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Automated Real-Time Rate of Penetration Optimization Using Trend and Dynamic Analysis in Drilling Operations.

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Abstract

Several drilling parameters influence the rate of penetration (ROP), including formation strength, normal compaction, bottom-hole pressure differential, flow rate, weight on bit (WOB), rotary speed (RPM), bit diameter, bit tooth wear, and bit hydraulics. Due to the complexity of the mathematical models, it is difficult to calculate and predict many of the drilling parameters involved in ROP calculations in real time, which makes ROP control and analysis difficult. The purpose of this study is to automatically extract trends from real-time ROP data using a moving window trend analysis, a new data analytics approach. As a result of this work, drillers will be able to detect changes in the ROP rapidly, learn the dynamics of the ROP in real time, and make better decisions regarding the deployment of the ROP. Using the time and depth characteristics of the ROP in combination with trend data can provide new insights into reducing drilling operation costs and improving drilling efficiency.

Using qualitative trend analysis (QTA), measured signals are analyzed and extracted to extract trends. The classification of trends into stationary, falling, and rising trends is a major result of the ROP trend extraction process. Testing of this methodology will be conducted in a drilling simulation environment with high fidelity. The simulator simulates real-life drilling operations by integrating a multiphase flow model with a transient torque and drag model, a cuttings transport model, a dynamic drilling string and BHA model, and a reservoir model. Afterward, ROP data is streamed in real-time from the simulator.

By observing how drilling parameters, such as the WOB and RPM, affect the ROP in real-time simulations, the presented algorithm is able to identify, analyze, and improve ROP trends. Results of this study indicate the potential for drilling automation based on data analytics to make drilling systems safer and more efficient. In addition, this method is capable of being incorporated into an advanced drilling control hierarchy, thereby supporting drilling engineering automation and intelligent decision-making.

Keywords – Trend analysis, ROP, Real time data analytics, Drilling automation.

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Uchenna Blesseth Ochije

List of Abbreviations

α	Confidential Level
β	Regression model coefficient
δ_k	Regression model standard estimated error
A.I	Artificial Intelligence
API	Application Programming Interface
BHA	BottomHole Assembly
BHP	Bottom Hole Pressure
BRNN	Bayesian Regularized Neural Networks
CR	Change rate
CSV	Comma-separated values
KNN	K-Nearest Neighbors
MD	Measured Depth
ML	Machine Learning
MSE	Mechanical Specific Energy
NORCE	Norwegian research Center
NPT	Non-productive time
PDMs	Positive Displacement Motors
PID	Proportional-Integral-Derivative
QTA	Qualitative Trend Analysis
ROP	Rate of Penetration
RPM	Revolution per Minute
TA	Trend Analysis
TOB	Torque on Bit
TVD	True Vertical Depth
UCS	Unconfined Compression Strength
WOB	Weight on Bit

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Chapter 1

Introduction

1.1 Background and Motivation

The extraction of hydrocarbons remains essential, and global demand for hydrocarbons continues to increase despite the urgent need to reduce our hydrocarbon footprint. Even with advances in drilling safety technology, large-scale production has increased the likelihood of encountering risks. As a result, many wells still rely on older and simpler technologies.

Data collected from the surface and downhole (high volumes, high speeds, and high variances) is increasingly used by engineers to ensure safe operations and reduce rig downtime. The drilling parameters that are relevant to real-time drilling can significantly affect drilling performance, and if interpreted incorrectly, only limited value can be extracted from the measured signals. Data-based methodologies allow for the analysis of real-time data to determine correlation between classification parameters and regression variables, to predict drilling trends, to analyze drilling dynamics, to identify potential problems, and to provide advice on drilling parameters to enhance drilling efficiency and reduce incident risk. According to Fjetland (2019), the oil and gas industry has adopted data analytics and machine learning (ML).

Business ventures aim to minimize costs and operational uncertainty while maximizing profits. It is no different in the drilling industry. Most of the costs associated with field development can be attributed to oil and gas drilling activities, geothermal energy production and carbon dioxide storage. Drilling speed, or rate of penetration (ROP), is one of the key cost drivers, and if ROP is monitored, analyzed, controlled, and eventually optimized, large cost savings can be achieved. The optimization of ROP represents a significant milestone in the drilling industry. An overview of the literature is provided by Barbosa et al. (2019), Hegde et al. (2017, 2019), Nystad (2021), Soares and Gray (2020), and Tunkiel et al. (2021). Using emerging technologies in data analytics, artificial intelligence, and automation produces sufficient volume and variety of data that allows for the detection of subtle patterns in time series.

It is desirable to use sophisticated models with higher accuracy in certain scenarios, such as when results of models are used in numerical calculations or when precision control is required within narrow operating windows. However, it is sometimes useful to forecast and analyze data stream trends while considering changes in data that deviate from stationary values. In this manner, drillers can detect potential problems, activate control algorithms in order to suggest new set points for drilling control parameters, and avoid further damage to drilling equipment. Therefore, ROP models can be evaluated based on their trend forecasting capabilities as well as their dynamics analysis capabilities.

1.2 Objectives and Scope

Aiming to assist drillers in detecting changes in ROP trends for ROP optimization and accident management, this study uses the QTA tool to extract a real-time ROP data stream from a real-time ROP data stream. The following activities are designed to address this issue:

- Simulation of real-time ROP data points provided by a drilling simulator based on changes in environmental or operational variables, such as adjustments to the WOB and RPM setpoints, formation changes, vibrations, etc.;
- Analyze drilling data over time to determine whether a trend is increasing, decreasing, or stable using the QTA method;
- Assess the QTA method's optimization abilities.

An artificial measurement environment (Saadallah et al., 2018 and Gravdal et al., 2021) has been utilized to develop and test the QTA method in this study. In addition to generating transient and realistic calculations of well flow and drillstring mechanics, the simulator calculates mechanical forces on the drillstring, bottom hole assembly, bit, as well as the interaction between the drillstring and surrounding formation. As part of my research, the simulator was accessed via a Matlab client as a web service.1.2.

1.3 Methodology

In chapter 3, a comprehensive methodology is presented for achieving the objectives outlined earlier, which includes well configuration, well simulation, real-time trend analysis, dynamics evaluation, and Rate of Penetration (ROP) optimization. Figure 3.1 illustrates the complete methodology flow chart.

We also explore the application of the trend method to analyze ROP, proposing set points for Weight on Bit (WOB) and Rotations Per Minute (RPM) based on ROP dynamics. By leveraging this information, real-time ROP optimization can be designed more precisely, taking into account real-time change rates and transient data. Additionally, we discuss how sudden changes in ROP, WOB, and RPM can serve as reliable indicators of potential incidents, highlighting the importance of closely monitoring these parameters.

1.4 Innovation

Identifying a dominant trend or assessing how it will develop over time is the purpose of trend analysis. It helps identify relevant concepts and opportunities which makes it an excellent idea to conduct trend analysis during early design phase of projects. Trend analysis data is usually analyzed to identify a trend and its development over time. However, determining the cause of the trend is more difficult than determining the trend. Certain factors such as time of day, season, geographical location etc, affect trends and such factors are recorded while monitoring the trend.

The QTA method used in this study to optimize ROP acts as a second layer of confidentiality for drillers in their pursuit of reaching target depths in the most efficient and safe manner.

Chapter 2

Rate of Penetration (ROP) Optimization

As defined by Oxford dictionary, optimization refers to making the most appropriate use of a situation or resource. The concept is often viewed differently when paired with drilling or engineering operations, especially when automation is involved.

Since the rate of penetration is dependent on factors such as formation strength, rock compaction, bit diameter, bit hydraulics, cuttings generation and transportation, weight on bit, rotary speed, etc., safety and effective use of drilling equipment should always take precedence. As a matter of fact, ROP optimization is not directly associated with an increase in drilling speed, rather it indicates the safest speed at which a driller may reach the desired depth. In this chapter, we will examine several ROP models and compare data driven ROP models with physics-based ROP models.

2.1 ROP Models

In order to optimize drilling operations, models of drill bit penetration rates are essential. Two approaches to ROP prediction are examined in this chapter, the physics-based modeling and data-oriented modeling. Three physics-based models and three data-driven models have been compared in this study. Data-driven models are built using machine learning algorithms, based on surface measured input features - weight-on-bit, RPM, and flow rate to predict ROP.

2.1.1 Physics-based ROP Models

Physics models usually have governing equations obtained during laboratory experiments and we shall look at some examples. The governing equations help us better understand the input parameters and their significance. Among the earliest traditional models that can be applied to any bit type is the Bingham (1965) model.

<u>Bingham's Model:</u>

$$\text{ROP} = a*\text{RPM}\left(\frac{WOB}{D_b}\right)^b, \qquad (1)$$

Where,

ROP = rate of penetration (ft/hr)
RPM = rotary speed of the drill bit (revolutions/sec)
D_b = bit diameter (in)

‘a’ and ‘b’ are constants determined for a given rock formation and they represent a quantification of the ease of drilling through a formation. The constants are determined for each formation by conditioning them to trained data.

<u>The Motahhari's model (Motahhari et al., 2010):</u> This model was PDC-bit-specific and incorporated within it a wear function as shown below.

$$\text{ROP} = W_f \left(\frac{RPM^{\gamma} * WOB^{\alpha}}{UCS * D_b}\right), \tag{2}$$

Where,

UCS = unconfined rock strength (psi)
W_f = wear function

α and γ are ROP related model exponents.

<u>The Hareland's model (Hareland and Rampersad, 1994):</u> This model proposed a bit-specific model – specific to the drag bit. ROP is modeled with a correlation factor to account for properties such as bit cleaning, imperfections in bit geometry, and microscopic variations in rock strength.

$$\text{ROP} = 14.14 * N_c * \text{RPM} * \left(\frac{A_v}{D_b}\right), \tag{3}$$

Where,

N_c = number of cutters
A_v = area of rock compressed ahead of a cutter (in2)

The other variables repeat themselves from the Bingham model. A_v is set based on the type of drag bit: in the case of a polycrystalline diamond cutter (PDC) bit it can be represented as:

$$A_v = \cos\boldsymbol{\alpha}\sin\Theta * \left(\left(\frac{d_v}{2}\right) cos^{-1} * \left(1 - \frac{4*WOB}{COS\theta*\pi*N_c*\delta_c*{d_c}^2}\right) - \left(\frac{2*WOB}{COS\theta*\pi*N_c*\delta_c}\right) - \frac{4*WOB^2}{\left(COS\theta*\pi*N_c*\delta_{c*d_c}\right)^2}\right)^{0.5}\Big) \left(\frac{WOB}{COS\theta*\pi*N_c*\delta_c}\right)\Big), \tag{4}$$

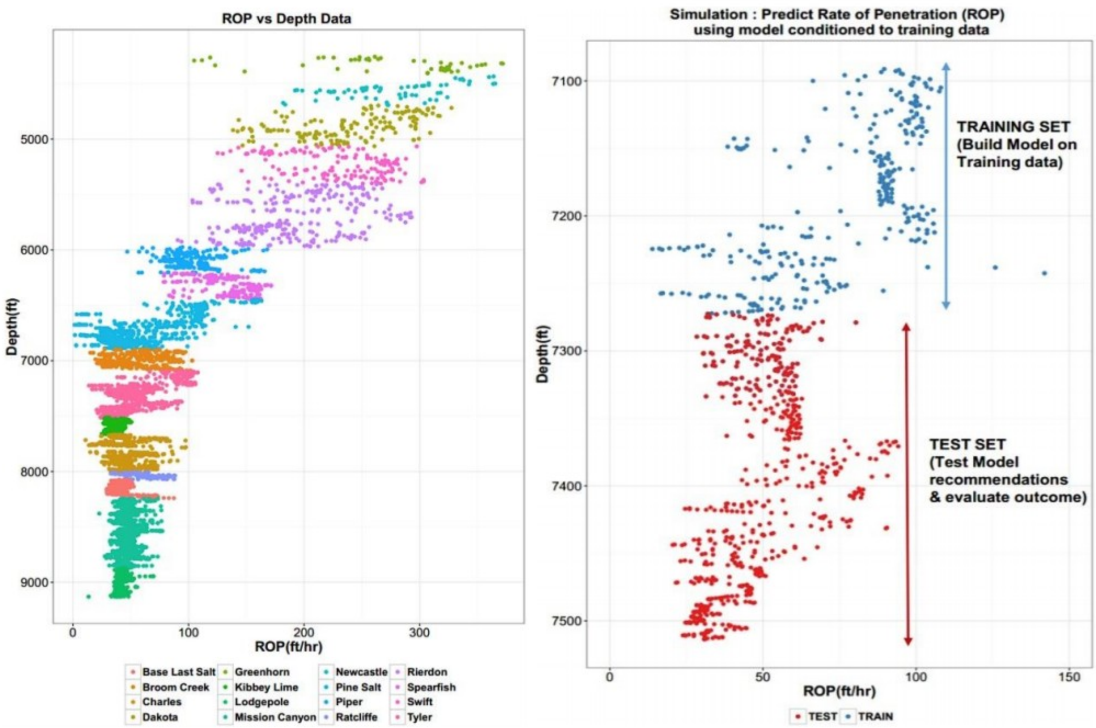
Where,

α = cutter side rake angle (degrees),
Θ = cutter back rake angle (degrees),
d_c = cutter diameter (in),
δ_c = unconfined compressive strength (psi).

In addition to being decisive and easy to optimize, traditional or physics models have several limitations, including low ROP prediction accuracy, an increased dependency on empirical coefficients based on continuously changing lithologies, and a requirement for static parameters as inputs, which are often not available.

2.1.2 Data-Driven ROP Models

Machine learning and artificial intelligence form the basis of data-driven models. This often requires training of data used to generate the mathematical model. The test data is compared with the predicted data once the model fits the training data. Several papers have been written about data-driven models but in this study, we try to briefly explain data training process.



(a) (b)

Figure 2.1: ROP vs Depth plot for field data and an example of ROP simulations schematic. Source : (Hegde, Daigle, Millwater, & Gray, 2017).

The training data as shown in Figure 2.1 a and b is used to build the data model, which can be used to predict ROP thereafter. Figure 2.1a shows an example of ROP vs Depth plot for field data used in simulations while Figure 2.1b shows an example of ROP simulations schematic.

Figure 2.2 shows an example of Pair-wise correlation of drilling data with each plot having a numbered "window" for easy evaluation. Depth, RPM and flow-rate are correlated to ROP and used as input parameters to the data-driven model. Numbering follows matrix indexing, e.g. window(i,j) represents a row and column window. The X-axis in each sub plot represents the units for that input parameter. Thus, each input parameter or each window would contain an X & Y axis with each window in the plot, containing two parameters plotted against each other. A window (1,2), for example, plots depth along the x-axis and ROP along the y-axis. The window (2,1) displays the correlation between the variables plotted in the window (1,2). Based on the analysis of the pairs plot, some input features may be discarded if they are not correlated with the target or if they are redundant. There would be enough reason to drop one of the two features if a pairs plot yields a perfect or very high correlation between the two variables. Pair wise correlation helps to simplify data processing and analysis. It also helps to identify linear relationships between drilling parameters and formation properties thereby optimizing drilling operations, reducing costs and minimizing risks.

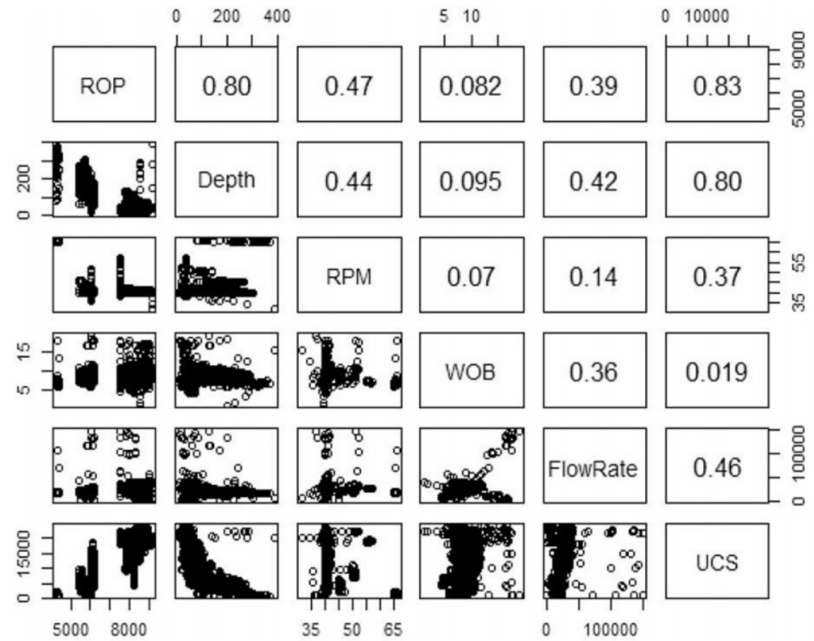


Figure 2.2: Pairs plot to analyze relationship of data for data-driven modeling.
Source: **(Hegde, Daigle, Millwater, & Gray, 2017)**.

Three data-driven models are explained below;

<u>K-Nearest Neighbors (KNN)</u>: The KNN algorithm is a simple machine learning algorithm. It is an instance-based method of learning, in which new data is classified using stored, labeled instances. The KNN algorithm can be applied to both classification and regression problems. However, it is more widely used in classification problems in the industry. In order to calculate the distance between the stored data and the updated instance, similarity measure is typically applied, such as Euclidean distance, cosine similarity, or Manhattan distance (city block distance). A KNN can be used when outliers are present. Due to its insensitivity to outliers, it is resilient to classification errors. This model is highly dependent on the number of nearest neighbors chosen, i.e. determining the value of K. As a result, tuning is done by varying K over several values to examine how well the KNN algorithm generalizes data. To avoid time and processing power constraints, a value equal to the square root of the observations can be used directly for K.

Random Forest: In Breiman (1996), random forest is used to predict ROPs and model non-linear data accurately. Due to the nonlinear nature of ROP data, random forest is generally more effective than linear regressions (Hegde, 2016). As a result of fitting and averaging many trees (based on feature vectors), random forests can be used to predict ROP. Random forest is a method of ensemble learning defined by Zhao (2009) as a machine learning paradigm in which multiple learners work together to solve a problem. A significant difference between this approach and conventional machine learning techniques is that it learns by combining hypotheses. Learning algorithms (decision trees, neural networks, etc.) create ensembles of learners from training data and this process is repeated until the most popular combination is selected.

Bayesian Regularized Neural Networks (BRNN): These are specific types of neural networks. It consists of a collection of computational units (or nodes, or neurons) organized into layers. Neurons receive input, process it based on a transfer function and pass the result on to the next layer until they reach the output layer. Using layers, an input vector's features are connected to those of its output vector. Neural networks can be trained to model primary relationships in data by using a back-propagation algorithm. A tuning grid search or manually altering neurons' values is usually used to tune the system. A neural network serves as the basis of Deep Learning, a method of learning that relies on neural networks with many layers (hence the name 'deep'). Clustering algorithms are not employed in this method. Instead, they are used to perform complex tasks, such as image recognition, natural language processing, and so on. Unlike KNNs, they do not simply memorize training data, but also learn from it. A Bayesian Regularized Neural Network uses computational units to receive inputs, process them according to an activation function, and forward the results.

2.1.3 Physics-based Models vs Data-driven Models

The desire to develop new technologies and methods to extend current model capabilities and decision workflow practices has become increasingly popular as a result of the abundance of data and persistent absence of physical laws to satisfactorily explain the complexity of assets and operations. Within the last few years, data science and machine learning have become widespread disciplines that could contribute to generating cutting-edge technologies derived from data. While the oil and gas industry has traditionally relied on empirical and numerical models for explaining reality, the advent of data-driven technologies has undoubtedly shaken this premise as multiple parameters can be simultaneously analyzed to uncover underlying physical laws. It has also been observed that most theoretical methods in the industry are derived from differential equations based on conservation laws, and physics principles.

It seems that some practitioners remain skeptical that a data-driven model can truly overperform or satisfactorily reproduce what current physical models are capable of. Most physics-based models, given their specificity or commercial scope, are conceptually and computationally unsuitable for accommodating additional physical processes. As data-based models are deployed to optimize field production operations, well completion designs, or investment portfolios under uncertain conditions, computational demand has increased geometrically. It is interesting to note that these data-driven models can be trained with both simulations and field data. Decision costs can thus be calculated by multiplying the cost of simulation by the cost of optimization by the cost of evaluating uncertainty scenarios. An ideal data-driven model would simultaneously reduce all these multipliers so as to make computational costs manageable and allow real-time workflows to be implemented.

$$\text{Decision cost} = \text{Simulation cost} * \text{Optimization cost} * \text{Uncertainty evaluation cost} \quad (5)$$

The development of improved predictive models of complex real-world problems requires a balanced perspective. Physical models cannot be replaced by data alone but when combined with an informed and detailed knowledge of the physical problem and its constraints, it is likely to yield successful solutions.

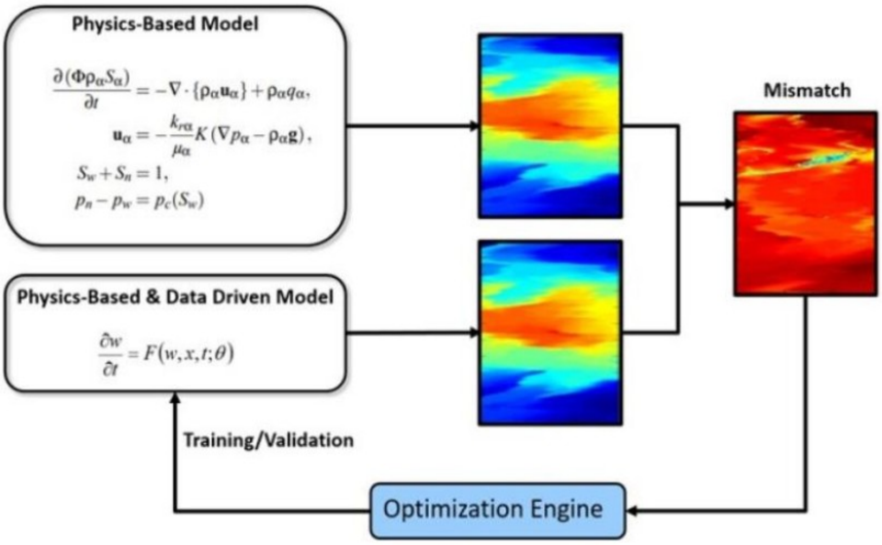


Figure 2.3: An example on how to generate a data-driven or reduced physics model (or combination of both) from a high-fidelity physics-based model using optimization. **Source**: (Klie, 2021).

2.2 A Review of Data driven ROP Optimization Models

The field of drilling optimization has seen extensive studies to maximize Rate of Penetration (ROP). According to the study by C. Gan et al., our understanding of optimal strategies has been shaped by three types of optimization (2019): robust, moving horizon, and metaheuristic. In parallel, E. Wiktorski et al. (2017) emphasize the importance of considering wellbore trajectory, inclination, and azimuth in the Burgoyne and Youngs' model.

Building on the foundation of these prior studies, research into empirical modeling has begun to consider the dog leg severity factor (DLS). These strides in optimization underline the importance of machine learning models. This is highlighted by C. Hedge et al. (2017, 2018), which investigate various optimization algorithms in the pursuit of creating the most effective model. In a similar vein, A. M. Alali et al. (2020) introduced a two-phase optimization model that modified drilling controllable variables in real time.

Further research into drilling optimization introduces the estimation of downhole torque, also known as torque-on-bit (TOB). Teele (1965) and Maurer (1962) underscore the importance of accurate TOB estimation as it improves Mechanical Specific Energy (MSE) and ROP accuracy. A significant leap in this domain was the development of the ROP model for roller-cone bits as a function of various factors, proposed by Bingham (1965), and later enhanced by Bourgoyne and Young (1974).

Progress made in ROP study is closely tied to technology advances. The advent of downhole sensors has transformed the industry, although their application to measuring TOB near the bit remains limited. Nevertheless, strides have been made with the development of a downhole automation system (Trichel et al., 2016), and the use of torque and drag models to estimate TOB (Sheppard et al., 1987).

In the era of machine learning, numerous authors, including Bilgesu et al. (1997), Jahanbakhshi et al. (2012), Gandelman (2012), and Amer et al. (2017), have implemented neural networks for ROP prediction. This approach to data-driven ROP optimization has only been possible through continuous drilling operations monitoring and observation. Ultimately, this comprehensive body of research has paved the way for data-based ROP optimization, underscoring the critical role of technological and methodological advancements in the field. Figure 2.4 depicts the commonly recognized safe drilling window that drillers typically take into account during the drilling process.

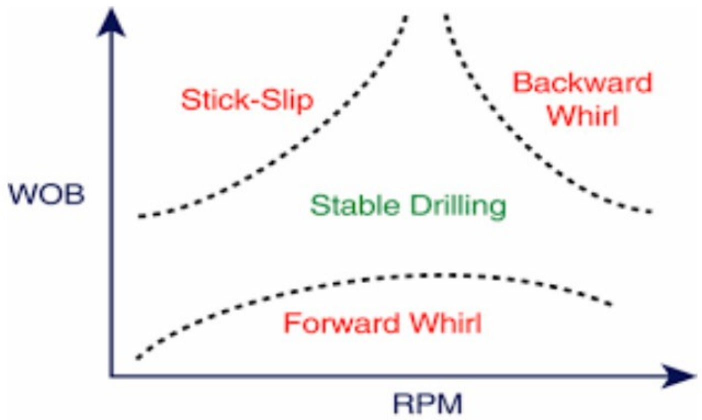


Figure 2.4: WOB x RPM drilling modes.
Source : (**Akinniranye, Elsweisy, Goobie, & et al., 2007**).

Chapter 3 – Methodology

The Qualitative Trend Analysis Method

3.1 Trend Analysis

According to Janusz and Venkatasubramanian (1991), qualitative trend analysis (QTA) is a method for extracting trends from data by segmenting it into nonoverlapping episodes and analyzing those episodes by assigning primitive sequences to each episode and creating maps from primitive sequences to process states (Villez and Rengaswamy, 2013).

It has been proposed several times since the Janusz and Venkatasubramanian algorithm was introduced in 1991 to identify the same trend primitives. Using an interval-halving method, Dash et al. (2004) automatically extracted the trend from the dataset by parameterizing it as a sequence of primitives, whereas Zhou and Ye (2016); Zhu et al. (2017) determine the primitives based on a polynomial-fit-based method of trend extraction that is supported by hypothesis testing. According to Thurlimann et al., 2018, as well as Guo et al., 2021, numerous fault detection applications have been developed using the QTA method.

