Improving drilling performance through optimizing controllable drilling parameters

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Abstract

The prediction of the drilling rate of penetration (ROP) is one of the key aspects of drilling optimization due to its significant role in reducing expensive drilling costs. Many variables could affect ROP, which can be classified into two general categories; controllable operational variables and uncontrollable or environmental variables. Minimizing the drilling cost can be achieved through optimizing the controllable drilling parameters. As a direct result, the drilling speed will be increased while maintaining safe practices. The primary purpose of this study is to address the simultaneous impact of controllable parameters such as weight on bit (WOB), revolutions per minute, and flow rate (FR) on the rate of penetration (ROP). Response surface methodology was applied to develop a mathematical relation between operational controllable drilling parameters and ROP. To accomplish this, actual field datasets from several wells drilled in Southern Iraq in different fields were used. The second purpose of this study was to identify all prospective optimal ranges of these controllable parameters to obtain superior drilling performance with an optimum ROP. The obtained results showed that the developed model offers a cost-effective tool for determining the maximum ROP as a function of controllable parameters with reasonable accuracy. In addition, the proposed model was used to estimate optimal combinations of controllable drilling parameters for various depths. The results have shown that FR has the most significant effect on ROP variation with a sum of squares values of 23.47. Applying high WOB does not permanently improve ROP but could result in reducing ROP for some cases. The developed mechanical specific energy model for polycrystalline diamond compact (PDC) bit with vertical and deviated wells can estimate combinations of controllable drilling parameters. The developed model can be successfully applied to predict and optimize the drilling rate when using PDC bits, hence reducing the drilling time and the associated drilling cost for future wells.

Keywords Drilling rate · Response surface methodology · Controllable operational parameters · Drilling optimization

Introduction

Drilling operation is one of the most critical parts of any exploration and developmental project. Operational costs related to drilling processes have increased substantially in the last ten years (Amer et al. 2017). A number of related actions have been stimulated by the high costs, which involve more than half of the budget of any field development plans (Lashari et al. 2019). Therefore, drilling engineers and operations teams are often motivated to reduce the well drilling duration and associated costs. Drilling optimization has an important role in improving drilling performance and reducing unnecessary drilling costs. These issues influence drilling time, the drilling rig's productivity, and, consequently, increase the profitability of oil and gas projects (Mohammed et al. 2018).

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Numerous methods such as optimizing ROP, mechanical specific energy (MSE), the torque on bit (TOB), and cost per foot of drilling have been developed for drilling optimization (Hegde and Gray 2018). Although all these methods aim to enhance and achieve the best drilling performance, the ROP optimization methods are the most commonly used (Arabjamaloei and Shadizadeh 2011). However, high ROP does not always correspond to enhanced drilling performance. It is significant to know that high ROP may lead to improper hole cleaning, jeopardize bit life, and result in wellbore instability problems, etc. (Abbas et al. 2018). All of this may extend the time of well delivery and lead to a problematic scenario when more complicated operations occur due to wellbore instability and collapse (Akgun 2002). Unfortunately, this will increase the non-productive time and the well cost, accordingly. Consequently, it is crucial to adjust the relationship between the drilling rate and the related variables to improve drilling efficiency while maintaining safe practices.

The optimization procedure classically emphasizes increasing the ROP, which can be simply defined as the progress of a bit into rocks in time units (Eskandarian et al. 2017). In general, ROP is surveyed instantaneously by measuring the constrained time and distance during drilling. Maximizing ROP can be achieved by fully understanding the major variables that could directly or indirectly affect the drilling rate (Chen et al. 2016). However, prediction and optimization of penetration rate is still a significant challenge within the petroleum industry due to the complicated and nonlinear performance of variables with ROP (Perrin et al. 1997; Bataee and Mohseni 2011). Additionally, some of these variables cannot be changed without influencing the others, making it challenging to assess the real impact of an individual variable on the ROP (Elkatatny et al. 2017).

Based on the information provided in the literature and according to the field experience, the most important variables have been identified as rig/bit associated variables, associated mud variables, and formation variables (Yi et al. 2015; Hankins et al. 2015; Shi et al. 2016). These variables can be classified into two comprehensive categories: controllable parameters and uncontrollable or environmental parameters (Elkatatny 2018). The controllable parameters can be changed immediately to improve the ROP without negatively affecting the economics of the operations substantially, such as pipe weight force exerted on the bit (WOB), revolutions per minute (RPM), flow rate (FR), and total flow area (Keshavarz Moraveji and Naderi 2016; Abbas et al. 2020). While, the uncontrollable parameters are challenging to adjust due to economic or geological reasons such as the rock formation, which defines the constraints that affect the selection of the mud weight and type, wellbore azimuth and inclination, pore pressure gradient, unconfined compressive strength, and the three principal stresses (Kahraman et al. 2003; Ataei et al. 2015; Al-AbdulJabbar et al. 2018).

