallel in a short amount of time. The results obtained from these experiments can be tabulated with inputs (completion sensitivities) and outputs (production results such as best 1-, 3- and 12-month production and 5-year cumulative production). Predictive analytics techniques are applied on this set of results to identify trends and capture the relationship between input and output parameters. These techniques include random forest, gradient boost, linear regression, decision tree etc. The technique that provides the best prediction for the set of data is used to train and create the proxy model. The accuracy of the predictive proxy model can be further improved by using new data and training the proxy for more accurate prediction with the newer data obtained as the drilling and completion cycle evolves on the wellsites. A process flow guide to creating the proxy model is shown in Figure 3.

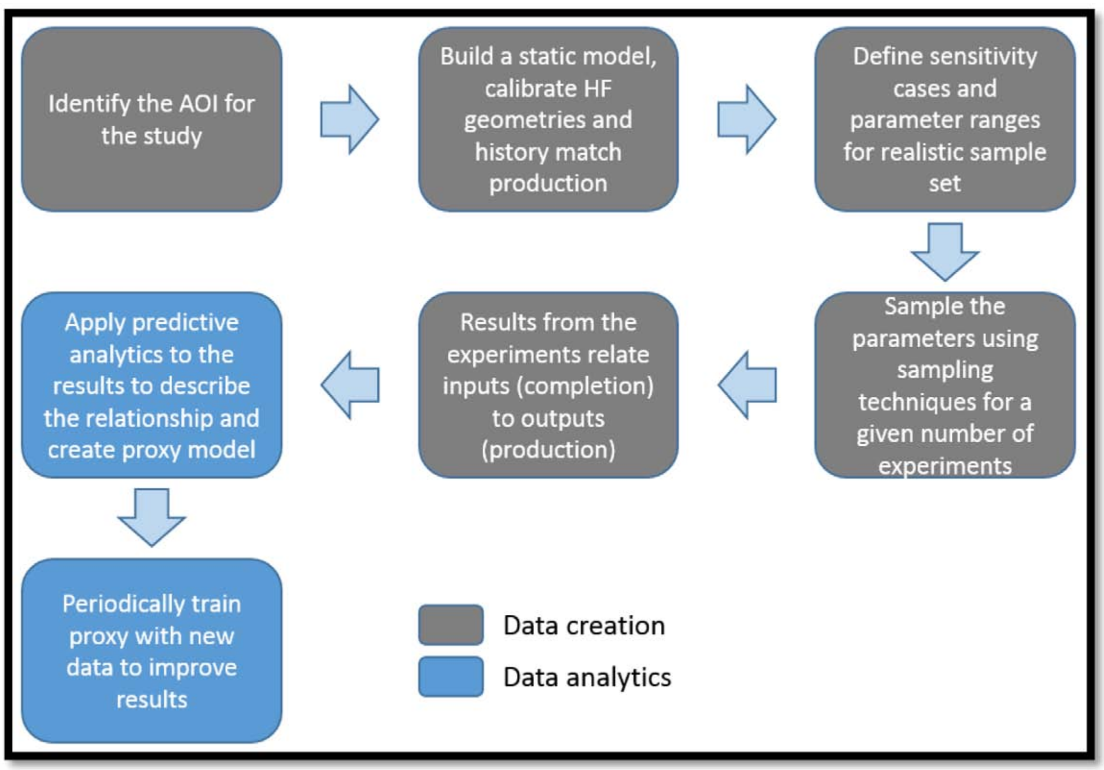


Figure 3—Generic workflow to build a predictive proxy model for completion optimization

After a robust proxy is built, it gives the user a comprehensive predictive tool that allows performing sensitivity analysis on completion designs and pump schedules within minutes. It enables a direct translation of user-controlled parameters such as completion strategy and pump schedules to production performance (Figure 4). The model will work if the geology and petrophysical properties are reasonably similar to the base model that served as the fundamental of the proxy model. As soon as the geology is drastically different, the proxy may need to be rebuilt for the newer area.

