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Drilling in the Digital Age: Case Studies of Field Testing a Real-Time ROP Optimization System Using Machine Learning

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Abstract

O&G operators seek to reduce CAPEX by reducing unit development costs. In drilling operations this is achieved by reducing flat time and bit-on-bottom time. For the last five years, we have leveraged data generated by drilling operations and machine learning advancements in drilling operations. This work is focused on field test results using a real-time global Rate of Penetration (ROP) optimization solution, reducing lost time from sub-optimal ROPs. These tests were conducted on offshore drilling operations in West Africa and Malaysia, where live recommendations provided by the optimization software were implemented by the rig crews in order to test real-world efficacy for improving ROP. The test wells included near-vertical and highly deviated sections, as well as various formations, including claystones, sandstones, limestones and siltstones. The optimization system consisted of a model for estimating ROP, and an optimizer algorithm for generating drilling parameter values that maximize expected ROP, subject to constraints. The ROP estimation model was a deep neural network, using only surface parameters as inputs, and designed to maximize generalizability to new wells. The model was used out-of-the-box, with no specific retraining for the field testing.

During field-tests, increased average ROP was observed after following recommendations provided by the optimizer. Compared to offset wells, higher average ROP values were recorded. Furthermore, drilling was completed ahead of plan in both cases. In the Malaysian test well, following the software's advice yielded an increase in ROP from 10.4 to 31 m/h over a 136 m drilling interval. In the West Africa well, total depth was reached ~24 days ahead of plan, and ~2.4 days ahead of the expected technical limit. Importantly, the optimization system provided value in operations where auto-driller technologies were used. This work showcases field-test results and lessons learnt from using machine learning to optimize ROP in drilling operations. The final plug-and-play model improves cycle efficiency by eliminating model training before each well and allows instantaneous, real-time intervention. This deployable model is suitable to be utilized anytime, anywhere, with retraining being optional. As a result, minimizing the invisible lost time from sub-optimal ROP and reducing costs associated with on-bottom drilling for any well complexity and in any location is now part of the standard real-time operation solutions. This deployment of technology shows

how further optimization of drilling time and reduction in well cost is achievable through utilization of real time data and machine learning.

Introduction

Organizations in the Oil and Gas sector are increasingly adopting Machine Learning (ML) into their operations, stemming from abundant data generated from monitoring equipment, as well as the high project costs, driving efforts to reduce unit development costs and increase operational efficiency. In drilling operations, this is achieved by reducing flat or nonproductive time (NPT), and bit-on-bottom time. ML methodologies have been used for early identification of stuck pipe risks (Meor Hashim 2021a, Meor Hashim 2021b, Payrazyan 2023), assisting in seismic interpretation (Bandura 2018), formation evaluation (LeCompte 2021), and corrosion (Majors 2020). Examples of machine learning tools specifically applied to drilling include improving the rate of penetration (ROP) (Batruny 2019, Singh 2019, D. Cao 2020, Singh 2021, Ghamdi 2021, Ambrus 2022, Berrocal 2022, J. Cao 2022, Erge 2022, Robinson 2022a, Singh 2022), estimate downhole characteristics based on surface data (Robinson 2022b), identification of drilling/rig events (Zhao 2017, Robinson 2023), improving well placement (Zhong 2021) and synthesizing data for well planning applications (Batruny 2022).

During a sample time period from 2019 to 2020, drilling on-bottom contributed ~12% of the time spent by the operator in each well, corresponding to a total of 480 days. An improvement of just 10% could have saved 48 days of operations time, which would translate to considerable cost savings, with the exact amounts depending on the types of wells being drilled (onshore, deepwater, etc). Hence, improving ROP remains a key value-add application of ML in the upstream sector. However, most prior works implementing ROP optimization approaches using ML have been field-based, with ML models limited in their applicability to specific fields. To be applied on a new field, a new model would need to be developed in these cases, which could be a time-consuming, inconvenient and costly exercise. The work of Najjarpour (2021) reviews various applications of ML in predicting ROP over recent decades; from this, it is evident that prior ROP optimization efforts have been field-based or even formation-based in some cases. The most common input variables used in the ROP optimization methodologies are weight-on-bit (WOB), rotary speed (RPM), formation properties, depth, mud flow rate, torque, standpipe pressure and mud properties. Promising results were reported by Singh et al. (2021), in one of the earlier works to apply ML to ROP optimization in real-time. However, Singh's work was field-based with similar BHAs and lithologies, and a strong dependence on differential pressure as an input variable, which limits the solution's applicability to drilling with positive displacement motors (PDM) (Li 1999) or motorized BHAs. Therefore, new models would need to be developed and trained for each subsequent specific application if using this methodology. Other published works in this space have applied complex optimization algorithms, such as Genetic Algorithms (J. Cao 2022, Erge 2022), to identify drilling parameters that improve ROP. However, these are computationally expensive and unsuitable for real-time usage due to processing times required for the algorithms to converge (order of hours), thus limiting their practical utility.

