OPTIMIZING OIL WELL DRILLING PERFORMANCE

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Abstract

The purpose of this study was to investigate the factors that most influence the Rate of Penetration (ROP) in drilling operations with particular focus on the roles of geology, drilling parameters, and operational modes. An initial analysis of drilling data revealed that geologic variations had a little impact on ROP. After further investigation, it was found that certain key drilling parameters had statistically significant impacts on ROP, but the main driver was overwhelmingly the drilling operation mode (i.e. sliding vs rotating). The study highlights that rotating mode operations consistently had higher ROP than the sliding mode. This suggests that prioritizing rotating mode can substantially enhance overall drilling efficiency. The report concludes with recommendations for drilling practices to focus on operational modes and critical parameters to improve ROP, ultimately leading to reduced operational time and costs.

Introduction

Although it is not the most sustainable practice, all global industries rely heavily on oil and gas extraction. Most of the easy to access hydrocarbon reserves have already been targeted and extracted, especially in the United States. As such, far more difficult and costly reservoirs are currently being targeted. This means that better technologies as well as more efficient drilling techniques need to be developed to operate on these slimmer margin assets. A critical performance metric in drilling operations is the Rate of Penetration (ROP), which measures the speed at which the drill bit advances through the subsurface. Optimizing ROP can significantly reduce drilling time and overall costs, making it a key focus in drilling operations.

Several parameters influence ROP, but some that were evaluated in detail in this study include:

- **Torque (Tq):** The rotational force applied to the drill string, enabling the drill bit to cut through formations effectively. Proper torque management is essential for maintaining drilling efficiency and preventing mechanical failures.
- **Rotary Speed (RPM):** The speed at which the drill bit rotates in revolutions per minute. While higher RPM can increase ROP, it must be balanced with torque and formation resistance to avoid equipment damage.
- **Weight on Bit (WOB):** The downward force exerted on the drill bit. Higher WOB typically improves penetration but requires careful control to prevent bit wear or instability, particularly in softer formations.
- **Differential Pressure (Diff):** The pressure difference between the drilling fluid in the wellbore and the surrounding formation. Maintaining the appropriate differential pressure is vital for cuttings removal, preventing formation damage, and maintaining wellbore stability.
- **Flow Rate (FLOW):** The volume of drilling fluid pumped into the wellbore. The flow rate affects cuttings transport, cooling the drill bit, and cleaning the wellbore, all of which influence ROP.

The operational mode can also significantly influence ROP. The two modes were focused on in this evaluation were Rotating and Sliding. Descriptions for the modes are below, but simple diagrams are provided as **Figure A.1** in **Appendix A**.

1. **Rotating Mode:** The entire drill string is rotated from the surface, providing continuous rotation of the drill bit. This mode creates much more rotation of the bit itself as well as creating more efficient cuttings removal.
2. **Sliding Mode:** In this mode, the drill string remains stationary, while the bit rotates using a downhole motor. Sliding mode is primarily used for directional adjustments, allowing precise control over the well path.

The interaction of these parameters and operational modes determines the overall efficiency of the drilling process, and they are very often catered to the specific rock formations being drilled. This study examines data from four horizontal wells drilled in South Texas, leveraging detailed depth-based logs and operational summaries to explore how these factors influence ROP.

Problem Statement and Data Sources

The purpose of this study is to evaluate the drilling data from 4 recently drilled oil wells in South Texas (H15, H16, H17, and H18) to find ways to maximize ROP, thereby reducing overall costs. These results won't generalize all oil and gas drilling, but there are plans to start up another drilling campaign the following year, and hopefully the results of this study can be applied to the drilling program for direct offset wells. A simple plot of the 4 well paths along with the target plan was plotted in R, and it can be seen below as **Figure 1**.

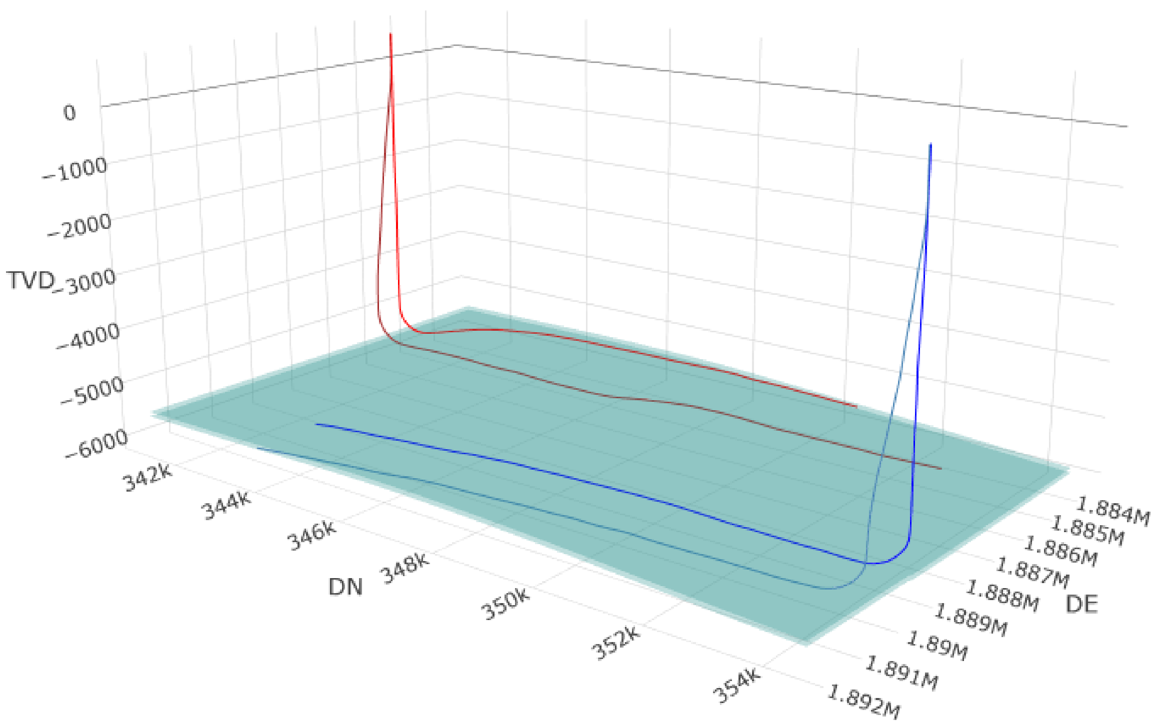

Figure 1 – *Plot of 4 well paths and target drilling plane*

The entire dataset includes high-resolution time-based logs, depth-based logs, and operational summaries, offering a detailed view of drilling conditions and parameters. However, due to the complexities associated with the time-based logs, these had minimal use in the evaluation. Much of the analysis was performed on the operational summaries compiled by a field expert monitoring drilling operations, which were subsequently tied to the depth-based data. The drilling process spanned multiple weeks, and the wells reached depths of up to ~18,000 feet. The data set was provided by the oil and gas company that one of the team members works at and is broken down into the following:

1. **Depth-Based Logs**: High-resolution logs collected at one-foot intervals, capturing parameters such as ROP, pump pressures, weight on bit (WOB), torque, directional data (azimuth and inclination), and gamma radiation.
2. **Operational Summaries**: Aggregated data grouped by directional drillers based on operational modes (sliding vs. rotating), summarizing drilling parameters for consistent operational states.
3. **Geological Evaluations**: Rock formation classifications derived primarily from gamma radiation measurements, differentiating between shale and non-shale formations and capturing the geological variability along the well path.

