Machine learning algorithms for real-time prediction of the sonic logs based on drilling parameters and downhole accelerometers

Stanislav Glubokovskikh, Curtin University; Andrey Bakulin, Robert Smith, Ilya Silvestrov, EXPEC Advanced Research Center, Geophysics Technology, Saudi Aramco*

Summary

We evaluate the feasibility of predicting seismic velocities based on drilling dynamics. In practice, drilling is often inefficient, resulting in the drilling dynamics losing correspondence with the mechanical energy required to penetrate a rock mass. Based on real data for a 1400 ft interval intersecting carbonate, clastic, and anhydrite formations, we show that downhole accelerometers provide sufficient information to distinguish the effects associated with the "drillstring noise" and rock properties. To this end, we modified the forward stagewise regression to provide a quantitative measure of the importance of various measurements while drilling. The three most critical features were found to be the intensity of axial vibrations (RMS of the accelerations in the 35-170 Hz range), mean specific mechanical energy (related to the drilling efficiency), and the rate of drill-bit penetration. The final regression equation provides much better goodness-of-fit for the challenging geological conditions compared to existing methods.

Introduction

Drilling efficiency is a crucial concern for hydrocarbon recovery because extra time and/or incidents mitigation often incur high costs. Accurate knowledge of the mechanical properties of the subsurface is necessary to find the appropriate equipment and drilling parameters for a given formation. Usually, the mechanical model relies on the sonic logs from adjacent wells. For a nonreservoir part of the section, these logs are very limited and are typically only run in appraisal wells located tens of kilometers apart. Extrapolation of such sparse data may easily fail due to the spatial variability of geology.

To facilitate timely decision-making at the rig, one needs to update the estimated properties as the drill bit penetrates the rocks. The formation stiffness has to be estimated in real-time from indirect measurements while drilling (MWD), as sonic logging while drilling (LWD) is not widely used. Any type of LWD, in general, is rarely available outside the target formation, so petrophysical correlations between gamma ray (GR) or other nonelastic measurements provide only limited coverage along boreholes. Instead, we propose a methodology that relies on the relationship between the dynamics of drill-bit penetration through rocks and their stiffness.

In a controlled laboratory environment, the rate of penetration (ROP) reflects the rock stiffness (e.g., Teale, 1965). In the field, drilling may easily become inefficient with its dynamics having little to do with the mechanical energy required to penetrate a rock mass. For this reason, ROP-based models calibrated in a laboratory (e.g., Hareland and Nygaard, 2007) can be inaccurate and are often applicable only within a narrow range of drilling parameters. Near-bit vibrations (NBV) may provide sufficient information to distinguish the signal from crushing rock and drillstring-related noise. We believe that the physics may be too complex to have a universal analytical model relating the drilling parameters, NBV, and elastic moduli of the rock. In contrast, local regressions can gain reliable predictive power when trained on a sufficient number of existing wells with similar drilling programs. Machine learning algorithms have proven successful when applied to processes with obscure physics behind the observed data, like biomedical sciences and physical chemistry (e.g., Hastie et al., 2013). Here, we study the feasibility of applying machine learning algorithms to the identified problem using field data from a recent field trial of the DrillCAM system (Bakulin et al., 2019).

Dataset from the first DrillCAM trial

The DrillCAM project focuses on the research and development for a system that integrates geophysical measurements while drilling into real-time positioning of the drill and prediction of formation properties near and ahead of the bit. For the first field trial, data was acquired in a deviated section (inclination ranging from 10º to 70º) drilled by an 8.5" polycrystalline diamond compact (PDC) bit through high-contrast carbonate, clastic and anhydrite intervals. NBV were recorded at the drill sub by 3C accelerometers with sampling of 1.5 kHz and dynamic range ±200g. In this study, we focus on analysis of the axial (along the drillstring) component of the vibrations shown in Figure 1a. The spectrogram has a clear striped texture in both vertical and horizontal directions. The former one occurs due to changing dynamics of the drilling process, e.g., time intervals corresponding to the drillstring augmentation (the kinks in the bit-depth curve) are blank and intervals of the inefficient drilling feature frequent bursts of energy.

