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Estimation and Control for Efficient Autonomous Drilling through Layered Materials

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Abstract— **Drilling is a repetitive, dangerous and costly process and a strong candidate for automation. We describe a method for autonomously controlling a rotary drilling process as it transitions through multiple materials with very different dynamics. This approach classifies the drilling medium based on real-time measurements and comparison to prior drilling data, and can identify the material type, drilling region, and approximately optimal set-point based on data from as few as one operating condition. The controller uses these set-points as initial conditions, and then conducts an optimal search to maximize performance, e.g. by minimizing mechanical specific energy. The control architecture is described, and the material estimation process is detailed. The results of experiments that implement autonomous drilling through a layered concrete and granite sample are discussed.**

I. INTRODUCTION

Rotary drilling is a complex process that is largely controlled by highly trained and experienced human expert operators. Drilling conditions change constantly due to heterogeneous rock formations, bit wear, and interactions between the drillstring and the wellbore. Furthermore, observed conditions at the surface may be drastically different than conditions downhole. The US drilling products and services industry is $60B [1], and improving drilling performance can have an enormous economic impact by reducing time spent per foot drilled and costly equipment failures.

Drilling operations are highly repetitive and inherently dangerous, making drilling a strong candidate for automation [2]. Automation and autonomous control have the potential to improve safety, enhance operations in harsh environments, and increase efficiency. Field tests show that automated drilling systems can achieve improvements in penetration rate by over 10% [3]. In spite of the enormous potential benefits from automation, field drilling remains a startlingly manual process, with operators making continuous manual adjustments even to achieve basic regulation of low-level control set-points.

One approach to autonomous drilling is to attempt to optimize high-level drilling performance metrics such as the rate of penetration (ROP) or the mechanical specific energy (MSE). MSE is the amount of energy required to remove a unit volume of rock, with units typically in psi [4]. The ExxonMobil Fastdrill technology estimates MSE online and prompts suggested setting changes to the driller [5]. Recently, several research groups have developed and tested optimizing automation tools that attempt to maximize ROP based on measured signals in the rock [3,6,7]. A central feature of these works is that they exploit a model that can be used to predict drilling performance. In [7], the authors employ the Bourgoyne and Young model [8]. Similarly, the authors in [9] employ the Jorden and Shirley model [10]. In [3,6], the authors employ a phenomenological rock-bit interaction model developed by Detournay [11,12]. The use of model fitting approaches is complicated by the unknown nature of the rock formations and their inhomogeneity. Different rock types have very different characteristics defined by unique model parameters, and indiscriminate fitting across rock types will result in inaccurate predictions. Furthermore, key parameters in the most effective rock-bit interaction models also depend on bit characteristics, including wear over time. Therefore, the ability to determine the rock-type and detect changes in real time is essential to successful automation. In [3,6], a Bayesian change point detector is used to determine a change in rock formation. The Detournay parameters for the data segment are then determined and used to determine optimal drilling settings which are then presented to the driller or used in closed-loop control to maximize ROP.

We describe a new approach to fully autonomous drilling that focuses particularly on the autonomous management of transitions between multiple layers of different material. This approach has been validated using experiments at Sandia's Hard Rock Drilling Facility (HRDF), shown in Fig. 1. Like the prior works [3,6], we exploit the Detournay model for rotary drag bit drilling. However, our approach uses a classifier and database from previous drilling data to correlate

Figure 1. Sandia's Hard Rock Drilling Facility with an engineered multilayered rock sample and 5-blade PDC bit.

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measured rock properties with rock types and desired drilling control parameters. This means that data from only one operating point is sufficient to estimate the rock type, the drilling region, and the optimal drilling settings for that rock type. The rock type is estimated continuously. When changes in the rock type are detected, the drilling set-points are updated. In order to handle small deviations from the database data, local searches are performed around the prescribed optimal settings to determine the true optimal. Low-level PI controllers are used to regulate to desired settings.

Section II summarizes key drilling background, including an introduction to drilling regimes, common models for rotary drag bit drilling, and drilling performance metrics. Section III provides an overview of our control approach. Section IV presents our approach to material property estimation and material classification. Section V describes experiments and results performing closed-loop autonomous drilling through multi-material samples. Section VI provides discussions and conclusions.