The various aforementioned limitations motivated the authors to develop a real-time "global" ROP optimization solution using ML, capable of performing well on new wells and fields without the need for rebuilding models in each case, and agnostic to specific BHAs or equipment choices to enable usage across a broad variety of operations This was reported in a previous article (Robinson 2022a), which built on Batruny's (2019) earlier work on this topic. These works were focused on developing the optimization system itself, and provided positive but preliminary field test results. The results reported in this work are focused on field tests using the ROP optimization solution on live operations, which intended to investigate its efficacy in reducing the lost time from sub-optimal ROPs.

Methods and Procedures

Field tests were conducted on offshore drilling operations in West Africa and Malaysia, where live recommendations provided by the optimization software were implemented by the rig crews in order to test real-world efficacy for improving ROP. For systems providing recommendations that need to be actioned to observe their effects, field testing on live operations is essential for proving the system's efficacy; this cannot be obtained from historical testing alone where parameter recommendations could be generated, but not practically implemented, meaning that these counterfactuals do not exist and cannot be used to claim the optimized ROP estimates would be realized. Hence, historical testing of such solutions is limited to providing a view of what may have been possible, in this case conditioned on the underlying ML model's capability to accurately estimate ROP with varying drilling parameter values.

The ROP optimization system utilized in this work consumes real-time surface measurements as inputs, and provides recommendations for weight-on-bit (WOB), surface rotary speed (RPM), and mud flow rates as outputs to end-users. Data measured using downhole tools were not used, in order to ensure applicability across the broadest possible group of wells, many of which may not run expensive downhole tools during drilling operations. The optimization system consisted of a global model for estimating ROP, not intended to be limited to any particular field, formation-type or region, and an optimizer module for generating drilling parameter values that are expected to maximize the estimated ROP, subject to constraints controllable by the end-user through a browser-based application for configuring the system and setting up jobs for specific wells. Further details on the ML model for estimating ROP, its performance on historical well datasets, and the system's drilling parameter optimization methodology are provided by the authors in their previous work (Robinson 2022a). The system was used out-of-the-box, without any specific retraining for or during the field testing process.

Operational process for field testing

For the purposes of field testing, the solution was deployed to a cloud server; this was then remotely connected to the operator's WITSML data store for (1) reading data from the rig, and (2) writing back outputs generated by the ROP optimizer. These outputs were then accessible to remote monitoring engineers based in the Real-Time Operating Center (RTOC) and rig site teams via their pre-existing commercial real-time WITSML viewer applications, as shown in Figure 1. The communication protocol between the RTOC and rig was determined before operations started. As those with the most detailed knowledge of the operations, the project teams were responsible for deciding whether or not to implement drilling parameter recommendations provided by the software. During rotary drilling, the optimizer generated recommendations for WOB, surface RPM and mud flow at regular 50 cm (measured) depth intervals. At the beginning of each 50 cm depth-increment, the system would generate a set of recommendations for the upcoming 50 cm to be drilled, using the most recent drilling parameter values as a baseline for the interval, and using the recent drilling context extracted from the time-series data sourced from the remote WITSML store. The recommendations provided were the set of drilling parameter values that yielded the maximum estimated ROP relative to the baseline ROP estimate for the depth interval.