The horizontal bands correspond to the resonances that occur due to interference of the signals in various components of the drillstring, such as the bottomhole assembly, and periodic rotation of the drill bit (see Figure 1b). A rigorous classification of the major controlling factors within

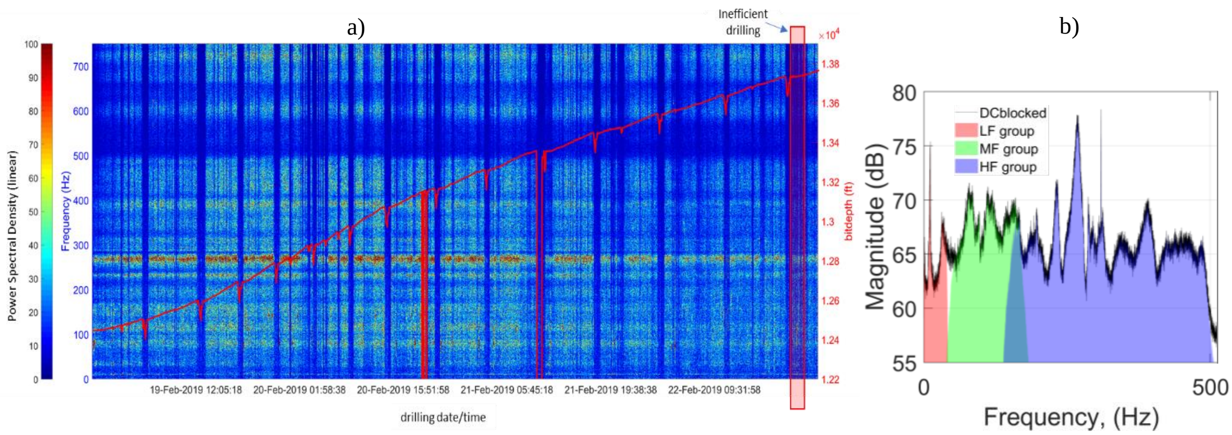

Figure 1: Spectral composition of the near-bit vibrations recorded during the first DrillCAM test. The data shown corresponds to the studied interval that has sonic logs. The time-frequency distribution of energy has a clear striped pattern (a), where the horizontal bright bands indicate resonance frequencies in the drillstring and forced oscillations by the periodic oscillations of the drillbit. Eventually, we segment the spectrum into three bands shown in (b): low 0.1-35Hz (g1), middle 35-150Hz (g2), and high 170-500Hz (g3).

different frequency ranges is challenging. Typically, lower frequencies and high-intensity signals correspond to inefficient drilling regimes (Macpherson et al., 2015). The eigenmodes up to 40 Hz correspond to multiples of revolutions per minute (RPM). Seismic-while-drilling literature offers several phenomenological models to estimate the bandwidth of seismic emission from the interaction of the PDC bit with rock (e.g., Poletto and Miranda, 2004) that predict maximum frequency around 120 Hz for the used drilling parameters. High-frequency vibrations are likely related to the drillstring characteristics. Eventually, we analyze RMS energy in a 30 s windows for three frequency ranges of the axial NBV (Figure 1b): low 0.1-35Hz (g1), middle 35-150Hz (g2), and high 170-500Hz (g3).

The 1400 ft test interval has wireline sonic (V_P and V_S) and density ρ logs that we use as ground truth for training a regression model. Besides NBV measurements, the set of input MWD logs is supplemented by the drilling parameters recorded by sensors deployed at the drilling rig: ROP, RPM, weight on bit (WOB), and torque (TOR). A wireline GR log that was run after the well completion serves as a proxy to LWD GR. Eventually, we would like to have a single predictor for the entire interval regardless of the wide spread in the velocities between the carbonate, clastic, and anhydrite formations.

