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How Deep Learning can Provide Consistent Improvement on ROP Through Different Drilling Environments

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Abstract

Using multidimensional analysis of historical drilling parameters combined with deep learning (DL) techniques, consistent ROP improvement in different drilling environments can be achieved. This discussion is focused on how offset well data can be properly analyzed and modeled to generate valuable outputs that improve not only drilling performance but also sustainability across the entire upstream.

The workflow starts by history-matching comparable wells based on different variables such as well shape, hole size, wellbore design, downhole tools, etc. This first step is heavily based on the collaborative effect between subject matter experts working closely with data scientists to ensure only the right variables that are known to effect ROP are used and that a stable and scalable model can be aheived for different drilling environments. The process then moves to the data scientists where using multilayer perceptron models and random forest techniques allow determination of the ranking of features that affect ROP the most. The top tier features are then used to train a machine learning (ML) model to determine the average threshold of historic performance. Once the threshold is known, ML is again used to determine the optimal combination of drilling parameters that yield above-average ROP performance. This process is then repeated for each formation type and hole size. The performance range of the historical offset well data is then reviewed to determine the recommended threshold and fl score to output the highest modeling performance and the output parameter recommendations are then uploaded on a dashboard for real time guidance.

Introduction

After decades of drilling experience, the Oil and Gas industry has managed to optimize processes based on scientific analysis, engineering studies, growth of personnel expertise and technology development. These processes have led to drilling operations that are faster and safer. Nonetheless, operators and service companies alike are seeking the next step of improvement through digital transformation initiatives.

The adaptation of big data and ML techniques allow for analysis of very large amounts of historical and real time (RT) data to determine the most suitable execution path that provides the best results. These models can include data available from a specific drilling location, a field, or an entire basin. The automation of the learning process of the models is key to accomplish the advanced detail necessary when dealing with a large amount of data.

The use of machine learning (ML) techniques as the advanced data modeling approach allows different advantages such as faster response, high accuracy in the analysis, automated model re-training, versatility at handling large amount of data and above all-the identification of the drivers that affect positively or negatively the drilling performance.

ML models also evolve with time through the continuous re-training as new data becomes available. The incoming real-time data allows the model to adapt to new conditions and to recognize promptly the conditions and results previously experienced. In consequence, it is possible to plan and execute a strategy that increases the drilling efficiency of the upcoming projects.

Exploratory Analysis

The drilling operations have procedures, tools, and cutting-edge sensors that produce large amount of data. That output data can be integrated methodically to artificial intelligence (AI) models. The nature of the data along with its considerable size allows deep learning models to be built to obtain faster, more accurate results with the possibility to be re-trained. This has an important impact when making decisions in real-time such as risk mitigation and project planning.

An optimum drilling process includes several stages from gathering and analyzing historical information, selecting the drilling location, selection of the drilling rig, defining the well trajectory, and determining the proper downhole tools to use. Due to the variability of the input/output during these stages, the deep learning algorithms present an advantageous approach to consistently increase the performance.

Most companies in the Oil and Gas Industry gather drilling parameters such as WOB, MSE, RPM, Flow Rate, Torque, SPP. These parameters are associated to a well design, architecture, type of downhole tools, and geological conditions. The historical behavior of these parameters from a project are normally extrapolated to future projects. Normally, the interaction of two or three of these parameters are analyzed to try to predict a future behavior. This analysis is time consuming and sometimes is not easy to perform. Because of this, a holistic analysis that include a multi-layered interaction is rarely seen and therefore the recommendations can often lack relevance to the increase of the operational efficiency. Therefore, some questions may still be unresolved: Why is there so much variability of the ROP within the same formation? Why is it so complex to implement a process that can dramatically improve the drilling performance? How can we secure a process that permits a continuous learning of previous experiences?

The model presented in this paper has demonstrated to yield a significant increase in the ROP while improving the accuracy through continuous learning. Also, the implementation of this model is scalable to other drilling conditions and environments. The model involves random forest for variable ranking and multilayer perceptron technique to determine the variables that affect the rate of penetration the most. This in combination with subject matter expert feedback, cross-checked with physics-based results, has confirmed high accuracies in the behavior of the prediction.

A case study where an optimization model was implemented for the Eagle Ford and Austin Chalk formations is presented. The three main milestones identified include:

Each project is unique and different in its kind: Therefore, the identification process to determine the variables that affect the drilling process the most varies along the specific nature of each well.

The optimization process is best aheived through a multi-dimensional analysis: This analysis includes variables that are controlled by the driller or drilling engineer (such as drilling parameters), and also should consider those variables that cannot be controlled or seen from surface. The ML process should though only suggest variables that can be controlled from the rig floor in real-time. Because of this, some accuracy may be sacrificed.

The model must be able to be replicable and scalable.

Description of the construction and implementation of the optimization model

An exploratory analysis of the information was implemented to identify and correlate the common problems that affect the efficiency of ROP among wells with similar characteristics such as trajectory, mechanical architecture, BHA, rock type, and the geology. An analysis of the events that affect the ROP was taken from a sample of 18 wells. From those samples, 12 wells possessed similar characteristics.

Figure 1 presents the ROP distribution in the field study through the different formations, starting with Wilcox Formation and drilling the lateral section with the target formations Austin Chalk and Eagle Ford. A low consistency in the drilling performance was identified across all the formations studied. The variability in the rate of penetration represents an important challenge among operators and hence-the motivation behind the study to be conducted. As much a consequence, this ROP variability grants a unique opportunity for the improvement of future wells.

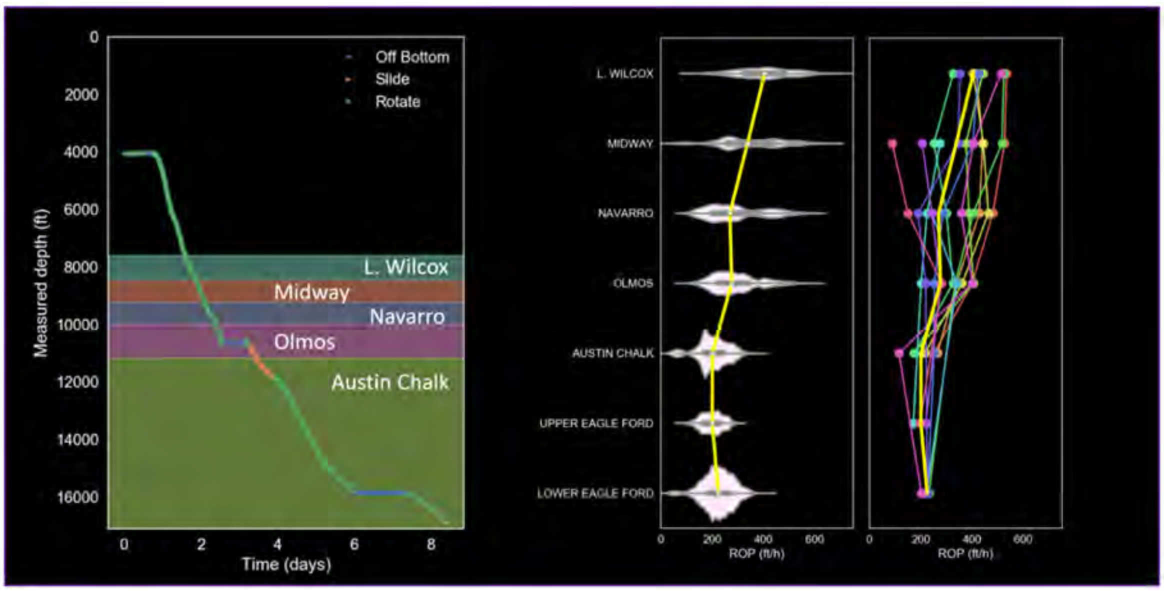


Figure 1—ROP distribution

Evaluating the ROP performance becomes a classification problem with a binary outcome representing above or below the average ROP performancee for given formation and bit size. The observed ROP and the combination of drilling parameters are used to train the ML model as seen in Figure 2.

