Proceedings of the 3rd IFAC Workshop on Automatic Control in Offshore Oil and Gas Production, Esbjerg, Denmark, May 30 - June 1, 2018

Real-time Rate of Penetration Optimization of an Autonomous Lab-Scale Rig using a Scheduled-Gain PID Controller and Mechanical Specific Energy

Enrique Z. Losoya [*] **Eduardo Gildin** [**]
Samuel F. Noynaert [***]

[*] *Petroleum Engineering at Texas A &M University, Texas, USA (e-mail: e.zarate@tamu.edu).*
[**] *Petroleum Engineering at Texas A &M University, Texas, USA (e-mail: eduardo.gildin@tamu.edu)*
[***] *Petroleum Engineering at Texas A &M University, Texas, USA (e-mail: sam.noynaert@tamu.edu)*

Abstract: Automation in the oil & gas industry has become a golden goal for major operators, increasing R&D expenditures, and automation related projects are increasingly more common. A miniaturized autonomous drilling machine was built with the objective of performing optimal operations regarding the rate of penetration and energy efficiency the lab-scale rig employs control algorithms, and innovative instrumentation solutions, leading to a large amount of data to be analyzed in real-time to accurately control important drilling parameters such as weight on the bit (WOB) and rotary speed. An scheduled-gain PID Controller was designed and implemented in a micro-controller to accurately adjust the amount of weight on the bit (WOB) and avoid disturbances. High-frequency data was acquired using LabVIEW and analyzed in real-time through the MATLAB programming environment. The data was then passed to MATLAB, where the automated algorithm analysis is performed. The results of the analysis are used in a closed-loop control algorithm to optimize the rate of penetration, energy efficiency and mitigate drilling failures. The algorithm uses real-time instrumentation data to implement an automated step-test and optimize drilling parameters on the fly. Increasing the average rate of penetration and reducing vibration-induced borehole irregularities.

Keywords: Drilling, Drilling Automation, LabVIEW, PID Control, Bit dysfunctions.

1. INTRODUCTION

The Oil & Gas industry has seen an explosion in the number of wells being drilled, mainly due to the development of unconventional reservoirs in the last decade leading to an increase in horizontal and highly deviated wells. Consequently, drilling complexity has increased as technology, capability and the demand for worldwide reserves are growing. In this context, drilling safer and faster has been the goal of many operators. Drilling system automation has shown to provide the capabilities for achieving this goal. Although the benefits of such framework are clear, automation adoption in our industry has been behind other industries where the automation track has proved positive improvements. Several operators and service companies have expressed the need for an uptake in drilling systems automation since they see an alternative to handle the uncertainties in the current price scenario. The word automation was mentioned in more than half of the technical talks presented at the 2016s SPE Drilling Conference in Fort Worth. The Society of Petroleum Engineers

⋆ The authors would like to thank the partial support from Foundation CMG through the FCMG Research Chair at Texas A&M and the lively discussions with the A&M's Drillbotics 2016 Team.

Automation has proved remarkable improvements in other industries, such as the manufacturing or aviation industry where automated systems compose a higher stake in daily operations (Macpherson et al. (2013)), but only recently it has caught the attention of the whole industry. The idea has been around since the 60s, whereby a combination of electronics and mechanics was the main topic of discussion (Bromell (1967)). Nowadays, the idea has evolved to applications of advanced machine learning and artificial Intelligence drilling advisory systems (Bello et al. (2016)). An accelerating pace of change in the industry, coupled with exponential growth in computer power and efficiency.