Each trend segment is evaluated based on trend prediction accuracy in addition to calculating evaluation metrics. Through the analysis of data dynamics during the drilling process, it is also possible to better understand the transient/stationary phases of drilling processes in order to facilitate control, detection, and decision-making processes. The goal of this paper is to demonstrate how data analysis tools can be used to extract valuable information from data and to interpret data-driven models. The QTA approach is generally used when evaluating models with black box properties. A more important advantage of using powerful analytics tools in data-driven model evaluations and interpretations is that they will assist researchers in developing machine learning models that take into account multiple design factors rather than concentrating solely on accuracy, such as dynamics, trends, similarity, etc.

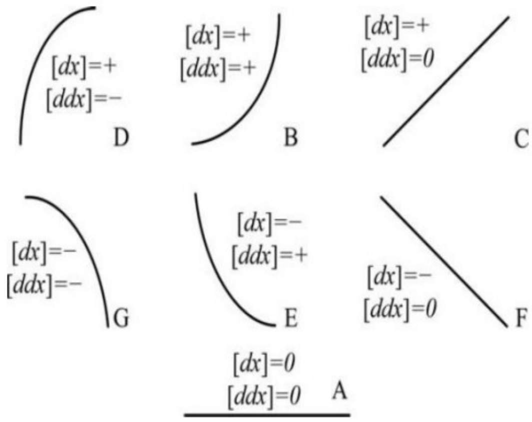


Figure 3.1: Seven primitives (Janusz and Venkatasubramanian,1991), where dx means the first order derivative of x, ddx is the second order derivative of x, + is the positive sign, and − is the negative sign.

3.2 Moving Segment Strategy Trend Analysis Methodology

Trend analysis can be performed using a variety of methods, including simple linear regression, moving averages, exponential smoothing, and seasonal adjustments. When it comes to drilling operations, the Qualitative Trend Analysis is preferred over other methods of trend analysis, however, the choice of method depends on the nature of the data. The reason is that it provides an opportunity to identify trends and patterns in data that may not be evident using other methods. The tool is effective for identifying drilling problems and equipment failure trends in the petroleum industry (Ochije, Gravdal, & Sui, 2023).

In this work, we will examine the QTA algorithm proposed by Zhou and Ye (2016), where a polynomial fitting algorithm is used to add new data points to the sliding window. Here we propose a new way to analyze the real-time data stream based on moving segment strategy. After a new segment with trend information is detected, this new segment is kept in the dataset and the old segments are removed from the dataset. By using moving segment strategy, the amount of data points we analyzed at a defined time step is well controlled to relax the computational loads and reduce the side-effects, like time-delay issue. The important parameters used in the moving segment strategy QTA method are listed below:

Moving window length: N;

Analyzed dataset at initial time t_i: $D_i = \{(t_0, q_o), \ldots, (t_i, q_i)\}$, $i \geq N$, and (t_0, q_0) is the starting point;

Segment with the same trend at time t_n: $S_n = \{(t_k, q_k), \ldots, (t_n, q_n)\}$, where q_k are the variable values at time t_k;

Analyzed dataset at time t_{n+N}: $D_{n+N} = \{S_n, (t_{n+1}, q_{n+1}), \ldots, (t_{n+N}, q_{n+N})\}$.

This QTA algorithm can be described in eight stages for extracting the trends of the data points in the dataset D_i at initial time t_i:

First Stage: Develop a polynomial regression model

At initial time t_i, for the first sub dataset = {(t_0 , q_0),…, (t_k , q_k)}, the following second order polynomial function is calculated:

$$\hat{q}(t) = \beta_0 + \beta_1 t + \beta_2 t^2 \tag{6}$$

where $\beta_0, \beta_1, and\ \beta_2$ are the regression model coefficients. They are obtained by minimizing the sum of the squared approximation errors defined below:

$$J_k = \sum_{i=1}^{k}(q_i - \hat{q}_i)^2$$

where q= $\hat{q}(t_i)$ and

$$\beta = (\mathrm{T}'\ \mathrm{T}\ )^{-1} * T'\mathrm{X} \tag{7}$$

where $\beta = [\beta_0, \beta_1, \beta_2]'$ and $(T)\ j{,}m = t_{j-1}^{m-1}$, for $1 \leq j \leq \mathrm{k} + 1$, and $1 \leq m \leq 3$ while $\mathrm{Q} = [q_0, \dots, q_k\ ]'$. The first stage of the analysis involves using a polynomial regression model to approximate the shape of the data.

Second Stage: Identify the trend change point

At time t_{k+1}, for new data point x_{k+1}, the approximated error is

$$e_{k+1} = q_{k+1} - \hat{q}_{k+1}, \tag{8}$$

where $\hat{q}_{k+1}$ is calculated from Eq (1) with $t = \mathrm{t}_{k+1}$. The condition proposed by Zhou and Ye (2016) to identify the trend change point is given by:

$$\text{(First condition, C1)} : |e_{k+1}\ | \leq th_{1,k+1}, \tag{9}$$

where $th_{1,k+1}$is the first threshold, which is determined in the hypothesis testing framework. Referring to Zhou and Ye (2016), it is given by:

$$th_{1,k+1} = t_{1-\frac{\alpha}{2}} * \delta_k - \sqrt{1 + a_k{}' a_k} \tag{10}$$

where $t_{1-\frac{\alpha}{2}}$ is the t-critical value from the distribution table that corresponds to the confidential level α, and

$$\delta_k = \sqrt{\frac{\sum_{i=0}^{i=k}(q_i - \hat{q}_i)^2}{k-2}}, \tag{11}$$

$$a_k = ((\mathrm{T}'\ \mathrm{T}\ )^{-1} * T\ ')'\ [1\ \ (t_{k+1} - t_0\ )\ (t_{k+1} - t_0)^2]\ '. \tag{12}$$

If the first condition C1 holds, the point q_{k+1} is not a change point but further analysis of the trend is conducted (see Third Stage); else, the algorithm checks to determine whether q_{k+1} is an outlier. If q_{k+1} is identified as an outlier, the algorithm proceeds to the Third Stage; else, it proceeds to the Fifth Stage if q_{k+1} is considered a trend change point.

Third Stage: Calculate the cumulative error

To further check if q_{k+1} is a new change point or not, the cumulative error is considered, which is defined as:

$$cusum(e_{k+1}) = cusum(e_k) + e_{k+1} \tag{13}$$

where $cusum$ is the cumulative sum. Another condition to detect the change point proposed by Zhou and Ye (2016) is the cumulative sum of approximation errors in the dataset D_i that shall be less than some pre-defined threshold. It is given as:

$$\text{(Second condition, C2)} : cusum(e_{k+1}) \leq th_{2,k+1}, \tag{14}$$

where $th_{2,k+1}$is the second threshold and is calculated by

$$th_{2,k+1},= t_{1-\frac{\alpha}{2}}{*}\delta_k\sqrt{b'_{k+1} * b_{k+1}} \tag{15}$$

where $b_{k+1} = [(a_k + b_k\ )\ '\ 1]'$. If the second condition (C2) holds, then the point q_{k+1} is not the change point and the algorithm proceeds to the Fourth Stage; else, q_{k+1} is a trend change point. The point is marked, and it proceeds to the Fifth Stage.

Fourth Stage: Update the dataset

The dataset is expanded by adding the point q_{k+1}, which the First Stage is repeated to identify the new trend change point at t_{k+2}.

Fifth Stage: Mark the change point

When the point q_{k+1} is identified as the change point, the dataset must be reformulated by setting $t_0 := t_{k+1}$, $q_0 := q_{k+1}$ and returning to the First Stage when there are at least five points in the dataset.

Sixth Stage: Trend extraction

Each change point is saved, and according to their nature, the trends are extracted. The algorithm then terminates once all the data points inside $D_i = (t_0\ ,\ q_0),\ldots, (t_i\ ,\ q_i\ )\}$, $i \geq N$ have been analyzed.

Seventh Stage: Moving window strategy

At time t=t_i, identify the segment with the same trend close to the last point (t_n , q_n) as:

$$S_i = \{(t_k , q_\mathrm{k}),\ldots, (t_n , q_n)\};$$

The new QTA method will be processed at time t = t_{i+N}, with the moving window size N. For the new time t_{i+N}, the new dataset for trend analysis is prepared as

$$D_{i+N} =\{S_i, (t_{i+1}, q_{\mathrm{i+1}}),\ldots, (t_{i+N} , q_{i+N})\}. \tag{16}$$

Then the work will be repeated by setting D_i =D_{i+N}, t_i= t_{i+N}, and go back to the First Stage.

Eighth Stage: Algorithm termination

The algorithm then terminates once all the data points inside D_{i+kN} have been analyzed, where $(t_{i+kN,}q_{i+kN})$ is the last data point for QTA analysis.

The algorithm is written in MATLAB and it performs real-time trend analysis using a sliding window approach. Here is a summary of the code's application at the initial build up stage:

Import and selection of data: The script loads two datasets extracted from a CSV file: 'measured depth' (MD) and 'rate of penetration' (ROP). The measured data is sorted and then the corresponding ROP data is rearranged according to the measured data sorted order. Further analysis is conducted on the wellbore section selected for analysis.

Trend Analysis: An analysis of the ROP data is performed by the script. It calculates the 'change rate' in the ROP by identifying 'change points'. On these datasets, trend analysis (TA) is performed from a MATLAB function, with settings such as figure number and confidence level (alpha).

Recording of Change Rate: In an array named Trend_p, the script records the change rate for each zone identified as being part of a trend.

$$CR = (yend - ystart)/\Delta t * 100\%, \tag{17}$$

The change rates are calculated by iterating through identified change points. In equation 17, $ystart$ and $yend$ represent the first and last data points of the segment respectively, and Δt signifies the time change associated with this segment. Typically, a negative CR indicates a declining trend, while a positive CR signifies an increasing trend. Additionally, the CR value provides insights into the severity of data dynamics.

Data Visualization: The trend analysis results are visualized in two figures:

i. a display of the ROP data plotted against simulation timesteps

ii. calculated change rates plotted against simulation timesteps.

3.3 General Use Cases

In order to perform QTA trend analysis, simulated ROP data sets were generated using the Drilling Simulator. The OpenLab Drilling simulator used in this study is designed by NORCE (Norwegian Research Centre) in collaboration with the University of Stavanger. It has been available to students, researchers, and engineers working on technology development, demonstration, and education since 2018. Simulations are conducted using generic well and rig templates in the simulator, which accurately simulates drilling well responses through differential equations.

In this experiment, the purpose was to determine how changes in the Weight on Bit (WOB) affect ROP while drilling a formation of varying hardness. A well with a depth of 2,500 meters is used in this case study to illustrate the principle. A detailed description of the hole section, drillstring architecture, wellbore trajectory, drilling mud and formation properties is provided. In most cases, this information will be taken from the Drilling Operations Plan and updated during execution, with real-time data acquired. Figure 5a and b shows the work structure of this study.

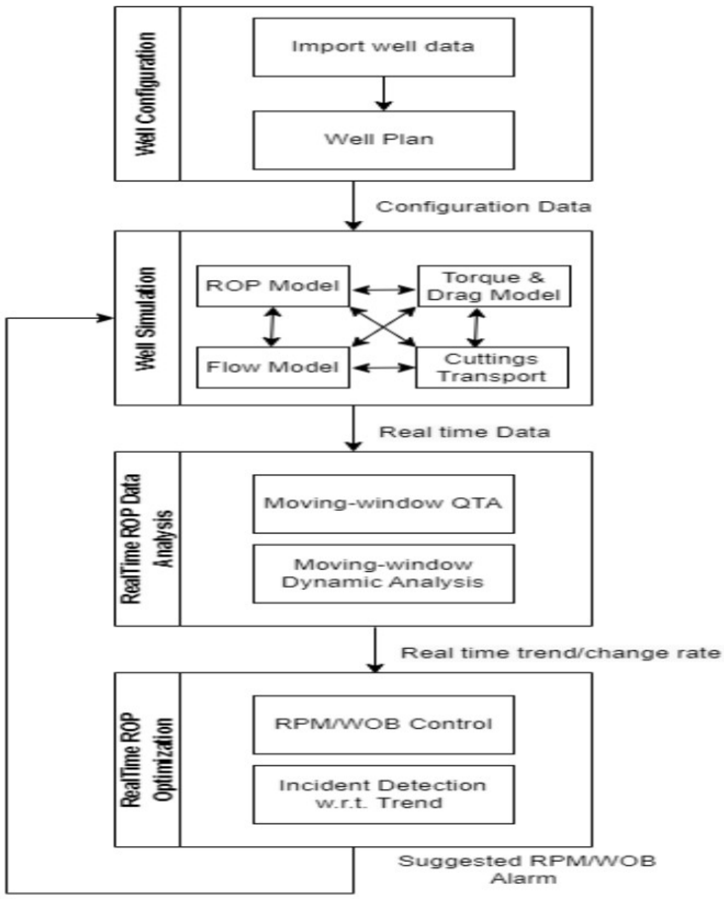


Figure 3.2: Thesis workflow - Proposed Methodology for ROP data analysis and related ROP optimization.

3.3.1 Configuration

A realistic scenario was developed in which we drilled a hole through a formation that had varying hardness levels and evaluated the QTA trend analysis tool. A formation zone is represented by the Unconfined Compression Strength (UCS) in our simulator. Table 3.1 illustrates the results of editing a 12-meter zone in which UCS differs between zones and 100 MPa represents a very hard formation.

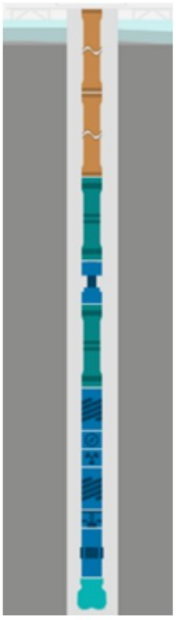


Figure 3.3: Description of drillstring components.

Measured Depth (m)	UCS (MPa)
0	100
2500	100
2502	50
2504	20
2506	20
2508	60
2510	60
2512	100

Table 3.1: The depth based UCS values used in the case study.

Additionally, Figure 3.3 describes the components of the drillstring, bottom hole assembly, and bit. It allows for a realistic simulation of mechanical forces and their interaction with the surrounding formation. Simulation results were obtained using drilling mud with a density of 1.650 kg/m3, as well as other configuration parameters. As the configuration inputs are not directly related to the current study, we will not discuss them here.

3.3.2 Run a Simulation

The test setup in this study utilizes a drilling simulator to provide real-time data from the obtained ROP, which is fed to the QTA trend analysis tool via an API connection through a separate client. Figure 3.4 illustrates this.

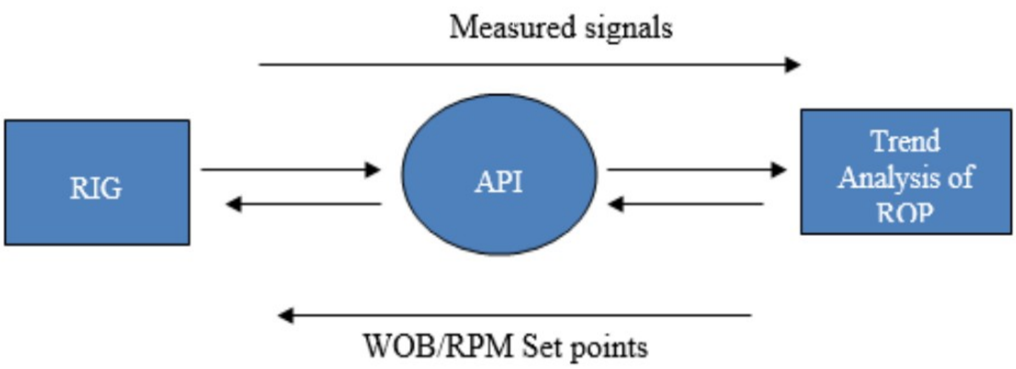


Figure 3.4: Data Communication between drilling simulator and backend QTA model.

WOB and RPM are input set points, whereas ROP is calculated as an output using QTA trend analysis.

For this study, we also use a moving window strategy in real-time to analyze ROP. As an example, we observe the previous ROP for 20 seconds without taking any action during a trend increase or stationary trend (flat trend). We maintain constant WOB and RPM in this manner. However, when the ROP is decreasing, the code is configured to give an additional 10 seconds to confirm that the ROP is continuously decreasing.

$$WOB_{new} = (n+i)(100+percentage) * WOB_{old} \qquad (18)$$

Where, WOB_{old} is the original weight on bit value and not the optimized value and 'n' is the increment parameter.

More simulations are run to see what percentage would be suitable to initiate ROP optimization with the conditions below;

$$x \leq WOB \leq y$$

where x and y are minimum and maximum boundaries respectively.

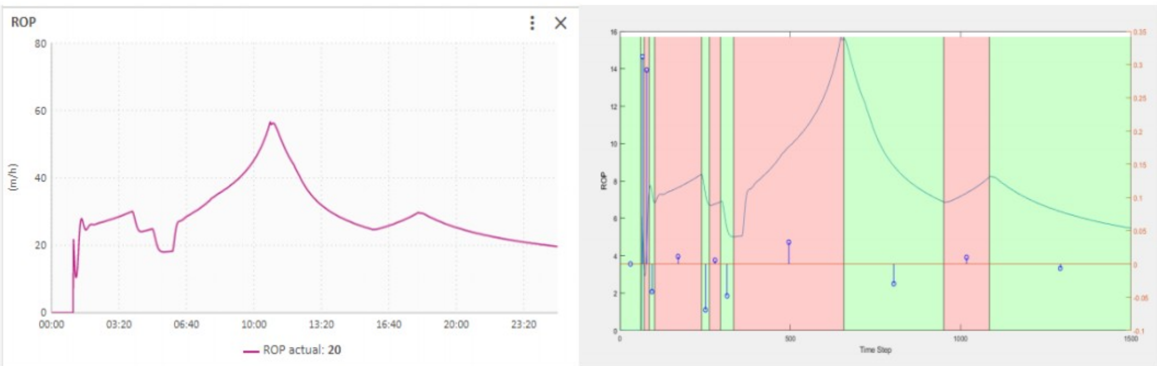


Figure 3.5: Illustration of ROP Trend Analysis.

This study also takes a novel approach to Rate of Penetration (ROP) optimization by conceptualizing it as a classification problem, whereby the ROP is classified as low or high based on user-specified thresholds. Various factors can guide the choice of these thresholds. They can be determined by an expert with knowledge of drilling conditions or based on prior experience with wells drilled in the same region. Additionally, business objectives can influence this decision, as high ROP thresholds may be preferred to reduce drilling time. In contrast, lower thresholds may be chosen to minimize hole-related issues like vibrations and stick slip.

The action points of this study, then, are strategically focused on cases where the ROP dips below a driller-defined threshold. The study prompts drillers to act when they encounter significant fluctuations in ROP trends. This is particularly important in instances where the change rates in a decreasing ROP trend exceed the predefined ROP threshold. As an added benefit, the code used in this study also provides drillers with the ability to identify and manage any trend overshooting effectively.

The mechanism of action behind this methodology is elucidated through the simulation code incorporated into the study. It uses a loop that operates like a vigilant sentinel, diligently verifying at each timestep whether the ROP is on a downward trend. Depending on the conditions at each timestep, the loop adjusts control variables to influence the system state, such as depth and penetration rate. Once the loop has completed its iterations, it concludes its operation and moves onto the next task - determining the threshold for calculating the change rate. If the change rate crosses this threshold, modifications to the Weight on Bit (WOB) are made. In this way, the study presents a holistic approach to optimizing ROP. It underlines the symbiotic relationship between technology and human expertise in drilling optimization.

Chapter 4

OpenLab

OpenLab is a web enabled drilling simulator and lab facility for research, education and demonstration of drilling technology that is developed and managed by the Drilling and Well Modeling group of NORCE (The Norwegian research Center) Energy in collaboration with the University of Stavanger.

The drilling simulator provides artificial measurements of state variables based on the user's input. It is based on high-fidelity transient models and allows the user to change setpoints between each simulation step. The models use specifications (configurations) of the user's choice of specific well and drillstring architecture, fluid properties and formation properties. During simulation the user can adjust drilling parameters (set-points) and retrieve depth-based and time-based results from each simulation step. In this work, 1 Hertz was used, and considered suitable with a simulation step equal to 1 second. The simulator consists of several interconnected simulation models for calculation of wellbore hydraulics and mechanical forces on the drillstring, bottom hole assembly (BHA) and bit.

The main models relevant for this work are:

- Drillstring dynamics model
- ROP model
- Flow model
- Cuttings transport model
- Temperature model.

The models are coupled to ensure a realistic simulation of the drilling operation. The ROP model is closely connected to the Drillstring dynamics model and the Flow model. It provides a continuous calculation of ROP based on fluid flowrate, in-situ well pressure around the bit, WOB, RPM, bit properties, and the Unconfined Compressive Strength (UCS) which is the commonly used measure of the formation's strength (Chau and Wong, 1996).

Figure 4.1: The OpenLab Drilling Simulator Environment.

For this work, all simulations are based on a combination of the OpenLab default rig template and the supplied "Aker BP" rig configuration for a 16 inch well section. A brief overview of the key parameters and the basic functionality of the OpenLab drilling simulator is discussed below.

4.1 Hole section and Well path

Hole section: Well configuration usually comprises a riser, multiple casings and liners, and a defined open hole section. Every well includes an open hole section, a segment with no casing which is susceptible to stability issues and potential collapse of the adjacent formation into the wellbore. All measurement attributes within this section are associated with depth, as shown in Figure 4.2.

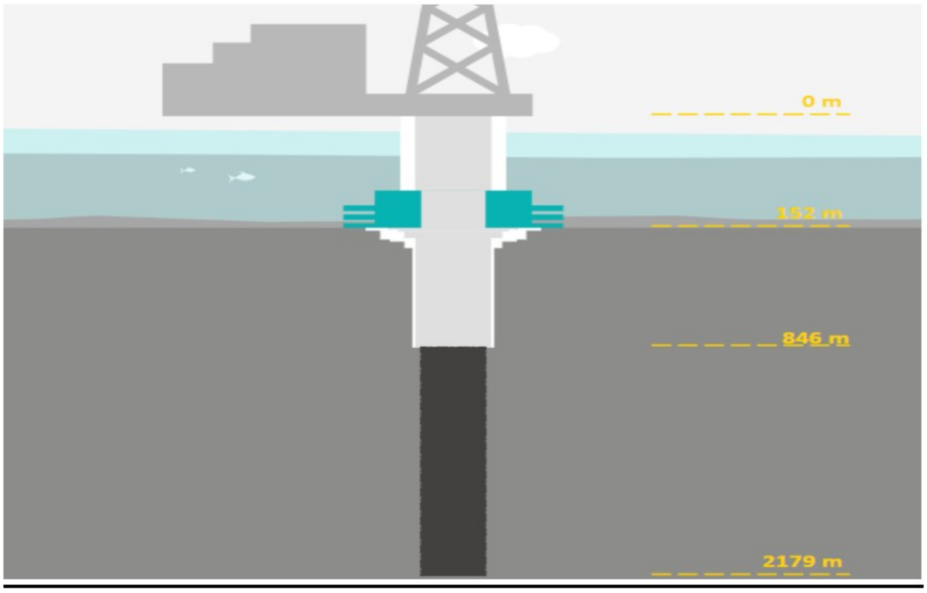


Figure 4.2: The OpenLab Hole section.

Wellpath: Adding or altering the well path meter by meter can completely alter the difference between the measured depth (MD) and the true vertical depth (TVD). This will result in MD and well pressure having a nonlinear relationship due to the difference in well inclination. Figure 4.3 shows a 3D visualization of the wellpath structure. A wellpath influences both drill string mechanics and cuttings transport in a simulation. In the OpenLab web application, the trajectory of the well is defined by a series of survey stations, which can be modified directly within the application or imported from an existing file. As shown in Figure 4.2, the color-coded section illustrates the dogleg severity, which impacts drilling capability.

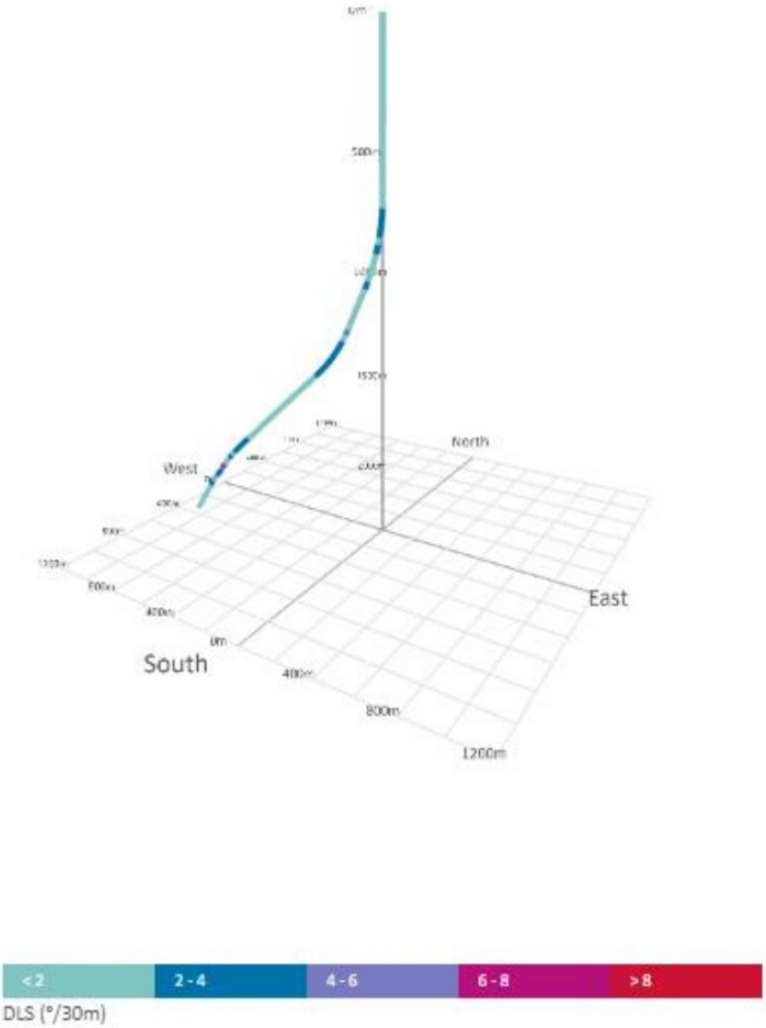


Figure 4.3: The OpenLab well path for an inclined well.

