

Characterizing Drilling Vibrations by Interlinking Surface Data, Drillstring Design and Lithology of Rock in Utah FORGE Deep Test Well 58-32

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ABSTRACT

Dealing with vibrations is inevitable during drilling operations. Monitoring these vibrations is crucial for safe and efficient drilling. While surface vibrations are a good indicator of drilling conditions, the severity of downhole issues cannot be easily discerned from surface data. Although utilizing downhole sensors is a reliable solution to the issue at hand, obtaining real-time downhole data is both complex and expensive. This brings us back to the question of whether surface vibrations can help us to identify drilling dysfunctions?

This paper aims to provide an in-depth review of the surface data obtained in Utah FORGE deep test well. Going a step further, the surface vibration data is combined with mud logs and daily drilling reports to build an algorithm to first differentiate and then identify harmful drilling vibrations in isolation to other vibration patterns. Understanding lithology changes is a key step in this analysis. While characterizing surface vibrations help in recognizing drilling dysfunctions, not every vibration pattern can be easily distinguished as harmful or within operational limits of the drill-string. The paper discusses the use of a classification model, which is a machine learning algorithm that classifies vibrations based on its level of severity.

The paper thus presents a solution to the complex nature of surface data measurements by selecting inputs such as surface torque, rpm, rate of penetration and weight on bit as major indicators of vibrations. By examining these parameters, the paper successfully classifies the data into regions of severe torsional and axial vibrations leading to a potential stick-slip and bit bouncing phenomenon.

1. INTRODUCTION

Evaluation of drilling performance remains a difficult task. Successfully identifying and assessing issues such as vibrations, low rate of penetration, loss of circulation and excessive torque and drag adds further complexity. Although the drilling industry collects huge amounts of data from multiple downhole sensors, the real-time utilization and implementation of downhole data remains challenging.

In order to increase drilling rates while keeping drilling related issues to the minimum, the driller relies on surface data measurements which have a degree of deviation from the downhole data. Numerous techniques have been implemented by drillers to improve this process. Drill rate tests include experimenting with one drilling parameter while keeping the others constant to find a relatively better rate of penetration setting. Drill off tests include string elongation tests to find the optimum weight on bit required to achieve a maximum rate of penetration (Lubinski, 1958). Real-time surveillance of mechanical specific energy (MSE) is another tool that has been extremely successful in detecting efficiency changes in the drilling system (Dupreist et al., 2005). These changes in efficiency help in choosing the optimum drilling parameters at any given time. Another popular method is machine learning, which is helpful in recognizing patterns in the data being analyzed. Christian, 2005 uses dimensionality reduction followed by decision tree models to identify optimum zones in the drilling data based on weight on bit and RPM vibration data, as shown in figure 1.

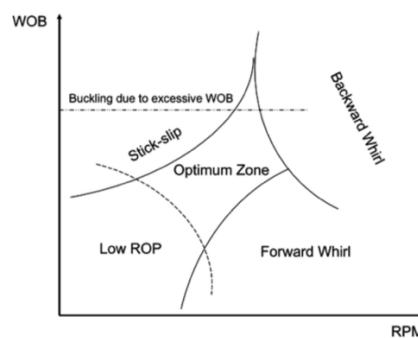


Figure 1: Optimum drilling zone identification (Wu et al., 2010)

Although data driven techniques are helpful in identifying the best combination of drilling parameters for optimized drilling, the model training component remains complex and computationally expensive. These techniques fail to take in missing data and noise into consideration and have to go through a time-consuming iterative process to perform optimally. The drilling data amassed from the sensors requires thorough pre-processing to improve the efficiency of these techniques. The paper recognizes the importance of proper measurement and analysis of surface measurements including weight on bit, top drive rotations and torque along with an analysis of drilling reports, lithology and logs. In doing so, the paper highlights drilling sections that have a tendency to experience drillstring vibrations.

2. UTAH FORGE DRILLING DATA

The drilling data is obtained from the DOE Geothermal Data Repository, Energy and Geoscience Institute at the University of Utah. The public data set used belongs to Well 58-32(MU ESW1), which is a deep, test well. The data file includes extensive logs (pressure, temperature, coring, fracture) and drilling data. The drilling data included is summarized below.

