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Modeling of Drilling Rate of Penetration as a function of Operating Parameters Using Step-wise Linear Regression Model

John Lander Ichenwo and Barinem Peter

Abstract
In obtaining petroleum, there is a need to make a hole through the formation to the reserves where petroleum is found. The process of this hole-making is termed drilling. The nature of the costs involved during drilling is such that the longer spanned the drilling activity, the greater the cost. One way to reduce the drilling cost is by reducing the number of days spent in the drilling process, this can be achieved through series of practices called drilling optimization. One key component of the drilling optimization is the rate of penetration (ROP) optimization which would help predict the optimum rate of penetration consequently reducing excessive time and saving cost. The widely used model in ROP optimization is the Bourgoyne and Young model, however there are 8 parameters captured in this model making it difficult to work with. In this project, the ROP is modeled as a function of the operating parameters only, which are the weight on bit and the rotary speed by modifying the Bourgoyne and Young Model using a step-wise linear regression with a a step size of 5. In the end, the ROP predictions from the model is compared with that from BYM and the actual field data

Keywords: *rate of penetration; Bourgoyne and Young model; rotary speed; weight on bit; Step-wise Linear Regression.*

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NOMENCLATURE

BYM	Bourgoyne and Young's Model
FR	Flow rate
MSE	Mechanical Specific Energy
ROP	Rate of Penetration
RPM	Revolution per minute
SLRM	Stepwise Linear Regression Model
TOB	Torque on bit
WOB	Weight On Bit

I. Introduction

Drilling operations, an inevitable part of the exploration and production of the liquid gold, however not without it associated costs accounting for over 35% of the overall costs (Lashari et al. 2019. The drilling costs can be broken into series of fixed costs which are unavoidable costs like rig costs, and variable costs like the drilling rotating and non rotating costs, whilst the fixed costs are unavoidable, the variable costs are time dependent directly related to the effective period for drilling the well. Therefore, drillers and their team are regularly seeks to decrease the period for drilling a well and its related costs.

This has led to series of techniques designed to curb non productive time and increase the efficiency of drilling activities. This is referred to asdrilling optimization. Drilling optimization includes techniques such as ROP optimization, mechanical specific energy (MSE), the effective torque on bit (TOB), and cost per foot of drilling all in a bid to optimize drilling.(Hegde and Gray2018). Amongst techniquesaimed atimproving and attainingoptimal drilling performance, the ROP optimization methods are the widely used (Arabjamaloei and Shadizadeh2011).A high rate of penetration, ROP does not alwaystranslates intoimproved overall drilling performance. In certain cases, high ROP can result in inappropriate hole cleaning, reduced bit life, instability threats to the wellbore, etc. (Abbas et al. 2018). All these issues would lengthen the drilling time of the well, resulting to challenging situationsrequiring more complex remedial operations (Akgun2002). Regrettably, this results in non productive timeconsequently increaseddrilling cost of the well. Therefore it is imperative to efficiently manage the relationship between the drilling rate and the other associated variables for improved overall drilling efficiency in tune with standard practices.

The method for ROP optimization focuses on increasing the effective rate of penetration, ROP, which isdescribe as the advancement of a bit into rocks in time units (Eskandarianet al.2017). Generally, ROP is assessed instantly by evaluating the controlled time

and distance during drilling. Maximizing ROP could be realized by completely understanding the main variables that can directly or indirectly affect the drilling rate (Chen et al. 2016). However, predicting and optimizing rate of penetration is still a major challenge in the oil and gas industry as a result of the intricate and nonlinear performance of variables with ROP (Bataee and Mohseni2011). Furthermore, a number of these related variables cannot be altered without having influence on the others, which makes it difficult to assess the actual impact of an individual variable on the ROP (Elkatatny et al. 2017).

Fromprevious work from severalliterature and in accordance with field experience, variables shown to have the greatest impact on the ROP have been classifiedinto rig/bit related variables, mud-related variables, and formation characteristics variables (Yi et al. 2015; Hankins et al. 2015; Shi et al. 2016).

These variables have beensubdivided into controllable and uncontrollable or environmental parameters (Elkatatny 2018). The controllable parameters are all parametersthat can be easily manipulated to improve the ROP without impacting the economics of the operations considerably, they include paramteters such as effective pipe weight force exerted on the bit (WOB), bit revolutions per minute (RPM), drilling fluid flow rate (FR), and effective flow area (KeshavarzMoraveji and Naderi 2016; Abbas et al. 2020). The uncontrollable parameters on the other hand are difficult to control as a result of economic or geological reasons. They include parameters such as the rock formation properties which determines the choice of the mud weight and mud type, well-bore inclination and azimuth, pore fluids pressure gradient, loose compressive strength, and the three principal stresses (Kahraman et al. 2003; Ataei et al. 2015; Al-AbdulJabbar et al. 2018).

