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Response Surface Methodology Applications in Drilling Engineering: Toward Multi-Objective Optimization of Bit Hydraulic Performance—A Critical Review

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ABSTRACT

Response Surface Methodology (RSM) has been widely applied in drilling engineering to model and optimize multivariable operational systems. This review critically evaluates recent RSM applications in drilling engineering, identifies their methodological limitations, and examines the extent to which bit-level hydraulic performance parameters have been incorporated into drilling optimization frameworks. A structured review of studies published between 2021 and 2026 was conducted. The selected studies were classified into three categories: mechanical performance optimization, drilling-fluid optimization, and hybrid optimization approaches. Each study was evaluated according to its input variables, response variables, modeling techniques, optimization objectives, reported performance improvements, consideration of physical and operational constraints, and integration of data-driven methods such as Artificial Neural Networks (ANN). The review indicates that most RSM-based studies prioritize outcome-based indicators, particularly rate of penetration (ROP), drilling-fluid rheology, and operational parameter selection. In contrast, bit-level hydraulic parameters, specifically Bit Hydraulic Horsepower and Jet Impact Force (JIF), are rarely treated as primary optimization objectives despite their direct influence on hydraulic energy transfer, rock fragmentation, and cuttings removal at the bit–rock interface. The findings also show that most existing studies employ single-objective optimization and second-order polynomial models, which may limit their ability to represent nonlinear and coupled hydraulic behavior under field operating conditions. This review adds to the existing literature by systematically identifying the limited integration of physics-based hydraulic indicators into RSM-driven drilling optimization and by defining a research direction for hybrid frameworks that combine RSM-based design-space validation, ANN-based nonlinear prediction, and constrained multi-objective optimization of BHHP and JIF. Such frameworks could support more robust, scalable, and field-applicable drilling optimization strategies.

1. Introduction

The art of drilling optimization has been a major issue in petroleum engineering as it is a complex interaction of mechanical, hydraulic, and formation-related variables [1].

Conventionally, the optimization has been conducted mostly on the rate of penetration (ROP)

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by changing manipulable surface variables, including weight on bit (WOB), rotary speed (RPM), and flow rate (Q) [2]. Although they have been seen to enhance performance, they often do not consider the hydraulic processes underlying energy transfer in the event of the bit-rock interface [3].

In this regard, bit-level hydraulic performance parameters, specifically Bit Hydraulic Horsepower (BHHP) and Jet Impact Force (JIF), are important in increasing the rock fragmentation [4], better cuttings removal, and maintaining efficiency in wellbore cleaning [5]. These parameters have a direct effect on drilling performance because they reduce the distribution of hydraulic energy at the bit face. Despite their obvious physical significance, both BHHP and JIF are highly underestimated as the major response variables in drilling research, as they are often regarded as "byproducts" rather than as direct response variables [6, 7].

Though conventional performance metrics such as ROP reflect the overall performance of the drilling system from the combined effect of multiple factors, BHHP and JIF describe the physics of fluid energy transferred to the drilling bit [8]. Specifically, BHHP is the power dissipated to the bit and JIF is the momentum transfer of fluid jets used to fracture rock and clean out chips [9]. Therefore, the manipulation of these drilling parameters provides a more physically sound means to achieve the optimal drilling performance, rather than relying entirely on such performance indicators [10].

The Response Surface Methodology (RSM), originally developed by Box and Wilson (1951), has been widely used for statistical modeling and optimization of a multivariate system. RSM can be used to easily estimate the main effects, the interaction effects as well as the curvature behavior of a constrained design space by using structured experimental designs like Central Composite Design (CCD) and Box-Behnken Design (BBD).

RM has been applied in drilling engineering applications for the optimization of mechanical properties and drilling fluid, where it has been shown to be capable of determining key factors and improving efficiency [11, 12]. However, most applications of RSM suffer from a major drawback with regard to their reliance on a second-order model and unidimensional optimizations [13].

These limitations limit their ability to understand the complex and strongly coupled nature of the drilling hydrology. Consequently, existing RSM models can fail to capture the multifaceted character of interaction between flow behavior, pressure losses, and energy transfer through bit-level mechanisms [14].

Simultaneously, the Artificial Neural Networks (ANN) have been receiving more and more interest in the field of drilling engineering because of their greater capacity to represent non-linear and data-driven relationships [15]. There has been a high predictive accuracy of ANN-based models in the estimation of drilling performance indicators in different operating conditions [16]. Nevertheless, such models are not generally formulated with a formal experimental design structure and are therefore less interpretable, lack robustness when structured out of constrained conditions, and lose their correspondence to physically relevant parameter space [7, 17].

Such a lack of communication between statistically structured modeling (RSM) and data-oriented nonlinear prediction (ANN) is an important gap in the literature of the field. In particular, no combined frameworks have been proposed that can capitalize on the advantages of RSM in the experimental design and screening of variables with the predictive capability of ANN [18], especially to multi-objective optimize the bit-level hydraulic performance.

Thus, this paper is an attempt to critically discuss RSM applications in drilling engineering and also to point out research prospects in formulating hybrid RSM-ANN methods in optimizing BHHP and JIF on the basis of surface manipulable drilling parameters.

2. Methodology of the Review

This literature review will concentrate on the more recent advances in the Response Surface Methodology (RSM) application to drilling engineering with a specific focus on the publications that are published since 2021 to 2026. Peer-reviewed journals, conference papers, and other academic databases such as ScienceDirect, Springer and Google Scholar were searched to acquire relevant literature.

The inclusion criteria were the studies which:

- Drilling optimization using applied RSM,
- Parameters of mechanical or fluid performance that are investigated, and
- Spreadsheet/modeling/delivered results.

The studies that were solely related to areas of study that are not closely linked to engineering were dropped. The gathered literature was then divided into three broad categories, i.e., optimization of mechanical performance, optimization of drilling fluids, and hybrid optimization methods. A comparative analysis was made to find out common trends, methodological weaknesses, and research gaps, especially when considering bit-level hydraulic performance parameters like Bit Hydraulic Horsepower (BHHP) and Jet Impact Force (JIF), and the links between RSM and Artificial Neural Networks (ANN).

3. Fundamentals of RSM

Response Surface Methodology (RSM) is a statistical process utilized to model and optimize a relationship between several input variables and system reactions in an empirical form of a multi-polynomial [19, 20]. RSM is used in engineering applications based on structured experimental design, like Central Composite Design (CCD) and Box-Behnken Design (BBD), to effectively scan the design space and measure the main effects, interaction effects and curvature behavior [19].

RSM has also been used extensively in drilling engineering to determine the effect of each controllable parameter, such as weight on bit (WOB), rotary speed (RPM), flow rate (Q) and pump pressure, on performance metrics, such as rate of penetration and drilling fluid properties [3, 11]. It is especially appropriate to field-constrained contexts since it can minimize the number of experiment runs, yet, still, it can resolve the effects of interaction [20]. Nonetheless, the use of RSM in drilling systems is per se restricted by the fact that it is based on second-order approximations [19].

These models are relatively smooth response surface and can potentially fail to sufficiently model the highly nonlinear and strongly charged behavior of drilling hydraulics which involve pressure losses, jet velocity and fluid-rock interactions are complex [7, 21].

Consequently, the models based on RSM are often valid only to the calibrated range of designs and can lose predictive quality when operated in different conditions. These considerations are still more important for bit-level hydraulics. Parameters like Bit Hydraulic Horsepower (BHHP) and Jet Impact Force (JIF) are not linear functions of flow rate, nozzle geometry and pressure distribution and cannot be readily modeled at low order (using a low-order polynomial) [22].

RSM, therefore, might not be a suitable approach for describing hydraulic performance with the precision required for its variable significance and interactions, even though it provides useful insights. The latter limitations underscore the necessity to use RSM together with more sophisticated data-driven methods that could help to capture the nonlinear behavior of the system [21].

More specifically, a combination of RSM and the Artificial Neural Networks (ANN) is a potential avenue, in which RSM is employed to conduct pre-structured experimental design and screening of the variables, whereas ANN can be employed to collect predictions over and above the ability of the polynomials to do so [21, 23].

Such considerations are especially important in drilling hydraulics where energy transfer is inherently nonlinear and coupled. The interdependencies among flow rate, pressure drop, nozzle dimensions and jet speed affect BHHP and JIF, and cannot be represented by low order polynomials. Therefore, RSM may not adequately represent the physics of energy transfer to the bit.

4. Application of RSM in Drilling Engineering

4.1 Mechanical Performance Optimization

Optimize mechanical performance indicators, especially rate of penetration (ROP), by examining parameters that can be controlled, including weight on bit (WOB), rotary speed (RPM), and flow rate (Q) [3]. It has been proven that using RSM is able to potentially reproduce the effects of interaction and find the optimal

operating conditions that maximize the efficiency of drilling [3, 19].