Methodology

The analysis began with an exploration of the data, specifically with the focus on the role of geology in influencing ROP. Geologic distinction is often done based on natural gamma radiation (GR) from the rock, which is a measure of the natural radioactivity in rock formations. Geologists use this to classify separate rock formations, which are usually from distinct geologic eras or depositional environments. **Figure A.2** in **Appendix A** shows a typical GR log with some example formation distinctions from Geologists. As the well is drilled Geologists use these GR signals to specify where the rock formations are. **Figure 2** below shows a partial plot of one well steering through the formations. In this case, the red highlighted region was the targeted zone.

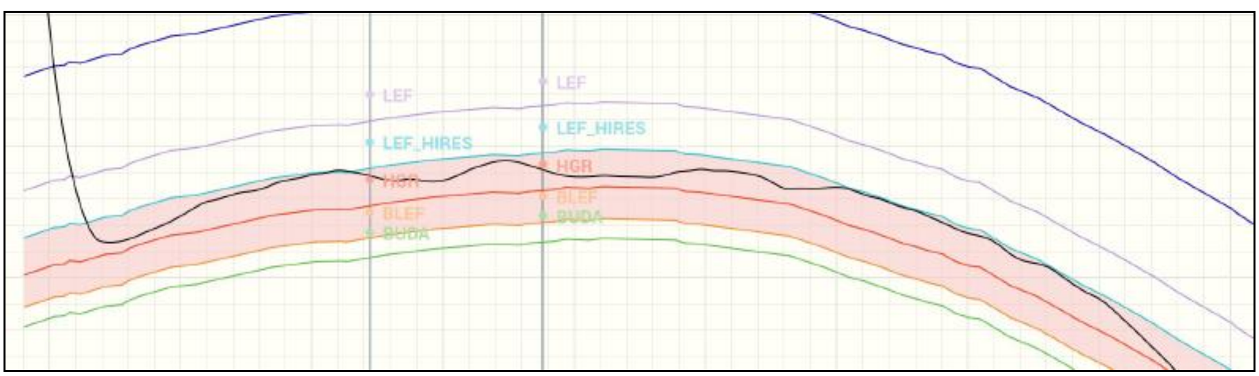

***Figure 2 –** Partial plot of one well showing steering through rock formations*

This initial data analysis step involved simple plotting of ROP with regards to geological parameters, including GR and Geologist identified horizons. This was paired with some basic statistical testing to gauge the relative influence of Geology on ROP. Ruling out geology as a primary influence would allow for greater emphasis on drilling parameters, which are more actionable for optimization. If significant geological influence had been identified, a more detailed geological study would have been warranted.

Following this preliminary assessment, advanced statistical and machine learning techniques were employed to evaluate the relative importance of drilling parameters, such as Weight on Bit (WOB), Torque (Tq), Rotary Speed (RPM), Differential Pressure (Diff), and Flow Rate (FLOW). The methodologies included clustering, regression analysis, and random forest modeling, each contributing unique insights into the data:

1. **Clustering**:
    - **K-Means Clustering**: This unsupervised learning method grouped observations into various clusters based on parameters like WOB, RPM, FLOW, and operational hours. Clustering helped identify distinct operational regimes and patterns within the data, providing a framework for optimizing parameter settings associated with higher ROP.
2. **Regression Analysis**:
    - **Linear Regression**: Applied to predict ROP using drilling parameters as predictors. Coefficients were extracted and analyzed for significance, with p-values indicating the significance of relationships between predictors and ROP. Separate models were built for sliding and rotating modes, acknowledging their operational differences.
3. **Random Forest Modeling**:
    - Random Forests is a robust ensemble learning method that was employed to evaluate the importance of drilling parameters. By constructing multiple decision trees, this model reduces overfitting and highlights key variables driving ROP in both sliding and rotating operations. Variable importance was determined based on reductions in node impurity, offering actionable insights into which parameters have the greatest influence.

Finally, leveraging the insights gained from these analyses, a financial model was constructed to quantify potential cost savings. The analysis was done using wells H15 and H17 to compare the impact of sliding and rotary drilling methods on performance and cost. Key parameters such as total vertical depth (TVD), mud weight (MW), and cumulative drilling costs were reviewed. Time and cost savings were calculated by comparing daily operations and extrapolating these results to longer timeframes. This model assumed an ability to maintain an optimal ROP across future drilling campaigns, estimating reductions in drilling time and associated costs.

Analysis and Results

Geologic Evaluation

Based on domain knowledge, if any rock layer were to have the largest significance on ROP, it would be the High Gamma Ray (HGR) rock layer. As such, the data was split into two subsets: In HGR and Out HGR. A Shapiro-Wilks normality test revealed significant deviations from normality ($p = 6.153e-08$ for In HGR and $p = 2.2e-16$ for Out HGR). As a result, a Wilcox Test was performed instead of a T-test to check for differences in central tendency as opposed to differences in the mean. The Wilcox

Test yielded a p-value of 6.32e-08, indicating a potential difference in ROP between the two groups. However, the magnitude of this difference is hard to quantify.

To qualitatively look at this significance, a histogram of ROP values in and out of HGR (**Figure A.3**) showed no noticeable differences. To remove subjective interpretation from the Geologist, a scatter plot of ROP versus GR was plotted with 100 as the cutoff for high versus low GR (**Figure A.4**). This plot also failed to visually suggest any strong influence of GR on ROP. Finally, ROP was plotted against Dog-Leg Severity (DLS) in **Figure A.5**. DLS is a measure of well path curvature and is directly related to drilling parameters. This plot revealed a correlation, indicating that drilling parameters likely play a more significant role in influencing ROP compared to geological factors. This isn't a robust exclusion of geologic influence, but it is an indication that drilling parameters are more significant.

Clustering Analysis

Since it is believed the operational mode will likely be influential, the data was subset according to sliding vs rotating, and a straight average of the ROP was calculated, which can be seen below in **Table 1**. Also in **Table 1** is a pseudo efficiency, which is ROP divided by an aggregate of influential drilling parameters (like WOB, Flow, and RPM). This is just an indication about the relative magnitude of ROP given the parameters for each operational mode. For a better visual of these differences, **Figure A.6** in the Appendix shows the ROP and Efficiencies plotted against each other for each mode.

Table 1 - ROP and Pseudo Eff. by Mode

Operation	Average ROP	P. Efficiency
Rotating	163.29	0.0001437
Sliding	48.5	0.000035

Rotating mode clearly has better overall ROP than sliding, but to determine if it's strictly the operation that creates the difference, the various drilling parameters still need to be investigated. To get a feel for how some of these parameters interact, parameters like ROP, FLOW, WOB, RPM, and Hrs spent in operational mode were factored into a clustering algorithm to see if there are any distinct groupings that can be targeted for optimization. The results of the clustering are plotted below in **Figure 3**.

