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Design and Experimental Validation of a Machine Learning Estimation System for Down-hole Drilling Performance

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ABSTRACT

Achieving robust and efficient drilling is a critical part of reducing the cost of geothermal energy exploration and extraction. Drilling performance is often evaluated using one or more of three key metrics: depth of cut (DOC), rate of penetration (ROP), and mechanical specific energy (MSE). All three of these quantities are related to each other. DOC refers to the depth a bit penetrates into rock during drilling. This is an important quantity for estimating bit behavior. ROP is the simply the DOC multiplied by the rotational rate, and represents how quickly the drill bit is advancing through the ground. ROP is often the parameter used for drilling control and optimization. Finally, MSE provides insight into drilling efficiency and rock type. MSE calculations rely on ROP, drilling force, and drilling torque. Surface-based sensors at the top of the drill are often used to measure all these quantities. However, top-hole measurements can deviate substantially from the behavior at the bit due to lag, vibrations, and friction. Therefore, relying only on top-hole information can lead to sub-optimal drilling control. In this work, we describe recent progress towards estimating ROP, DOC, and MSE using down-hole sensing. We assume down-hole measurements of torque, weight-on-bit (WOB). Our hypothesis is that these measurements can provide more rapid and accurate measures of drilling performance. We show how a multi-layer perceptron (MLP) machine learning algorithm can provide rapid and accurate performance when evaluated on experimental data taken from Sandia's Hard Rock Drilling Facility. In addition, we implement our algorithms on an embedded system intended to emulate a bottom-hole-assembly for sensing and estimation. Our experimental results show that DOC can be estimated accurately and in real-time. These estimates when combined with measurements for rotary speed, torque, and force can provide improved estimates for ROP and MSE. These results have the potential to enable better drilling assessment, improved control, and extended component life-times.

1. INTRODUCTION

Drilling is necessary for energy exploration and extraction. Therefore, techniques that improve the efficiency and robustness of drilling systems can positively impact a range of energy industries including petroleum and geothermal. Depth of cut (DOC) heavily influences drilling performance, and is a measure of how deep the bit penetrates into the rock (Zhou et al., 2017). DOC can be used to determine whether rock fracture is ductile or brittle (Huang and Detournay, 2008; He et al. 2017). Similarly, DOC plays a key role in understanding drilling mechanics (Detournay et al., 2018; Detournay and Detournay, 1992; Menzes et al., 2014). Additionally, DOC can influence damaging vibrations (Zhu et al., 2014). Many control and optimization algorithms utilize rate of penetration (ROP), which is related to DOC (Spencer et al., 2017; Chapman et al., 2012; Hegde and Gray, 2017). These algorithms make use of ROP to enable closed loop drilling control, which can help optimize drilling efficiency or preserve components. This is because ROP reflects the rate at which the drill moves through rock. DOC or ROP can also be used to compute the Mechanical Specific Energy (MSE) (Dupriest, 2005; Hashmi, 2000). Therefore, DOC and MSE serve as key metrics for drilling efficiency and bit behavior.

While using DOC works well in capturing overall system performance, DOC is often measured using surface measurements for displacement and rotation. Top-hole measurements may not accurately represent the behavior at the rock-bit interface. For example, axial and torsional compliance can cause the surface measurements to differ substantially from the down-hole (bit-level) behavior. Similarly, wall friction can cause both top-hole torque and top-hole force to deviate from the weight-on-bit and torque-on-bit. In fact, experimental studies have shown dramatic differences between downhole torques and surface torques (Pavone, 1994). Therefore, conventional surface measurements can be an inaccurate and/or slow indicator of acute drilling dysfunction, which is when potentially destructive events occur (whirl, stick-slip, interfacial severity, bit bounce).

MSE relies on good estimates for the force-on-bit and the down-hole ROP/DOC. Therefore, MSE estimates are especially susceptible to errors stemming from a reliance on surface measurements. Calculating MSE for the bit relies on corrections for vibrations, torque and drag (Rickard et al., 2019). Determining MSE from bit measurements has become increasingly popular (Rickard et al., 2019). In contrast to surface measurements, down-hole measurements at the bit bypass friction and elasticity and are therefore scalable at depth. However, measuring DOC and ROP at the bottom of the hole is difficult due to the lack of a ground reference. Previous studies (Detournay et al., 2008; Spencer et al., 2017) have shown how ROP is correlated with axial force, torque, and speed. Therefore, a Bottom-Hole-Assembly (BHA) that measures axial force, torque, and RPM at the bit has the potential to provide more rapid and accurate estimates of DOC and MSE than either direct or indirect top-hole signals. We envision cases where a BHA estimates DOC and MSE. These measurements can then be fed into the drilling controller to maximize performance or minimize wear by modulating surface WOB, torque, or speed. Down-hole DOC estimates can also be used to rapidly engage down-hole safety systems in order to protect the bit from damage. Communication between a BHA and the top can be achieved through several methods. Wired pipe systems have emerged as potential options (Holta and Aamo, 2021; Macpherson et al., 2019). Alternatively, mud-pulse or acoustic communication can provide a lower-bandwidth mode of communication (Klotz et al., 2008; Neff and Camwell, 2007; Gardner et al., 2006).