II. Rotary Drilling Model

Detournay et al. describe a phenomenological model of the drilling process for drag bits with polycrystalline diamond compacts (PDC) as the cutting surface [11,12]. This model describes drilling as a three dimensional relationship between scaled weight (w), scaled torque (t), and depth of cut (d), which we will refer to as Detournay parameters. In the model, these quantities are employed as opposed to weight on bit (WOB), torque (τ), and ROP, to provide physical meaning that is not dominated by the impact of bit size and rotational speed.

A. Three Drilling Regimes

The Detournay model describes three drilling regimes referred to as phases I, II, and III. Phase I is characterized by contact area of the cutter wear flat increasing as depth of cut slowly increases with w. An ideal sharp bit would have no phase I. Phase II begins once a critical depth of cut has been reached such that the rock cannot support additional normal stress generated on the fully engaged wear flat. Because of this lack of support, any further increase in w drives the cutter into the rock and directly translates into an increase in cutting force, causing the bit to increasingly act as if perfectly sharp. Phase II is associated with productive and efficient drilling, and thus represents the target operating region. Phase III is the region which occurs after the founder point. In this region, the relationships between the Detournay parameters are not generally unique. However, the efficiency decreases as w increases in phase III. Drilling performance at higher weight can be degraded through a number of mechanisms including stick-slip and bit balling [13].

B. Drilling Mechanics Model

The drilling response in Detournay's model describes phases I and II as having linear relationships between w, t, and d in three-dimensional space. Furthermore, phase I is constrained to intersect the origin. While the model uses physical parameters to define the equations of these lines, we find that knowing that these relationships are linear is sufficient for finding useful models from data. For simplicity, we also assume that phase III can be characterized by a linear relationship. Thus, our model for rate-independent rock-bit interaction is a piecewise continuous function in three-dimensional space with three linear segments as shown in Fig. 2.

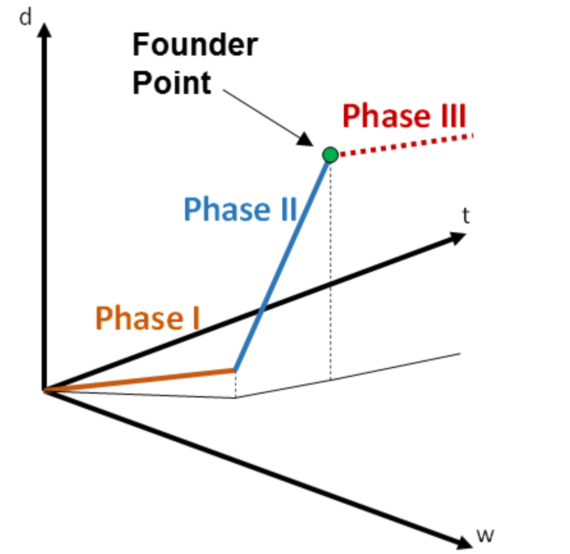


Figure 2. A cartoon diagram illustrating the 3 phases of the Detournay drilling model.

Because we have control of weight-on-bit, we define w as the independent variable. Our model necessitates two critical values to separate the three regions. We define w_{12} and w_{23} to denote the scaled weight at the phase I-II transition and phase II-III transition respectively. To ensure continuity and intersection of the origin we use the following equation for scaled torque:

$$t = \begin{cases} a_1 w & w < w_{12} \\ a_2(w - w_{12}) + t_{12} & w_{12} < w < w_{23} \\ a_3(w - w_{23}) + t_{23} & w > w_{23} \end{cases} \qquad (1)$$

where

$$t_{12} = a_1 w_{12}$$

and

$$t_{23} = a_2(w_{23} - w_{12}) + t_{12}.$$

Depth of cut, d, is defined similarly but with different scalars.

C. Drilling Performance Metrics

Our primary metric for drilling optimization is MSE. According to the Detournay model, the minimum MSE should occur at the transition from phase II to III. This transition begins when further increases in w no longer translate into pure cutting of virgin rock, and drilling proceeds in a less efficient manner (due, for example, to regrinding of cuttings, poor energy transfer, etc.). To compute MSE utilizing the Detournay parameters we use the following equation:

$$MSE = \frac{w}{\pi R} + \frac{t}{d} \qquad (2)$$

where R is the bit radius. For a full cross-section (non-coring) bit, this equation computes the sum of linear and rotational energy per volume of rock removed.

