MICRO-TESTING WHILE DRILLING FOR RATE OF PENETRATION OPTIMIZATION

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ABSTRACT

The Rate of Penetration (ROP) is one of the key parameters related to the efficiency of the drilling process. Within the confines of operational limits, the drilling parameters affecting the ROP should be optimized to drill more efficiently and safely, to reduce the overall cost of constructing the well. In this study, a data-driven optimization method called Extremum Seeking is employed to automatically find and maintain the optimal Weight on Bit (WOB) which maximizes the ROP. To avoid violation of constraints, the algorithm is adjusted with a combination of a predictive and a reactive approach. This method of constraint handling is demonstrated for a maximal limit imposed on the surface torque, but the method is generic and can be applied on various drilling parameters. The proposed optimization scheme has been tested on a high-fidelity drilling simulator. The simulated scenarios show the method's ability to steer the system to the optimum and to handle constraints and noisy data.

Keywords: Data-Driven, ROP, Drilling Optimization, Micro-Testing, Constraint Handling, Extremum Seeking

INTRODUCTION

A substantial part of offshore field development costs originates from drilling, with most of these costs being related to time. There is a great potential for cost reduction by drilling safer, faster and with less non-productive time, which is why drilling optimization has been the subject of research for more than six decades, a process which has been traced by Eren and Ozbayoglu [1]. Methods used for real-time drilling optimization often focus on tuning physics-based models of the drilling process to fit available data from current or offset operations. The tuned models are used to predict how the drilling process will react to different values of the controllable parameters such as WOB, drill string rotational speed (RPM) and flow rate. Based on this prediction, the models can be used to provide estimates of the optimal drilling parameters, which can be supplied to the driller as suggestions or directly fed to the control system on the rig in a closed loop [1-5]. Field tests of an ROP optimization algorithm using physics-based models have shown good results, with the largest increases in ROP obtained when the algorithm was run in closed loop [2,3] and a reduction in downhole tool failures when applying the optimization algorithm [3].

A potential drawback to real-time optimization with the physics-based models is that the analysis is based on a mathematical description of the drilling process, and the existing models might not be very accurate in predicting the ROP [5,6]. A possible remedy for model inaccuracies could be the use of data-driven modelling techniques, or a hybrid between data-driven and physics-based modelling methods. The latter approach was applied by Spencer et al. [7] in a study on how to automatically minimize Mechanical Specific Energy (MSE) when drilling through layered materials with a lab-scale rig. A physics-based drilling model was used to find an initial estimate of the optimal WOB. A data-driven algorithm was subsequently utilized while drilling to search the neighborhood of the initial estimate for WOB values which could further reduce the MSE. Hegde et al. [8] found that a data-driven model gave better ROP predictions compared to physics-based models when both approaches were using the same input parameters. The selection of which type of data-driven model that can be used for real-time optimization is a tradeoff between runtime and performance where more advanced models will give more accurate ROP predictions but suffer from longer computational time and vice versa [9]. A recent study investigated the application of a data-driven optimization strategy with low computational cost called Extremum Seeking (ES) to maximize the ROP [10]. Using simulated data, it was shown that ES can identify the WOB

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which maximizes the ROP and automatically steer the WOB to this optimal value in an unconstrained environment.

The drilling process is subject to a multitude of operational constraints which affect the safe operational space of the input parameters. Chapman et al. [3] gives a detailed list of factors that could directly limit the application of the controllable parameters such as a maximal WOB and RPM dictated by the drilling equipment, as well as listing more indirect factors related to torque, vibrations and hole cleaning which will limit certain combinations of input parameters. Dunlop et al. [2] further describe the implementation of these constraints for real-time drilling optimization. Factors limiting the amount of energy that can be applied to the drilling process through the controllable input parameters and factors which diminish the efficiency of the energy transferal between input parameters and ROP have also been investigated [11,12]. A solution for constraint handling in data-driven modelling is to limit the data used as the training set to values that do not violate constraints and not allowing the model to extrapolate results outside of this region [9].

The data used to tune or train the models used for real-time optimization, both physics-based and data-driven, needs to be representative of the current drilling conditions (e.g. from the same formation) to yield more accurate predictions [1,8]. A changepoint algorithm which determines what historical data is relevant for the task of ROP modelling and optimization has been implemented [2]. Using a sliding window of data containing a fixed amount of the most recent measurements to tune a physics-based drilling model has also been suggested [4,5]. In addition to using representative data, the models need a varied sample of input (e.g. WOB and RPM) and output parameters (e.g. ROP) within this dataset to generate a representative data-driven model [9] or to tune the parameters in a physics-based model. A drilling advisory system which suggests changes in input parameters to the driller for the purpose of exploring the parameter space and identifying the operational point which minimizes the MSE has been field tested with good results [13].

Extremum seeking has previously been implemented successfully in a variety of engineering systems ranging from yield optimization in bioprocesses to jet engine stability control and many others [14], as well as in the petroleum industry for gas lift [15,16] and has been investigated for the purpose of drilling optimization [10]. The ES algorithm is a gradient ascent (or descent) method which requires a process with well-defined steady-state characteristics, so that for a given constant input, the system settles to a constant output within a reasonable time. It also needs the existence of a unique extremum in the output which corresponds to some value in the input variable(s) within the operational envelope. A more thorough review of these conditions and convergence criteria can be found in Tan et al. [14] or Ariur and Krstić [17]. When the system conditions are satisfied, the ES algorithm will automatically seek and maintain the value of the optimal input variable(s), without knowing the details of the relationship between the system's input and output.