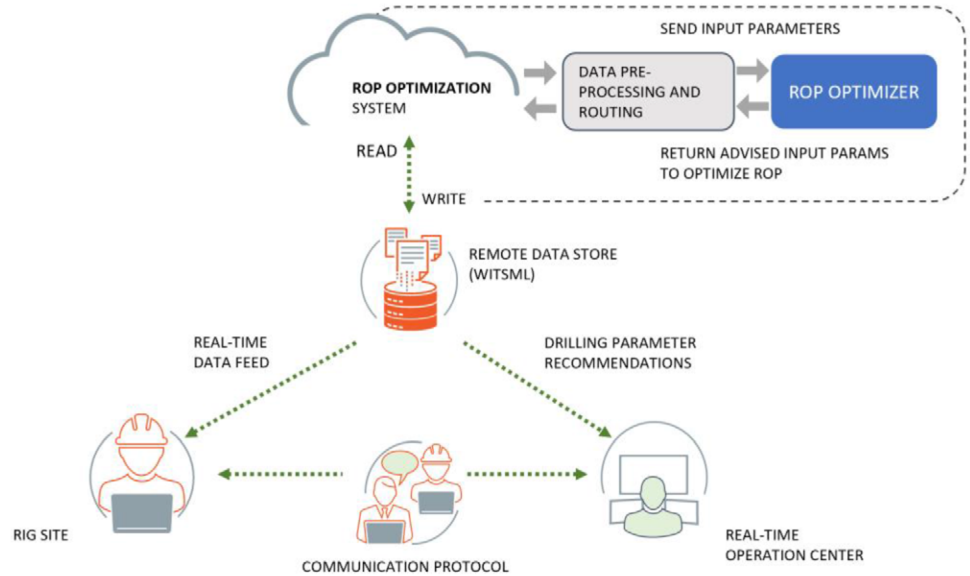

Figure 1—Schematic for how the ROP optimization system was deployed and integrated with live drilling operations during field tests. The RTOC received real time feed-back via a WITSML data stream. The communication protocol between the RTOC and rig was determined by the operator before the operations started.

The operator's guidelines issued to the project and RTOC teams were for the RTOC engineers to monitor the drilling parameter recommendations, and advise on changes in drilling parameters to the rig site teams only two or three times per stand, based on trends in the recommendations, which were updated every 50 cm drilled. The rig crew was asked to act on the optimizer's advice only when the recommended ROP was significantly higher than the baseline ROP (using the latest drilling parameter values at the beginning of the 50 cm increment to be optimized), and only as long as the advice did not pose risks to equipment or operational safety.

Field test well characteristics

Field tests were carried out on two wells; the first was an ultra-deepwater well located in the West Africa region, and the second was a side-track for a shallow water offshore well in Malaysia. The test wells included near-vertical and highly deviated sections, as well as various formations, including claystones, sandstones, limestones, salt and siltstones. An overview and section-wise technical details relating the field test wells are provided in Table 1 and Table 2 respectively.

Table 1—Overview of the offshore field-test wells located in the West Africa and Malaysia regions.

	Well 1: Offshore West Africa	Well 2: Offshore Malaysia
Well type	Exploration	Development
Well design	Vertical	Horizontal
Rig type	Dual derrick drillship	Semi-sub TAD rig
Water depth	2105m	80m

Table 2—Section-wise technical details from the offshore field-test wells in the West Africa and Malaysia regions.

Well 1: Offshore West Africa				Well 2: Offshore Malaysia			
Section Size / Depth MD	**Bit type**	**Lithologies**	**Mud type**	**Section Size / Depth TVD / MD**	**Bit type**	**Lithologies**	**Mud type**
36″ jetted conductor 2213 m	n/a	Marine shales	Seawater	26″ pre-driven conductor / 194 m / 194 m	n/a	n/a	n/a
24″ hole /3335 m	Mill-tooth	Partly shale dominant, partly sand/clay interbedded.	Seawater	17.5″/ 991 m / 1215 m	Roller cone	Alternating sand & clays	Seawater
17.5″ hole /4486 m	PDC	Sand/shale, then salt	Oil based	12.25″ / 1140 m / 1659 m	PDC with RSS	Alternating sand & clays	Synthetic based
12 ¼″ hole /5526 m	PDC	Sand interbedded shale.	Oil based	8.5″ / 1143 m / 1995 m	PDC	Alternating sand & clays	Synthetic based

West Africa. The ROP optimization system was used in both the 17 ½″ and 12 ¼″ sections. Both sections were drilled with a polycrystalline diamond compact (PDC) bit. Auto-driller technologies were used for this well. The lithologies in the 17 ½″ section are mostly shale dominated with argillaceous limestone and sands. The bottom 476m thick Anhydrite / Halite formation. The 12 ¼″ section was sand dominated with interbedded shale. Two wells previously drilled by the operator in the area recorded issues with vibration and formation hardness, resulting in sub-optimal ROP. In the first offset well, a 6-5/8″ drill pipe was used with a PDM and resulted in an average on-bottom ROP of 15 m/h. The other offset well used a 5-7/8″ drill pipe with an RSS and drilled at an average on-bottom ROP of 16 m/h. Optimizations and best practices such as using a straight, high-performance, PDM on 6-5/8″ drillpipe were used in the West African well described in this paper to avoid vibration issues.

Malaysia. The optimizer was primarily used in the 12 ¼″ section, with a maximum inclination of 85 deg and using a rotary steerable system (RSS) BHA and a polycrystalline diamond compact bit. The lithologies in this section are interbedded sands an shales. Some of the horizons were very thin (~1m upwards). The system's recommendations were also infrequently followed in the 8.5″ section.