While maximizing ROP is commonly desired, MSE minimization is more reliable for achieving high rates of penetration while avoiding potentially deleterious effects introduced during inefficient drilling. On our test drill rig we have found that we can enter phase III while still increasing ROP. This has led to inefficient drilling that is often accompanied by undesired oscillations in RPM due to stick-slip or torque saturation.

III. Control Approach Overview

Our overall approach to the autonomous control of rotary drilling is depicted schematically in Fig. 3. The drilling system controls the force applied to the rock by the bit, termed the weight-on-bit (WOB), and the angular velocity ω. The interactions between the bit and rock then determine the outcomes of the drilling process, including: the torque τ between the bit and rock, the linear velocity or ROP, and higher-level metrics such as the drilling efficiency or MSE. Our approach uses a high-level control system to generate desired set-points for ω and WOB. Low-level PI controllers are used to regulate these inputs, which are generally controlled via hydraulic or pneumatic valves, depending on the drilling rig details.

An autonomous operating point control (AOPC) system is used to produce desired set-points. This high-level control system includes an estimator that uses measured drilling process inputs and outputs to estimate the Detournay parameters associated with the current rock type. (The details of this estimator are discussed in the next section). These parameters are then compared with a database to select predetermined appropriate set-points. The Detournay parameters are also supplied to a supervisory controller that performs two functions. First, it determines whether the parameters have changed enough to indicate that a new material has been encountered. If there is no significant change, then the set-point values from the database are passed through to the low-level control system. If a material change is indicated, then the supervisory controller triggers and executes a local search for optimal operating conditions. Generally, the system searches for settings that minimize MSE, but it can also maximize ROP, co-optimize the two, or

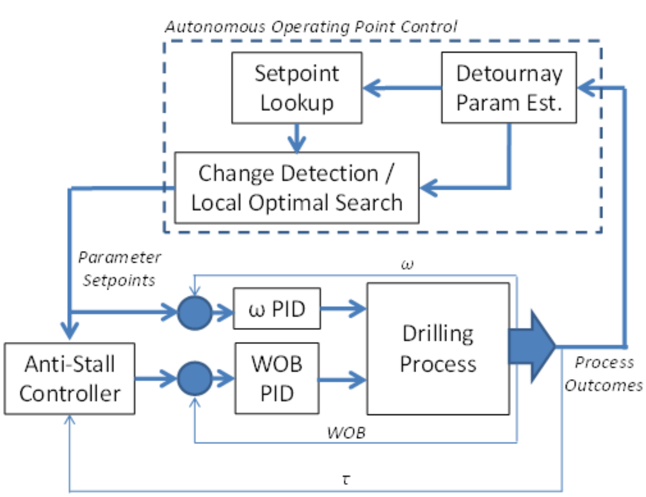


Figure 3. A schematic diagram of the autonomous drilling system.

optimize other metrics. In this work we employ a Golden Section Search around a fixed interval around the AOPC set-point. This method can be expanded to adaptively find an initial search interval (rather than relying on a fixed interval).

Finally, we include an anti-stall controller. Stall conditions can arise when transitioning from a hard material that requires a very high WOB to a much softer material that cannot tolerate high WOB. Softer rocks create significantly higher ratios of torque to WOB than harder materials. Torques may exceed system limits under high WOB, causing the bit to stall. To avoid this, our anti-stall controllers can monitor torque. If the torque exceeds a threshold (e.g. 80% of the drill rig limits), the anti-stall controller intervenes and reduces the target WOB by an amount determined by a barrier function. This is designed to respond more rapidly to material changes than the higher-level AOPC system, which generally has a time constant of several seconds to avoid reacting to noise in the drilling process.

The remainder of this paper focuses primarily on the AOPC. Low-level controllers are implemented and discussed briefly. The anti-stall controller has been simulated but not yet implemented for the experiments described herein.