The method we employ in this study is an ES algorithm that searches for the WOB which optimizes the ROP by use of real-time drilling data. While drilling ahead, the ES algorithm prescribes a continuous series of micro-tests by sending commands for variations in the WOB to the autodriller. The micro-tests are performed by periodically varying the input WOB around some base value to gather information about the current drilling conditions, and the data generated from this procedure is the training data used by the ES algorithm. The magnitude and frequency of the WOB variations are determined before the start of drilling and should be designed to induce a measurable change in the ROP, without interfering much with the overall drilling process. The algorithm relates the changes in the output ROP to the corresponding variations in the input WOB and uses this information to estimate the gradient of the output in the local region which has been investigated by the micro-test procedure. A sliding window of recent data is used to estimate the current gradient by means of linear least-squares regression. The gradient is automatically used to determine the direction and magnitude in which the WOB base value should be changed to increase the ROP by providing the autodriller with updated setpoints for the WOB. By continuously repeating this procedure, the ES algorithm can navigate the system to its optimal point and keep the process at its optimum by continuing to probe for changes in the system conditions.

Hegde, Wallace and Gray [18] found that regression modelling methods gave acceptable ROP prediction, but the accuracy of the prediction suffers from the nonlinearity between the ROP and the regressors, among others the WOB. The gradient estimated by the ES algorithm is based on a relatively small region defined by the extent of the most recent variations in the WOB. In this local region the accuracy of a linear approximation of the nonlinear relationship between the ROP and the WOB will suffer less than when one considers a wider range of ROP and WOB values.

We focus in this study on the practical aspects related to using ES for drilling optimization. The ES algorithm is automatically making changes to the applied WOB to maximize the ROP. To ensure that the algorithm does not steer the WOB to values which will result in e.g. the torque exceeding its maximal limit, a combination of a predictive and a reactive constraint handling technique is proposed. The constraint handling is based on real-time measurements while drilling and is demonstrated for a maximal limit imposed on the surface torque, but the method is generic and can be applied on various drilling parameters. The proposed optimization scheme is able to handle the process and measurement noise inherent to the drilling process, which can have a strong effect on the algorithm performance. Compared to the classical filter-based ES scheme (see e.g. Aarsnes, Aamo and Krstić [10]), the proposed method is also adjusted to ensure easier tuning of the system by using a least-squares method to estimate the gradient, which reduces the number of tuning parameters in the algorithm.

The paper is organized in the following way: first, the background of the problem is given, before the ES algorithm is described. Then, a control strategy for handling drilling constraints is detailed, followed by a section containing details on instantaneous ROP estimation. The last two sections contain simulation results and conclusions.

BACKGROUND

Drilling is a complicated process with a multitude of factors affecting the ROP, such as personnel and rig efficiency, formation characteristics, mechanical and hydraulic factors, and drilling fluid properties [4]. These many and often interconnected effects make accurate modelling of the process in real-time a complex task, because many of the parameters needed to correctly model the situation are not measured directly and will change over time. However, the general mechanics of the interaction between the bit and formation are well understood [19]. The instantaneous ROP can be described by

$$ROP = f(WOB, \boldsymbol{r}), \tag{1}$$

where $\boldsymbol{r}$ is a vector containing all parameters other than the WOB which affect the ROP, such as RPM, flow rate, bit condition, bottomhole pressure and formation properties. The nonlinear function f which governs the relationship between the WOB, $\boldsymbol{r}$ and the ROP is not known explicitly, but for any set of values for the parameters contained in $\boldsymbol{r}$ it is assumed that f as a function of WOB inhibits several characteristic drilling regimes. Figure 1 shows a nominal relationship between the ROP and the applied WOB, where it is assumed that the values of the parameters in $\boldsymbol{r}$ are constant. The ROP-WOB relationship is characterized by three distinct phases: 1) Inefficient drilling caused by low WOB, where the depth of cut is inadequate, 2) efficient drilling where all added WOB is transferred to cutting action at the bit in a straight-line fashion, and 3) inefficient drilling caused by founder [11,19]. The locations of the different phases in the ROP-WOB relationship are subject to change as parameters in the vector $\boldsymbol{r}$ vary, but the general shape of the three regions is expected to remain. A change in formation properties or an increase in RPM could alter the WOB at which foundering occurs, but WOB lower than the foundering value would still correspond to efficient drilling and values above founder would constitute inefficient drilling. The shape of the third region depends on what type of inefficiency is causing it, which could be excessive vibrations or inadequate cleaning at the bit. Depending on the cause of founder, its onset could be delayed by manipulation of combinations of drilling parameters or reengineering of the system [11,12], but these approaches are beyond the scope of this paper.

The transition between the last two regions in Figure 1 is referred to as the founder point, and it is drilling at WOB which corresponds to this point or slightly below that is mainly desired. In this way, the possibly detrimental effects causing the founder as well as the bit wear resulting from a large increase in WOB for a small increase in ROP can be avoided. A convenient way of approaching this situation is to try and maximize not the ROP itself, but a performance function on the form

$$J = ROP - \mu WOB, \tag{2}$$

where μ is a tuning parameter which penalizes the use of excessive WOB [10]. As the ES optimization scheme outlined in the next section is driven by an estimated gradient of J with respect to the WOB, the algorithm seeks the optimum given by

$$\frac{\partial J}{\partial WOB} = \frac{\partial ROP}{\partial WOB} - \mu = 0. \tag{3}$$

From equation (3), the physical meaning of μ can be interpreted as a limiting value at which the ROP gradient is deemed too low to want to further change the WOB, even though the maximal ROP is not yet achieved. A larger value for μ will therefore correspond to a more conservative estimate of what the optimal operating point is.

In practice, the drilling process is subject to constraints which might limit how much WOB can be applied, so that drilling at the founder point may not be feasible. A multitude of constraints like this have been identified by Dupriest and Koederitz [11] and Chapman et al. [3], such as available BHA weight, solids handling capacity and top drive torque rating. A method of avoiding violation of limitations while searching for the founder point is outlined in the constraints handling section.

