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APPLYING RESPONSE SURFACE METHODOLOGY TO DETECT VARIABLES THAT HAVE A SIGNIFICANT IMPACT ON BIT HORSEPOWER AND IMPACT FORCE

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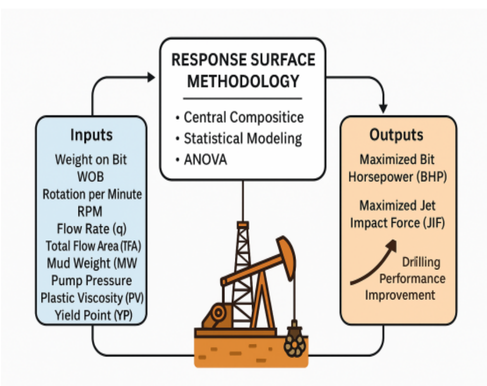
Graphical abstract



Abstract

Bit hydraulics as jet velocity of nozzles (Vn), pressure loss of bit (dPb), Hydraulic horsepower of bit (HHP), hydraulic horsepower of bit per square inches (HSI), jet impact force (Fj), and total flow area of nozzles (TFA), are integral to drilling, especially in soft rocks like shale. The poor bit hydraulic design makes it hard to clean the bottom of the hole; This can lead to "balling" when cuttings build up on the bit face and slow or stop drilling in extreme cases. This study investigates the optimization of drilling operations in soft rock formations, focusing on maximizing bit horsepower and jet impact force for enhanced drilling efficiency. Through a statistical analysis of ten wells in the X-field, controlled and uncontrolled drilling parameters are evaluated for their impact on achieving these optimization goals. Response surface methodology is employed to develop mathematical models that address key questions regarding the effects of these parameters on the two-bit criteria. The study aims to determine the influence of both controlled and uncontrolled parameters on maximizing bit horsepower and jet impact force simultaneously. Results from the analysis reveal insights into which parameters are more effective in driving the optimization process. By identifying optimal values of drilling operation parameters, this study provides valuable insights for achieving maximum performance in drilling operations, thereby minimizing issues such as balling and improving overall drilling efficiency.

Keywords: Hydraulic optimization, bit hydraulic, bit optimization, bit horsepower, impact force

1.0 INTRODUCTION

Efficient and productive outcomes in drilling operations remain an ongoing challenge. The optimization of hydraulics plays a crucial role in enhancing the pressure drop across the drill bit and reducing parasitic pressure losses, directly influencing the penetration rate (ROP) and hole-cleaning efficiency [1]. The drill bit, as the primary tool for entering formations and accessing production zones, must exhibit both high penetration rates and durability for reuse in future wells [2]. In drilling through shale or other soft rocks, bit hydraulics become particularly vital. Inadequate hydraulic design can lead to challenges in cleaning the hole bottom, resulting in the undesirable condition known as "balling," where cuttings accumulate on the bit face, potentially halting drilling operations [3]. Bit optimization typically employs two main methods: jet impact force and hydraulic horsepower [4]. Both methods aim to optimize the hydraulic forces for optimal penetration rate and hole-cleaning efficiency [5]. The hydraulic design of bits has always relied on guesswork and field experience [6].

Prior research projects, such as those carried out by Novieri and Torfi [7], had primarily focused on increasing bit horsepower as a single strategy to achieve cost savings. This study adopted a more comprehensive approach, aiming to optimize a range of drilling parameters, including weight on bit (WOB), rotation per minute (RPM), flow rate (q), and total flow area (TFA). The findings showed that by reducing the nozzle size and mud flow rate, it is possible to increase the bit's horsepower consumption, which lowers the cost of drilling per foot of drilled section. Additionally, the study showed that improving the weight on the bit and the rotational speed can increase the horsepower of the bit, which has a positive impact on the cost of drilling per foot. Therefore, the study suggested that improving these parameters could lead to greater drilling efficiency and significantly reduce costs.