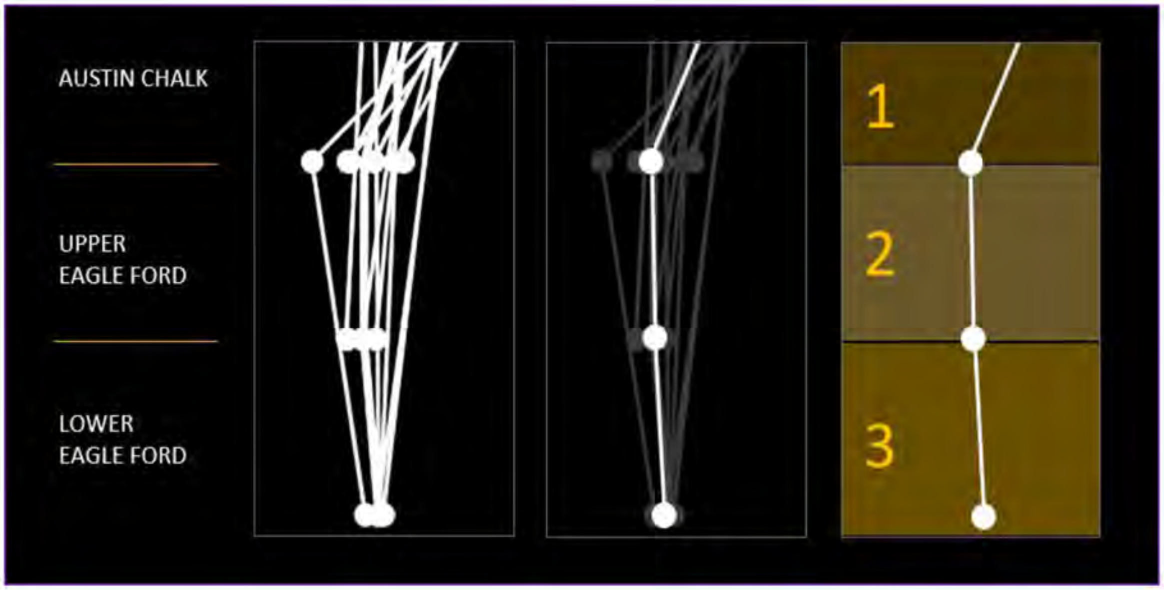


Figure 2—ROP classifacation

During the initial scope of work, the average ROP (P50) was established as a threshold to ensure a balanced and stable model with enough data density for both above and below the threshold. Once the desired performance (P50) was determined, other factors that affect the ROP performance for specific well conditions were included to the analysis. This process yielded a ranking of the variables that historically affect the most the ROP outcome Figure 3. These variables are determined based on the importance from randon forest analysis, the importance ranking is unitless, the higher the value, the more important features are. In more detail the importance of a feature is computed as the normalized total reduction of the impurity criterion brought by that feature (averaged across multiple trees).

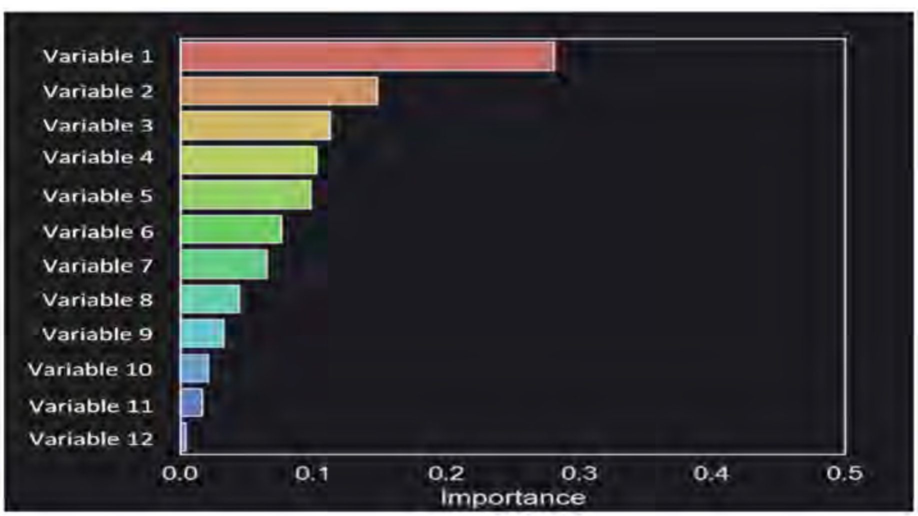


Figure 3—Feature Importance Ranking

Those variables that produced a negligible impact on the ROP performance were clustered to produce the minimum number of variables that generates a considerable impact on the performance and a higher accuracy of the model prediction.

Implementing this methodology allowed to produce a model prediction accuracy above 93% across the Austin Chalk formation with a bit size of 8 ¾-in. The accuracy is significatively high considering that the sample size was relatively small for training purposes.

Once the desired ROP performance was established (P50) and the variables that affect the model ranked, the optimization model was built using artificial neural network (ANN) to determine the suitable combination of drilling parameters that yielded the highest ROP values (above threshold).

These suitable combination of drilling parameters are gathered by formation type, bit size, BHA, and bit type and presented as the suggested parameters to follow for wells with similar conditions to achieve a consistent improvement of the ROP Figure 5.

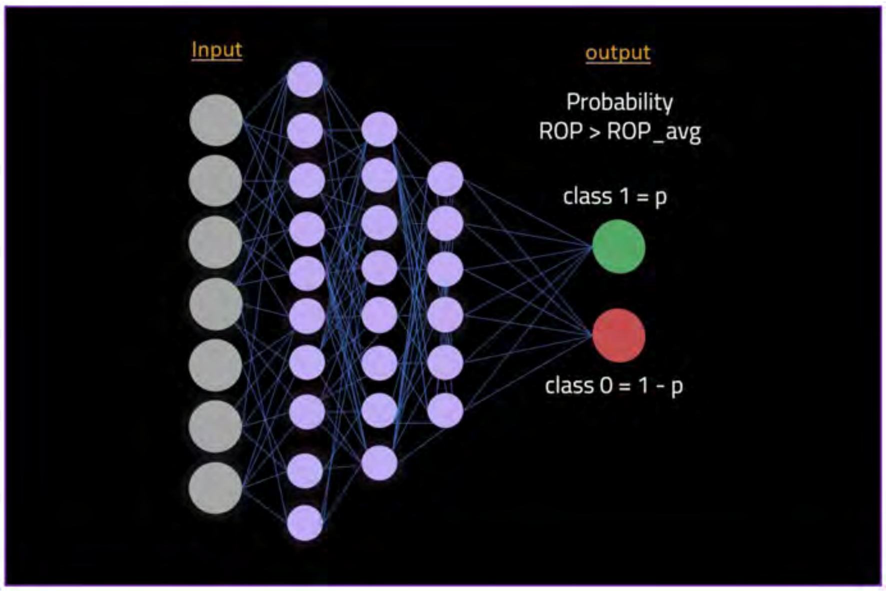


Figure 4—ANN

Well	Target Formation	Mean Accuracy (%)	Schedule Accuracy (%)
Well A	Austin Chalk		
Well B	Austin Chalk		
Well C	Austin Chalk		
Well D	Austin Chalk	93.7	74.5
Well E	Austin Chalk		
Well F	Austin Chalk		
Well G	Austin Chalk		
Well 1	Upper Eagle Ford		
Well 2	Upper Eagle Ford	89.5	76.7
Well 3	Upper Eagle Ford		
Well 4	Lower Eagle Ford		
Well 5	Lower Eagle Ford	84.5	56.3
Well 6	Lower Eagle Ford		
Well 7	Lower Eagle Ford		

Figure 5—Accuracy Results

Some of the combinations can be followed only in ideal conditions mathematically speaking. The focus of the methodology presented in this paper focuses on transferring the model output of suitable drilling parameter combinations in the form of road maps with boundary conditions to be modified at the rig floor by the driller or the person in charge of the drilling operation without affecting significatively the model accuracy. If the road maps are followed, the model predicts a higher-than-average ROP performance.

The validation process consisted in a series of simulations named variations 1D, 2D and 3D. These simulations were run based on the number of variables that could be evaluated and analyzed. These variables include those parameters that can be modified from the rig floor and that has yielded at least the ROP performance desired Figure 6.