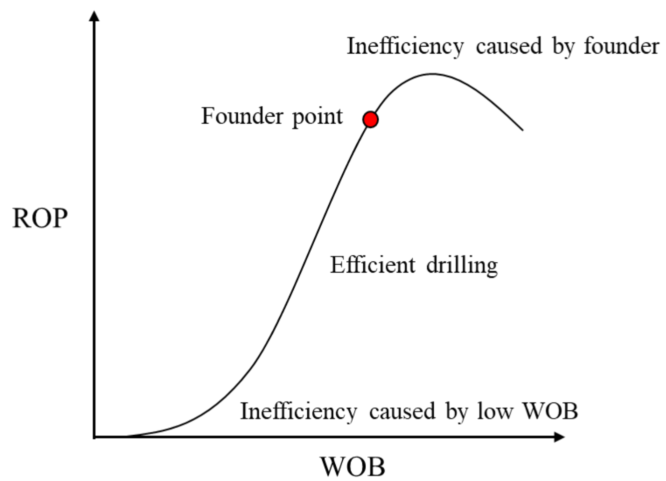

FIGURE 1: NOMINAL RELATIONSHIP BETWEEN ROP AND WOB, MODIFIED FROM DUPRIEST AND KOEDERITZ [11].

EXTREMUM SEEKING FOR ROP OPTIMIZATION

The variables that the driller or an algorithm can readily control from the rig floor to affect the ROP are the WOB, the RPM and the flow rate. In this paper, we consider the case of optimizing the ROP by means of controlling the WOB in a constrained ES approach, with constant RPM and flow rate. The method is illustrated in Figure 2, where a continuous excitation signal is applied to the WOB to investigate the steady-state characteristics of an output performance function defined by equation (2). Under the assumption that the ROP-WOB relationship is subject to the different drilling regimes outlined in the Background section, the drilling process has a unique optimal WOB at which foundering starts to occur and is well suited for optimization with ES.

Although drilling is a continuous process, the sampled measurements and the commands given to the control system on the rig are performed in discrete time. This motivates the notation used here: t is the current time, Δt is the time interval between both measurements of drilling parameters and updated setpoints provided to the autodriller (here assumed to be the same), so that $t + \Delta t$ signifies a value for the coming timestep.

The ES algorithm can be divided into three main components: 1) The excitation signal, which introduces a variation in the input of the system, 2) the gradient estimator, used to quantify how the system reacts to the excitation, and 3) the optimizer, which changes the input WOB based on the estimated gradient. These components are described in detail in the following sections.

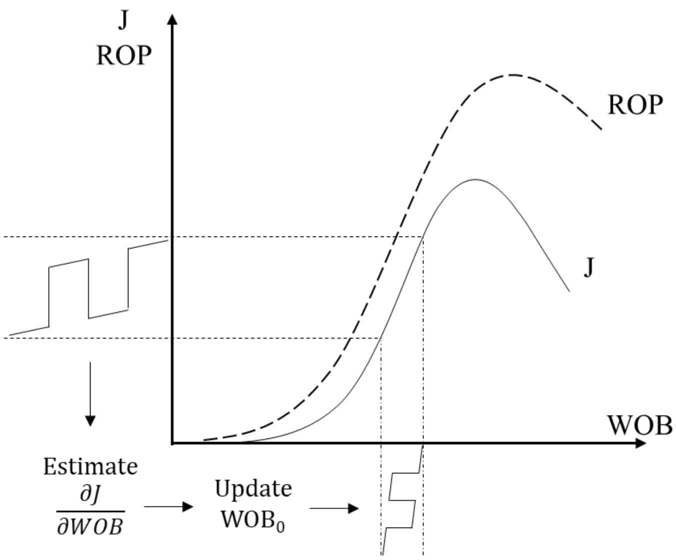

FIGURE 2: CONCEPT ILLUSTRATUION OF EXTREMUM SEEKING APPLIED TO DRILLING.

The Excitation Signal

Some best estimate of the optimal input value, WOB_0, is initially applied to the system. This estimate could be based on calculations from an available drilling model or experience from a similar offset well. While drilling ahead, the ES algorithm continuously explores the neighborhood of WOB_0 and how the system responds to small variations in the WOB by conducting a series of micro-tests. This is done by automatically varying the WOB-setpoint provided to the autodriller according to

$$WOB(t) = WOB_0(t) + d(t, A, P). \qquad (4)$$

The last term in equation (4) is the excitation signal, which for any integer, n, is given by

$$d(t, A, P) = \begin{cases} A & t \in \left[nP, \left(n + \frac{1}{2}\right)P\right\rangle \\ -A & t \in \left[\left(n + \frac{1}{2}\right)P, (n+1)P\right\rangle \end{cases}. \qquad (5)$$

This signal is a square wave with an amplitude of A kg and a period of P seconds, which oscillates symmetrically about WOB_0. For each period, the magnitude of A approximately determines the extent of the WOB-interval which is being investigated by the algorithm. A should be small enough to not detrimentally affect the overall drilling process, but at the same time be large enough to elicit a measurable change in the ROP which can be used for gradient estimation. The period of the excitation signal determines the amount of historical data used to estimate the gradient of the performance function and needs to be tuned accordingly. The parameter P should be designed large enough to generate a dataset that contains enough information so that it can be used for gradient estimation, while at the same time considering that a very large value for P will result in a lot of previous drilling data (which might no longer be representative of the current drilling conditions) being used for gradient estimation.

