1

A practical application of synthetic logs derived from drilling parameters for geomechanical modeling and drilling optimization

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Summary

This case study applies machine learning to generate synthetic acoustic and density logs from gamma-ray and drilling parameters. We further derive various geomechanical properties from the synthetic logs and show how they can be utilized for drilling efficiency monitoring and drilling optimization.

Introduction

Modern drilling faces many challenges and often requires extensive subsurface information to avoid drilling hazards, select optimal well trajectories, and achieve a high rate of penetration. Seismic imaging provides broad areal coverage of the subsurface conditions but has limited vertical resolution. Therefore, well logs remain the primary source of high-resolution data. The obvious drawback is that the information is usually available post-drilling (wireline logs) or with a significant delay (logging-while-drilling). On the other hand, surface drilling measurements are always available in real-time. The recent advancement in machine learning techniques unlocked the possibility of predicting petrophysical logs from the drilling parameters. For instance, Gan et al. (2019) generated synthetic logs from drilling parameters and mudlogging data, while Glubokovskih et al. (2020) predicted logs from surface drilling parameters and downhole accelerometer data. Bentosa et al. (2022) derived synthetic logs from the surface drilling parameters, gamma-ray, various mud logs, and gas data and used them to estimate the geomechanical parameters.
This case study applies machine learning to generate synthetic acoustic and density logs from gamma-ray and drilling parameters. We further derive various geomechanical properties from the synthetic logs and show how they can be utilized for drilling efficiency monitoring and drilling optimization.

Method

A schematic overview of our approach is shown in Figure 1. We generate synthetic sonic and density logs from the surface drilling parameters and gamma-ray log (GR) using an ensemble of fully connected neural networks selected via genetic algorithm optimization.

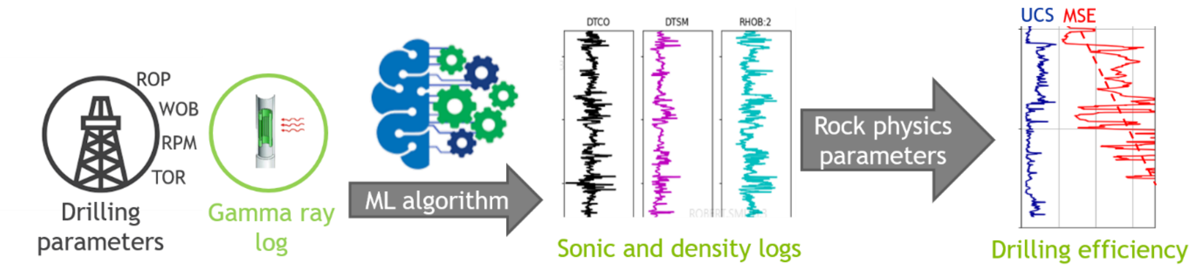

Figure 1: Overview of the proposed approach: from conventional drilling measurements to synthetic logs to geomechanical properties required for monitoring and optimizing drilling efficiency.

Next, we use the predicted synthetic logs to calculate essential geomechanical parameters. The predicted V_P/V_S ratio, acoustic impedance AI, and Poisson's ratio ν_d are calculated directly from the predicted sonic and density logs. The dynamic Young's modulus can be expressed through dynamic Poisson's ratio, density, and S-wave velocity. The static Young's modulus is further obtained using empirical correlation from Ameen et al. (2009):

$$E_s(GPa) = 0.541 * E_d + 12.852 . \quad (1)$$

The Unconfined Compressive Strength (UCS) is estimated from the synthetic logs using an adjusted empirical relationship from Khan et al. (2019):

$$UCS(MPa) = 0.76 V_P^{3.32} , \quad (2)$$

where V_P is the predicted P-wave velocity (km/s) from the synthetic log.