MD (m)	Azimuth (°)	Inc. (°)
0	0	0
43.5	0	0
1449.7	45.08	57.8699
1486.3	44.99	58.0899
1522.7	45.35	57.8602
1559.4	45.97	56.59
1595.7	43.53	56.22
1634	40.52	56.48
1670.9	34.22	57.09
1707.4	27.18	57.14
1744.1	23.67	56.31
1780.9	23.68	57.4602
1817.5	24.78	57.8602
1854	24.03	56.98
1890.8	22.7	56.8
1927.5	22.49	56.94
1965.9	22.69	57.5101
2002.6	24.75	57.9501
2039.1	24.09	56.54
2077.2	26.02	55.75
2120.5	25.64	55.86
2162.5	25.54	56.5
2179.6	25.74	56.73
2198.8	25.93	56.76
2215	26.02	55.75
2226.5	26.72	57.16
2273.9	27.44	57.08
2310.2	28.23	57.1
2353.8	28.28	56.9
2383.8	27.88	56.79
2420.6	27.45	56.31
2456.9	26.18	55.28
2493.8	24.08	55.28
2531.8	20.57	55.63
2568.6	16.88	55.74
2604.8	13.33	56.21
2645.6	9.57	56.3
2678.3	6.45999	56.56
2714.9	3.04	56.9

Table 4.1: The OpenLab well path trajectory for a 16-inch hole section.

4.2 Rig Parameters and Drill string

<u>Rig parameters</u>: The rig parameters define the operational limits and characteristics of simulations. To accurately represent the drilling process, it is necessary to know the parameters of the drilling rig. An overview of the rig layout can be found in Figure 4.4. Maximum pump acceleration and choke adjustment speed are examples of these parameters. In the oil and gas industry, these operational boundaries play an important role in providing a more accurate picture of drilling operations.

Parameters	Values
Main pump flow rate (max) (l/min/s)	100
MPD pump flow rate (max) (l/min/s)	100
MPD Choke max change rate (%/s)	5
BOP Choke max change rate (%/s)	5
Travelling block weight (tons)	20
Top drive max rotation acceleration (rpm/s)	6
Draw works max acceleration (m/s²)	0.3
Shaker Mud loss proportion (%)	0
Main Tank volume (m³)	40
Reserve Tank volume (m³)	40

Table 4.2: The OpenLab Generic offshore drill rig setup.

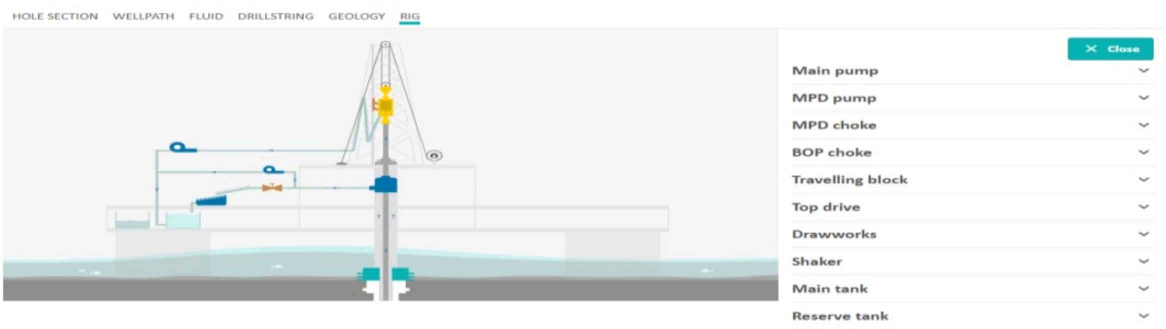


Figure 4.4: The OpenLab Drilling Simulator rig configuration parameters.

<u>Drillstring</u>: In this study, the drill pipes and bottom hole assembly components are configured based on Aker BP well data. Figure 4.5 shows OpenLab's drill string, which is composed of drill pipes, bottom-hole assembly elements, and a drill bit. All components, except the drill bit, are characterized by their length, inner and outer diameters, and weight. OpenLab allows users to adjust the inner and outer parameters of the drill pipe. Upon hovering over the simulator rig interface with the PC cursor, detailed information is displayed regarding each drill string component. The drill string configuration and properties play a significant role in influencing diverse aspects of the simulation process. Such factors encompass elements like torque, drag, heat transfer, fluid flow, and the transportation of cuttings, all of which are integral to a comprehensive and accurate simulation of the drilling operation.

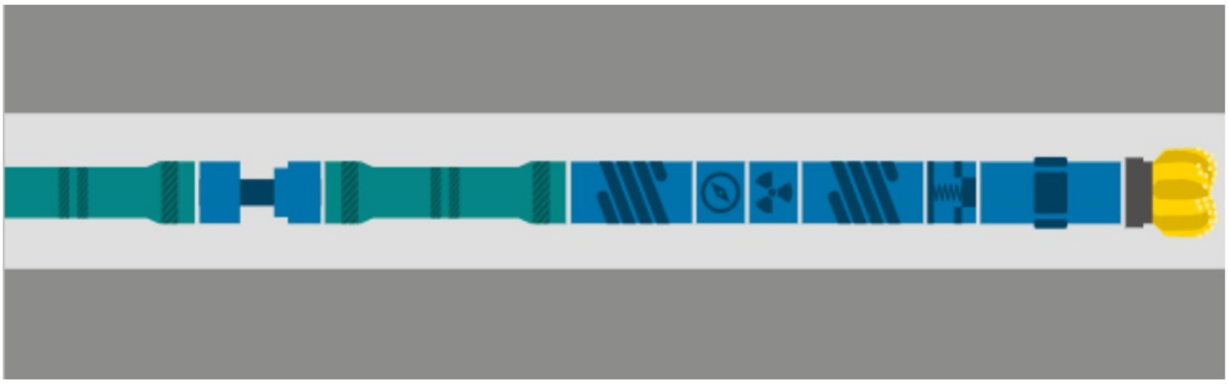


Figure 4.5: The OpenLab drill pipes and bottom hole assembly components.

4.3 Geology

As part of the simulation process, Openlab utilizes formation pressure profiles, thermal profiles, and strength profiles in order to provide a full geological profile. An analysis of the pressure profile describes the pressure window associated with the pore pressure and fracture pressure of the formation. Temperature profile provides details of thermal dynamics, while formation strength shows unified compressive strength (UCS) per meter. For OpenLab geology configuration used in this study, Figures 4.6a, b, and c shows pictures of formation strength, pressure profiles and temperature profiles respectively.

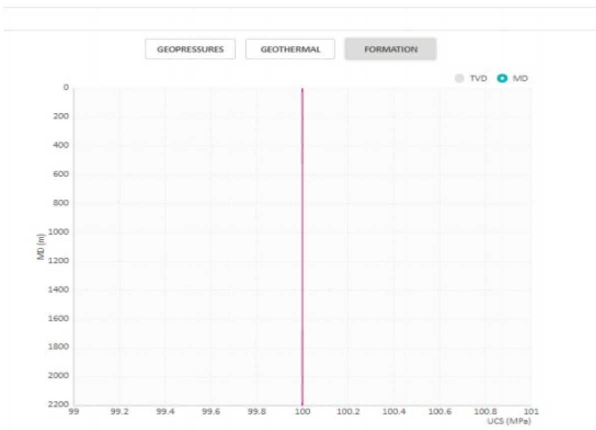


Figure 4.6a

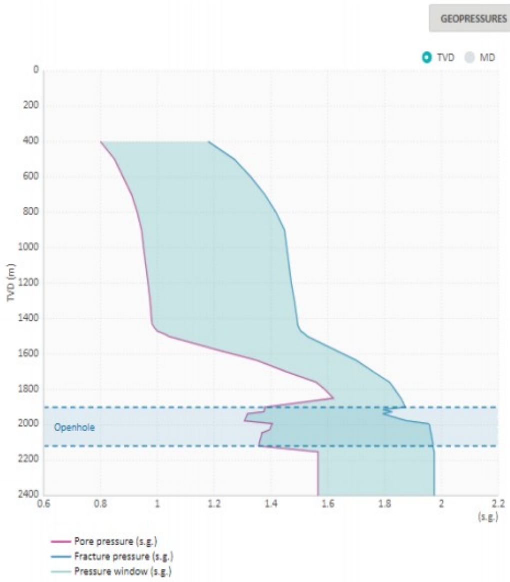


Figure 4.6b

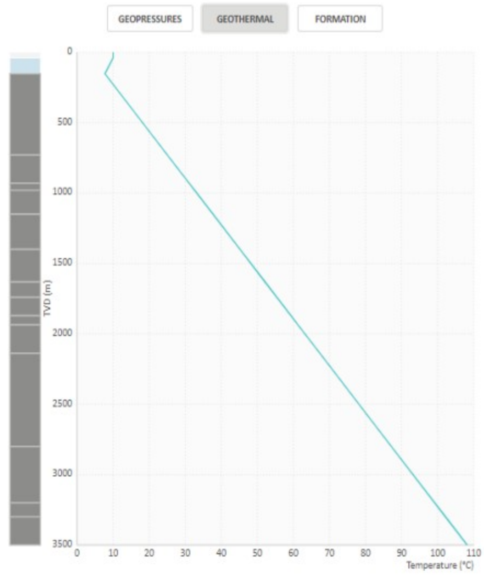


Figure 4.6c

Figure 4.6: Image series of formation strength, pressure profiles and temperature profiles respectively.

4.4 Drilling fluid (mud)

With OpenLab, drilling fluid configurations are customizable, both in terms of fluid mix and density. When the fluid is edited, further specific changes, such as gel strength over time, oil density in different pressure and temperature zones, and fluid rheology, can be made. It is also possible to design a reserve fluid that will be used in the simulations. For simulating control scenarios involving influx, the reserve fluid can be simulated as heavy mud. However, all fluid densities used in this paper are based on Aker BP fluid data.

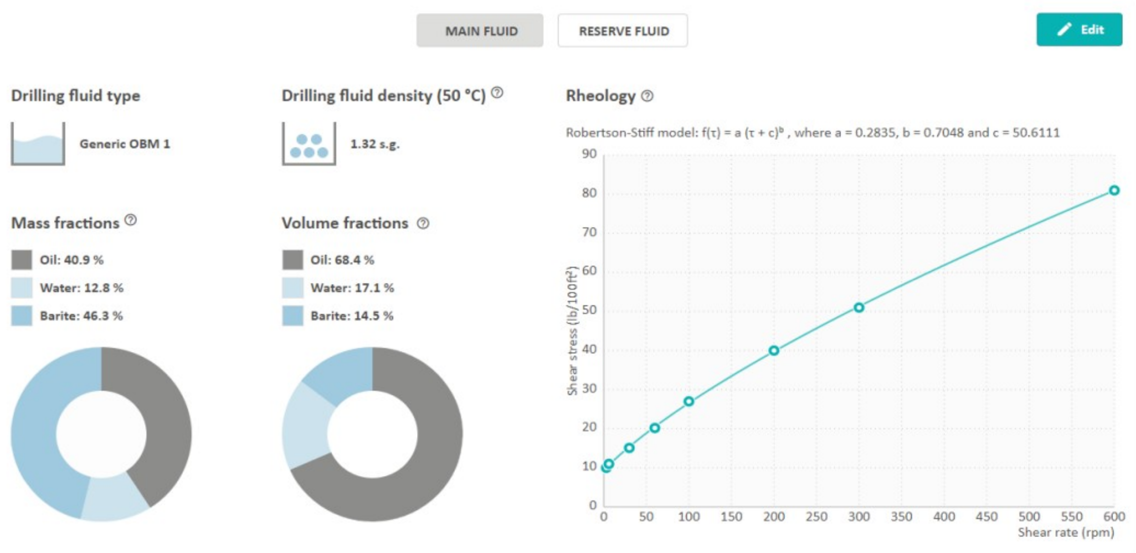


Figure 4.7: The OpenLab drilling fluid configuration set up.

Data from a 16-inch hole section was used to set up the well in this study. Table 4.3 provides a concise summary of the data utilized to configure the well, capturing the essential parameters and information considered for the configuration process. However, the drilling simulator environment in which the well was configured has some default values that cannot be modified. Listed below are some configuration data used to plan the well:

Hole section	Well path	Drilling Fluid	Drillstring	Geology	Rig
Riser	Measured depth (m)	Fluid type	Drill pipe	Geo-pressures	Main pump (litre/min/s)
Casing	Inclination (°)	Fluid density	BHA	Geothermal	Top drive (rpm/s)
Openhole	Azimuth (°)	Rheology	Drill bit	Formation	BOP choke (%/s)
	TVD (m)	Gel strength			Travelling block (ton)
	DLS (°/30m)	Oil-water ratio			
		Mass fraction			
		Volume fraction			
		base-oil-pvt (sg)			

Table 4.3: Well configuration parameters.

Considering how ROP is dependent on RPM, WOB, formation strength, flow rate, etc, several simulations were run under different case studies to see how ROP reacts. The aim of running simulations is to generate ROP real-time data from which trend analysis can be done for further optimization.

Chapter 5

Implementation, Results and Discussion

Simulation results will be shown in this chapter. Using the steps shown in Figure 5.1, and configuration data for a 16-inch hole section, simulation results for different case scenarios will be presented with highlights on the performance of the trend analysis code, its progress from static phase to dynamic phase and finally to optimize ROP where necessary.

The rate of penetration (ROP) is a critical element within the oil well drilling industry, recognized for its significant role in influencing operational costs. Therefore, methods aimed at enhancing the rate of penetration can effectively reduce the time taken in drilling operations, leading to decreased costs. For an in-depth understanding, refer to (RiceUniversity) for a comprehensive summary on factors impacting the rate of penetration of rock bits.

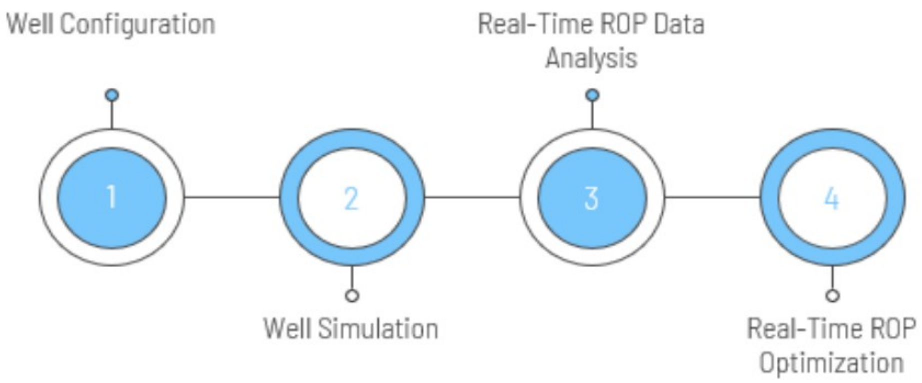


Figure 5.1: Implementation steps towards ROP optimization.

In a bid to observe how ROP reacts with UCS, WOB and RPM, the following phases (static and dynamic) and case scenarios will be considered.

5.1 Static Phase

- A simulation is run
- ROP data is extracted as a CSV file
- Trend Analysis is done on the extracted ROP data

5.1.1 Case study 1: Varying Formation Strength (UCS)

In this case, we are drilling a well with different formation strength. However, RPM and

WOB were kept constant as we run a simulation to see how ROP reacts to the different formation strengths.

A geological formation encountered during drilling stands out as the one factor that cannot be controlled in this context. There are various formations frequently drilled, including shale, sticky shale, salt, plastic clay, sandy shale, soft sand, sand, gravel, hard sand, sandstone, limestone, hard limestone, dolomite, and granite. Each of these formations possesses unique characteristics that impact their resistance to penetration. As such, the management and disposition of remaining drilling factors must be optimized to achieve the maximum economical rate of penetration.

For case study 1, we will concentrate on three different Unconfined Compressive Strength (UCS) values, namely 100 MPa, 150 MPa, and 200 MPa. These values are representative of three key geological formations frequently encountered in drilling operations: Shales, Sandstones, and Carbonates, respectively.

Formation	UCS (Mpa)	Type
Shales	100	Soft
Sandstones	150	Medium-Hard
Carbonates	200	Hard

Table 5.1: Illustration of sedimentary rock types.

Shales and Clays: These are soft, sedimentary formations usually found at the top of a drill site. They consist of compacted clay minerals. Shale rocks are unique because they are often the source rocks for oil and gas.

Sandstones: These are medium-hard sedimentary rocks composed of sand-sized grains cemented together. Due to the space between its grains, sandstones serve as reservoir rocks for oil and gas.

Carbonates: These are hard sedimentary rocks made up primarily of calcium carbonate (for limestones) or calcium magnesium carbonate (for dolostones). Like sandstones, carbonates also serve as major reservoir rocks, as they often have significant porosity and permeability that allow them to hold oil and gas.

The average values of RPM, WOB, flowrate, velocity is used for this simulation which drilled a total of 20.78 meters in 28 minutes.

Simulation time = 28 minutes
Average WOB = 8 tonnes
Average RPM = 150.5 revolutions per minute
Average flowrate = 1173.8 litres per minute
Velocity = 0.1 meter per seconds

Start Depth = 2179 meters
Ending Depth = 2200 meters
Initial Bit Depth = 2176 meters
Drilled Depth = 20.78 meters

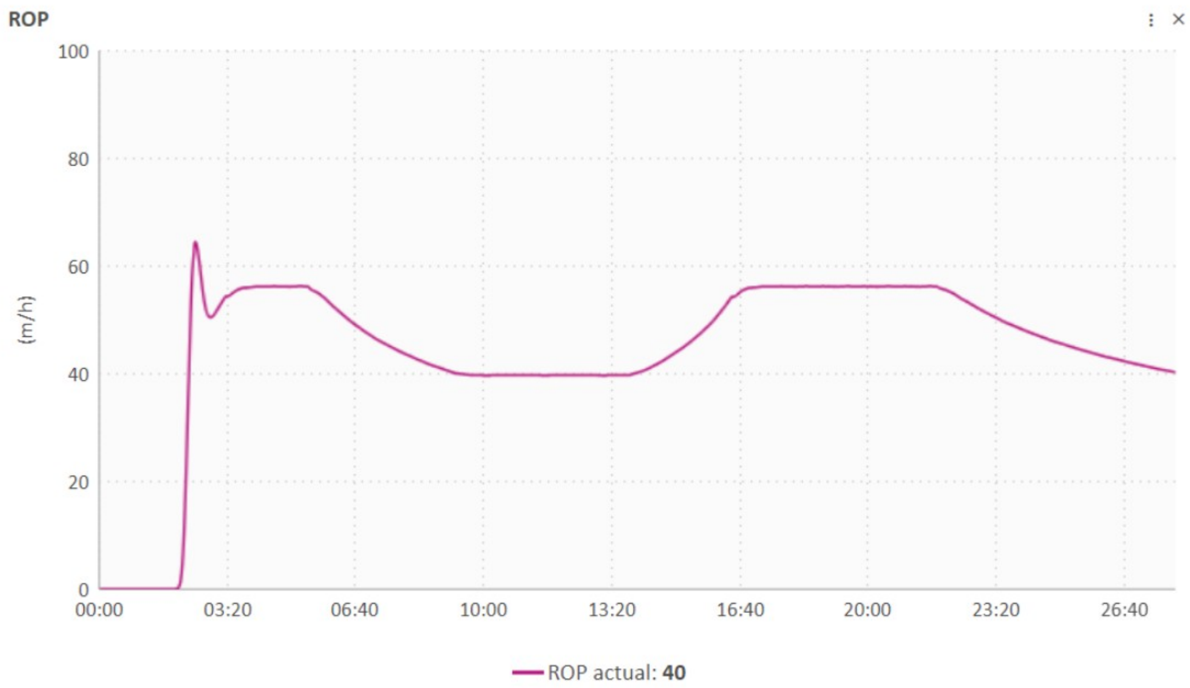


Figure 5.2: ROP results.

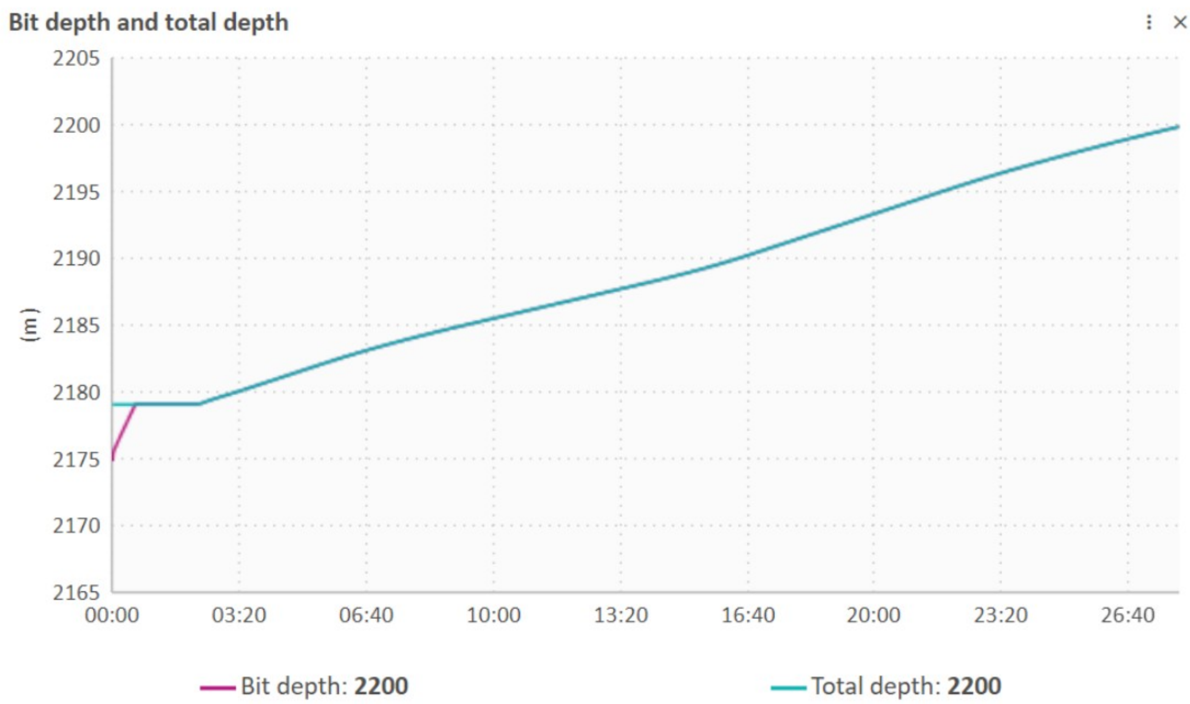


Figure 5.3: A graph of Bit Depth (meters) plotted against simulation time step (minutes).

Table 5.2 presents the assigned UCS values corresponding to different depths. It is important to note that as external users of the OpenLab drilling simulator, we do not have direct access to the proprietary code developed by the software provider. After careful examination of the simulation results, we noticed that the anticipated changes in ROP due to varying formation strengths were not precisely depicted at the configured depths in the simulator, using the provided drilling data. Instead, it was postulated that interpolated depth values (via linear or regression methods) were employed to represent the UCS shift points over time, as can be inferred from Figure 5.3.

Figure 5.2 illustrates the ROP's response to alterations in UCS, noting the specific timeframes when these changes occurred. Given that simulation figures 5.2 and 5.3 are time-dependent, we extrapolated the accurate depths at which UCS transformations took place. This insight is invaluable for drillers, offering a predictive guide to the downhole conditions they might encounter during drilling.

The Unconfined Compressive Strength (UCS) values and their corresponding time of change have been added to Figure 5.2 and the result is illustrated in Figure 5.4. This modification enhances the visualization of UCS variations and their temporal patterns, providing valuable insights into the evolving mechanical properties of the formation.

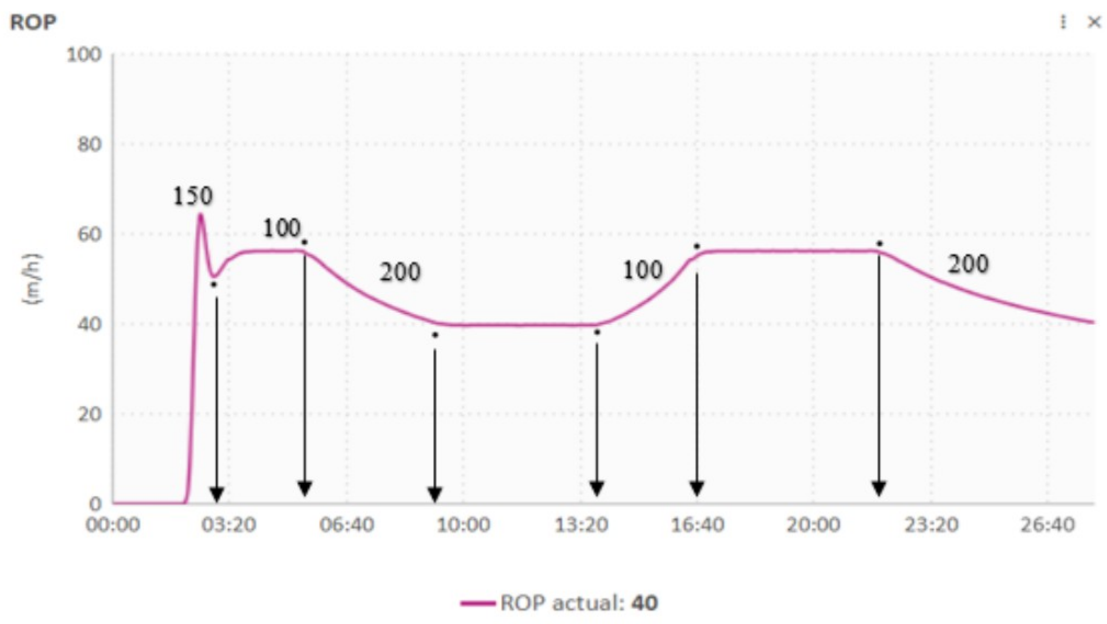


Figure 5.4: Updated graph to mark time steps where ROP changes were observed.

A more accurate estimation of the depths at which UCS changes occur is provided by Figure 5.5, which tracks instances in which a change in the ROP trend occurs.

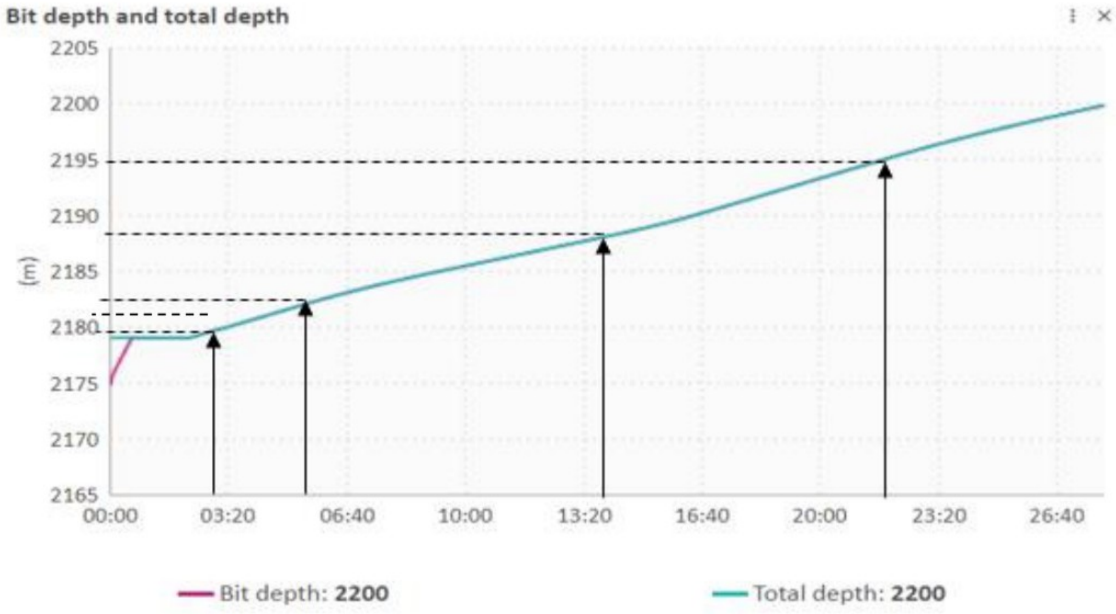


Figure 5.5: Updated illustration of depth at which UCS changes occurred.