Existing approaches

The idea to infer rock stiffness from drilling dynamics is not new and has several proposed methods that range from physics-based to purely data-driven. Waltman and Laking (2018) model the NBV as seismic emission from the drill-bit teeth grinding rocks. Yang (2019) identifies the type of rock using a wavelet analysis of the NBV. Both methods focus on the exclusive use of vibrations alone. We argue that one should augment the vibrations with drilling parameters to account for the influence of the drilling regime. In such a manner, Naville et al. (1996) propose a universal heuristic approach to the prediction of the elastic properties called SNAPLOG. The authors introduce a new parameter, the Pseudo-Impedance (PI):

$$\mathrm{PI} = \frac{RMS_{acc}}{\mathrm{RPM}\times\mathrm{ROP}}, \tag{1}$$

where RMS_{acc} denotes a window estimate of the RMS average of the axial accelerometer in the entire frequency range. PI is expected to be equal to the acoustic impedance of the penetrated rock mass ($\mathrm{AI} = \rho \cdot V_P$). One issue with such a simple ad-hoc equation is that it lacks the flexibility to incorporate the vast range of instrumentation types, drilling regimes and lithology variations that may result in similar values of RPM, ROP, and NBV energy. For our data set, R-squared between the PI and AI is only R^2=0.2.

Evaluation of the importance of the parameters

As indicated in the introduction, we anticipate that data-driven regression techniques may provide more robust predictions when offset wells have sufficient amount of training data. The first step has to do with selection of an appropriate group of machine learning algorithms for a particular dataset. Essentially, we need two interconnected components: (1) a set of the predictive features (combinations of the MWD parameters that are used as input), and (2) a functional form of the relationship (e.g., multilinear regression, neural network etc.). The DrillCAM

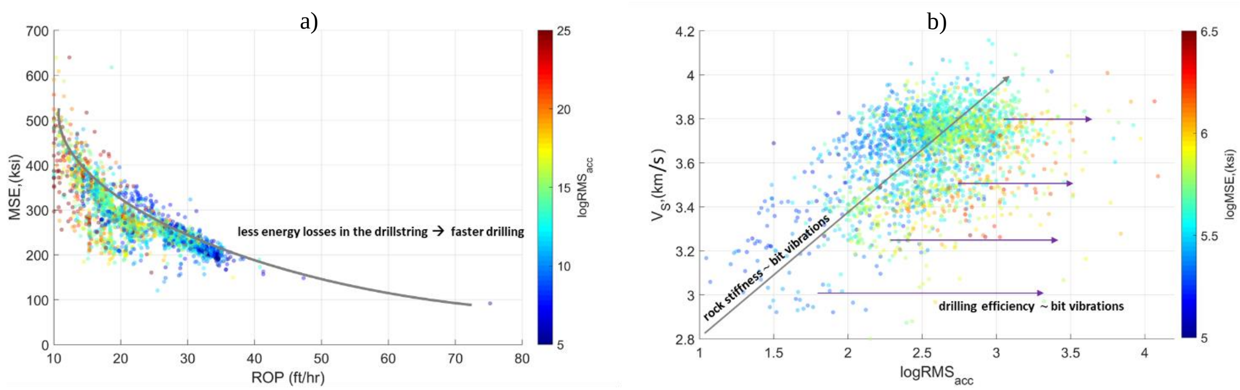

Figure 2: Relationships between the parameters characterizing the drilling efficiency, dynamics of the drillbit penetration, and near-bit vibrations. Both the vibrations and mean specific energy of drilling, increase when drilling becomes inefficient. Therefore, they are inversely proportional to the rate of penetration that is maximized for efficient drilling (a). The intensity of the near-bit vibration shows a clear correlation with the shear velocity (b), however, the vibration energy tends to increase when drilling becomes inefficient.