Next, we compare estimated UCS with the Mechanical Specific Energy (MSE) (Teale, 1965), which is usually calculated from the surface drilling parameters as

$$MSE(kpsi) = 4\frac{WOB}{\pi D^2} + \frac{480*RPM*TOR}{D^2*ROP}, \tag{3}$$

where WOB (klbf) is Weight On Bit, RPM (min^{-1}) is Revolutions Per Minute, TOR (klbf.ft) is rotational torque, ROP (ft/hr) is Rate Of Penetration, and D (in) is the bit size. Following Dupriest and Koederiz (2005), we assume the drilling mechanical efficiency factor (EFF_M) of 0.35 and use adjusted MSE for our analysis:

$$MSE_{ADJ} = MSE * EFF_M\ . \tag{4}$$

During efficient drilling, the MSE_{ADJ} is close to UCS. The growing trend of MSE and deviations of MSE significantly above UCS identify periods of inefficient drilling. This information can be used in real time to adjust drilling parameters and optimize the drilling.

Example

We apply our method to an offshore dataset consisting of 13 primarily vertical wells. The ~2000 ft long interval of interest consists mainly of Paleocene and Cretaceous carbonates with sandstone stringers. Twelve wells were utilized for the ML model training and validation. Two validation wells adjacent to the blind test well were used for genetic algorithm model ensemble building. The final model was tested on blind well. Figure 2 shows the compressional slowness (DTC) log predictions. The blue curves represent the measured wireline logs, whereas the orange curves correspond to the synthetic logs. Let us define the following equations for the metrics: normalized root-mean-square error NRMSE and coefficient of determination R^2:

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum_1^N (x(i)-y(i))^2}}{\frac{1}{N}\sum_1^N x(i)},\ R^2 = 1 - \frac{\sum_1^N (x(i)-y(i))^2}{\sum_1^N (x(i)-\bar{x})^2}, \tag{5}$$

where x is observed data, $\bar{x}$ is the mean value, and y is the predicted data. One may observe a good accuracy in prediction for both training and blind wells, with NRMSE varying between 5% to 14%, and coefficient of determination R^2 between 0.14 and 0.92.

The R^2 metric carries valuable information describing the percentage of data variability in the dependent variable (compressional slowness in this case) captured by the ensemble model. For example, in the case of low contrast, a constant prediction with the mean value of the data may result in small NRMSE but always produces R^2=0. In contrast, say R^2=0.6 would imply that the models correctly capture 60% of the data variability. Synthetic shear sonic and density logs were also predicted in the same manner.

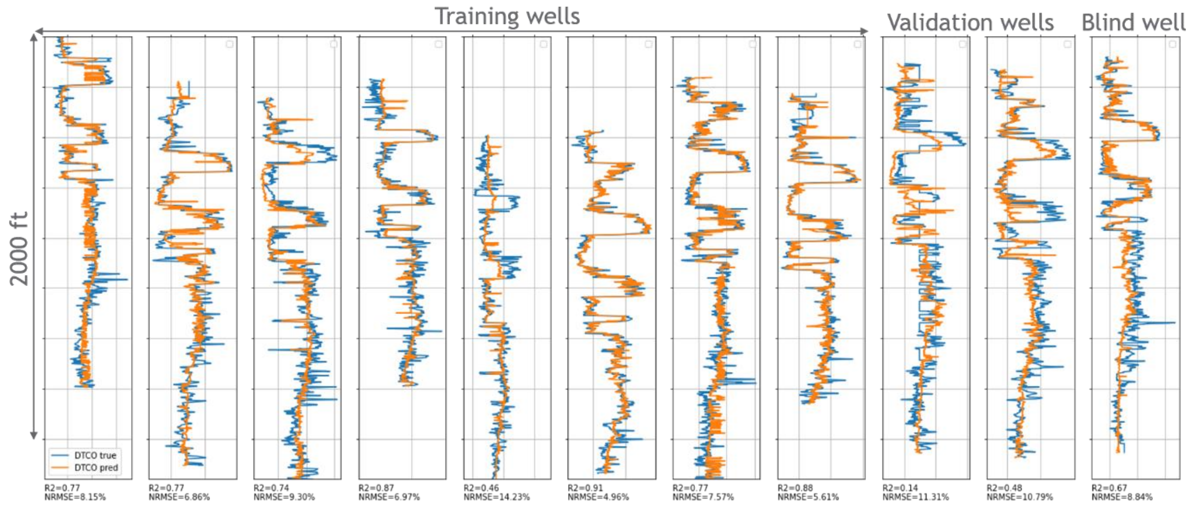

Figure 2: Comparison of the true (blue) vs. predicted (orange) compressional logs (DTCO). Training, validation, and blind testing wells are shown.