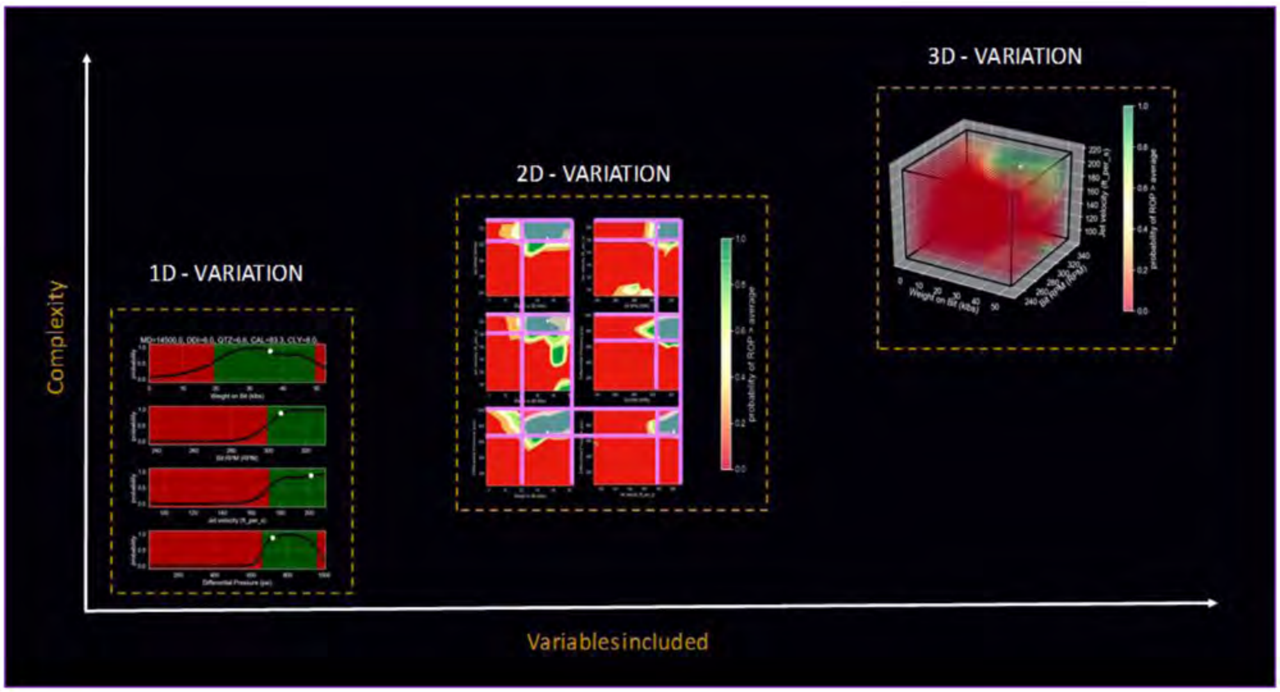


Figure 6—Simulations

After the validation process, the suitable combination of parameters that can be modified from the rig floor that has yielded high ROP and accuracy are synthetized in the form of "envelopes" or parameters roadmap per formation, BHA, bit size, and well trajectory Figure 7. As part of the control measurement for the ROP performance, the association between Mechanical Specific Energy (MSE) vs ROP represents in a quick view how efficient is the optimization process suggested. Thus, the optimization process is successful when low MSE and high ROP values are consistently achieved during the drilling process.

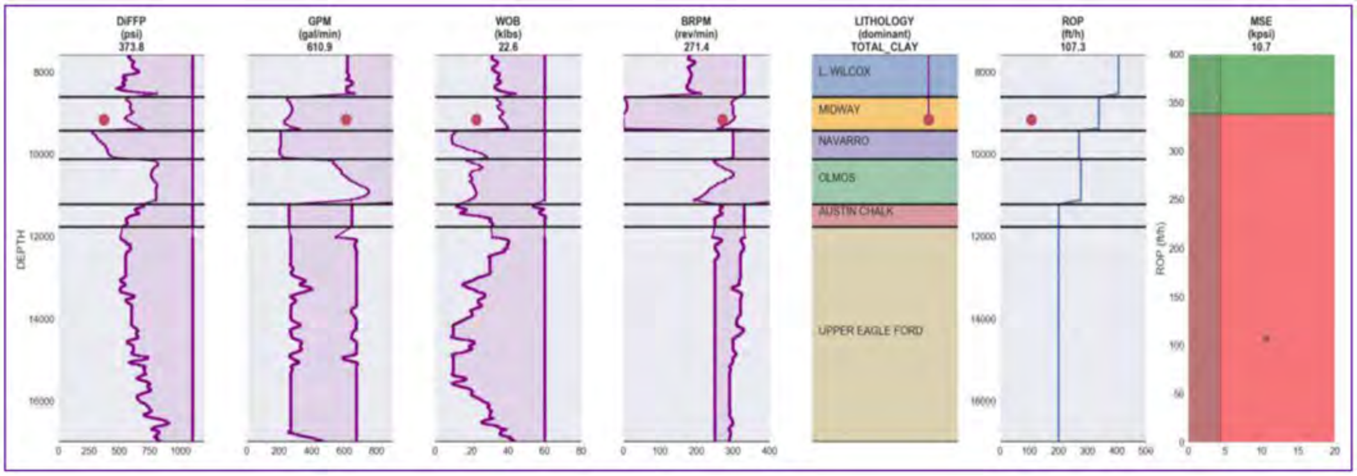


Figure 7—Envelopes

These envelopes or road map parameters are uploaded in an interactive platform that integrates real-time data from the well being drilled and the AI models described before. The interface allows the person responsible for the drilling process to modify the drilling parameters on the fly to achieve above average ROP. Additionally, the interface generates visual alerts that inform the user when the parameters are not being followed or when the drilling efficiency is suboptimal Figure 8.

Figure 8—DO Dashboard

The objective of the model is to predict the expected behavior of the ROP for the well being drilled and to determine the increment proportion in the ROP if the parameter combinations are followed. Forecast of the performance can be accomplished and the model re-trained with new data, permitting the enhancement of the model to future projects Figure 9.

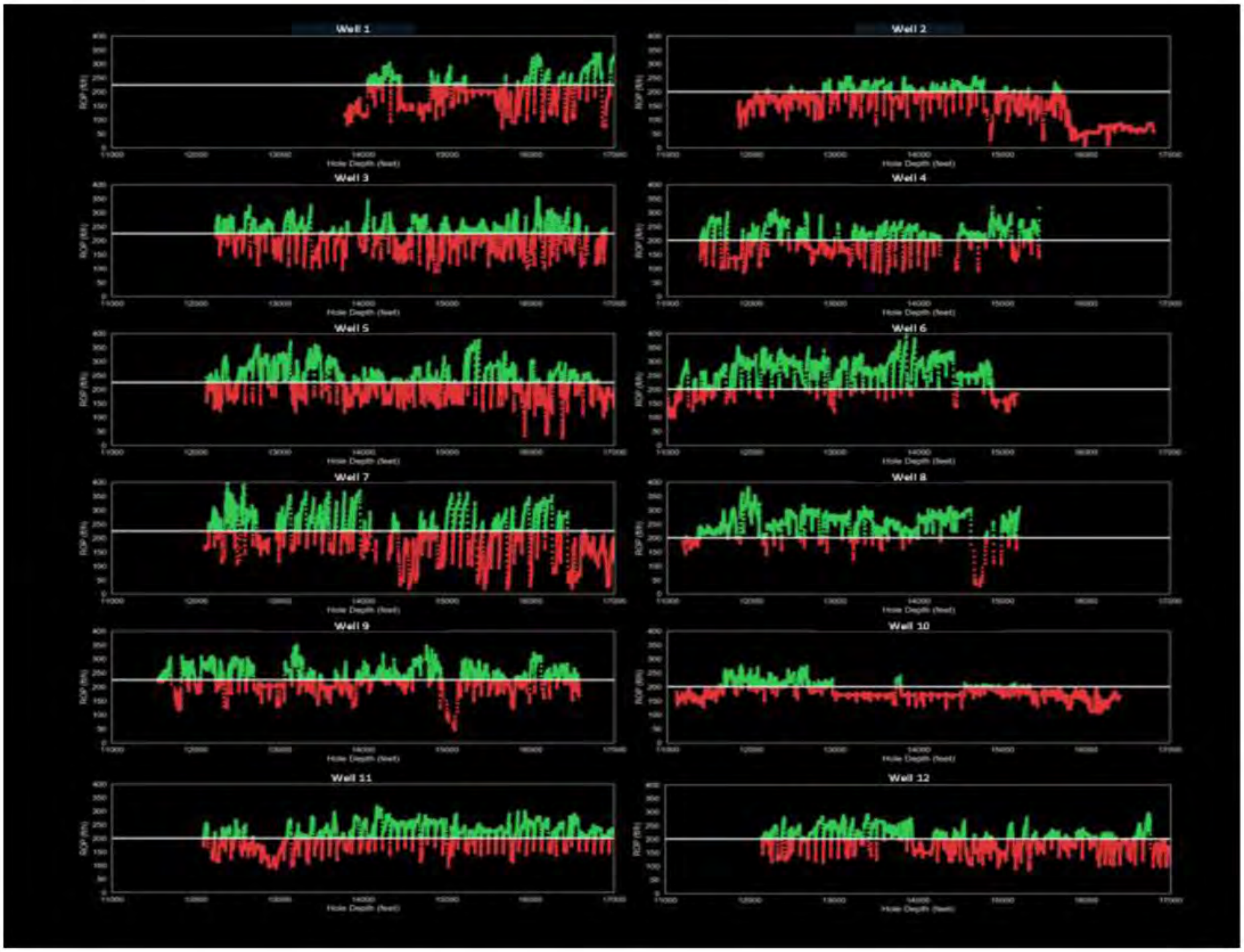


Figure 9—Performance comparison

The optimization model was designed to be a scalable to other environments and replicable to ensure the consistent improvement of the accuracy of the prediction. The model was conceived to capture information obtained from a previous implementation to be included as input data for re-training purposes. In consequence, it is expected that the consistent re-training of the model with optimal parameters will push higher the ROP average (P50) consistently every time a new well is drilled, as shown in Figure 10a **and** 10b, following the rhythm of 1: Implementation, 2: New data received, 3: Retraining, and 4: Improvement.