However, specific quantitative data on the exact relationship between weight on bit, rotary speed, and bit horsepower is not provided. Guan, Z., et al. [8], addressed the necessity for an enhanced hydraulic design approach in drilling operations, with a specific focus on attaining maximum bit hydraulic horsepower and enhancing bottom hole cleaning. They introduced a novel hydraulic design methodology, which enables achieving greater bit hydraulic horsepower compared to the existing method, particularly suitable for low pump capacities. The new approach prioritizes optimizing pump pressure and enhancing the pressure-bearing capacity of the circulation system to maximize hydraulic energy. A comparative analysis conducted under various pump pressures illustrates that elevating the restricted pump pressure significantly boosts bit hydraulic horsepower. In summary, the research underscores the significance of enhancing the pressure-bearing capacity of the circulation system to augment drilling performance. While Wang, Y. and S. Salehi [9], focused on applying real-time field data to optimize drilling hydraulics using a neural network approach. The authors implemented an artificial neural network (ANN) model to predict hydraulics and conducted a sensitivity analysis of input parameters on the model they created. They introduced a hydraulic optimization technique that increased the average bit of hydraulic power between consecutive trips, demonstrating improved drilling rates compared to conventional methods. The study utilized actual field data collected from an operator in LA to validate the computer models. The simulation results showed promising accuracy compared to the collected field data. The developed model accurately predicted pump pressure versus depth in analogous formations, demonstrating the potential of the approach for predicting real-time drilling hydraulics. To better understand, Herianto, T[10], utilized the bit hydraulic horsepower (BHHP) method to optimize the hydraulic horsepower of the drilling bit, involving adjustments to the nozzle size and circulation rate to achieve the desired optimization. The focus was on attaining a BHHP/HPs ratio of 65%, deemed the optimal level for hydraulic configuration. Evaluation of bit hydraulics and cuttings removal predicted an increase in the rate of penetration. Additionally, the study analyzed factors such as weight on bit, rotation per minute, and horsepower to understand their impact on penetration rate. Specifically, it centered on a vertical well in the "Tranusa" field, evaluating bit hydraulics at various depth intervals to gauge the effectiveness of the optimization process. The results indicated a significant improvement in penetration rate following hydraulic optimization, validating the efficacy of the BHHP method in enhancing drilling performance. For Yasin, A., et al.[11], conducted a study on optimizing drill bits for better efficiency and lower costs in oil and gas exploration. They looked at factors like drilling speed, cost, and duration across several wells. By analyzing various parameters like weight on bit, RPM, and others, they developed a model to predict drilling rates. Their findings showed which factors had the most impact on drilling speed. They also gave practical advice on selecting drill bits. Overall, their study helps improve drilling efficiency and save money. Finally, Al-Rubaii, M.M., et al.[12], highlighted the critical role of bit hydraulics in optimizing drilling rates, or the rate of penetration (ROP), and ensuring effective hole cleaning. They stressed the importance of understanding how drilling bit hydraulics impacts operations for achieving optimization.

The study focused on maximizing hydraulic impact, bit hydraulic horsepower(BHP), and jet impact force (JIF) to enhance hole cleaning and ROP. Key factors in bit optimization included the total flow area of nozzles (TFA), influencing fluid delivery for cleaning and cooling, and the jet velocity of nozzles (Vn), affecting fluid impact force for efficient rock cutting. Pressure loss of bit (dPb) significantly influenced hydraulic efficiency and power consumption. Hydraulic horsepower of bit determined drilling power availability and ROP. Jet impact force plays a crucial role in efficient rock cutting and removal.

Leveraging daily drilling reports for 10 wells in the X-field and utilizing State Ease (360) software, this study aims to comprehensively understand the influence of drilling operation parameters, both controlled and uncontrolled, including weight on bit (WOB), rotation per minute (RPM), flow rate (q), total flow area (TFA), mud weight (MW), pump pressure(Ppump), mud plastic viscosity (PV), and mud yield point (YP) on maximizing both the horsepower and jet impact force of the PDC bit during vertical well drilling. State Ease (360) software, renowned for its advanced data analytics capabilities, will enable the extraction of detailed insights from the drilling data, facilitating a deeper exploration of the relationship between various operational parameters and the performance of the PDC bit. Additionally, Response Surface Methodology (RSM) is employed to enhance the analysis and provide insights into the optimal combinations of these parameters for achieving the desired outcomes, thus contributing to the advancement of drilling optimization strategies in the oil and gas industry.

2.0 METHODOLOGY

This study is designed to optimize drilling operation parameters to maximum bit horsepower and jet impact force, including controlled and uncontrolled parameters. The methodology involves two stages:

2.1 Data Collection and Statistical Techniques

The drilling process's complexity, influenced by numerous variables, presents a challenge in integrating them into a mathematical model [13]. Our study exclusively incorporates operational parameters under both direct and indirect control, as illustrated in Table 1. The dataset comprises daily drilling reports from 10 wells in Iraq's X-field, all sharing similar characteristics such as the use of a PDC bit type and three sections: a 26" top hole, a 17.5" intermediate section, and a 12.25" production section. Data collection pertains solely to the production section. To maintain data accuracy amidst potential human and equipment errors, we implemented a rigorous "data cleansing" process, excluding measurements displaying abrupt changes. Furthermore, we employed Winsorizing, a statistical technique introduced by Winsor in 1946, to address outliers in the dataset [14]. This technique entails replacing the top and bottom 5% of values with the 5th and 95th percentiles, respectively. This procedure facilitates a normal distribution and aids in model development, addressing a fundamental challenge in drilling data acquisition: ensuring dataset accuracy. Figure 1 outlines the procedures involved in this stage.