- Daily drilling report: this includes the well profile, operations summary, pre-decided drilling parameters, survey reports, bit and BHA design, mud report as well as safety record
- Directional survey: this includes the actual well trajectory along with measured survey data that identifies the dog leg severity in the well profile
- Unprocessed drilling logs: these logs are the most critical part of the drilling performance analysis. The individual data files include 18 labels and approximately 86,000 rows on an average. The drilling data included in the logs range from 81ft to 7536ft, broken down into 40 individual files. The labels include time, top drive and bit position, pump parameters, top drive torque and rotation, hook load and rate of penetration data. The data included is sampled at 1 Hz.

3. DATA PREPARATION

The data preparation stage begins by merging all the individual drilling log files to form a single analysis file. This is followed by data pre-processing steps that include outlier detection, addressing missing attributes, visualization, differentiating outliers from noise and dimensionality reduction.

3.1 Data cleansing

This includes addressing missing values as well as recognizing faulty measurements from sensors on the rig. On preliminary analysis, it is noted that a drilling section from 5708 ft to 6507 ft is missing. The well is analyzed from 6507 ft to 7536 because stick slip vibrations are expected in the lower, harder formation portions of the well. Uniformity is also maintained by considering a complete section of the well.

Also, erroneous values in travelling block position, RPM, hook load are all identified and deleted from the dataset. Moreover, the unprocessed dataset does not report weight on bit data. It does include hook load (klbs) reading. Since hook load is the summation of off-bottom string load and weight on bit, the paper overlooks the calculation of weight on bit and assumes changes in hook load to be directly related to mirrored changes in weight on bit.

3.2 Outlier detection

Top drive rotations, top drive torque and hook load values are plot on a boxplot for outlier analysis as shown in figure 2. The hook load values are spread uniformly whereas the surface torque and RPM values have datapoints much beyond the maximum (third quartile plus 1.5*interquartile range) value.

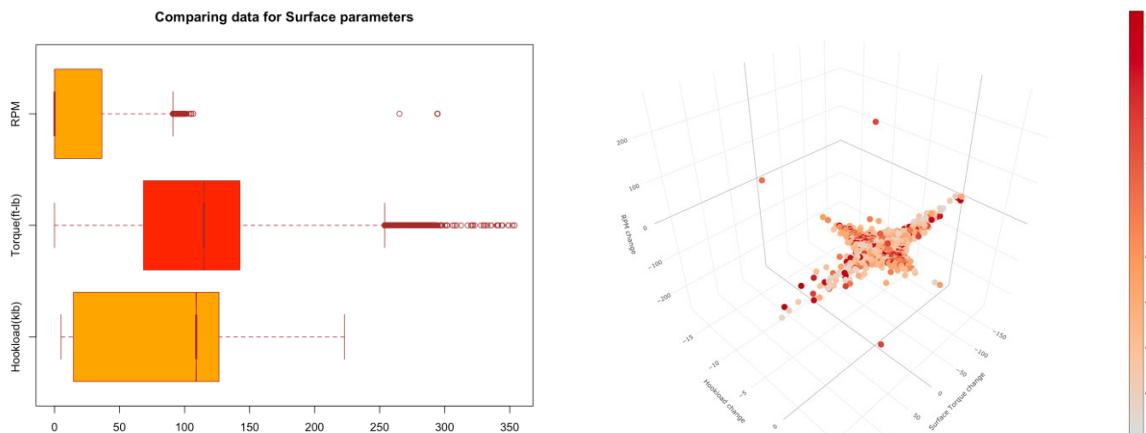


Figure 2: Comparing surface parameters (Left) and 3D scatter plot of surface parameters (Right)

Although the boxplot helps identify outliers in surface torque and RPM values, the dataset is not univariate in nature. Since RPM, torque, hook load and rate of penetration are interdependent, simply deleting outliers in RPM or surface torque does not make complete sense. The 3D scatter plot shown in figure 2(right) is a good way of looking at changes in RPM, surface torque and hook load. As predicted, the lowest rate of penetration lies when surface parameters remain the same (vibrations are kept to the minimum). The change in drilling parameters is instantaneous in nature and is calculated at every datapoint. A deviation in surface torque, hookload and RPM results in a significant drop in the rate of penetration. This paper addresses the amount of change in surface parameters that lowers the rate of penetration in the latter sections. Moreover, outliers in the 3D scatter plot are deleted to avoid issues related to scaling.