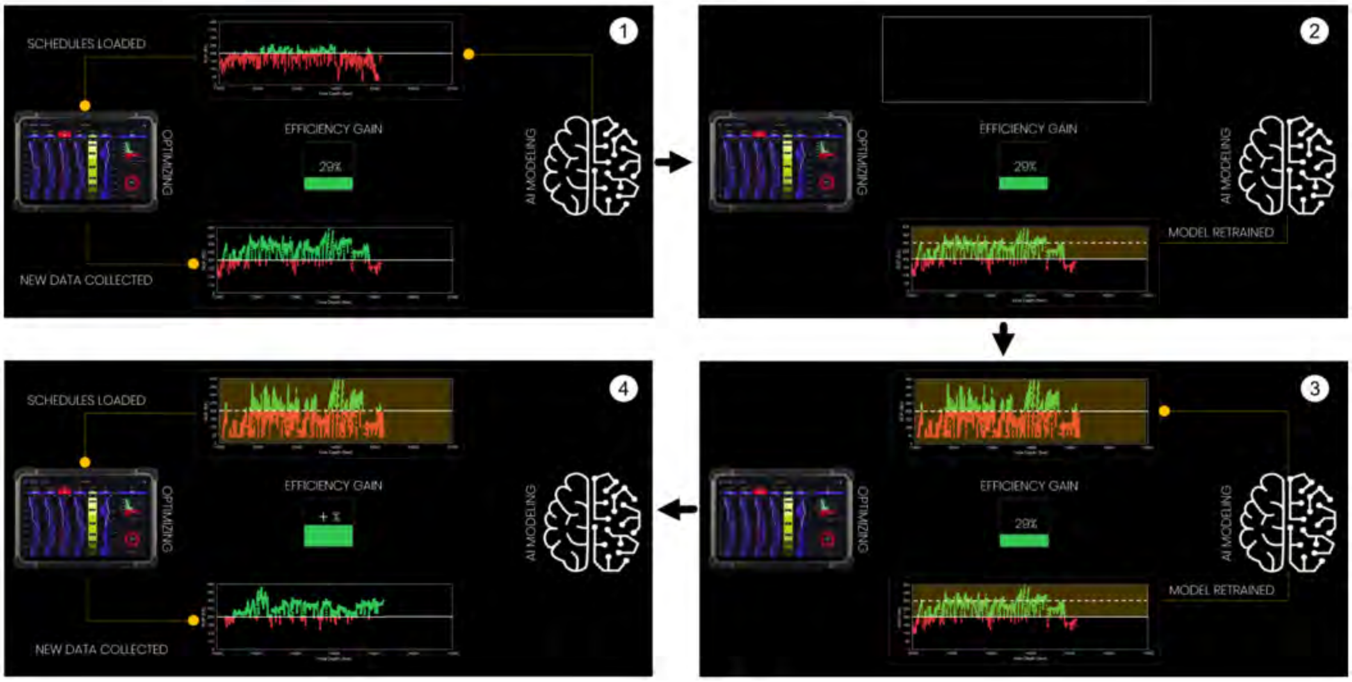


Figure 10a—Application Process 1-4

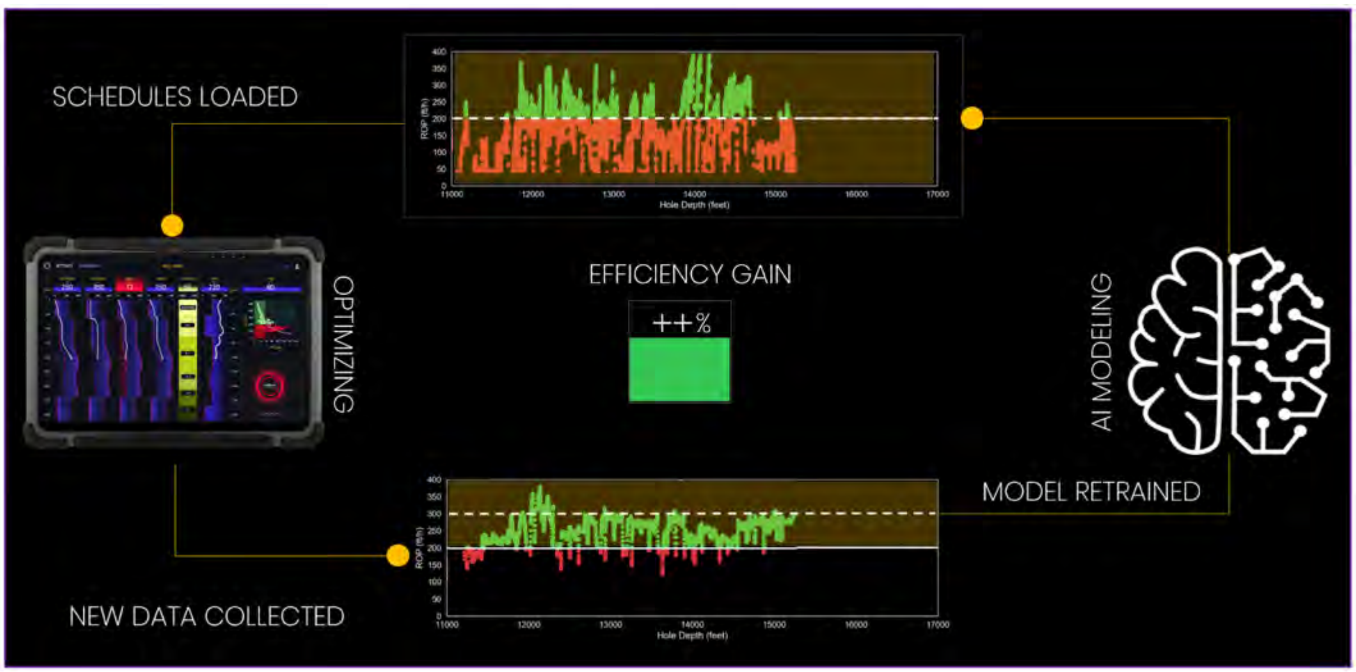


Figure 10b—Application Process lifesycle

Application Description

Machine Learning workflow

ROP optimization workflow includes several steps:

1. Historic drilling data collection

2. Application of automated preprocessing procedures to raw data (standardization of naming and units, data cleaning-removing outliers, handling missing values, applying signal smoothing, assigning rig activities) to generate accurate time-based data for each well
3. Conversion of time-based to depth-based drilling data with additional multivariate outlier removal step and selection of rotary drilling data only
4. Prefilter wells by removing data with operational problems
5. Partition data by combining only comparable data (e.g. group by similar wellbore design, neural network models (to be exact, multilayer perceptron) using the best performing feature set (obtained from our research results) for each combination of bit size and formation to predict ROP class: higher or lower than a threshold defined by historic performance
6. In order to generate data for optimization problem, run multidimensional simulations using trained models to predict ROP class for a grid of the selected drilling parameters (e.g. weight on bit, surface torque, flow rate, and bit rpm)
7. Solve the optimization problem to provide continuous envelopes of the optimal combinations of drilling parameters (schedules) that correspond to higher ROP outcomes during operations
8. Deliver results in dynamic dashboard and static report forms. Note that recursive application of this workflow, which implies increasing threshold, continuously improves the ROP drilling performance

Machine learning approach requires availability of at least two wells per model constant. In the event only one comparable well is available steps seven (7) and eight (8) are skipped and only actual data is used to solve the optimization problem to provide drilling parameters envelopes, i.e., pure statistical analysis is performed to generate the schedules.

Simulation results for ROP prediction: figures 1D->2D->3D

Simulation results for ROP prediction: >3D

Results

Follow the summary of the obtained results in a Project in south America basing. The results show the step by step of the improvement process based on drilling optimization model.

Nine wells were provided for the analysis of this study, with one well as Candidate Well (Well 123) to be analyzed / drill:

• Historic wells filtering analysis

The filtering was performed to confirm that all selected wells included on the analysis are comparable each other. Well trajectory, well design, and stratigrafic column are the main features to compare in order to assure the proper parameters envelopes generation on wells with similar conditions (See Fig 14 – 15).