Such models are known to show good performance in statistics and offer sensible advice in the parameter tune-up to field constraint [20]. Nevertheless, along with these benefits, there is still a lack of studies that specifically consider the underlying hydraulic processes that control the drilling performance. Hydraulic effects are in most cases implicitly modeled as part of the model as opposed to them being considered as independent optimization variables. As a result, parameters like Bit Hydraulic Horsepower (BHHP) and Jet Impact Force (JIF) which have a direct effect on energy transfer in the bit are not regarded as key response parameters [7, 22]. This weakness inhibits the capacity of RSM-based models to depict comprehensively the physics of driving forces of drilling efficiency. This is a major limitation of the approach as mechanical responses (such as ROP) do not explicitly capture the underlying energy transfer processes. By not including BHHP and JIF as key response variables, these models do not account for the role of hydraulic energy in the rock fragmentation and cuttings transport processes, returning partial solutions and potentially non-optimal results.

4.2 Drilling Fluid Optimization

This is a complicated process that is pushed by a number of factors including drilling fluids, production fluids and well technology[11, 24, 25]. RSM has also been extensively utilized in order to maximize the drilling fluid characteristics as well as plastic viscosity (PV), yield point (YP), and fluid density in an effort to enhance hole cleaning and wellbore stability [11, 25].

Research in this field of study has demonstrated that RSM can be used to model the relationship between fluid properties and operational parameters to allow better fluid design and performance [11]. Those applications underscore the adaptability of RSM in operating multivariable systems and the minimization of complex fluid behavior [20]. However, these research papers are mostly restricted to the surface liquid properties and fail to develop a direct correlation between fluid optimization and a bit level of hydraulic performance. Particularly, the association between optimized fluid attributes and such parameters as BHHP and JIF is seldom measured or introduced into the modeling scheme.

Consequently, the effects of fluid optimization on hydraulic energy transfer at the bit have not been adequately studied and hence the effectiveness of such strategies combined in total optimization of drilling. In summary, physically, drilling fluid properties affect hydraulic performance by affecting pressure drop, regime of flow, and jet velocity. But studies that don't connect these properties to BHHP and JIF do not provide a direct link between the optimization of drilling fluid properties and the effective energy transfer to the bit, and hence can't directly impact drilling efficiency.

4.3 RSM with Hybrid Methods

Over the past few years, there have been a number of studies covering the subject of hybrid methods which incorporate RSM with optimization algorithms or intelligent methods to improve drilling performance [6, 21]. To give an illustration, RSM is combined with metaheuristic algorithms to enhance the selection of parameters and attain superior optimization results [6]. These methods show better scores as compared to single RSM models, and the possibilities of integrating statistical and computational approaches [14].

Nevertheless, the vast majority of hybrid methods can only be used in single-objective optimization, thus, most methods aim to maximize the ROP or minimize the mechanical-specific energy. Little is discussed of the multi-objective character of the drilling operations, where mechanical and hydraulic performance have to be optimized at the same time. Moreover, these hybrid models are not usually integrated with some advanced nonlinear predictive methods like Artificial Neural Networks (ANN) that can predict the behavior of a complex system beyond what can be predicted using a polynomial model [21].

The current hybrid systems are therefore not maximizing the mutual strength of RSM and ANN, especially when it comes to the optimization of bit-level hydraulic performance parameters like BHHP and JIF. While hybrid approaches increase the speed of optimization, they are still largely decoupled from the physics of drilling. Specifically, the lack of BHHP and JIF in the optimization process means that these models fail to account for the interaction between the

energy delivered to the bit and the mechanical performance.

To provide a structured comparison of recent RSM applications in drilling engineering, the reviewed studies were classified into three main categories according to their primary research focus: (i) mechanical and operational drilling-performance optimization, (ii) drilling-fluid formulation and rheological optimization, and (iii) hydraulic behavior, hole-cleaning, and integrated modeling approaches, as shown in Table 1. This classification facilitates the identification of dominant research trends and clarifies the extent to which bit-level hydraulic indicators, particularly Bit Hydraulic Horsepower (BHHP) and Jet Impact Force (JIF), have been incorporated into existing optimization frameworks.

As shown in Table 1, most RSM-based studies have focused on either outcome-based drilling indicators, such as ROP and MSE, or drilling-fluid properties, such as viscosity, rheology, and filtration behavior. A smaller number of studies have addressed hydraulic behavior through ECD modeling, cuttings-transport analysis, or casing-running hydraulics. However, none of the reviewed studies presents an integrated framework in which BHHP and JIF are simultaneously treated as primary optimization objectives under explicit operational constraints. Although the integration of RSM with neural-network modeling has been reported in drilling-fluid treatment applications, its use for nonlinear prediction and constrained multi-objective optimization of bit-level hydraulic performance remains limited. Figure 1 shows the most common classification of reviewed studies using RSM in drilling engineering.

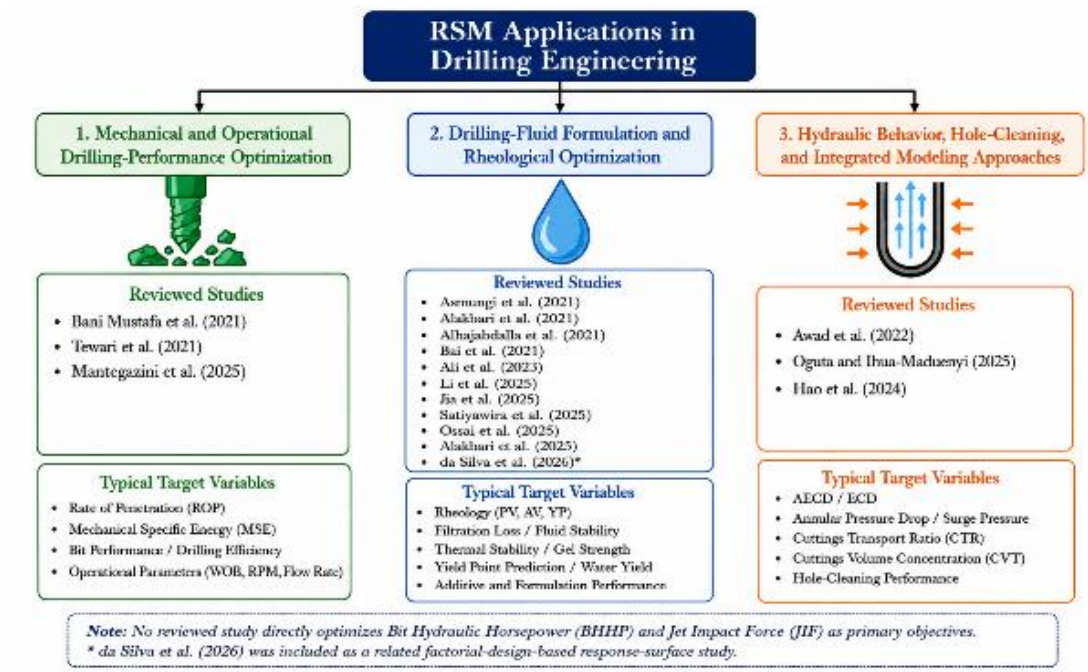

Figure 1. Classification of reviewed studies according to the primary application area of RSM in drilling engineering

As illustrated in Figure 1, recent RSM applications in drilling engineering are predominantly concentrated in two areas: drilling-fluid formulation and rheological optimization, and mechanical or operational drilling-performance optimization, particularly ROP improvement. A smaller group of studies has examined hydraulic behavior through ECD modeling, annular-pressure analysis, and cuttings-transport evaluation. However, bit-level hydraulic performance remains insufficiently addressed, as BHHP and JIF are rarely incorporated as primary optimization objectives. This imbalance highlights the need for more integrated optimization frameworks that explicitly account for hydraulic-energy transfer at the bit under operational constraints

Table 1: Recent drilling-related studies relevant to RSM-based optimization and the identified hydraulic gap (2021–2026)