Results and Discussion

Overview

In this section, the field results are analyzed from both a macro-level for the entire well based on their time-depth curves for the West African well, since the ROP optimization system was used on both the key sections of the well, supported by more detailed analysis of specific sections where drilling parameter recommendations generated by the software were followed by the project teams. For the well drilled outside Malaysia, the section overview is presented, as the ROP optimizer was used for a single section only in this well.

West Africa field test well

Figure 3 shows a scenario where the drilling was close to optimum from the beginning of the chart up until point (A); here, the ROP Optimizing system recommended to increase WOB and RPM. Although the rig crew were controlling rotary speeds at this point of the operation, the WOB recommendations were followed, with WOB gradually increased after point (A). This corresponded with higher observed ROP, indicated by the arrow at point (B) tracking the trend in the green ROP curve (average ROP values calculated over successive 50 cm intervals).

Figure 3 shows a scenario where both RPM and WOB recommendations provided by the software were implemented by the rig crew. At point (A), the RPM was increased, giving a small increase in ROP. At point (B), recommendations to increase both RPM and WOB were acted on by the rig team; following this, a sustained period (approximately 12 hours) of noticeably higher ROP relative to the preceding interval was observed, as indicated by point (C). The optimized estimates for ROP are shown as a dashed red line in the leftmost track; the green current ROP curve, is consistently close to the red line after the recommendations were followed at point (B), suggesting the ROP may have been close to optimum in this interval, in the 40-60 m/h range on average.

A time-depth curve comparing the planned and realized measured hole depths with time for the West Africa test well is shown in Figure 4. The green curve shows the planned measured depth values according to the Approval For Expenditure (AFE), while the blue curve shows the actual improvements observed during the operation. Total depth was reached well ahead of plan stated in the AFE, approximately 24 days ahead of the AFE. Furthermore, this was 2.5 days ahead of the expected technical limit.

A further comparison can be drawn between the observed time-depth curves of the West Africa field test well, and two other wells drilled in a nearby, albeit different offshore field. These are shown in Figure 5, although for more direct comparability, only time spent actively drilling has been counted for each well to remove any other sources of elapsed operational time, such as different amounts of time spent in connections between stands, non-productive time, or any other non-drilling activity. While the results reflect positively on the ROP optimization tool, with less than half the time required on the field test well to reach the reference measured depths indicated by the dotted lines, this is not an exact "apples to apple" comparison. The differences in ROP between the different wells cannot be fully attributed to the use of the software. Unlike when comparing realized and planned time-depth curves for a specific well, differences in equipment used between the different wells are expected to affect the observed ROP. Hence, the planning stage optimizations and BHA improvements based on lessons learnt from the offset wells would have also partially accounted for the improved ROP observed in the field test well.

The realized on-bottom ROP in the West Africa field test well using the real-time optimizer was significantly higher than that of offset wells that drilled similar formations. The ML ROP model underpinning the ROP optimizer provided accurate estimates, using only surface parameters as inputs; these collectively were able to improve ROP for a PDM through the parameter recommendations. On multiple occasions, there was a clear increase in ROP when optimized parameter suggestions were followed, even when drilling at a perceived optimum. This led the team to conclude that following trends and the directions of recommended changes, rather than absolute values results in optimization even when the boundaries of the model are limited. The observation that the estimated optimum and actual (measured) ROP are consistently aligned validated the project team's efforts and design-stage optimizations used in the latest of the three wells. This shows that the global ROP model is not only beneficial in real-time ROP optimization, but can also be used in ROP benchmarking and future well planning by informing equipment choices based on recommended optimal drilling parameters obtained from running the optimization system on historical data and offset wells.

The application of the real-time ROP optimizer, as well as improvements to the BHA from lessons learnt in previous wells, auto-driller technologies used during the operations and a modern rig all contributed to the drilling performance in this well. It is clear, as illustrated in Figure 2 and Figure 3, that the ROP optimizer further enhanced the ROP in the two sections where it was used, thereby proving good results in highly engineered wells using advanced rig systems, and contributing to the strong overall performance reflected in the time-depth curves of Figure 4 and Figure 5.