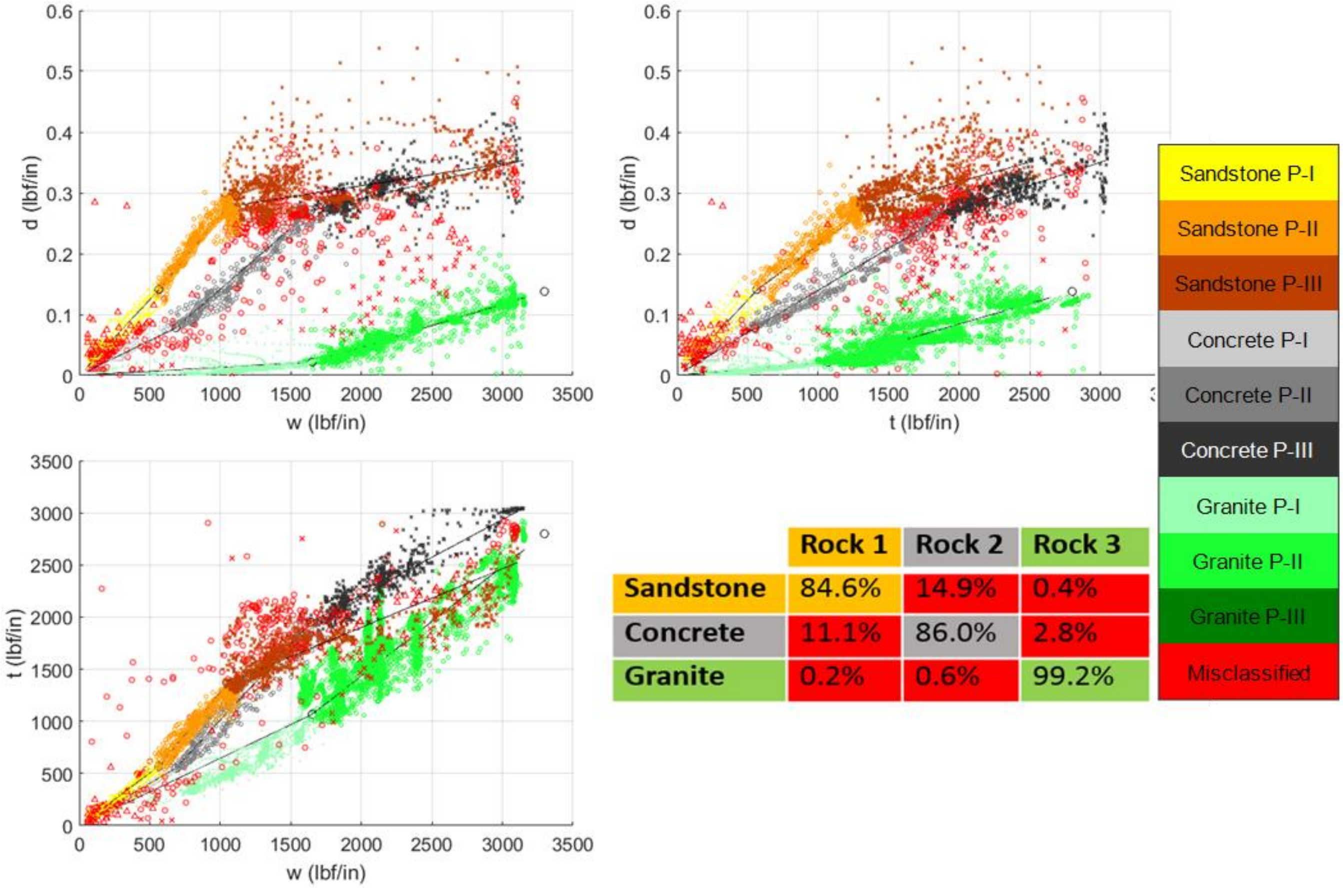
IV. Material Estimation

Our approach for material estimation is to first create Detournay models for each general type of rock we expect to drill. When drilling, the rock type and drilling phase (I, II, or III) are then classified as the Detournay model which is closest to the measured Detournay parameters. The three types of "rock" we were interested in classifying for test purposes were sandstone, concrete, and granite. Detournay parameters are specific not only to the drilling medium, but also to the design of the bit. Therefore this approach requires either training experiments with the specific bit in question, or extensive modeling to capture the relevant bit characteristics.