Although we had to manually align the correct depths with their respective UCS change points due to the unknown specifics of the underlying software code, it is crucial to note that the software performed as expected. The need for manual alignment was primarily a measure to increase our understanding of the system's responses to depth changes, rather than an indication of the software's inadequacy.

MD (m)	UCS (MPa)	Friction angle (°)
0	150	30.00007015
2179	150	30.00007015
2180	100	30.00007015
2182	100	30.00007015
2185	200	30.00007015
2188	200	30.00007015
2190	100	30.00007015
2195	100	30.00007015
2200	200	30.00007015
2203	200	30.00007015

Table 5.2: Formation strength table.

MD (m)	UCS (MPa)	Friction angle (°)	MD_changepoints (m)
0	150	30.00007015	0
2179	150	30.00007015	2179.57
2180	100	30.00007015	
2182	100	30.00007015	2182.11
2185	200	30.00007015	
2188	200	30.00007015	2188.38
2190	100	30.00007015	
2195	100	30.00007015	2194.94
2200	200	30.00007015	
2203	200	30.00007015	

Table 5.3: Updated Formation strength table with change points in MD.

The MD_changepoints (m) parameter denotes the formation depth at which a shift in Unconfined Compressive Strength (UCS) occurred, leading to the identification of a new change point or trend.

An alternative method to identify the MD_changepoints (m) is through trend analysis (Figure 5.7a) by examining the change points of the Rate of Penetration (ROP). It is possible to back calculate the formation depth (MD) at which ROP changes occur as a result of variations in Unconfined Compressive Strength (UCS). This approach allows for a comprehensive understanding of the relationship between ROP changes and the underlying mechanical properties of the formation.

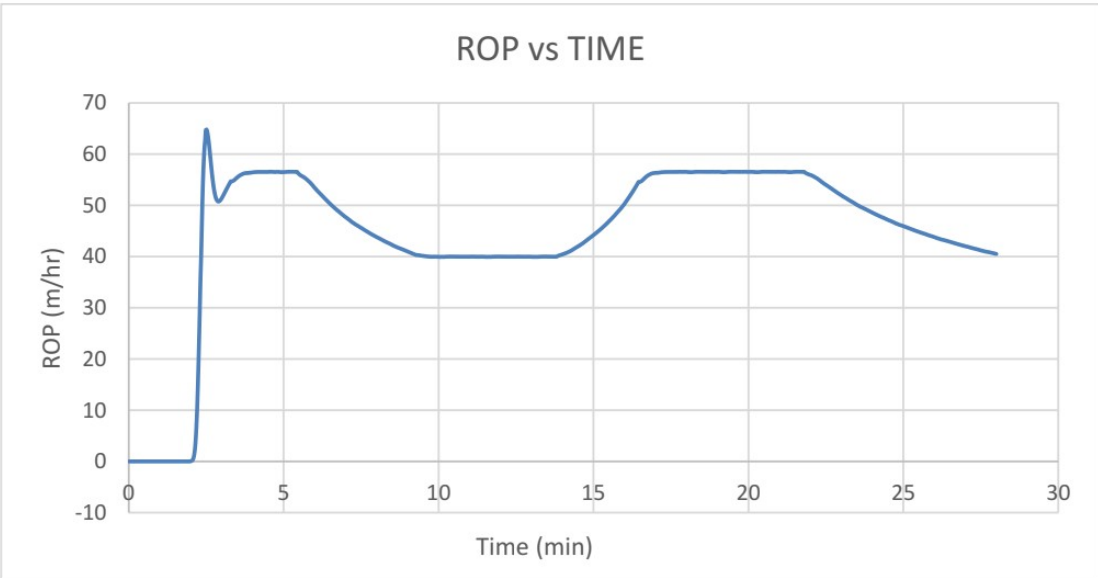


Figure 5.6: ROP data extracted as a CSV file.

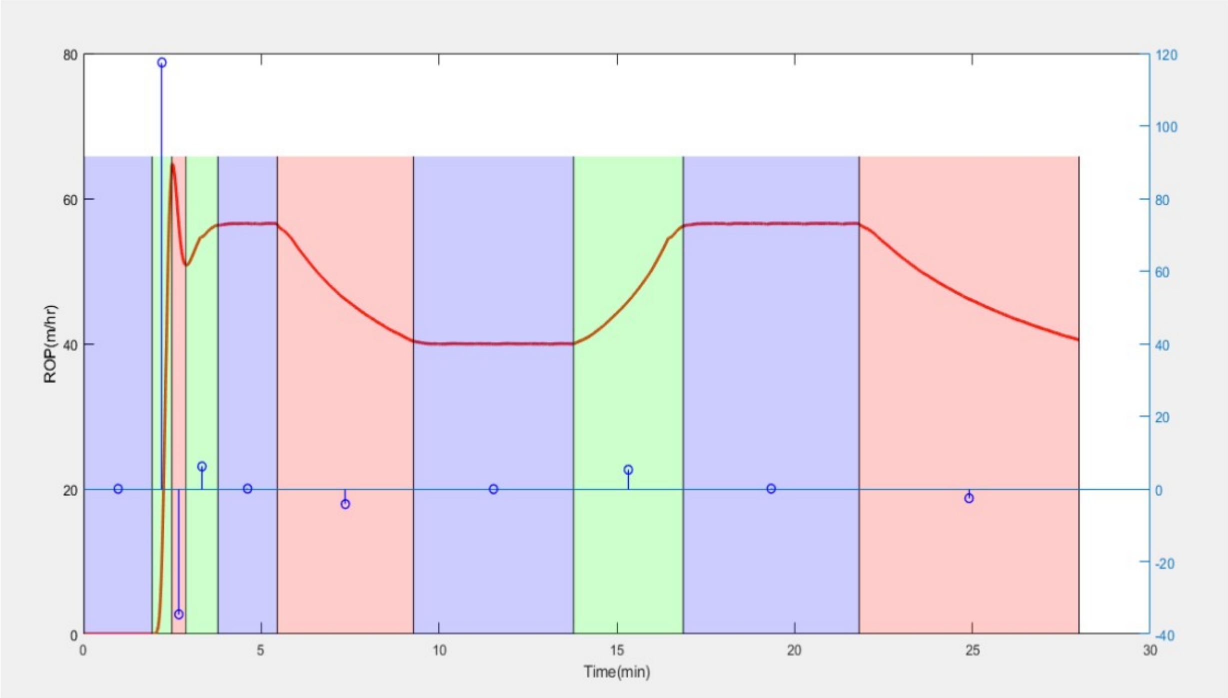


Figure 5.7a: ROP trend analysis.
(Alpha = 2, Tolerance = 35)

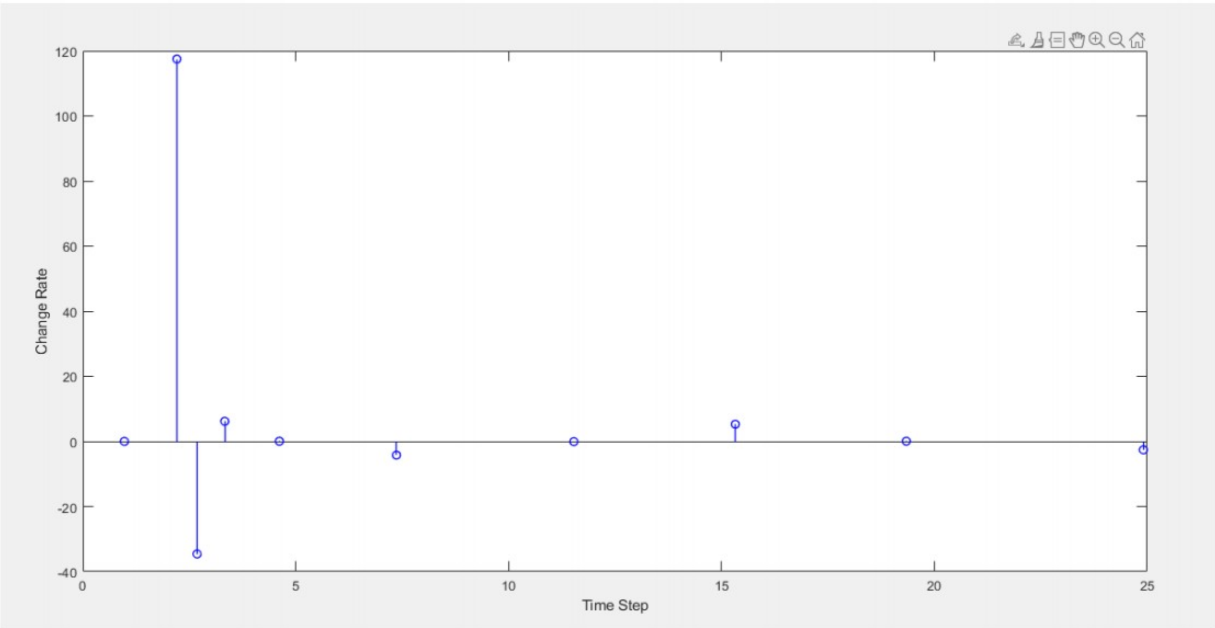


Figure 5.7b: Change rate.

Figure 5.7: Image series for ROP trend analysis and change rate plotted against simulation time step.

The Trend analysis MATLAB algorithm has a parameter named 'alpha (α)' that adjusts the trend classification accuracy. On setting the alpha value to 2, the degree of accuracy of the trend analysis as seen in Figure 5.7, has a proper capturing of the rising, falling and stationary trends. Maintaining an appropriate alpha value is crucial, as a low alpha value can cause the

MATLAB algorithm to be overly sensitive, registering even the slightest variations in the trend. Hence, it's essential to select an alpha value that appropriately balances sensitivity and specificity, ensuring that the algorithm accurately captures meaningful changes in the trend without being influenced by minor fluctuations in WOB.

The tolerance is a configuration parameter for flat region in the trend. It leverages the rate of change to dictate the number of segments within the trend. To elaborate, should the rate of change fall beneath the established tolerance value of 35, it would not be included as a segment within the overall trend.

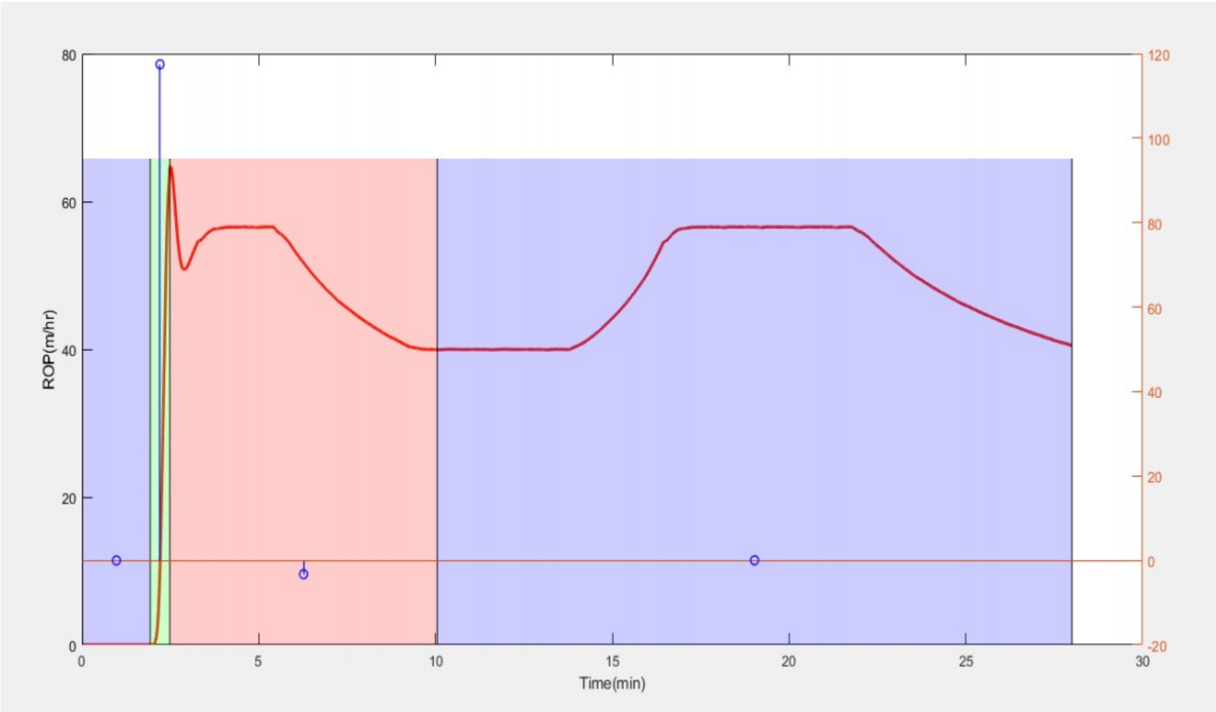


Figure 5.8a: Illustration of a poorly classified ROP trend due to high alpha and tolerance values. (Alpha = 3, Tolerance = 55)

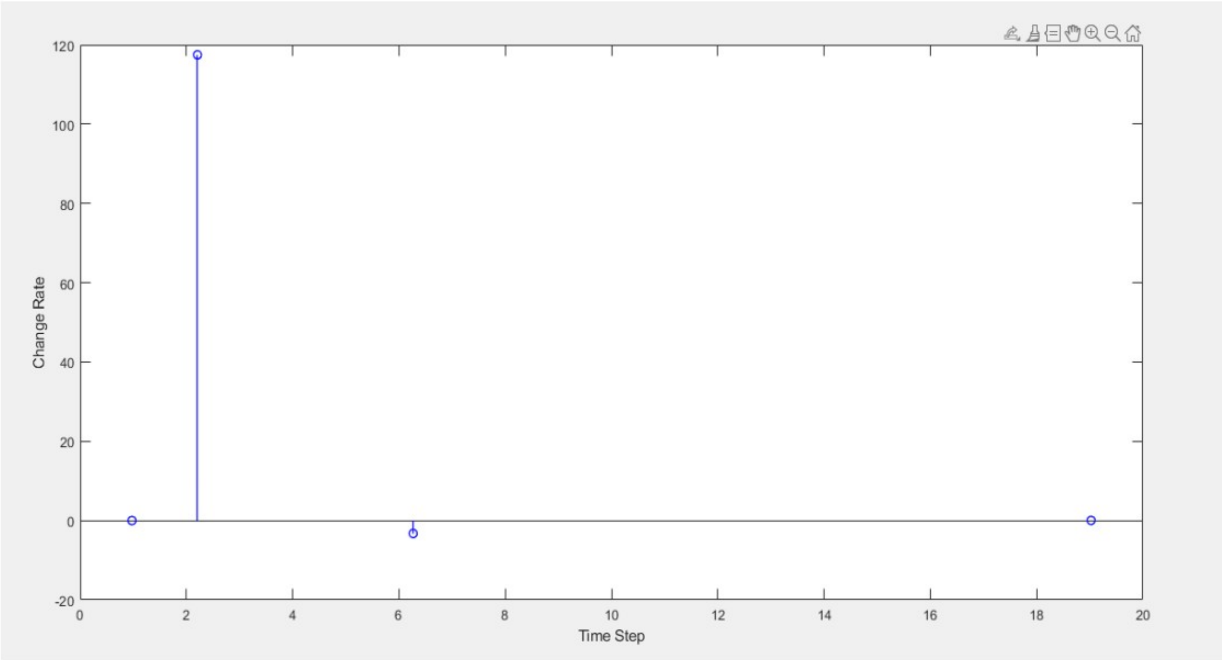


Figure 5.8b: Change rate plotted against simulation time step.

A simulation of real-time ROP streams fed from the simulator is shown in Figure 5.7. It is important to note that the ROP data points in Figure 5.7a are identical to those in Figure 5.8a. The green region in Figure 5.7a represent increasing ROP trends, while the red region represents decreasing trends, and the blue region represents stationary trends. Rate of penetration with different change rates are shown as blue vertical lines with each segment. The QTA uses the alpha value as a configuration parameter for tuning performance (parameter for confidentiality level, see Equation (15). To improve trend extraction results, the QTA method's behaviour could be adjusted to have a lower confidential level. We have noticed, for example, that when alpha is set equal to 3.0, some change points are missed, resulting in larger segments. The variation in ROP (up and down) can be seen in the second segment (green region) in Figure 5.8a. While ROP in this segment is increasing and decreasing, the QTA could not detect more change points associated with small ROP changes. Therefore, the trend analysis presented in Figure 5.8a does not capture the exact region of rising or falling, hence the need to adjust (reduce) the alpha value.

WINDOW COLOUR	***TREND***
Green	*Rising*
Blue	*Flat*
Light Red	*Falling*
Blue vertical lines	*Gradient showing degree of rise and fall (Change rate).*

Table 5.4: ROP trend window key.

Without a doubt, the Quantitative Trend Analysis (QTA) has proven successful in identifying the Rate of Penetration (ROP) trend accurately. With the use of QTA, drillers or algorithms can automate the detection of shifts in drilling parameters, thereby averting Non-Productive Times (NPTs) and alerting to potential issues.

A crucial element in measuring data dynamics is the data change rate (CR), depicted as blue vertical lines in the ROP trend window in Figure 5.7b (Equation 17).

It's important to also mention that during drilling operations, should the change rate exceed a pre-established threshold, the driller would be alerted to take action. This threshold is commonly set by the operator.

The highest change rate in Figure 5.7a occurs between the 2^{nd} and 3^{rd} minutes. There is a clear evidence of high dynamics here, which warns drillers of a possible drilling incident. In contrast, a small change rate value indicates little or no dynamics (stationary). We will not consider the change at timestep 1 as the largest since it was an overshoot that was normalized by the PID controller. In the MATLAB algorithm for dynamic trend analysis phase, a threshold has been included to alert the driller when this occurs.

When contrasting the change rates depicted in Figures 5.7b and 5.8b, it is apparent that Figure 5.8b demonstrates fewer trend fluctuations relative to Figure 5.7b. This decrease in trend activity can be attributed to the increased alpha and tolerance values applied in the scenario represented in Figure 5.8b.

5.1.2 Case study 2: Constant (UCS) and RPM

Here, we will see how ROP reacts to different WOB set points at specific timesteps. RPM and UCS were constant during this simulation.

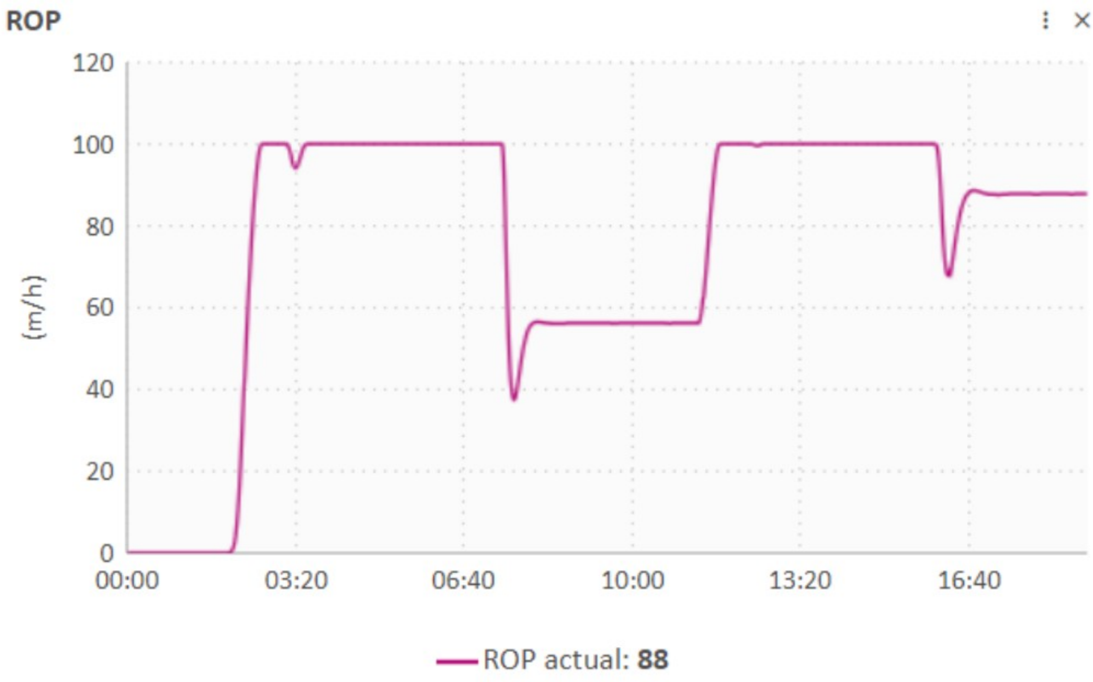
Simulation time = 19 minutes
Formation strength (UCS) = 100 Megapascal
Average RPM = 150.5 revolutions per minute
Average flowrate = 1173.8 litres per minute
Velocity = 0.1 meter per seconds
Start Depth = 2179 meters
Ending Depth = 2203 meters
Initial Bit Depth = 2176 meters
Drilled Depth = 24.04 meters

Time (s)	Time (min)	Main pump flow rate (l/min)	Top of string speed (m/s)	WOB setpoint (ton)	Surface RPM (rpm)	Choke opening (%)	BOP opening (%)
1	0.01666667	1173.8	0.1	5	150.5	100	100
120	2	1173.8	0.1	15	150.5	100	100
240	4	1173.8	0.1	28	150.5	100	100
420	7	1173.8	0.1	8	150.5	100	100
680	11.3333333	1173.8	0.1	17	150.5	100	100
750	12.5	1173.8	0.1	17	150.5	100	100

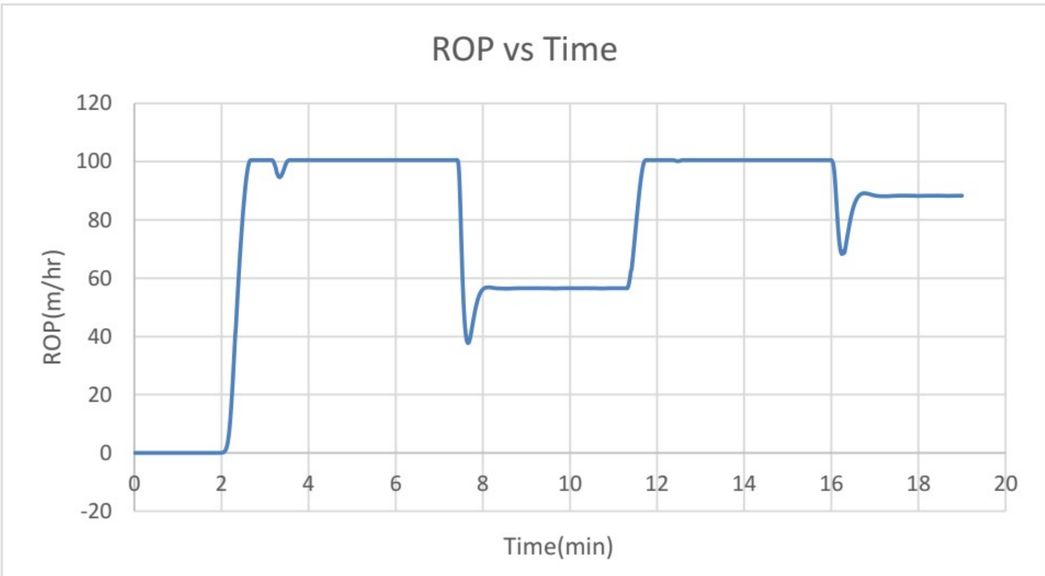
Table 5.5: Simulation setpoints with varying WOB.

Figure 5.9: Simulation setpoints for WOB.

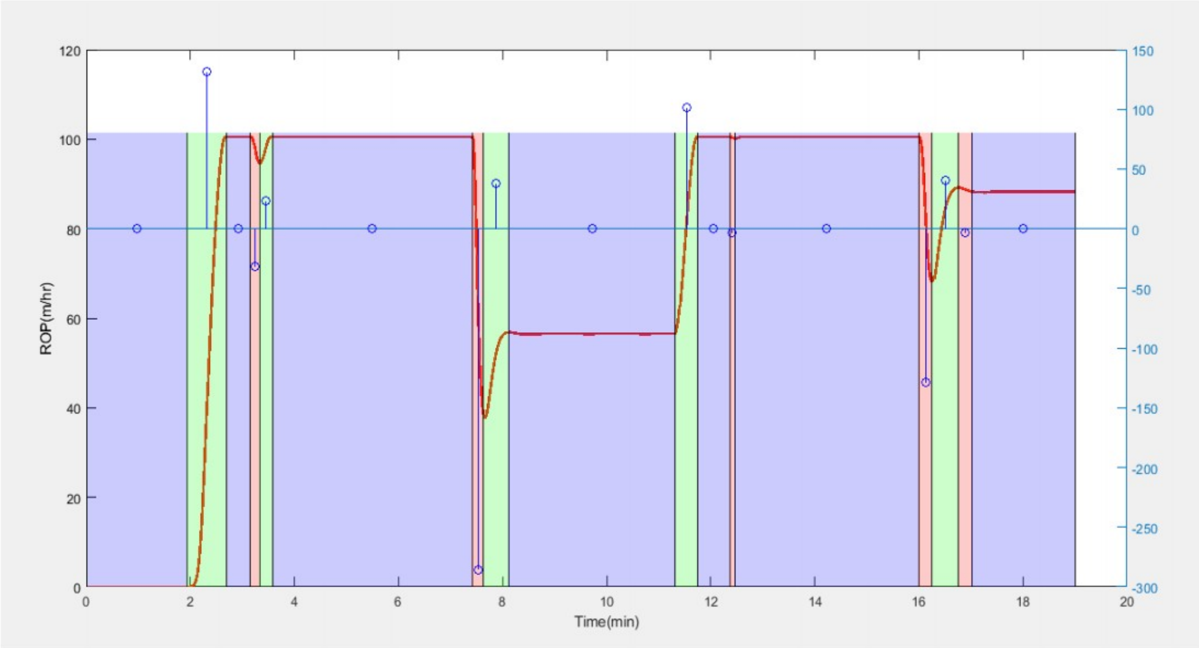
When adjusting the Weight on Bit (WOB) set points, we observe an initial overshoot that requires stabilization through the PID controller. This overshoot subsequently triggers a reaction in the Rate of Penetration (ROP), which may not be stable and can potentially lead to misleading indications of ROP fluctuations. To address this, it becomes crucial to modify the optimization code to ensure that any ROP changes resulting from WOB or RPM adjustments are verified as genuine signals and not influenced by overshoot effects.