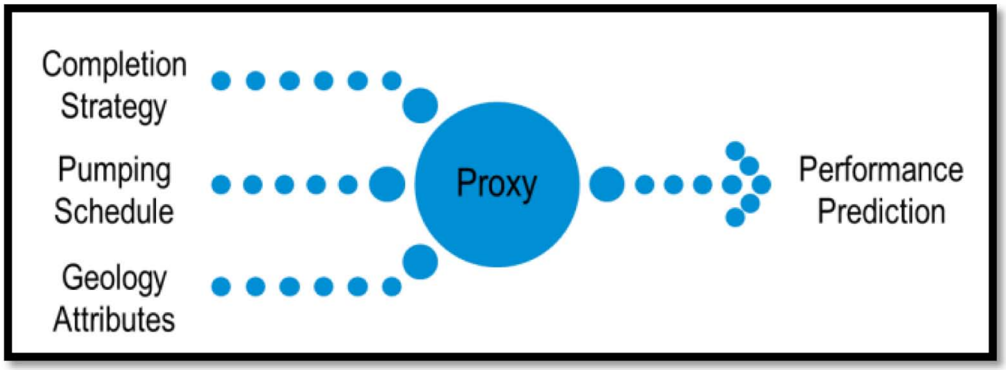


Figure 4—Input and output from a predictive proxy model

Design – Data Creation

A calibrated earth model from the Eagle Ford was used to build a predictive proxy model for the wells that were planned to be completed around the region (Figure 5). The earth model had one candidate well that was fractured with 21 stages and 6 clusters per stage. The lateral length of the well was 5,850 ft, and the true vertical depth (TVD) was 7780 ft. The hydraulic fracture geometries for this well were calibrated using microseismic data and pressure history match. Proppant mass per stage was ~400,000 lbm which translated to 1,435 lbm/ft along the lateral. Pump rate in the base case (original well completion) was 90 bbl/min. Presence of natural fractures was incorporated in the earth model as a discrete fracture network generated using the image log data available in the area of interest (AOI). Complex hydraulic fractures were simulated using a complex fracture model (Wu et al. 2012) (Figure 6). As a calibration step, the hydraulic fractures were pressure matched with the actual treatment data. The complex hydraulic fractures were gridded in an unstructured grid pattern (Figure 7). The grid carried the footprint of hydraulic fractures and the proppant distribution. Numerical simulation was made on this grid to perform production history match and production forecast (Figure 8). Reservoir calibration was made through altering properties such as reservoir permeability, relative permeability, and fracture permeability to match the observed production data. This calibrated model formed the base case and a starting point for creating the proxy model.