Among all the previous variables, WOB, RPM, and FR, known as the controllable operational drilling parameters, play an important role in the drilling operation, as they can influence ROP (Edalatkhah et al. 2010). Several direct and indirect traditional methods have been used to optimize these parameters for improving the productivity of the drilling process (Arabjamaloei et al. 2011; Ahmed et al. 2019). The direct method (drill rate and drill-off tests) relies mostly on human drilling experience and available standards developed in the field. In this method, the controllable drilling parameters can be continuously adjusted by the drilling engineer at the surface to identify the founder point at which the drilling rate is maximized (Dupriest and Koederitz 2005). This method can also be used to protect downhole tools from excessive vibrations, dysfunctions, and stick-slip.

In contrast, several models and formulae have been developed to predict the penetration rate. In the past, fundamental physics and mathematical equations and empirical components derived from multiple regression analysis of the field data have been applied to establish a relation between the most influential variables and ROP (Bourgoynne and Young 1974; Warren 1987; Winters et al. 1987). However, these traditional models could result in low accuracy and comprehensive ROP estimation (Bodaghi et al. 2015; Soares et al. 2016). The empirical method's implementation has some disadvantages, such as the determination of the empirical constants, bit specifications, the requirement for auxiliary data, and unsatisfactory accuracy in ROP predictions (Hegde et al. 2015). In the previous few years, the development in drilling technology led to the implementation of more predictive data-driven approaches, which are purely based on actual field data. These approaches, such as the broader windows statistical learning model, integrate machine learning for drilling rate prediction (Payette et al. 2015; Wallace et al. 2015; Hegde et al. 2017). An important characteristic regarding the machine learning method is its ability to generalize outcomes based only on the knowledge contained in a training dataset. As a result, these methods have been used to address system identification and function approximation difficulties, such as the one focused herein, which is strongly associated with discovering a reliable ROP prediction model.

Nonetheless, most previous studies have analyzed the dataset from drilled well to develop models for ROP prediction. The procedure shown in this study leverages the constant finding of all possible optimum combinations of controllable operational drilling parameters to maximize ROP. First, a total number of 9356 cases were gathered from several drilled wells in Southern Iraq. The operational controllable drilling parameters collected as the input dataset contain WOB, RPM, and FR. Then, RSM methodology was used to develop mathematical and statistical regression models to model and optimize ROP subject to the main three drilling parameters, namely WOB, RPM, and FR. Finally, the optimal WOB, RPM, and FR were selected to create

better drilling efficiency by reducing drilling time and well costs for the future well on the same pad.

Methodology

This paper followed a two-stage approach to optimize the controllable drilling parameters. The optimization approaches are as follows:

Sample and data collection

Many variables can affect the drilling process's behavior; however, it is impossible to contain all of the parameters in a mathematical model since it will increase the complexity and practical aspects (Bataee and Mohseni 2011). According to literature surveys and the drilling experience, only operational drilling variables operated by the drilling engineer on the rig floor were gathered. These parameters include weight on bit (WOB), revolutions per minute (RPM), and flow rate (FR) (Mantha and Samuel 2016). The approach used in this work needs only controllable drilling variables that can be optimized easily to improve drilling efficiency. In general, these parameters can directly control the drilling process's performance (Al-Betairi et al. 1988).

In this study, the drilling datasets were gathered randomly from daily drilling reports (DDR) of five development wells in Southern Iraq. The wells used in this study were similar in terms of profile. Also, the bit type (IADC), bottom hole assembly (BHA), and mud weight and type used to drill these wells were similar. It should be noted that a polycrystalline diamond compact (PDC) bit was used to drill these wells. Furthermore, the hole diameter is 8.5 in. (production section), which implies that the same formation lithology is present in this section.

The major challenge with the collected datasets was their quantity. The operational drilling variables (i.e., WOB, RPM, and FR) and ROP are captured instantaneously from real-time sensors that logs the measurements on footage based. Due to both the human and equipment error, obtaining an accurate dataset while drilling is the main challenge (Iversen et al. 2013). It is well-known that unusual values can produce critical problems in predicting and optimizing the developed model's functions. Consequently, according to the drilling experience, the collected drilling datasets were investigated to remove all measurements that have sudden large changes and unusual values. Data from this screening and filtering process known as "data cleansing," were considered valid datasets with normal distribution and were used to build the ROP model. Finally, the data was also Winsorizing at 5% and 95% level. This process replaces the top and the bottom 5% by those limits' values (5th percentile and 95th percentile, respectively). The final numbers of the datasets used in developing the model were 9356 data records.

