# Drillbit vibrations enable sonic logs prediction in lateral boreholes using machine learning

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## Summary

The development of unconventional resources requires accurate delineation of formation stiffness along extended horizontal borehole segments. This paper studies the feasibility of prediction of rock stiffness using drilling parameters recorded at the rig, downhole measurements while drilling, and near-bit vibrations. We used a machine learning-assisted workflow to model the wireline logs and assess the importance of various input data. The use of near-bit vibrations reduces the prediction error (of sonic data?) from ~5.3% achieved relying on to 1.8%, which is sufficient for drilling/completion applications. The machine learning algorithm also quantifies the quality of the wireline logs used for training: shear and density logs have ~20% of noisy data while the compressional velocity ~35%. Prediction of wireline shear and compressional sonic data using downhole vibrations measured while drilling has vast potential to reduce logging cost for borehole completion industrywide.

## Introduction

The development of unconventional resources requires accurate delineation of mechanical and reservoir properties along extended horizontal laterals. Such characterization serves as a foundation for optimal planning of complex multistage completions utilizing hydraulic fracturing in drilled wells, and for planning of future laterals in a field. Wireline or logging while drilling (LWD) is the best way to achieve this. It is associated with significant cost, rig time, and moderate operational risk, especially for long laterals. Relying on simple interpolation of existing wireline logs to predict geologic parameters in undrilled locations may carry significant uncertainty. In some unconventional reservoirs, such as in tight sand, geologic parameters vary significantly both along and between lateral wells at distances comparable to well spacing. In these geologic settings, the interpolation of logging results may give large errors in estimated formation properties of subsequent wells, thus undermining drilling and completion process. In an attempt to predict wireline sonic data in a well, one approach uses legacy data to establish relationships between formation properties and drilling parameters measured at the surface (DDS) and limited petrophysical measurements while drilling with gamma ray (MWD GR). Initially, this approach relied on laboratory measurements of the rate of penetration (ROP) observed in various rock types for a range of drilling parameters and instrumentation types (e.g., Teale, 1965; Hareland and Nygaard, 2007). On the opposite extreme, data-driven predictors of the sonic logs discard the physics behind rock stiffness and drilling dynamics and train machine learning algorithms to recognize similar drilling features persistent to particular formation types. Kanfar et al. (2020) repurposed a sophisticated neural network that was initially designed for Google speech recognition/synthesis applications.

The issue with such data-driven predictors arises from the fact that the drilling parameters for the same formation can vary significantly between boreholes within the same formation and field, or even within the same borehole between different bit runs. Drilling can quickly become inefficient due to the action of the driller or complex interaction of a long drillstring, complex bottomhole assembly (BHA), and challenging formation. Downhole sensors of near-bit vibrations (NBV) provide a tool to diagnose such inefficiencies at a much more fundamental level (Macpherson et al., 2015). Glubokovskikh et al. (2020) demonstrated that the machine learning technique could predict synthetic acoustic logs from NBV and drilling parameters in the curve section of the well. It was noted that DDS+NBV prediction was significantly better than DDS+GR. Here, we expand the previous study to a lateral