In this paper, we demonstrate the benefits of creating a fully autonomous drilling machine and explore how data can enhance the drilling operations and performance. To this end, a miniaturized autonomous drilling machine was built with the objective of performing optimal operations in terms of rate of penetration and energy efficiency. The miniaturized rig uses commonly available industrial sensors that lead to large amount of data to be analyzed in real-time. Instrumentation data was collected at a rate of 65 KHz, totaling over 130 million data points for each on average. A PID Controller was designed and implemented

Table 1. Rig instrumentation

Measurement	Sensor Type	Sensor	Error
WOB	Wheatstone bridge	Futek LSB300	*0.05 %*
ROP	Laser distance	OPT2011	*1.0 %*
ROP 2	String linear displacement	UniMeasure LX-PA	*0.03 %*
RPM	Infrared digital	IR Leds	*0.01 %*
Top drive Current	DC Hall effect magnetic	DCT100-42	*1.0 %*
Top drive Current 2	Hall effect IC	ACS712	*1.5 %*
Drawworks Current	Intrusive IC	VH5019	*10.0 %*
Surface vibrations	$\pm 3G$ *AO* Accelerometer		*0.3 %*
Alarm system	Ultrasonic sensor	MaxSonar	*5.0 %*
Downhole vibrations	Low energy Module	DLIS3DH	*0.0062%*
Downhole temperature	Low energy Module	DTEMP112	*0.6 %*
Flow velocity	Pump controller	Speed regulator FB	*10 %*

in a micro-controller to accurately adjust the amount of weight on the bit (WOB) and avoid disturbances. Raw data was collected, filtered and averaged over to mitigate sensor noise and drift. The data was then passed to MATLAB, where the automated algorithm analysis is performed. The results of the analysis are used in a closed-loop control algorithm to optimize the rate of penetration, energy efficiency and mitigate drilling failures. The algorithm uses real-time instrumentation data to implement an automated step-test and optimize drilling parameters "on the fly".

We implemented a predictive regression model to estimate the response to the rate of penetration (ROP) as a function of Revolutions per Minute (RPM) and Weight on Bit (WOB) in order to determine probable causes of the most common drilling dysfunctions. Frequency domain examination of high-frequency data showed specific vibrational signatures when bit dysfunctions were occurring. A step test is used to estimate the efficiency and causes of potential dysfunctions, or inefficient drilling conditions, using mechanical specific energy (MSE). The system operates and changes important drilling parameters autonomously.

This paper is organized as follows. In Section 2, we show how the drilling rig was conceived and present the main mechanical, electrical and electronics parts associated with the data acquisition, controller, and data processing. In Section 3 , we introduce the idea of Mechanical Specific Energy, and build up on this idea to show how the drilling parameters are designed. Finally, we show PID the controller design and final results in Section 5.

2. LAB-SCALE RIG

In the fall of 2014, a lab-scale drilling rig was built to participate in the first SPE's DSATS competition. The competition objective encourages the use of control systems, to build and a completely automated drilling rig to drill an unknown formation (Vishnumolakala et al. (2015)). The main instrumentation sensors and structure of the machine used in this study are shown in Fig. 1.

The limitations of the system are apparent as the hoisting system is not capable of making connections and laying down the drilling strings, which is ignored because of the experiment primary focus the development and understanding of an automated drilling system with emphasis on bit-rock interaction and rate of penetration optimization. The rig needs to drill through a $1ft^3$ formation block with a 1.125 in diameter polycrystalline diamond cutter (PDC) micro-bit. The power system is limited for safety reasons to the civilian power grid with a a maximum power rating