Of all the variables, WOB, RPM, and FR are known as the controllable operational drilling parameters, because theyare essential role parameters in every drilling operationthatdirectly influences ROP (Edalatkhah et al. 2010).Several conventional techniques have been employed in the optimization of these variables towardsimproving the productivity profile of the drilling operations (Arabjamaloei et al. 2011; Ahmed et al. 2019).

Direct techniquessuch as drill rate and drill-off tests focuses mainly on human drilling experience and available standards developed in the field. In this method, one or more of the controllable drilling variables are adjusted by the drilling engineer at the surface to find the point at which the optimal drilling rate is attained (Dupriest and Koederitz2005).

Indirect techniques on the other hand involves the formulation of several models and formula developed to calculate the rate of penetration. This involves the use of basic physics and mathematical equations andempirical components using multiple regression analysis of the field data in the establishment of a relation between the most influential variables and ROP (Bourgoyne and Young 1974). Nevertheless, some of these conventional models lacksprecision resulting in broad assessments of ROP.(Bodaghi et al. 2015; Soares et al. 2016). The empirical method's execution has some drawbacks, such as the empirical constants determination, specifications of bits, the auxiliarydata requirement, and inadequate precision in ROP predictions (Hegde et al. 2015).Over the past decades, the growth in drilling technology led to the implementation of more predictive data-driven approaches, which operates based on actual field data. These approachessuch as the broader windows statistical learning model integrates machine learning for drilling rate prediction (Payette et al. 2015; Wallace et al. 2015; Hegde et al. 2017).

Drilling optimization is key to minimizing costs and ensuringthe economic feasibility of drilling operations. The construction of a model to predict the drilling rate of penetration through a formation requires adequate understanding of the factors that affects drilling rate of penetration (ROP). Accurate prediction of ROP avoids unnecessary spending,considerably reducing the drilling budget.

For this reason, several authors and researchers had made attempts to develop a model for ROP prediction. Generally, the drilling rate of penetration depends on several independent parameterstherefore it can be modeledin terms of independent drilling parameters. Some models have been proposed in the past to predict the ROP including Bingham model, Bourgoyne and Young model, Warren model etc. although these models are not so accurate in predicting ROP, they are always used as guidelines for modification of mathematical models in these days.

In This paper, a Step-wise Linear Regression Model SLRM is generated using inverse matrix method. A set of data from an oilfield in Niger Delta formation was used to train and test the model. Then, comparison and diagnostic plots are obtained for the developed SLRM and the Bourgoyne and Young model (BYM) predictions with reference to the actual data.

From the results, the SLRM model shows a high performance in predicting ROP against the real data. Therefore the model is usefulin ROP prediction foradjacent wells in the same reservoir. However, the model hereby generatedis validated within the Niger Delta in Nigeria region, for ROP prediction in fields in other geography, the model would have to be be retrained using data from that reservoir before it is used.

II. Materials and Methods

The model developed by Bourgoyne and Young's is selected and modifiedin this study, the reason being it is a more comprehensive mathematical model and quite notable for being used extensively in the petroleum industry for roller-cone bit types. Furthermore it establishes the basic relationship between the ROP and it dependent parameters which is useful in deriving models for ROP estimation.

The modeling technique used is a step-wise linear regression with a step size of 5 data point generated by modifying the BYM.

In developing this model, necessary oilfield drilling data from a well in the Niger delta basin is obtained. The name of the well was deleted from the given data for confidential purpose, the name of the well was renamed as Well ND with a total depth of 9664ft. The Well data consist of drilling parameters such as well depth, rate of penetration, weight on bit, flow rate, rotation per minute, torque, bit diameter, stand pipe pressure, etc.

Data within well depth range of 1000ft to 9000ft was selected for this analysis at an interval of 200ft. In this model there are some unknown coefficients which was determined as shown below:

According to the general BYM:

$$\mathrm{ROP} = \frac{\mathrm{dF}}{\mathrm{dt}} = f_1 * f_2 * f_3 * \ldots f_8$$

In this project, we shall modify the ROP equation to be a function of only two operating parameters namely: the weight on bit and the rotary speed.