Gradient Estimation

The applied WOB and the resulting values of J calculated from equation (2) are stored in a buffer containing P seconds of history for these two parameters, denoted by WOB_B and J_B. At each update of measurements, the past values of $J(t)$ and WOB(t) stored in the buffer are used to solve the 1st-order least-squares problem given by

$$\min_{a,b} \sum_{i=0}^{P-1} \left(J_B(t - i\Delta t) - (aWOB_B(t - i\Delta t) + b)\right)^2, \qquad (6)$$

where a and b are the slope and intercept of the least-squares fit, respectively. These two parameters represent a linear approximation to how J has changed with the varying WOB for the past P seconds. The slope parameter a is used as an estimate of the gradient of the performance function at the current timestep,

$$\frac{\partial J}{\partial WOB}(\mathrm{t}) \approx a(t). \qquad (7)$$

In this way, a sliding window of data corresponding to one full period of the excitation signal is used to estimate the current gradient of J. On average, this estimate corresponds to the formation which was drilled $P/2$ seconds earlier, as this is the center of the sliding window. The excitation signal is symmetric about the slowly varying WOB_0, so that equation (7) represents a gradient evaluated approximately at WOB_0.

This technique of gradient estimation is a variant of the method proposed by Hunnekens et al. [20], where least-squares estimation was used in an ES algorithm without an excitation signal. This way of calculating the gradient is robust with respect to noise and sensor bias, since much of the noise is filtered out over the least-squares window, and any sensor bias is captured by the b-parameter, which is not used by the algorithm. In addition to this, the method is easier to apply than the classical filter-based ES approach. This is because the least-squares gradient estimation does not require any tuning apart from determining the amplitude and period of the excitation signal, while the classical ES approach needs to tune both the excitation signal parameters and the filters to obtain an estimated gradient.

Optimizer

From Figure 2 it can be seen that the performance function has a positive slope when drilling with a WOB to the left of the maximal value of *J*, and a negative slope for WOB values beyond this point. The gradient obtained from equations (6) and (7) can thus be used to determine how the WOB should be altered to increase the performance function, *J*. This is done by calculating an updated WOB_0 value for the coming timestep from

$$WOB_0(t+\Delta t) = WOB_0(t) + \gamma \frac{\partial J}{\partial WOB}(t)\Delta t, \qquad (8)$$

which will move the drilling system to a slightly higher value of *J*. The parameter γ is a gain which determines the *learning dynamics* of the algorithm. That is, how fast the ES scheme should vary WOB_0 as a response to the estimated gradient of *J*. The new WOB_0 value calculated from equation (8) is used to update the WOB which will be sent to the autodriller in the next timestep, as dictated by equation (4) evaluated at $t + \Delta t$. The algorithm will subsequently repeat the process of estimating a new gradient based on new measurements and adapting to the newest information. It is worth noting that this update takes place at each timestep, with γ tuned so that WOB_0 varies slowly compared to the variations in WOB caused by the excitation signal. In the constrained case, the WOB_0 value requested by the algorithm is calculated from equation (14).

A block diagram of the described optimization structure is shown in Figure 3. Each timestep constitutes a loop through this diagram, where the algorithm will vary the WOB according to equation (4), record and quantify the system response with equations (6) and (7) and use this information in equation (8) to update the WOB which should be applied to initiate a new iteration of the algorithm.

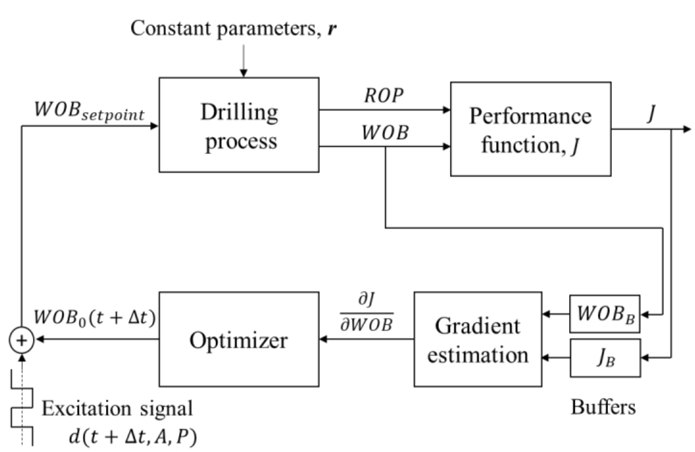

FIGURE 3: ES SCHEME FOR UNCONSTRAINED DRILLING OPTIMIZATION.

ROP OPTIMIZATION WITH CONSTRAINT HANDLING

The optimization algorithm proposed in the previous section will be able to steer the drilling system to the optimum dictated by the performance function. In practice, operating at this point might not be feasible. Some reasons for this could be that the required WOB might exceed the available BHA weight or allowable WOB, there could be a maximal ROP limit related to cuttings transport or handling of cuttings at the surface, or the torque generated at the bit or at the surface could exceed the allowable values. Two methods for making the ES algorithm avoid violation of this type of constraints while searching for the optimum is presented below. The methods are illustrated for a maximal limit imposed on the surface torque, but the techniques are generic and could also be used on other limiting parameters.

Predictive Constraint Handling

The changes in the drilling process caused by varying the WOB can be a good source of information about the current system conditions and how other drilling parameters are affected by the WOB. The same methodology as was used to extract an estimate of the gradient of *J* in equations (6) and (7) is also able to estimate gradients of other drilling parameters and how they vary with the changing WOB. By storing measured values of the surface torque in an additional buffer, T_B, containing *P* seconds of data, the gradient of the surface torque can be calculated from

$$\min_{\alpha,\beta} \sum_{i=0}^{P-1} \left(T_B(t-i\Delta t) - (\alpha WOB_B(t-i\Delta t)+\beta)\right)^2, \qquad (9)$$

$$\frac{\partial T}{\partial WOB}(\mathrm{t}) \approx \alpha(t). \qquad (10)$$

The parameters α and β are the slope and intercept of the least-squares fit, respectively. The gradient estimate given by equations (9) and (10) can be used to predict how the surface torque will react to further changes in the WOB, and how to avoid violation of constraints based on this information.