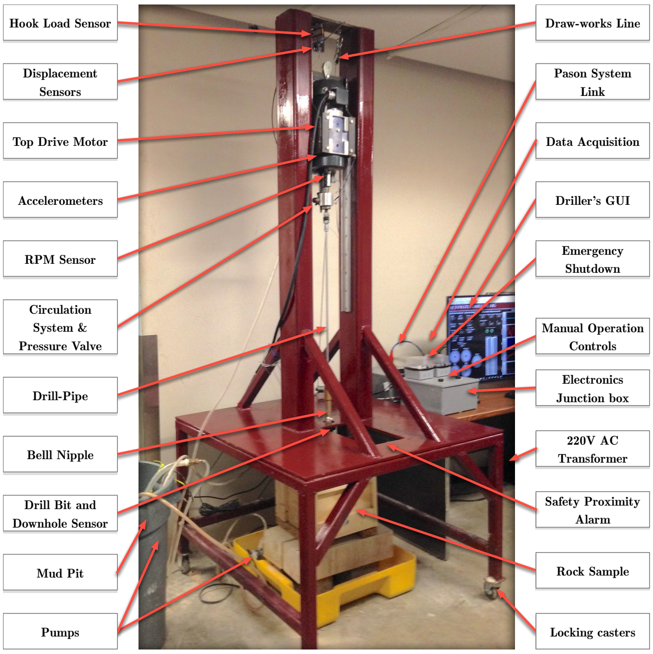

Fig. 1. Miniaturized drilling rig main components

of 2.5-HP. Setting casing is not considered in the design either. The instrumentation used in this experiment is shown in Table 1.

Rock cubes with different formations and dips were manufactured to test and validate models; the rocks were $1-4ft^3$ and primarily composed of sandstone, granite, cement, hard cement and carbonated rocks. The rocks are mostly composed of sandstone and silt stone with a compressive strength of 2 ksi to 8 ksi. Granite layers of around 19 ksi, and soft and hard commercial concrete of approximately 2 ksi - 7 ksi. Each rock sample was drilled at least four times and data was logged. Drilling occurs due to ductile or brittle failure of the rock. Each formation has an unique rock strength and material properties that affect drilling performance. In addition, several inclination angles and dips per formation were introduced to assess the time response of the drilling operation. The rock samples structure used in this study are shown in Fig. 2.

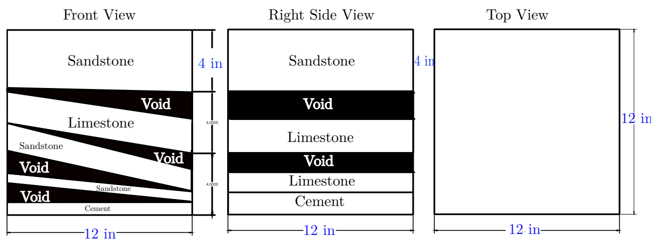

Fig. 2. Rock formations and structure used to validate performance, dips were introduced test the stability of the WOB controller

3. MECHANICAL SPECIFIC ENERGY

Mechanical Specific Energy (MSE) was first used to model the drilling process of mines excavation as a crushing process in which more significant volumes of rock are fragmented into much smaller pieces that allow recovering

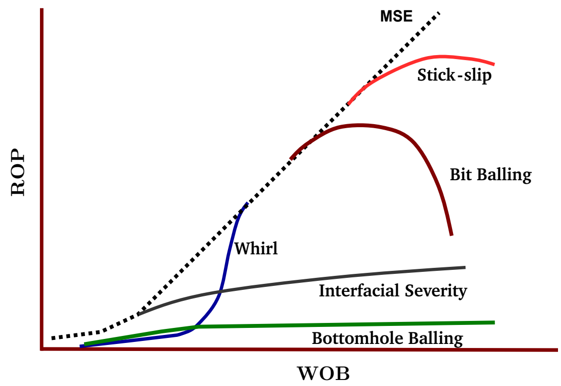

Fig. 3. Mechanical specific energy and its relationship to common drilling dysfunctions, adapted from Dupriest and Koederitz (2005)

the material economically. Teal (Teale (1965)) proposed the MSE model, which relates the amount of work applied in rotary drilling from its relating trust and rotating components to a given cross-sectional area from which rock is being removed (Teale (1965)).

This concept has been ported to the drilling industry and is used to monitor drilling performance, using MSE to measure the efficiency of the drilling operation. MSE is defined as the energy used per volume of rock drilling. MSE tends to increase, decrease or remain constant depending on bit dysfunctions and the overall drilling efficiency. Different types of dysfunctions are encountered down-hole and each dysfunction has a particular drillers response to mitigate it. Under manual operation, the efficiency of this method is entirely dependent on how experienced, fast and efficient the human driller is; which often leads to errors and delays that can be improved.