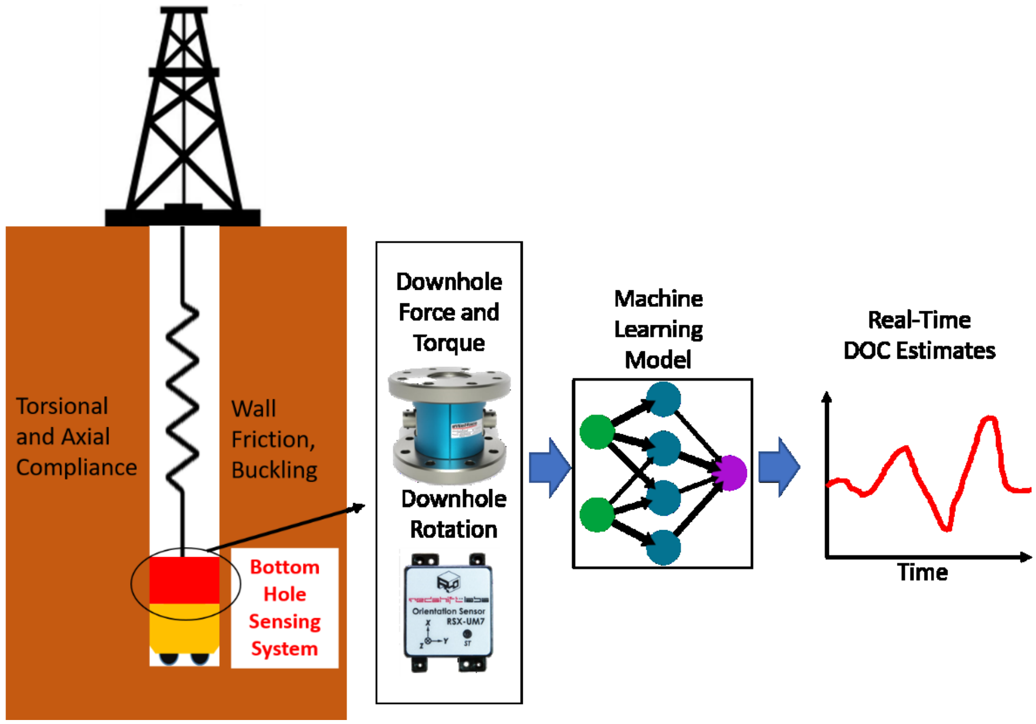

Figure 1: Overview of down-hole sensing and estimation.

Our team's previous work in this area focused on designing a machine learning algorithm for estimating DOC using only down-hole sensors (Sacks et al., 2021). We showed that a multilayer perceptron (MLP) architecture was the most effective based on experimental data. In this work, we build upon the previous results by implementing and experimentally validating the MLP algorithm and extending the results to MSE estimation.

An overview of our approach is shown in Figure 1. The key contributions of this work are 1) the development of an optimized multi-layer perceptron (MLP) based algorithm for down-hole DOC estimation, 2) the experimental validation of our DOC and MSE estimation methods using a BHA emulator deployed at Sandia National Labs' Hard Rock Drilling Facility (HRDF). This paper builds upon preliminary work which quantitatively compared machine learning models (Sacks et al., 2021) by describing an improved model and providing real-time experimental validation.

This paper begins with a review of relevant work in the area. The paper then outlines the potential benefits of down-hole performance estimation and describes how this approach requires machine learning methods. Next, we summarize our machine learning algorithm design. Finally, we describe our implementation of our proposed method on a BHA emulator and provide experimental results that illustrate good DOC estimation performance.

2. BACKGROUND AND MOTIVATION

We are interested in down-hole estimates of DOC and MSE, as top-hole and down-hole behaviors can differ during transient behaviors. Example situations include rock property transitions or stick-slip. During these periods, which can last seconds, top-hole estimates for drilling performance can be inaccurate (Schlumberger et al., 2010). This can cause poor control decisions. For example, we show a simple case where a long drill transitions from a soft rock to a harder rock. Even with perfect information, the top-hole estimate for ROP and DOC do not match for a few seconds. For example, Figure 2 illustrates a simulated rock transition around 45s. The DOC based on top-hole information and the DOC based on bottom hole information differ for ~5s. This simple simulation highlights how top-hole information can be inaccurate under certain conditions. This poor information can lead to suboptimal control and inaccurate predictions of tool wear/life.

When considering down-hole DOC and MSE, we use the following expressions:

$$DOC = \frac{ROP}{RPM} \tag{1}$$

$$MSE = \frac{WOB}{\pi R^2} + \frac{RPM\tau}{R^2 ROP} \tag{2}$$

Down-hole RPM, RPM, can be measured directly using an inertial measurement unit (IMU). Similarly, down-hole torque, τ, and down-hole WOB, WOB, can be measured using a force/torque sensor located near the bit. Additionally, the bit radius, R, is a fixed known quantity. In contrast, down-hole ROP cannot be measured directly and must be estimated. Machine learning models have the potential to handle the complex drilling behaviors better than simplified physics-based models (Hegde et al., 2017). Several past works have studied using machine learning algorithms to predict quantities related to drilling performance, such as the Poisson ratio (Elkatatny, 2018; Siddig et al., 2021) or Young's modulus (Siddig et al., 2021) of the rock, rock unconfined compressive strength (Gamal et al., 2021), fracture pressure of the well (Ahmed et al., 2021; Yang et al., 2021), and pump pressure (Wang and Salehi, 2015). For ROP prediction specifically, papers have examined random forests (Hegde et al., 2017; Hegde et al., 2020, Osman et al., 2021), artificial neural networks (Jahanbakhshi et al., 2012; Abbas et al., 2019; Elkatatny, 2020), and linear regression (Hegde et al., 2017). While these works have achieved impressive accuracy results, they often rely on a range of features are not always available. In this work, we examine machine learning models that use features that can be measured using down-hole sensors: torque-on-bit, weight-on-bit, and rotational speed.