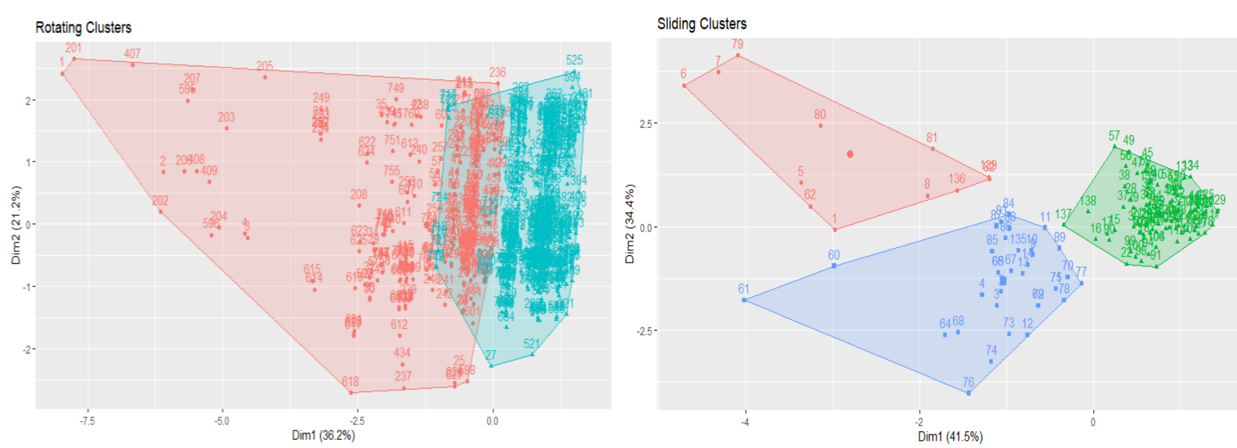

***Figure 3 –** Clustering for rotating mode (left) and sliding mode (right)*

There is less clear distinction between groupings in the rotating mode, but there are three distinct groups in the sliding mode. When averaging the parameters by cluster, it appears that maximizing the parameters corresponds to higher ROP in general. The grouping averages are summarized in **Table 2** below. However, it should be noted that the red cluster for sliding is very sparse and has a low concentration of data. Most of the data is concentrated in the green cluster, which may indicate that the red and blue clusters could be outliers, extremes of parameters, or transition states.

Table 2 - Average values by cluster for sliding mode

Cluster	FLOW	WOB	RPM	Hrs.	ROP
1	529	21	51.9	0.543	127
2	655	29.3	73.8	0.364	165
3	658	29.9	0.492	0.445	47.9

A bar plot of the feature means by cluster are displayed in **Figure A.7**, and the feature importance for these clusters is listed in **Figure A.8**. Tentatively, it looks like FLOW has the most significant separation factor in clusters. The results are summarized below:

- **FLOW:** Most critical factor (55.56% importance) for cluster separation.
- **RPM and WOB:** Secondary but notable impacts (4.27% and 3.73%, respectively).
- **Hrs.:** Least influence among evaluated parameters (2.61%).

Regression Analysis

To do a deeper evaluation of the interplay between parameters, a simple linear regression model was applied to the data. Only three of the coefficients came out as significant based on the p-value: Torque (Tq), Weight on Bit (WOB), and Revolutions per Minute (RPM). The coefficients and p-values for these variables are listed below in **Table 3**. It's clear that although the parameters are statistically significant, their magnitudes are incredibly small, effectively removing the influence of some of the variables.

Table 3 - Significant Linear Regression Parameters

Predictors	Coefficients	Significance
Tq	1.22E-34	p-values <0.001***
WOB	3.03E-13	p-values <0.001***
RPM	1.72E-01	p-values <0.05*

Linear Regression models were then created for each well individually and for the individual wells after subsetting into sliding vs rotating. The R^2 and Adj. R^2 for the linear regression models are listed below in **Table 4**. Although some of the models have very strong R^2 values, there is not good consistency from model to model, discounting the confidence in either their predictive or descriptive power.

Table 4 - R2 and Adj. R2 values for each sub-model iteration

	Combined Mode				Subset to Rotating				Subset to Sliding			
	H15	H16	H17	H18	H15	H16	H17	H18	H15	H16	H17	H18
R2	0.18	0.07	0.62	0.57	0.18	0.08	0.19	0.57	0.51	0.28	0.93	0.32
Adj R2	0.16	0.05	0.61	0.56	0.16	0.06	0.17	0.56	0.49	0.25	0.93	0.27

A box plot of the coefficients from these models was created, which can be seen as **Figure A.9**. The large range in the statistically significant coefficients further degrades confidence in these models. For additional visualization, **Figures A.10** and **A.11** display the relative influence of the predictive variables by well in Rotating and Sliding operations for A.10 and A.11 respectively.

Random Forest Analysis

Overall, the results from regression analysis were inconclusive, but since there appeared to be some clear distinction in clustering analysis, it was decided to apply Random Forrest modeling to see if there was any additional predictive or descriptive power. The model itself didn't provide any strong predictive power, but it did shed light into some of the variables that appeared to have the most influence on ROP.

Data from the two oil wells H15 and H16 indicate that the 5 predictors would suggest rotating mode of drilling to be more efficient to improving ROP than the sliding method. **Figures A.12** and **A.13** display the feature importance from the random forest models after subsetting between sliding and rotating. This could mostly be because of the rock formation in these wells being stable and harder requiring the entire rotation of the drill string and drill head bit.

Using random forests to predict rate of penetration during drilling of oil wells H17 and H18 indicate that the sliding mode of drilling, based on three predictor values, would provide optimal ROP. This can likely be attributed to fractured rock formation that would require controlled directional movement. **Figures A.14** and **A.15** display similar feature importance plots for the H17 and H18 wells respectively.

Cost and Time Savings Analysis

A cost and time savings analysis focused on comparing the drilling performance of wells H15 and H17, with H15 having the least sliding time and H17 the most. The results showed that H15's reduced sliding time translated into lower overall costs and higher efficiency, achieving similar or better performance metrics compared to H17. Cost and time savings were calculated by extrapolating daily operational efficiencies over extended periods. The findings, as shown in **Table 5**, indicated that minimizing sliding time could save approximately $227,000 annually while reducing operational time by five days. Over 20 years, these savings grow to $5.6 million and 3.5 months of operational time. This analysis highlights the significant cost and efficiency advantages of reducing sliding time, providing a robust basis for optimizing future well designs.

Table 5 - Cost and Time Savings

Time Period	Time Savings	Cost Savings
1 Year	5 Days	$277k
5 Years	27 Days	$1.3 Million
10 Years	55 Days	$2.8 Million
20 Years	3.5 Months	$5.6 Million

Conclusions

The analysis performed here helped deepen our understanding of what factors were most influential to the rate of penetration (ROP). While geologic variability is often assumed to significantly influence drilling efficiency, this study found that it had minimal impact in ROP in these wells. Initial evaluations, including comparisons of ROP within and outside high gamma-ray (HGR) zones, showed no substantial differences. This indicates that the drilling parameters and operational strategies, rather than geologic features, are the primary drivers of ROP in these wells.

Attempts to model the influence of specific drilling parameters such as torque (Tq), weight on bit (WOB), rotation per minute (RPM), differential pressure (Diff), and flow rate (FLOW) on ROP yielded mixed results. Regression and random forest analyses identified Tq, WOB, and FLOW as significant in various contexts, but the results were not consistent between wells and data subsets. Their predictive power was insufficient to reliably optimize drilling performance. This lack of robust predictive models suggests that ROP is influenced by complex, interdependent factors that the current methodologies could not fully capture.