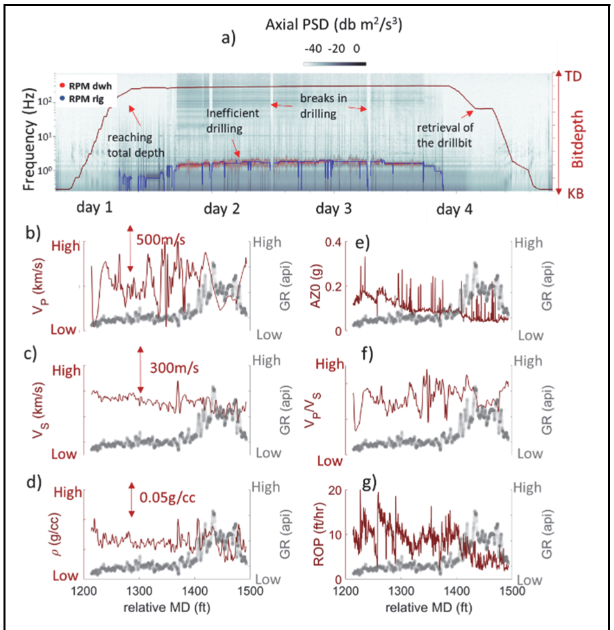


Figure 1: An example of the near-bit vibrations, drilling parameters, and wireline geophysical logs (Run 3). Power spectral density of the axial vibrations (a) is plotted versus the acquisition time, while compressional (b), shear (c), and density (d) logs are in sanitized relative measured depth (MD). The intenisty of the drilling vibrations (e), and rate of penetration (g) are resampled to the measured depth during pre-processing.

section, which poses two main challenges for the proposed methodology: (1) The predictor needs to capture small contrasts of physical properties within the same formation, and the (2) sensitivity of the data to the type of steering used for drilling and borehole trajectory. Synthetic logs from DDS+NBV are one of the deliverables from a DrillCAM system that contains a multipurpose downhole tool also used for seismic-while-drilling and drilling optimization (Bakulin et al., 2019). In this study, we assess the potential for machine learning prediction of sonic logs (compressional and shear) in laterals and to estimate the value of information of NBV and other input data types for quality of the prediction.

**Dataset**

Our test dataset consists of 3,500 ft of DDS, NBV, MWD GR, and mud logs corresponding to seven drilling bit runs in one well through a section containing tight sandstones, siltstones and infrequent shaley intervals. The wireline logs were acquired in the open hole after drilling was completed. Figure 1 shows measurements from Run 3, which contains some features that are typical for the entire dataset. The spectrogram (up to 750 Hz) of the axial NBV (Figure 1a) contains patterns related to the drilling dynamic as well as drilling inefficiencies (red arrows). Variability of the NBV related to the variation of lithology/rock stiffness is less pronounced. The compressional sonic log (b) features numerous errors, while shear velocity (c) and density (d) are stable and correlatable with GR. The intensity of axial vibrations (e) and penetration rate (g) both show a decreasing trend with depth likely associated with drillbit wear. At the same time, a shaley interval at the end of the drilling run (high GR) is also evident in the measurements.

Each of the seven runs features a different combination of the drillbit and rotary steering system (RSS) listed in Table 1, except Run 4 for which downhole accelerometers failed. The first five runs correspond to a more standard RSS technology using "push-the-bit" for steering, while the bit type (number of blades and cutters etc.) varies. The last two runs required higher directional control and used a more sophisticated RSS, with the last run including additional motorized assistance.

Table 1: RSS and bit types for each run. The same bits are in bold.

| Run # | Bit type | RSS type |
|---|---|---|
| 1 | PDC 6-blade | Push-the-bit |
| 2 | PDC 6-blade | Push-the-bit |
| 3 | PDC 5-blade | Push-the-bit |
| 5 | PDC 6-blade | Push-the-bit |
| 6 | PDC 6-blade | Point-the-bit |
| 7 | PDC 6-blade | Motorized push-the-bit |

**Predictive features**

Raw measurements could not be fed into ML algorithms predicting logs because that would inflate the dimensionality of the input parameters, which would result in the tendency of the predictor to overfit the available data set. For example, seismograms for each NBV component (AX – radial relative to the drillbit center, AY – tangential to the edge, AZ - axial) have values for each frequency between 0 and 750 Hz with step 0.25 Hz. Our dataset is insufficient for training a machine learning algorithm with such a large number of parameters. Therefore, the cleaned and edited dataset is transformed into a collection of predictive features that were found to be related to the logs during the exploratory stage of the data analysis.