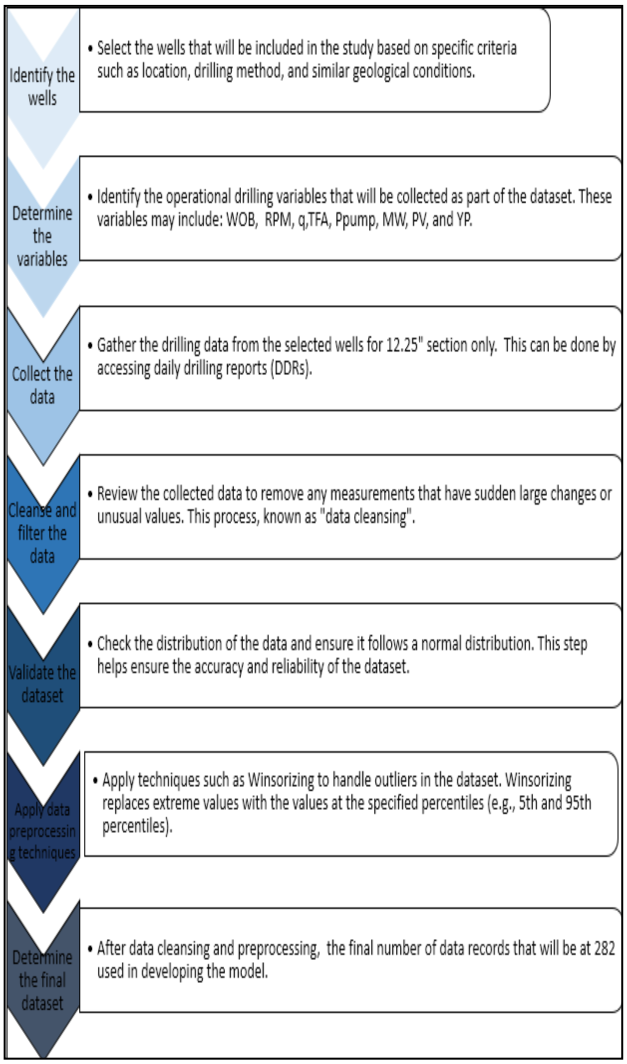


Figure 1 The steps involved in the first stage

2.2 Respond Surface Methodology

Response Surface Methodology (RSM), a statistical technique was employed to analyze collected data and unveil correlations between variables and responses [15]. Design Expert software facilitated this process, generating 3D or cubic plots to enhance understanding [16]. Experiments were designed using central composite design (CCD) to explore factor space efficiently and predict linear and quadratic interaction effects among parameters [17]. Quadratic models were fitted, and subsequent data analysis via ANOVA assessed model significance and adequacy [18]. The F-value from ANOVA indicated overall model significance, typically falling within the range of 0 to infinity, where a higher F-value suggests a more significant relationship between the variables [19]. Similarly, the R-squared value assessed model fit, typically ranging from 0 to 1, with a higher R-squared value of more than 0.5 indicating that independent variables can explain a larger portion of the variation in the dependent variable [20]. Optimization aimed to maximize response variables (BHP and JIF) based on influential factors, involving three stages of response surface optimization: initial exploration, focusing on parameters positively impacting responses, and encompassing all parameters within the recommended range. Figure 2 depicts the flowchart illustrating all the steps in the RSM model.