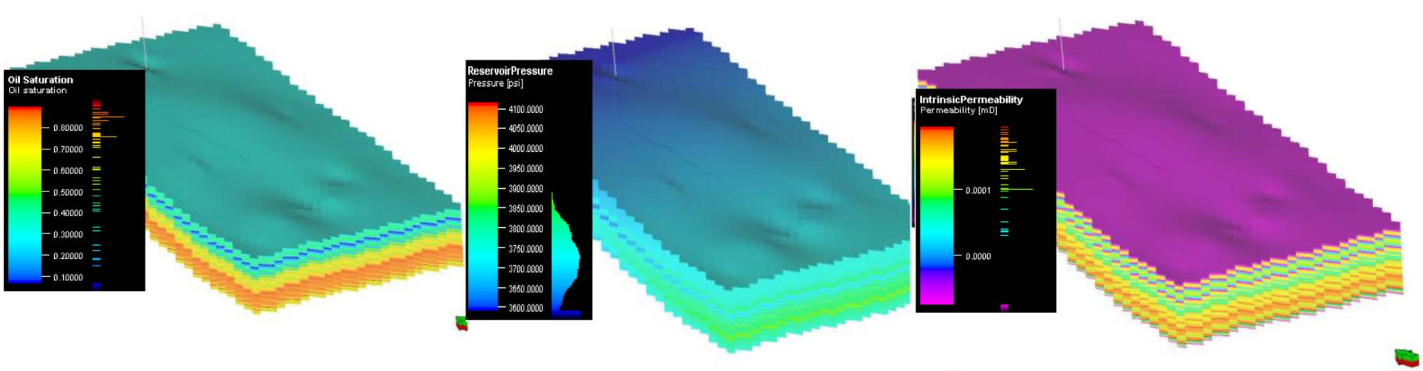


Figure 5—Static earth model with petrophysical and geomechanical properties

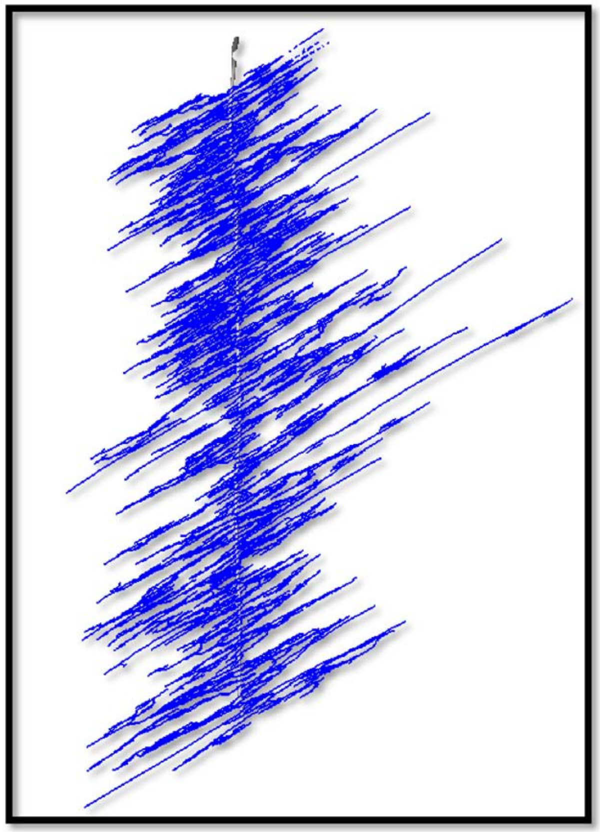


Figure 6—Hydraulic fracture network around the wellbore

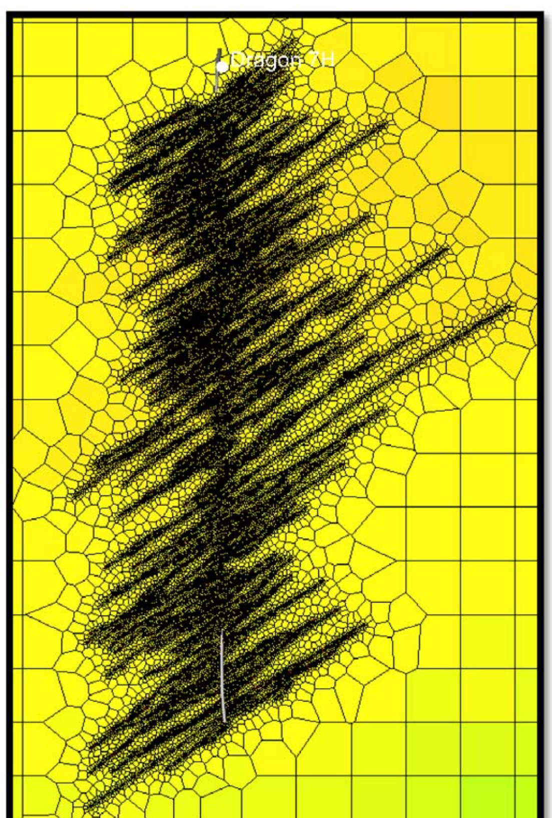


Figure 7—Production grid for numerical simulation

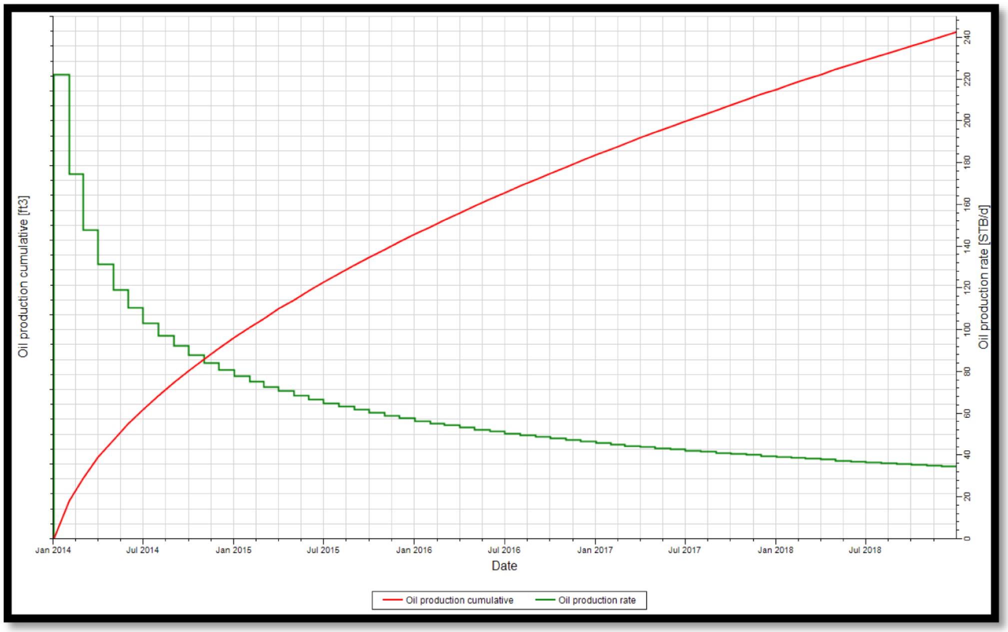


Figure 8—Production simulation and forecast

For generating the analytics dataset, eight different parameters were varied: number of stages, clusters per stage, fluid type, proppant type, proppant size, proppant amount, pump rate, and flowing bottomhole pressure (BHP) (Figure 9). The range of variation for the sensitivity parameters was chosen around the inputs in the base case and considering the practical values that can be applied in the wellsite. Figure 9 shows the input data ranges and the expected outputs from the model. The fracturing fluids ranged among slickwater, linear gel, and crosslinked gelled fluids at different gel loadings. The different fluids and gel loadings had a direct impact on attaining varied viscosities of the fracturing fluid. Fracturing fluid viscosity can have a considerable impact in the hydraulic fracture geometry and therefore productivity. The proppant type variations were simple white sand, resin-coated sand, ceramic sand, and resin-coated ceramic sand. Proppant sizes captured smaller to large size proppants including 100-, 40/70-, 30/50-, 20/40-, and 12/20-mesh sizes. To capture the variability in proppant types, proppant sizes, and fluid types, 60 different pump schedules were generated to capture various permutations and combinations of proppants and fluids that could be pumped.

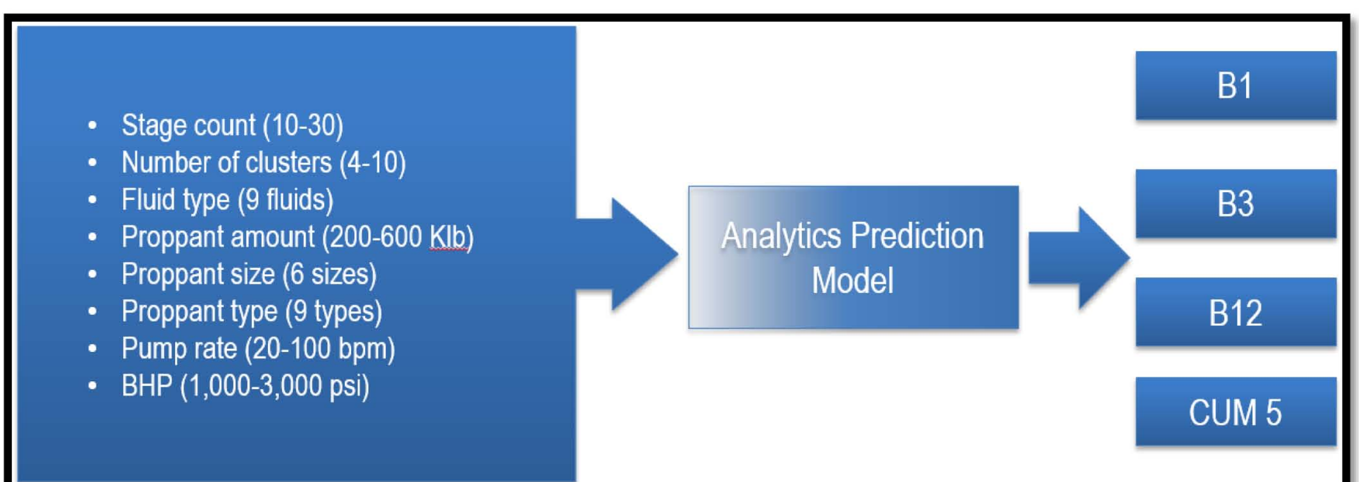


Figure 9—Sensitivity parameters and the outputs from the predictive model