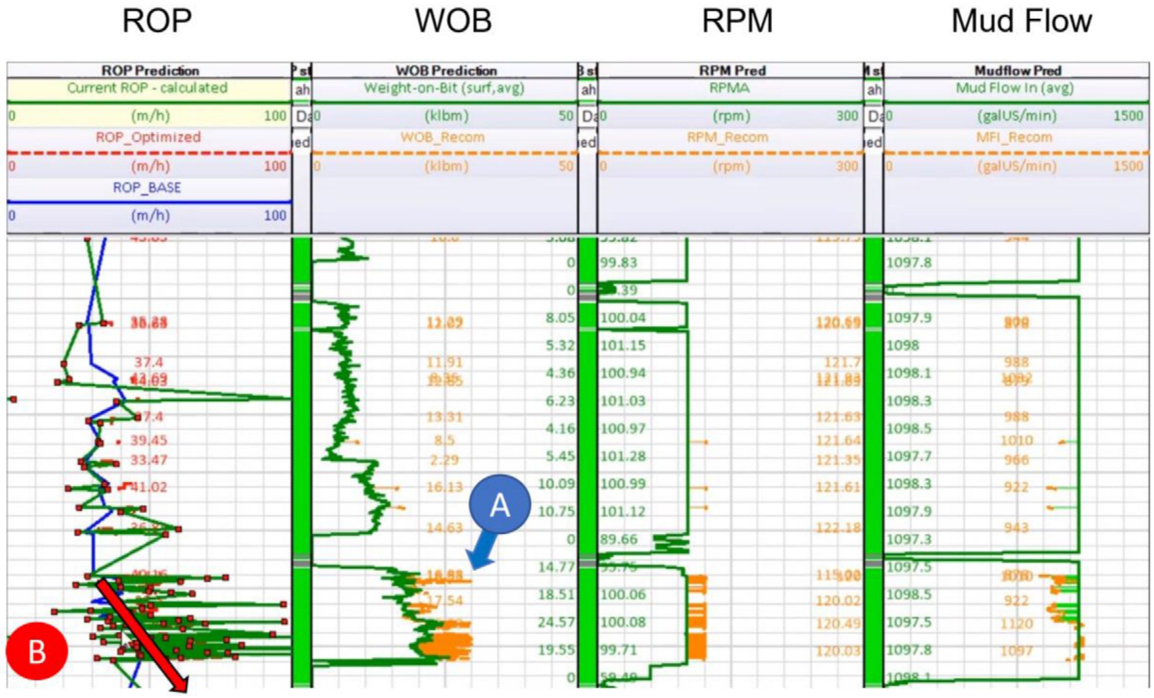

Figure 2—An example interval with drilling data from the West Africa field test where the recommendation to increase weight-on-bit, generated by the ROP optimizer, was followed by the rig crew, in this case at point (A). (B) shows the average ROP increasing as the WOB was increased during this stand. Reproduced with permission from the authors' previous work (Robinson 2022a).

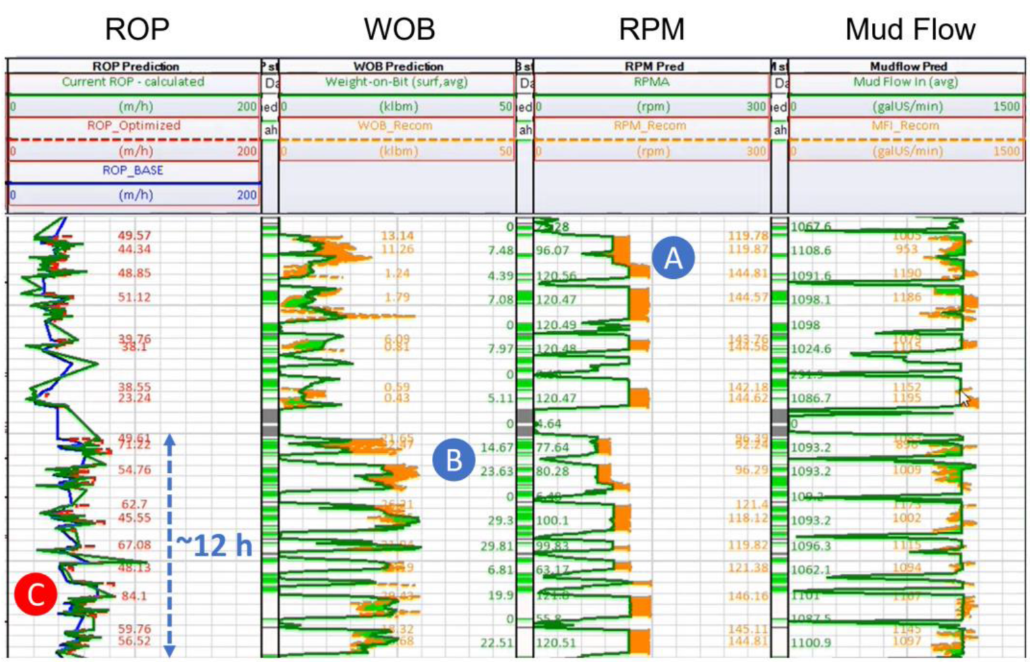

Figure 3—Drilling data from an example interval in the West Africa field test well, where parameter recommendations to increase rotary speed and weight-on-bit were followed by the rig crew at points (A) and (B) respectively, and higher average ROP was observed following the changes during the interval (C). The data is visualized in a commercial WITSML viewer. Reproduced with permission from the authors' previous work (Robinson 2022a).