dataset is relatively small, hence we need a technique that allows for clear interpretation of the results to avoid overfitting and fine-tune the training algorithms. Therefore, we avoid the use of neural networks, that operate as a black box, since they are quite sensitive to the composition of the input data and details of the network architecture (e.g., Gan et al., 2019). Instead, we stick to stepwise nonlinear regression. This algorithm gradually increases the complexity of a polynomial function to improve the goodness-of-fit to the data (R-squared for this study). The selection of predictive features is necessarily intuitive because we need to compile a set of parameters that might be useful without explicit instruction on how to do so. For this study, we put together various combinations of the drilling indicators that were proposed in specialized literature.

Eventually, the features may be split into three groups:

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

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

- Physical measurements at the bit-rock interface: GR and RMSg1, RMSg2, and RMSg3.

Figure 2 illustrates the interdependence of these three categories of input. Figure 2a shows that MSE is inversely proportional to ROP which implies a simple fact – faster drilling occurs when the drilling regime is efficient and incurs less vibrations of the drillbit. Also, the intensity of NBV (RMS_{acc}) does relate to rock stiffness (V_S). It is, however, contingent on the drilling efficiency (MSE), which we need to compensate for in the regression equation. The advantage of the stepwise regression is that we may evaluate the importance of different input variables by their popularity in the final regression equations, trained on pieces of the data. So, we can progress from a visual analysis of the data to a quantitative assessment.

Figure 3a illustrates the progress of the regression algorithm for a trial run. It begins by assigning the mean value to the constant term. At the next step, the algorithm finds a linear term that maximizes R^2 – natural logarithm of RMSg2. Then, we may add either another linear term or a non-linear term that involves RMSg2. It turns out that log (MSE)/log (Sq) is preferred. The process stops when the improvement of the goodness-of-fit becomes marginal. Then, the training is repeated for another piece of the dataset (bootstrapped correlated segments of the input data) and results in a new set of predictive features and corresponding coefficients. The final run of stagewise regression uses the entire dataset for training and begins with a combination of the two most important features. As a result, the predictor for shear-wave velocity Vs has the form:

$$V_S = D + A\cdot\log(\frac{\mathrm{RMSg2}}{\mathrm{RPM}\times\mathrm{ROP}}) + B\cdot\frac{\log(MSE)}{\log(S_q)} + C\cdot\log(ROP), \quad (3)$$

where A, B, C, and D are constants found from training. Figure 3b,c show the accuracy of the regression. We see that the predicted V_S agrees well with the recorded values (R^2=0.6), with most of the errors concentrated in the last 400 ft of the interval, where high MSE values and several caliper