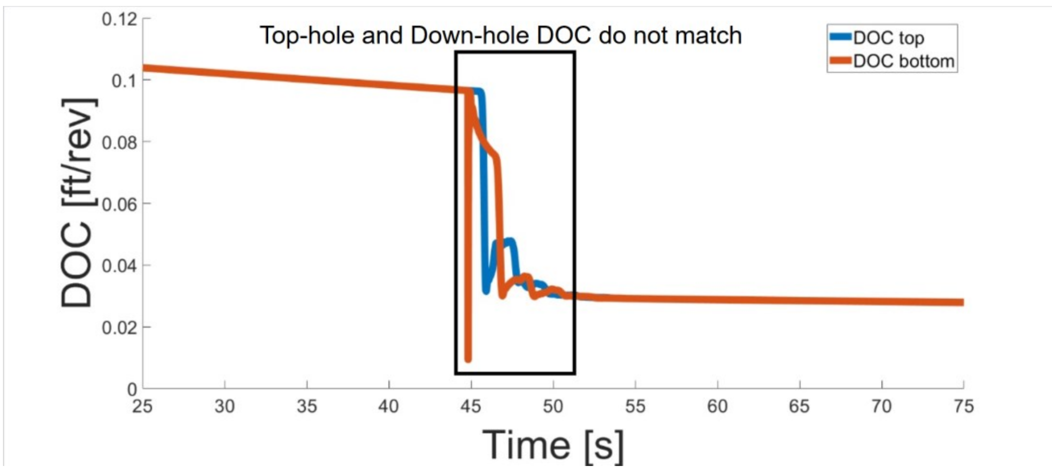

Figure 2: Simulation illustrating how top- and bottom-hole DOC can differ for a significant length of time under changes in rock behavior.

3. DOWN-HOLE ROP ESTIMATION

We propose estimating ROP using sensors that can be used on a down-hole BHA: torque-on-bit, weight-on-bit, and rotational speed. If we know the ground-truth ROP, our task is to solve a regression problem to learn a model which accurately predicts down-hole ROP. Specifically, we assume we are given N training examples $\{(x_1,y_1),...,(x_N,y_N)\}$, where the $x_i \in X$ are the input features for the i-th example, and the $y_i \in Y$ are the corresponding target outputs. We wish to find a model $f: X \rightarrow Y$ which outputs a prediction $\hat{y} = f(x)$ close to the ground-truth target y according to some specified loss function $L: Y \times Y \rightarrow R$. Generally, we assume that the function f is parameterized by some θ, and we wish to solve the following optimization problem:

$$\theta^* = argmin_\theta \sum_{i=1}^{N} L(y_i, \hat{y_i}) + \lambda R(\theta) \tag{3}$$

Neural network models offer substantial flexibility and can capture a large range of nonlinear effects (Hornik et al., 1989). In this paper, we consider a class of feedforward neural networks known as multilayer perceptrons (MLPs), which consist of at least three layers of nodes. Except for the input layer, each layer of the network is followed by a nonlinear activation function. The most common choice of activation function is the rectified linear unit (ReLU), which is simply $\varphi(x) = \max(0,x)$.

$$\hat{y_i} = W_2 \phi(W_{1x} + b_1) + b_2 \tag{4}$$

For a single hidden layer MLP, we have a model of the form where $\theta = \{W_1, W_2, b_1, b_2\}$ are the weight matrices and biases of each network layer that together make up the learnable parameters of the network. The downside of neural networks is that there is no analytic solution for such models. Therefore, optimization is generally carried out through an iterative procedure, such as stochastic gradient descent.

Figure 3: Photograph of Sandia's Hard Rock Drilling Facility.

4. EVALUATING NEURAL NETWORK MACHINE LEARNING MODELS

We trained our MLP algorithm using drilling data taken at Sandia National Labs' Hard Rock Drilling Facility (HRDF). The HRDF utilizes a hydraulic top-drive for rotation and hydraulic cylinders to apply weight on bit (WOB). The system is capable of applying up to 6000 lbf for WOB and 560 lbf-ft for torque-on-bit. The torque is transmitted through a 3in. diameter drill string. Water is used as a drilling fluid and circulated through the bit. Two 3.75" OD bits, a 4 bladed PDC bit, and a 5 bladed PDC bit were used to generate the training data. Photos of the HRDF and a sample drill bit are shown in Figure 3. Drilling was performed in Sierra White granite blocks with a unconfined compressive strength of around 22 ksi. The total available data for training, validation and testing comprises approximately 2 hours of drilling.

The drilling torque and WOB are measured using force/torque sensors (when available). Some experiments relied on hydraulic pressures for force and torque estimates. The drill rotational speed (RPM) was measured using force/torque sensors (when available). Some experiments relied on hydraulic pressures for force and torque estimates. The drill rotational speed (RPM) was measured using a counter mounted on the rotary motor. Drilling depth was measured using a Linear Variable Differential Transformer (LVDT). The time derivative of the depth measurement was used for ground truth ROP.