Response surface methodology (RSM)

RSM technique was employed to analyze the collected data to find the optimal solution. RSM is a collection of statistical methods, which use quantitative data to optimize and model response variables using regression. The main objective of this technique used in this study is to optimize ROP with related independent variables (FR, RPM, and WOB) using regression modeling to fit a quadratic surface as well as the interaction of several affecting factors. The second-order regression model used in this study can be presented in the following equation:

$$\text{ROP} = \beta_o + \sum_{i=1}^3 \beta_i x_i + \sum_{i=1}^3 \beta_{ii} x_i^2 + \sum_{i=1}^2 \sum_{j=2}^3 \beta_{ij} x_i x_j + \epsilon \quad (1)$$

where β_o is intercept or the constant term, x_i represents the independent variables (FR, RPM, and WOB), β_i is linear coefficients, β_{ii} is quadratic effect coefficients, β_{ij} is cross-product or interaction coefficients, and $\epsilon \sim N(0, \sigma^2)$ is the statistical error term. A popular commercial software (Minitab 17 2010) was used to construct and evaluate models. The software was also applied to plot contours and three-dimensional (3D) response surface curves, which use for data processing (Myers 1971; Montgomery 2014). The collected data were fitted using a second-order polynomial equation, and regression coefficients were acquired. The model only includes the second-order term since adding more higher-order terms to the model (cubic, quartic) did not add too much value to the results in terms of goodness of fit indicators (MSE and R-Squared). The variance analysis was conducted and generated from the proposed model, checking the developed regression model's significance and adequacy. Three contours were obtained to include the variation of response for each factor with the remaining factors. The holding values of all the parameters are the corresponding center levels.

Even though RSM results in statistically validated predictive models (Alsanusi and Bentaher 2015), the data analysis using response surface models are validated by running the suggested model on half (split-half) of the data resulting in almost similar results, resulting in nearly the same maximum value of ROP with a slight difference in values of three factors (WOB, FR, and RPM). The suggested models were also robust by not including a higher order of polynomial in the proposed model to depict ROP changes more accurately (with the second-order of predictors, including their interaction). A backward stepwise procedure was adopted to select which variables and their interactions (quadratic terms) should remain in the final model. Starting from a full model incorporating all variables (with quadratic terms), decisions as to which variables to retain in the final model were based on comparisons of the differences in R^2 , Standard error, and Mallows' C_p . This method seeks to identify the "best" subset of predictors while simultaneously removing those

redundant variables (Hegyi and Garamszegi 2011). The final model fit is also assessed and validated using standard model diagnostic tools using residual analysis and checking assumptions (Bani-Mustafa et al. 2019).

Results

Descriptive statistics and correlations

Table 1 shows descriptive statistics of the study parameters. As shown in this table, the mean value of the rate of penetration (ROP) is 17.6 m/hr, with a minimum of 0.13 and a maximum of 62.34. The median value of the ROP is 16.2, which is slightly less than the mean, which indicates that the ROP is 50% of the time less than 16.2. The mean value of the WOB is 10 ton (with almost the same median) with a range varies between 0 (min) and 20 (max). The RPM's mean value is 168.9, with a range that varies between 21 (min) and 276 (max). The maximum RPM exceeds the top-recommended operation level (250). The FR's average value is 2558.8 l/min, which is relatively high concerning the recommended operating range (1500–2200) with a minimum of 425 and a maximum of 2973. The median (2673) is also high and above the recommended maximum operating value (2600). The data also show that 67% of the time, FR is above the recommended maximum value.

Table 2 displays Pearson's correlations for all independent variables and the dependent variable. The correlations are consistent with the hypothesized relationships for all selected variables (WOB, RPM, and FR) with ROP. The least correlation is for the WOB with the same correlation (0.39) for RPM and FR. Additionally, WOB has a low and a significant negative correlation with RPM (0.039). FR is positively and significantly correlated with WOB and RPM (0.25 and 0.75, respectively).