Training data for the models came from 13 tests in sandstone, 10 in concrete and 17 in granite. Detournay models for each of the three rock types were fit to the test data using a least squares approach. An optimization fit seven parameters: a_1, a_2, and a_3 in the equations for both t and d, as well as w_{12}. The parameter w_{23} was chosen through a separate process as the w which provided the minimum MSE. Before computing the residuals, the data were normalized based on the filtered maximum values for t and d over all tests.

Measuring the distance to the models was broken down into two steps. Step one is to use the two bisecting planes of the three phases to determine which line segment is closest to the current set of Detournay parameters. This step is performed for each of the models being tested. Once the closest segments are identified, standard computation of the distance from a point to a line is used to determine the distance to the model. Again, the data is normalized before distance is computed. These distances are compared and the closest model is chosen as the estimated rock for the current data point. An added benefit of this approach is that phase is also predicted by the model from the first step.

Fig. 4 shows the results of running this classifier on the training data. A confusion matrix is also included, indicating



	Rock 1	Rock 2	Rock 3
Sandstone	84.6%	14.9%	0.4%
Concrete	11.1%	86.0%	2.8%
Granite	0.2%	0.6%	99.2%

Figure 4. Plots illustrating the Detournay classifier performance using experimental data. For misclassified data, identified rock type is denoted by triangles, circles and x's for sandstone, concrete, and granite respectively. True rock type of misclassified data is not indicated.

84% success in identifying sandstone, 86% success in identifying concrete, and 99% success in identifying granite. Most of the confusion results from the fact that the models for sandstone and concrete are fairly close to each other in some portions of the *t-w-d* space. When integrated with the autonomous controller, a mode filter was implemented on the classifier output to prevent control behavior transitions from occurring in response to noise in the classifier output. This filter takes the mode of the rock estimate over a 4s window.

V. EXPERIMENTS

Laboratory experiments were conducted to demonstrate the ability to autonomously drill through unknown multi-layered material samples using an implementation of the control architecture diagrammed in Fig. 3.

A. *Experimental Apparatus*

1) *Hard Rock Drilling Facility*

Rotary drilling tests were conducted at the Hard Rock Drilling Facility (HRDF) at Sandia (Fig. 1). The HRDF consists of structural steel frame that houses a hydraulic top-drive motor and hydraulic cylinders used to apply weight-on-bit (WOB). The test facility can apply up to 6000 lbf of WOB and 560 lbf-ft of torque. A 3 in. diameter drillstring transmits torque from the top drive to the drill bit. Facility-supply water is used as a drilling fluid and is circulated through the bit [14]. Drilling tests were performed with a 3.75" diameter 5-bladed PDC bit from Ulterra (Fig. 5).

The facility is configured to house a 36"x36"x20" test specimen for drilling. The rock sample can be positioned at various locations beneath the drill head allowing multiple holes to be drilled for each rock sample.

2) *Engineered Rock Sample*

Initial classifier training was completed on uniform material samples. Subsequent autonomous drilling tests were conducted using custom-made layered test articles. Each of these engineered rock samples consists of four 17.75"x 17.75"x10.75" (LxWxH) concrete samples reinforced horizontally with ½" grade-8 threaded rods and an underlying

Figure 5. Photograph of the Ulterra 5-blade PDC bit used in drilling tests.

36”x36”x5” slab of Sierra White Granite (SWG). Each of the concrete samples were post-tensioned to an average compressive stress of 150 psi and vary by aggregate type, aggregate volumetric fraction, and compressive strength. Compressive strength tests were conducted according to ASTM C39 at curing intervals of 7, 14, and 21 days and on the first day of drilling (52 days). The results are listed in Table I. Quadrants QII and QIII are most similar in compressive strength and were used for the autonomous drilling experiments presented in this paper.

TABLE I. CONCRETE CONTENT AND MEASURED STRENGTH

Mold 1 (4000 psi concrete mix)	*52-day strength (psi)*
Q I (73% basalt aggregate)	3450
Q II (68% basalt aggregate)	7890
Q III (73% standard aggregate)	7860
Q IV (68% standard aggregate)	8450

3) Data Acquisition and Control

The HRDF controller is a PC-based system integrated with data acquisition hardware. Displayed data includes WOB, torque, rotary speed, and drill head position. WOB is calculated from measured differential pressure across the hydraulic cylinders. Torque is determined by measuring the input pressure to the fixed-displacement hydraulic drive motor. Rotary speed is monitored using a rotary pulse generator on the hydraulic motor. A linear potentiometer is used to determine the drillstring position relative to the frame.