Although, it is clear that no single value of MSE can be used as an indication of the efficiency of every drilling operation due to variations in rock homogeneity, percussion frequency, and other complex drilling dynamics variables. An average trend over a homogeneous section of rock was determined to be enough to calculate, model and predict future performance. It was later discovered that drilling specific dysfunctions are also identifiable using mechanical specific energy as described in Fig. 3. In this experiment mean MSE values were obtained for different drilling operations configurations for a given bit and formation type.

The MSE model estimates the rotational and axial work as a function of the volume of rock drilled. Other parameters such as rock compressive strength, overburden, bit type are intrinsically correlated. MSE is primarily used as an efficiency index which states that if the bit is 100% efficient, the Mechanical Specific Energy will equal the rock compressive strength. We know, however, that that's never the case, thus an correction factor is usually added to account for other losses in efficiency in the system.

The MSE equation without a correction factor is:

$$MSE = \frac{480 \cdot T \cdot RPM}{OD^2 \cdot ROP} + \frac{4 \cdot WOB}{\pi \cdot OD^2} \quad (1)$$

The advantages of using real-time tracking of Mechanical Specific Energy has been reported to archive remarkable improvements in drilling efficiency Dupriest et al. (2005). Drilling performance is difficult to be equitably measured and compared from well to well, because many performance indexes that are used as correlation factors, are based on data from offsets wells and different rig configurations, or wellbore trajectories. Therefore, a new approach was taken by an operator and a pilot program in 2003 was established to verify the usefulness of onsite MSE tracking first displayed as a rig site surveillance tool in 2003 (Dupriest and Koederitz (2005)).

One downside of MSE surveillance is that several real-time parameters such as rate of penetration (ROP), revolutions per minute (RPM), and accurate weight on bit are needed to perform this type of analysis. However, with the advent of instrumented rigs and more advanced data acquisition services, those parameters are easily available, and many operators now employ this type of surveillance tools to assess and improve drilling performance.

ROP should conceptually respond linearly to the applied WOB or RPM. The point when the relationship becomes non-linear is called the founder point. Several factors can influence the location of the founder point for a given set point of WOB/RPM such as rock strength, hole size or pressure conditions. However, the MSE relationship will remain equal to rock strength being drilled if being efficient; in practice the driller has to determine the only one trend line and correlate it with parameter changes, making the real-time MSE readings a stronger parameter to watch while drilling.

4. PID CONTROLLER

This type of controller is widely used in the oil and gas industry from upstream to downstream operations. PID controllers are usually responsible for controlling pump pressures, flow rates and heating sources for chemical processes among others. In the drilling industry, these controllers are used by most 'auto-drillers' to control the rate of penetration (ROP), weight on bit (WOB) and revolutions per minute (RPMs) set-points. Most controllers rely only in up-hole instrumentation, and include fixed gains ignoring current drilling conditions such as bit type, drill-string properties and rock strength. Fixed gain controllers have caused issues in the field as drillers mistakenly interpret the current drilling response for a downhole dysfunction when in reality the oscillations are driven by unstable gains in the controller (Pastusek et al. (2016)).

A closed loop controller was used to accurately control both RPM and WOB. One of most important parameter in this design is the amount of weight on bit that is being applied while drilling. To analyze the single input single output system (SISO) system, the system was analyzed under static conditions, this is, without external disturbances acting on the motors. The magnitude of disturbances due to the drilling operation and polar inertia were regarded as random and harmonic perturbations.

The most important parameter in this design is the magnitude of the weight on bit (WOB) that is being applied while drilling, especial consideration was put into it. The difference in magnitude between the top drive assembly weight and the load cell tension times a transfer-ability ratio pre-determined for a given depth is how the weight on bit is calculated. Basically, in this experiments the weight on bit is calculated using Eq. 4.

$$\text{WOB} = F_t - \frac{F_{lc}}{C_r(Td)} \tag{2}$$

Where F_t is the force being applied to the load cell, F_t is the amount of force generated by the pulling action of the draw works motor, and Td is the amount of force exerted to both pulleys by the total weight of the top drive and drilling string assembly. Finally C_r corresponds to a wob correction factor used to account for small variations in the drillstring setup.