Overall, the operational mode emerged as the most critical factor affecting ROP. Rotating mode consistently outperformed sliding mode, with an average ROP more than three times higher. Rotating mode's advantage likely stems from the continuous drill string rotation, which enhances cutting efficiency and facilitates cuttings removal. Sliding mode is typically designed for steering and making course corrections to the well path.

Sliding is a necessary mode when drilling to stay in zone, but this analysis highlights how much of an impact it can have on overall drilling efficiency and the time it takes to drill a well. When compared to H17, adopting H15's optimized parameters led to significant savings. For future wells, there likely should be more emphasis on planning the direction of the wells to minimize steering complexity. These results demonstrate the importance of minimizing sliding time in future well designs to enhance operational efficiency and cost-effectiveness. It is also suggested to keep as broad a geologic target as is reasonably acceptable so that few course corrections can be made.

Lessons Learned

The lessons learned from our group are listed below and are separated into lessons learned from the course and specifically from this project:

Course

- All of my previous courses up to this point had much more emphasis on the code, models, and outputs. This course was way more focused on how to convey the results in a meaningful and interpretable way. I really enjoyed this aspect of the course, but I wish I understood this better before the first HW assignment.
- The math in the lectures was very high level compared to the expectations of what we needed to do to succeed. A lot of time was spent early in the course trying to follow all the derivations and proofs, but this led to being laxer later in the course when following the slides.

- Not having any graded quizzes after the last few weeks of lectures is very nice as it allowed us to focus more on the project and preparation for the final, but it resulted in less effort following the lectures.

This Project

- The data came from real world sources, but this meant it was very complex. One member of the group had significant domain knowledge about the data and the background, but the other members had to spend extra time understanding the drilling process.
- Data sources are massively important to the success of a project. Real world data takes significantly more time and effort in processing and preparing than the curated data sets used in many of these courses.
- Drilling oil wells is incredibly complex with many intercomparing factors. Even if there are some aspects that seem like they could be descriptive of the process, it requires much more background knowledge to understand how everything is connected.
- Prediction of rate of penetration as a function of drilling variables and optimal drilling method suiting the nature of the rock formation paves the way to formulate best drilling practices to maximize ROP. Early predictions can guide changing drilling parameters to reduce non-productive time and achieve optimum ROP. These analyses highlight that applying machine learning techniques and predictive models in real-time optimizations in drilling initiatives can result in potential benefits.

Appendix A: Supplementary Plots & Figures

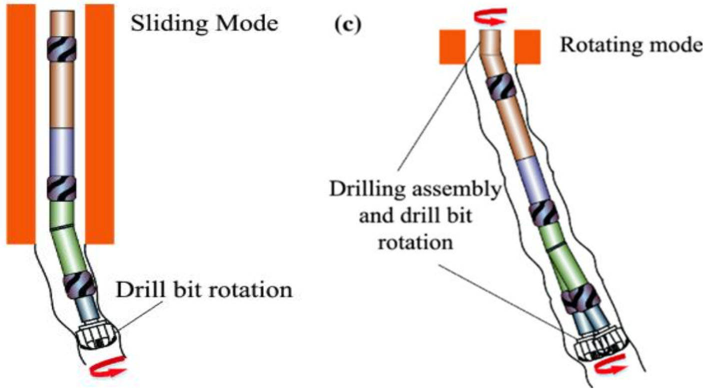

Figure A.1 – *Sliding (Left) diagram showing only the bit rotating. Rotating (Right) diagram showing the whole drill string and bit rotating. Source for images in **Appendix B***

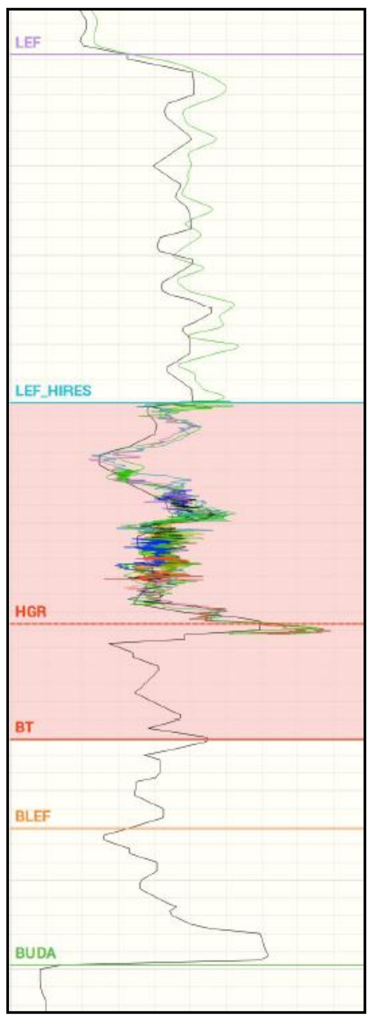

Figure A.2 – *Representative plot of GR showing Geologist identified rock layers (i.e. HGR, BT, etc...)*

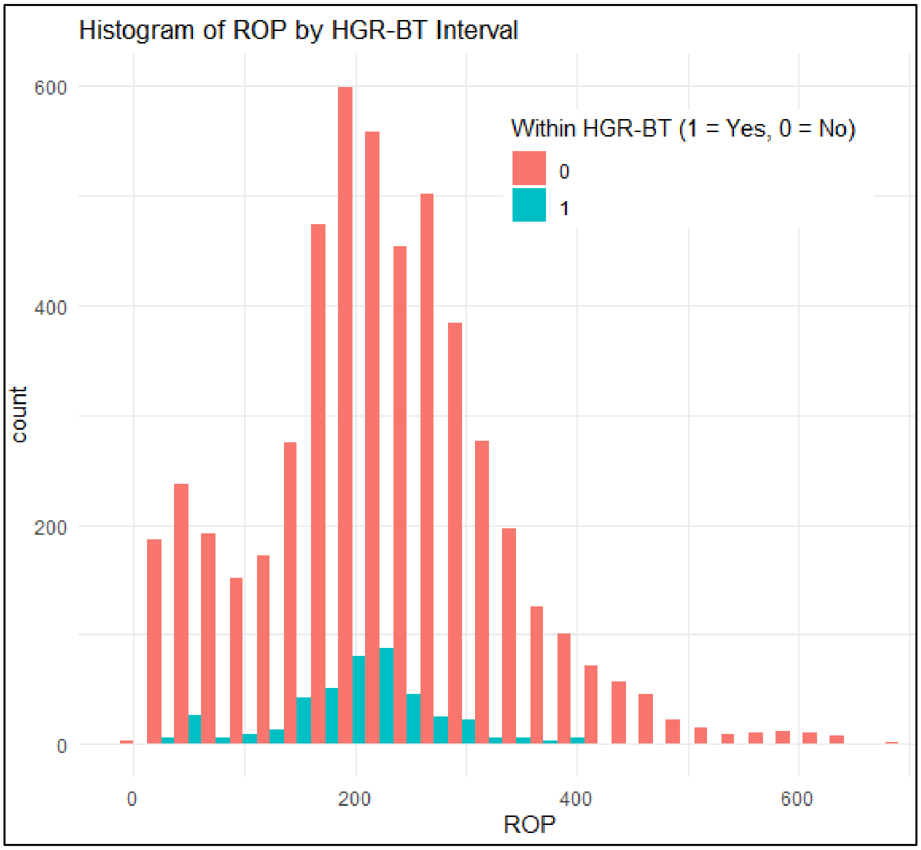

Figure A.3– *Histogram of ROP differentiating based on Geologist identified formation (HGR)*