3.3 Dimensionality reduction

For dimensionality reduction, feature extraction and feature selection are performed on the dataset. PCA (principal component analysis) is a helpful technique for feature extraction as it includes orthogonal transformation of high dimensional correlated data into principal components, which includes an optimized feature subset. The features selected for analysis are rate of penetration, depth, hook load, surface rotation and top drive torque as they contribute to a cumulative 80% of the data as seen in the first two principal components(PC) in figure 3. PC1 distinguishes rate of penetration from rotary speed and torque while PC2 is dominated by hook load and increasing depth. For further analysis, the change in surface parameters is plotted vs rate of penetration. The first two principal components in this case comprise of only 41% of variance in data. The first component relates changes in torque to changes in rotary speed, as seen in the previous plot. Interestingly, PC2 distinguishes change in ROP and change in hook load. This makes sense as change in hook load is equal to a negative change in weight on bit. This proves that changing weight on bit will be the closest indicator to changing rate of penetration.

Another important consideration is the identification of drilling scenarios appropriate for identification of downhole vibrations. The dataset features depth drilled and bit depth parameters. Since identification of torsional vibrations excludes all off-bottom scenarios, only hook load measurements for active drilling are considered. In other words, the dataset is filtered to keep rows where bit depth is equal to well depth.

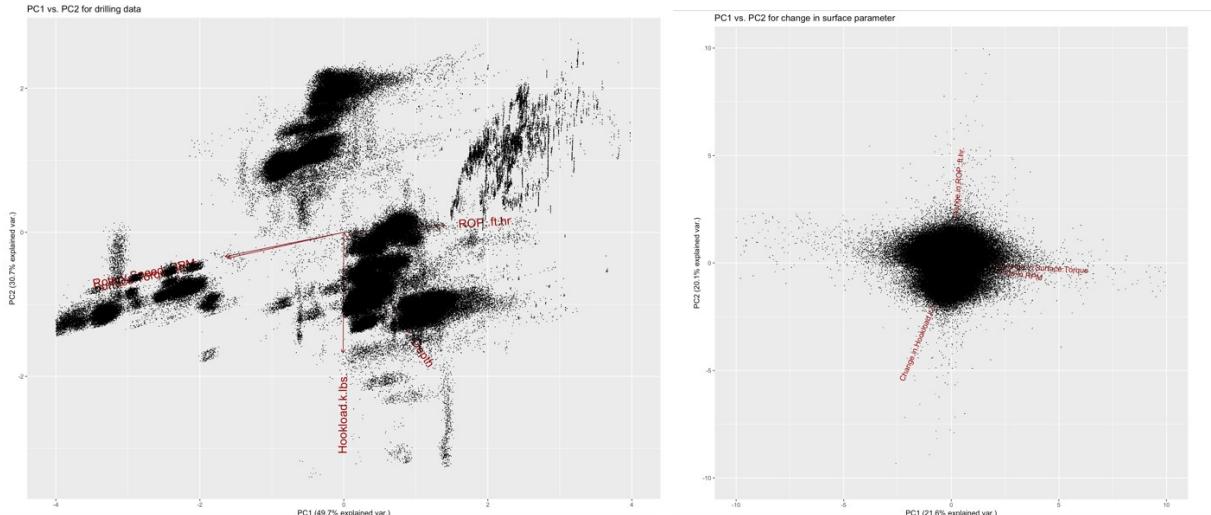


Figure 3: PCA analysis of drilling parameters (Left) and instantaneous change in drilling parameters (Right)

4. ANALYSIS OF SURFACE PARAMETERS

Analysis of surface parameters is aided by visualization. The parameters included for visualization are depth, rate of penetration, hook load, surface torque and rotary speed. As seen in figure 3, these parameters successfully account for 80% of the total variance. Figure 4 plots these parameters together in a matrix format with inter-related Pearson correlation value and individual histograms. Since the dataset considers only 6500ft to 7500ft of drilling depth, the lithology is mostly granodiorite. The takeaways from this plot include:

- Although the rate of penetration remains fairly constant, there is a slight positive correlation with depth. There is positive skewness in the rate of penetration data, most likely due to peaks around 7000 ft and 7300 ft. These depths are analyzed again in the next section.
- The variation in rate of penetration values can be seen at fixed ranges in the drilling parameters which include hook load (around 130 klbs), surface torque (around 150 ft-lbs) and RPM (around 50). This information will be crucial for analysis in the next section.
- The variation in drilling parameters with depth is very straightforward. Since the rock lithology is same throughout, the surface torque and RPM remain constant as they are not dependent on the depth of wellbore. However, the hook load is expected to increase due to an increased length of drillstring.