The standard approach to control system design is to base the model on physical laws and restrictions to the corresponding physical parameters. This is called the classic or white box approach. Control systems are required to function based on noisy measurements and inaccurate instruments. Models that are set with adjustable parameters are called gray box models. In many control applications cases, linear models that do not completely represents a system based on an exact analytical solution to the relationship between the subprocesses involved, but approximate them are enough to acquire an acceptable level of controllability. These models are called black boxes models and are derived using system identification techniques (Liung (1999)).

System identification modeling is the process of developing or improving an more accurate depiction of a physical system by analyzing it from actual measured data. The properties and assumptions used in the development of many mathematical models vary because the full availability of observed data and limited knowledge of a given system prevent an exact mathematical representation of the system. Furthermore, even if a great understanding of the system dynamics exists together with observable data to corroborate, a very complex model is often not desired. If an abstract representation of a process becomes too complicated, the control laws and models associated with it will also be complex. However, the actuators delays, limited bandwidth, and plant boundaries usually hinder the implementation of higher order systems and control algorithms. It is important to obtain experimentally verified models to utilize them for design improvements, performance evaluation, and cost reduction (Alvin et al. (2003)).

A system identification approach was used to derive the transfer function of our rig, using the following procedure:

(1) A calibration procedure was taken before, and after each run.
(2) High frequency sampled raw data was acquired and saved using LabView cDAQ at a high enough sampling frequency.
(3) The excitation loop was fed directly into the basic proportional controller and ran continuously until each test was finished.
(4) Instrumentation data was re-sampled and analyzed using the MATLAB System Identification Toolbox.
(5) A transfer function was extracted from the linear response observed under static conditions.

The PID controller was implemented in a micro-controller running at 84MHz. Using a micro-controller reduces the size, costs and energy consumption compared to a design based on a microprocessor or a full sized computer. Modern consumer level micro-controllers are capable of archiving remarkable high operating speeds and efficiencies (Koomey et al. (2011)). An example of an excitation run and the signal acquired to derive the transfer function is observed in Fig. 4.

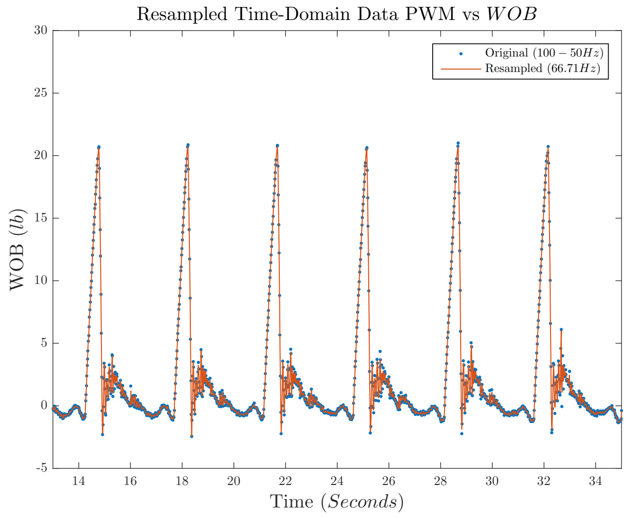

Fig. 4. Drawworks excitation response under steady state conditions.

Gears motors are susceptible to overheating easily due to the amount of current being drawn to generate torque and the friction between internal gears; the input gain supplied should be kept between the maximum and minimum values specified by the manufacturer. The controller uses Pulse Width Modulation (PWM) at 30 KHz to regulate the maximum voltage supplied to the motor while reducing coil whining. We use the 12 bit DAC value as our motor gain in our controller with a 50% saturation point. The PWM value varies then from 0 to 4095 to limit the amount of voltage supplied to the gear motor. Furthermore, the algorithm also incorporates an *anti-windup* feature using a back-calculation anti-windup method, to flush the PID Controller's integrator buffer when the controller hits the specified PWM saturation limits. This prevents the integral term from saturating and stops calculating the integral gain until the plant stabilizes to normal control margins.