The controller consists of a LabView virtual instrument (VI) integrated with MATLAB for data processing. Real-time estimation and control calculations are performed in the Labview VI, in some cases using embedded MATLAB scripts. The VI interfaces with the data acquisition hardware and displays the process variables to the operator via the display shown in Fig. 6. Data is acquired at a sampling rate of 2048 samples per second and collected in 256 sample increments. The collected data is then processed in MATLAB for analysis.

Figure 6. A screenshot of the HRDF LabView Control Interface

4) Low-level closed-loop control

Rotational speed of the drill head is controlled using voltage-controlled proportional valves which modulate the hydraulic fluid flow to the rotation motor. A pressure relief valve limits output torque. WOB is controlled using voltage-

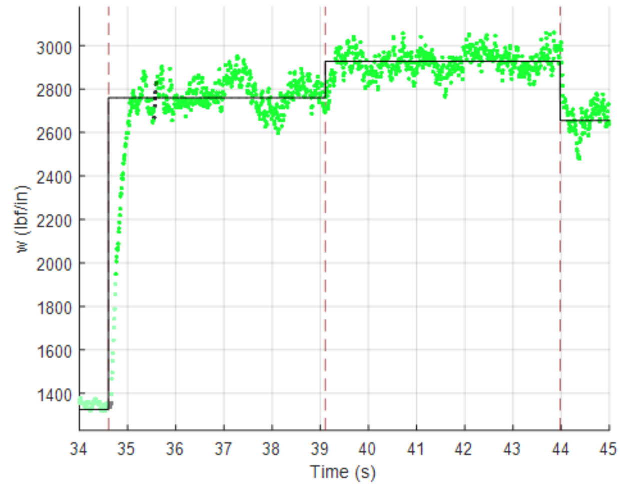


Figure 7. Time response data for three reference step changes illustrating performance of the low-level WOB system under PI control.

controlled proportional valves which modulate the hydraulic cylinder pressures.

PI feedback controllers are used to achieve low-level control: to regulate rotary speed and applied WOB. Sensor measurements are as described above, and the control signals direct the behavior of the hydraulic valves. Fig. 7 shows example step responses for the low level WOB controller. Rise time were typically less than 0.5 s for large steps and as low as 0.1 s for small steps. The longer time for larger steps is due to nonlinear effects of the plant.

B. Multi-Material Drilling Results

AOPC control was implemented along with low-level drilling parameter regulators as diagrammed in Fig. 3, and a number of holes were drilled autonomously in the engineered composite rock sample (Fig. 1). Anti-stall control was not implemented for these experiments.

Tests were conducted with a constant rotation rate of 100 RPM, with WOB varied autonomously. The system was allowed to reach the desired speed set-point with no load. After the rotation rate was reached, the drill head was manually lowered onto the rock to initiate drilling. After the initial contact, the autonomous control was engaged. Drilling continued through each sample until the end of the drill head stroke was reached. The drilling operator took no action between the engagement of autonomous control and the automatic termination of drilling, and only monitored the process.

Quadrant QIII was used primarily to train the concrete classifier and to develop control set-points. Subsequently, evaluation holes were drilled in quadrant QII. Fig. 8 shows the time histories of the Detournay parameters *w*, *t*, and *d* (scaled WOB, torque and depth of cut) as well as the MSE, for a representative test run. The plots are color coded to indicate the real-time estimate of rock type and phase. The actual transition from concrete to granite occurs just before the 30 second mark and is indicated by the significant transients in each parameter. During the initial WOB ramp, just before the AOPC was engaged, concrete is misclassified as sandstone. This estimate is quickly corrected as the WOB reaches more significant levels. The controller then performs