Regression analysis of ROP

The second-order regression was used to model the ROP with respect to main factors of WOB, RPM, FR, their second-order and their interactions of the main variables have been investigated in the drilling process, and the results of the regression model (Eq. 1) and analysis of variance are shown in Table 3. The result presents that the FR is a

significant factor and the most useful term in explaining the variation in ROP based on the sum of squares values (SS), 23.47, along with FR's quadratic term and its interaction with other factors. All interaction and quadratic terms are significant, as illustrated in Table 3 with p values < 0.0001. The analysis of variance in Table 3 can be represented in the following regression model:

$$\begin{aligned} \text{ROP} = & 4.115 - 0.00538\text{WOB} - 0.000\text{RPM} - 0.002297\text{FR} \\ & - 0.004586\text{WOB}^2 + 0.00002\text{RPM}^2 + 0.00000\text{FR}^2 \\ & + 0.000208\text{WOB} * \text{RPM} + 0.000032\text{WOB} * \text{FR} \\ & - 0.000002\text{RPM} * \text{FR} \end{aligned} \quad (2)$$

The F value of 601.31 with a p value < 0.0001 demonstrates that the model is significant. The model explains (R-squared) a total of 36.67% of the total variation in ROP as the primary purpose is not to model all parameters that affect ROP but to emphasize the most important factors having an impact on ROP, according to Abbas et al. (2019).

Regression model assumptions, including normality, randomness, and constant variance, are checked by residual plot 4 in 1, generated from a commonly used software, as illustrated in Fig. 1. Residual plots indicate no violation of regression model assumptions for the fitted data.

Optimization of rate of penetration (ROP)

Response surface methodology (RSM) was fitted to optimize ROP subject to WOB, RPM, and FR. The model predicted a total of 36.67% of the ROP. In response surface optimization, values of the three factors (WOB, RPM, and FR) were restricted to the recommended drilling parameters without exceeding the maximum recommended values, as illustrated in Table 1.

Table 2 Pearson's correlation matrix for all variables

Variables	ROP	WOB	RPM	FR
ROP	1			
WOB	0.140*	1		
RPM	0.39*	0.039*	1	
FR	0.39*	0.25*	0.57*	1

*Significant at the 0.001 level

Table 1 Descriptive statistics of variables after data cleansing

Variables	Mean	Median	SD	Min	Max	Recommended Value	Max. Operating
ROP (m/hr)	17.6	16.2	10.3	0.13	62.34	–	–
WOB (ton)	10.0	10.2	3.8	0	20	6–11.5	15
RPM	168.9	184	38.6	21	276	100–200	250
FR (l/min)	2558.8	2673	301.8	425	2973	1500–2200	2600

Table 3 Analysis of variance and regression model results

Source	Coefficient	<i>T</i> value	DF	Adj SS	Adj MS	<i>F</i> Value	<i>P</i> Value
Regression	—	—	9	785.38	87.2645	601.31	< 0.0001
constant	4.115	20.35	—	—	—	—	—
WOB	− 0.0061	− 0.6	1	0.05	0.0525	0.36	0.547
RPM	− 0.00057	− 0.37	1	0.02	0.0204	0.14	0.708
FR	− 0.002590	− 12.72	1	23.47	23.4735	161.75	< 0.0001
WOB*WOB	− 0.005170	− 18.24	1	48.28	48.2782	332.67	< 0.0001
RPM*RPM	0.00002302	7.57	1	8.32	8.322	57.34	< 0.0001
FR*FR	0.00000069	12.4	1	22.31	22.3144	153.76	< 0.0001
WOB*RPM	0.0002344	5.53	1	4.44	4.4448	30.63	< 0.0001
WOB*FR	0.00003595	6.89	1	6.88	6.8846	47.44	< 0.0001
RPM*FR	− 0.00000227	− 4.25	1	2.62	2.6185	18.04	< 0.0001
Error	—	—	9346	1356	0.1451	—	—
Total	—	—	9355	2141.71	—	—	—

Fig. 1 Residual plots for ROP

The first response surface optimization based on second-order regression model (Eq. 1) has a maximum of ROP of 18.5075 m/hr (58% percentile) with the recommended operation parameters (Table 1) ($\text{RPM} \leq 200$, $\text{FR} \leq 2200$ l/min and $\text{WOB} \leq 11.5$ tons). As indicated by Fig. 2, the relationship between FR and RPM with ROP is positive, meaning that the more FR and RPM, the higher the ROP. For the WOB, the relationship with ROP is concaving down with a maximum ROP at 10.6 tons. In addition, the composite desirability score is 0.40935.