Table 1: Mean absolute error in ft/hr of the optimal linear, polynomial, and MLP models on each dataset split.

Model	Train MAE	Validation MAE	Test MAE
MLP	0.876	1.27	1.79

4.1 Data Pre-processing

For all experiments, we used the same 70% of collected drilling sequences as a training set, 20% as validation set for hyperparameter tuning, and 10% as a test set for reporting performance. Each drilling sequence consists of measurements of down-hole WOB, RPM, torque, and depth. We estimated the ground-truth ROP/DOC using a forward finite difference of depth. Prior to computing the finite-difference, we filtered the depth with a moving average filter using a window length of approximately 5 seconds in order to produce a less noisy ROP signal. All other signals were filtered with a window length of approximately 0.2 seconds.

4.2 Training Details

We trained the MLP model to optimize the mean squared error of the ROP prediction compared to the ground truth measurements and report performance in terms of the mean absolute error, or

$$L(y) = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y_i}| \quad (5)$$

We trained one- and two-layer multi-layer perceptrons (MLPs) with ReLU activation functions using PyTorch (Paszke et al., 2019). Network parameters were optimized by a variant of stochastic gradient descent named ADAM (Kingma and Ba, 2014). We varied the learning rate, fixed all other optimizer hyperparameters at the PyTorch defaults, and trained all networks for 100 epochs. We also regularized the networks with dropout (Srivastava et al., 2014), which randomly drops weights from the network during training. To determine the architecture of the network, we performed a grid search over the number of hidden nodes, number of layers, dropout probabilities, and learning rates. Specifically, we chose the number of nodes to be powers of two between 32 and 1024, networks with one or two layers using the same number of nodes, dropout probabilities of 0 (no dropout), 0.1, 0.25, and 0.5, and learning rates of 0.01, 0.001, and 0.0001. Again, we chose the optimal hyperparameters according to the performance on the held-out validation set.

4.3 Results

In Figure 4, we plot the test results of our MLP DOC prediction algorithm. The figure shows RPM, torque, WOB, and predicted DOC for the MLP. In Figure 5, we zoom in to a sudden change in WOB and illustrate the model response. These results show the effectiveness of the MLP model.

4.4 Improved Generalization with Noisy Data

In the previous subsection, we discussed how we pre-processed all of the input data used to train the models by applying a filter. The previous results used input data that was pre-processed through filtering. However, we found that the MLP could also work with raw (noisy) signals. Specifically, the use of the raw signals empirically improved generalization on held-out data. Because we do not filter the inputs, this results in a fairly noisy ROP estimate from the model over time. To remedy this issue, we apply a moving average filter with a window length of approximately 0.2 seconds on the ROP estimates from the model.

In Figure 6, we illustrate the performance of an MLP trained on pre-processed vs. raw data on a held-out test sequence. We can see that the MLP that was trained on the raw data generalizes better to the new test sequence than the model trained on preprocessed data. Applying a filter to the raw data seems to remove information that improves the training of the network. By letting the training algorithm decide what information is most useful, we appear to learn a better model.

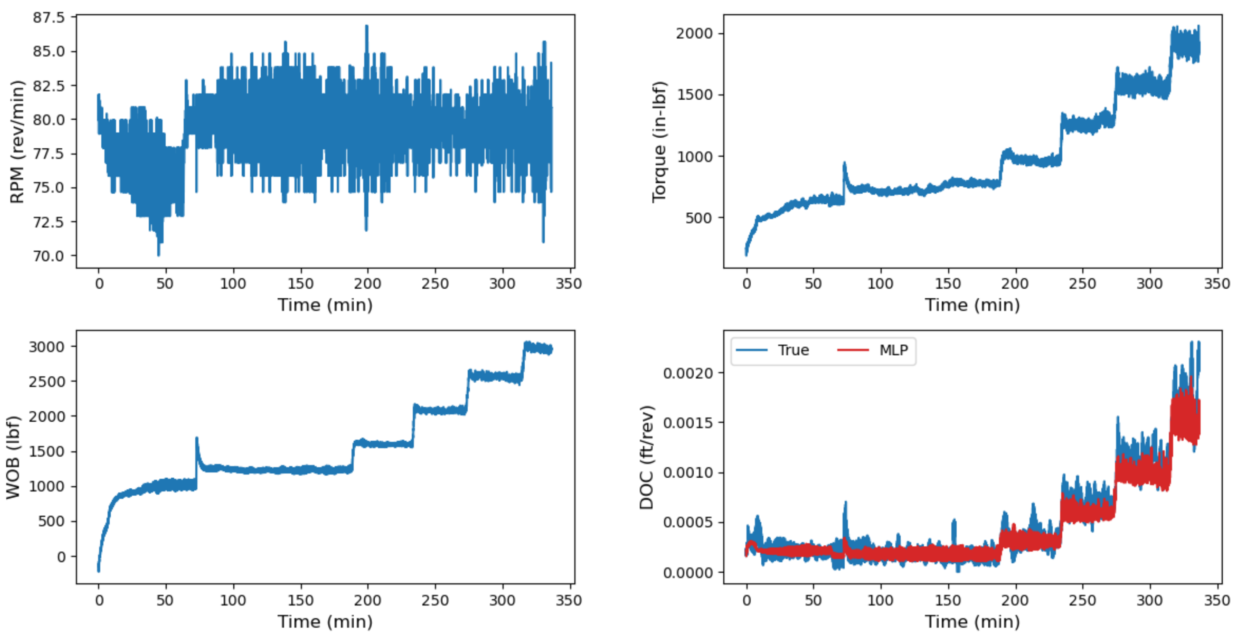

Figure 4: A plot illustrating the performance of the MLP model in predicting DOC from RPM, torque, and WOB measurements on a held-out test sequence.