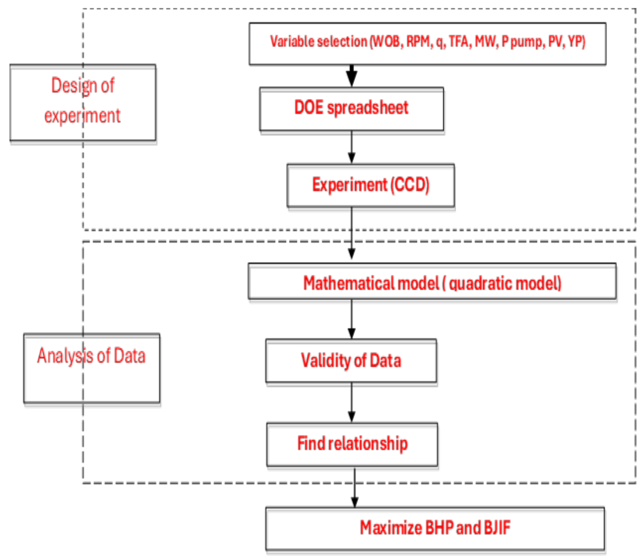


Figure 2 The flow chart of the second stage

3.0 RESULTS AND DISCUSSION

The objective was to elucidate the nature and form of the relationship between drilling operation parameters (WOB, RPM, c, TFA, MW, P pump, PV, and YP) and to optimize these variables to achieve the maximum values for bit horsepower and jet impact force. Before moving to the result, Table 1 represents the descriptive statistics of the variables obtained from the first stage of methodology which shows the maximum and minimum values; additionally, the maximum operating value appears from the DDR of the field data. Tables 2 and 3 present the impact of the variables used, also known as independent variables, on the responses. It is shown from these tables that Lack-of-fit (P) values for the two responses (Bhp and JIF) were less than 0.05, confirming their statistical accuracy, signifying their adherence to pure error for all variables.

Table 1 Descriptive statistics of the variables

Variables	Minimum	Maximum	Max. operating value	Recommended value
BHP	33.7	168	/	/
JIF	287.85	941.32	/	/
WOB	5	30	25	8-22
RPM	95	180	180	100-170
q	808	950	940	800-930
TFA	1.335	1.635	1.633	1.353-1.553
MW	9.33	10.85	10.78	9.53- 10.67
P pump	1100	3850	3900	1500-3700
PV	14	25	22	18-21
YP	20	28	27	22-25

Table 2 Analysis of variance and regression model results of bit horsepower

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	1.136E+05	44	2581.45	177.40	< 0.0001	Significant
A-WOB	12.81	1	12.81	0.8801	0.3491	
B-RPM	49.32	1	49.32	3.39	0.0669	
C-q	24983.54	1	24983.54	1716.86	< 0.0001	
D-TFA	865.14	1	865.14	59.45	< 0.0001	
E-MW	143.22	1	143.22	9.84	0.0019	
F-P pump	51247.28	1	51247.28	3521.70	< 0.0001	
G-PV	24.93	1	24.93	1.71	0.1918	
H-YP	1144.60	1	1144.60	78.66	< 0.0001	
AB	29.31	1	29.31	2.01	0.1571	
AC	140.71	1	140.71	9.67	0.0021	
AD	8.27	1	8.27	0.5686	0.4516	
AE	109.07	1	109.07	7.50	0.0067	
AF	464.81	1	464.81	31.94	< 0.0001	
AG	435.24	1	435.24	29.91	< 0.0001	
AH	0.0304	1	0.0304	0.0021	0.9636	
BC	73.61	1	73.61	5.06	0.0254	
BD	6.71	1	6.71	0.4613	0.4977	
BE	0.2880	1	0.2880	0.0198	0.8882	
BF	121.66	1	121.66	8.36	0.0042	
BG	41.05	1	41.05	2.82	0.0944	
BH	195.80	1	195.80	13.46	0.0003	
CD	2485.95	1	2485.95	170.83	< 0.0001	
CE	140.96	1	140.96	9.69	0.0021	
CF	456.66	1	456.66	31.38	< 0.0001	
CG	18.30	1	18.30	1.26	0.2633	
CH	28.15	1	28.15	1.93	0.1656	
DE	185.31	1	185.31	12.73	0.0004	
DF	28742.41	1	28742.41	1975.17	< 0.0001	
DG	43.76	1	43.76	3.01	0.0842	
DH	272.79	1	272.79	18.75	< 0.0001	
EF	46.83	1	46.83	3.22	0.0741	
EG	127.47	1	127.47	8.76	0.0034	
EH	26.17	1	26.17	1.80	0.1812	
FG	20.93	1	20.93	1.44	0.2316	
FH	3.14	1	3.14	0.2155	0.6429	
GH	34.12	1	34.12	2.34	0.1270	
A^2	15.93	1	15.93	1.09	0.2965	
B^2	10.51	1	10.51	0.7225	0.3962	
C^2	374.39	1	374.39	25.73	< 0.0001	
D^2	235.52	1	235.52	16.18	< 0.0001	
E^2	10.51	1	10.51	0.7225	0.3962	
F^2	93.85	1	93.85	6.45	0.0117	
G^2	10.51	1	10.51	0.7225	0.3962	
H^2	47.44	1	47.44	3.26	0.0723	
Residual	3448.79	237	14.55			
Lack of Fit	3371.30	227	14.85	1.92	0.1260	not significant
Pure Error	77.48	10	7.75			
Cor Total	1.170E+05	282				