The recorded surface torque is often plagued by noise, both from inaccurate measurements and process noise in the form of drillstring vibrations. Because of this, there is some uncertainty as to what the value of the surface torque is. To remedy this issue, the average value of the torque buffer, $T_{B,avg}$, is taken as the surface torque, which approximates the torque experienced by the system when drilling with a weight on bit of WOB_0. This averaging will reduce the amount of noise in the torque value used by the algorithm, but it will also introduce a time delay in the averaged torque value corresponding to half of the averaged period, the same delay that is inherently present in the gradient calculated in equations (9) and (10).

To avoid the WOB being steered to values which cause a violation of the allowable torque, T_{limit}, the gain parameter γ in equation (8) is calculated as

$$\gamma = \begin{cases} \gamma\,, & \left(T_{B,avg} + A\dfrac{\partial T}{\partial WOB}(t)SF\right) < T_{limit} \\ 0\,, & \left(T_{B,avg} + A\dfrac{\partial T}{\partial WOB}(t)SF\right) \geq T_{limit} \end{cases}, \qquad (11)$$

where SF is a safety factor greater than 1. Because the algorithm varies the weight on bit about WOB_0 with a magnitude of A kg, equation (11) will stop the optimizer from exceeding the torque limit with a margin dictated by the SF parameter. This method also allows the excitation signal to continue the micro-testing for changes in the drilling conditions, even when the torque is close to the highest allowable value. The value for T_{limit} used in equation (11) should be lower than the maximal limit the drilling system can handle, as an added safety measure.

Reactive Constraint Handling

In some instances, the predictive constraint handling detailed in equation (11) might not be enough to ensure that the torque stays within the allowable boundaries. This could be caused by either very noisy measurements which makes the calculated torque gradient inaccurate, or abrupt changes in drilling conditions, such as a formation change, which alters the torque in a short span of time. To ensure safe operations, a reactive constraint handling technique is implemented using a variable which is equal to zero if the constraint is not violated and proportional to the violation if the torque limit is exceeded,

$$e(t) = \begin{cases} 0\,, & T_{avg} < T_{limit} \\ T_{avg}(t) - T_{limit}\,, & T_{avg} \geq T_{limit} \end{cases}. \qquad (12)$$

T_{avg} is an average value spanning a few seconds of the most recent torque measurements, e.g. 5 seconds, to remove some of the measurement noise while still being representative of the current torque. This average parameter is introduced so that the constraint handling routine will not react to very short-term spikes in the measured surface torque. The value for T_{limit} should be lower than the actual system limit, because the reactive constraint handling will only start to affect the system when T_{avg} is larger than T_{limit}. The variable e from equation (12) is used to calculate a penalty variable, λ, by use of a discrete PI controller,

$$\lambda(t) = K_P e(t) + K_I \sum_{i=0}^{t} e(i)\Delta t. \qquad (13)$$

K_P and K_I are the proportional and integral gains, respectively, which are the tuning parameters that determine how aggressively the controller should penalize torque values above the limit. The penalty term calculated from equation (13) is used to reduce the weight on bit demanded by the ES algorithm according to

$$WOB_{0,constrained}(t + \Delta t) = WOB_0(t + \Delta t) - \lambda(t). \qquad (14)$$

The parameter $WOB_{0,constrained}$ is used in equation (4) to calculate the constrained WOB setpoint which is sent to the autodriller. The first term on the right-hand side of equation (14) is the unconstrained WOB_0 value found by the optimizer, equation (8), which is calculated independently of the reactive constraint handling. If the torque limit has not been violated, λ will be equal to zero and the constrained WOB_0 value will be equal to the WOB_0 found by the optimizer. If the torque limit is exceeded, the WOB demanded by the ES algorithm will be reduced until the torque is again below its limiting value, at which point λ will retain a value determined by the summation term in equation (13). How fast the reduction in WOB takes place once the constraint is violated is controlled by the gain parameters K_P and K_I in equation (13). They should be large enough to ensure that the penalty variable, λ, reduces the requested WOB faster than the adaptation gain, γ, is able to demand increases in the WOB.

PRACTICAL CONSIDERATIONS

Instantaneous ROP Estimation

The proposed optimization algorithm relies heavily on causing a change in the ROP by varying the WOB and being able to quantify this change. The ROP is not a directly measured parameter, but rather calculated as a derivative of the position of the travelling block or other surface equipment, possibly with a model to account for the elasticity of the drill string. This differentiation procedure will amplify any inaccuracies in the measured block position, making the calculated ROP imprecise. These inaccuracies could be caused by measurement noise, rig heave or unaccounted for elongation and shortening of the drilling line when the hook position is estimated from the drawworks. A common way of dealing with this issue is to use ROP values averaged over a certain time or depth increment, which will reduce the inaccuracy but cause a time-delay in the estimated ROP.

In this paper, the instantaneous ROP is approximated as the velocity of the travelling block. This is done by means of a Kalman Filter (KF), which is designed to account for process and measurement noise to yield a better ROP estimate. The KF is based on a linear state-space model which describes the relationship between the block position, h_{block}, and its derivative, the ROP, in consistent units as

$$\begin{bmatrix} h_{block} \\ ROP \end{bmatrix}(t + \Delta t) = \begin{bmatrix} 1 & -\Delta t \\ 0 & 1 \end{bmatrix}\begin{bmatrix} h_{block} \\ ROP \end{bmatrix}(t) + w(t). \qquad (15)$$

The last term in equation (15) is the process noise, which represents any forces which affects the ROP and makes it non-constant, which in turn will affect the hook position. This could be a change in drilling conditions or variations in the input WOB, RPM or flow rate. The measurement of the block position is described by

$$y(t) = \begin{bmatrix} 1 & 0 \end{bmatrix}\begin{bmatrix} h_{block} \\ ROP \end{bmatrix}(t) + v(t). \qquad (16)$$

In equation (16), y represents the measured block position, which is made inaccurate by the measurement noise, v.