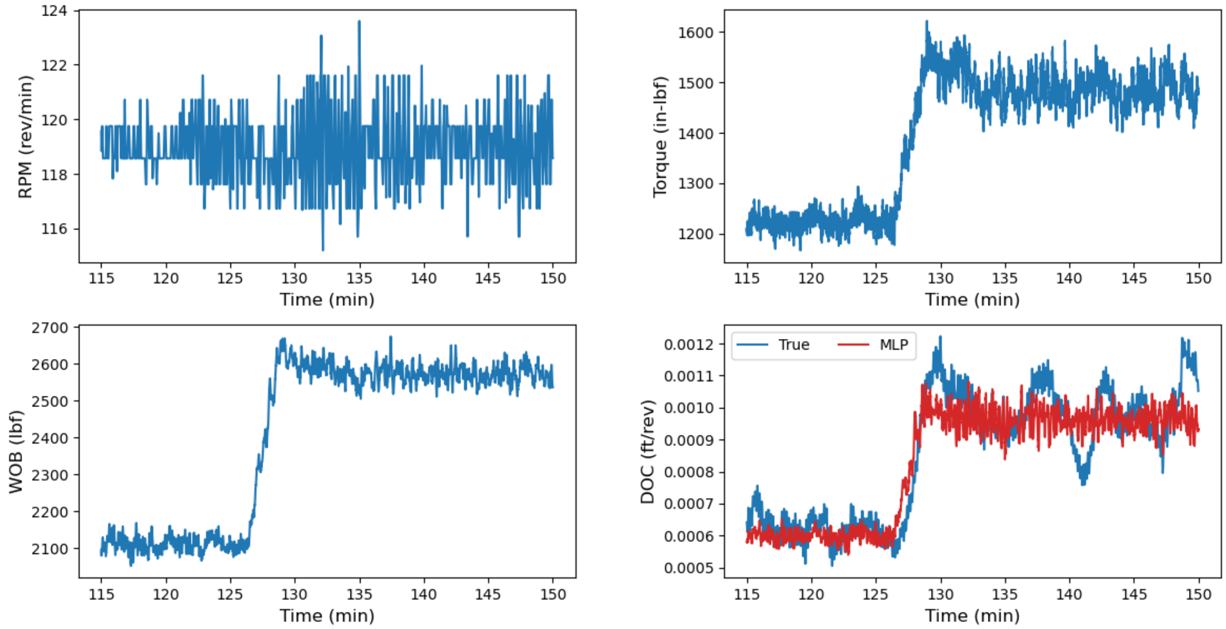

Figure 5: A plot illustrating the performance of the MLP model in predicting DOC given a sudden change in WOB from a held-out test sequence.

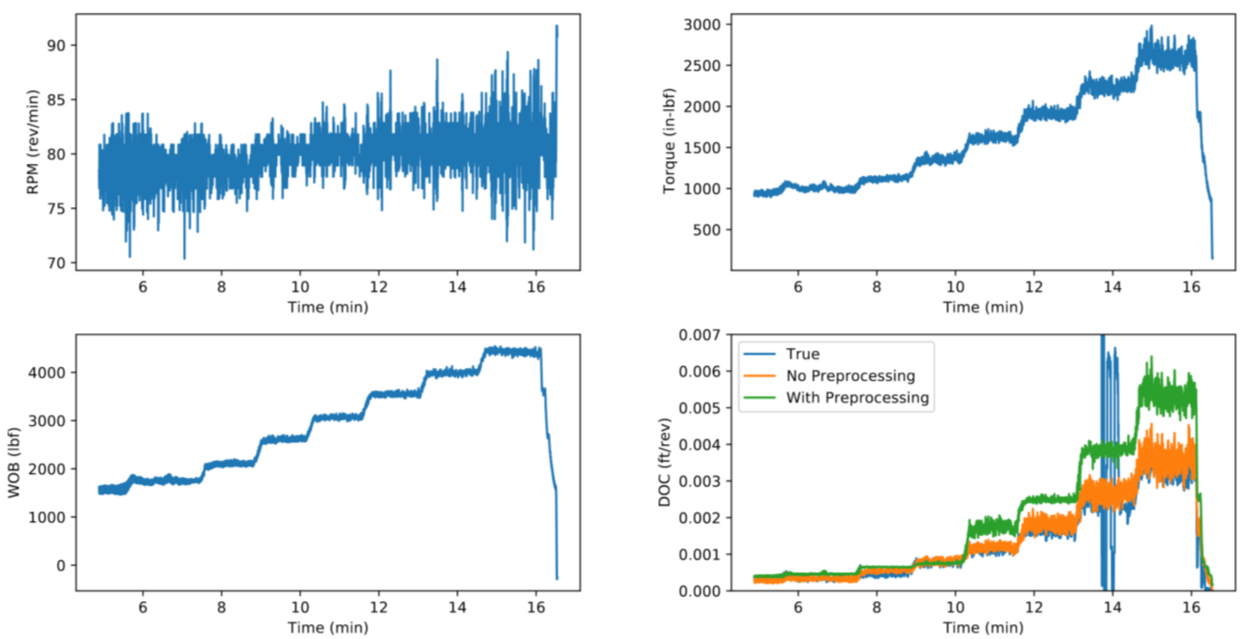

Figure 6: Comparison between the generalization ability of an MLP trained on preprocessed, filtered data (green) and raw data (orange) on a held-out test sequence.