- Surface torque is more uniformly distributed than rotary speed and both have a good correlation with each other

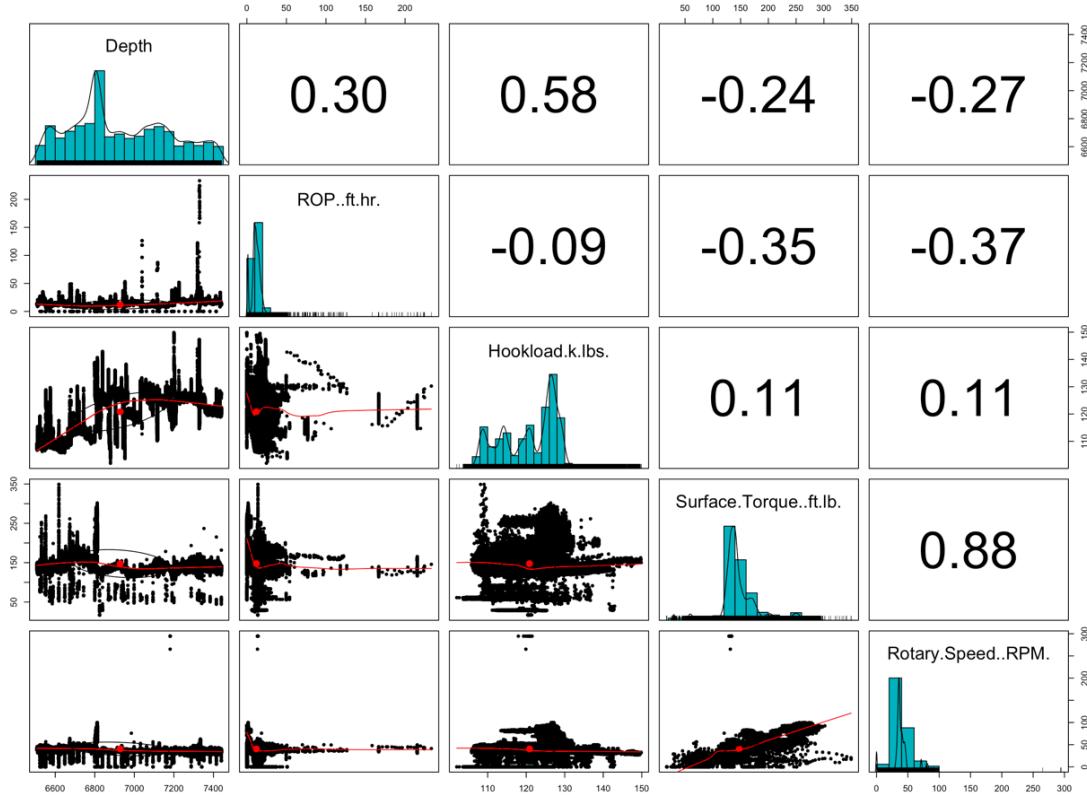


Figure 4: Matrix plot of drilling parameters showcasing correlation and individual dispersion

5. SECTION WISE ANALYSIS

Zha and Pham, 2018, proposed combining surface data with downhole data and training a time series classification model based on downhole RPM threshold to decide the onset of drilling vibrations. While this provides a high accuracy of prediction, there is no downhole data available in the geothermal drilling dataset. Instead, a rigorous manual inspection is needed to highlight areas prone to downhole vibrations in order to accumulate training data for classification. For this purpose, the dataset is split into two sections, one from 6500ft to 7000ft and the other from 7000ft to 7500 ft for an in-depth analysis. In these sections, the variation of surface parameters with depth are compared to drilling reports and mud logs to identify vibration prone sections of drilling.