The KF uses a combination of the h_{block} and ROP predicted by equation (15) and the measured y from equation (16) to yield an estimate of what the true ROP is. This combination is done based on how much noise is affecting equations (15) and (16), where the KF will trust the ROP from equation (15) more if there is a lot of measurement noise compared to process noise, and vice versa. The values of v and w at any given time are not known by the filter, but some assumptions are made about them. The KF assumes that the disturbances are normally distributed variables which continuously affect the system, and that their distribution is described by

$$w \sim N(0, Q), \qquad Q = \begin{bmatrix} \frac{(\Delta t)^4}{4} & \frac{(\Delta t)^3}{2} \\ \frac{(\Delta t)^3}{2} & (\Delta t)^2 \end{bmatrix} \sigma_p^2, \qquad (17)$$

$$v \sim N(0, R), \qquad R = \sigma_m^2. \qquad (18)$$

In equations (17) and (18), Q and R are the covariance matrices of the process and measurement noise, respectively. The parameter σ_m is the standard deviation of the measurement noise and is presumed known from the specifications of the applied sensor or measurement technique. The standard deviation of the process noise, σ_m, is then the only unknown factor in equations (15) - (18) and is used as a tuning parameter for the KF. It should be noted that equations (15) and (17) can be derived from the 1st and 2nd equations of motion, where w captures the effect of a normally distributed acceleration affecting the system.

In practice, it is not expected that the process noise affecting the drilling rate and hook position is normally distributed and continuously affecting the system, as is assumed in equation (17). It is more likely that this noise is displayed as more discrete variations in the system caused by changing drilling conditions and the fluctuating WOB. Despite this, the Kalman filter will still be able to provide good estimates of the instantaneous ROP when properly tuned. A block diagram of the complete ES scheme with constraint handling and ROP estimation is shown in Figure 4.

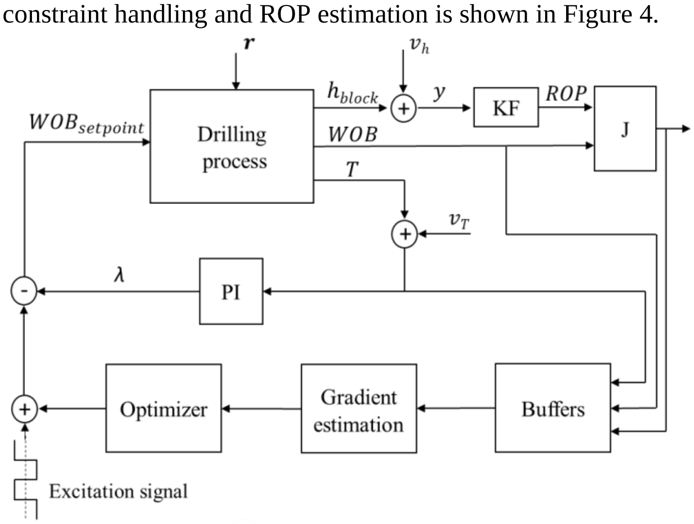

FIGURE 4: ES SCHEME FOR CONSTRAINED DRILLING OPTIMIZATION.

SIMULATION RESULTS

Drilling Simulator

The simulator used to study the proposed optimization technique is OpenLab, a high-fidelity drilling simulator developed by the Norwegian Research Centre (NORCE) in collaboration with the University of Stavanger. The simulator consists of a set of integrated numerical models covering different aspects of the drilling process, including torque and drag effects, cuttings transport, multi-phase flow and heat transfer [21]. The models on the OpenLab platform are run by supplying the simulator with setpoints for input variables, which the simulator translates to actions on the drill-floor with built-in functions which limits the allowable rate of changes according to equipment specifications [22].

To simulate the effects of measurement noise, an option to add white gaussian noise to the surface torque and block position was included in the system. These sources of noise are denoted by v_T and v_h, respectively, and can be seen in Figure 4. The noise parameters used in the simulations have been taken to match the noise from logged drilling operations.

Simulation Results

A series of simulations have been performed in OpenLab to investigate the applicability of the proposed optimization scheme. The simulations detailed here are all carried out in the 8.5" section of a vertical well, with drilling commencing at a depth of 2500 meters through a homogeneous formation. The system is set up to start the drilling of each new stand at an initial constant value of WOB for three minutes, followed by a full oscillation period of the excitation signal to estimate an initial gradient of J, before the ES algorithm starts the WOB-adaptation according to equation (14). Both RPM and flow rate are held constant throughout the runs, except when ramping up and down for connections every 27 meters. Parameters common for all the simulated scenarios are listed in Table 1. The value for μ used in the simulations signify that the optimum determined by J is reached when the ROP increases less than 5 m/hr for a 1000 kg increase in WOB. The simulations are all initiated at a conservative WOB value of 2000 kg, at which the ROP is 23 m/hr. The optimum point sought by the ES algorithm is found at 4700 kg of WOB and corresponds to a drilling speed of 43 m/hr, meaning that there is a potential increase in the ROP of 20 m/hr by drilling at the optimum WOB value.

TABLE 1: PARAMETERS COMMON FOR ALL SIMULATIONS.

Parameter	*Value*	*Unit*
A	200	kg
P	240	s
μ	0.005	m/hr/kg
Δt	1	s
K_p	0.5	kg/Nm
K_i	0.25	kg/Nm
SF	3	-
RPM	150	rpm
Q	2000	lpm
$WOB_0(t = 0)$	2000	kg

Simulations Without Measurement Noise

This section covers two simulated scenarios where three stands are drilled. The gain parameter γ in equation (8) is here set to a value of 400 $kg^2 \cdot hr/m/s$. No noise is added to the measurements, and the ROP used is the actual drilling rate reported by the simulator. The two simulation conditions are identical, with the exception of a limiting value for the surface torque of 5000 Nm which is imposed on the system in the second run. Figure 5 shows the resulting ROP, *J*, WOB and surface torque from these two simulations.