Eventually, we limited ourselves to a set of 23 features, which may be split into four groups:

- Surface drilling parameters: ROP, revolutions per minute (RPM), torque (TOR), and weight on the bit (WOB);
- Characteristics of the drilling efficiency such as mechanical energy spent on drilling: Mean Specific Energy (MSE) and Sq - reduced MSE (Armenta, 2008):

$$\begin{cases} \mathrm{MSE} = \frac{\mathrm{WOB}}{A_B} + \frac{120\times\pi\times\mathrm{RPM}\times\mathrm{TOR}}{A_B\times\mathrm{ROP}} \\ Sq = 4\sqrt{\pi}\frac{\mathrm{WOB}\times\mathrm{RPM}}{\sqrt{A_B}\times\mathrm{ROP}}. \end{cases} \quad (2)$$

where $A_B$ is the area of the drillbit (borehole diameter is 8.375 inches for our data set);

- MWD values: GR, downhole RPM, and the root-mean-square of its difference with the surface RPM (RPM is measured by same downhole tool as NBV);
- The intensity of the NBV for each component in the entire frequency range, low-frequency range (0-35 Hz), seismic frequency range (35-150 Hz), high-frequency range (150-500 Hz).

**Feature importance and quality of the input data types**

After the set of predictive features is defined, we need to choose a machine learning approach for log prediction. Then, a brute force assessment of the features' importance would consist of tracking the accuracy of the predicted logs for all subsets of the input data. Such a direct search quickly becomes nonfeasible computationally as the number of features grows. Glubokovskikh et al. (2020) proposed a workflow for sampling the importance of the predictive features using a greedy algorithm – an ensemble of stagewise quadratic regressions. This algorithm gradually incorporates the predictive features and their cross-terms according to the highest increase of the goodness-of-fit at each step (Hastie et al., 2013). The algorithm stops once the increment of the goodness-of-fit becomes negligible. To reduce the effect of bad data intervals, each ensemble member is trained/tested on a subset of the input data. The ensemble of such predictors provides statistically smoothed



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log curves. Otherwise, the regression equations become highly dependent on the split between train/test datasets, as the data variability is relatively low and the errors can easily dominate the training.

We estimate the prediction error using cross-validation: for each iteration of this process, one run is excluded from the training of the ensemble of the regressions, and the predictions for this run are compared with the actual wireline logs. As a result of the cross-validation, we obtain four values that quantify the features' importance:

- Training error – how well the ensemble fits the five runs that were used for training;
- Test error – how well the ensemble predicts the data that it did not see during training;
- Feature popularity – how often the greedy algorithm incorporated a term that included a particular feature;
- Importance – how good were the training errors of the regressions that included a particular feature.

Figure 2 illustrates the cross-validation using Run 6 as a blind test for the input data, including only DDS and GR (left column), or DDS, GR, and NBV (right column). We see that the training error is uninformative; both input data sets fit the training data. The test error is drastically different: NBV allows a very accurate prediction of the shear log. The values of popularity and importance suggest that the low- and high-frequency axial vibrations, ax1 and ax3, augment the GR, ROP, and *log*(TOR/RPM), which is important for the regression that relies on DDS and GR only.