Table 3 Analysis of variance and regression model results of jet impact force

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	1.267E+06	44	28799.58	400.03	< 0.0001	Significant
A-WOB	0.1692	1	0.1692	0.0024	0.9614	
B-RPM	114.61	1	114.61	1.59	0.2083	
C-q	7603.24	1	7603.24	105.61	< 0.0001	
D-TFA	5000.650	1	5000.650	7848.35	< 0.0001	
E-MW	1318.32	1	1318.32	18.31	< 0.0001	
F-P pump	2000.927	1	2000.927	4066.08	< 0.0001	
G-PV	218.29	1	218.29	3.03	0.0829	
H-YP	6895.02	1	6895.02	95.77	< 0.0001	
AB	313.72	1	313.72	4.36	0.0379	
AC	2422.78	1	2422.78	33.65	< 0.0001	
AD	39.26	1	39.26	0.5453	0.4610	
AE	1096.77	1	1096.77	15.23	0.0001	
AF	7758.25	1	7758.25	107.76	< 0.0001	
AG	4064.18	1	4064.18	56.45	< 0.0001	
AH	100.79	1	100.79	1.40	0.2379	
BC	2160.78	1	2160.78	30.01	< 0.0001	
BD	770.43	1	770.43	10.70	0.0012	

BE	412.63	1	412.63	5.73	0.0174	
BF	3282.46	1	3282.46	45.59	< 0.0001	
BG	860.27	1	860.27	11.95	0.0006	
BH	561.64	1	561.64	7.80	0.0056	
CD	32292.11	1	32292.11	448.54	< 0.0001	
CE	3020.85	1	3020.85	41.96	< 0.0001	
CF	6863.21	1	6863.21	95.33	< 0.0001	
CG	1101.33	1	1101.33	15.30	0.0001	
CH	1137.21	1	1137.21	15.80	< 0.0001	
DE	676.61	1	676.61	9.40	0.0024	
DF	2.945E+05	1	2.945E+05	4091.16	< 0.0001	
DG	351.69	1	351.69	4.89	0.0280	
DH	2040.48	1	2040.48	28.34	< 0.0001	
EF	1298.34	1	1298.34	18.03	< 0.0001	
EG	1903.75	1	1903.75	26.44	< 0.0001	
EH	188.78	1	188.78	2.62	0.1067	
FG	1128.64	1	1128.64	15.68	< 0.0001	
FH	13.25	1	13.25	0.1841	0.6683	
GH	44.38	1	44.38	0.6165	0.4331	
A^2	247.48	1	247.48	3.44	0.0650	
B^2	16.63	1	16.63	0.2311	0.6312	
C^2	8579.61	1	8579.61	119.17	< 0.0001	
D^2	344.63	1	344.63	4.79	0.0297	
E^2	80.11	1	80.11	1.11	0.2926	
F^2	462.46	1	462.46	6.42	0.0119	
G^2	267.82	1	267.82	3.72	0.0550	
H^2	953.27	1	953.27	13.24	0.0003	
Residual	17062.49	237	71.99			
Lack of Fit	16468.85	227	72.55	1.22	0.3887	not significant
Pure Error	593.64	10	59.36			
Cor Total	1.284E+06	282				

3.1 Statistical analysis (ANOVA)

The constructed regression model was subjected to variance analysis, commonly referred to as analysis of variance (ANOVA), to determine its significance. This analysis compares the variation between the observed data and the interpretation that the regression model can explain [18]. According to statistical analysis (ANOVA), a quadratic polynomial model for BHP and JIF represented the experimental data well. Results revealed that the coefficient determination of R^2 for two responses (BHP and JIF) was 0.891 and 0.889 higher R-squared (R^2) values, approaching unity, indicate a more robust model, while lower values suggest an inadequate explanation of behavioral variations in response variables [21]. In this study, the proximity of R^2 to unity underscores the influence of variables (WOB, RPM, q, TFA, MW, P pump, PV, and YP) on response variables (BHP, JIF). These relationships are well captured by the RSM equations in design expert software, as depicted in Figure 3 Lack-of-fit values ($P \leq 0.05$) for all models confirm their statistical accuracy, signifying their adherence to pure error for all variables [22].