5. EXPERIMENTAL RESULTS ON A BHA DEVICE

5.1 Improved Generalization with Noisy Data

To evaluate the generalization ability of our trained model, we developed a down-hole sensing module that provides ROP estimates in real time. We refer to this is a BHA emulator because it consists of components that could eventually be used in a BHA. However, the system used in this work has not been optimized for size, weight, or power. Therefore, it would require further engineering development to be capable of operating down-hole. This is why we clarify that it is an ``emulator" and not a true BHA.

A wiring diagram of our BHA emulator is shown in Figure 7. This system was integrated into Sandia's HRDF drilling system, and a photograph of the integrated system is provided in Figure 8. The BHA emulator feeds down-hole measurements of WOB, RPM, and torque to a micro-controller which continually runs our model and filters the resulting ROP estimates at approximately 180 Hz. The micro-controller is a Raspberry Pi 3 Model B+ with the MCC-118 Voltage Measurement and MCC 152 Voltage Output DAQ HATs. We use a UM7 Orientation Sensor as our IMU to measure RPM and an Interface Force 5611-10K Axial Torsion Load Cell for measuring WOB and torque. We integrated our module with the HRDF setup, which provides us with a ground truth ROP signal estimated via finite differences from the DOC measurements. This enables us to evaluate the quality of the ROP estimates and how well its performance translates to the real world. The BHA emulator was used to collect some additional machine learning training data which was used to refine the MLP model. This enabled training on the actual measurements that are used for down-hole estimation.

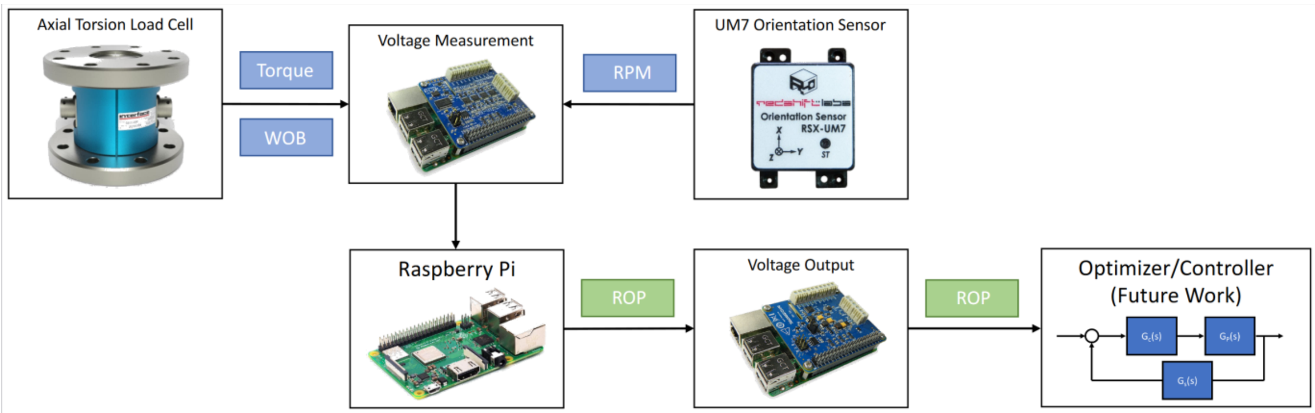

Figure 7: A block diagram of the Bottom-Hole Assembly (BHA) emulator.

5.2 Results

After updating the MLP with BHA emulator data, we ran the optimal MLP on the BHA described in Section 5.1. We show the results of validation experiments in Figure 9. While the MLP does sometimes seem to overshoot the ground truth DOC, it does a good job matching the signal over the course of the experiment. The MLP was trained on a dataset generated by using a drill with a bit that has 4 blades. To briefly examine the generalization capabilities of our model, we performed experiments with a 3-bladed drill bit. This bit design had not been used for any training data. We provide a quantitative comparison of the 3- vs. 4-bladed bit setup in Table 2 and illustrate the results in Figure 10. In this scenario, the MLP consistently undershoots the ground-truth DOC and the MAE over the course of the experiment is much higher. However, the MLP is able to capture the general upward trend, and its output is smoother than the ground truth signal.

Figure 8: Photograph of the Bottom-Hole Assembly (BHA) emulator integrated with the Sandia HRDF.