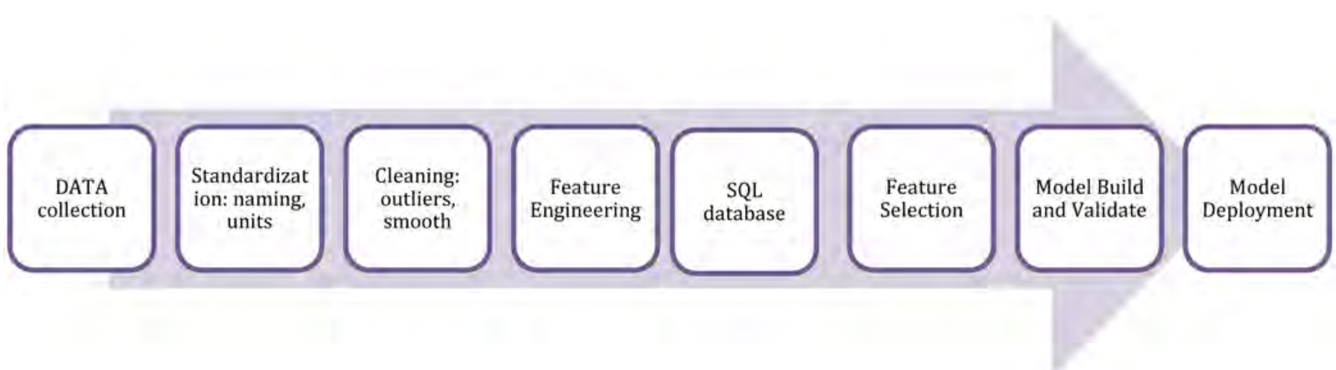


Figure 11—Machine Learning workflow

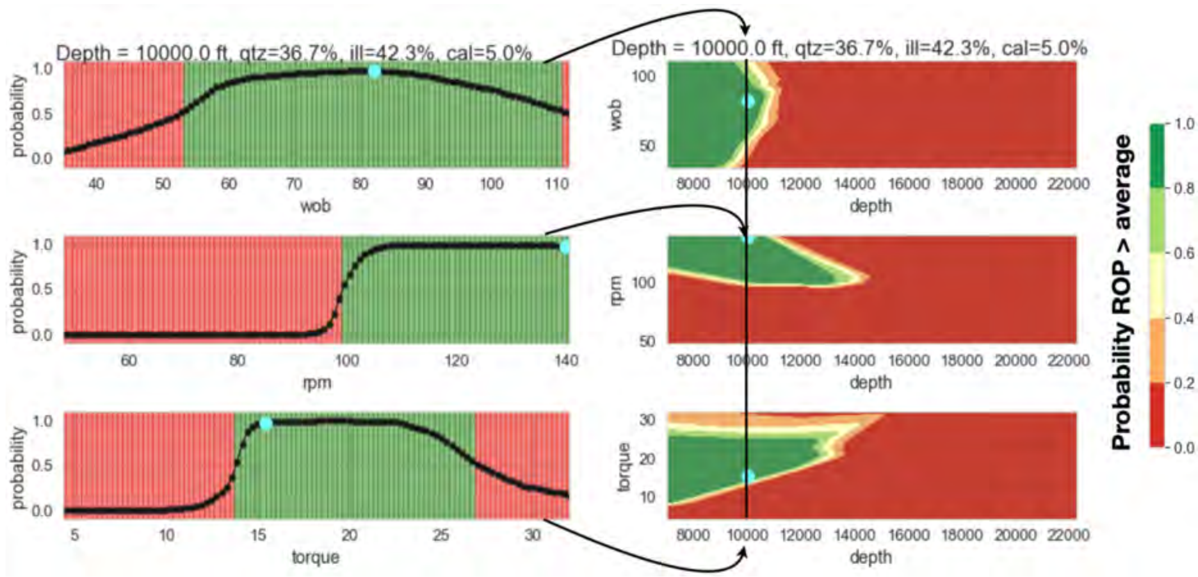


Figure 12—Simulations results 2D

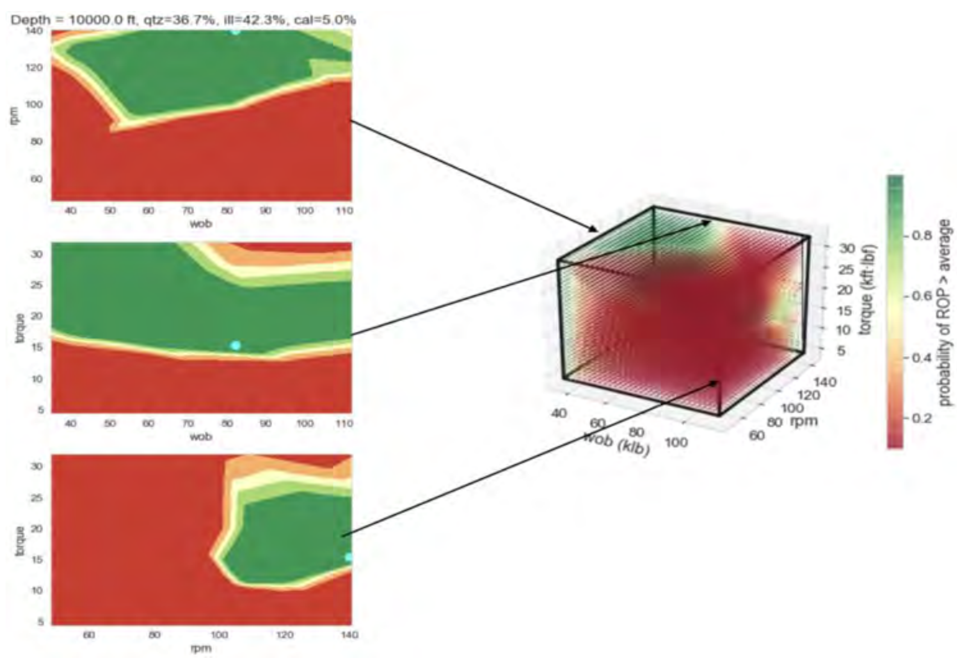


Figure 13—Simulations results 3D

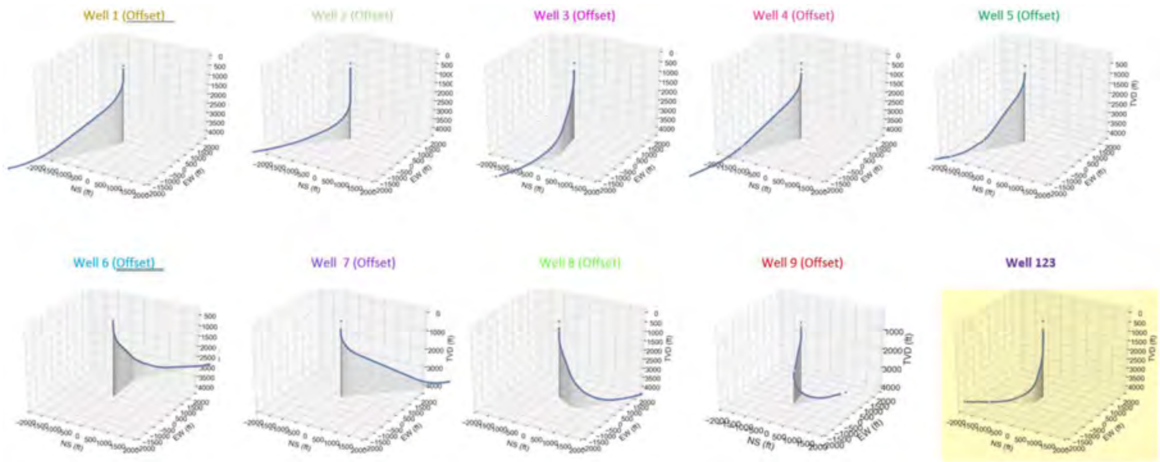


Figure 14—Historic Wells trajectory comparison

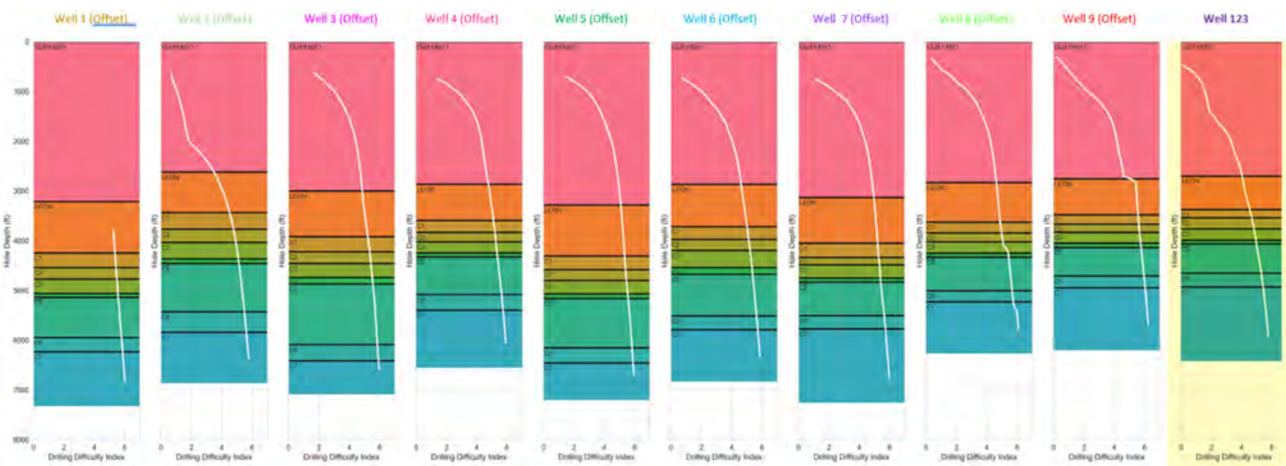


Figure 15—Historic Wells stratigrafic colum comparison

• Historic wells ROP analysis

Historic well performance analysis is conducted to determine variability in terms of ROP, this analysis helped to determine the best performance well and the corresponding variation compared with the others offset wells, for the thereshold identification for stable ROP optimization model.

• Schedules generation

Schedules generation process include the entire offset well data set. In this process the ROP optimization model implementation is evaluated by 3 different meassurements; ***Model Accuracy*** which is accuracy of the machine learning (deep learning) model that given drilling parameters predicts above or below average, ***simulation accuracy*** is the optimal envelope accuracy given simulated data (a whole data set with regular grid for all drilling parameters and ROP above/below ML model predictions) and the ***schedule accuracy*** Schedule accuracy is the optimal envelope accuracy given only actual historic drilling data.