Authors	Study Focus	Target Variable	Method	Main Findings / Key Results	Missing Physical / Operational Considerations
Category I: Mechanical and Operational Drilling-Performance Optimization					
Bani Mustafa et al. (2021) [3]	Optimization of controllable drilling parameters	ROP	RSM	Applied RSM to 9356 field records. FR had the strongest influence on ROP variation, with a sum-of-squares value of 23.47. The maximum predicted ROP reached approximately 20.94 m/h when FR was increased to the recommended operating limit of 2600 L/min. The study also showed that increasing WOB does not always improve ROP.	Focused on ROP optimization; BHHP and JIF were not evaluated as hydraulic-performance objectives.
Tewari et al. (2021) [6]	Automated drill-bit selection based on optimum ROP	ROP and bit type	RSM + ABC	The RSM–ABC framework correctly selected the drill-bit type for all five target geological zones. The RSM objective function achieved a correlation coefficient of 81.23%, compared with 85.5% for ANN. The proposed approach produced a lower cost per foot than ANN–GA in Zone 1 and comparable costs in the remaining zones.	Hydraulic-energy transfer at the bit was not treated as an optimization objective; no simultaneous BHHP–JIF optimization.
Mantegazini et al. (2025)[26]	Multi-objective drilling performance optimization	ROP and MSE	RSM + multi-objective optimization	Single-objective optimization maximized ROP at 23.99 ft/h but produced an MSE of 156.43 kpsi. The selected multi-objective scenario achieved a more balanced ROP of 21.58 ft/h and MSE of 11.36 kpsi using WOB = 11.75 klb, RPM = 109.36 rev/min, FLOW = 803.32 gpm, and TOR = 3.34 klb-ft.	Focused primarily on mechanical efficiency; BHHP and JIF were not optimized as primary bit-level hydraulic responses.
Category II: Drilling-Fluid Formulation and Rheological Optimization					
Asmungi et al. (2021)[11]	Optimization of water-based mud rheology using natural additives	Plastic viscosity (PV), apparent viscosity (AV), yield point (YP)	RSM+ Box–Behnken Design (BBD)	The models achieved R^2 values of 0.9753 for PV, 0.9582 for AV, and 0.9513 for YP. The optimum formulation consisted of 4.02 g bentonite, 7.29 g tannin, and 0.53 g xanthan gum, producing predicted values of PV = 8.32 cP, AV = 24.41 cP, and YP = 32.19 lb/100 ft^2. Validation experiments showed good agreement with the predicted responses.	Focused on laboratory-scale rheological optimization; no direct evaluation of bit-level hydraulic performance, BHHP, JIF, or downhole operational constraints.

Alakbari et al.(2021)[27]	Prediction of apparent and plastic viscosities of nanoparticle-enhanced water-based drilling fluid	Apparent viscosity, plastic viscosity	RSM-based empirical correlations	The developed models achieved R^2 values of 0.978 for apparent viscosity and 0.961 for plastic viscosity, with predicted R^2 values of 0.969 and 0.941, respectively. Adequate precision values reached 109.54 and 59.191. Increasing bentonite and nanosilica concentrations enhanced both viscosities, whereas increasing temperature reduced the rheological responses.	Limited to rheological-property prediction; no direct coupling with ROP, BHHP, JIF, or field-scale hydraulic behavior.
Alhajabdalla et al.(2021) [28]	Optimization of fibrous-dispersion stability for drilling and completion operations	Fiber-suspension stability	RSM / BBD	The developed models showed good agreement with experimental measurements, with R^2 values ranging from 0.91 to 0.99. The base-fluid polymer concentration was identified as the dominant factor. Suspensions with viscosities above 50 mPa·s were sufficient to maintain stability at both 25°C and 80°C.	Focused on suspension stability rather than direct drilling-performance optimization; no BHHP, JIF, ROP, or field-scale hydraulic-energy analysis.
Bai et al. (2021) [29]	Synthesis and optimization of a starch-based copolymer for drilling-mud filtration control	Filtration loss and rheological performance	Central Composite Design (CCD)-based RSM	Synthesized and optimized sodium carboxymethyl starch-graft acrylamide/1-vinyl-2-pyrrolidone copolymers for use as a filtration-loss-control agent in drilling muds. The optimized copolymer enhanced fluid rheology and reduced filtration loss. Detailed optimum formulation conditions and quantitative reduction values were not reported in the accessible abstract.	Focused on drilling-fluid additive synthesis and filtration control; no direct linkage to ROP, BHHP, JIF, or field-scale bit-hydraulic performance.
Ali et al. (2023) [30]	Rheological and thermal-performance optimization of bentonite-free drilling mud modified with carboxymethyl irradiated tapioca starch (CMITS)	Plastic viscosity, yield point, gel strength, rheological stability	Central Composite Design (CCD)-based RSM	Increasing the CMITS degree of substitution to 0.66 and the additive concentration to 8 ppb improved plastic viscosity, yield point, and gel strength. Increasing salinity and temperature reduced the rheological responses. The study demonstrated the potential of CMITS as an alternative additive for improving bentonite-free drilling-mud performance. Focused on formulation-level rheological optimization; no direct assessment of drilling-performance indicators or bit-level hydraulic objectives such as BHHP	Focused on formulation-level rheological optimization; no direct assessment of drilling-performance indicators or bit-level hydraulic objectives such as BHHP and JIF.
Li et al. (2025) [23]	Optimization of glue breakage and water	Water yield	RSM + Radial Basis Function	The RSM model achieved $R^2 = 0.9939$, outperforming the standalone RBFNN model with	Applied to waste-fluid treatment rather than active drilling operations; ANN

	recovery from waste drilling fluids		Neural Network (RBFNN) + Genetic Algorithm (GA)	R^2 = 0.9778. Numerical RSM optimization predicted a maximum water yield of 62.37% at a glue-breaker dosage of 3.97 kg/m³, temperature of 51°C, and stirring speed of 419 rpm. The GA–RBFNN model further achieved R^2 = 0.998 and a maximum water yield of 61.97%.	integration was not used for bit-level hydraulic prediction or simultaneous BHHP–JIF optimization.
Jia et al.(2025) [24]	Optimization of nanosilica-enhanced polymer synthesis for water-based drilling fluids	Filtration loss, coefficient of friction, cutting-carrying capacity	RSM	The optimum synthesis conditions were 70.9°C, pH = 7, and an initiator concentration of 0.57 wt.%. The optimized nanosilica-based polymer reduced filtration loss by 46.0% and the coefficient of friction by 28.6%, while improving the YP/PV ratio and cutting-carrying performance.	Focused on additive synthesis and fluid performance; no direct assessment of hydraulic-energy transfer at the bit or constrained optimization of BHHP and JIF.
Satiyawira et al. (2025)[25]	Multi-temperature optimization of water-based drilling mud using CMC and an alkaline polymer	Viscosity, plastic viscosity, YP, gel strength, filtrate control	RSM + BBD + multi-response desirability optimization	At 150°F, the optimum formulation consisted of 3.5 g CMC and 3.6 g alkaline polymer. The optimized formulation achieved viscosity = 17.64 cP, PV = 12.46 cP, and YP = 7.72 lb/100 ft², with improved gel strength and consistent filtrate control compared with non-optimized systems. The study evaluated performance at 80°F, 150°F, and 250°F.	Addressed thermal stability and mud formulation under HTHP-related conditions, but did not directly optimize bit-level hydraulic indicators such as BHHP and JIF.
Ossai et al.(2025) [31]	Optimization of drilling-mud formulation using locally sourced materials	Apparent viscosity, plastic viscosity	RSM + BBD	The apparent-viscosity model achieved R^2 = 0.9737 with adequate precision = 19.2750, whereas the plastic-viscosity model achieved R^2 = 0.9566 with adequate precision = 14.5243. The optimum formulation consisted of 20 g clay, 1.5 g corn-cob ash, 2 g NaOH, and 5 g cassava starch, producing AV = 116.431 mPa·s and PV = 75.6167 mPa·s.	Addressed thermal stability and mud formulation under HTHP-related conditions, but did not directly optimize bit-level hydraulic indicators such as BHHP and JIF.
Alakbari et al. (2025) [32]	Yield-point prediction for water-based drilling fluids under varying operating conditions and additive concentrations	Yield point (YP)	RSM-based empirical correlation	Developed an RSM-based correlation to predict YP as a function of pressure, temperature, nanosilica concentration, nanoclay concentration, and bentonite concentration. The model agreed closely with measured data, achieving a Pearson correlation coefficient of 0.9947. Temperature and the concentrations of bentonite and nanosilica were identified as the most influential variables.	Focused on rheological-property prediction; no direct coupling with ROP, BHHP, JIF, or field-scale hydraulic-energy transfer at the bit.
da Silva et al. (2026)[33]	Rheological assessment of a sustainable babassu-	Apparent viscosity, yield limit,	RSM-supported analysis	Salinity was identified as the most influential factor, significantly enhancing yield limit,	Applied factorial-design-based response-surface analysis rather than a