Further variation in pump schedules was achieved by changing the proppant/fluid ratio for each pump schedule. This was varied between 0.47 lbm/gal to 1.42 lbm/gal to ensure that proppant mass per stage varies between 200,000 and 600,000 lbm. Based on the number of stages, the proppant per foot was different for each experiment. Figure 10 shows the ranges for sensitivity parameters for the 2000 experiments. The density of points in the range of variable parameters indicates comprehensive coverage of the sensitivity parameter. Bottomhole pressure, pump rate, pump schedule number, and proppant/fluid ratio were sampled using a uniform distribution whereas number of stages and clusters per stage were sampled using a discrete distribution. The Latin hypercube sampling technique was used to assign a value of each sensitivity parameter to the 2000 experiments. For these 2000 cases, the objective was to derive the production performance at different timeframes through numerical simulations. Hence, a complex hydraulic fracture simulator, explicit hydraulic fracture gridder, and the numerical reservoir simulator were all coupled together to run in single shot without having any manual intervention. The engines were not only optimized for improved performance, but also were parallelized for allowing multiple simulations to be carried out in parallel. The 2000 simulation/sensitivity scenarios were run in parallel using the improvised simulation engine in a batch of 160 cases at a time to obtain the results within one week's time frame. The cluster used for these experiments consisted of 40 nodes, and each node had 16 processors. Each simulation involved complex hydraulic fracture simulation incorporating the presence of the natural fractures, production gridding of the hydraulic fractures, and production simulation under production (minimum flowing BHP) constraint. At the end of the simulation, each case produces results for best 1-month, best 3-month, best 12-month, and cumulative 5-year production of oil and gas.