In this scenario accuracy range for different formation and bit size: ROP Model Accuracy: 77-92%, Schedule Accuracy: 49-73%, Simulation Accuracy: 59-90% (See fig 17)

model_constant	ROP_AVG: 9 wells	ROP_AVG: all 10 wells	ROP_AVG (%)	ROP_AVG best wells	ROP_AVG best wells (%)
(GUAYABO, 12.25)	608.6	634.0	4.2	634.0	4.2
(GUAYABO, 8.5)	394.7	395.5	0.2	453.1	14.8
(LEÓN, 8.5)	362.2	363.8	0.4	487.6	34.6
(C1, 8.5)	280.8	281.5	0.3	319.0	13.6
(C2, 8.5)	231.7	231.9	0.1	261.7	13.0
(C3, 8.5)	259.3	260.2	0.3	312.7	20.6
(C4, 8.5)	228.6	229.6	0.4	356.2	55.8
(C5, 8.5)	207.1	207.4	0.1	255.9	23.6
(C6, 8.5)	177.1	178.0	0.5	202.7	14.5
(C7, 8.5)	156.2	157.0	0.5	146.0	-6.6
(C7, 6.125)	131.3	131.3	0.0	151.7	15.5

Figure 16—ROP Analysis per formation.

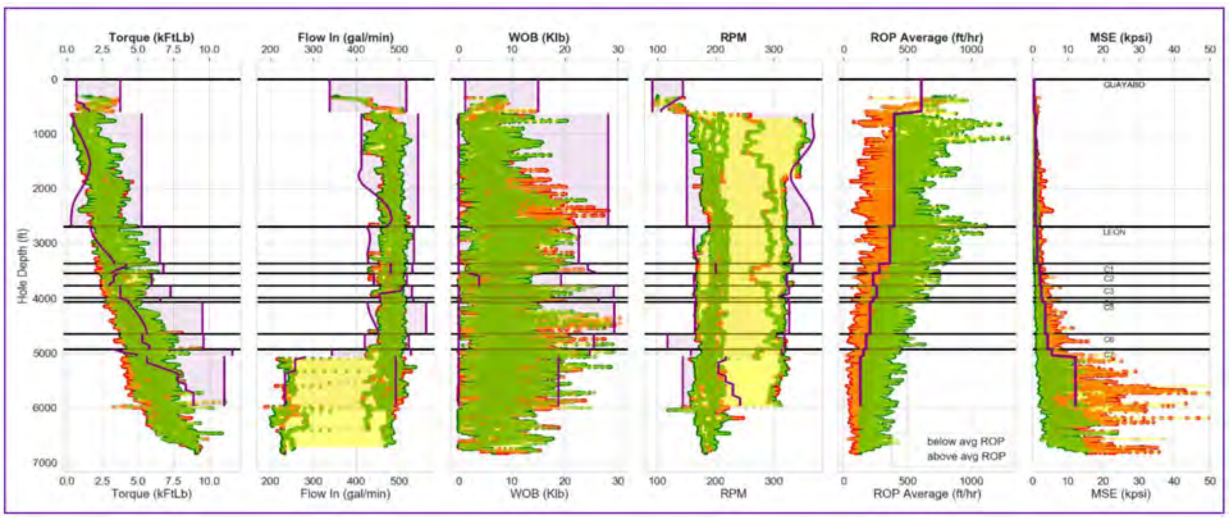


Figure 17—Parameters schedule based on 10 offset wells

In case the accuracy of the model simulation and schedules are low, an optional improvement process can be conducted by removing the worst performance wells, the schedules can be re-generated including only best performance wells of the historical data set. The threshold defined can be the same but the accuracy range of the model, schedules and simulations usually increase between 5 – 15% compared with the ones included full offset data set. (See fig 18)

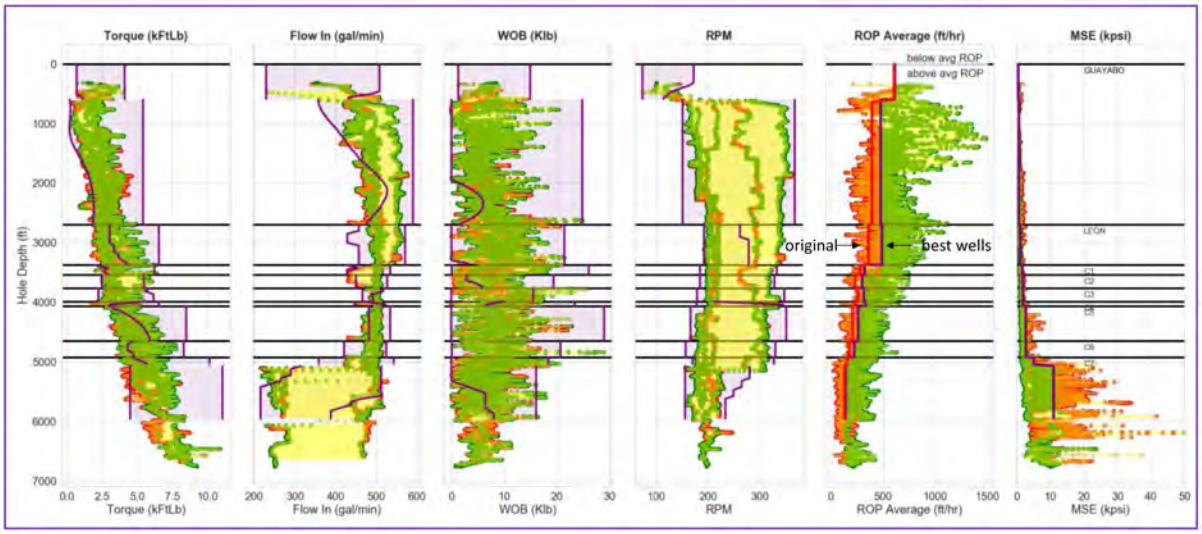


Figure 18—Parameters schedule based on 5 offset wells

Candidate well with computed envelopes for best 5 wells. Historical data envelopes shown in yellow refers to envelopes for particular formations and bit size (i.e. data was normalized by depth and bit size and shifted according to the current formation depth and bit size used for Candidate Well "Well 123"). (see Fig 19)

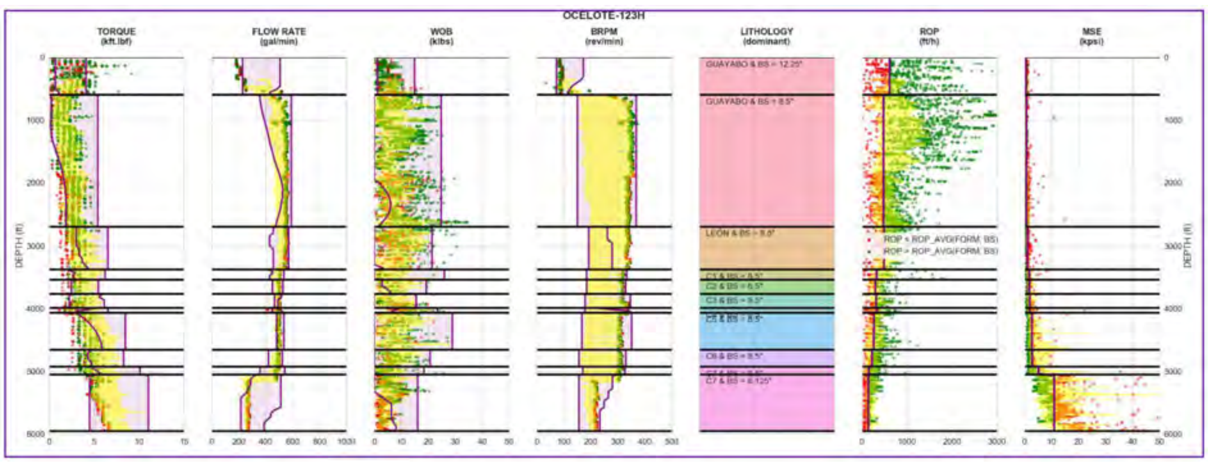
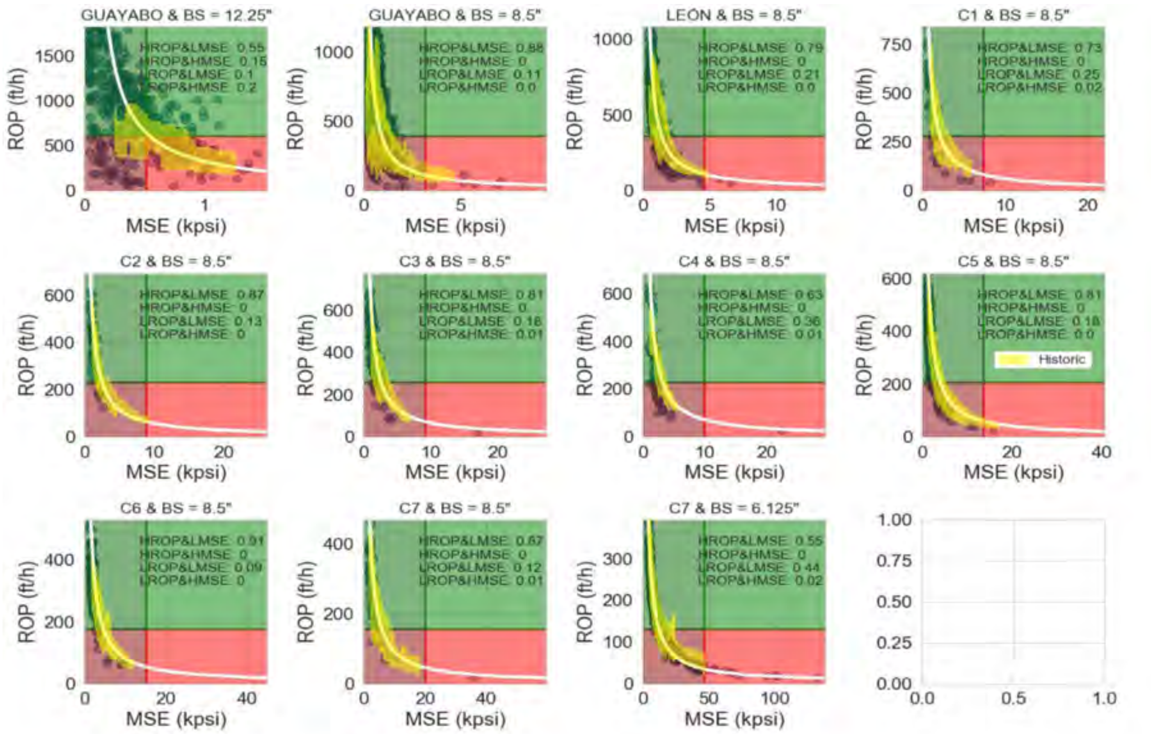