ROP
120
100
80
60
40
20
0
(m/h)
00:00
03:20
06:40
10:00
13:20
16:40
ROP actual: 88

5.10a


ROP vs Time
120
100
80
60
40
20
0
-20
ROP(m/hr)
0
2
4
6
8
10
12
14
16
18
20
Time(min)

5.10b



5.10c

Figure 5.10: Image series for ROP trend analysis (static phase – case study 2).

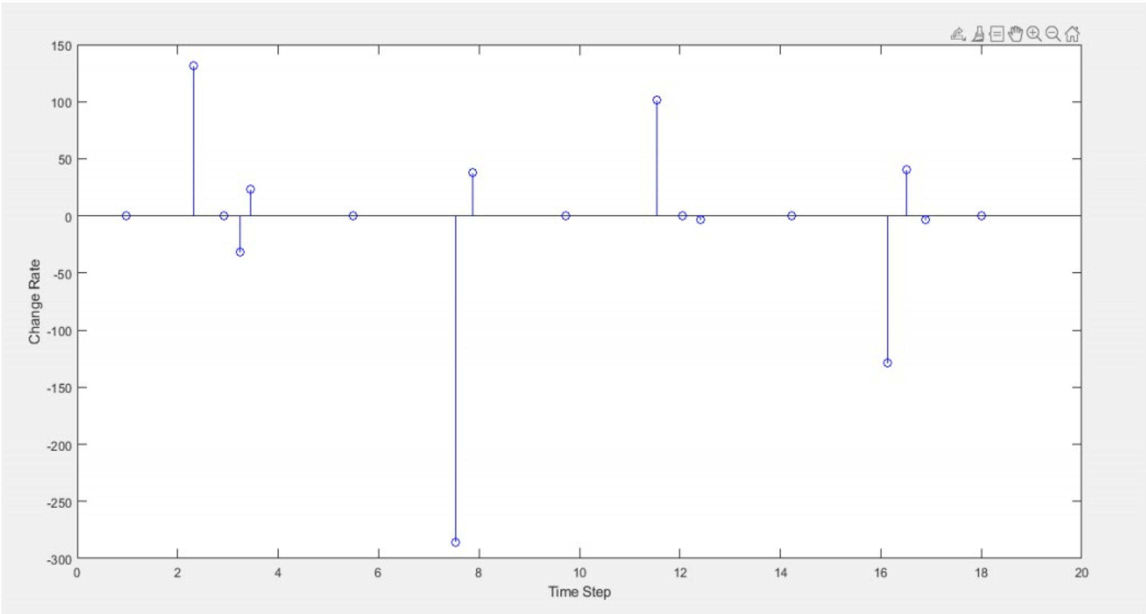


Figure 5.11: Change rate for ROP results (static phase – case study 2).

From Figure 5.11, the presence of a prominent blue vertical line on the negative axis (y-axis) of the change rate graph indicates heightened activity around the 7.5-minute mark. If the threshold value is set to be below the change rate observed at the 7.5-minute mark, the driller would be alerted when the change rate exceeds the predefined threshold, or the system would automatically optimize the Rate of Penetration (ROP). This emphasizes the significance of closely monitoring the change rate as it enables effective control of unusually high ROP fluctuations.

5.1.3 Case study 3: Constant UCS and WOB

Here, we will see how ROP reacts to different RPM set points at specific timesteps. For this simulation, a total of 11.43 metres was drilled in 19 minutes with WOB and UCS kept constant.

Simulation time = 19 minutes
Formation strength (UCS) = 100 Megapascal
Average WOB = 8 tonnes
Average flowrate = 1173.8 litres per minute
Velocity = 0.1 meter per seconds
Start Depth = 2179 meters
Ending Depth = 2190 meters
Initial Bit Depth = 2176 meters
Drilled Depth = 11.43 meters

A carefully selected set of RPM set points was chosen to accurately represent the dynamic relationship between Rate of Penetration (ROP) and Revolutions Per Minute (RPM).

Time (s)	Time (min)	Main pump flow rate (l/min)	WOB setpoint (ton)	Surface RPM (rpm)	Choke opening (%)	BOP opening (%)
1	0.016666667	1173.8	8	100	100	100
120	2	1173.8	8	60	100	100
240	4	1173.8	8	90	100	100
420	7	1173.8	8	40	100	100
680	11.33333333	1173.8	8	60	100	100
770	12.83333333	1173.8	8	100	100	100
950	15.83333333	1173.8	8	30	100	100
1140	19	1173.8	8	30	100	100

Table 5.6: Simulation setpoints with varying RPM.

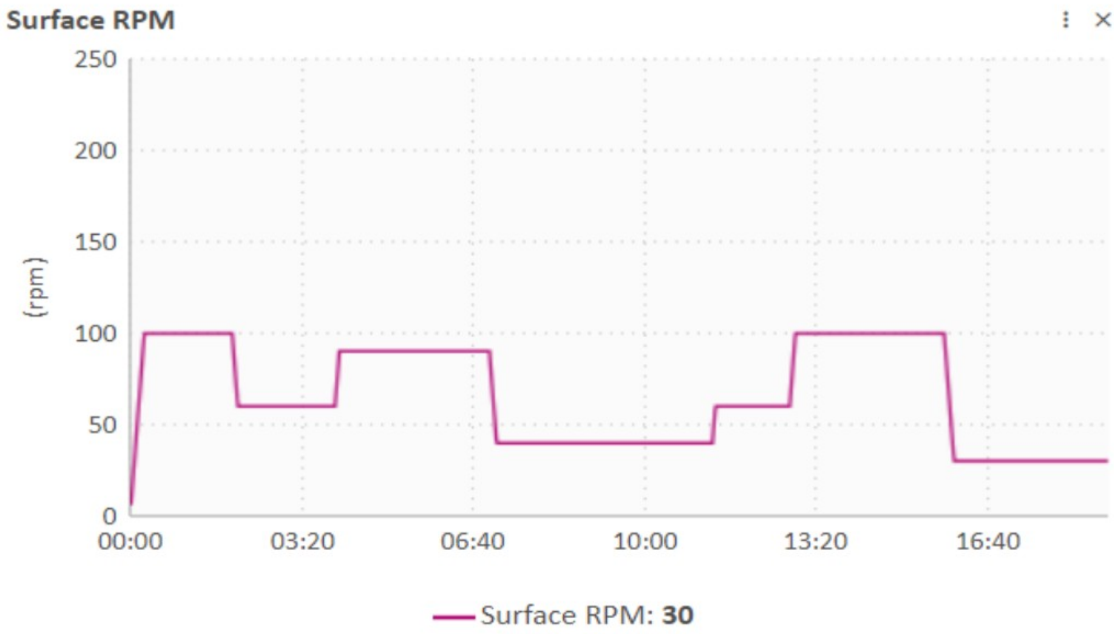
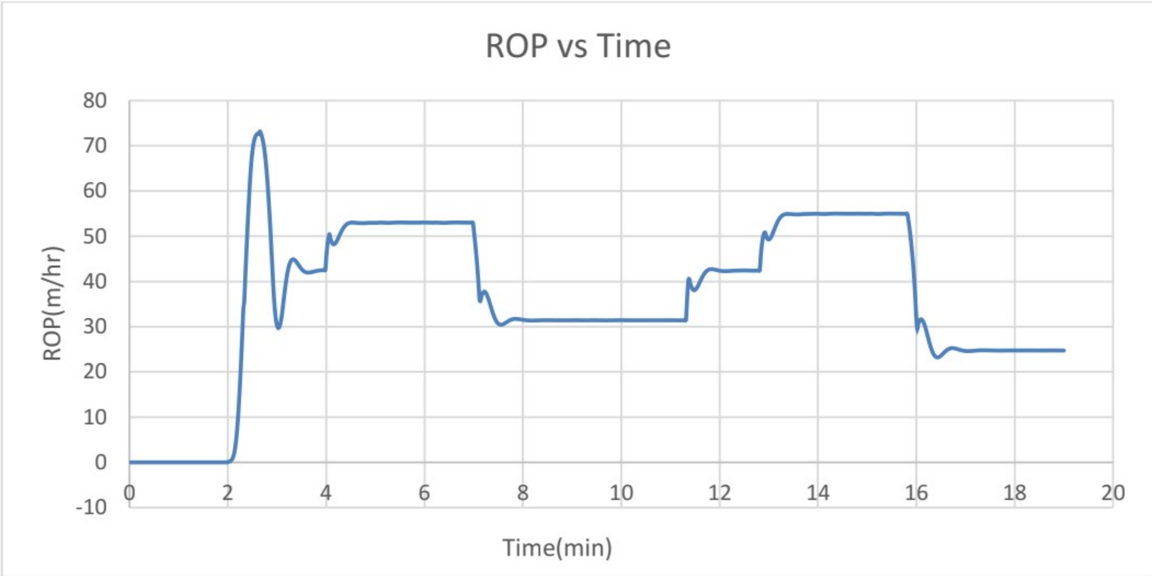


Figure 5.12: RPM set points (static phase – case study 3).

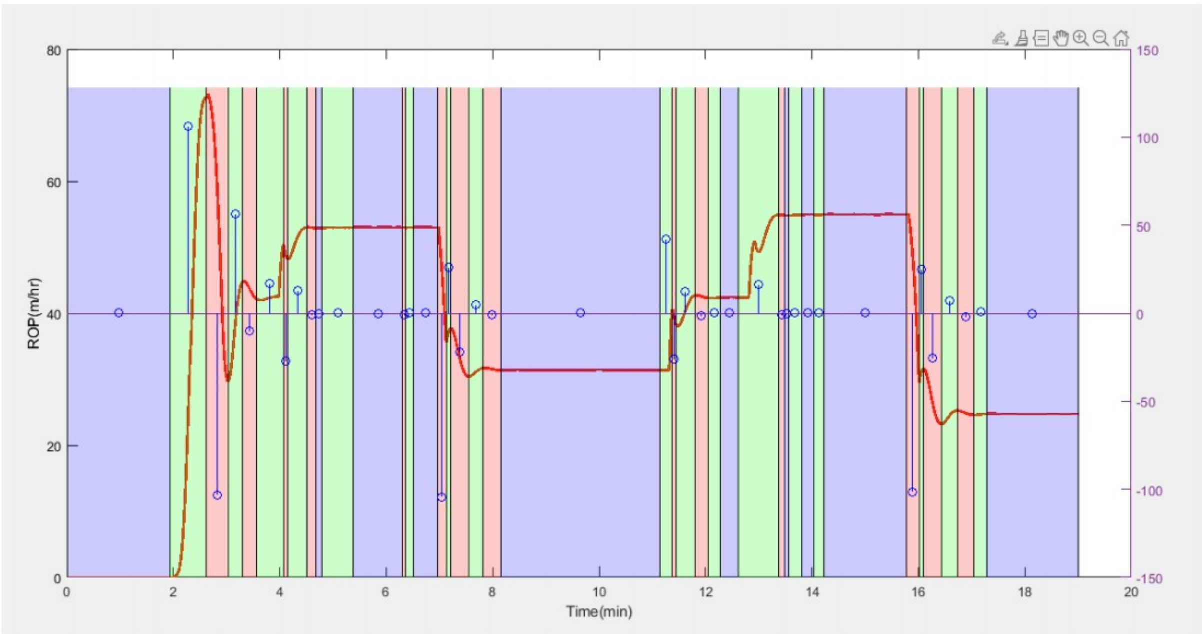
In contrast to Figure 5.9 in Case Study 2, which required frequent changes in WOB set points leading to fluctuations, Figure 5.12 demonstrates the desired stability of the plot.

5.13a

Occasionally, trend extraction may capture small segments even when the Rate of Penetration (ROP) is constant and the results can be misleading. However, the code can be improved so that these small trend segments are merged based on the change rate values. It is worth noting that the presence of these small segments is attributed to the ROP's response to changes in Weight on Bit (WOB), as depicted in Figure 5.15.



5.13b



5.13c

(Alpha=0.8, Tolerance=8, Zone size=4)

Figure 5.13: Image series for ROP trend analysis (static phase – case study 3).

Several simulations were conducted to determine the optimal values for alpha, tolerance, and zone size, ensuring the extraction and analysis of the best Rate of Penetration (ROP) trends. It is important to note that the zone size parameter was not used during the trend analysis in Case study 1, as we achieved a satisfactory classification of increasing, decreasing, and stationary trends without it. However, after multiple simulations, the zone size parameter was introduced and fine-tuned specifically for Case 3. This adjustment was made to achieve an improved trend analysis outcome. Additionally, the simulation time for Cases 2 and 3 was reduced from 28 minutes to 19 minutes to avoid the drillstring connection scenario in the drilling simulator, which caused the trend results of all parameters to drop to zero before resuming the simulation.

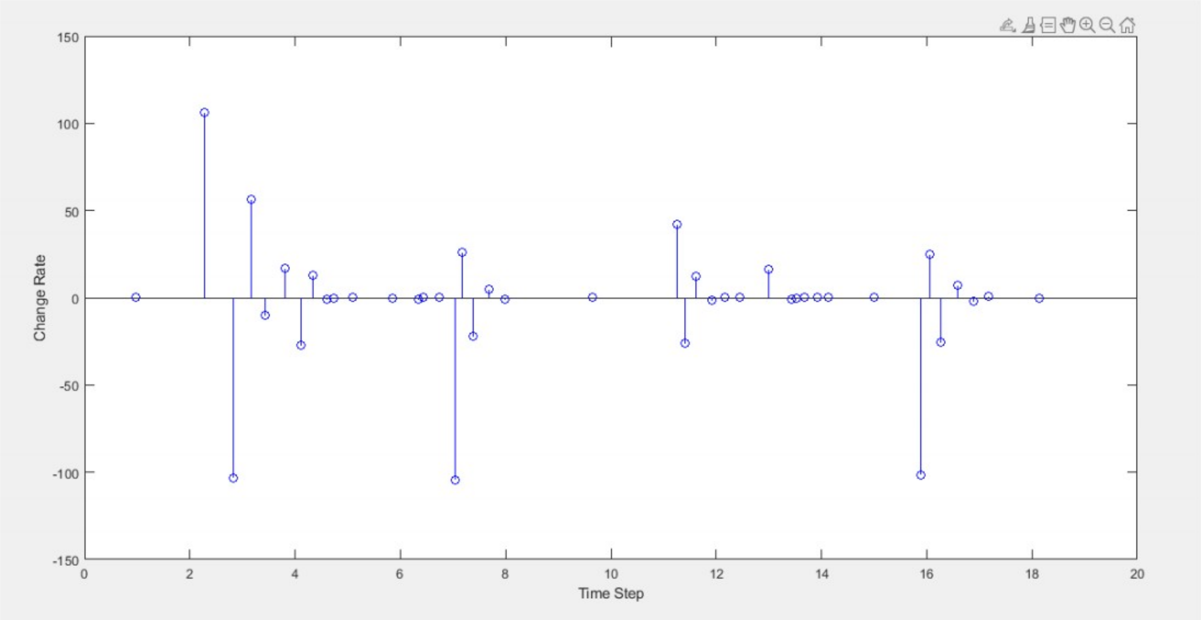


Figure 5.14: Change rate plot (static phase – case study 3).

Figure 5.15: Constant WOB (static phase – case study 3).

Figure 5.15 illustrates that the Weight on Bit (WOB) is subject to slight fluctuations caused by factors such as the downhole environment, reaction forces, and bit-rock interaction. Consequently, these minor variations in WOB result in minimal changes in the Rate of

Penetration (ROP). Therefore, numerous small segments emerge, representing subtle ROP variations characterized by a low change rate. While these segments may be perceived as distractions by drillers, it is essential to acknowledge that they are primarily influenced by small WOB deviations.

5.2 Dynamic Trend Analysis (Phase) and ROP Optimization

Continuing with our discussion of Case study 1, we will examine dynamic ROP trend analysis in this section. Unlike the static phase where the simulation is run, and ROP data is extracted to a CSV file which is then imported into the trend analysis code, the dynamic phase involves direct running of the simulation from a single MATLAB code. This is because the trend analysis code has been upgraded from static to dynamic using the moving window strategy (chapter 3.2). It has also been integrated with the drilling simulator API. Due to the modification to the dynamic trend analysis code as a MATLAB function, the trend analysis may be initiated directly from the drilling simulator's main MATLAB script. As shown in Figure 5.16, the change rate is plotted along with the moving window segment to visualize the simulation result.

To ensure accurate trend visualization and facilitate effective comparison between Static and Dynamic Trend Analysis, the configuration from Case Study 1 was utilized with simulation time reduced from 28 minutes to 21 minutes. This approach allows for consistent and meaningful analysis across both methodologies. The trend color code used for visualization is illustrated in Table 5.7, providing a comprehensive reference for interpreting the trends accurately.

Window Color	Trend
Red	Rising
Yellow	Flat
Green	Falling

Table 5.7: Colour code for dynamic trend analysis.

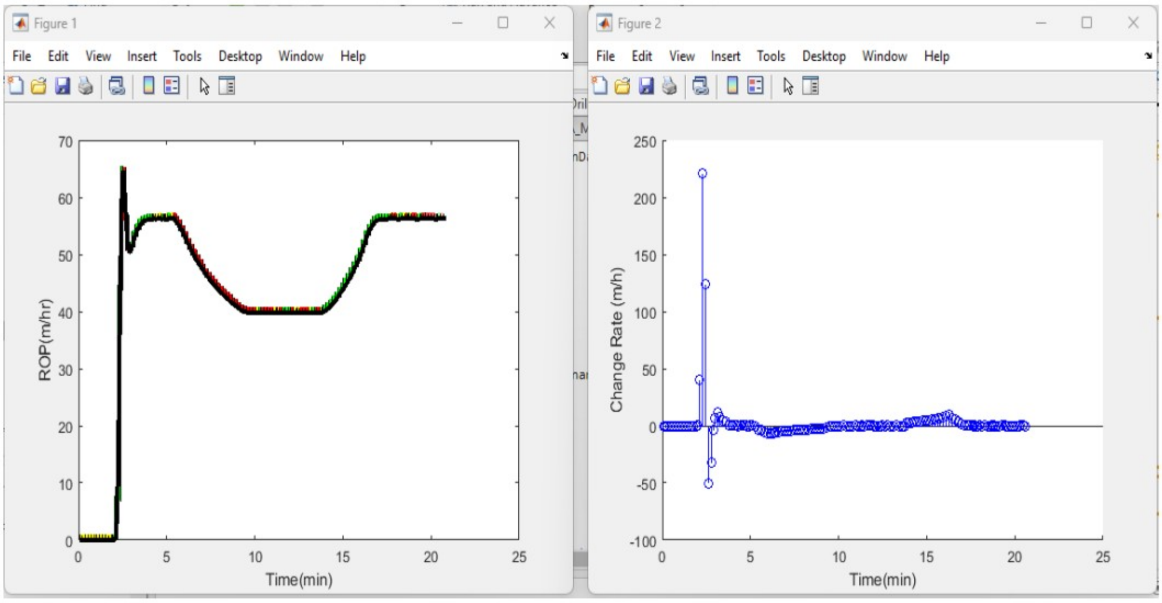


Figure 5.16: Dynamic trend analysis of Case study 1.

For the optimization of ROP in this study, we shall focus on ensuring that the ROP change rate does not decrease beyond a set threshold. The driller applies his experience to set a range of ROP values that is safe for drilling a particle hole section based on field data. In using the change rate as the condition parameter, a loop is included in the MATLAB main script to update the WOB to a value that results in an increase in ROP whenever the change rate decreases beyond the threshold. The code successfully updates WOB when the conditions inside the if statement (last_element<change_threshold) block are met. However, this does not automatically guarantee that the trend function will be updated with these changes immediately.

Over time, V_trend in the code represents a change in the Actual Rate of Penetration (ROP).

V_trend=[V_trend;Sim.ActualROP*3600]

This appends the current value of Sim.ActualROP*3600 to the V_trend array at each time step. Sim.ActualROP represents the current rate of penetration (ROP), which is a measure of how fast the drill bit drills into the formation. Multiplying by 3600, ROP is converted to m/hr. V_trend builds up a historical record of the ROP as the code progresses through time steps, which is then used for trend analysis.

5.2.1 ROP Optimization

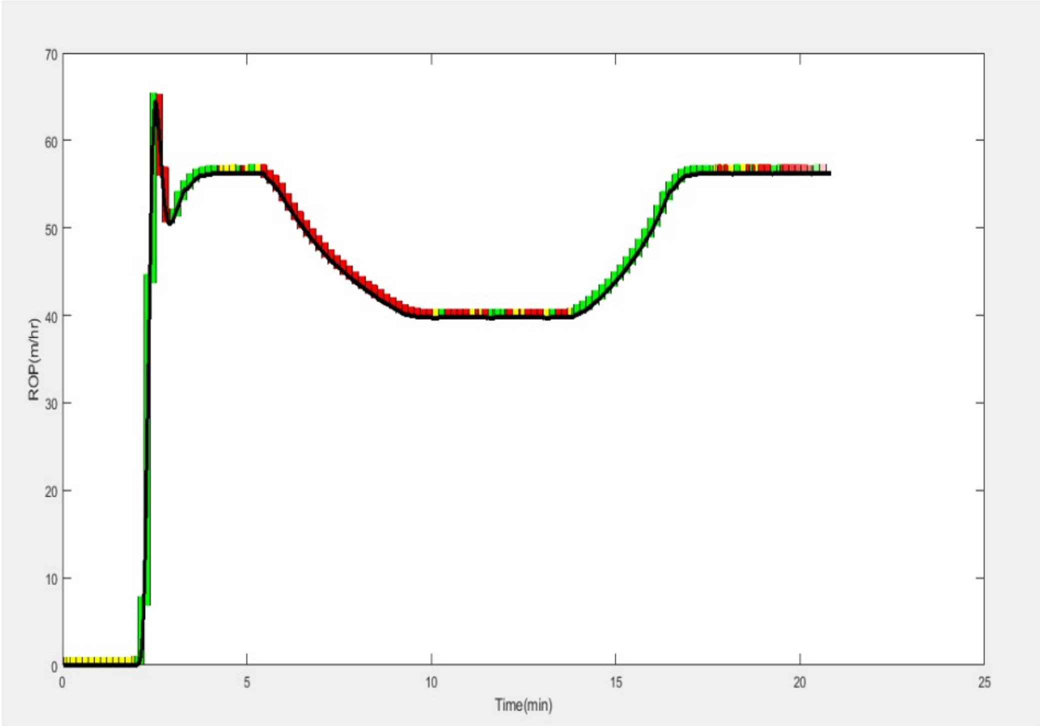
For further demonstration of ROP optimization results, the simulation is run with setpoints that trigger the optimization loop in the MATLAB script. A change rate threshold of 2% has been set in this case. A command is also implemented to alert the driller if ROP overshoots when WOB is updated.

The goal here is to see how ROP reacts as we drill into a formation with varying strengths (the same as Case study 1 – Static Phase). The WOB, flowrate, RPM are kept constant. A depth of 15.2 meters is drilled for 21 minutes.

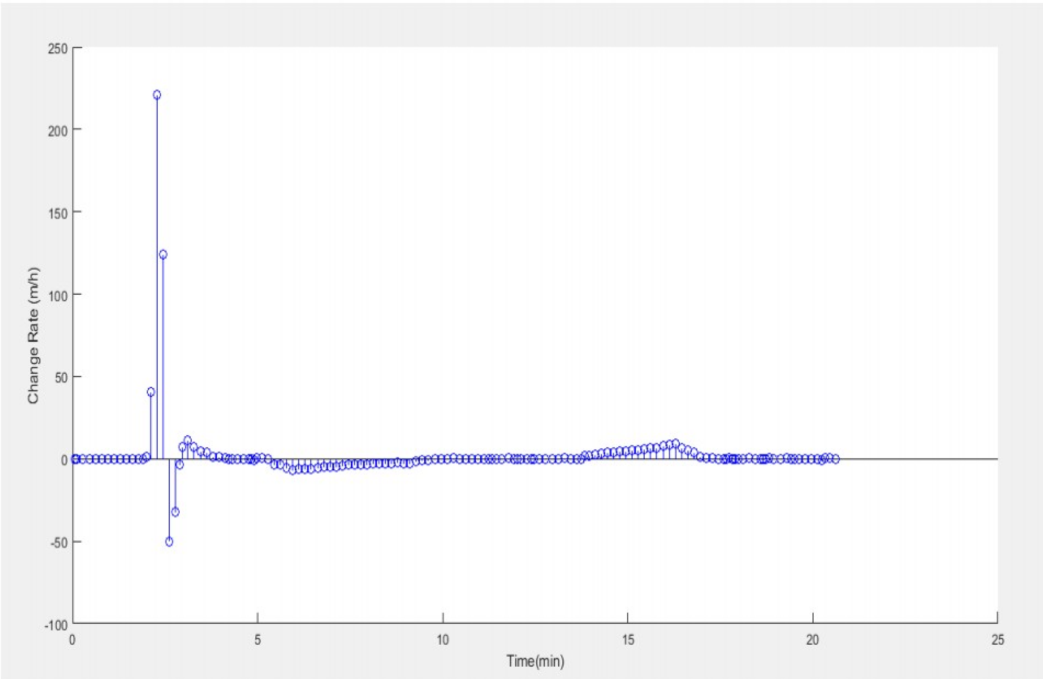
Simulation time = 21 minutes
Average WOB = 8 tonnes
Average RPM = 150.5 revolutions per minute
Average flowrate = 1173.8 litres per minute
Velocity = 0.1 meter per seconds
Start Depth = 2179 meters
Ending Depth = 2194 meters
Initial Bit Depth = 2176 meters
Drilled Depth = 15.2 meters

For a comprehensive view of the simulation results, including relevant figures and tables, please refer to Case Study 1.

5.17a



5.17b



5.17c

Figure 5.17: Image series for Dynamic trend analysis of case study 1 before optimization.