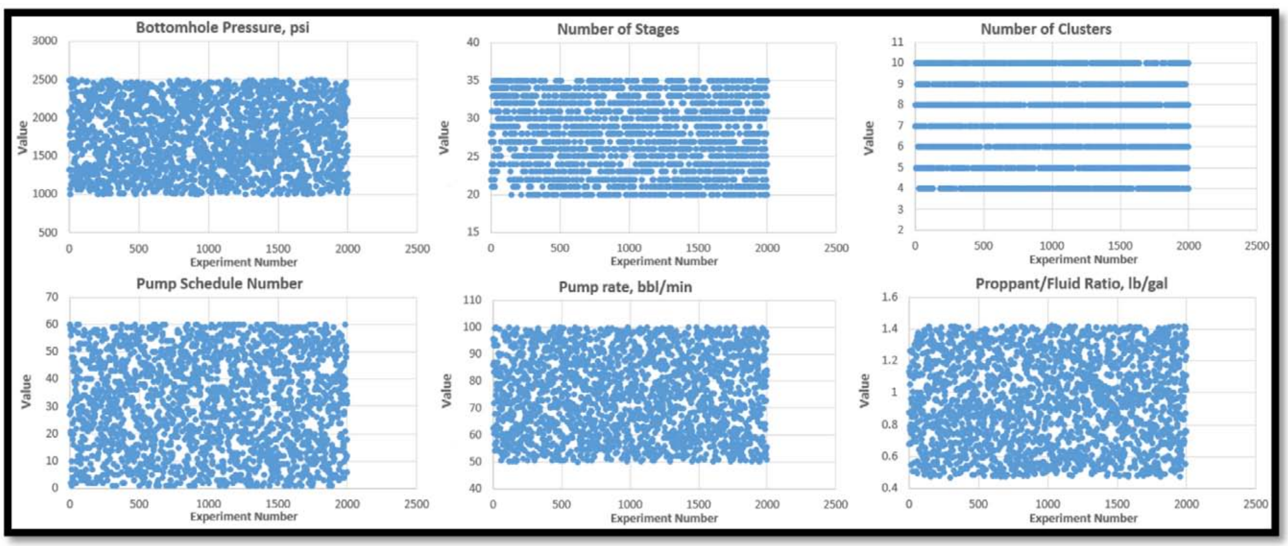


Figure 10—Variation of sensitivity parameters for 2000 experiments

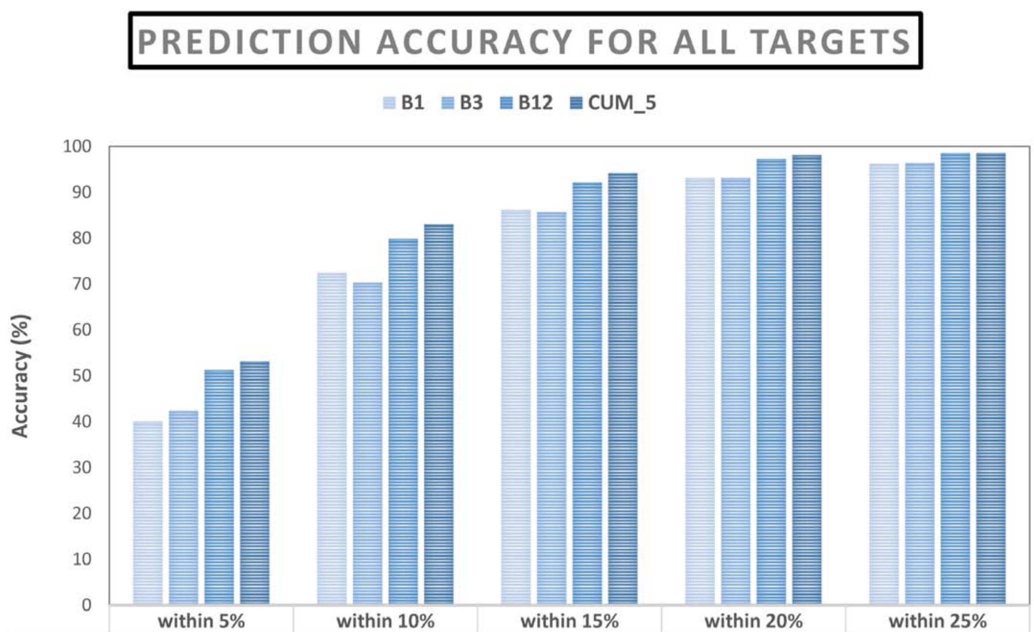
Results – Data Analytics

The 2000 simulation results of hydraulic fractures and resulting production served as an input in the form of a tabulated report. This report purposefully served as the "big data" for analysis with having direct response of input parameters on the output (hydrocarbon production). On these big data, advanced AI and data analytics techniques can be used to create a predictive proxy. It is also to be noted here that although 2000 experiments were performed, some experiments failed to complete due to numerical convergence at either fracture simulation or numerical reservoir simulation. Therefore, 1867 experiments contained valuable results to feed into the process for creating the proxy. The data analytics algorithms were tested on 1572 experiments' results. A 70:30 train:test sample split was used, which means that 70% sample were used to train the dataset and 30% was used for prediction. Ten-fold cross-validation was used, which ensures that all the observations are used for both training and testing. Table 1 shows a comparison of different analytics approaches used on the output dataset and shows the prediction accuracy of each. The data in Table 1 capture the predictability of 20-year cumulative oil production. It was found that the gradient boost technique resulted in the highest prediction accuracy on this dataset. Therefore, the gradient boost method was chosen for further analysis of results for creating the predictive proxy model.