Figure 19—Real parameters vs schedule based on 5 offset wells

• Performance Analysis (ROP vs MSE)

Additional performance analysis by section is showed to identify improvement opportunities, this allows to adjust the threshold for further implementation, identify better parameters and design for the current well conditions. (see Fig 20)



	Well 123	Offset Wells
ROP-MSE Distribution	HIGH ROP & LOW MSE: 76% HIGH ROP & HIGH MSE: 2% LOW ROP & LOW MSE: 19% LOW ROP & HIGH MSE: 3%	HIGH ROP & LOW MSE: 40% HIGH ROP & HIGH MSE: 10% LOW ROP & LOW MSE: 40% LOW ROP & HIGH MSE: 10%

Figure 20—Formation performance Analysis ROP Vs MSE

Each plot shows data distribution for all ROP vs MSE quadrants. For example, LEON formation with bit size 8.5" has 79% of data with high ROP and low MSE (HROP&LMSE) and 21% of data has low ROP and low MSE (LROP&LMSE).

• Candidate well ROP Performance after optimization model implemented

After ROP optimization model implementation, the performance is also evaluated comparing the current performance vs the defined threshold, this identify when the variation on the ROP was reduced, and where the variation is still significant, in order to improve the model, simulation, and schedules once the retrain of the model is conducted for next well. (See figures 21 and 22)

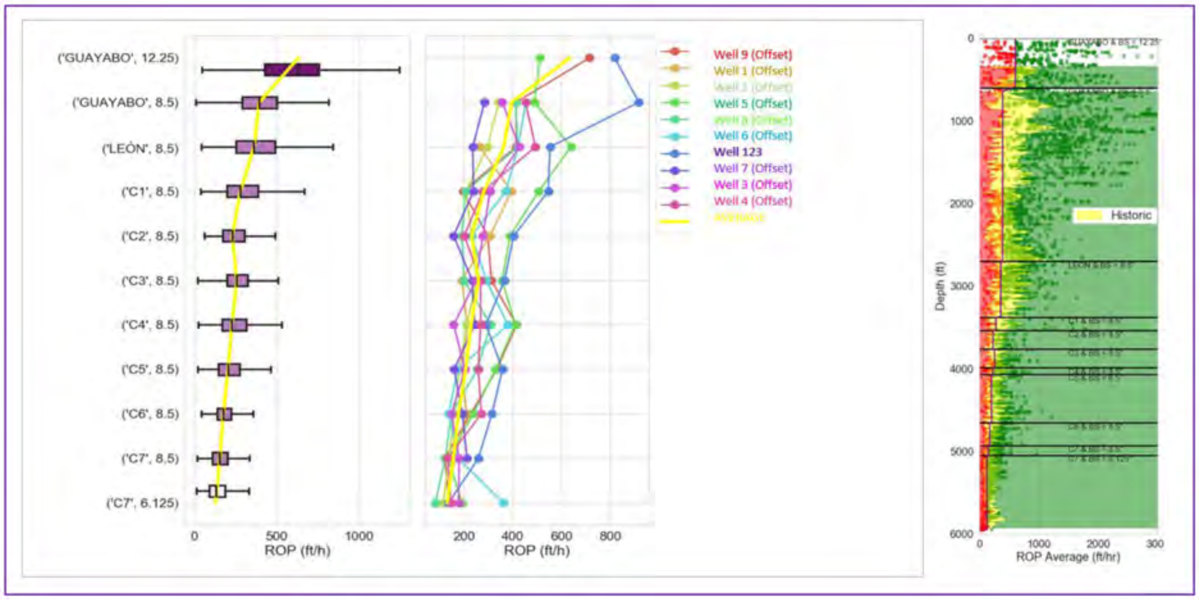


Figure 21—Rop distribution on candidate well.

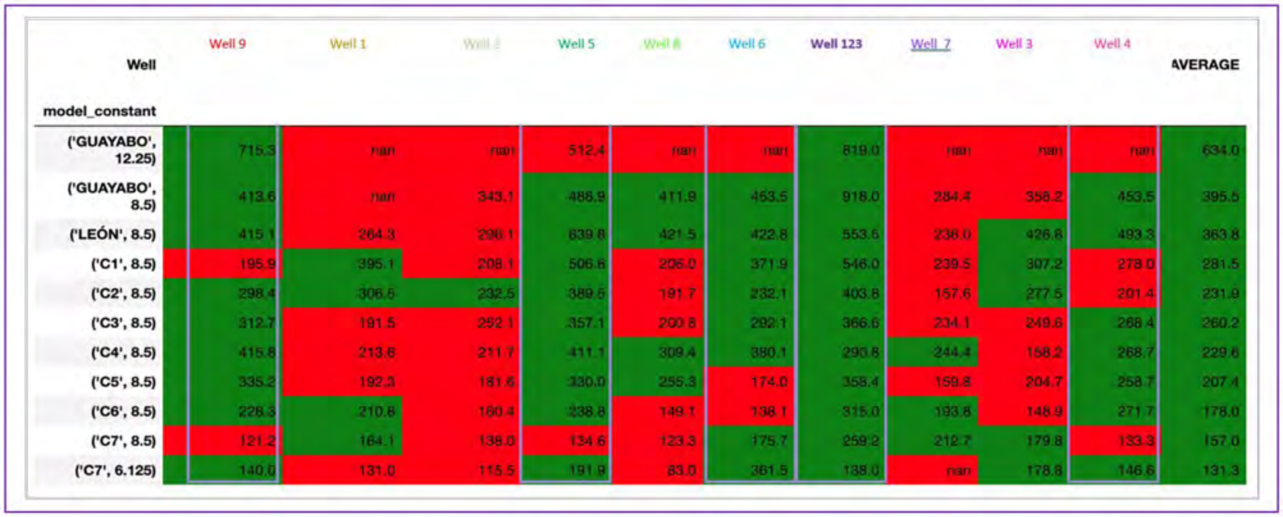
Well / model_constant	Well 9	Well 1	Well 2	Well 5	Well 8	Well 6	Well 123	Well_7	Well 3	Well 4	AVERAGE
('GUAYABO', 12.25)	715.3	nan	nan	512.4	nan	nan	819.0	nan	nan	nan	634.0
('GUAYABO', 8.5)	413.6	nan	343.1	488.9	411.9	453.5	916.0	284.4	358.2	453.5	395.6
('LEÓN', 8.5)	415.1	264.3	296.1	639.8	421.5	422.8	553.5	236.0	426.8	493.3	363.8
('C1', 8.5)	195.9	395.1	208.1	506.6	206.0	371.9	546.0	239.5	307.2	278.0	281.5
('C2', 8.5)	298.4	306.5	232.5	389.5	191.7	232.1	403.8	157.6	277.5	201.4	231.9
('C3', 8.5)	312.7	191.5	252.1	357.1	200.8	292.1	366.6	234.1	249.6	268.4	260.2
('C4', 8.5)	415.8	213.6	211.7	411.1	309.4	380.1	290.8	244.4	158.2	268.7	229.6
('C5', 8.5)	335.2	192.3	181.6	330.0	255.3	174.0	358.4	159.8	204.7	258.7	207.4
('C6', 8.5)	228.3	210.8	160.4	238.8	149.1	138.1	316.0	193.6	148.9	271.7	178.0
('C7', 8.5)	121.2	164.1	138.0	134.6	123.3	175.7	259.2	212.7	179.8	133.3	157.0
('C7', 6.125)	140.0	131.0	115.5	191.9	83.0	361.5	138.0	nan	178.8	146.6	131.3