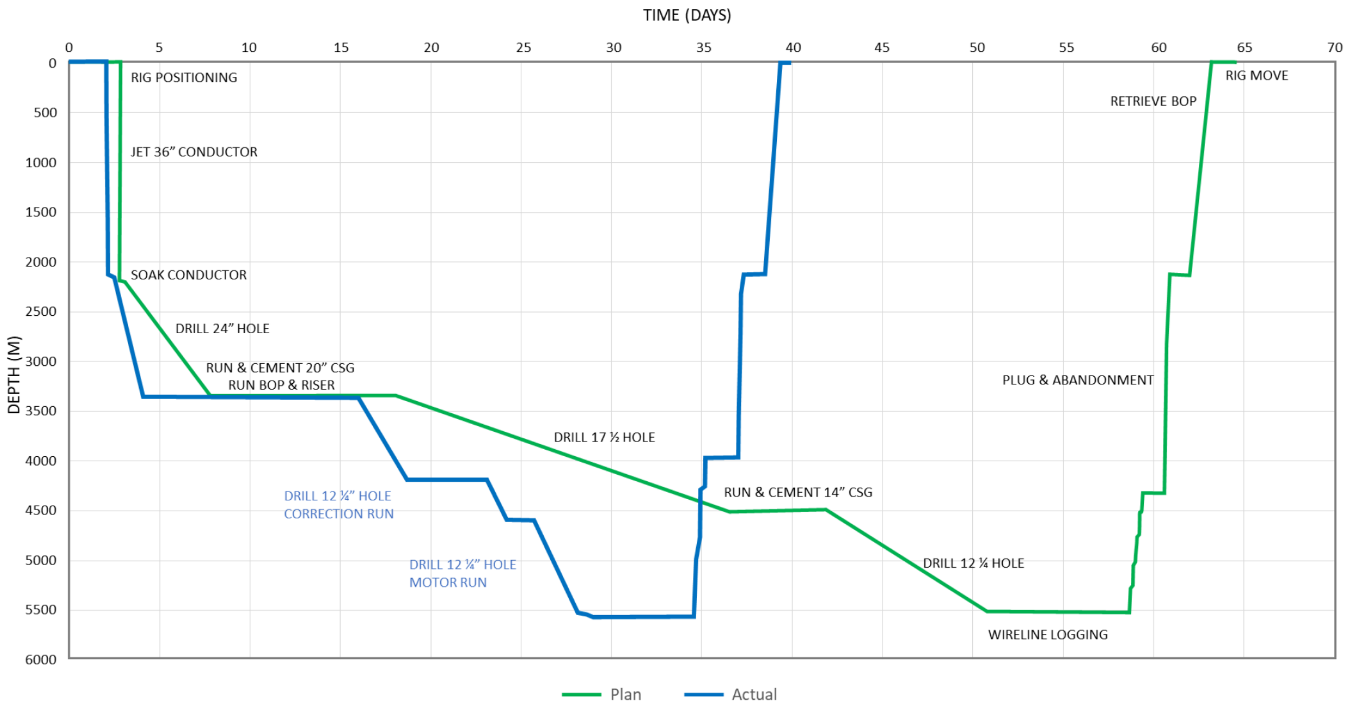

Figure 4—Time-depth curve from the West Africa well where the Rate of Penetration (ROP) optimization software was actively used during operations, and drilling parameter recommendations were implemented by the rig crew. Total depth was reached #24 days ahead of plan (Approval For Expenditure), and 2.5 days ahead of the expected technical limit.