The following assumptions are stated to account for the six other parameters in the BYM:

1. The first parameter, the formation reliability is usually a constant
2. The mud-weight is usually constant for a hole section, until another section is drilled, so we can say the mud-weight for a hole section is fairly constant.
3. The above-mentioned mud-weight condition also implies that the density and viscosity of the drilling fluid will also be constant.
4. The bit used in drilling a hole section is constant implying the bit nozzle diameter for a hole section also is constant.
5. Good hydraulics and hole cleaning is achieved.
6. The effect of other parameters in predicting the ROP excluding the operating parameters are fairly constant or negligible.

The implication of this assumption is that $x_1, x_2, x_3, x_4, x_7 and x_8 = Constant$.

Such that the multiplication of the exponents of these constants will also be a constant which is represented as K.

Therefore the BYM reduces to:

$$\mathrm{ROP} = \frac{\mathrm{dF}}{\mathrm{dt}} = k * f_5 * f_6$$

Where $K = e^{c}; f_5 = e^{a_5 x_5}; f_6 = e^{a_6 x_6}$

Therefore, $\mathrm{ROP} = \frac{\mathrm{dF}}{\mathrm{dt}} = e^{c} * e^{a_5 x_5} * e^{a_6 x_6}$

$$\mathrm{ROP} = \frac{\mathrm{dF}}{\mathrm{dt}} = e^{c + a_5 x_5 + a_6 x_6}$$

Therefore $\ln \mathrm{ROP} = c + a_5 x_5 + a_6 x_6$

Let $Y = \ln \mathrm{ROP}$

$$Y = c + a_5 x_5 + a_6 x_6$$

For this regression, we made the following simplifications on the normalized weight on bit and rotary speed parameters based on the standard laws of logarithm:

$$\text{From BYM,} \quad x_5 = \ln\left(\frac{\frac{W}{d} - \frac{W}{db_t}}{4 - \frac{W}{db_t}}\right)$$

$$\ln\left(\frac{\frac{W}{d}-\frac{W}{db_t}}{4-\frac{W}{db_t}}\right)=\ln\left(\frac{W}{d}-\frac{W}{db_t}\right)-\ln\left(4-\frac{W}{db_t}\right)\ =\ln\left(\frac{W}{d}-\frac{W}{db_t}\right)-k_2$$

$$x_5=\ln\left(\frac{W}{d}-\frac{W}{db_t}\right)$$

Similarly:

From BYM, $x_6 = \ln\left(\frac{N}{60}\right)$ x_6 = lnN/60

$$\ln\left(\frac{N}{60}\right) = \ln\left(\frac{1}{60}*N\right)=\ln\left(\frac{1}{60}\right)+\ln N = k_1 + \ln N$$

$$x_6 = \ln N$$

$$d = c - a_5k_2 + a_6k_1$$

Therefore $Y = d + a_5x_5 + a_6x_6$

Generating the Normal Equations

$$\sum Y = nd + a_5\sum x_5 + a_6\sum x_6$$

$$\sum x_5Y = d\sum x_5 + a_5\sum {x_5}^2 + a_6\sum x_5x_6$$

$$\sum x_6Y = d\sum x_6 + a_5\sum x_5x_6 + a_6\sum {x_6}^2$$

Rewriting in Matrix Format, it becomes

$$A\,X = b$$

Where A = Matrix of Coefficients

X = Matrix of Unknowns

b = Matrix of Constants

$$A = \begin{bmatrix} n & \sum x_5 & \sum x_6 \\ \sum x_5 & \sum {x_5}^2 & \sum x_5x_6 \\ \sum x_6 & \sum x_5x_6 & \sum {x_6}^2 \end{bmatrix};\ X = \begin{bmatrix} d \\ a_5 \\ a_6 \end{bmatrix};\ b = \begin{bmatrix} \sum Y \\ \sum x_5Y \\ \sum x_6Y \end{bmatrix}$$