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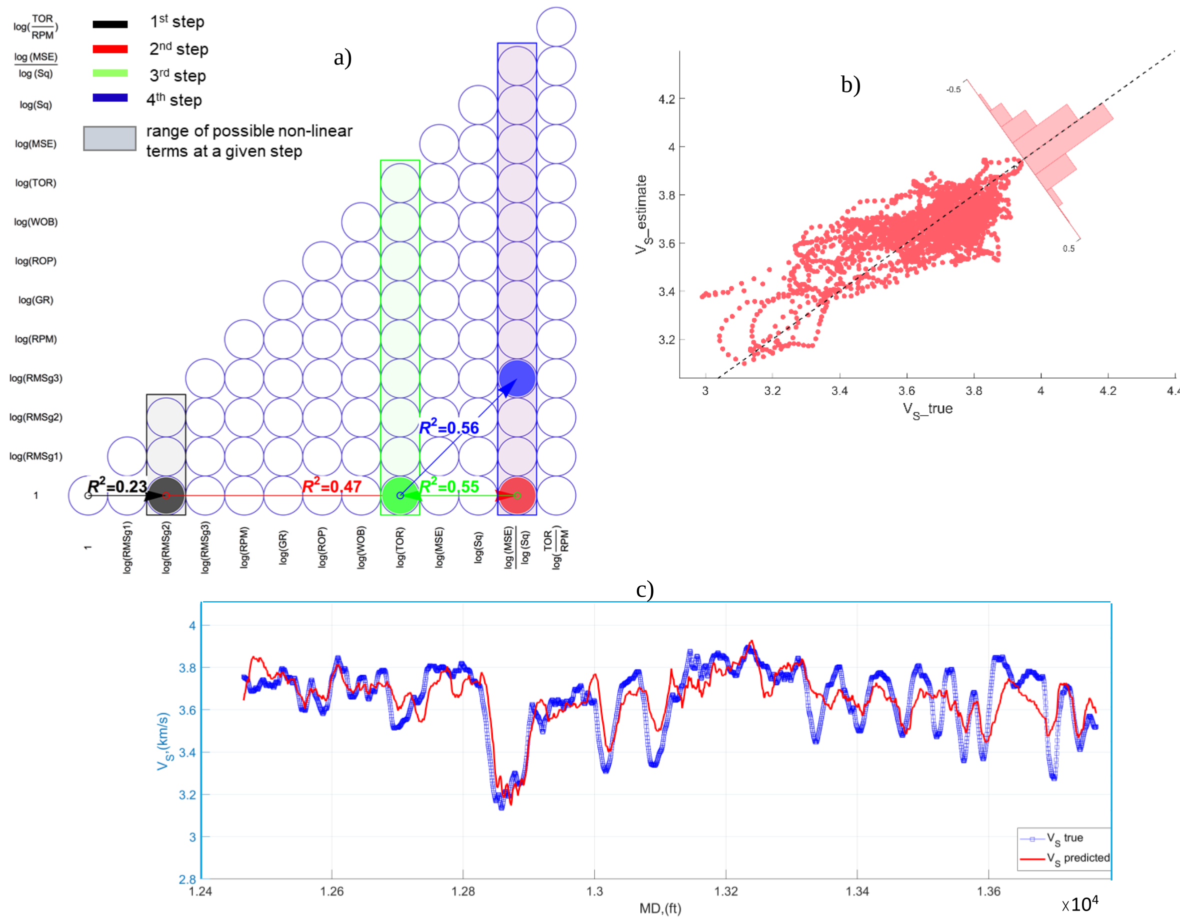

Figure 3: The forward stepwise regression of the shear velocity with selected predictive features. The algorithm proceeds by augmenting the polynomial function with a term that improves goodness-of-fit the most (a). The final regression uses the entire interval of V_S log and provides relatively good fit to the measured values (b and c) with most of the errors concentrated in the last 400 ft of the interval, where quality of the logs is questionable.

logs suggest reduced credibility of both – drilling parameters and sonic logs. Without the NBV, achievable accuracy drops to R^2=0.1.

Conclusions

This study is a first attempt to evaluate the potential to use downhole accelerometers and drilling parameters for the prediction of the sonic logs in real time. We modified a forward stepwise linear regression algorithm to gain insight into the relationships between the rock stiffness, drilling parameters, and near-bit vibrations from the first field trial of the DrillCAM system. The primary roles for the prediction of sonic velocities belong to RMS amplitude of axial accelerations in the 35-170 Hz range; the rate of drill-bit penetration, and mean specific drilling energy. Without the accelerometers, achievable accuracy drops from R^2=0.6 to R^2 = 0.1.

We found that the gamma ray log has negligible predictive power for the sonic velocities, which is a typical situation in carbonate sections. Since there is no physical link between the properties, we suppose that ubiquitous applications of neural networks to logging-while-drilling data fail in the studied geological conditions.

If the RMS of accelerometer records can be transmitted while drilling, we can get a reasonably accurate proxy for the sonic logs at the bit. The proposed methodology can synthesise elastic logs at a fraction of the cost of conventional well logs. Such information is particularly helpful in the overburden that is often not logged or horizontal reservoir sections without wireline logs.

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