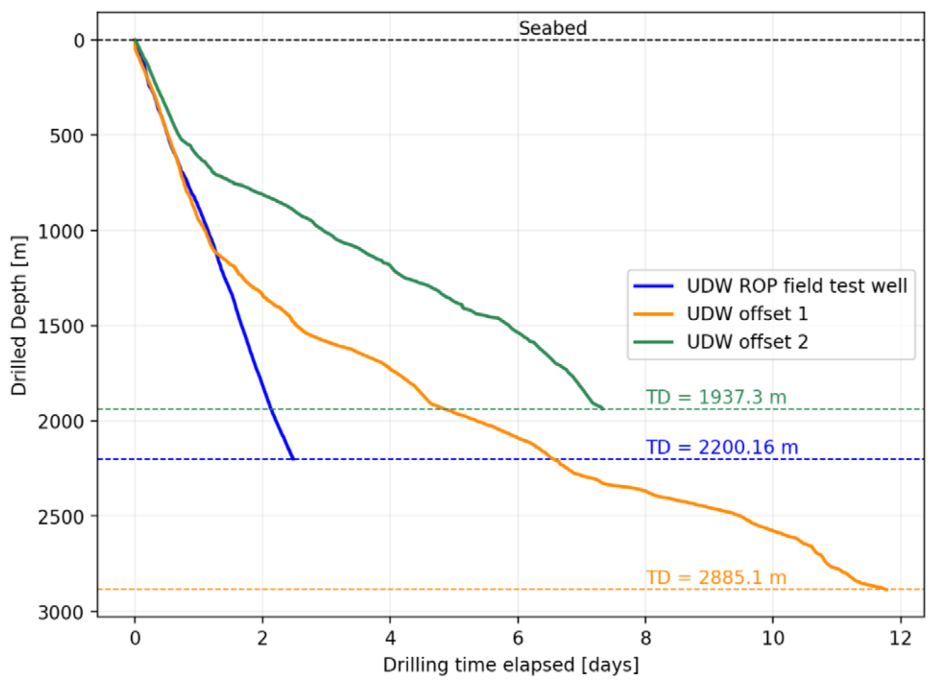

Figure 5—Realized time-depth curves for the West Africa field test, as well as two other wells from a nearby, albeit different, ultra-deepwater (UDW) field. For comparability, only active drilling time has been included, in order to remove the effects of differences in time spent in connections between stands or other non-drilling activities. The total depths (T.D.) marked for each curve are measured relative to the seabed (zero depth).

Malaysia well

In this well, the ROP optimizer was consistently used in the 12 ¼″ section. Figure 6 shows the section in its entirety. The rig crew started to follow the recommendations at the top-most blue stars. As a result, the ROP increased from 6 m/h to 25 m/h. However, gaps between the actual and recommended ROP were observed, indicating potential for further drilling parameter optimization. The team continued to follow the ROP optimizer's recommendations by increasing WOB from 1 klbm to 5 klbm, rotary speed from 128 to 140 rpm, and mud flow from 750 gpm to 850 gpm, resulting in an ROP of 31 m/h. Reviewing the drilling of the 12 ¼″ side-track section between 1244 m to 1380 m, the agent's advice resulted in a significant increase in ROP from 10.4 m/h to 31 m/h. The Gamma ray log and lithology profile show alternating, interbedded shales and sands throughout the interval, and there are no indications in the data suggesting that the increased ROP was the result of changes in the lithology.