5.1 Section 1 – 6500 ft to 7000 ft

- The lithology is 100% granodiorite. The section is an 8-3/4" inch hole which is drilled with mud motors. A survey is planned at 6800 ft for position and P, T measurements.
- The section is primarily drilled by mud motor till 6800ft, after which a coring is performed. The remaining 200ft is drilled using slide and rotate technique. For uniformity, only the section continuously drilled by the mud motor is analyzed for downhole vibrations.
- The mud motor experiences high rotary torque causing it to stall and lose pump pressure while drilling from 6507ft to 6552ft. The section is highlighted in figure 5.

On a closer look of the drilling logs, one can notice the fluctuations in surface measurement data. While this can also result from noise in data collection, another possible cause is the high frequency low amplitude torsional vibrations. While these vibrations are commonly observed in drilling operations, the onset of severe stick slip vibrations is very likely. In figure 5, one can observe vibration peaks in top drive rotation, torque and hook load reading. This is a very distinct signature of stick slip vibrations in which the top drive experiences a drop in RPM due to a sudden increment in downhole torque. This is also described as the stick phase of torsional vibrations. This phase is instantaneously followed by a slip phase in which there is a sudden release of the accumulated energy through chaotic downhole vibrations. In some cases, the high amplitude vibrations can be experienced at the surface through sudden changes in surface torque and weight on bit as seen in figure 5. Apart from a reduction in the rate of penetration, these vibrations can also result in bit RPMs reaching thrice the surface RPM causing damage to downhole tools. Since the drilling reports suggest motor stall due to high rotary torque, stick slip vibrations seem like a plausible cause considering the severe vibrations close to 6550ft.