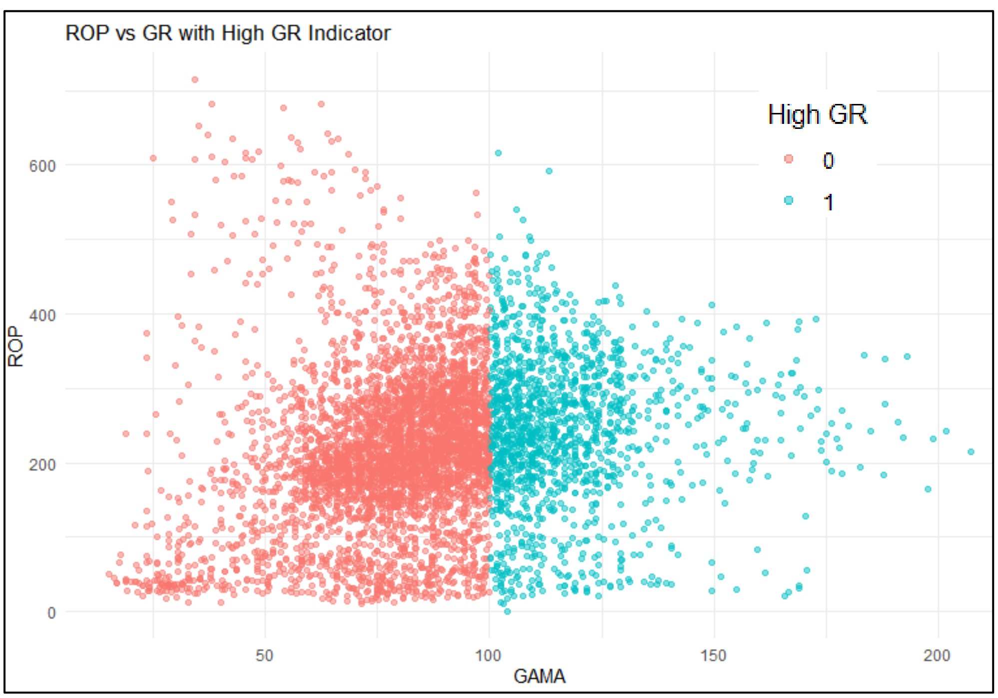

Figure A.4 – *Scatter plot of ROP vs raw gamma values with 100 units as a cutoff*

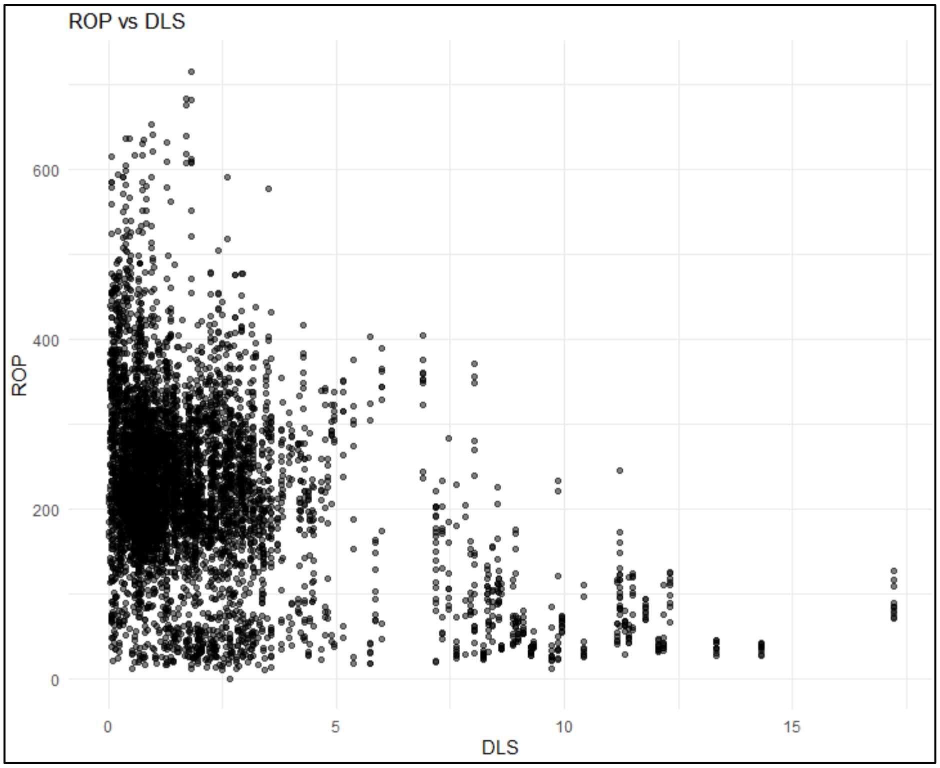

Figure A.5 – *Scatter plot of ROP relative to the severity of curvature of the well path (DLS)*