Table 1—Comparison of various data analytics approaches for predicting 20-year cumulative oil production

Approach	Collinearity of Prediction	within 5%	within 10 %	within 15%	within 20%	within 25%	Predicted Sample Length
RandomForest	77.20%	34.84	62.07	80.09	90.37	95.84	1572
GradBoost	91.00%	52.73	82.1	93.44	97.04	98.77	1572
LinearRegression	84.90%	35.78	69.55	87.7	93.97	97.17	1572
DecisionTree	77.00%	33.91	61.94	79.43	90.77	95.71	1572
AdaBoost	82.00%	35.38	65.55	84.91	92.65	96.38	1572
MF OLS	84.10%	41.35	69.72	87.15	94.98	97.27	1572
MF NN	87.20%	45.4	76.07	90.53	96.61	98.23	1572

Figure 11 shows the prediction accuracy for the four different target outputs using the gradient boost approach. It can be observed that accuracy increases when the margin of error increases. For example, for cumulative 5-year production, only 53.18% of the predictions are within 5% of the target, whereas 98.6% of the predictions were accurate within 25% of the target.



	within 5%	within 10%	within 15%	within 20%	within 25%
B1	40.08	72.52	86.13	93.13	96.18
B3	42.37	70.36	85.75	93.13	96.44
B12	51.27	79.90	92.24	97.33	98.60
CUM_5	53.18	83.08	94.27	98.09	98.60

Figure 11—Summary of prediction accuracy with Gradient Boost

While creating the proxy model, it was found that not all the parameters had equal impact on production. A tornado chart (Figure 12) depicts the importance of the parameters in the prediction. Whereas stage length, number of clusters, and proppant amount had most dominating effect, proppant size and type of proppant had minimum impact.

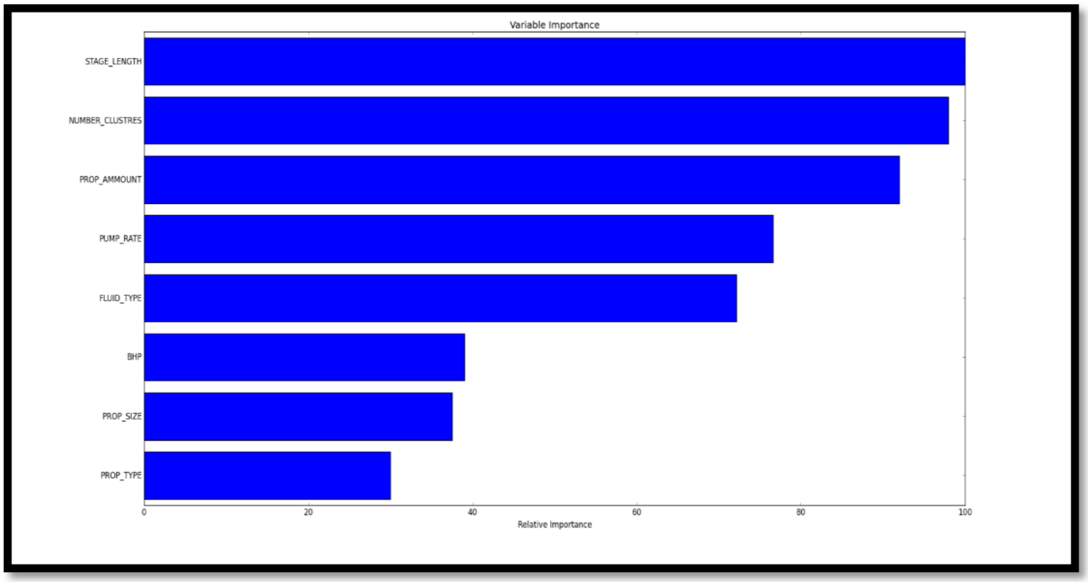


Figure 12—Tornado chart for relative importance of completion variables on the final prediction