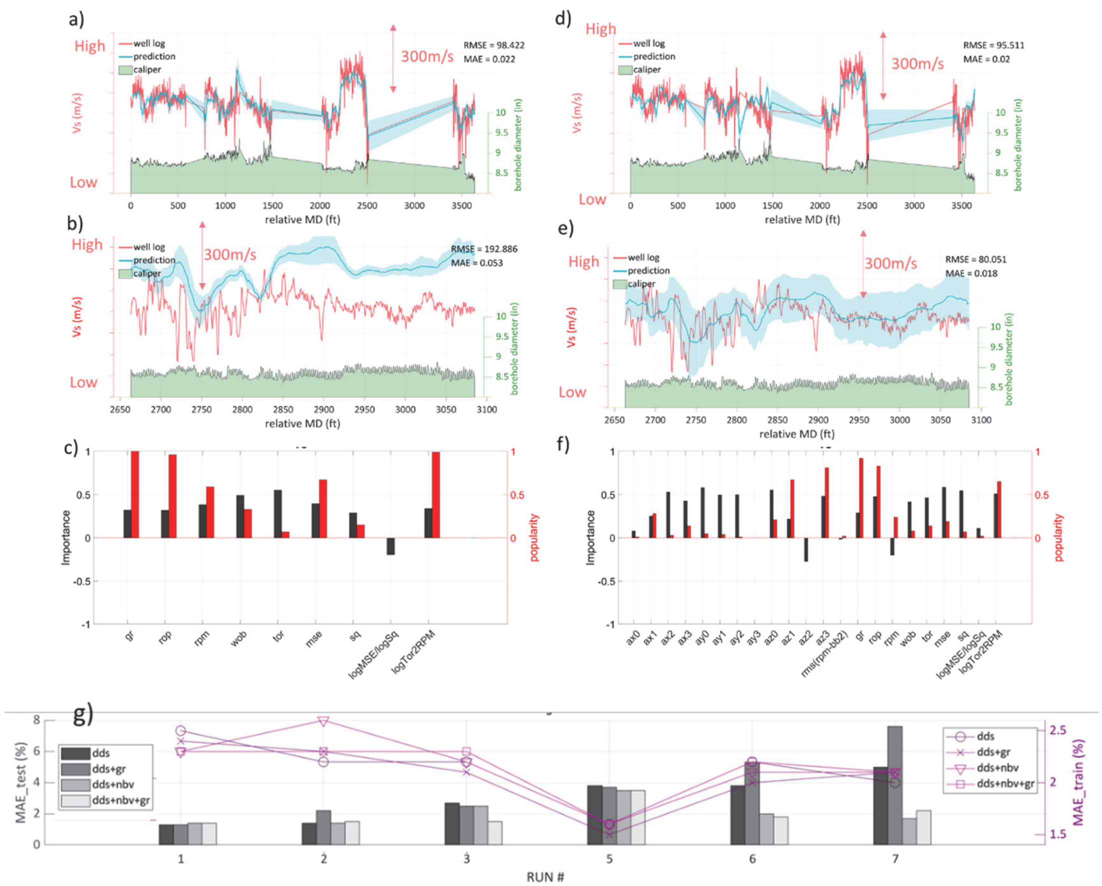


Figure 2: Application of the cross-validation of the shear log prediction as the assessment of the importance of different types of input data: Drilling dynamic recorded at the surface (DDS), gamma ray (GR), and near-bit vibrations (NBV). First, an ensemble of polynomial stagewise regressions is trained on all runs excluding Run 6 for the set of input features, which include only DDS and GR (a) and DDS, GR, and NBV (d). The predicted shear log (blue line surrounded by the blue shadow that denotes the extent of the confidence bounds) is compared with the ground truth that was not used for training DDS and GR (b) and DDS, GR and NBV (e). Error values shown are mean absolute error (MAE) and root-mean-square error (RMSE). Popularity and importance are integral parameters that qunatify the importance of the input features for accurate prediction using DDS and GR only (c) and DDS, GR, and NBV (f). The importance of the NBV for accurate predictions is obvious for Run 6 and all other runs (g).

Figure 2g shows that this conclusion holds for all runs: prediction of the shear log is always more accurate when using NBV. We speculate that the largest positive effect of the NBV occurs for Runs 6 and 7 because these runs feature a different RSS compared to the other four runs. We do not show the results of cross-validation for the compressional velocity and density logs. Nevertheless, the conclusions remain the same – NBV is critical for prediction, and the prediction errors are much lower. Poor performance of the prediction algorithm may be caused by the low quality of the ground truth, compressional velocity, and density. Polynomial regression, the building block of the proposed predictor, provides several metrics that estimate the data quality (Hastie et al., 2013). Figure 3 shows one of the commonly-used metrics, normalized Cook's distance for the well logs. Qualitatively, we see that the Cook's distance is high in the intervals where significant changes in the physical properties are not accompanied by changes in the lithology, like at the end of Run 2 and Run 5. Roughly 35% of the compressional log is consists of outliers according to Cook's distance.