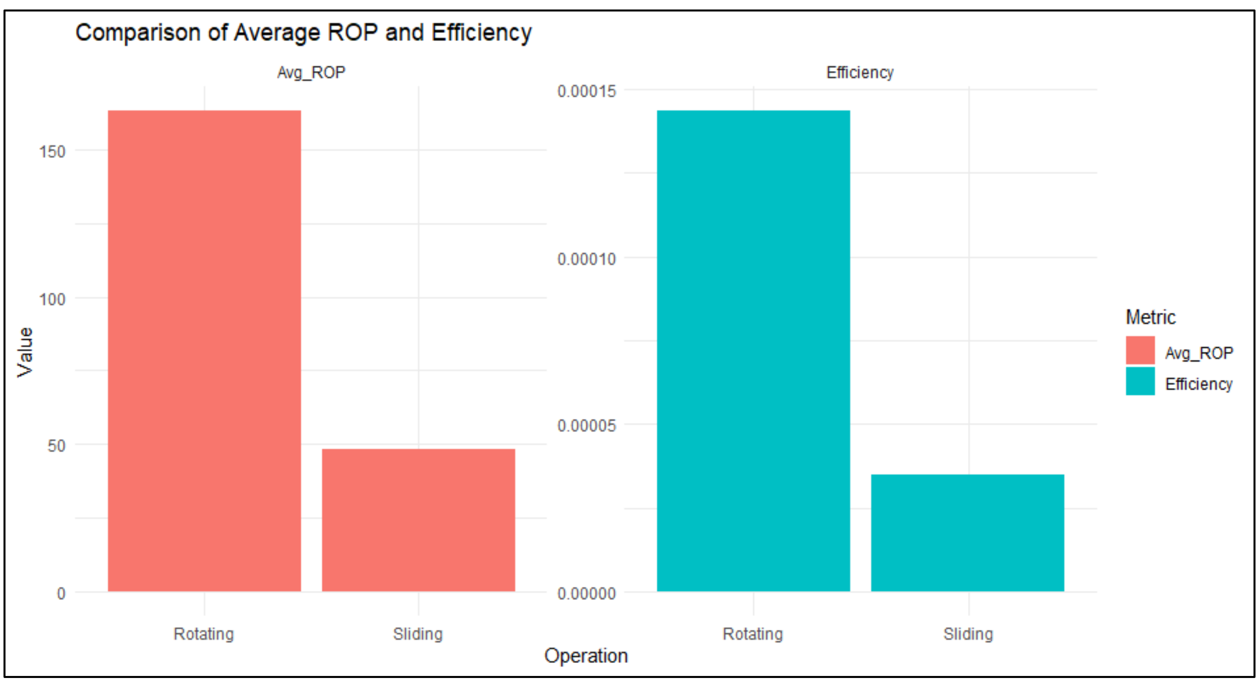

Figure A.6 – *Average ROP and Pseudo Efficiency by operational mode*

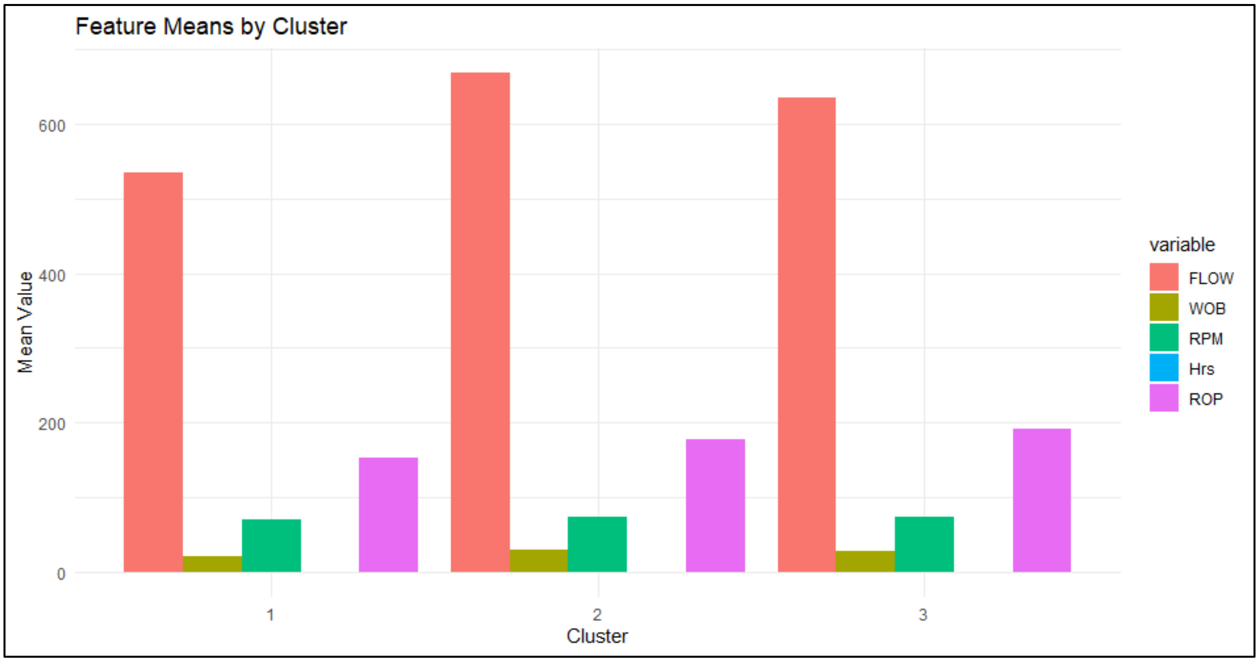

Figure A.7 – *Feature mean by cluster for sliding*

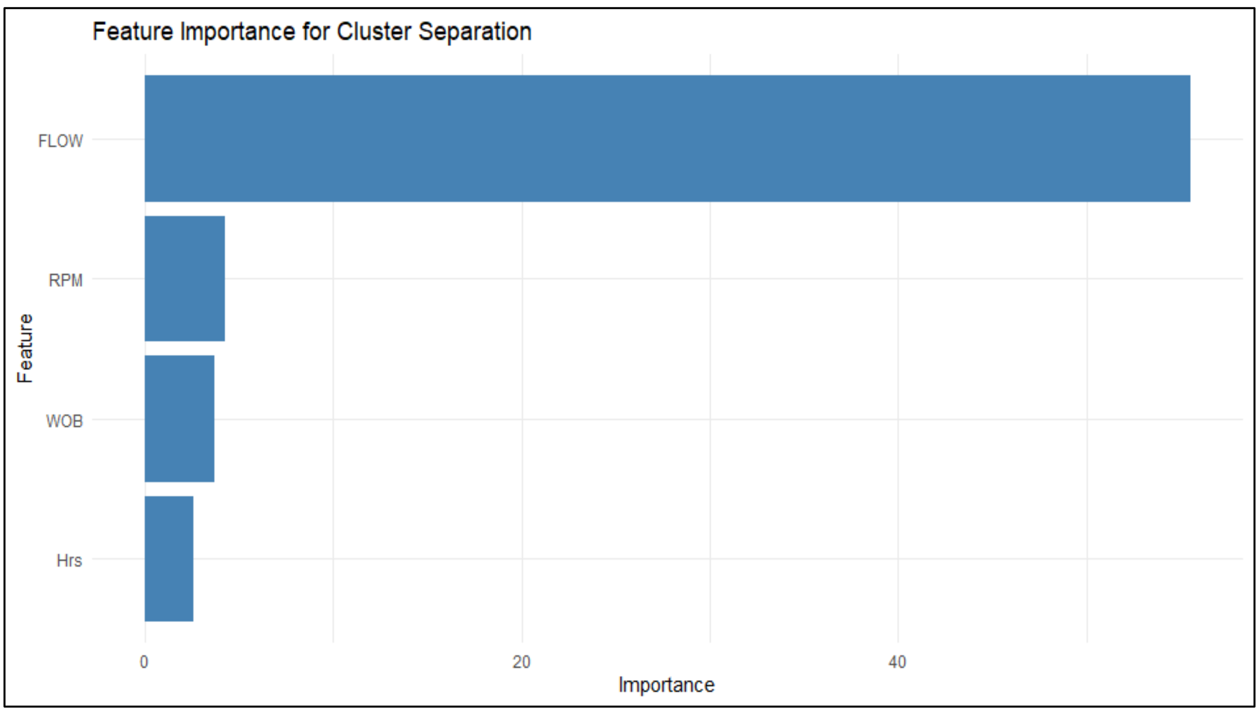

Figure A.8 – *Feature importance from cluster separations*

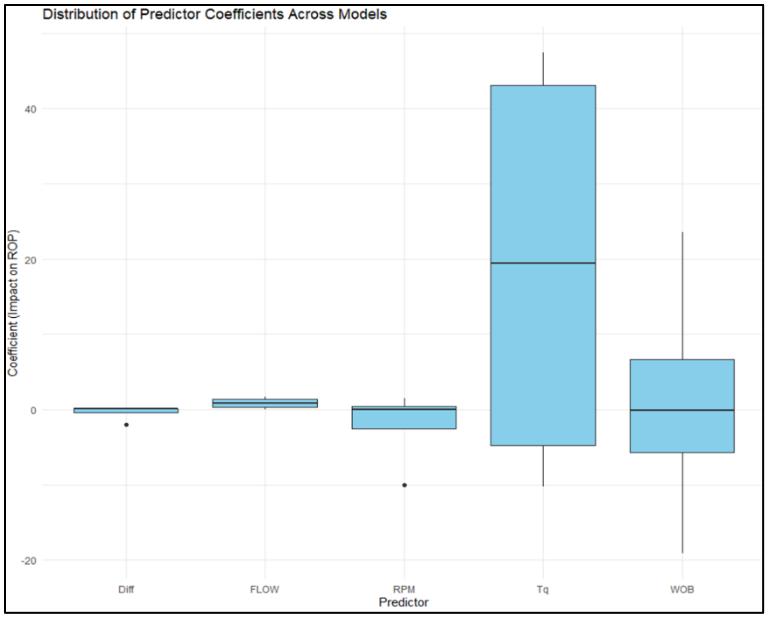