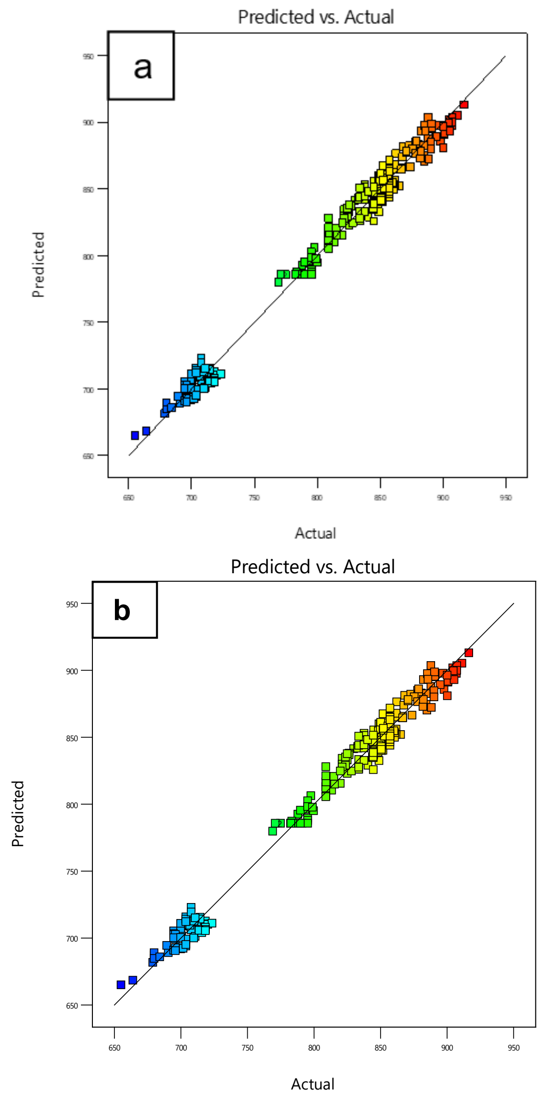
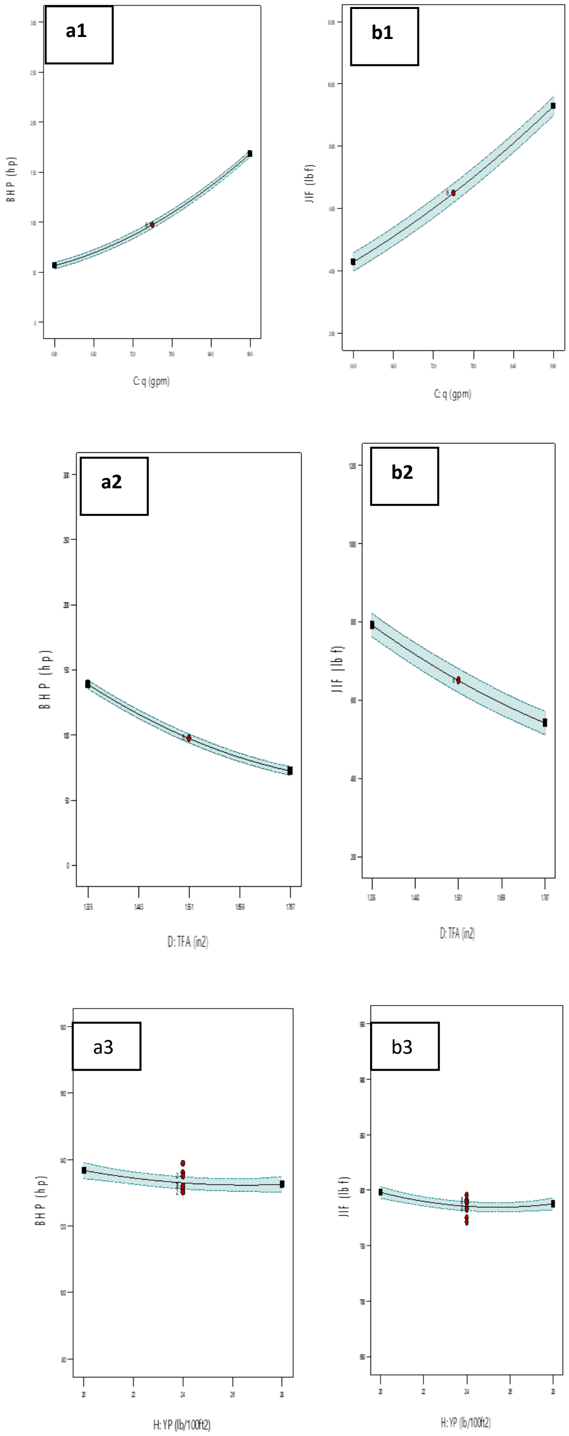


Figure 3 Predicted vs. actual values. (a) Predicted vs. actual values of BHP; (b) Predicted vs. actual values of JIF