Gain scheduling is a common strategy to control systems whose dynamic conditions can change (Rugh and Shamma (2000)). The developed PIDs controller structures use a lookup table from which the P, I and D gains proved to be stable are drawn. Thus, a gain-scheduled setup was defined for each PID controller. This is, a controller whose gains are automatically adjusted as a function of the operating condition, which in this case is determined by both the revolutions per minute and the magnitude of the WOB set-point. In addition, the current average rate of penetration and efficiency derived from the linear regression fit using Mechanical Specific Energy also specifies what controllers'

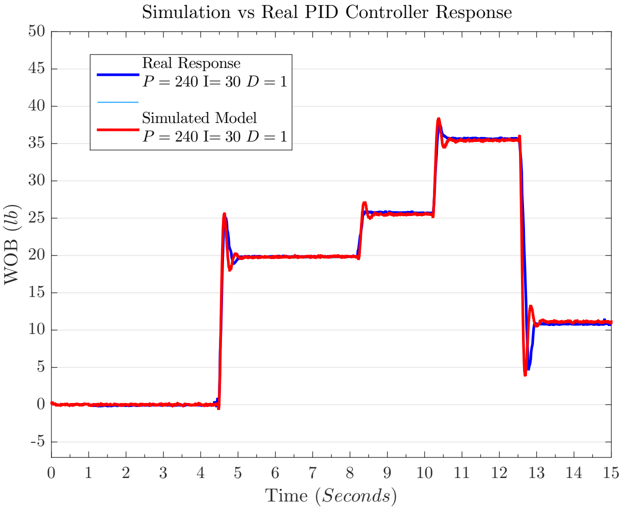

Fig. 5. Simulated vs actual response of the controller

reference inputs should be assigned. Three gain parameters were chosen and defined as aggressive, moderate and conservative controller gains.Astrom and H gglund (2006).

Eq. 3 is the plant's discrete linear transfer function that was derived from the identification signals shown in Fig. 4, a controller sampling frequency of 66.6 Hz ($T_s = 0.015s$) was used. The excitation signal used to generate this plot consisted of a 50% of the maximum allowable voltage signal being on for 200 ms followed by a negative excitation of the same magnitude and duration and off period of 700ms Even though the response is clearly non-linear in the second half of each excitation run. The objective is to accurately avoid over applying weight on the bit. The final linearized PID controller scheduled gains and performance are summarized on table 2.

$$H(z) = \frac{-0.1424z + 0.1616}{z^2 - 1.967z + 0.9671} \quad (3)$$

5. RESULTS

Under static conditions, the closed-loop step response of the drawworks controller matched adequately the simulated PID feedback response. The response under dynamic drilling conditions where much more volatile as expected, however, the controller rejected disturbances in a timely matter.

Table 2. PID controller response

	Aggressive	Conservative
P,I,D gains	240, 30, 1	120, 20, 2
Rise time t_r	0.0644 s	0.83 s
Settling time t_s	0.39 s	0.8 s
Overshoot	18%	0%
Peak	1.18	1
Gain margin	15 dB @ 58 Rad/s	15 dB @ 58 Rad/s
Phase margin	43.3 deg @ 18.3 Rad/s	43.3 deg @ 18.3 Rad/s

In addition to MSE, the average rate of penetration for a given WOB and RPM was automatically computed and compared to account for changes in rock formation and torque to define a new WOB set-point using linear regression. An example of the fit is observed in Fig. 6, for that run a WOB set-point of 20 lbf and south Texas' sandstone was used to validate the MSE relationship. An step test increase the WOB/RPM set-points and measures it's response on the average ROP for given interval. MSE should increase proportionally until a founder point is observed. This is, the linear relationship is lost.