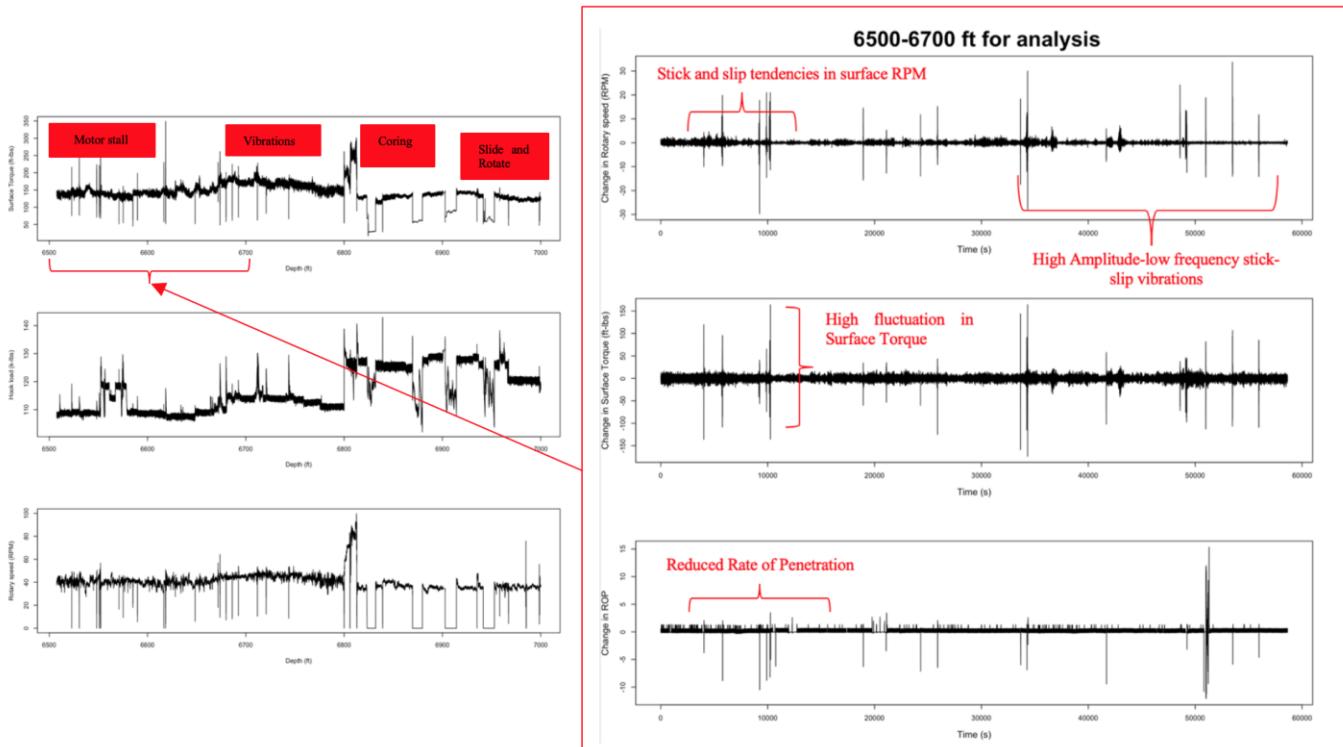


Figure 5: Analysis of stick-slip vibrations in 6500-7000ft of drilling

5.2 Section 2 – 7000 ft to 7500 ft

The noise in surface measurement data tends to make vibration analysis challenging. Plotting instantaneous changes vs. depth is a helpful technique as seen in figure 5. A similar analysis is done for 7000-7500ft of drilling section. The takeaways from this plot include:

- A similar signature of torsional vibration is observed in figure 6. The changes in surface RPM's are characteristically accompanied by high amplitude fluctuations in the surface torque causing variations in the rate of penetration.
- These high amplitude vibrations provide sufficient information that the vibrations downhole are severe in nature. The suspicion is confirmed when the mud motor is pulled out of hole at 7200 ft and reported to have external damage. The reason could possibly be the erratic lateral vibrations which accompany the slip phase of torsional vibrations.
- Interestingly, a new mud motor is used from 7200 ft onwards and the drilling graphs depict a stronger torsional vibration pattern as seen from 7200 – 7300ft. Even though drilling is resumed for the remainder of the well, the well is prone to severe stick-slip situations as one can notice the evident vibration signature throughout.
- Expectedly, as the bit achieves the target depth and is pulled out of hole, it is reported to be broken out.

5.3 Classification of vibrations

In order to make the driller aware of downhole vibrations that can potentially affect the life of tool, a real-time vibration management system is needed. Seamless integration of the system with both surface and downhole sensors will greatly enhance its accuracy. A decision tree vibration model is developed which is essentially a supervised learning-based classification model. The model classifies drilling vibrations according to its severity, resultant reduction in rate of penetration and changes in surface data measurements. The levels are described below as:

- Level 0: This represents smooth drilling conditions with positive instantaneous rate of penetration
- Level 1: This represents the onset of high frequency vibrations in the system that can potentially reduce the rate of penetration by 5ft/hr. or under. These vibrations can be imagined as instantaneous forward and backward rotation along the length of the drillstring
- Level 2: This represents a more severe form of torsional vibrations in which a significant drop in top drive rotation is observed due to high torque conditions at the bit. Although the data is not sufficient enough to prove high torque induced sticking of the bit (bit rpm equals 0), the reduction rate of penetration is large (up to 10ft/hr.)
- Level 3: This represents the onset of severe stick-slip conditions in which the torque experienced by the bit overcomes the input torque of the system. This can cause the bit to stop momentarily and resume with detrimental vibrations. Naturally, penetration rates drop significantly as seen in the previous examples.

The classification model is trained on 6500-6700 ft of drilling which includes a dataset of approximately 300,000 observations. Although the levels of vibrations are quantified primarily based on changes in rate of penetration, the vibrations label is further trained on changes in surface torque, hook load and rotary speed. The decision tree model is plot in figure 6. At the top node one can observe that 62% of the data is level 1 vibrations. For hook load changes < -0.7 klbs, the resultant vibrations are all level 0. Similarly, trends on the node's right can be realized based on further hook load and RPM changes. The model is then tested on a drilling section of 7100-7150 ft for identifying potentially severe vibrations.