	ester-based drilling-fluid system	consistency index, thixotropy | (2^3) factorial experimental design + ANOVA + Pareto analysis + response-surface analysis		consistency index, and apparent viscosity. Fluids with an oil/water ratio of 60/40 generally exhibited higher apparent viscosity. Unexpected viscosity increases were observed in some formulations at 90°C, indicating possible thermal degradation or saponification effects and the need for further nonlinear modeling.	full second-order RSM optimization framework. The study focused on sustainable fluid formulation and rheological characterization; it did not directly link the optimized properties to ROP, BHHP, JIF, or field-scale bit-hydraulic performance
Category III: Hydraulic Behavior, Hole Cleaning, and Integrated Modeling Approaches					
Awad et al. (2022)[22]	Cuttings-transport and hole-cleaning optimization in non-Newtonian drilling fluids	Cuttings transport ratio (CTR), cuttings volume concentration (CVT), annular pressure drop	CFD + RSM	Drill-pipe rotation was identified as the dominant operational factor affecting hole-cleaning performance, particularly in highly deviated and horizontal wells. Eccentric pipes produced up to 73% higher CVT than concentric pipes. Highly inclined and horizontal sections exhibited CVT values of 9–29%, compared with 4–5.8% in vertical sections. Increasing eccentricity from 0 to 0.8 increased CVT by 22–28% in 45°-inclined and horizontal wells, but by only approximately 5% in vertical wells. The optimization results indicated that low rotational speeds (N < 20 rpm) and nearly concentric annuli (e < 0.2) are preferable in vertical wells, whereas higher rotational speeds of approximately 200 rpm combined with low eccentricity improve cuttings transport in horizontal wells.	Focused on annular cuttings transport and pressure-drop behavior rather than hydraulic-energy transfer at the bit. BHHP and JIF were not treated as optimization objectives. The CFD analysis also neglected the orbital motion associated with drill-pipe rotation
Ihua-Maduenyi and Oguta (2025) [34]	Modeling and optimization of annular equivalent circulating density (AECD) in extended-reach wells	Annular ECD	Landmark WellPlan simulation + RSM + Box–Behnken Design (BBD)	The hybrid WellPlan–RSM framework evaluated the effects of pump rate, ROP, rotary speed, and cuttings density on AECD in a 35,017-ft extended-reach well. Increasing pump rate from 200 to 300 gal/min reduced AECD from 18.91 to 14.94 ppg, corresponding to a 21% reduction. Increasing ROP from 25 to 50 ft/h increased AECD by 0.87 ppg because of higher cuttings loading and frictional pressure loss. Increasing cuttings density from 2.10 to 2.16 sg raised AECD from 16.97 to 17.64 ppg. The quadratic RSM model achieved $R^2 = 0.9630$,	Addressed annular hydraulics and AECD management rather than bit-level hydraulic performance. The framework did not optimize BHHP or JIF and did not integrate ANN-based nonlinear prediction.

				adjusted $R^2 = 0.9259$, predicted $R^2 = 0.7866$, CV = 1.7%, and a model F-value of 38.41 with $p < 0.0001$. The study reported that the framework could support safer hydraulic management and reduce non-productive time by up to 12%.	
Hao et al. (2024) [35]	Evaluation of casing-to-wellbore clearance and ECD during casing-running operations	ECD and surge pressure during casing running	Transient surge-pressure calculation model + RSM fitting	The study analyzed ECD behavior under 10,000-m well conditions and identified a minimum allowable casing-to-wellbore clearance of 27 mm under fracture-pressure constraints. For a maximum safe ECD limit of 1.71 g/cm³, the recommended operating ranges were drilling-fluid density = 1.65–1.68 g/cm³, casing-running speed = 1–24 m/min, and casing-to-wellbore clearance = 28–72 mm. When the clearance was fixed at the minimum value of 27 mm, the drilling-fluid density had to be maintained at 1.65 g/cm³ and the casing-running speed limited to 1–12 m/min, producing a maximum ECD of 1.663 g/cm³. Focused on surge pressure and ECD during casing-running operations rather than active drilling at the bit. The study did not address BHHP, JIF, ROP improvement, cuttings transport at the bit, or ANN-based prediction.	Focused on surge pressure and ECD during casing-running operations rather than active drilling at the bit. The study did not address BHHP, JIF, ROP improvement, cuttings transport at the bit, or ANN-based prediction..

5. Critical Discussion

The reviewed studies reveal a clear imbalance in the application of Response Surface Methodology (RSM) within drilling engineering. As summarized in Table 1, the majority of recent RSM applications focus either on drilling-fluid optimization or on mechanical-performance improvement, whereas direct optimization of bit-level hydraulic performance remains largely unexplored.

Within the mechanical-performance category, [3] applied RSM to 9,356 field records and demonstrated that flow rate was the most influential variable affecting ROP, achieving a maximum predicted ROP of approximately 20.94 m/h. Similarly, [6] integrated RSM with the Artificial Bee Colony algorithm and achieved a drill-bit selection correlation coefficient of 81.23%, while [26] reported a balanced multi-objective solution that achieved an ROP of 21.58 ft/h with a significantly reduced MSE of 11.36 kpsi. Although these studies demonstrate the effectiveness of RSM for improving drilling performance, the optimization objectives remained focused on mechanical indicators such as ROP and MSE. None of these studies incorporated BHHP or JIF as primary hydraulic-performance objectives.

There is more literature reviewed on the drilling-fluid formulation and the optimization of the rheology of the drilling fluid. For instance, Asmungi, et al. [11] had R^2 greater than 0.95 for PV, AV, and YP predictions, respectively, and Alakbari, et al. [27] reported R^2 of 0.978 and 0.961 for apparent and plastic viscosity predictions, respectively. More recent work by Jia, et al. [24] and Satiyawira, et al. [25] showed that filtration control, rheological stability, and water-recovery performance were significantly improved, and in some instances predictive accuracy was as high as $R^2 = 0.998$. Ossai, et al. [31] and Li, et al. [23] also showed significant improvements in these areas with predictive accuracy as high as $R^2 = 0.998$ in some cases. Despite these improvements, the optimization goals were still focused only on fluid properties and/or formulation performance and not on the impact of these improvements on the hydraulic energy transfer at the bit.

The data reviewed here is just a fraction of what is available in the literature related to hydraulic applications. Awad, et al. [22] developed a CFD-RSM model to study the transport of cuttings and AECD inside the annulus, while Ihua-Maduenyi and Oguta [34] employed a WellPlan-RSM model to optimize AECD, and they reported a 21% decrease in AECD under optimized operation. Hao, et al. [35] also studied the ECD behavior for operations of casing running and established the safe ECD operation window for fluid density and running rate. These studies are significant advances in introducing hydraulic constraints in drilling optimization. They do not, however, concentrate on hydraulic transmission of energy at the bit but mainly on annular hydraulics.

Another fact is that regarding hybrid and intelligent optimization, there is a fragmentation. Li, et al. [23] were able to combine RSM with neural-network modeling and genetic algorithms, but the framework was used for treatment of waste drilling fluid rather than for drilling-performance optimization. There has been thus far no comprehensive exploration of the synergy between structured experimental design and nonlinear machine-learning prediction for the task of bit-level hydraulic optimization.

Most significantly, none of the reviewed studies integrated BHHP, JIF, ECD limits, MPD operating windows, HPHT rheological behavior, formation-strength constraints, and drilling-dynamics parameters (stick-slip and whirl vibrations) in a single optimization framework. This is directly in response to the concerns of recent developments in drilling automation and digital drilling, in which decisions for operations are increasingly based on integrated hydraulic, mechanical, and safety constraints.

In general, the literature reviewed shows that RSM is still a strong optimization tool in the field of drilling engineering. But today, there is still a definite bias in the use of mechanical performance and drilling-fluid properties and little direct optimization of the hydraulic energy-transfer mechanisms at the bit. This gap offers the motivation to develop integrated frameworks of RSM-ANN that are able to optimize BHHP and JIF simultaneously, subject to realistic field-operational constraints.

6.Research Gap and Critical Analysis

The literature review has shown that Response Surface Methodology (RSM) has been

extensively used in drilling engineering; however, it has been applied primarily to result-based responses such as Rate of Penetration (ROP), Mechanical Specific Energy (MSE), and properties of drilling fluids. These answers are significant for assessing the performance of the drill but are not a direct representation of the physical mechanisms of hydraulic energy transfer at the bit.

Physically, the Bit Hydraulic Horsepower (BHHP) and Jet Impact Force (JIF) are more closely related to the delivery of hydraulic energy to the bit, rock fragmentation, cutting removal, and wellbore cleaning efficiency. It is therefore important to exclude BHHP and JIF from optimization models if the physical causes of drilling performance are not to be included. As shown in Figure 2, most of the current RSM applications are based on optimizing mechanical or fluid-based responses with a relatively limited representation of bit-level hydraulic responses.