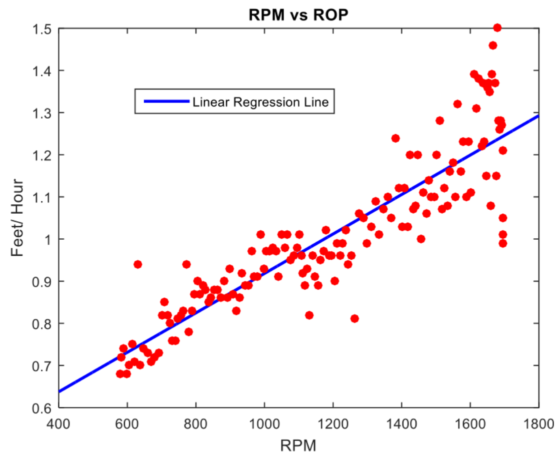

Fig. 6. Example of linear regression of the average rate of penetration as a function of revolutions per minute for a given homogeneous rock layer and constant drilling parameters

As mentioned before, performance under dynamic drilling conditions was much more volatile as observed in Fig. 7 automated changes to RPM, rock layers' changes and other non-harmonic perturbations were observed. Still, the draw-works performed better than the original open loop controller, leading to an increase in drilling performance while reducing and bit wear and pipe failure considerably.

This experiment was a greatly limited by the maximum torsional strength of the 0.375 in. aluminum pipe, which severely limited the amount of torque that can be applied to the string without failure, limiting the amount of depth of cut that can be archived, and increasing the need for more accurate WOB control. Those limitations led to an environment that promotes an increase in the magnitude of bit whirl. Though the experiments, whirl induced inefficiencies were noticed especially when the WOB controller wasn't properly tuned yet. Fig. 8 clearly

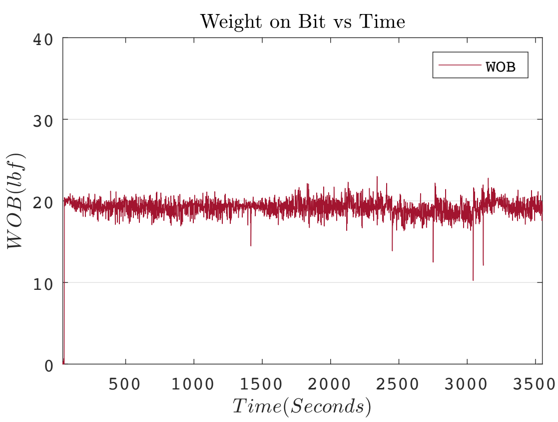

Fig. 7. PID controller performance while drilling

shows the importance that precise WOB control has in borehole quality.

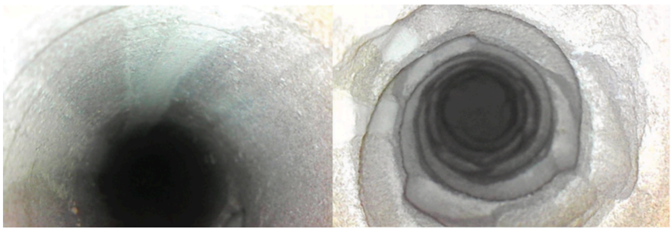

Fig. 8. Left: Dysfunction free borehole, Right: Severe borehole patterns caused by excessive bit whirl