$$X = A^{-1}b$$

III. Results and Discussion

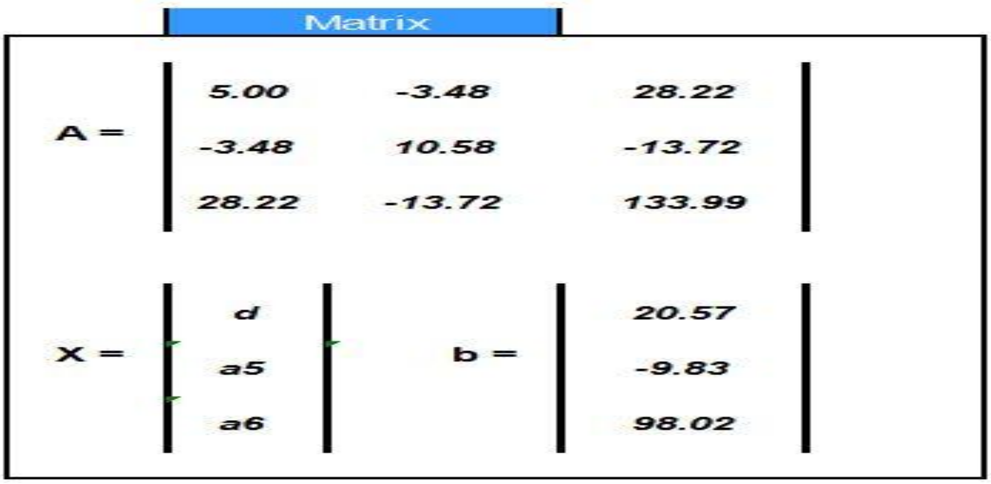

Figure 1. Resulting Matrix, generated by the developed superb statistical tool.

Displayed on the left hand side above is the resulting matrix generated after substituting the values for the parameters in the normal equation for depths ranging from 1200 - 2000ft. On the right you have a column showing you details of your parameters

Solutions

$$\begin{vmatrix} d \\ a5 \\ a6 \end{vmatrix} = \begin{vmatrix} 0.0597 \\ 0.0259 \\ 0.7216 \end{vmatrix}$$

Figure 2.solution matrix generated by the developed superb statistical tool

In the above-displayed are the values for the coefficient in the model generated for section depth 1200ft to 2000ft, proceeding sections coefficient are obtained following the methods described above

Depth (ft)	ROP (Actual)	ROP (BYM)	ROP(Model)
1200	29.520	25.443	28.600
1400	31.550	58.872	33.500
1600	45.630	85.741	36.691
1800	42.660	100.879	39.678
2000	52.360	122.785	51.235

Table 1: SLRM against BYM against Actual Data Performance

The table above provides a comparison between the predictions from the stepwise linear regression model developed in this research and the BYM prediction with actual data as the reference.

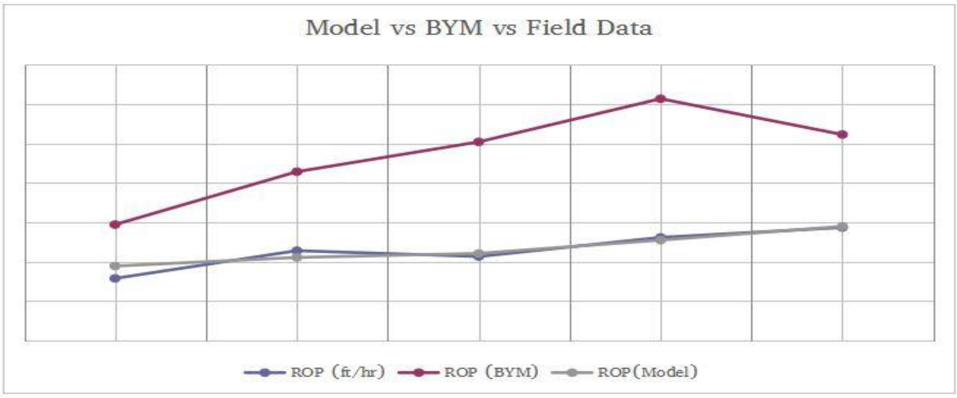

Fig 3: SLRM and BYM ROP prediction against actual ROP

The chart above gives the comparison between the SLRM developed in this project, the BYM and the actual data.

The blue line in the graph indicates the actual ROP, the red line reads the BYM predictions and the ash line indicates the SLRM predictions for the 1200 - 2000 ft depth interval.

Using the concept of error as the deviation from actual, the BYM has the greater deviation from actual when compared with the SLRM. This indicates that the prediction of the SLRM is the more accurate. For the statistics the SLRM has an r-squared value of 0.972 whilst the BYM scored 0.6156.

IV. Conclusion

1. The SLRM has a greater accuracy in ROP prediction and estimation when compared with the BYM.
2. The SLRM is accurate even in predictions at floundering regions where the BYM usually fails.
3. The SLR model is proven to give a high performance with an error as low as 1.47% and correlation coefficient of 97%.
4. Therefore the SLR model is well suited for the accurate estimation of the ROP consequently the duration of drilling activities in wells within the same reservoir using relevant data.
5. The SLRM is also amenable to general approximation and estimation of any nonlinear function.

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