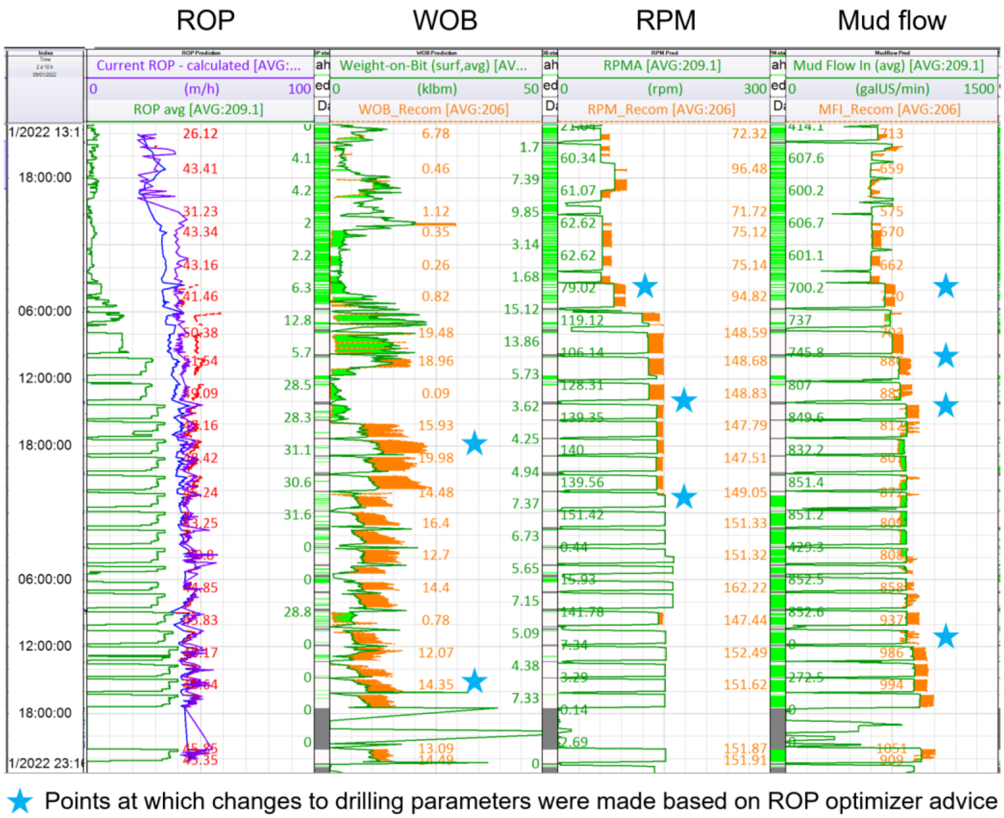

Figure 6—Extended drilling interval from the Malaysia field-test well where the ROP optimization advice was followed at multiple points by the rig crew, indicated by the blue stars. Drilling parameter recommendations are indicated in the second through fourth columns; orange shaded areas indicate a recommendation to increase the drilling parameter, green shaded areas show recommendations to decrease. The observed average ROP (green curve, first column) increased steadily after drilling parameter advice was implemented and maintained. As the drilling parameters reached their recommended values, the baseline ROP (blue curve, first track) and estimated optimal ROP (red curve, first track) converged, indicating that the ROP had reached an estimated optimal value.

The ROP optimization system was also infrequently used in the 8.5″ section, as illustrated in Figure 7; this shows that the RPM was increased in three steps (blue stars) and the flow was slightly increased once (blue star). As can be seen in the figure, the red optimized ROP remained fairly constant (43-55 m/h) throughout the interval, whereas the green mud-logger ROP increases (30 to 40 m/h) as a result of the actions taken to follow the recommendations given from the ROP optimization system. It can be seen at the bottom of the interval that the green mud-logger ROP approached the red optimum ROP curve.

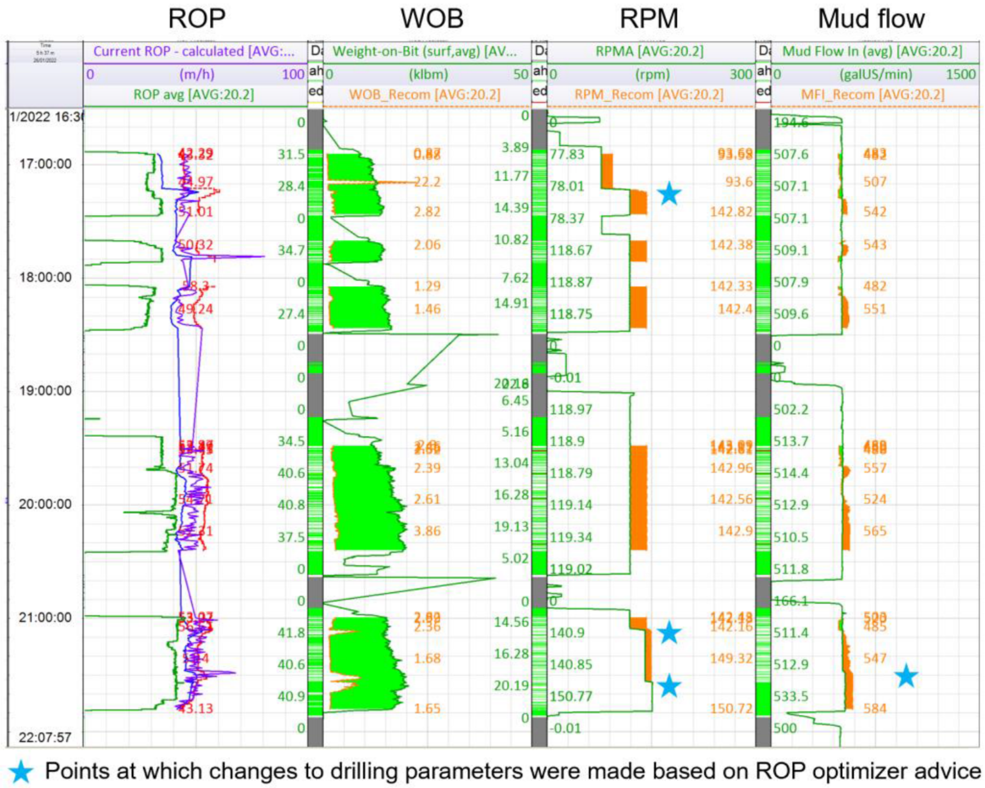

Figure 7—Drilling interval from the Malaysia test well, where drilling parameter advice from the ROP optimizer was implemented at the points indicated by blue stars. The same color coding scheme as in Figure 6 is used for the curves shown.

Conclusions

The case studies conducted in the field provide evidence of the ROP optimization's efficacy. The use of the same model in these two wells in geographically distinct localities, different hole sizes, different localities, different bits and different mud demonstrates an out-of-the-box usage of the optimization system and its underlying ML model, without specific retraining to suit the field test wells, indicates that a global ROP model can be used successfully, a departure from many previous works using field-specific models.

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