Figure 22—Performance summary per well and formation

	Well 123	Offset Wells
Overall ROP Distribution	HIGH ROP: 78% LOW ROP: 22%	HIGH ROP: 50% LOW ROP: 50%
Conclusion	**Well 123** had superior ROP performance in comparison with the available historic wells, since 78% of data has above average ROP	

• Model Retraining for Continues Improvement

To retrain the model for the next well, only the best performing wells were selected, so to produce schedules that will allow parameters suggestions to operate at a higher ROP threshold. In this instance, five of the highest performing wells were selected with the following modeling output re-generated for the next well, wells nine, five, six, four and candidate were included on the new schedule generation, model performance summary: ROP model accuracy: 77-95%, Schedules accuracy: 39-77%, Simulation accuracy: 77-91% (see figures 23 and 24)



Well model_constant	Well 9	Well 1	Well 2	Well 5	Well 8	Well 6	Well 123	Well 7	Well 3	Well 4	AVERAGE
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('GUAYABO', 8.5)	413.6	nan	343.1	488.9	411.9	453.5	918.0	284.4	358.2	453.5	395.5
('LEÓN', 8.5)	415.1	264.3	296.1	639.8	421.5	422.8	553.5	236.0	426.8	493.3	363.8
('C1', 8.5)	195.9	395.1	208.1	506.6	206.0	371.9	546.0	239.5	307.2	278.0	281.5
('C2', 8.5)	298.4	306.5	232.5	389.5	191.7	232.1	403.8	157.6	277.5	201.4	231.9
('C3', 8.5)	312.7	191.5	252.1	357.1	200.8	292.1	366.6	234.1	249.6	268.4	260.2
('C4', 8.5)	415.8	213.6	211.7	411.1	309.4	380.1	290.8	244.4	158.2	268.7	229.6
('C5', 8.5)	335.2	192.3	181.6	330.0	255.3	174.0	358.4	159.8	204.7	258.7	207.4
('C6', 8.5)	228.3	210.8	160.4	238.8	149.1	138.1	315.0	193.8	148.9	271.7	178.0
('C7', 8.5)	121.2	164.1	138.0	134.6	123.3	175.7	259.2	212.7	179.8	133.3	157.0
('C7', 6.125)	140.0	131.0	115.5	191.9	83.0	361.5	138.0	nan	178.8	146.6	131.3

Figure 23—Selected Wells for retrain based on performance per formation

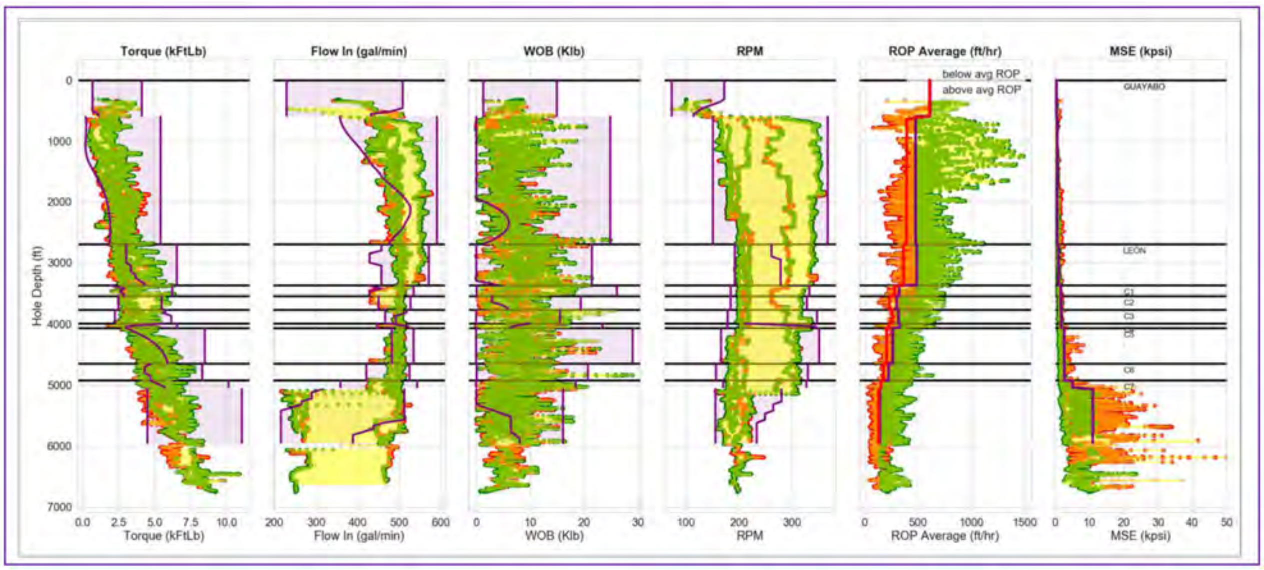

Figure 24—Well candidate performance and schedules

Conclusions

The prescriptive procedure has been developed to build optimal envelopes for controllable drilling parameters, such as weight on bit, bit rpm, flow rate and torque, that yield above average ROP. It consists of three parts:

1. Training machine learning model (to be exact Multilayer Perceptron) to predict whether ROP is above or below historic average. Here key factors that improved the model performance are (a) data partition by model constants: formation and bit size, i.e., different models are built for each formation and bit size combination and stack together for final predictions; (b) usage of optimal for classification problem F1-score metric that balance precision and recall and hence leads to better performing model.
2. Machine learning model is used to run simulations and generate synthetic data that cover the whole parametric space of the selected drilling parameters. Models with high test scores 80-90% are used for synthetic data generation that allow for more complete search on the best drilling parameters combinations.

3. Optimization problem is solved using machine learning model generated data to find a region in parametric space with maximal proportion of above average ROP observations. Because of the restrictive nature of the problem (search for continuous drilling parameter envelopes), optimized envelopes typically yield lower accuracy in the 60-70% range but appear to be more practical by providing drilling envelopes that are easy to follow.

The novelty of this work is that it provides a framework for consistent improvement of ROP performance. Since the historic data affects the ROP threshold defined as historic median, by keeping the best performing wells in the training set and adding only wells with improved performance, the designed procedure will yield envelopes producing higher ROP.

The ROP optimization process was intended to improve the current solutions that incorporte Artificial Intelligence, adding the technical expertise and physical models which combined with Machine Learning models, helped to create a hybrid approach that build replicable and scalable models for different drilling environments.

The techniques and processes included on the construction of the model, allow the users to implement a consistent improvement plan for their operations based in the retrain of the model, that will deliver the option not only to improve ROP, but also reach consistensly highes levels of performance, adjusting variables and parameters that affects most of the drilling operations in every implementation.

On fields where the high ROP was already reached, the implementation of the drilling optimization model showed an increased consistency, by delivering a more stable performance. This help the customer to improve the strategic planning and execution on the long-term drilling campaigns, since more accurate prediction of the ROP can be considered.

Additional approaches can be included in the future in this model, in order to create a multipurpose robust solution; since data, as shock and vibration maps, directional tendency measurements and bit wear grades, can be analyzed and correlated with drilling parametes, which will help to create a more efficient operation by reducing downhole tools failures, and increase directional management.

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References

Mayowa Oyedere, Ken Gray, ROP and TOB optimization using machine learning classification algorithms, *Journal of Natural Gas Science and Engineering*, Volume **77**, 2020, 103230, ISSN 1875-5100. https://doi.org/10.1016/j.jngse.2020.103230.

Chiranth Hegde, Ken Gray, Evaluation of coupled machine learning models for drilling optimization, *Journal of Natural Gas Science and Engineering*, Volume **56**, 2018, Pages 397-407, ISSN 1875-5100, https://doi.org/10.1016/j.jngse.2018.06.006.

Singh, Kriti, Yalamarty, Sai Sharan, Kamyab, Mohammadreza, and Curtis Cheatham. Cloud-Based ROP Prediction and Optimization in Real Time Using Supervised Machine Learning. Presented at the SPE/AAPG/SEG Unconventional Resources Technology Conference, Denver, Colorado, USA, July 2019. doi: https://doi.org/10.15530/urtec-2019-343

Noshi, Christine Ikram. Application of Data Science and Machine Learning Algorithms for ROP Optimization in West Texas: Turning Data into Knowledge. Presented at the Offshore Technology Conference, Houston, Texas, May 2019. doi: https://doi.org/10.4043/29288-MS

Mantha, B, R. Samuel. ROP Optimization Using Artificial Intelligence Techniques with Statistical Regression Coupling. Paper presented at the SPE Annual Technical Conference and Exhibition, Dubai, UAE, September 2016. doi: https://doi.org/10.2118/181382-MS

Batruny, Peter, Yahya, Hanif, Kadir, Norazan, Omar, Amir, Zakaria, Zahid, Batamale, Saravanan, and Noreffendy Jayah. Drilling in the Digital Age: An Aproach to Optimizing ROP Using Machine Learning. Paper presented at the Abu Dhabi International Petroleum Exhibition & Conference, Abu Dhabi, UAE, November 2019. doi: https://doi.org/10.2118/197157-MS