## Conclusions

We analyzed 3,500 ft of drilling data, well logs, and near-bit vibrations to assess their potential for sonic and density log prediction in lateral boreholes. We applied a machine learning-assisted workflow to the data set based on a greedy regression algorithm. The workflow proved successful for capturing the low-magnitude variations of the well logs in the lateral segment of the borehole of interest. All four metrics of the feature importance provided by the workflow indicated that near-bit vibrations are critical for accurate prediction of sonic and density logs. The vibrations allow for accurate prediction in the intervals drilled with the variety of rotary steerable systems and bit parameters.

The proposed prediction algorithm also provides a means to estimate input data quality. Average Cook's distance shows that ~35% of the compressional log is poor, which explains the low accuracy of the predictions. We think that this study reveals the big potential of the downhole measurements of drillbit vibrations for optimization of borehole drilling/completion, not only for mere log prediction. However, development of the production grade workflow for the proposed strategy requires a bigger data set.

## Acknowledgments

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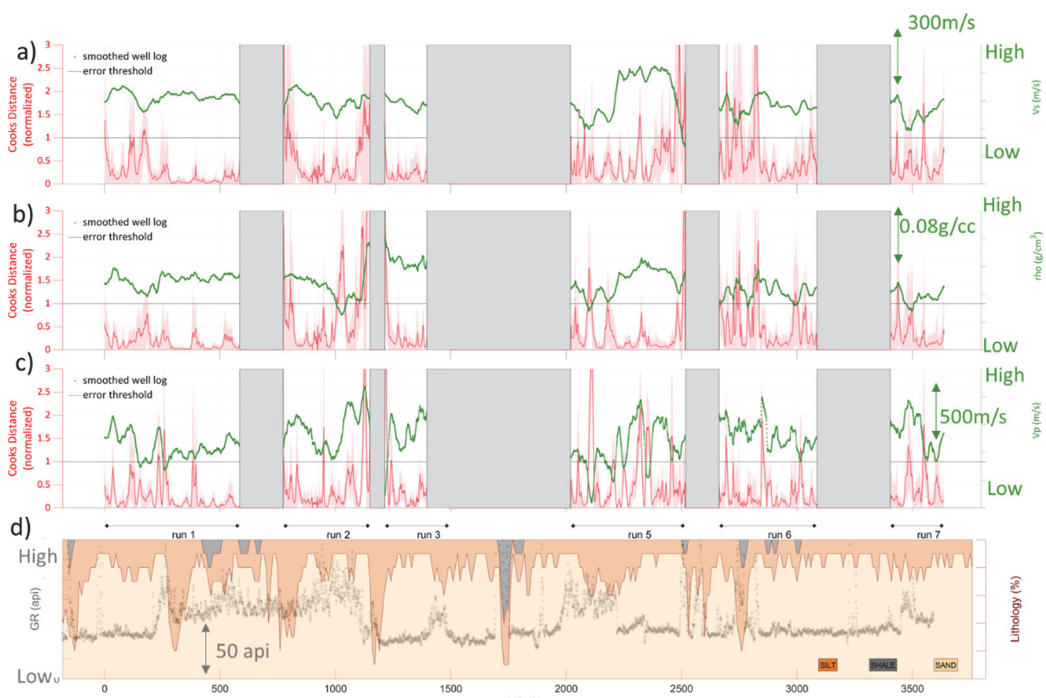


Figure 3: Estimation of the quality of the input log measurements using a greedy regression algorithm (grey rectangles indicate absent data). Values of the normalized Cook's Distance exceeding 1 indicate a likely outlier. Shear velocity (a) and density (b) have ~20% of the anomalous data, while the compressional velocity has ~35%. According to drilling cuttings analysis (d), most anomalous intervals correspond to lithological boundaries.

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