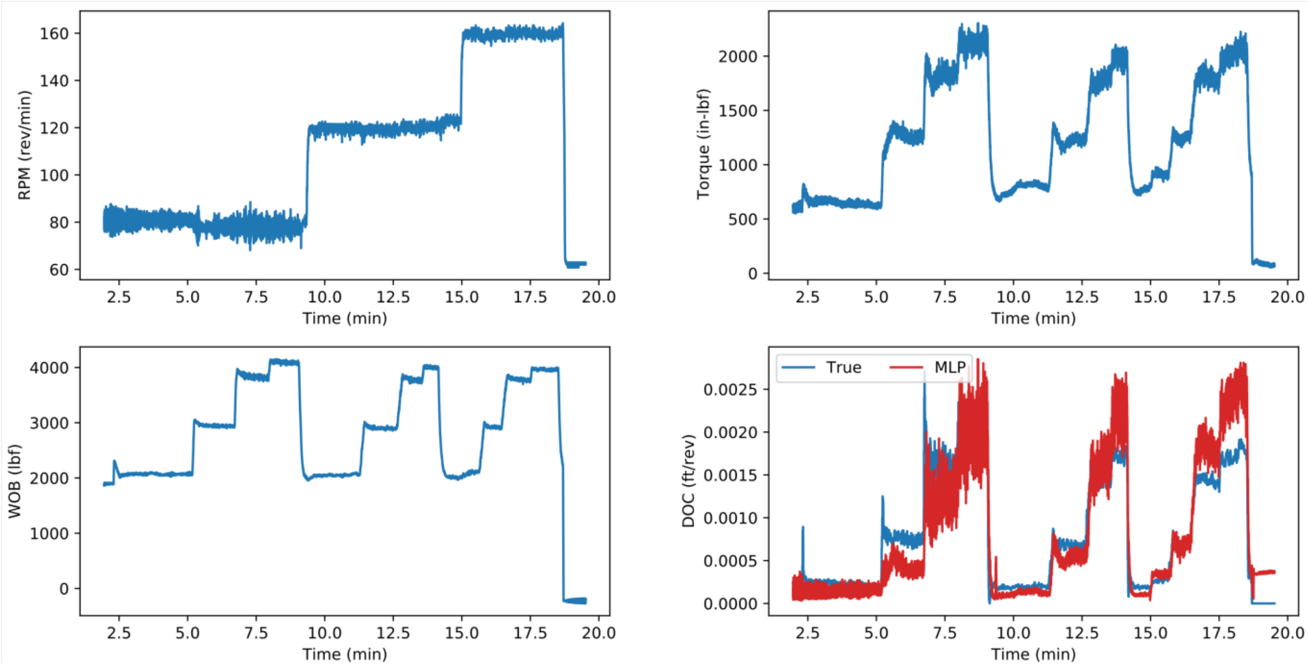

Figure 9: A plot illustrating the performance of the MLP model in predicting DOC running on the down-hole sensing module attached to a drill using a bit with 4 blades.

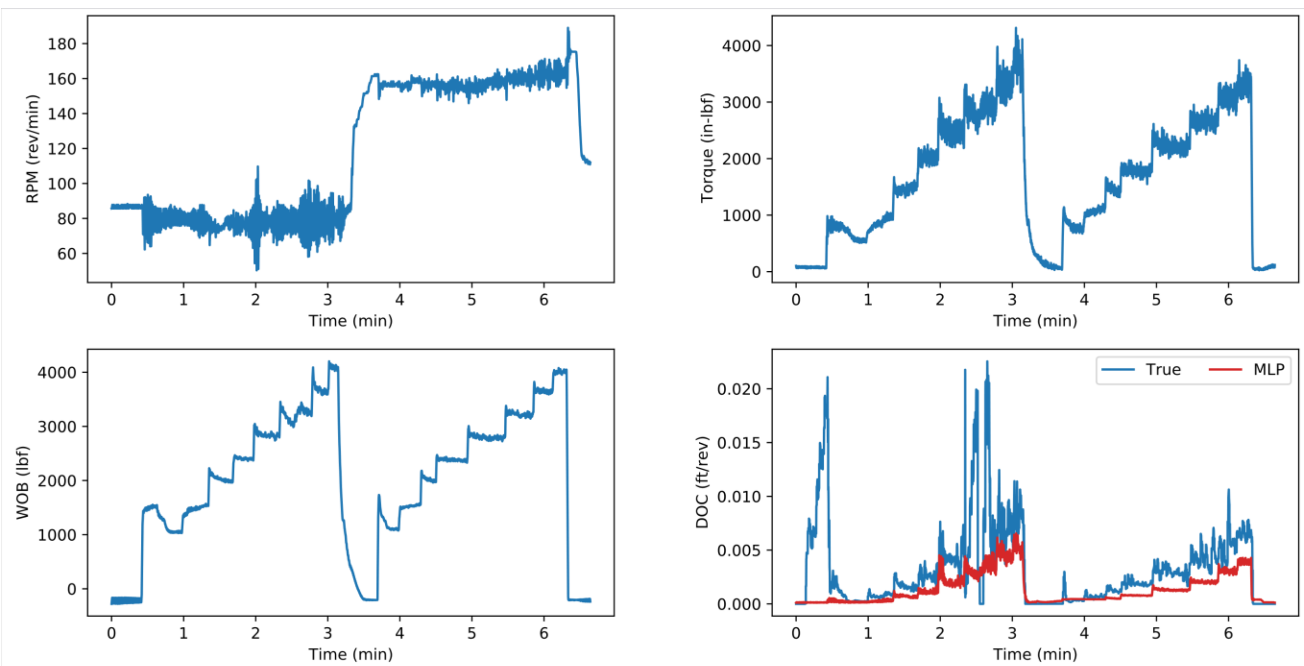

Figure 10: A plot illustrating the generalization ability of the MLP model by testing it on a drill using a bit with 3 blades.