The lack of a quantitative classification of the studies reviewed also supports this gap. Drilling-fluid optimization is the largest category of the reviewed RSM applications, with mechanical/ROP optimization, as shown in Figure 4, being the second largest category. However, in contrast, only a few studies have focused on hydraulic aspects such as the transport of cuttings and Equivalent Circulating Density (ECD) but not on the direct optimization of BHHP and JIF as the main variables. This validates that the existing RSM literature from the field of drilling engineering is still very much geared towards mechanical and fluid property optimization versus hydraulic performance optimization.

In terms of methodology, most existing studies based on RSM are conducted using second-order polynomial models and single-objective optimization. Although these techniques can be applied to determine the interactions of variables in a limited design space, they cannot effectively address highly nonlinear and coupled drilling hydraulics. This restriction is particularly significant for BHHP and JIF, which involve interactions between the flow rate, pressure losses, nozzle geometry, mud properties, and bit-rock contact conditions.

Artificial Neural Networks (ANNs) have more powerful modeling abilities for nonlinear relationships between the variables of a drilling system [36]. Typically, however, ANN-based models are developed without following a structured experimental design framework; therefore, the models might lack physical consistency and interpretability. This leaves a methodological gap between the statistically structured modeling based on RSM and nonlinear prediction based on ANN.

Moreover, none of the current optimization methods adequately consider field operational constraints [37] such as the ECD limits, managed pressure drilling (MPD) window [38], high-pressure high-temperature (HPHT) rheological changes, boundaries of formation strength, and drilling dynamics such as stick-slip and whirl vibrations. Failure to consider these factors can result in solutions that are theoretically appealing but not practical for safe drilling operations.

In view of the identified key research gaps, an integrated physics-guided framework that incorporates RSM-based experimental design, ANN-based nonlinear prediction, and multi-objective optimization of BHHP and JIF under realistic drilling constraints is recommended for future studies. Filling this gap would facilitate the creation of optimal drilling systems that are more accurate, scalable, and field viable.

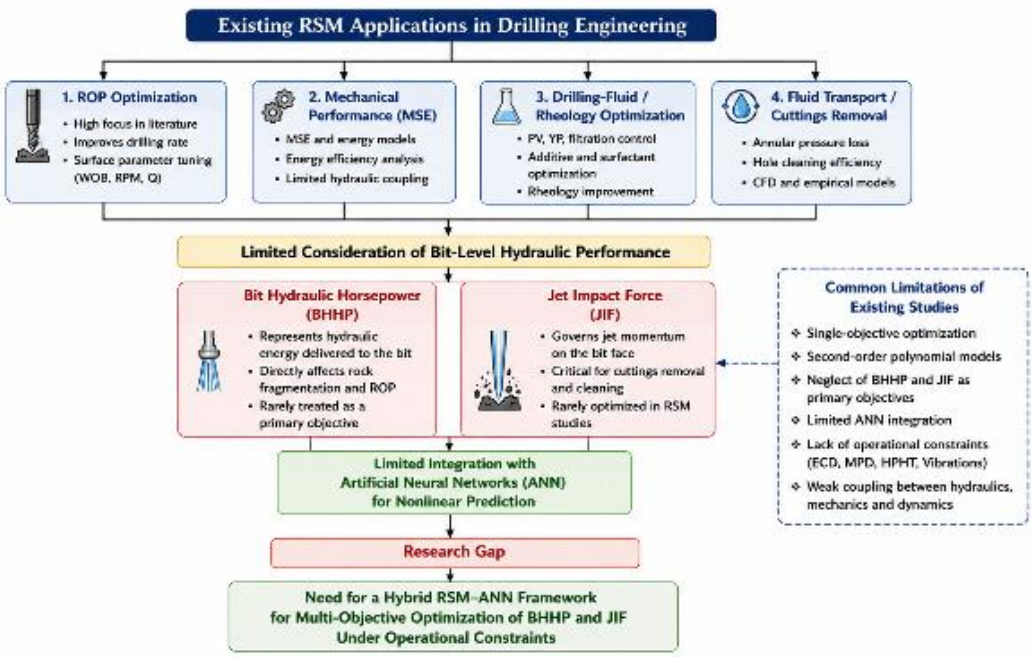

Figure 2. Research gap identified from the reviewed literature and the motivation for future hybrid RSM–ANN-based hydraulic optimization

6.1 Quantitative Assessment of Current RSM Applications

To provide a quantitative perspective on the current state of RSM applications in drilling engineering, the reviewed studies were classified according to their primary application area, as shown in Figure 3. The analysis indicates that drilling-fluid optimization represents the largest category of RSM applications, accounting for approximately 64.7% of the reviewed studies. These investigations mainly focused on rheological-property enhancement, mud formulation optimization, viscosity control, and drilling-fluid performance improvement.

Mechanical drilling optimization represents the second-largest category, accounting for approximately 17.6% of the reviewed studies. Most of these studies focused on improving Rate of Penetration (ROP), reducing Mechanical Specific Energy (MSE), and optimizing controllable drilling parameters such as Weight on Bit (WOB), Rotary Speed (RPM), and Flow Rate (Q).

Hydraulic-related applications, including cuttings transport and Equivalent Circulating Density (ECD) optimization, account for approximately 17% of the reviewed studies. Similarly, hybrid approaches integrating RSM with Artificial Neural Networks (ANN) or metaheuristic algorithms also represent approximately 17% of the available literature.

Most importantly, no reviewed study was found to directly optimize Bit Hydraulic Horsepower (BHHP) and Jet Impact Force (JIF) as simultaneous primary optimization objectives. This quantitative distribution confirms the existence of a significant research gap in current drilling-optimization research.

As shown in Figure 3, this quantitative distribution confirms that current RSM research remains strongly focused on fluid-property and mechanical-performance optimization, while bit-level hydraulic optimization remains largely unexplored.

In addition to the distribution of application areas, the reviewed literature demonstrates that RSM can generate measurable improvements in drilling-related responses. As illustrated in Figure 4, reported benefits include improved ROP, enhanced drilling-fluid rheology, better additive-formulation performance, improved ECD prediction, and more accurate mud-property estimation. These findings confirm that RSM is not only a statistical design tool but also a practical optimization methodology capable of producing

significant improvements across multiple drilling applications.

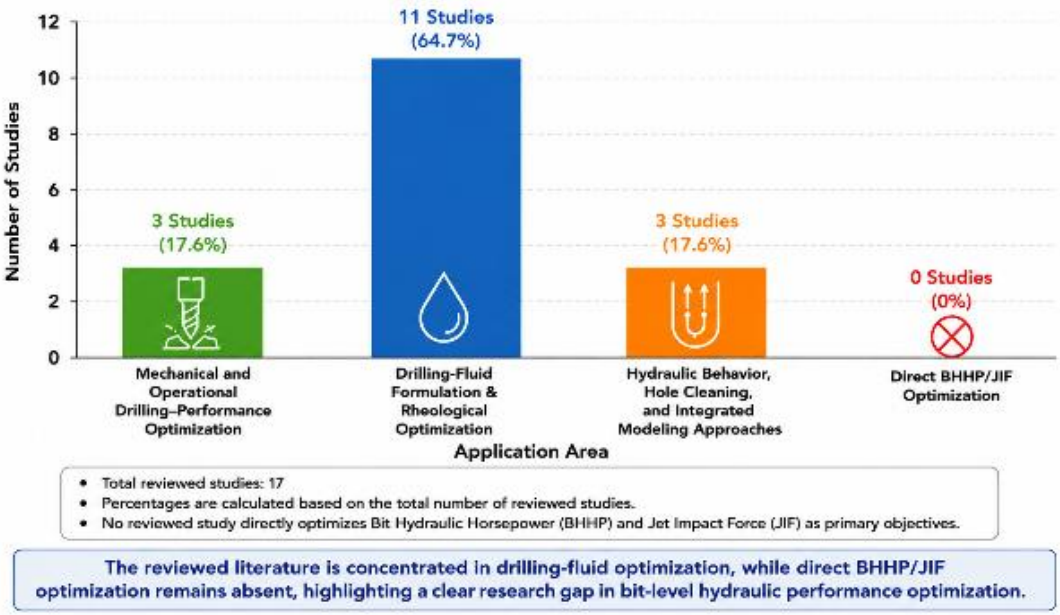

Figure 3. Quantitative distribution of reviewed RSM applications according to their primary application area in drilling engineering