Figure 2 shows that ROP increases by increasing FR and a slight improvement in ROP realized at moderate FR (1000 l/min), while a straight line response of the ROP was achieved at a high FR of more than 2000 l/min. The improvement in ROP by increasing FR occurs because of enhancing the circulating fluids' lifting capacity and, consequently, improving hole cleaning.

On the other hand, ROP rises by increasing WOB and then decreases. The reduction of ROP by rising WOB happens due to a bit floundering effect. For RPM, Fig. 2 reveals

Fig. 2 Main effect plot and interaction plots for the effect of FR, WOB, and RPM on ROP

that increasing RPM increases ROP. This performance may occur due to RPM's positive impact on bit teeth' shearing force to disintegrate more rock cuttings.

Contour plots provide more details regarding the three factors' interaction effects on ROP (Fig. 3). For example, the range 18–21 m/hr of ROP can be achieved with the same average value of WOB (10.6 tons) but with a higher rate of RPM (> 195) and FR of 2600 l/min or more. The

second RSM optimization will be analyzed, allowing FR to achieve a higher rate of a maximum of 2600 l/min, as this is the maximum recommended operating level for FR.

The same response surface analysis was re-run for our second-order regression model with the same range of WOB (6–12 tons) and RPM (100–200) but allowing FR to reach the maximum recommended operating limit (2600 l/min). The maximum ROP obtained is 20.94 m/hr

Contour Plots of ROP

Fig. 3 Contour plot of ROP versus WOB, RPM, and FR

(68.3% percentile) when $FR = 2600$ l/min (the maximum), $WOB = 11.5$ tons, and $RP = 200$ (Fig. 4). Figure 5 shows the results of the relationship between the three factors and ROP along with contour plots illustrating the interaction effect of each pair of independent variables. The maximum is 20.94 m/hr, but higher ROP values can be achieved, as shown in the contour Fig. 5.

The last response surface optimizing was run, allowing all parameters to reach the maximum recommended operating values; $6 \leq WOB \leq 15$, $100 \leq RPM \leq 250$, and $1500 \leq FR \leq 2600$ (Fig. 6). Results reveal that the maximum value of ROP can be 25.7 m/hr (83% percentile) when $WOB = 12.69$ tons, $FR = 2600$ l/min, and $RPM = 250$ illustrated in Fig. 7.

Fig. 4 Main effect plot and interaction plots for the effect of FR, WOB, and RPM on ROP

Fig. 5 Contour plot of ROP versus WOB, RPM, and FR

Conclusions

In this work, the simultaneous influence of the controllable drilling variables on ROP was examined. The significant controllable drilling variables that have been studied include FR, RPM, and WOB. Response surface methodology was applied for the prediction and optimization of ROP.

Optimum combinations of controllable drilling parameters for various depths were calculated based on the developed model and actual field datasets. The conclusions are made according to the obtained results as follows.

- The variance and regression analysis indicates that the FR has the most significant effect on ROP variation with

Fig. 6 Main effect plot and interaction plots for the effect of FR, WOB, and RPM on ROP

Contour Plots of ROP

Fig. 7 Contour plot of ROP versus WOB, RPM, and FR

the sum of squares values of 23.47, among the other controllable drilling parameters.

- Optimal ROP for various combinations of WOB, RPM, and FR for different depth intervals is in the range of 18.5–25.72 m/hr.
- The results demonstrate that the drilling rate is strongly related to the FR, where increasing the FR tends to increase ROP. A straight line response of the ROP was realized at a high FR of further than 2000 l/min. This performance may occur due to FR's positive effect on the carrying capacity of the circulating fluid to transport the rock cuttings, which enhances hole cleaning. Nevertheless, the annular velocities are limited by the availability of the drilling rig hydraulic power, allowable equivalent circulating density (ECD), and limitation of the open hole to hydraulic washout.
- The results show that the ROP response to the WOB was a semi-straight line until a founder point, increasing the WOB enhanced the ROP. The additional WOB will push the bit teeth more down into the rock being drilled, which smash further rock cuttings. When the founder point is reached, applying additional WOB may cause rapid excessive bit teeth wearing, resulting in a lower ROP. To accomplish an optimized ROP with a long bit life, the WOB should remain at or below the founder point (10.61–12.69 tons). It should be mentioned that this value of the founder point is case-specific, and it could yield different results for other drilling bits. It relies on the bit design and the structure of the bit teeth.
- The proposed statistical model provides an efficient tool for predicting ROP as a function of controllable variables with reasonable accuracy. The developed statistical model offers a cost-effective tool to predict and optimize the drilling rate as a function of WOB, RPM, and FR with reasonable accuracy.

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Compliance with ethical standards

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