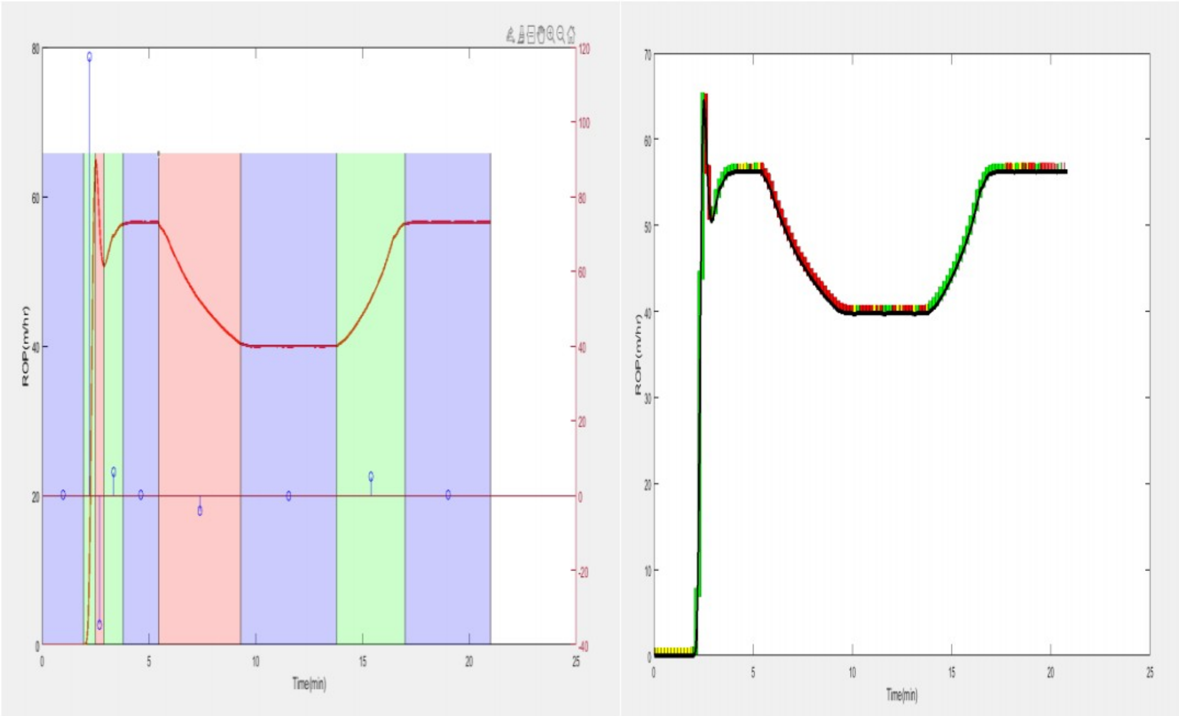


Figure 5.18: Illustration of the Static and Dynamic Trend Analysis before optimization.

As part of the optimization block of the MATLAB code, real-time trends in the rate of penetration (ROP) during drilling operations are analyzed. This refers to the speed at which the drill bit moves into the ground during drilling operations. Based on these trends, the weight on the bit (WOB) is adjusted accordingly. The objective is to ensure that drilling operations are efficient and safe. An overview of the code can be found below:

5.2.1 Defining threshold values

There are two threshold values set by the block:

- The change threshold is set to -0.02 (2%) to indicate a change in the rate of penetration (ROP). The weight on the bit (WOB) will be adjusted if the ROP change is less than this value.
- An overshoot threshold of 0.1 (10%) is used to detect overshoots in the WOB. An alert will be issued if WOB changes exceed this percentage.
- In this optimization loop configuration, WOB is configured to start at 12 tonnes.

5.2.2 Analysis and storage of ROP values

The next section of the code stores the values of time step and ROP over time.

5.2.3 Real-time Trend Analysis and Desired WOB Adjustment

This is followed by a calculation to determine whether the length of timesteps equals number multiplied by the window size.

length(Time_trend) == N (19)

Where,

N = Window size = 10

When this condition is met, it means that enough data has been collected to conduct a trend analysis using the Realtime Trend function. The function also takes the time steps and ROP values and returns the change point and the change rate. A change point represents a point in time when a significant change in the ROP trend was observed. The change rate represents the rate at which the ROP has changed at that point in time.

Once the trend analysis has been completed, the change rate is appended to the change rate list and it is checked for at least two elements (so that a comparison can be made). If the last value is less than the change threshold, then there has been a significant decrease in the ROP.

Consequently, the code checks to see if the difference between the last two change rate values is also less than the change threshold.

abs(second_last_element)-abs(last_element)<change_threshold) (20)

Upon finding out if the request is valid, it will increase the WOB by a certain percentage. The purpose of this technique is to increase drilling speed (ROP) by placing more weight on the drill bit. A proportional and integral gain is also adjusted as a result of the WOB controller. In order to track adjustments made to the WOB, parameter n is increased by one.

There is a further check in the script that ensures WOB does not overshoot. When the absolute percentage change in WOB exceeds or falls below the overshoot threshold, a warning is issued to the driller. For this study, the following parameters are used:

Percentage for WOB adjustment = 5%
WOBProportionalGain, K_p = 0.3e-5
WOBIntegralGain, K_r = 0.3e-6

Figure 5.19 illustrates the relationship between Weight on Bit (WOB) and Rate of Penetration (ROP) in a falling trend. Specifically, it demonstrates that whenever the ROP change falls below the set change threshold, the WOB increases accordingly. This behaviour indicates a reactive response to maintain the desired drilling parameters and compensate for the decrease in ROP. The figure showcases how the WOB is adjusted dynamically to optimize drilling performance in the presence of a falling ROP trend.

Simulation time = 21 minutes
Average WOB = 8 tonnes
Average RPM = 150.5 revolutions per minute
Average flowrate = 1173.8 litres per minute
Velocity = 0.1 meter per seconds
Start Depth = 2179 meters
Ending Depth = 2203 meters
Initial Bit Depth = 2176 meters

Drilled Depth = 24.23 meters

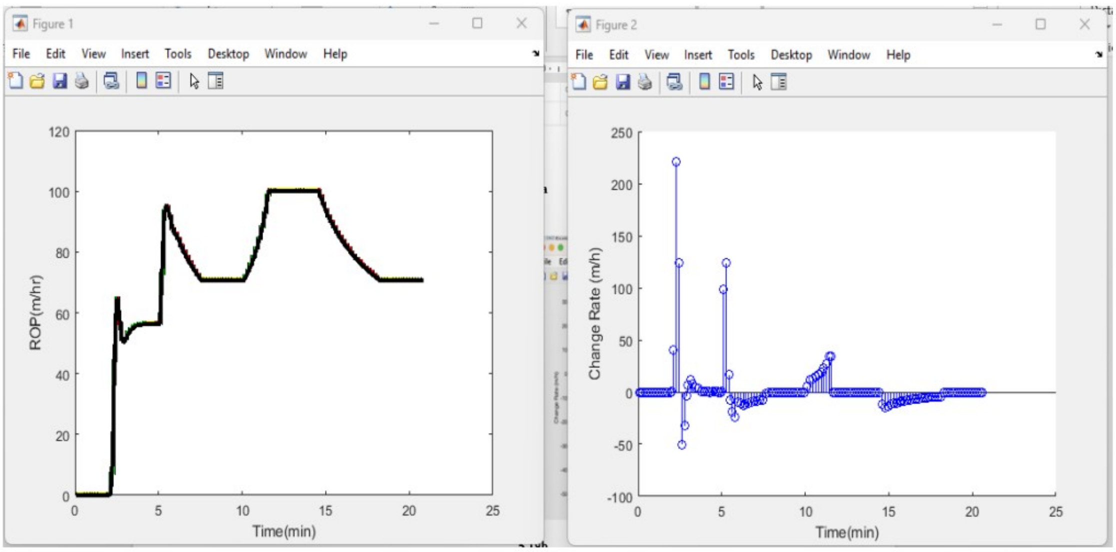
Completed simulation

EXPORT IMPORT DELETE

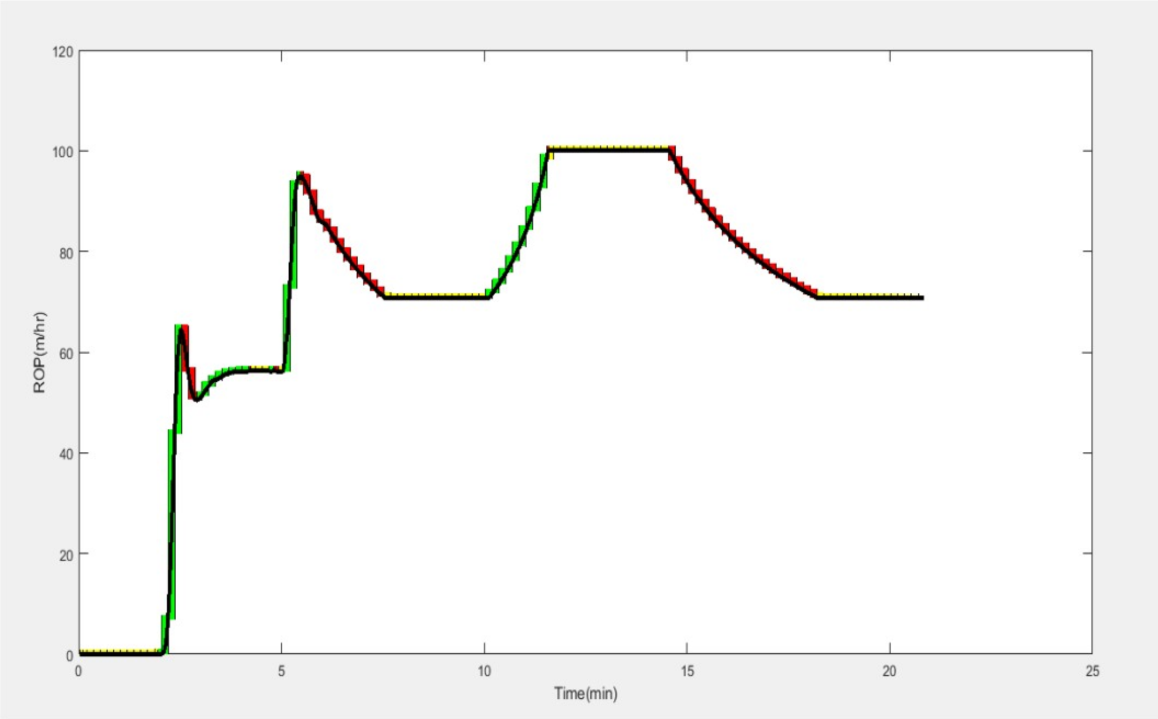
Time (hh:mm:ss)	Flow rate (l/min)	Velocity (m/s)	Auto driller	WOB (ton)	ROP (m/h)	RPM (rpm)	MPD control mode	Choke opn. (%)	MPD ref. (bar)	Choke flow rate (l/min)	BOP	Active pit	Return pit	Control active pit	Active pit density (s.g.)	Active pit temp. (°C)
00:00:01	1174	0.1	ROP	NA	0	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:02:00	1174	0.1	WOB	8	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:05:02	1174	0.1	WOB	12.6	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:05:52	1174	0.1	WOB	14.4	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:06:02	1174	0.1	WOB	16.2	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:06:22	1174	0.1	WOB	18	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:06:32	1174	0.1	WOB	19.8	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:14:52	1174	0.1	WOB	21.6	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:15:02	1174	0.1	WOB	23.4	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA

Finish time 00:21:00

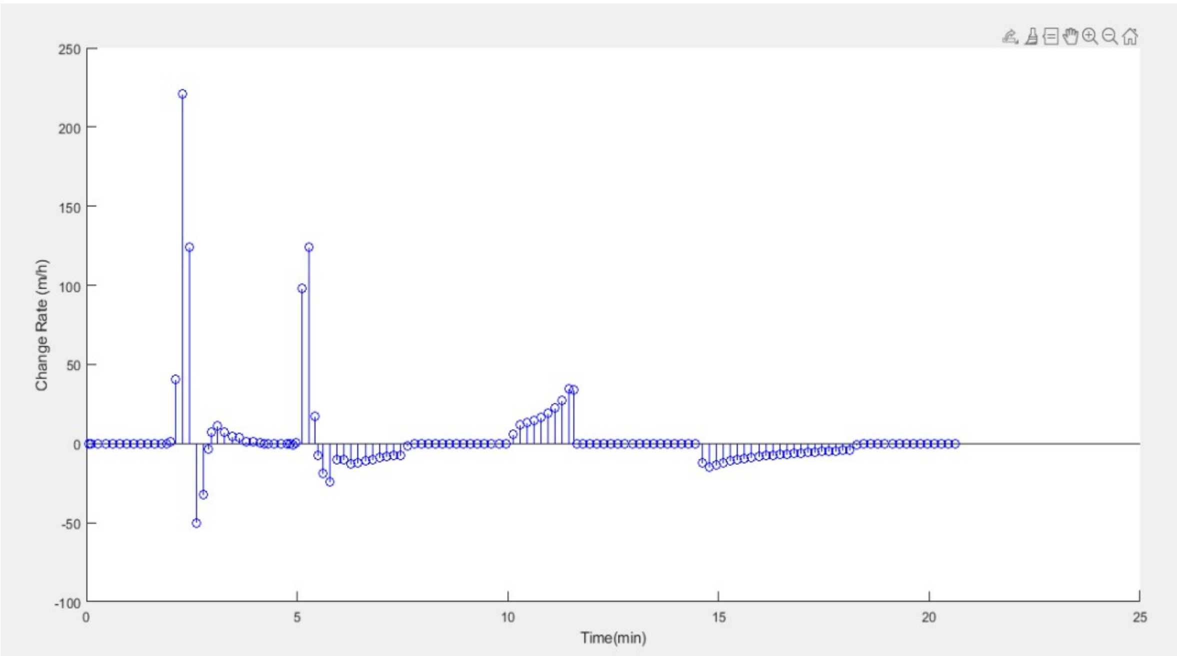
5.19a



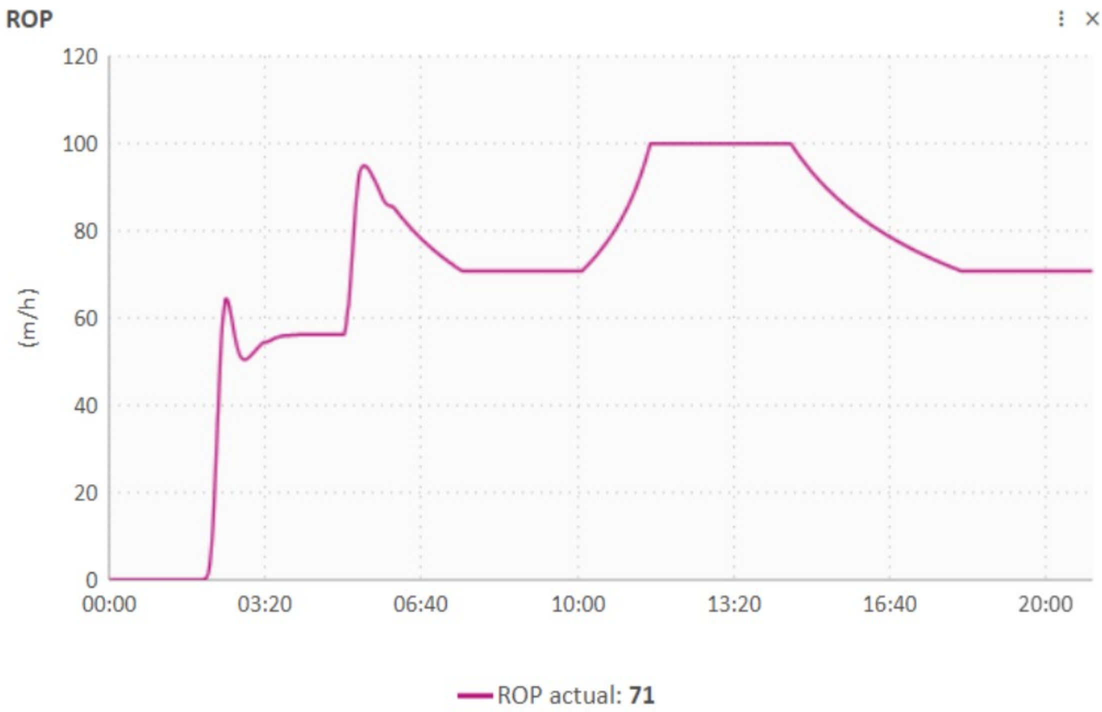
5.19b



5.19c



5.19d



5.19e

Figure 5.19: Image series for Dynamic trend analysis of case study 3 after optimization.

Figure 5.20: Updated WOB set points after ROP optimization.

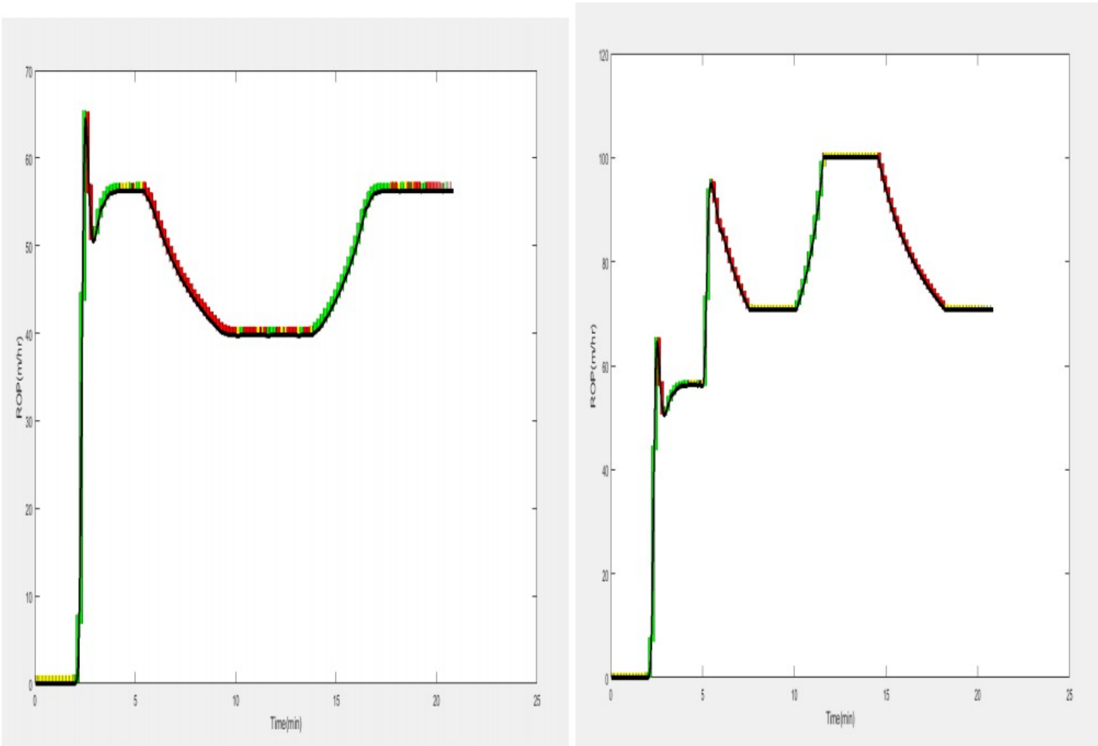


Figure 5.21: Dynamic trend analysis of case study 3 before and after optimization.

I would like to highlight the fact that MATLAB was used to simulate the Realtime dynamic trend analysis and optimization. The results can be visualized using MATLAB and the drilling simulator. For the purpose of ROP optimization, the real-time dynamic trend analysis code operates in the same manner as a controlling system that updates the weight on bit (WOB) in response to the rate of penetration (ROP) trend in real time. The method can be employed to improve drilling efficiency.

5.2.4 Percentage Increase in ROP

Percentage ROP increase = $\frac{\sum ROP_{opt} - \sum ROP_{old}}{\sum ROP_{old}}$ *100

Where,

$\sum ROP_{opt}$ = Summation of the optimized ROP = 87690.17 m/hr

$\sum ROP_{old}$ = Summation of the old ROP = 54974.55 m/hr

$= \frac{87690.17 - 54974.55}{54974.55} * 100$

= 0.595105 * 100 = 59.51%

Percentage ROP increase = 59.51%

Depth Parameters	Before Optimization	After Optimization
Start Depth (m)	2179	2179
Ending Depth (m)	2194	2203
Initial Bit Depth (m)	2176	2176
Drilled Depth (m)	15.2	24.23
%ROP increase	59.51%	

Table 5.8: Summary of ROP parameters after optimization.

Table 5.8 presents the impact of the optimization model on the drilled depth, showcasing the quantified percentage increase in the Rate of Penetration (ROP). This analysis highlights the effectiveness of the optimization model in achieving improved drilling efficiency and performance.

5.4 Sensitivity Analysis

A sensitivity analysis for the dynamic trend analysis is conducted to evaluate the performance of the MATLAB algorithm by adjusting various parameters. These parameters include Unconfined Compressive Strength (UCS), moving window size, K_p, and K_i. Through systematic parameter adjustments, the objective is to assess how these variations impact the algorithm's behavior and their effects on the desired outcomes. This analysis will contribute valuable insights towards optimizing the algorithm's performance and achieving the desired objectives outlined in this thesis.

5.4.1 UCS Adjustments

MD (m)	UCS (MPa)	Friction angle (°)
0	200	30.00007015
2179	100	30.00007015
2180	150	30.00007015
2182	100	30.00007015
2185	200	30.00007015
2188	150	30.00007015
2190	100	30.00007015

Table 5.9: UCS setpoints (sensitivity analysis).

Simulation 1

Simulation Time = 10 minutes
Window size = 10

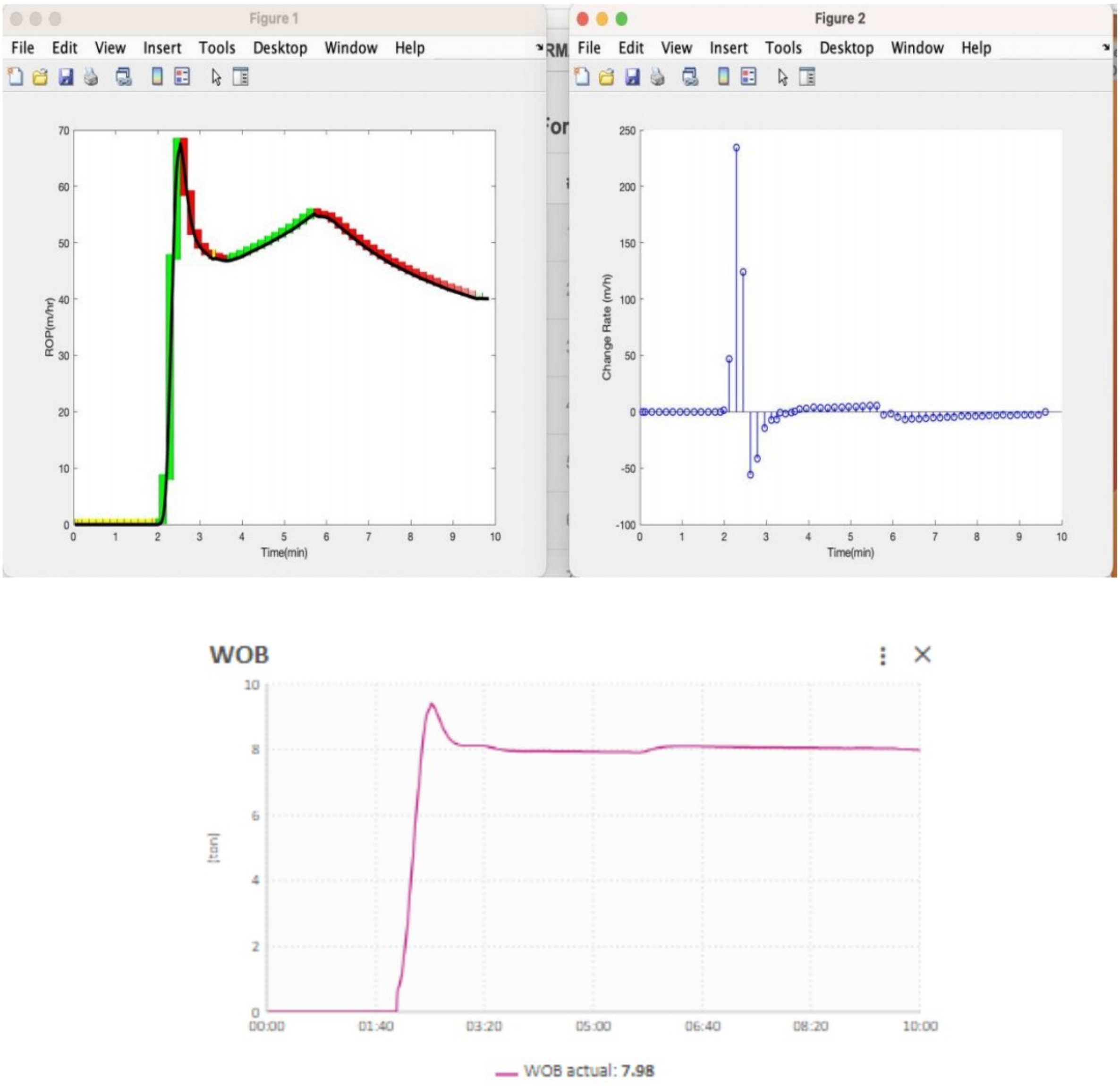


Figure 5.22: Simulation1 **-** ROP result before optimization (sensitivity analysis).