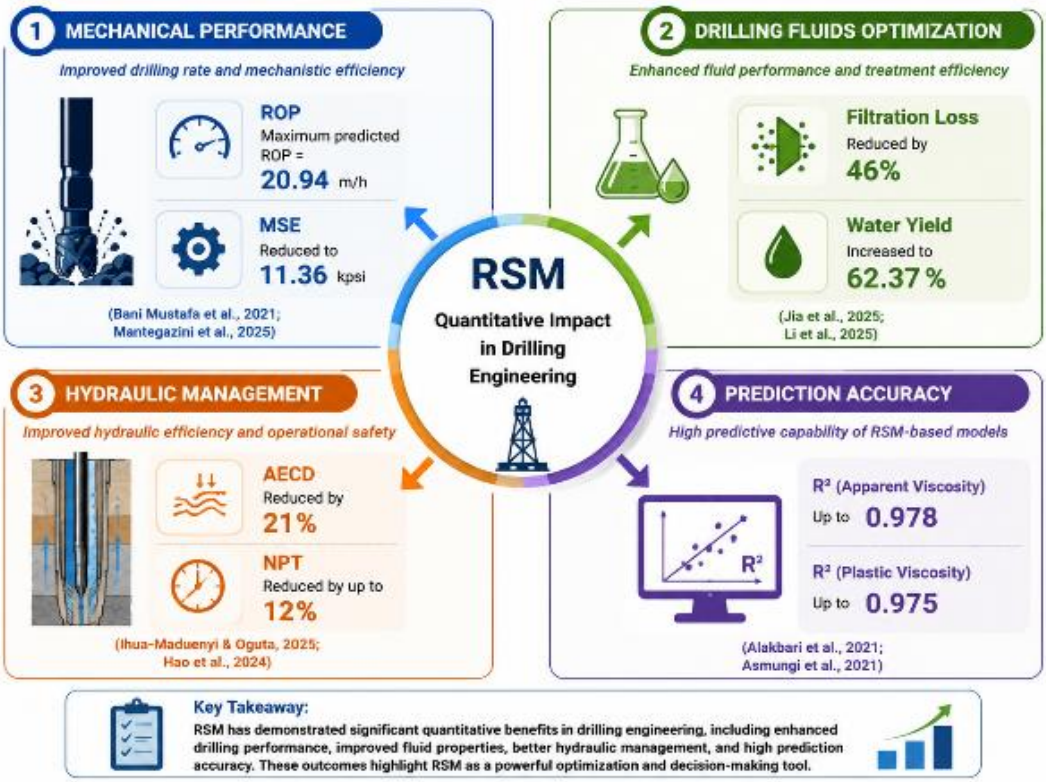

Figure 4. Representative quantitative outcomes of RSM applications in drilling engineering, highlighting reported improvements in drilling performance, drilling-fluid optimization, hydraulic management, and predictive-model accuracy

However, despite these demonstrated improvements, the reviewed studies remain largely focused on mechanical and fluid-related responses, whereas direct optimization of bit-level hydraulic energy-transfer parameters, particularly BHHP and JIF, remains largely unexplored. Therefore, future research should focus on extending RSM applications toward constrained multi-objective hydraulic optimization integrated with advanced nonlinear predictive models.

6.2 Limitations and Uncertainties

Although RSM has demonstrated clear value in drilling optimization, several limitations and uncertainties remain evident from the reviewed literature.

First, most studies focus on ROP, MSE, and drilling-fluid properties, whereas BHHP and JIF are rarely considered as primary optimization objectives. This limits the ability of existing models to represent the direct contribution of hydraulic energy transfer to drilling efficiency.

Second, the majority of RSM applications use second-order polynomial approximations. Although these models are useful for local response prediction, they may not be suitable for describing the highly nonlinear drilling-hydraulic behavior, such as pressure loss, jet velocity, mud rheology, nozzle geometry, and fluid–rock interaction.

Third, certain studies reviewed fail to consider operational factors that are crucial for field implementation. These include ECD limits, MPD operating windows, HPHT rheological variations [39], and drilling dynamics like stick-slip and whirl vibrations. Without these constraints, the optimization recommendations are not as reliable under real-field conditions.

Fourth, the use of RSM in association with ANN or other intelligent prediction methods is still limited. Hence, many models developed have limited generalization ability beyond the range of the experiments or operations performed for the calibration.

Last but not least, many existing studies rely on scaled-down experiments, simulations, or idealistic operating conditions. Future hybrid optimization frameworks must be validated using real field data to ensure their robustness, scalability, and deployment potential.

These restrictions suggest that further research should be directed toward physics-guided and constraint-aware RSM–ANN frameworks, which allow for the optimization of the BHHP and JIF within the boundaries of field operation.

6.3 Future Research Directions

The findings of this review indicate several promising directions for future research in drilling optimization. First, future studies should move beyond conventional mechanical-performance indicators and place greater emphasis on bit-level hydraulic performance parameters, particularly Bit Hydraulic Horsepower (BHHP) and Jet Impact Force (JIF), because these parameters directly govern hydraulic energy transfer, rock fragmentation, and cuttings removal processes.

Second, future optimization frameworks should integrate Response Surface Methodology (RSM) with Artificial Neural Networks (ANN) to combine the advantages of structured experimental design and nonlinear predictive modeling. Such integration can improve prediction accuracy while maintaining physical interpretability within the design space [40].

Third, drilling optimization should be formulated as a constrained multi-objective problem that simultaneously considers hydraulic performance, mechanical performance, and operational safety. Important operational constraints include Equivalent Circulating Density (ECD), MPD operating windows [41], High-Pressure High-Temperature (HPHT) rheological variations, formation-strength limits, and drilling dynamics such as stick-slip and whirl vibrations .

Finally, future research should focus on real-time implementation of hybrid optimization systems through integration with digital drilling platforms and automated rig environments [42]. Recent studies on autonomous drilling, closed-loop well placement, and real-time machine-learning-based drilling optimization demonstrate that automated drilling systems are increasingly moving toward continuous data-driven decision-making and field-level deployment [43] [42]. Such systems may support continuous updating of optimization models using field data and enable

intelligent decision-making during drilling operations.

The conceptual framework proposed in Figure 5 illustrates a possible pathway toward the development of an integrated RSM–ANN-based drilling optimization system capable of addressing these challenges.

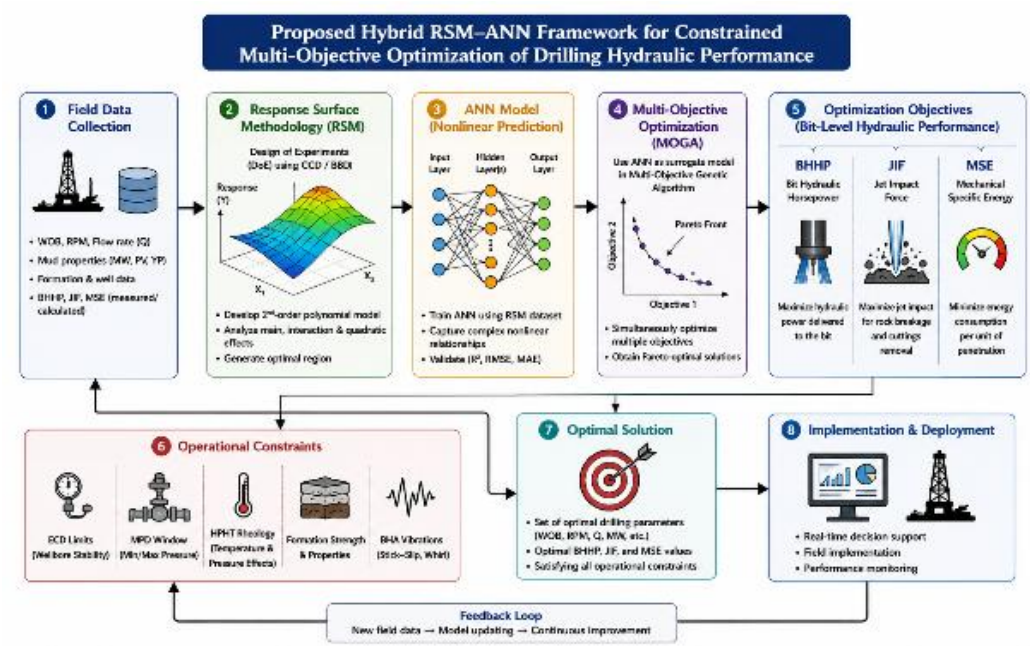

Figure 5. Proposed hybrid RSM–ANN framework for constrained multi-objective optimization of drilling hydraulic performance under operational constraints.