Figure 13 shows the actual versus prediction results for best 1-month (B1), best 3-month (B3), best 12-month (B12), and 5-year cumulative (Cum_5) production using 471 samples, which represents 30% of the sample size. Actual production is on the X-axis (simulation result), and predicted production of oil is on the Y-axis (predictive proxy model result). After a model is trained and through the process shown above, it is ready for prediction of results at any sample point that lies within the range of the predictive proxy model.

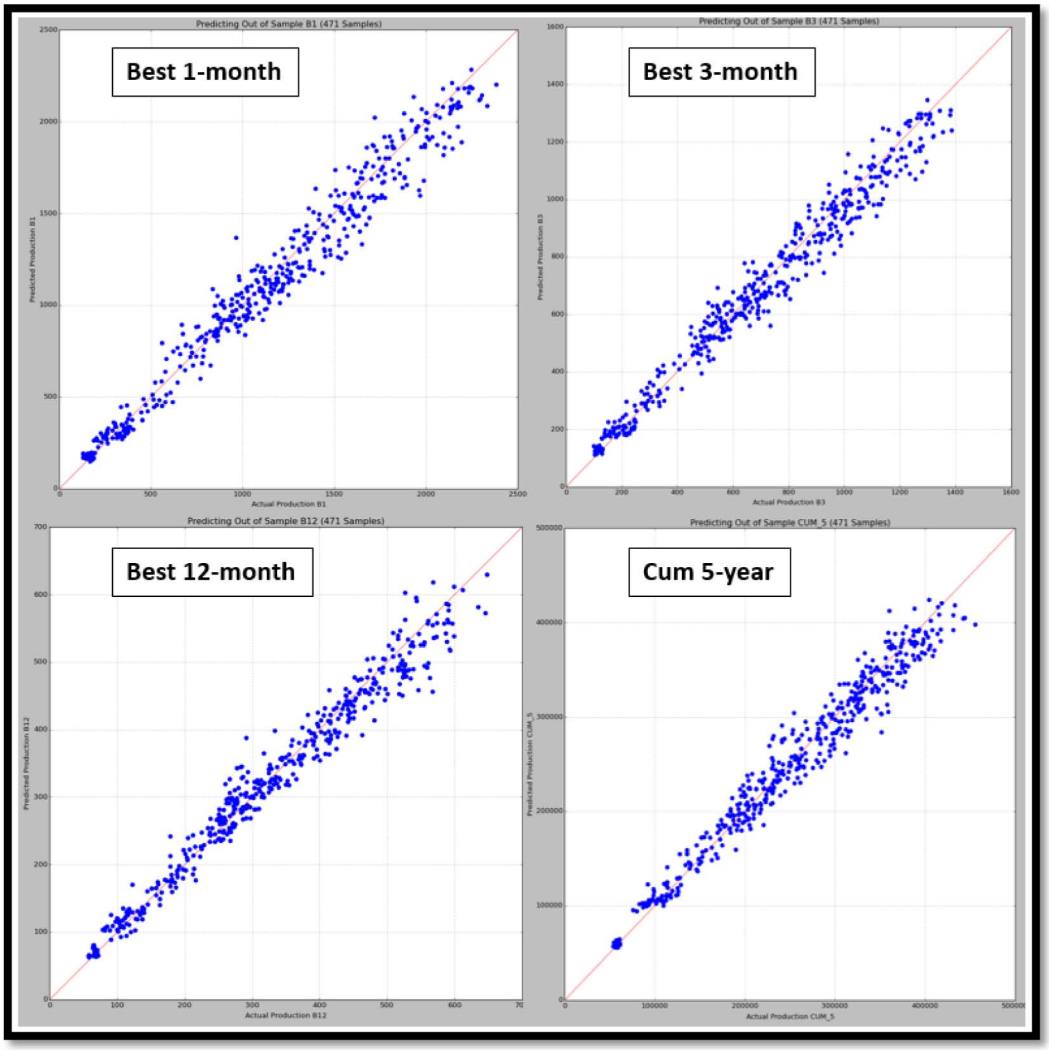


Figure 13—B1, B3, B12 and cum 5-year actual versus prediction for 471 samples (30% of the sample size)