In simulation 1, the weight on bit is steered from 2000 kg to a WOB_0 value of about 4300 kg during the drilling of the first stand, before a connection takes place at approximately 2850 seconds. This adjustment in WOB results in an increase in ROP of 18 m/hr, which is 90% of the interval between the starting point and the optimum. The next two stands are spent drilling while the ES algorithm slowly makes the system converge to the optimal WOB value, at which the performance function is seen to flatten out and become constant.

The second simulation is initially identical to the first, before the increasing WOB causes the surface torque to become too close to the limiting value after 1400 seconds. At this point, the predictive constraint handling part of the algorithm stops the WOB-adaptation before the constraint is exceeded. Because the system is forced to drill with a WOB lower than the optimal value, the second simulation spends about 23 minutes more than the first to complete the three stands.

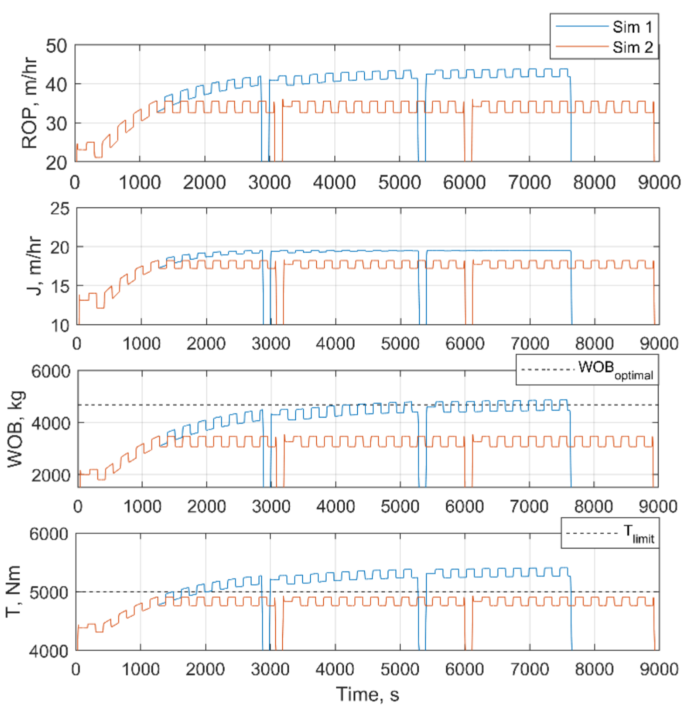

FIGURE 5: SIMULATIONS 1 AND 2, WHERE A TORQUE LIMIT IS IMPOSED ON THE SYSTEM IN SIMULATION 2.

Simulations with Measurement Noise

The results from simulations 3 and 4 are presented in Figure 6, where the latter run is limited by a maximal surface torque of 5000 Nm. Other than this, the scenarios are identical and are both performed with the parameters given in Table 2. A lower value of the adaptation gain, γ, is used in these simulations compared to the first two. The noise levels, v_h and v_T, are designed so that the measurements are disturbed by normally distributed random variables that take on values in the intervals $\pm$ 0.03 m and $\pm$ 500 Nm, respectively. The ROP used in the algorithm is estimated from noisy block measurements with the Kalman filter. The spikes seen in the estimated ROP at the start of each drilled stand in Figure 6 are caused by the KF, which overestimates the ROP initially, before it has more data to work with and is able to home in on the true ROP value. These ROP-spikes occur during the initiation of drilling where the weight on bit is held constant and are thus not used by the algorithm for adaptation of the WOB.

TABLE 2: PARAMETERS USED IN SIMULATIONS 3 AND 4.

Parameter	*Value*	*Unit*
v_h	$\sim N(0, 0.01)$	m
v_T	$\sim N(0, 167)$	Nm
σ_p	$3 \cdot 10^{-5}$	m/s^2
σ_m	10^{-2}	m
γ	250	$kg^2 \cdot hr/m/s$
T_{avg} interval	5	s

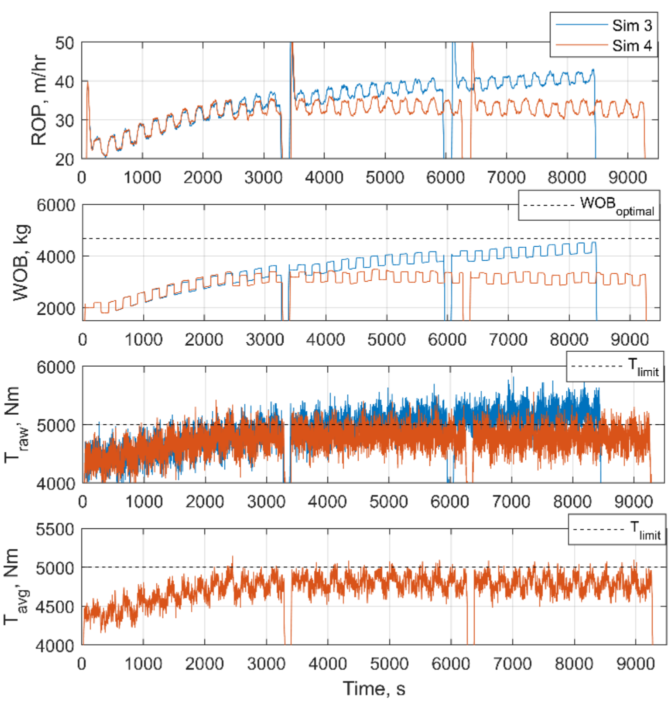

FIGURE 6: SIMULATIONS 3 AND 4, WHERE A TORQUE LIMIT IS IMPOSED ON THE SYSTEM IN SIMULATION 4.