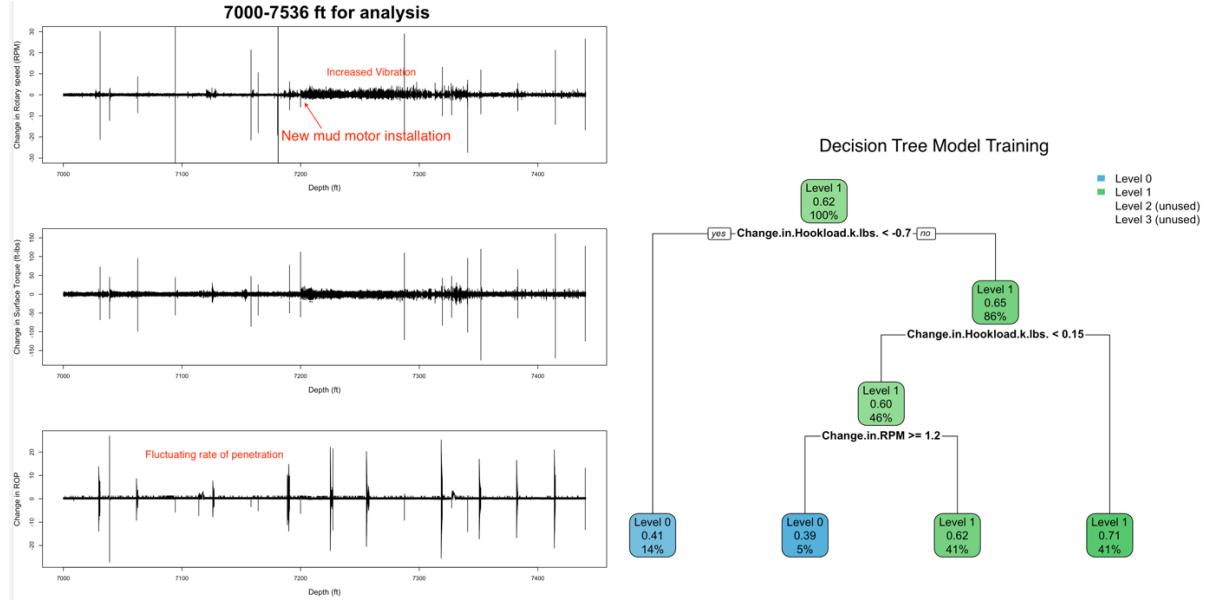


Figure 6: Analysis of stick-slip vibrations (7000-7500 ft) (Left) and decision tree-based classification model for vibration levels for 6500-6552ft (Right)

6. RESULTS

The vibration prediction model successfully classifies 71% of the test data(7100-7150ft) into levels of vibration. While there is scope for improvement, completely predicting downhole vibrations on solely surface data is challenging. Although training data for the factors in vibration analysis exist, the classification model uses only level 0 and level 1 in building the tree. A skewness in the representation of the vibration levels in the training data explains the disparity in the testing result. The classification model did not have sufficient training data available for level 2 and level 3 vibrations to successfully incorporate them into the prediction model. The data is currently sampled at 1 Hz. While this could mean that severe torsional vibration situations are rare, it most likely suggests that there is loss of critical vibration information at the current sampling rate of 1 Hz. This can be confirmed through the section wise analysis that highlights the severe torsional and lateral vibrations partially. Importantly, a higher sampling rate is needed to prevent the loss of high amplitude peaks in the recorded data. A sampling rate of 10Hz or higher is recommended to help collect vital data to aid the process of training a classification model for vibration identification.

7. CONCLUSIONS

- The paper successfully identifies drilling dysfunctions by a thorough analysis of the available surface data measurements. By combining drilling reports, mud and drilling logs, a complete in-depth review is presented in the section wise analysis for drilling vibrations. Potentially severe vibration prone sections have been examined. Timely recognition of such sections can help extend the life of downhole tools.
- The paper also presents the results from training a classification model for vibration identification. The model is trained in a vibration prone section and tested in a different drilling section. Promising classification result have also been presented. The need for an extensive dataset for training vibration models has been recognized.
- The paper also recommends utilizing a minimum of 10Hz of sampling frequency to reveal vibration patterns that are only partially recognized with a lower sampling rate. The collection of data at 10Hz is recommended for a comprehensive training dataset of machine learning algorithms for vibration analysis.
- Although a need for a vibration identification system is realized, the need for a proper data collection method is recommended. The paper highlights the processes involved in data pre-processing and also explains the curse of dimensionality when dealing with large datasets. Without proper storage, filtering, cleansing and dimensionality reduction of recorded dataset, the process of real-time vibration analysis of surface drilling data remains extremely challenging.

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