Applications

The predictive proxy model created in this exercise was used to evaluate the designs of the future completions planned in the area. Hydraulic fracture design in the offset wells (Figure 14) completed in the same area of interest (AOI) for which the proxy model was created needed no numerical modeling to predict the performance. Using the proxy-based predictive model provided a more engineered mode of completing the wells in "factory-mode" rather than using copy-paste design. Simply plugging in the completion and pump schedule parameters can provide the resulting production from the well completion

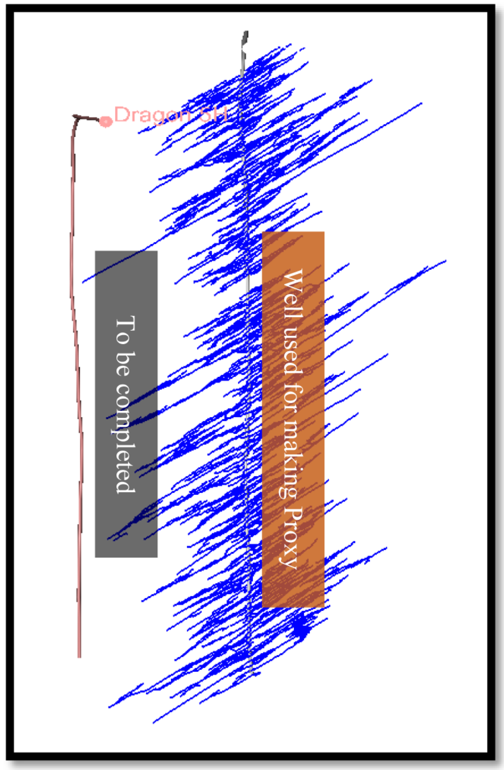


Figure 14—Well used for Proxy and offset well that derives completion change using the proxy model

In addition, the operational completion engineers could use it as a "plug and play" tool to determine the impact on production when a completion design change (variation in amount of fluid, proppant volume, pump rate, etc.) was made on-the-fly in the wellsite. Many jobs on the wellsite do not go as planned, and often, completion engineers encounter screen-out situations leading to understimulated rock volumes. A nearly real-time determination of the impact of the ineffective stimulation due to operational failure could be made. A long cycle of numerical simulation and look-back post-mortem analysis using a conventional modeling approach for any failed jobs would require much longer time and resources than using a proxy-based predictive model.

Field engineers can decide operational changes in wells completed in unconventional reservoirs with greater confidence since most of the operators are still trying to find the recipe and combination to optimize well completions (number of clusters, lbm/ft design, number of stages, etc.) and well spacing. Predictive proxy-based mode allows to fast-tracking the full cycle of optimizing unconventional reservoir completion in an efficient and effective platform.

Management had a more robust tool to decide the completion directionality for operating a lease. With having one calibrated model, the proxy model based on data science can enable predictions of the future performance, return on investment, and recovery from the asset to be made quickly.

Although the application has been demonstrated in the field of completion engineering, the workflow is equally applicable in other areas where simulation and modeling on one wellbore can serve as input for creating a predictive proxy to be applied for the future wells. Artificial lift, drilling, and numerical modeling could be potential areas for application of similar approach.

Conclusion

Proxy modeling is not a new concept and had been in the industry for many years. However, the workflow and approach described in this study are unique in creating "synthetic" big data out of simulations based on fundamental science honoring rock physics, fluid flow, hydraulic fracture propagation in complex environments, and numerical reservoir simulation. Using parametric explosion of sensitivity parameters, the synthetic big data use for creating a proxy model to predict hydraulic fracture performance in unconventional reservoirs has been demonstrated successfully.

This proxy model allows engineers to design the completions and predict the response to production and NPV almost real-time for the wells to be drilled and completed in the proximity of the base model. As long as the geology does not significantly vary, the directional response for optimum well completion can be derived from the proxy modeling much faster than full field/pad scale modeling and simulations converting the decision making a matter of minutes instead of days and months.

The specific learnings and observations from application of the workflow on the base model from Eagle Ford in this study are:

1. A calibrated model is a fundamental step to create a reliable predictive proxy.
2. The Predictive proxy models had an excellent predictability on all four targets of B1, B3, B12 and Cum_5
3. Higher accuracy is achieved for long term predictions (Cum 5 > B1)

The predictive proxy has a wide variety of application amongst the domains of completion engineers and management to undertake more informed decision making and completion optimization. Similar approach in the fields of drilling, artificial lift, production and numerical simulation can be applied to speed the model-to-decision cycle.

Acknowledgements
We would like to thank Schlumberger and EP Energy Corporation for allowing us to present this work.

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