Simulation 3 is from the second track in Figure 6 seen to be adapting towards the optimal WOB-value but is not able to reach it within the simulated interval. The fastest adaptation takes place during the drilling of the first stand, where he ROP is increased by about 12 m/hr from the initial value. This corresponds to 60% of the total ROP improvement sought by the algorithm in this scenario.

The third track in Figure 6 displays the "raw" noisy torque. This value is frequently seen to surpass the limiting torque, as the algorithm interprets it as very short-term fluctuations which it does not react to. The bottom track in Figure 6 shows the 5 second average torque value for simulation 4, which is used in equation (12) to determine when the torque is above the limit. After drilling for 2500 seconds and onwards, this T_{avg} value is seen to exceed the constraint for a short period of time on several occasions. Each time this occurs, a reduction in WOB takes place until the torque is again within its allowable values. As in simulation 2, the WOB in simulation 4 is not allowed to work its way further towards the optimum, which causes the drilling of the three stands to take more time.

Discussion of Results

Throughout the simulations, the ES algorithm is seen to adjust the WOB the fastest during the first drilled stand. This is caused by the adaptation being proportional to the gradient of the performance function. As the WOB closes in on its optimal value, this gradient will become smaller (see Figure 2). As can be observed in simulations 1 and 3, this property allows the ES algorithm to quickly modify the WOB to the neighborhood of the optimal value. After the initial fast adaptation, it slowly converges towards the optimum while continuously probing for any changes in drilling conditions. An important parameter which affects the adaptation rate of the algorithm is the gain parameter γ. On the one hand, it determines the rate of convergence of the WOB to the optimum. The larger it is, the faster is the convergence. On the other hand, higher values of γ will make the algorithm more sensitive to measurement and process noise, as the system makes larger adjustments even for small deviations caused by noise. Thus, finding a value for gamma which balances the convergence rate and sensitivity to noise is an important tuning task when using the ES algorithm.

The constraining torque value which is used in simulations 2 and 4 is only a fraction of what would be the allowable continuous torque of e.g. a top drive. The limitation is implemented to demonstrate the algorithm's ability to stay within constrictions in a practical manner while it searches for the optimum WOB, as is seen in the simulated scenarios. Simulation 4 demonstrates that when the constrained parameter (the torque) is very noisy, it can exceed the limit for short periods of time. This observation together with general HSE considerations necessitates that the maximal torque value implemented in the algorithm is lower than the actual system limitation.

The initial WOB_0 used in all the simulations is quite far from the optimal value. Even though the adaptation of the algorithm is faster when further away from the optimum, a more efficient optimization method in this scenario could be a hybrid between the data-driven and physics-based approaches, conceptually similar to what was done by Spencer et al. [7]. The information gathered from the initial WOB excitations could be used to roughly tune a physics-based drilling model, and the suggested optimal parameters provided by this model would be the starting point for the ES algorithm which would further home in on the founder point.

CONCLUSIONS

We present a data-driven optimization strategy which automatically seeks and maintains the optimal WOB maximizing the ROP. The algorithm does not require any model of the drilling process and utilizes continuous micro-testing of the drilling conditions to identify and implement adjustments of the WOB leading to higher ROP. The micro-testing procedure does not cause any significant perturbation to the drilling process and is run continuously to adapt to the current drilling environment. The algorithm has been tested on a high-fidelity drilling simulator where it demonstrated the ability to steer the WOB to values resulting in higher ROP both with and without the presence of noise in the data. The simulated scenarios show that the proposed optimization strategy is able to automatically search for and implement improvements in the ROP while adhering to process constraints, where the constraint handling was demonstrated with the example of a maximal limit imposed on the surface torque.

NOMENCLATURE

Parameters

a	Least-squares slope	(m/hr/kg)
α	Least-squares slope	(Nm/kg)
A	Amplitude of excitation signal	(kg)
b	Least-squares intercept	(m/hr)
β	Least-squares intercept	(Nm)
d	Excitation signal	(kg)
Δt	Time increment	(s)
e	Torque limitation variable	(Nm)
γ	Adaptation gain	($kg^2 \cdot hr/m/s$)
h_{block}	Height of travelling block	(m)
J	Performance function	(m/hr)
J_B	Buffer with past J values	(m/hr)
λ	Penalty variable	(kg)
μ	Parameter in J	(m/hr/kg)
N	Probability density function of the normal distribution	
P	Period of excitation signal	(s)
Q	Process noise covariance matrix	
r	Vector of drilling parameters	
R	Measurement noise covariance matrix	
σ_m	Measurement noise std. dev.	(m)
σ_p	Process noise standard deviation	(m/s^2)
t	Time	(s)
T	Torque	(Nm)
T_{avg}	5 second average torque value	(Nm)
T_B	Buffer with past torque values	(Nm)

$T_{B,avg}$	Average value of T_B	(Nm)
T_{limit}	Limiting torque value	(Nm)
v	Measurement noise	
v_h	Measurement noise in h_{block}	(m)
v_T	Torque measurement noise	(Nm)
w	Process noise	
WOB_0	Center WOB value in d	(kg)
$WOB_{0,constrained}$	Constrained WOB_0 value	(kg)
WOB_B	Buffer with past WOB values	(kg)
y	Measurement of h_{block}	(m)

Abbreviations

ES	Extremum Seeking	
KF	Kalman Filter	
MSE	Mechanical Specific Energy	
ROP	Rate of Penetration	(m/hr)
RPM	Revolutions per Minute	(rpm)
SF	Safety Factor	
WOB	Weight on Bit	(kg)

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