7. Conclusions

Based on the critical review of recent Response Surface Methodology (RSM) applications in drilling engineering, the following conclusions can be drawn:

1. RSM remains an effective tool for drilling optimization, particularly for improving mechanical performance indicators such as Rate of Penetration (ROP) and for optimizing drilling-fluid properties. The reviewed studies demonstrate that RSM provides a structured framework for identifying influential variables and evaluating parameter interactions within constrained operating conditions.
2. Most existing RSM applications focus on mechanical and fluid-related responses, while bit-level hydraulic performance parameters, particularly Bit Hydraulic Horsepower (BHHP) and Jet Impact Force (JIF), are rarely considered as primary optimization objectives despite their direct influence on hydraulic energy transfer, rock fragmentation, cuttings removal, and wellbore cleaning efficiency.
3. Current RSM-based drilling studies are largely limited by single-objective optimization and second-order polynomial approximations. These limitations restrict their ability to accurately represent the highly nonlinear and coupled behavior of drilling hydraulics, especially under varying operational conditions.
4. Artificial Neural Networks (ANN) provide strong nonlinear predictive capabilities, but existing ANN-based drilling models are generally developed independently from structured experimental-design methodologies such as RSM. As a result, current approaches fail to fully exploit the complementary strengths of statistical design and data-driven prediction.
5. A significant research gap exists in the absence of integrated RSM–ANN frameworks for multi-objective optimization

of BHHP and JIF under operational constraints. Future research should focus on developing physics-guided hybrid optimization frameworks that combine experimental design, nonlinear prediction, and hydraulic-performance objectives to achieve more accurate, scalable, and field-applicable drilling optimization systems.

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Abbreviations

Abbrevia	Full Form
ABC	Artificial Bee Colony
ANN	Artificial Neural Network
AV	Apparent Viscosity
BBD	Box–Behnken Design
BHHP	Bit Hydraulic Horsepower
CCD	Central Composite Design
CFD	Computational Fluid Dynamics
CTR	Cuttings Transport Ratio
CVT	Cuttings Volume Concentration
ECD	Equivalent Circulating Density
FR	Flow Rate
FRGA	Genetic Algorithm
HPHT	High-Pressure High-Temperature
HTHP	High-Temperature High-Pressure
JIF	Jet Impact Force
MPD	Managed Pressure Drilling
MSE	Mechanical Specific Energy
NPT	Non-Productive Time
RBFNN	Radial Basis Function Neural Network
ROP	Rate of Penetration
RPM	Revolutions Per Minute
RSM	Response Surface Methodology
TOR	Torque
WBM	Water-Based Mud

Symbols

Symbol	Description	Unit
Q	Flow rate	gpm
WOB	Weight on Bit	Klb
PV	Plastic viscosity	cP
YP	Yield point	lb/100 ft²
BHHP	Bit Hydraulic Horsepower	hp
JIF	Jet Impact Force	lbf

Conflict of interest

The author declares that there are no conflicts of interest or competing interests regarding the publication of this manuscript.

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Author Contribution

The authors were solely responsible for the conceptualization, literature review, analysis, writing, and revision of the manuscript.

AI Declaration Statement

The authors confirm that the manuscript has been written without the assistance of generative AI or AI-based writing tools.

References

[1] A. Schultz and R. Rallo, "Toward Drilling the Perfect Geothermal Well: An International Research Coordination Network for Geothermal Drilling Optimization Supported by Deep Machine Learning and Cloud Based Data Aggregation," Golden Field Office, Golden, CO (United States), 2025.

[2] A. N. Al-Dujaili, M. S. Asad, N. Saeed, and N. Tileuberdi, "Optimizing polycrystalline diamond compact bit selection and drilling parameters for deviated wells in the Majnoon Field, Iraq," *Scientific Reports,* vol. 15, no. 1, p. 3178, 2025, doi: https://doi.org/10.1038/s41598-025-87484-9.

[3] A. Bani Mustafa, A. K. Abbas, M. Alsaba, and M. Alameen, "Improving drilling performance through optimizing controllable drilling parameters," *Journal of Petroleum Exploration and Production,* vol. 11, pp. 1223-1232, 2021, doi: https://doi.org/10.1007/s13202-021-01116-2.

[4] G. Bi *et al.*, "Study on the mechanism of high-efficiency rock breaking by hydraulic jet based on explicit dynamics," *Processes,* vol. 11, no. 7, p. 2165, 2023, doi: https://doi.org/10.3390/pr11072165.

[5] M. Al-Rubaii, M. Al-Shargabi, D. Al-Shehri, A. Alyami, and K. M. Minaev, "A novel efficient borehole cleaning model for optimizing drilling performance in real time," *Applied Sciences,* vol. 13, no. 13, p. 7751, 2023, doi: https://doi.org/10.3390/app13137751.

[6] S. Tewari, U. D. Dwivedi, and S. Biswas, "Intelligent drilling of oil and gas wells using response surface methodology and artificial bee colony," *Sustainability,* vol. 13, no. 4, p. 1664, 2021, doi: https://doi.org/10.3390/su13041664.

[7] W. Zhu *et al.*, "A Hybrid Deep Learning Approach for Rate of Penetration Prediction in Deepwater Drilling," in *Offshore Technology Conference*, 2025: OTC, p. D011S007R004, doi: https://doi.org/10.4043/35771-MS.

[8] A. Al-Dujaili, "New advances in drilling operations in sandstone, shale, and carbonate formations: a case study of five giant fields in the Mesopotamia Basin, Iraq," *Mining Science and Technology (Russia),* vol. 9, no. 4, pp. 308-327, 2024, doi: https://doi.org/10.17073/2500-0632-2023-08-146.

[9] D. Mahmood, A. Sidek, K. A. Ganie, and N. S. Al-Zubaidi, "Enhancing Drilling Efficiency: A Comprehensive Review of Bit Hydraulic Optimization in Rotary Drilling Operations," *Petroleum Chemistry,* vol. 65, no. 5, pp. 550-557, 2025, doi: https://doi.org/10.1134/S0965544125040097.

[10] M. M. Al-Rubaii, "Real-Time Models of Rig and Drill Bit Hydraulics Optimizes Drilling Efficiency," presented at the Offshore Technology Conference Asia, Kuala Lumpur, Malaysia, 2026. [Online]. Available: https://doi.org/10.4043/36336-MS.

[11] A. H. Asmungi, N. A. Ghazali, S. F. Abdul Manaf, O. S. Jehan Elham, and N. I. Hammizul, "Optimisation of Rheological Properties of Water-Based Mud (WBM) with Natural Additives by Using Response Surface Methodology (RSM)," *Key Engineering Materials,* vol. 939, pp. 103-114, 2023, doi: https://doi.org/10.4028/p-zcg62q.

[12] H. Chen, Y. Jin, W. Zhang, J. Zhang, L. Ma, and Y. Lu, "Deep neural network prediction of mechanical drilling speed," *Energies,* vol. 15, no. 9, p. 3037, 2022, doi: https://doi.org/10.3390/en15093037.

[13] L. Velásquez, A. Rubio-Clemente, D. Tobón, F. Botero, C. Arrieta, and E. Chica, "Experimental Optimization of the Propeller Turbine Performance Using the Response Surface Methodology," *Sustainability,* vol. 16, no. 19, p. 8476, 2024, doi: https://doi.org/10.3390/su16198476.

[14] X. Feng, Y. Xie, S. Liu, and F. Yang, "Influence and Optimization of Geometric Parameters for Small-Radius Curved Tunnel Based on Response Surface Method," *Applied Sciences,* vol. 13, no. 6, p. 3800, 2023, doi: https://doi.org/10.3390/app13063800.

[15] M. O. Okwu *et al.*, "Investigating the accuracy of artificial neural network models in predicting surface roughness in drilling processes," *Procedia Computer Science,* vol. 232, pp. 1982-1990, 2024, doi: https://doi.org/10.1016/j.procs.2024.02.020.

[16] S. J. Arunachalam, R. Saravanan, S. Thanikodi, G. Vinuja, and A. J. Santhosh, "Hybrid ANN-Based Modeling and Optimization of Drilling Performance in Basalt Fiber Composites," *Engineering Reports,* vol. 8, no. 3, p. e70651, 2026, doi: https://doi.org/10.1002/eng2.70651.

[17] R. H. Allawi, W. J. Al-Mudhafar, M. A. Abbas, and D. A. Wood, "Leveraging Boosting Machine Learning for Drilling Rate of Penetration (ROP) Prediction Based on Drilling and Petrophysical Parameters," *Artificial Intelligence in Geosciences,* p. 100121, 2025, doi: https://doi.org/10.1016/j.aiig.2025.100121.

[18] M. Mansouri, M. Shayanmehr, and A. Ghaemi, "Exploring the adsorption desulfurization efficiency using RSM and ANN methodologies," *Scientific Reports,* vol. 15, no. 1, p. 20869, 2025, doi: https://doi.org/10.1038/s41598-025-05688-5.

[19] R. H. Myers, D. C. Montgomery, and C. M. Anderson-Cook, *Response surface methodology: process and product optimization using designed experiments*. John Wiley & Sons, 2016.