All predicted synthetic logs (DTCO, DTSM, and RHOB) and key geomechanical parameters derived from the actual and synthetic logs for the blind well are shown in Figure 3. All estimated parameters demonstrate good agreement between true and predicted synthetic logs and preserve the major boundaries and trends. In addition, the high R^2 and low NRMSE confirm the excellent prediction accuracy and justify the applicability of the synthetic logs for the calculation of the geomechanical parameters.

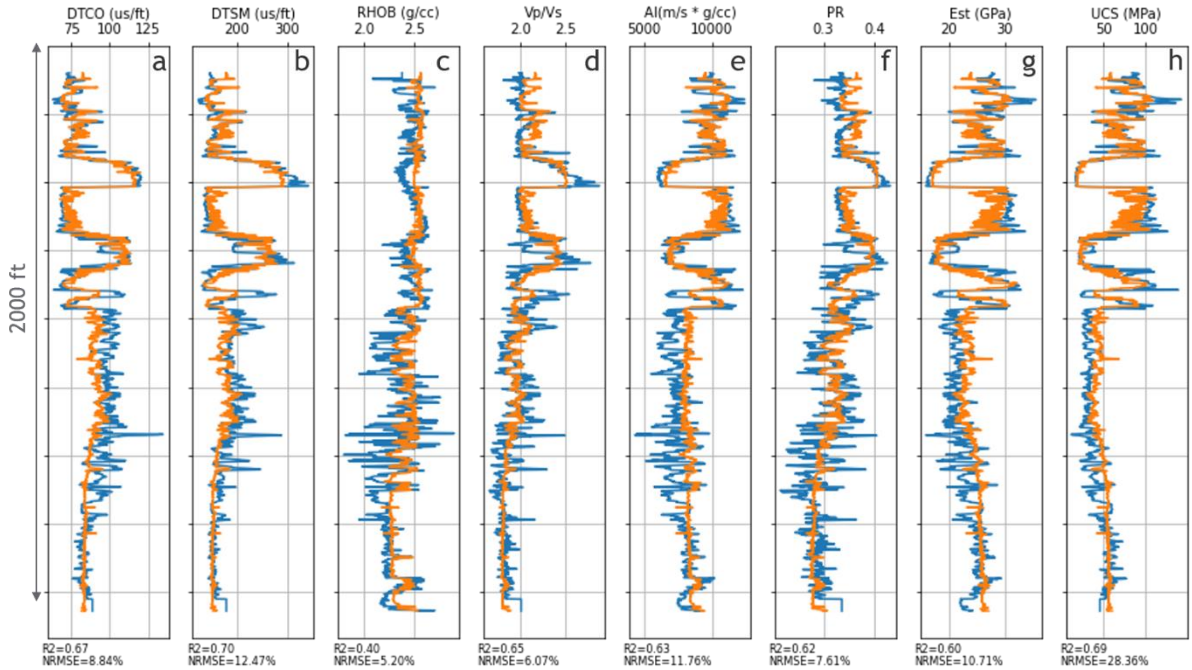

Figure 3: Measured and predicted sonic and density logs (a)-(c) along with the essential geomechanical parameters (d)-(h) derived from the logs for the blind well. Colors denote true (blue) and synthetic (orange) values.

Next, we estimated UCS together with the MSE_{ADJ} (derived from the drilling parameters using formulas (3) and (4)) to enable surveillance of drilling efficiency. Conventional MSE_{ADJ} surveillance (Dupriest and Koederitz, 2005) monitors MSE_{ADJ} trends that are easy to interpret only in a low-contrast environment with slowly varying UCS. However, highly contrasting mechanical layerings in the desert environment demand good knowledge of USC to decipher MSE_{ADJ} variations. Figure 4 shows the diagnostic plot for the blind test well. The depth sections were drilled without a mud motor with a single 12.25 bit size. Shallow sections experience extreme variations in MSE_{ADJ}. Some of these variations could be explained by underlying UCS variations, whereas others are not. Having both MSE_{ADJ} and UCS values enables a more accurate understanding of MSE incursions that could help efficient drilling optimization.