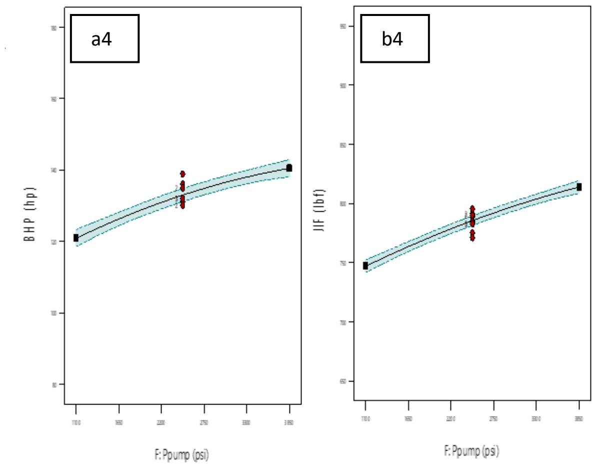


Figure 4 The relationship between inputs and responses. (a1) relationship between BHP and q ; (a2) relationship between BHP and TFA; (a3) relationship between BHP and P pump; (a4) relationship between BHP and Yp; (b1) relationship between JIF and q ; (b2) relationship between JIF and TFA; (b3) relationship between JIF and P pump; (b4) relationship between JIF and Yp

Figure 4 includes a1 to a4 for BHP and b1 to b4 for JIF to show the relationship between the response and input parameters. The investigation explores relationships between key parameters for bit optimization, specifically Bit Hydraulic Power (BHP), Jet Impact Force (JIF) with flow rate (q), Total Flow Area (TFA), pump pressure, and mud yield point. Positive correlations between flow rate and both BHP and JIF suggest a direct relationship, indicating heightened hydraulic power requirements with increased flow rates due to elevated resistance and enhanced cutting transport efficiency. Conversely, an inverse correlation between Total Flow Area (TFA) and BHP/JIF implies reduced hydraulic power needs as TFA enlarges, attributed to minimized pressure drops and smoother mudflow. Pump pressure is found to directly influence BHP and JIF, with higher pressure enhancing hydraulic bit.

3.2 Maximize of BHP and JIF

The utilization of response surface methodology (RSM) aimed at maximizing both bit horsepower (BHP) and jet impact force (JIF) entails the consideration of various controllable and uncontrollable drilling parameters. The primary objective is to ascertain optimal ranges for these variables, thereby enhancing drilling performance.

By RSM principles, the maximization process involves the optimization of input variables namely, WOB, RPM, q, TFA, MW, P pump, PV, and YP to achieve maximum values for the response variables, BHP and JIF. The methodology for maximizing these response variables typically unfolds across three distinct stages, as delineated by [23]. The outcomes of these stages are meticulously presented in Figures a, b, and c, alongside the corresponding tabulated results provided in Figure 5 and Tables 4, 5, and 6, respectively. These representations serve to elucidate the progression and efficacy of the maximization procedure, thereby furnishing valuable insights into the optimization of drilling parameters for heightened operational efficiency.

First stage: based on quartile regression model equations (1 and 2) and variables restricted to the recommended as shown in Table 1 without exceeding the maximum recommended values (WOB = 22, RPM = 170, q = 930, TFA = 1.553, MW= 10.67, P pump= 3700, PV= 21, YP= 25). The result included a maximum bit horsepower is 143.197m/hr (17% percentage) and a maximum bit jet impact force is 825.034lbf (15% percentage) as shown below in Table 4. Second stage: in this stage, the values of variables are based on the range of recommended values as shown in Table 1 for (WOB, RPM, PV) but allowing (q, TFA, P pump, YP) to reach the maximum operating limit and re-run for our quadratic regression model. The result included a maximum bit horsepower is 146.149m/hr (60.3% percentage) and a maximum bit jet impact force is 840.676 lbf (58% percentage) as shown below in Table 5.

Third stage: in this stage, the values of surface-controlled variables are based on the range of recommended values as mentioned in Table 1.Table 6 included the results of this stage.

Table 4 The First Stage of Maximization

No	WOB	RPM	q	TFA	MW	P pump	PV	YP	BHP	JIF	Desirability	
1	22	170	930	1.555	10.67	3700	21	25	143.197	825.034	0.667	Selected

Table 5 The second stage of maximization

No	WOB	RPM	q	TFA	MW	P pump	PV	YP	BHP	JIF	Desirability	
1	19.66	141.986	9400	1.633	10.78	3900	20.970	27	146.149	840.676	0.717	Selected

Table 6 The third stage of maximization

No	WOB	RPM	q	TFA	MW	P pump	PV	YP	BHP	JIF	Desirability	
1	20.760	160.089	929.988	1.553	10.689	3655	19.943	22	149.428	849.081	0.754	Selected