[20] A. Witek-Krowiak, K. Chojnacka, D. Podstawczyk, A. Dawiec, and K. Bubała, "Application of response surface methodology and artificial neural network methods in modelling and optimization of biosorption process," *Bioresource technology,* vol. 160, pp. 150-160, 2014, doi: https://doi.org/10.1016/j.biortech.2014.01.021.

[21] F. Mohammadinia, A. Ranjbar, F. Ghazi, and S. T. Hosseini, "Rate of penetration prediction in drilling operations: a comparative study of AI models and meta-heuristic approaches," *Journal of Petroleum Exploration and Production Technology,* vol. 15, no. 7, p. 115, 2025, doi: https://doi.org/10.1007/s13202-025-02020-9.

[22] A. M. Awad, I. A. Hussein, M. S. Nasser, S. A. Ghani, and A. O. Mahgoub, "A CFD-RSM study of cuttings transport in non-Newtonian drilling fluids: Impact of operational parameters," *Journal of Petroleum Science and Engineering,* vol. 208, p. 109613, 2022, doi: https://doi.org/10.1016/j.petrol.2021.109613.

[23] Y. Li, Z. Xu, J. Xi, H. Zhao, and Z. Fan, "Radial Basis Function Neural Network and Response Surface Methodology-Based Optimization of Glue Breakage in Waste Drilling Fluids," *Processes,* vol. 13, no. 2, p. 406, 2025, doi: https://doi.org/10.3390/pr13020406.

[24] X. Jia, N. Liu, and X. Zhao, "Optimizing Nanosilica-Enhanced Polymer Synthesis for Drilling Fluids via Response Surface Methodology: Enhanced Fluid Performance Analysis," *Journal of Composites Science,* vol. 9, no. 6, p. 263, 2025, doi: https://doi.org/10.3390/jcs9060263.

[25] B. Satiyawira *et al.*, "Drilling Fluid Optimization Using Response Surface Methodology," *Scientific Contributions Oil and Gas,* vol. 48, no. 4, pp. 281-294, 2025, doi: https://doi.org/10.29017/scog.v48i4.1900.

[26] D. Z. Mantegazini, A. Nascimento, M. H. Mathias, O. J. Romero Guzman, and M. Reich, "Optimization of Rate of Penetration and Mechanical Specific Energy Using Response Surface Methodology and Multi-Objective Optimization," *Applied Sciences,* vol. 15, no. 3, p. 1390, 2025, doi: https://doi.org/10.3390/app15031390.

[27] F. S. Alakbari, M. E. Mohyaldinn, M. A. Ayoub, A. S. Muhsan, and A. Hassan, "Apparent and plastic viscosities prediction of water-based drilling fluid using response surface methodology," *Colloids and Surfaces A: Physicochemical and Engineering Aspects,* vol. 616, p. 126278, 2021, doi:

https://doi.org/10.1016/j.colsurfa.2021.126278.

[28] M. Alhajabdalla, H. Mahmoud, M. S. Nasser, I. A. Hussein, R. Ahmed, and H. Karami, "Application of response surface methodology and Box–Behnken design for the optimization of the stability of fibrous dispersion used in drilling and completion operations," *ACS omega,* vol. 6, no. 4, pp. 2513-2525, 2021, doi: https://doi.org/10.1021/acsomega.0c04272.

[29] X. Bai, X. Zhang, Y. Xu, and X. Yong, "Synthesis and characterization of sodium carboxymethyl starch-graft acrylamide/1-vinyl-2-pyrrolidone copolymers via central composite design and using as filtration loss agent in drilling muds," *Starch-Stärke,* vol. 73, no. 3-4, p. 2000151, 2021, doi: https://doi.org/10.1002/star.202000151.

[30] I. Ali, M. Ahmad, S. Ridha, C. C. Iferobia, and N. Lashari, "Enhancing drilling mud performance through CMITS-modified formulations: rheological insights and performance optimization," *RSC advances,* vol. 13, no. 47, pp. 32904-32917, 2023, doi: https://doi.org/10.1039/D3RA06008J.

[31] J. E. Ossai, E. A. Oyedoh, V. O. Magbuwe, and M. I. Atapia, "Optimization of the Formulation of Drilling Mud using Box–Behnken Design," *NIPES-Journal of Energy Technology and Environment,* vol. 7, no. 2, pp. 166-173, 2025, doi: https://doi.org/10.5281/zenodo.15609815.

[32] F. S. Alakbari, M. E. Mohyaldinn, S. M. Mahmood, A. M. Hassan, R. Ashena, and A. Al-Fakih, "A Statistics-Based Correlation for the Assessment of Water-Based Mud Performance: Yield Point Prediction," *Arabian Journal for Science and Engineering,* vol. 50, no. 7, pp. 4927-4942, 2025, doi: https://doi.org/10.1007/s13369-024-09415-6.

[33] L. A. da Silva *et al.*, "Assessment of the rheological properties of a novel drilling fluid based on babassu esters for oil well applications," *Petroleum Research,* 2026, doi: https://doi.org/10.1016/j.ptlrs.2026.02.006.

[34] I. E. Ihua-Maduenyi and E. Oguta, "Modelling and Performance Analyses of Annular Equivalent Circulation Density in Extended Reach Wells Using Response Surface Methodology," *Asian Journal of Engineering and Applied Technology,* vol. 14, no. 2, pp. 1-17, 2025, doi: https://doi.org/10.70112/ajeat-2025.14.2.4298.

[35] C. Hao *et al.*, "Investigation of the Effect of Casing-to-Wellbore Clearance on Equivalent Circulating Density During Casing Running," *Processes,* vol. 12, no. 12, p. 2894, 2024, doi: https://doi.org/10.3390/pr12122894.

[36] A. S. Youssef, S. Elkatatny, A. Abdulraheem, and T. Al-Shafloot, "Enhanced Rate of Penetration Prediction for Complex Bottom Hole Assemblies Using Advanced Artificial Intelligence Techniques," in *SPE Gas & Oil Technology Showcase and Conference*, 2025: SPE, p. D021S036R002, doi: https://doi.org/10.2118/224471-MS.

[37] B. A. Mokaimi *et al.*, "Managed Pressure Drilling Technique Commingled High Pore Pressure Section with Depleted Section, Eliminate Drilling Hazard and Pore Pressure Uncertainty Related High-Pressure High-Temperature in West Kuwait Jurassic Deep Wells," in *Abu Dhabi International Petroleum Exhibition and Conference*, 2024: SPE, p. D031S085R004, doi: https://doi.org/10.2118/222742-MS.

[38] M. Al-Rubaii, M. Al-Shargabi, B. Aldahlawi, D. Al-Shehri, and K. M. Minaev, "A developed robust model and artificial intelligence techniques to predict drilling fluid density and

equivalent circulation density in real time," *Sensors,* vol. 23, no. 14, p. 6594, 2023, doi: https://doi.org/10.3390/s23146594.

[39] A. Aliyeva *et al.*, "MPD Technique Drive through Extreme Narrow Pressure Window, Eliminate Drilling Hazard Related to HPHT Salt Anhydrite & Limestone Formation in North Kuwait Jurassic Deep Well," in *IADC/SPE Asia Pacific Drilling Technology Conference and Exhibition?*, 2024: SPE, p. D021S005R005, doi: https://doi.org/10.2118/219571-MS.

[40] K. Amadi, I. Iyalla, and R. Prabhu, "Modeling and predicting performance of autonomous rotary drilling system using machine learning techniques," in *SPE Nigeria Annual International Conference and Exhibition*, 2021: SPE, p. D021S002R008, doi: https://doi.org/10.2118/208450-MS.

[41] M. Xiang, J. Li, H. Zhu, X. Wang, X. Zhang, and Z. Wang, "Study on the hydraulic parameter design method for managed pressure drilling in deepwater thick salt layers," in *Sixth International Conference on Materials Science, Energy Technology, and Environmental Engineering (MSETEE 2025)*, 2026, vol. 13997: SPIE, pp. 32-44, doi: https://doi.org/10.1117/12.3098269.

[42] S. M. Tharayil, I. M. Azmi, A. L. M, and A. M. M, "A Machine Learning Approach to Optimize Drilling Operations in Real-Time," in *Abu Dhabi International Petroleum Exhibition and Conference*, 2025: SPE, p. D041S145R003, doi: https://doi.org/10.2118/228907-MS.

[43] S. Wessling, O. Hummes, F. Jonsbraten, C. Hansen, V. Klemme, and S. Haberer, "Closing the loop with the subsurface: First deployment of autonomous well placement following reservoir boundaries," in *Abu Dhabi International Petroleum Exhibition and Conference*, 2023: SPE, p. D022S177R002, doi: https://doi.org/10.2118/216251-MS.