Table 2: Mean absolute error in ft/hr of the MLP model running on the down-hole sensing module attached to a drill using a bit with 3 vs. 4 blades.

3-Blade Bit MAE	4-Blade Bit MAE
5.08 ft/hr	1.22 ft/hr

6. POTENTIAL USE CASES FOR DOWN-HOLE ROP ESTIMATION

The experimental results illustrate that down-hole sensors can estimate ROP and DOC in real time. This information can be used for monitoring performance, engaging safety systems, or controlling drilling. This is highlighted in the far right part of Figure 7. Monitoring down-hole ROP can be used to understand drilling efficiency by computing the down-hole MSE. The down-hole MSE could provide better estimates of drilling efficiency than top-hole MSE because it considers the force applied directly at the bit. The down-hole sensing sub estimates or directly measures all the parameters needed to estimate MSE (Teale, 1965). The equation for MSE is shown in eq. 2. We show how our proposed methods can estimate MSE in Figure 11.

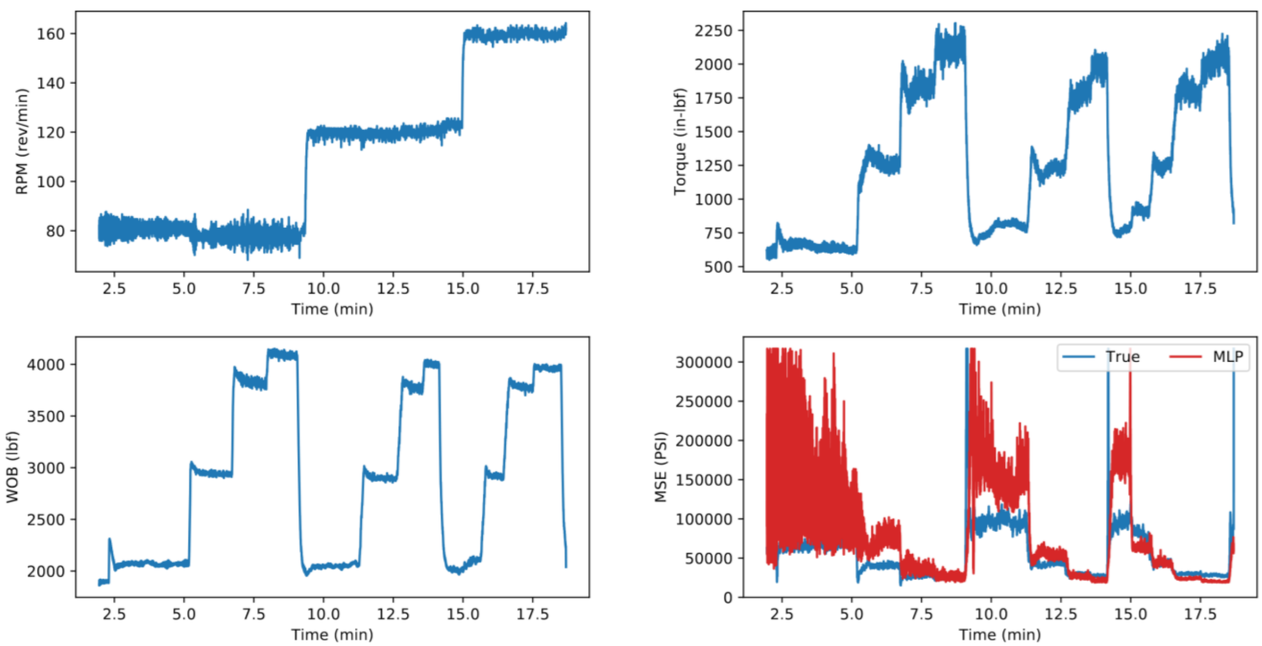

Figure 11: A plot illustrating how the MLP and down-hole sub can be used to estimate MSE.

Similarly, knowledge of down-hole performance can be used to protect the drilling system by engaging safety systems. For example, if excessive DOC is detected, a protective system such as a down-hole clutch can engage to protect the bit. Finally, the down-hole information can be transmitted in real-time to the top-hole control system to help modulate inputs (WOB, RPM). Mud-pulse is a popular technique for transmitting data, but is limited to relatively slow data rates. Nonetheless, additional down-hole information has the potential to improve how the top-hole inputs are determined.

7. CONCLUSION

In this paper, we have shown that machine learning can be used to successfully predict down-hole ROP and DOC from down-hole measurements of WOB, torque, and RPM. We showed that a multi-layer perceptrons (MLPs) was able to accurately predict down-hole DOC. Furthermore, we optimized the MLP algorithm by examining the role of pre-filtering and showed that removing pre-filtering improves data generalization. Finally, we experimentally illustrated the performance of our overall architecture on a BHA emulator. The optimized MLP ran on the BHA emulator's microcontroller and only utilized down-hole data. The results of these validation experiments showed that DOC can be predicted effectively for a 4-bladed bit. We examined generalization to a 3-bladed bit, in which accuracy degraded but the system still captured rough trends. The next steps are to integrate the BHA-emulator with top-hole control and downhole safety systems. The real-time down-hole estimates can then be used to optimize drilling, improve control, or protect the drilling system from damage.

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When making reference to previous work, please follow the scientific format, e.g. Verma and Pruess (1976).

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