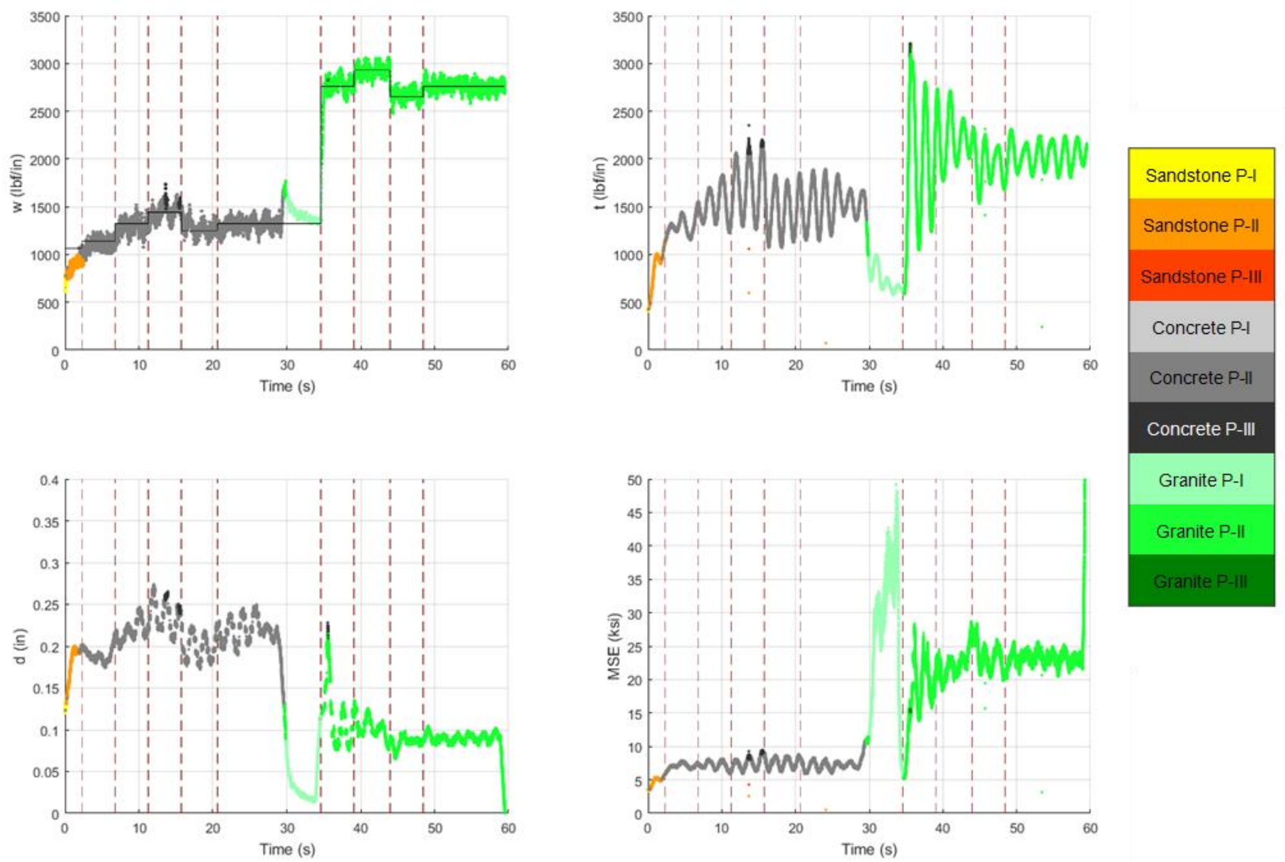


Figure 8. A plot illustrating the real-time performance of the drilling classification and optimizing system.

a local search for the optimal WOB that converges to a local minimum for MSE. Fig. 9 plots the average MSE versus *w* at each set-point as the AOPC conducts a golden search, and indicates the search order. The MSE is relatively insensitive to *w* in the local search range, and the minimum MSE is located within a fairly narrow *w* range from the initial set-point. This indicates that the initial set-point based on correct material classification and prior drilling is reasonably accurate, and the search need not deviate far.

When the drill transitions materials, granite is rapidly detected based on the significant change in Detournay parameters. Control action lags by approximately 4-5 seconds as the filter confirms that a real transition has occurred. With confirmation of a granite medium, the controller switches to the prescribed optimal WOB and starts a new local search, which also finds a local minimum MSE.

C. Comparison to Fixed Control Settings

The local search in concrete found a local minimum MSE of about 6.5 ksi at a scaled weight of 1320 lbf/in. The search in granite initially found a local minimum MSE of around 20.5 ksi at a scaled weight of 2780 lbf/in; however, upon returning to this setting at the completion of the search, the final MSE was slightly higher at 23.2 ksi.