Simulation 2

Simulation Time = 10 minutes
Window size = 35

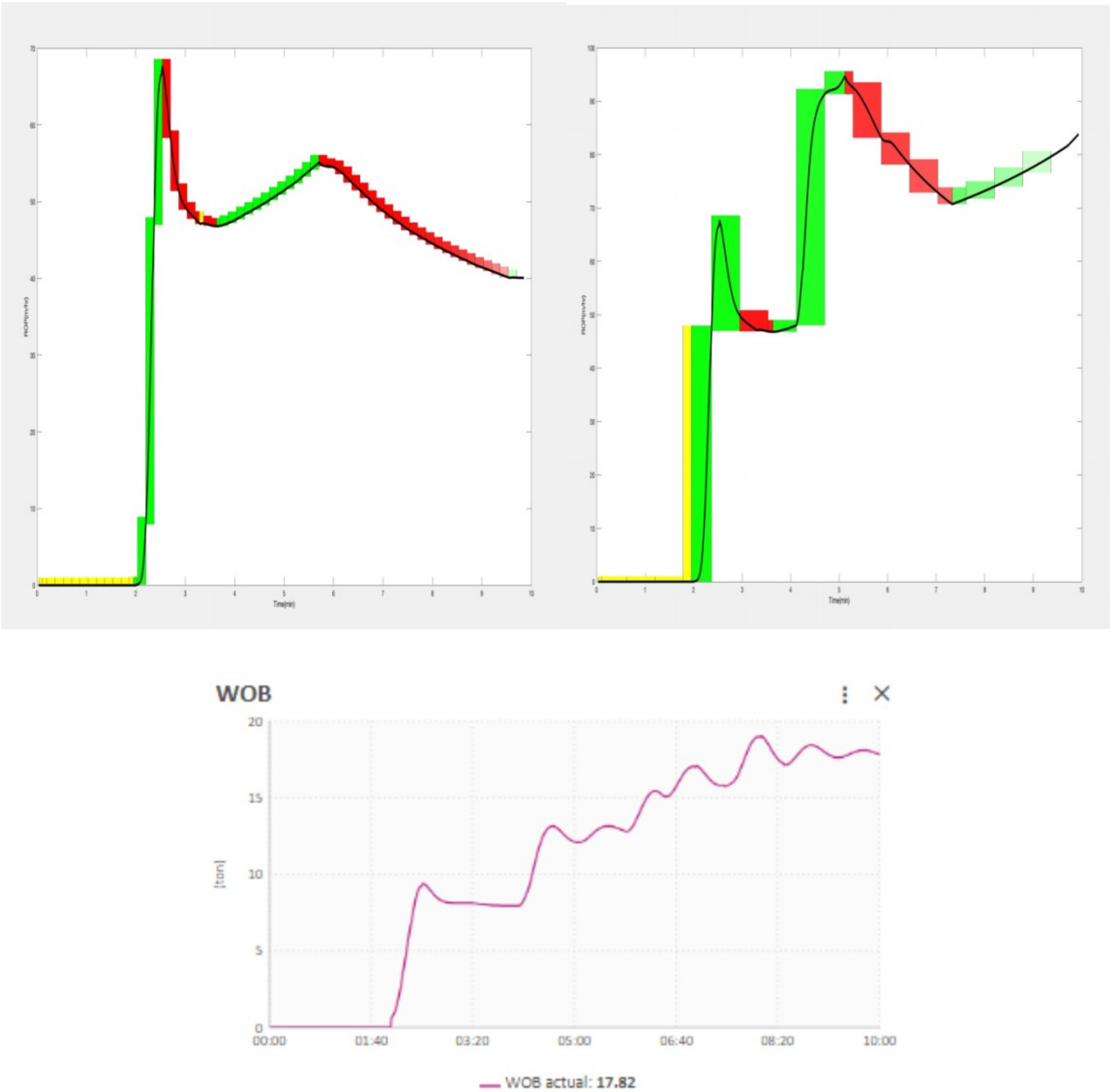


Figure 5.23: Simulation2 **-** ROP result after optimization (sensitivity analysis).

Simulation 3

Simulation Time = 10 minutes
Window size = 10

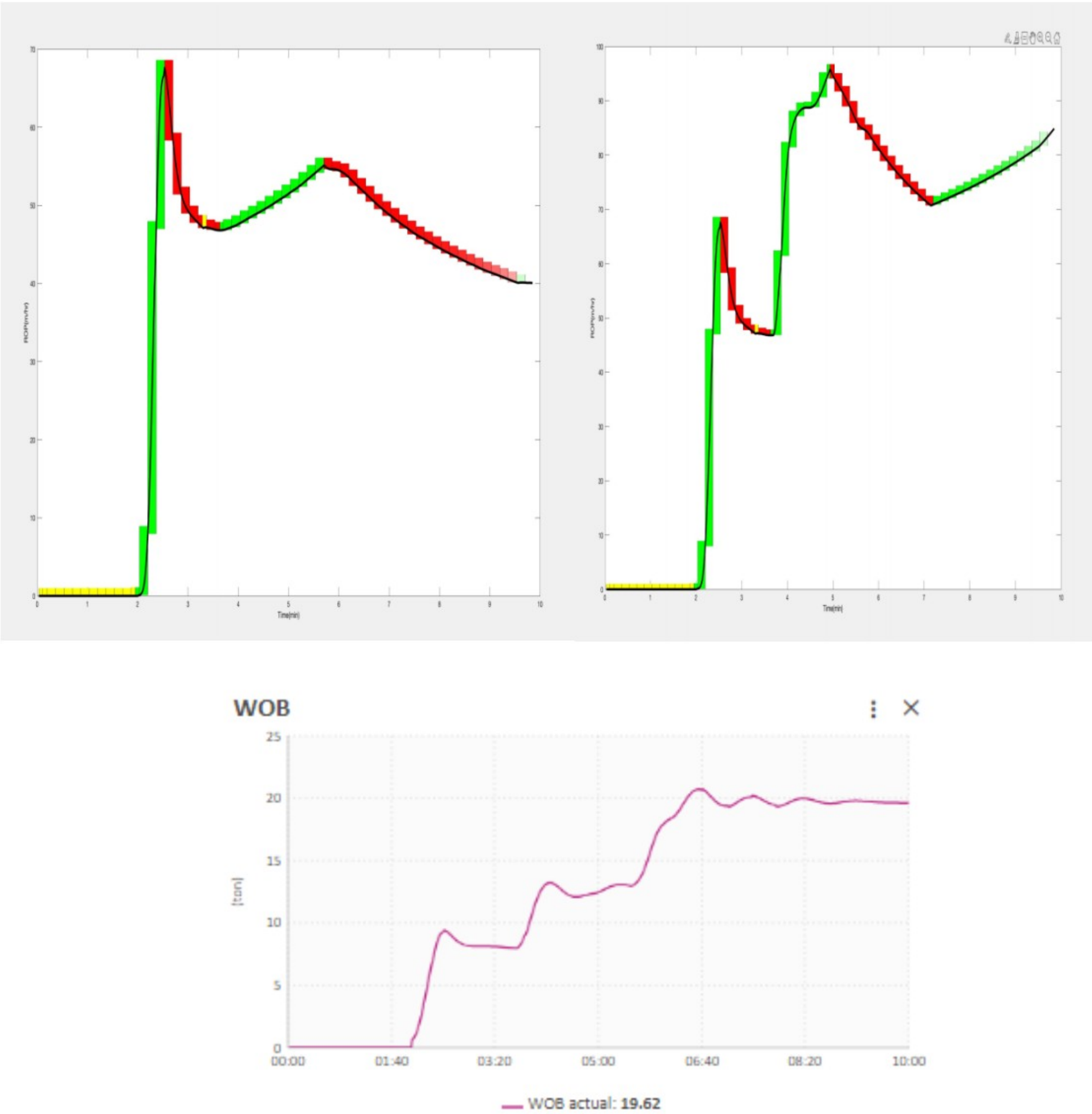


Figure 5.24: Simulation3 **-** ROP result after optimization (sensitivity analysis).

Simulation 4

Simulation Time = 10 minutes
Window size = 20

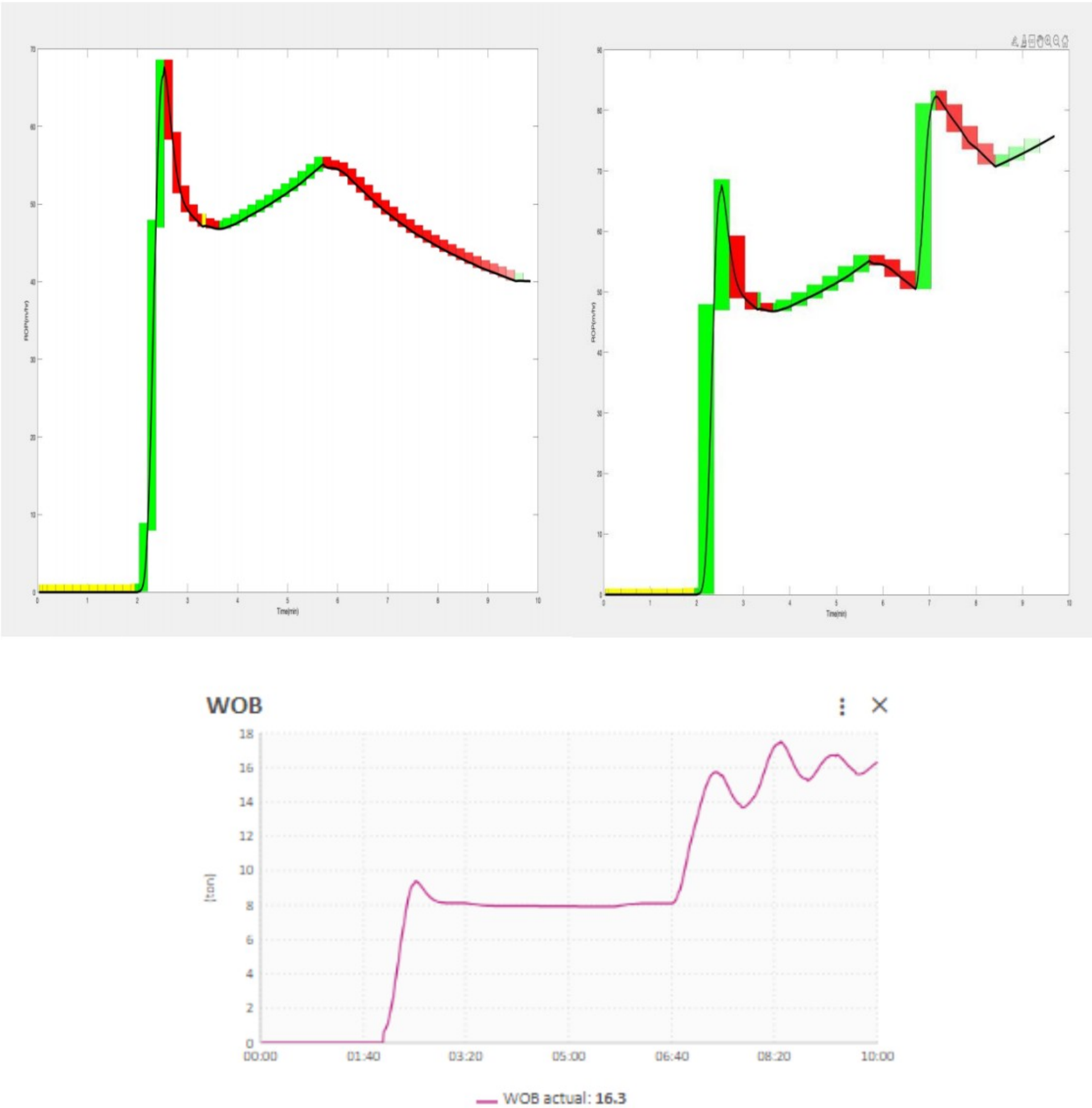


Figure 5.25: Simulation4 - ROP result after optimization (sensitivity analysis).

	Simulation1	Simulation2	Simulation3	Simulation4
	Windowsize10	Windowsize35	Windowsize10	Windowsize20
Depth Parameters	**Before Optimization**	**After Optimization**	**After Optimization**	**After Optimization**
Start Depth (m)	2179	2179	2179	2179
Ending Depth (m)	2194	2189	2185	2187
Initial Bit Depth (m)	2176	2176	2176	2176
Drilled Depth (m)	6.25	9.64	9.38	7.92
ΣROP	22585.42	33926.69	34861.85	28638.25
%ROP increase		**50.21%**	**54.36%**	**26.79%**

Table 5.10: Summary of ROP results with different window sizes after optimization (sensitivity analysis).

5.4.2 K_p and K_i Adjustments

Simulation 1

Here we will compare ROP trend analysis for both the original simulation and when K_p and K_i are adjusted. Where the initial values for K_p and K_i is 0.3e-5 and 0.3e-6 respectively.

Window size = 10
K_p = 0.5e-5
K_i = 0.5e-6

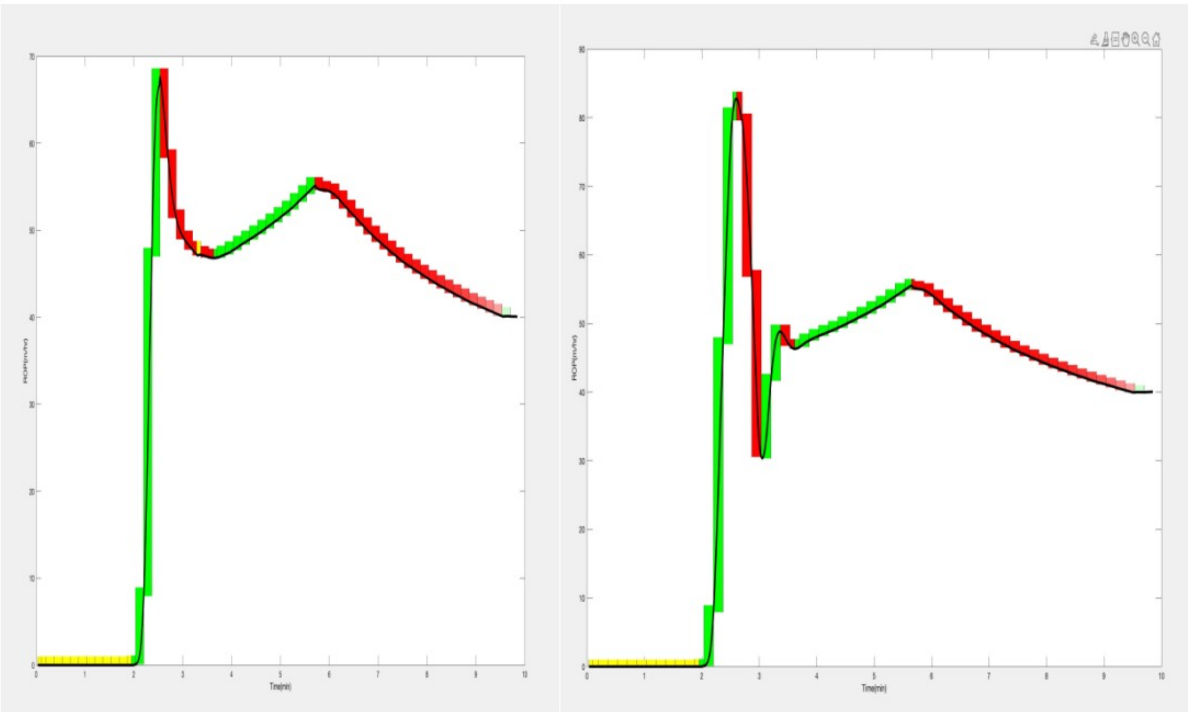


Figure 5.26: Sensitivity Analysis1 (K_p, K_i).

Simulation 2

Window size = 10
K_p = 1.0e-5
K_i = 1.0e-6

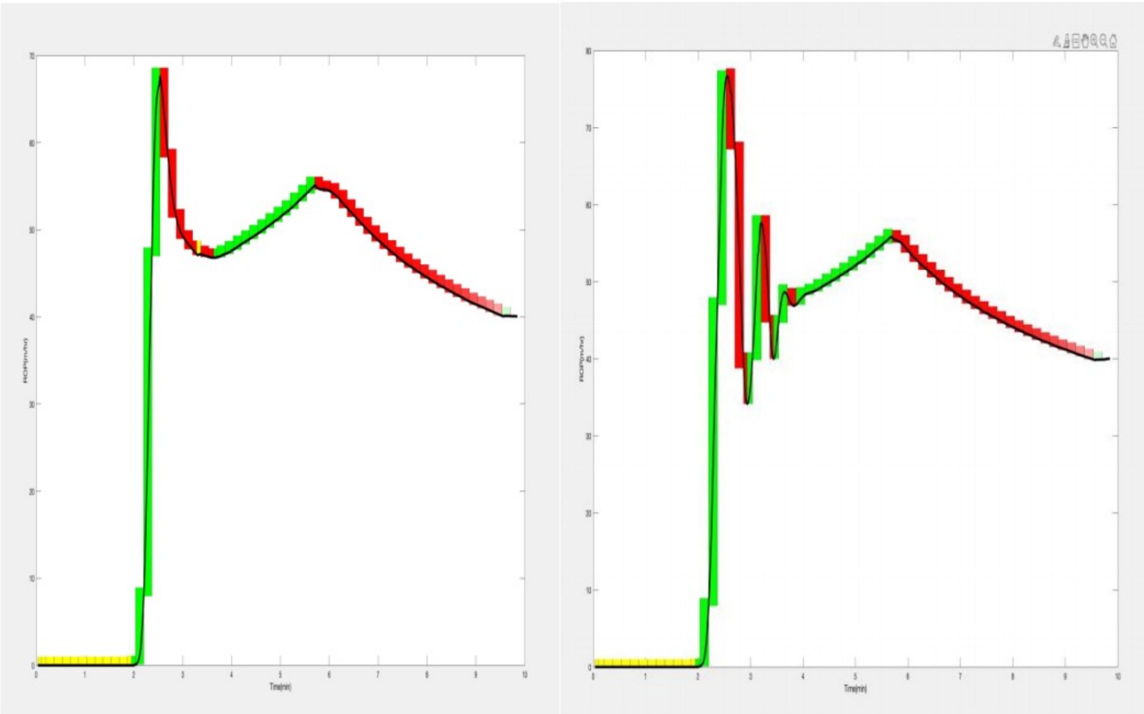


Figure 5.27: Sensitivity Analysis2 (K_p, K_i).

5.5 Limitations

In this study, a maximum WOB value (40000 tonnes) was specified in the script, which may not be appropriate or safe for all drilling operations. In order to compute the optimization, a value for the desired WOB, Dw (set WOB value for ROP optimization initiation) is used as an initial value. The selection of this initial value may have a negative impact on the optimization process if the value is incorrect.

By default, one timestep is equal to one second (if the user does not specifically select the Transient Torque and Drag model when starting the simulation) and this allows a maximum of five hours of simulation. In contrast, if you use the Transient Torque and Drag model, a Timestep is defined as 0.1 seconds (100 milliseconds) with a maximum simulation time of 30 minutes. This limits the drillable depth in simulations that require more than 30 minutes to reach the target well depth.

There is a clear focus on the rate of penetration (ROP) and weight on bit (WOB) in the script. Although these parameters are essential, drilling optimization also requires consideration of torque, rotary speed, and mud properties. The script may be limited in its effectiveness if these factors are not present.

OpenLab drilling simulator's maximum penetration rate (ROP) and weight on bit (WOB) are set by default to 150 meters per hour (m/hr) and 30 tonnes, respectively. This is done in order to prevent extreme values in the cuttings transport model. Therefore, when the ROP reaches 150 m/hr, it will not increase further. Instead, the weight on the bit (WOB) is automatically adjusted to be lower than the setpoint to keep ROP at 150 m/hr.

The WOB optimization based on the change rate appears to follow a linear assumption, which may not accurately reflect the nonlinearity of drilling operations in actual practice. There may be a need to use or develop a more complex model to make better predictions and perform better optimization.
As the ROP model calculates the change in wellbore depth per second, the resulting rate of cuttings generated by the bit can be calculated and fed to the Cuttings transport model. The ROP model used in this work is based on a traditional assumption that the ROP is expected to increase linearly with increasing RPM up to some threshold value, where the efficiency declines (the Founder point).

The size of the data window in trend analysis can have a significant impact on performance. Using small window sizes may result in false alarms or missed changes due to noise and fluctuation. In some cases, a large window will not be able to respond quickly enough to actual changes. A fixed window size used in this study may not be optimal in all circumstances. Values for detection of change and overshoot are static. These thresholds may, however, not be applicable to all drilling conditions and drilling rigs. A dynamic or adaptive threshold determination is necessary for the detection of meaningful changes and the avoidance of false alarms.

The MATLAB script does not handle errors and unexpected situations, such as a sudden loss of data or data that is out of range. Due to this limitation, the system may not be as reliable in real-world scenarios. It is most effective to conduct real-time dynamic trend analysis for wells drilled in existing fields in which previous well drilling data is available.

Chapter 6

Conclusion and Future Work

As part of this study, we examined the moving window methodology for analyzing trends in penetration rate (ROP) during drilling operations. In order to extract the ROP trend, we ran simulations (by varying WOB and UCS) to get variations in the ROP. A moving window algorithm was used to classify trends as stationary, falling, and rising based on the extracted results.

A connection between the OpenLab drilling simulator and MATLAB allows multiple simulations with longer time steps to be performed. Using the MATLAB login link, I was able to conduct simulations incorporating the moving window trend analysis strategy (as a function). In this way, it was possible to perform real-time dynamic trend analysis while running simulations in the OpenLab simulation environment through the MATLAB interface.

While the solutions in this study were mainly targeted at ROP optimization with dynamic trend analysis, it is also possible to detect influx (possibly kick) and predict bottomhole pressure. Utilizing moving window algorithms to analyze ROP trends, as demonstrated in this study, could significantly enhance drilling operations. The methodology is versatile enough to be applied across various drilling operations, locations, formations, and techniques. This will pave the way for more efficient, safer, and cost-effective practices in the industry.

6.1 Future Work

While this work was done with MATLAB, the code can also be translated to python programming language. Regardless of what programming language that is used, the incorporation of machine learning to this study would maximize its application to the energy industry. Some benefits of including machine learning to this project are listed below:

1. The application of ML to this work would make it possible for predictive analytics of drilling parameters (for this case, ROP) based on historic data. ML algorithms can work with multiple input variables and complex non-linear relationships thereby making its predictions accurate.

2. ML can also be used to set adaptive thresholds in place of fixed ones applied in this study.

3. By reducing the noise in drilling data, machine learning improves the accuracy of trend analysis.

4. It would be easier to detect anomalies in drilling operation data with ML. For example, sudden changes in ROP and abnormal torque. Adoption of anomaly detection algorithms can help with dynamic adjustment of threshold (change rate and overshoot) based on data distribution.

5. With reinforcement learning, it would be easier to optimize drilling parameters.

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APPENDICES

1. Static Phase Simulation Results

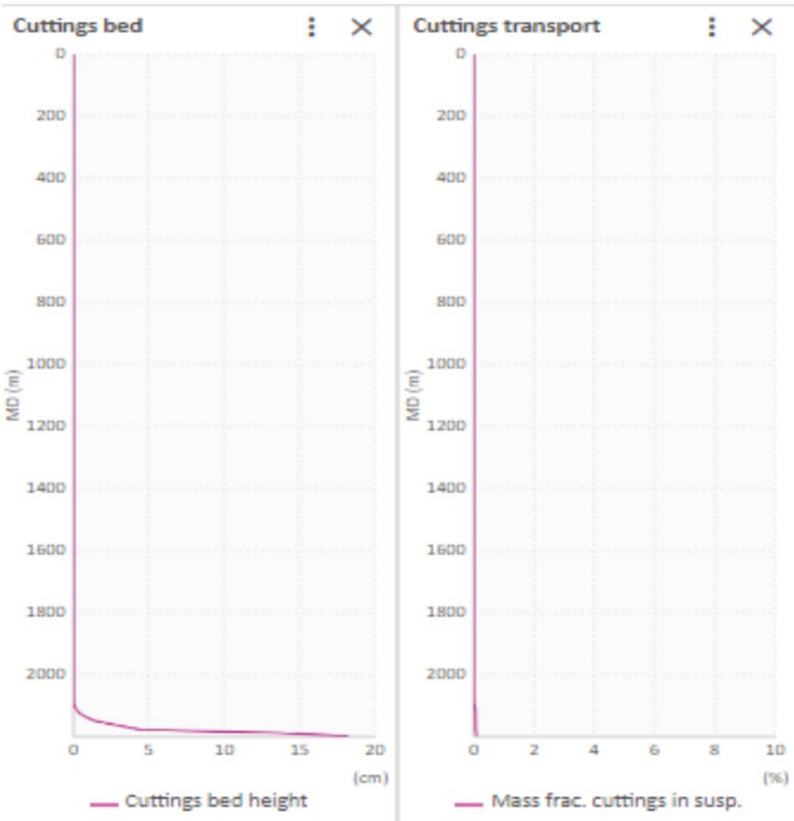
1.1 Case Study 1

Completed simulation

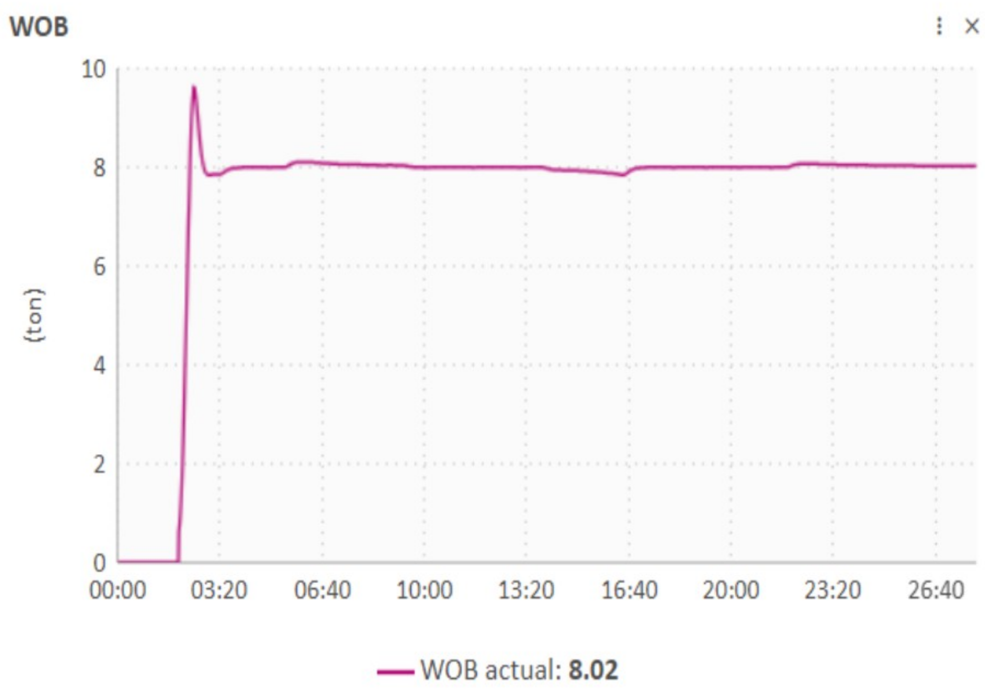
EXPORT IMPORT DELETE

Time (hh:mm:ss)	Flow rate (l/min)	Velocity (m/s)	Auto driller	WOB (ton)	ROP (m/h)	RPM (rpm)	MPD control mode	Choke opn. (%)	MPD ref. (bar)	Choke flow rate (l/min)	BOP	Active pit	Return pit	Control active pit	Active pit density (s.g.)	Active pit temp. (°C)
00:00:01	1174	0.1	ROP	NA	0	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:02:00	1174	0.1	WOB	8	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA