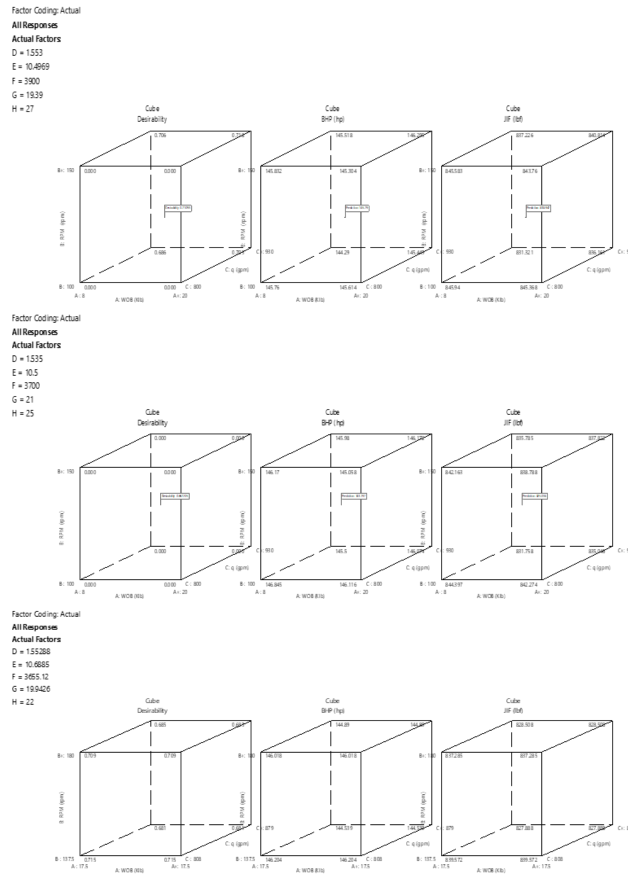


Figure 5 The stages of maximization. (a) The first stage of maximization; (b) The second stage; (c) The third stage

The investigation elucidates pivotal parameters crucial for optimizing drilling operations, including Bit Hydraulic Power (BHP), Jet Impact Force (JIF), flow rate, Total Flow Area (TFA), pump pressure, and mud yield point. It discerns a direct correlation between elevated flow rates and heightened requirements for hydraulic power, indicative of enhanced cutting transport efficiency. Conversely, an inverse relationship is observed between TFA and BHP/JIF, signifying diminished power requisites as the flow area expands, owing to reduced pressure differentials and smoother fluid flow.

Moreover, the study underscores the influential role of pump pressure in augmenting hydraulic power transmission and fluid jet force. Conversely, heightened mud yield points correlate with diminished BHP and JIF, attributed to escalated flow resistance and altered fluid properties. Leveraging Response Surface Methodology (RSM) optimization, the investigation discerns optimal parameter configurations, with the third stage exhibiting the highest desirability score, indicative of superior performance.

The findings substantiate practical applicability, as optimal parameter values align closely with field-recommended ranges. This confluence underscores the pragmatic feasibility of the study's outcomes within real-world drilling contexts. In broader academic discourse, these insights contribute to advancing drilling efficiency and underscore avenues for future research, particularly in elucidating additional factors influencing drilling dynamics and exploring interdisciplinary methodologies for enhanced optimization of the bit.

4.0 CONCLUSION

The RSM technique has been used successfully to understand and study the relationship between many variables (WOB, RPM, q, TFA, P pump, MW, PV, YP), and response variables in this study were bit horsepower and jet impact force. The RSM technique has been used successfully in developing models to maximize the bit horsepower and maximize jet impact force at the same time. Regression analysis reveals a direct relationship between two-bit criteria and several controlled variables, such as flow rate and total flow area. However, uncontrolled variables, notably pump pressure and mud yield point, exert the most significant influence as uncontrolled variables. Variance and regression analysis reveal that pump pressure, as one of the uncontrolled variables, has the most substantial positive impact on BHP variation, with a sum of square value of 51247.28. Conversely, among the controlled variables, flow rate (q) exhibits the most significant positive effect, with a sum of square values equal to 24983.54. Additionally, the flow rate (q) demonstrates the most substantial positive effect, with a sum of square values equal to 7603.24, among the controlled variables affected. where the mud yield point emerges as the most influential variable among the uncontrolled ones, with a sum of squares equal to 6895.02. The maximum BHP is in the range of 143-149 hp, and the maximum JIF is 825 - 849 lbf, for various combinations of WOB, RPM, q, TFA, MW, P pump, PV, and YP. There is no direct relationship between two-bit criteria (bit horsepower and jet impact force) and mechanical factors including weight on bit and rotation per minute. The proposed statistical model proves efficient in predicting BHP and JIF as functions of controllable and uncontrollable variables with reasonable accuracy, offering a valuable tool for optimizing bit in drilling operations.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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