Conclusions

This study presents a practical application of the synthetic logs derived from the surface drilling parameters and gamma-ray using machine learning to evaluate the mechanical properties of the rocks. This analysis can be done on historical data or in real-time while drilling when the pre-trained model already exists. We show that synthetic logs provide sufficient accuracy for calculating the geomechanical parameters, including UCS. The simultaneous monitoring of UCS and MSE_{ADJ} and their ratio could measure drilling efficiency and be utilized for real-time drilling optimization. Availability of the UCS is essential in a desert environment where highly contrasting layers are the norm rather than the exception. This method can be further improved by applying a machine learning approach to optimize ROP directly from the drilling parameters and synthetic logs.

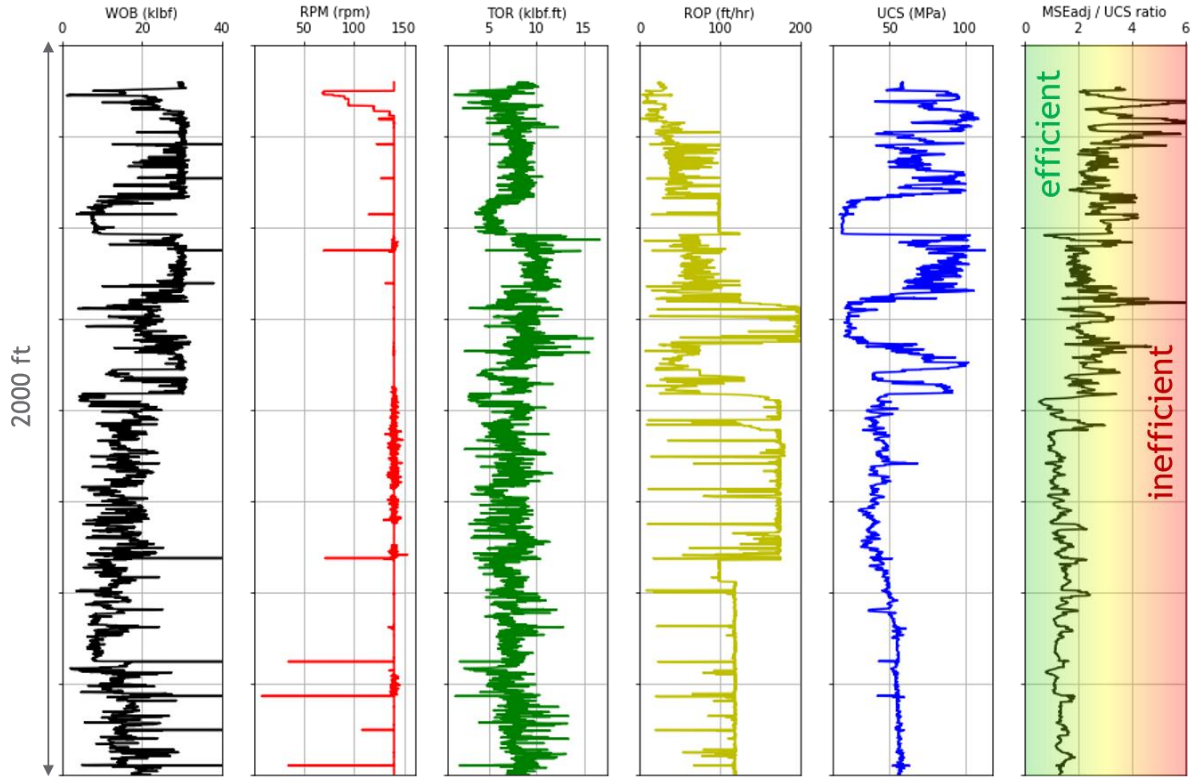

*Figure 4: Example of the drilling inefficiency monitoring using UCS derived from synthetic logs and MSE derived from surface drilling parameters. The upper section demonstrates a challenging interval where ROP decreased while MSE_{ADJ} remained highly elevated (MSE_{ADJ} up to 6*UCS) suggesting inefficient drilling. The lower interval exhibits more efficient drilling with MSE_{ADJ} ~UCS.*

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