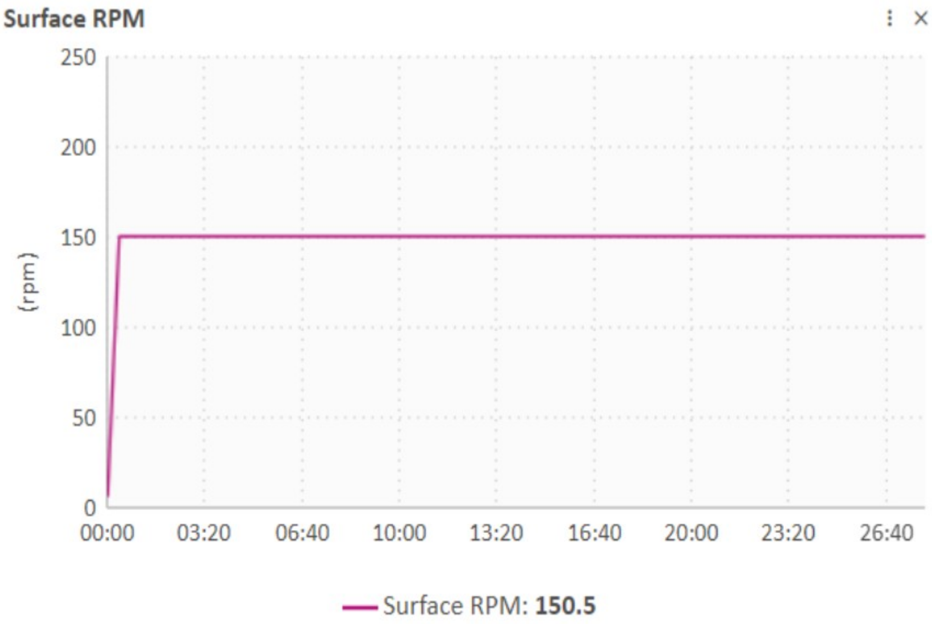
Finish time 00:28:00



ROP
100
80
60
40
20
0
(m/h)
00:00
03:20
06:40
10:00
13:20
16:40
20:00
23:20
26:40
ROP actual: 40



WOB
10
8
6
4
2
0
(ton)
00:00
03:20
06:40
10:00
13:20
16:40
20:00
23:20
26:40
WOB actual: 8.02



1.2 Case Study 2

Completed simulation

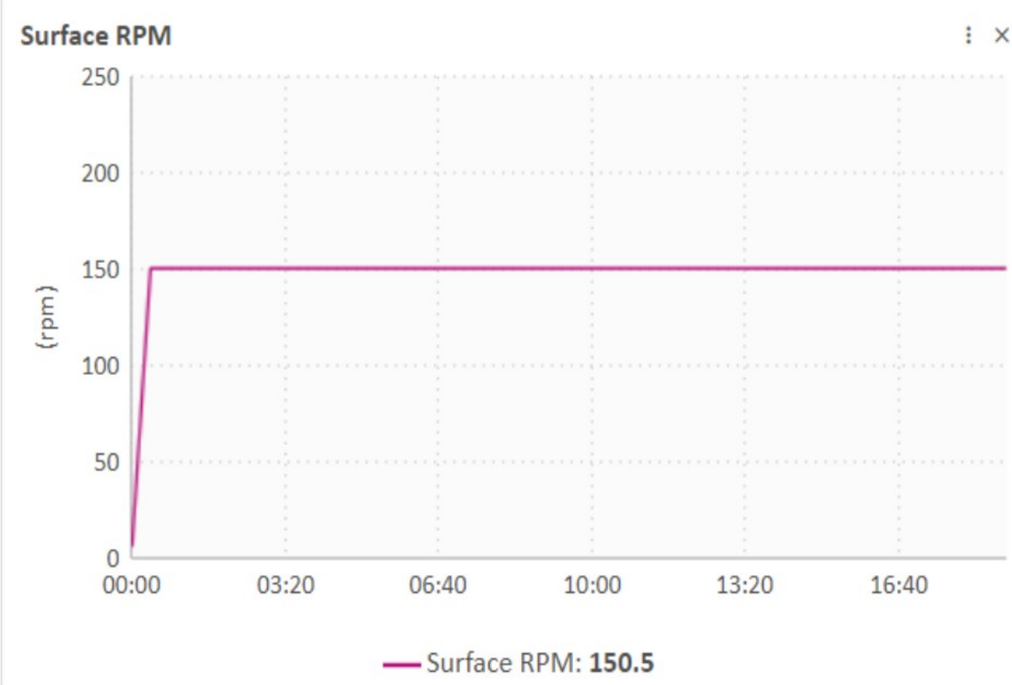
EXPORT IMPORT DELETE

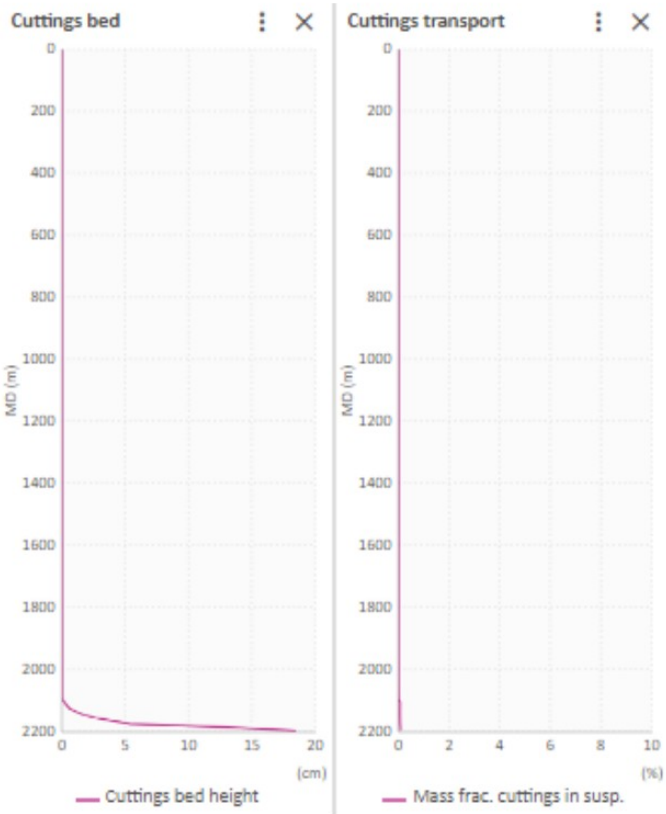
Time (hh:mm:ss)	Flow rate (l/min)	Velocity (m/s)	Auto driller	WOB (ton)	ROP (m/h)	RPM (rpm)	MPD control mode	Choke opn. (%)	MPD ref. (bar)	Choke flow rate (l/min)	BOP	Active pit	Return pit	Control active pit	Active pit density (s.g.)	Active pit temp. (°C)
00:00:01	1174	0.1	ROP	NA	0	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:02:00	1174	0.1	WOB	15	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:04:00	1174	0.1	WOB	28	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:07:00	1174	0.1	WOB	8	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:11:20	1174	0.1	WOB	17	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:15:50	1174	0.1	WOB	11	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA

Finish time 00:00:00


WOB
35
30
25
20
15
10
5
0
(ton)
00:00
03:20
06:40
10:00
13:20
16:40
WOB actual: 11


ROP
120
100
80
60
40
20
0
(m/h)
00:00
03:20
06:40
10:00
13:20
16:40
ROP actual: 88


Surface RPM
250
200
150
100
50
0
(rpm)
00:00
03:20
06:40
10:00
13:20
16:40
Surface RPM: 150.5


Cuttings bed
MD (m)
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
0
5
10
15
20
(cm)
Cuttings bed height
Cuttings transport
MD (m)
0
2
4
6
8
10
(%)
Mass frac. cuttings in susp.

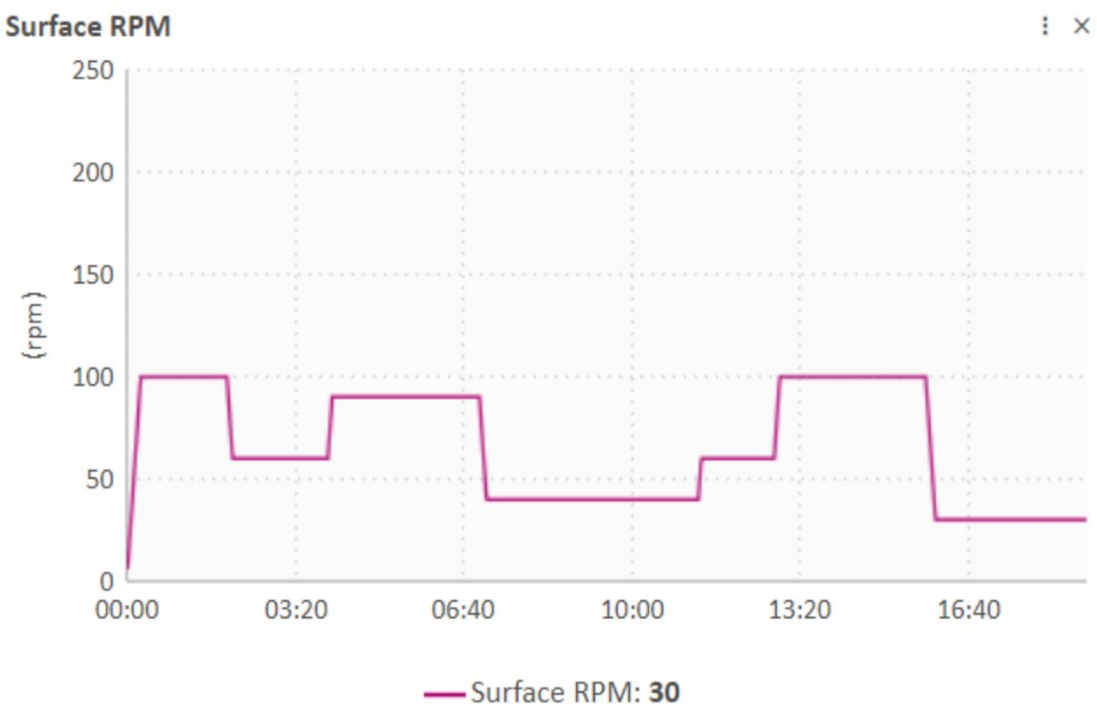
1.3 Case Study 3

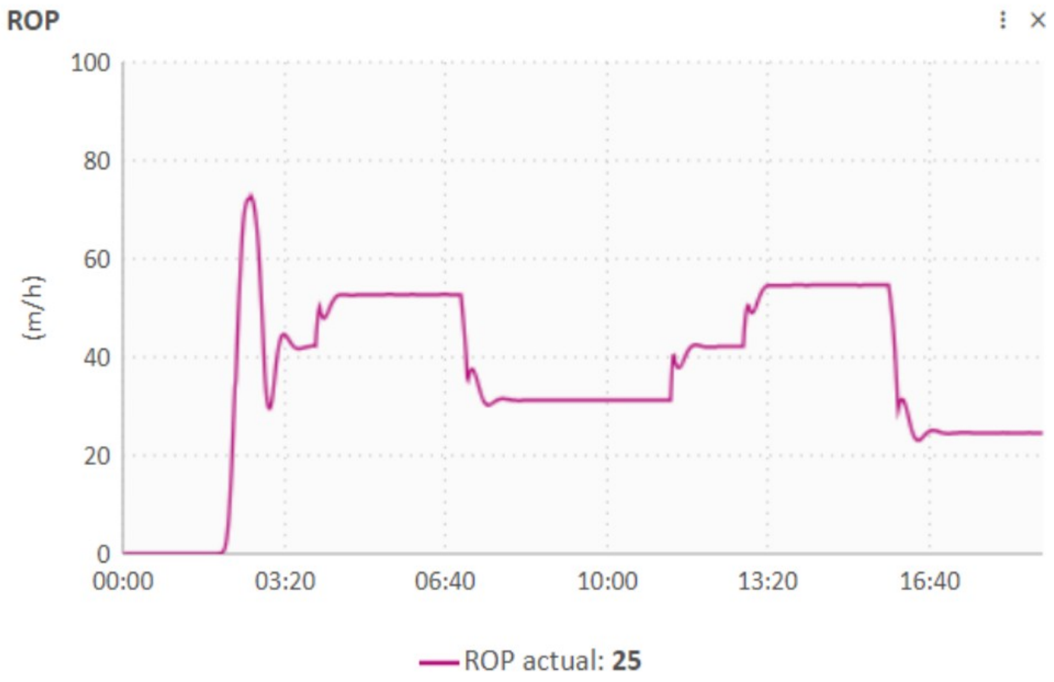
Completed simulation ×

EXPORT IMPORT DELETE

Time (hh:mm:ss)	Flow rate (l/min)	Velocity (m/s)	Auto driller	WOB (ton)	ROP (m/h)	RPM (rpm)	MPD control mode	Choke opn. (%)	MPD ref. (bar)	Choke flow rate (l/min)	BOP	Active pit	Return pit	Control active pit	Active pit density (s.g.)	Active pit temp. (°C)
00:00:01	1174	0.1	ROP	NA	0	100		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:02:00	1174	0.1	WOB	8	NA	60		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:04:00	1174	0.1	WOB	8	NA	90		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:07:00	1174	0.1	WOB	8	NA	40		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:11:20	1174	0.1	WOB	8	NA	60		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:12:50	1174	0.1	WOB	8	NA	100		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:15:50	1174	0.1	WOB	8	NA	30		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA

Finish time 00:00:00




ROP
100
80
60
40
20
0
(m/h)
00:00
03:20
06:40
10:00
13:20
16:40
ROP actual: **25**


WOB
14
12
10
8
6
4
2
0
(ton)
00:00
03:20
06:40
10:00
13:20
16:40
WOB actual: **8**

2. Dynamic Phase Simulation Results

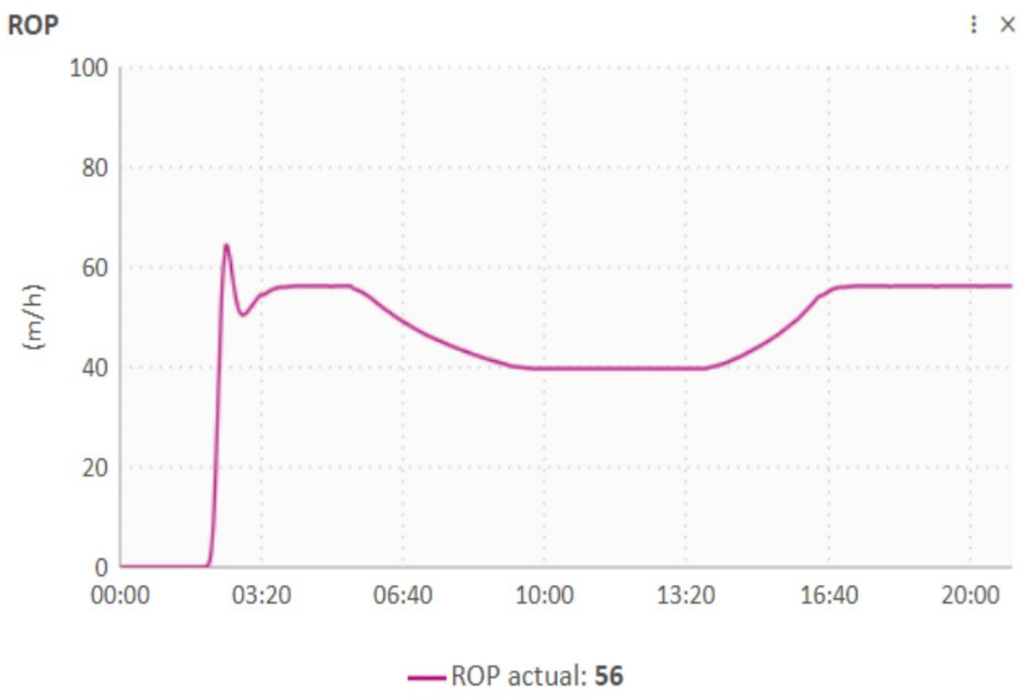
2.1 Control Phase

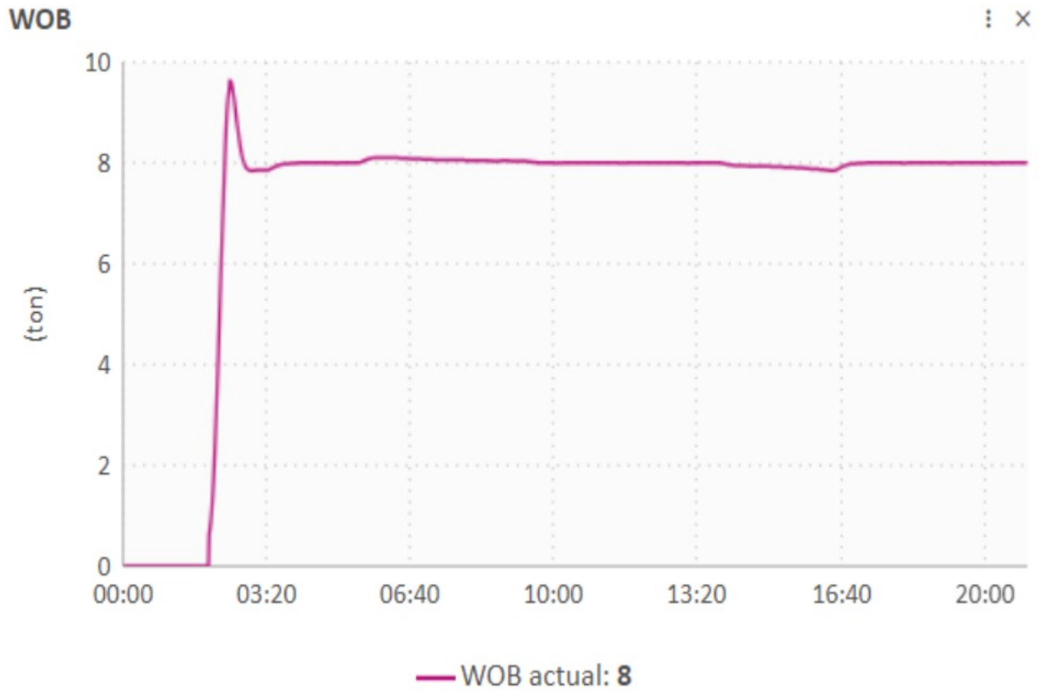
Completed simulation

EXPORT IMPORT DELETE

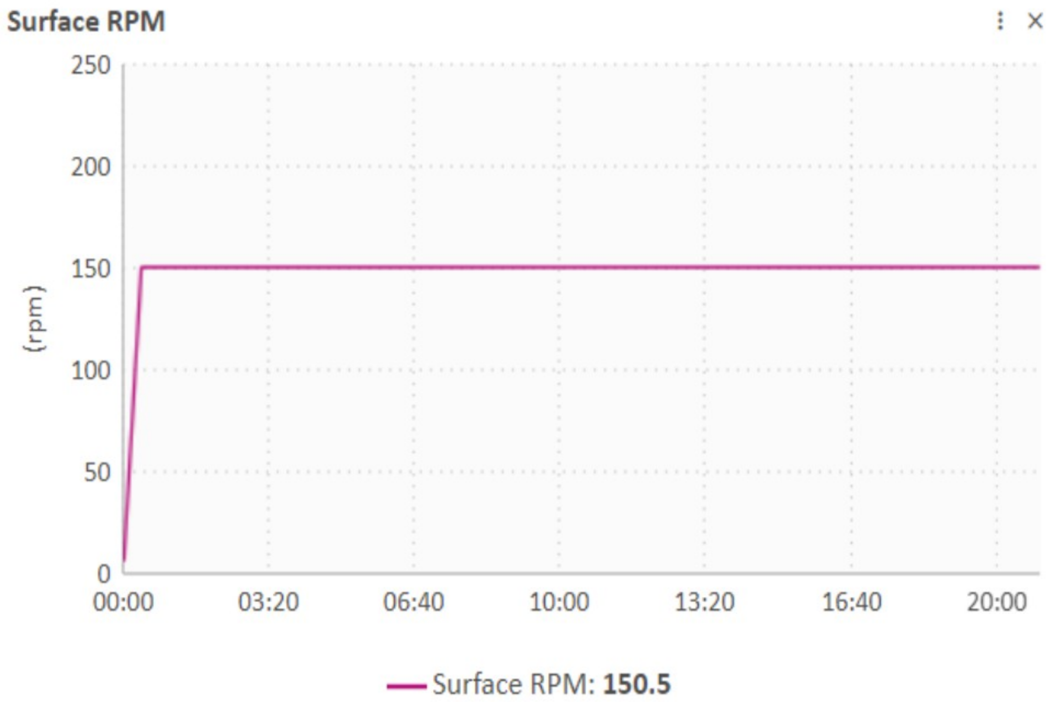
Time (hh:mm:ss)	Flow rate (l/min)	Velocity (m/s)	Auto driller	WOB (ton)	ROP (m/h)	RPM (rpm)	MPD control mode	Choke opn. (%)	MPD ref. (bar)	Choke flow rate (l/min)	BOP	Active pit	Return pit	Control active pit	Active pit density (s.g.)	Active pit temp. (°C)
00:00:01	1174	0.1	ROP	NA	0	105.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:02:00	1174	0.1	WOB	8	NA	105.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA

Finish time 00:07:30





WOB
10
8
6
4
2
0
(ton)
00:00
03:20
06:40
10:00
13:20
16:40
20:00
WOB actual: 8



Surface RPM
250
200
150
100
50
0
(rpm)
00:00
03:20
06:40
10:00
13:20
16:40
20:00
Surface RPM: 150.5

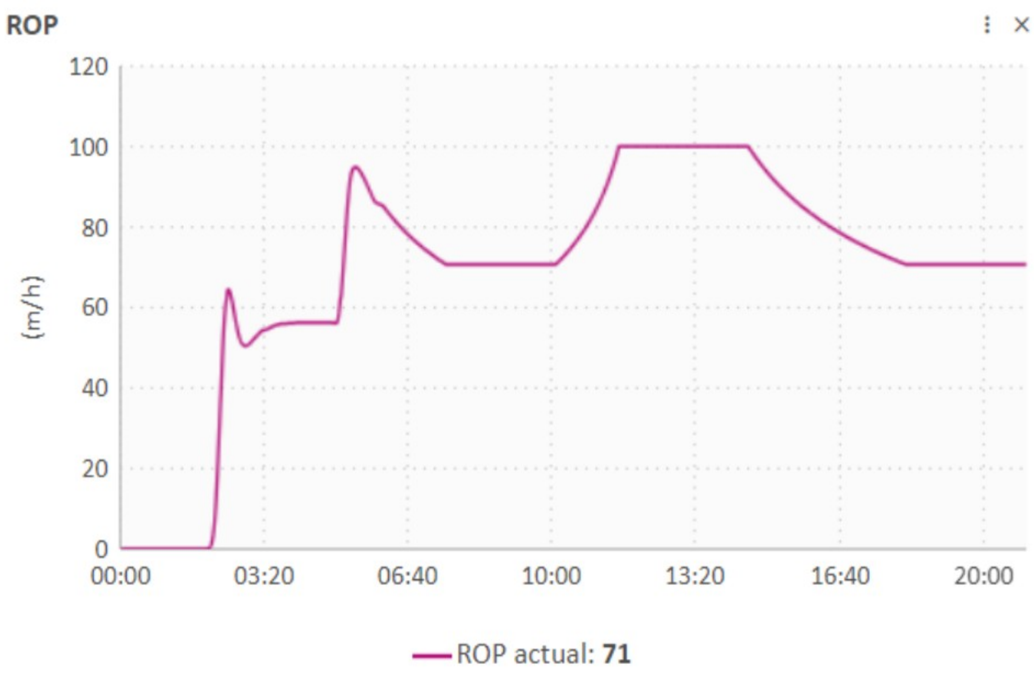
2.2 ROP Optimization Phase

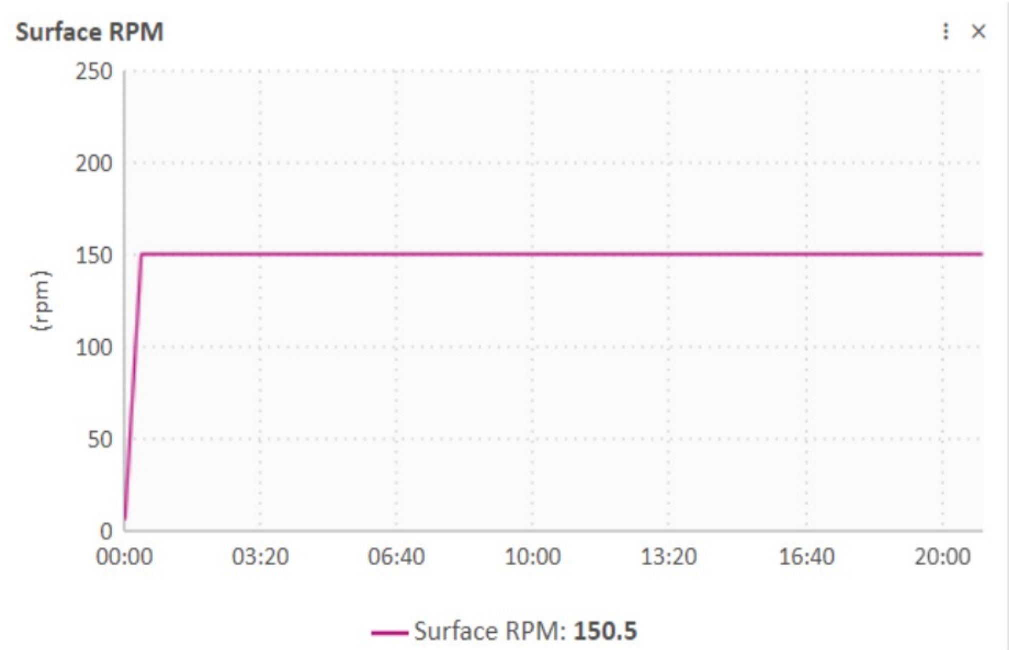
Completed simulation ×

EXPORT IMPORT DELETE

Time (hh:mm:ss)	Flow rate (l/min)	Velocity (m/s)	Auto driller	WOB (ton)	ROP (m/h)	RPM (rpm)	MPD control mode	Choke opn. (%)	MPD ref. (bar)	Choke flow rate (l/min)	BOP	Active pit	Return pit	Control active pit	Active pit density (s.g.)	Active pit temp. (°C)
00:00:01	1174	0.1	ROP	NA	0	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:02:00	1174	0.1	WOB	8	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:05:02	1174	0.1	WOB	12.6	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:05:52	1174	0.1	WOB	14.4	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:06:02	1174	0.1	WOB	16.2	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:06:22	1174	0.1	WOB	18	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:06:32	1174	0.1	WOB	19.8	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:14:52	1174	0.1	WOB	21.6	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA
00:15:02	1174	0.1	WOB	23.4	NA	150.5		NA	-	0	OPEN	MAIN	MAIN	OFF	NA	NA

Finish time 00:21:00




Surface RPM
250
200
150
100
50
0
(rpm)
00:00
03:20
06:40
10:00
13:20
16:40
20:00
Surface RPM: 150.5


WOB
30
25
20
15
10
5
0
(ton)
00:00
03:20
06:40
10:00
13:20
16:40
20:00
WOB actual: 23.4

3. Real-Time Dynamic Trend Analysis Tool

Contact the Author for the MATLAB script.