Figure A.9 – *Box plots of linear regression coefficients by well*

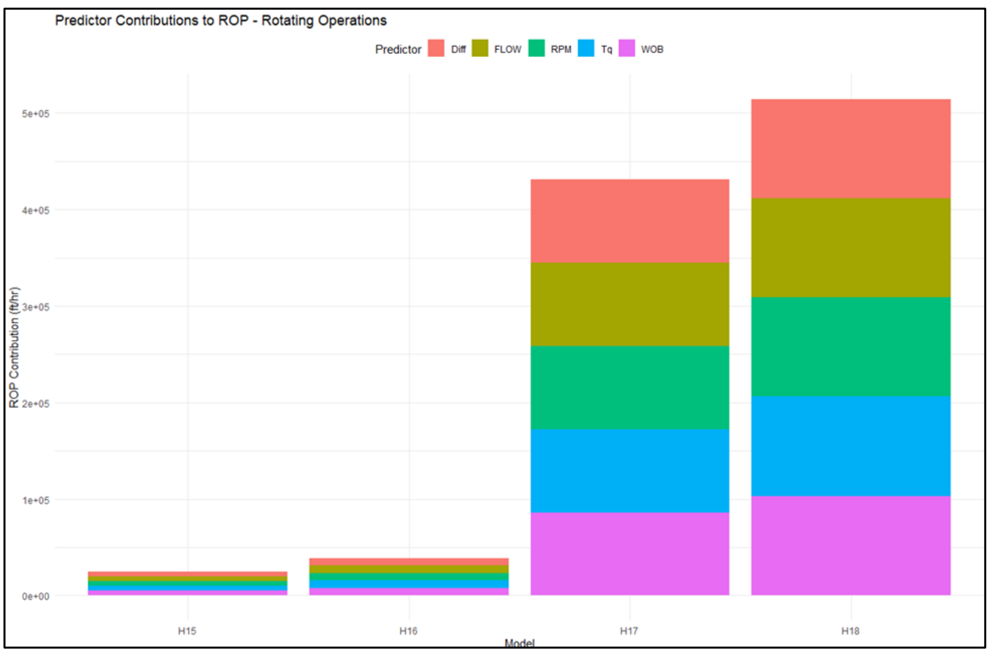

Figure A.10 – *Contributions of each predictor variable to ROP for each well for Rotating operation*

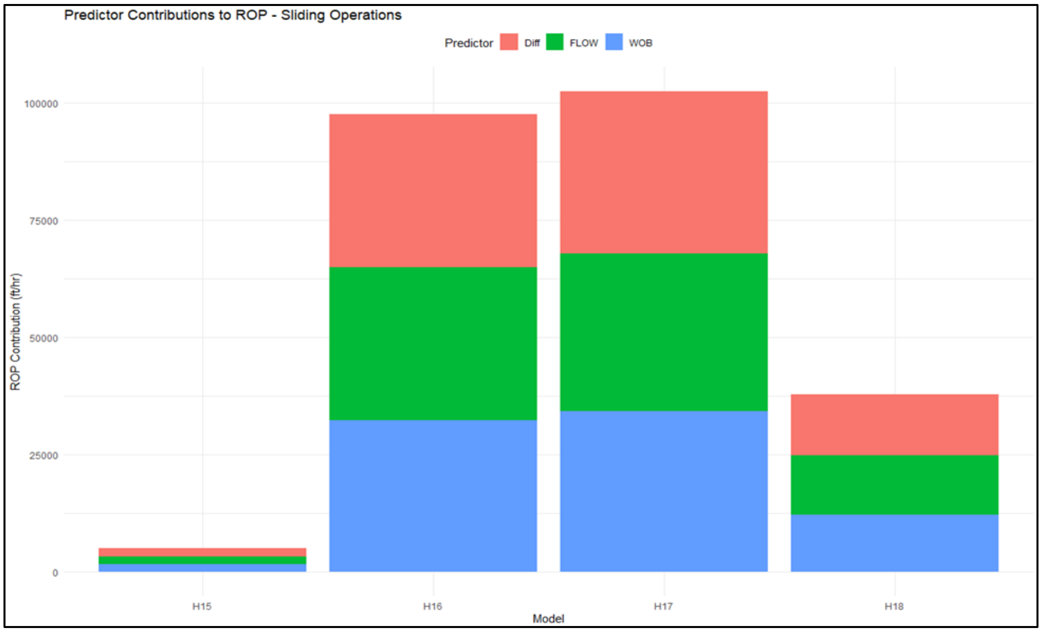

Figure A.11 – *Contributions of each predictor variable to ROP for each well for Sliding operation*