6. CONCLUSIONS

- An automated step test is used to estimate the efficiency and causes of possible dysfunctions, or inefficient drilling conditions, using mechanical specific energy (MSE).
- A linear regression model was used to estimate the response for the rate of penetration (ROP) as a function of Revolutions per Minute (RPM) and Weight on Bit (WOB) to determine probable causes of possible dysfunctions.
- Vibration-induced dysfunctions such as bit whirl were lessened by avoiding resonant frequencies and having a much better WOB controller response using a scheduled-gain PID controller.
- Up to a 70% ROP improvement for the same interval was observed compared to initial tests.
- The drawworks controllers' gains changed based on the amount of WOB and MSE trends being observed.
- Improved WOB and RPM control accuracy, led to better bit wear and borehole quality.
- The controller constantly samples, filters and compute the draw-works motor gain at around 60 Hz. Improving the WOB control performance under static conditions from a 150% to a 0.1% error response when compared to it feed forward open loop performance, and up to an average error of 10% accuracy under dynamic drilling conditions.
- Several rock formation samples were drilled using a 3/8"x 36" x 0.035" aluminum drill pipe using two-cutters micro-PDC bits.
- The addition of scheduled gains PID controllers coupled with a physics-driven efficiency method such as Mechanical Specific Energy was successfully implemented. Not only was WOB control accuracy improved avoiding common drill-pipe failure, but the machine also drilled faster autonomously.
- Even though testing on a scale rig doesn't compare to the complexity of a full-scale operation, the nature of the process, instrumentation, and rock-cutting processes are essentially the same. The potential use to test automated physics-based drilling models under lab - simulated situations are clear. The fundamental underlying principles to employ differences between physical and virtual data, and tune model parameters in real time from high-frequency instrumentation feedback. Providing continuous situational awareness to the driller or Real-time operating centers (RTOCs).

ACKNOWLEDGEMENTS

The authors would like to thank the partial support from Foundation CMG through the FCMG Research Chair at Texas A&M and the lively discussions with the Drillbotics Team at A&M.

REFERENCES

Alvin, K., Robertson, A., Reich, G., and Park, K. (2003). Structural system identification: from reality to models. *Computers & structures*, 81(12), 1149–1176.

Astrom, K.J. and H gglund, T. (2006). *Advanced PID Control*. ISA - The Instrumentation, Systems and Automation Society.

Bello, O., Teodoriu, C., Yaqoob, T., Oppelt, J., Holzmann, J., and Obiwanne, A. (2016). Application of artificial intelligence techniques in drilling system design and operations: A state of the art review and future research pathways. doi:http://dx.doi.org/10.2118/184320-MS. URL `http://dx.doi.org/10.2118/184320-MS`.

Bromell, R. (1967). Automation in drilling. *Journal of Petroleum Technology*. doi: http://dx.doi.org/10.2118/1842-MS.

Dupriest, F.E. and Koederitz, W.L. (2005). Maximizing drill rates with real-time surveillance of mechanical specific energy. doi:http://dx.doi.org/10.2118/92194-MS.

Dupriest, F.E., Witt, J.W., and Remmert, S.M. (2005). Maximizing ROP with real-time analysis of digital data and MSE. In *International Petroleum Technology Conference*. International Petroleum Technology Conference. doi:10.2523/iptc-10607-ms.

Koomey, J., Berard, S., Sanchez, M., and Wong, H. (2011). Implications of historical trends in the electrical efficiency of computing. *IEEE Annals Hist. Comput.*, 33(3), 46–54. doi:10.1109/MAHC.2010.28. URL `http://dx.doi.org/10.1109/MAHC.2010.28`.

Liung, L. (1999). *System identification-Theory for the user 2nd ed.*

Macpherson, J.D., de Wardt, J.P., Florence, F., Chapman, C., Zamora, M., Laing, M., and Iversen, F. (2013). *Drilling-Systems Automation: Current State, Initiatives, and Potential Impact*, volume 28. Society of Petroleum Engineers (SPE). doi:http://dx.doi.org/10.2118/166263-PA. URL `http://dx.doi.org/10.2118/166263-PA`.

Pastusek, P., Owens, M., Barrette, D., Wilkins, V., Bolzan, A., Ryan, J., Akyabi, K., Reichle, M., and Pais, D. (2016). Drill rig control systems: Debugging, tuning, and long term needs. doi:http://dx.doi.org/10.2118/181415-MS. URL `http://dx.doi.org/10.2118/181415-MS`.

Rugh, W.J. and Shamma, J.S. (2000). Research on gain scheduling. *Automatica*, 36(10), 1401–1425.

Teale, R. (1965). The concept of specific energy in rock drilling. In *International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts*, volume 2, 57–73. Elsevier.

Vishnumolakala, N., Gildin, E., and Noynaert, S. (2015). A simulation environment for automatic managed pressure drilling control. 48, 128–133.