Additional experiments confirm that these results clearly outperform any fixed *w* setting for drilling this composite rock as measured by MSE. For example, if *w* is set at the average between the two optimal conditions (*w*, 2050 lbf/in), MSE is 7.6 ksi in concrete (17% worse than the AOPC) and 33 ksi in

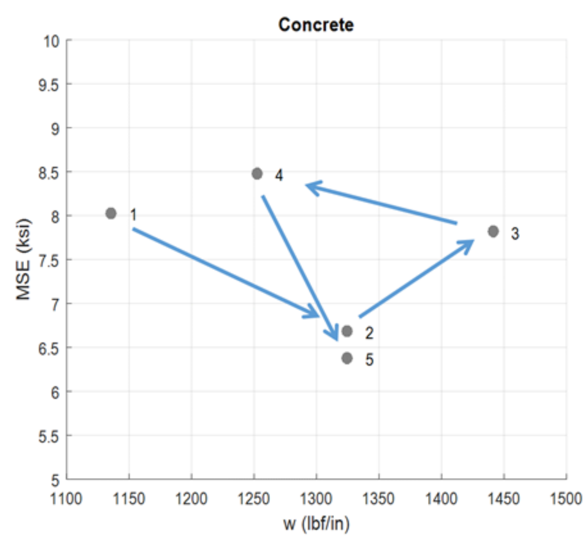


Figure 9. A plot illustrating the MSE optimizing golden search. The weight on bit sweeps from point 1 to 5.

granite (42% worse). Increasing *w* above 2050 lbf/in, to improve granite drilling performance, results in stick-slip behavior and significant vibrations during concrete drilling. Operating at lower *w* to improve concrete performance results in slow, inefficient drilling in granite. For example, operating at the optimal w for concrete causes MSE to rise above 40 ksi in granite, as can be seen in the interval in Fig. 8 after the material transitions but before the controller responds (time=30-34 secs). Allowing the controller to detect the rock and change the set-point using our AOPC provides significant improvements in average MSE and makes multi-material drilling without operator intervention possible.

VI. Discussion and Conclusions

This work describes the design and successful experimental demonstration of a control system to enable autonomous rotary drilling through layered multi-material samples. The experiments demonstrate control that converges to MSE values approximately equal to the ultimate compressive strength of the drilled materials (concrete and granite), indicating highly efficient drilling that approaches the ideal. By applying the widely-accepted Detournay model for drilling with PDC bits, this approach is able to explicitly classify materials and determine initial set-points for those materials based on prior drilling. In experiments, these set-points prove to be near optimal, but a search for optimal conditions is initiated upon detection of material transitions in case the classifier is incorrect or the material differs significantly from the available library of tested materials. The autonomous controller is shown to significantly outperform any single fixed setting in multi-material drilling.

Future work would significantly extend the capability and further test its value. We would like to implement and verify the anti-stall controller describe in section III. This would add a significant safeguard to the system by reducing WOB rapidly when torque rises unexpectedly near its limit.

Expanding the controller's material library database by conducting additional drilling tests in different rocks could enhance the versatility of the system. We note that as more rock types are added, the probability of some pairs having Detournay models with nearly intersecting lines increases. This would result in having higher probability of misclassifying the rock. Our local search should help the controller reach an optimum in the event of initial misclassification, however, more research should be done on the consequences of having a large library of materials. One possible solution for reducing misclassification rates when operating with a large library would be to add prior probabilities for the various rocks and use a Bayesian analysis to pick the rock of maximum likelihood.

Finally, additional study into the applicability of this approach for more realistic, deep-hole drilling is required. Several challenges exist for moving out of the laboratory environment:

1) The wear state of the bit is not constant as we have been able to assume here. Thus, the material database should dynamically update to account for a model of the estimated wear of the bit based on the drilling history.
2) The rock-bit interaction parameters are also dependent on the downhole pressure. Thus, the database must also account for the measured downhole pressure.
3) Depth of cut resolution and other measurements in the field are often poor due to the drillstring dynamics. A key goal for further research is to determine how the quality of Detournay model estimates degrades with less controlled and more compliant drilling dynamics, and also what techniques can be used to restore the fidelity of downhole parameters using surface measurements. Much of this can be done in a simulated manner at our existing facility [14].

Acknowledgment

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