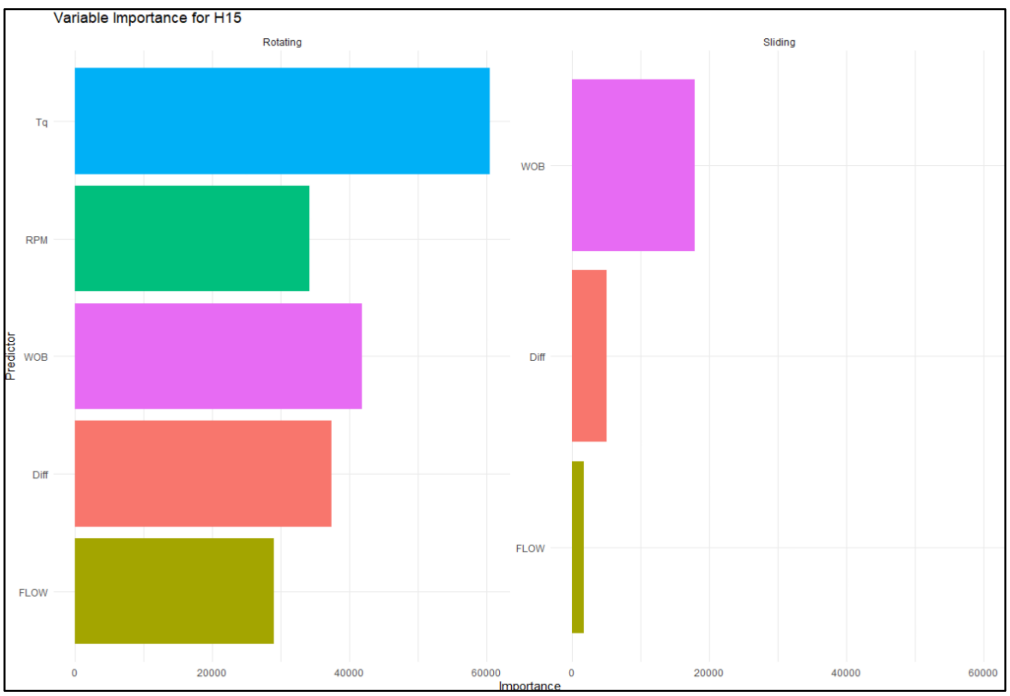

Figure A.12 – *Variable importance of Random Forest model for well H15*

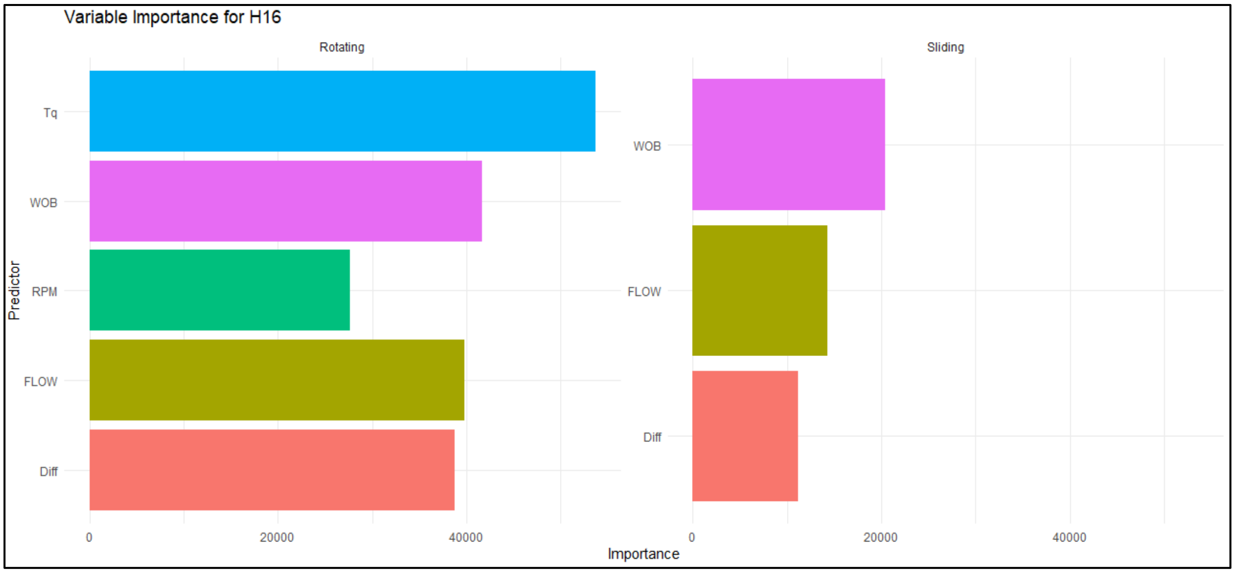

Figure A.13 – *Variable importance of Random Forest model for well H16*

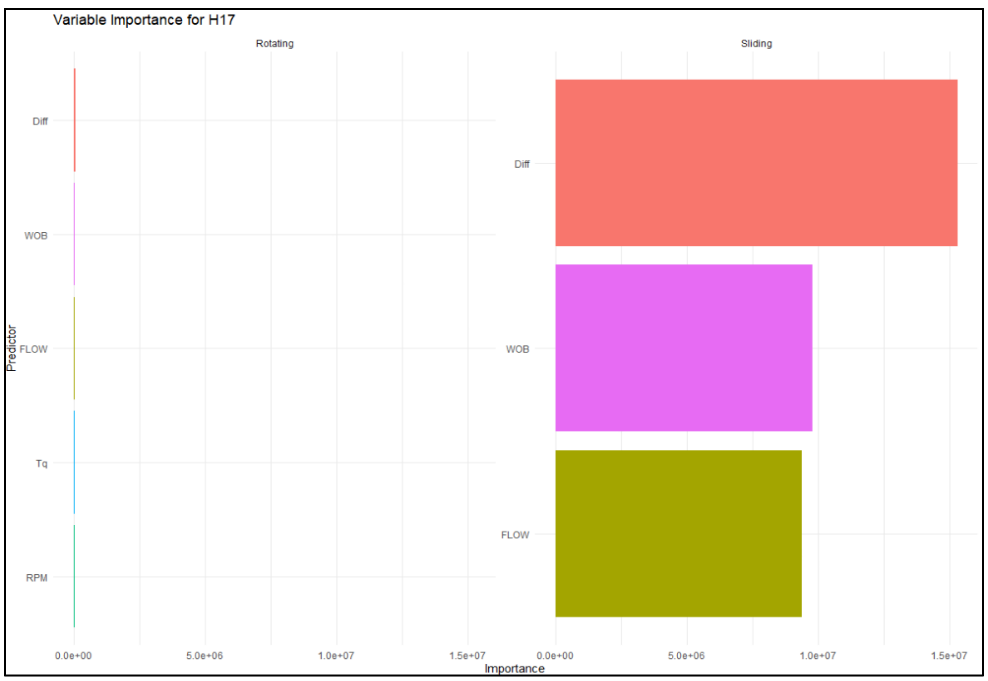

Figure A.14 – *Variable importance of Random Forest model for well H17*

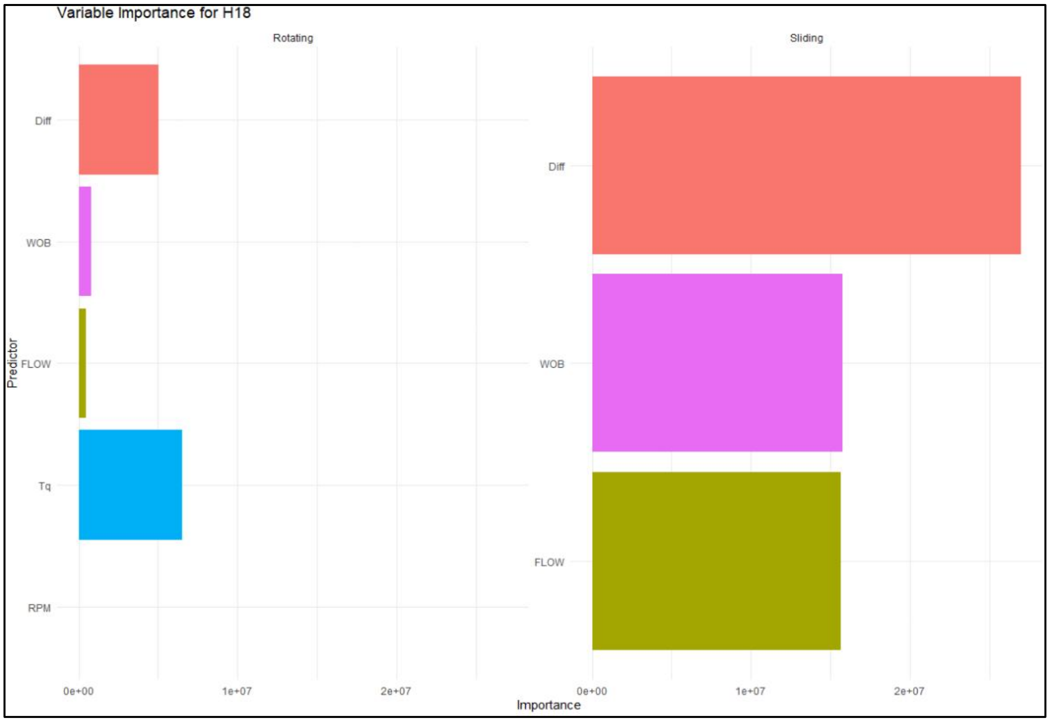

Figure A.15 – *Variable importance of Random Forest model for well H18*

Appendix B: Citations

Gooneratne, Chinthaka P., et al. "Downhole Applications of Magnetic Sensors." *MDPI*, Multidisciplinary Digital Publishing Institute, 19 Oct. 2017, www.mdpi.com/1424 8220/17/10/2384.