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Theme

Optimizing Drilling Parameters and Drill Bit Selection using machine learning in Hassi messaoud oilfield

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Rayane, Aymen and Karim

DEDICATIONS

I have the honor to dedicate this modest work

To the most precious and dearest person in my life, to the sun that lights my way, the holiest living, my mother.

To the one who made me a woman and who carried me on his shoulders all the way, my father.

To my support in life, to the stars that light up my world, my brother Salah and sister Rimah.

Rayane

DEDICATIONS

I dedicate this modest work to

My dearest Mom and Dad

My dear little sister

My brothers

I dedicate it also to

My friends Zaki,Haythem,Foudhil and Youcef

Aymen

DEDICATIONS

I dedicate this humble work to

My support,

my precious mother and

my father

My sister and my brother and all my friends and to everyone

is dear to myheart.

Karim

Abstract

Abstract

Improving drilling efficiency is a key focus in the oil and gas industry, particularly in drilling engineering. The goal is to develop technologies that can maximize drilling efficiency, reduce time and costs, and minimize safety and environmental risks. One of the primary factors in improving drilling efficiency are optimizing the rate of penetration (ROP). Traditional ROP models are often empirical and inconsistent in field environments, leading to low predictive accuracy. Machine learning is a new technology that is being used to better predict the impact of different parameters on drilling operations. By applying machine learning techniques, operators can gain a more accurate understanding of how factors like drilling parameters, formation characteristics, and equipment performance affect ROP and overall drilling efficiency. This research proposal focuses on the integration and optimization model for drilling parameters and drill bit selection, and employ machine learning algorithms particularly neural networks, a type of deep learning model, can be used for regression by learning a mapping from input features to the target out put, and data analytics to predict and enhance drilling performance. Additionally, to validate this model we applied it to some wells in Hassi Messaoud field.

Keywords: drilling, machine learning,optimization,drilling parameters, bit selection, ROP, neural networks, deep learning

Résumé

L'amélioration de l'efficacité du forage est un objectif clé dans l'industrie pétrolière et Gazière, en particulier dans l'ingénierie de forage. L’objectif est de développer des Technologies capables de maximiser l’efficacité du forage, de réduire le temps et le Coûtet de minimiser les risques pour la sécurité et l’environnement. L'un des Principaux facteurs permettant d'améliorer l'efficacité du forage est l'optimisation du taux De pénétration (ROP). Les modèles ROP traditionnels sont souvent empiriques et Incohérents dans les environnements de terrain, ce qui entraîne une faible précision Prédictive. L'apprentissage automatique est une nouvelle technologie utilisée pour Mieux prédire l'impact de différents paramètres sur les opérations de forage. En Appliquant des techniques d'apprentissage automatique, les opérateurs peuvent Acquérir une compréhension plus précise de la façon dont des facteurs tels que les Paramètres de forage, les caractéristiques de la formation et les performances de L’équipement affectent le ROP et l'efficacité globale du forage. Cette proposition de Recherche se concentre

Abstract

sur le modèle d'intégration et d'optimisation des paramètres de Forage et de la sélection des outils, et utilise des algorithmes d'apprentissage Automatique, en particulier neural networks, un type de modèle d'apprentissage Profond, qui peuvent être utilisés pour la régression en apprenant une cartographie des Caractéristiques d'entrée vers la cible mise en place et analyse de données pour prédire Et améliorer les performances de forage. De plus, pour valider ce modèle, nous l'avons Appliqué à certains puits du champ de Hassi Messaoud.

Mots-clés : forage, apprentissage automatique, optimisation, paramètres de forage, sélection Des outils, ROP, neural network, apprentissage profond

ملخص

يعد تحسين كفاءة الحفر محورًا رئيسيًا في صناعة النفط والغاز، وخاصة في هندسة الحفر. الهدف هو تطوير التقنيات التي يمكنها تحقيق أقصى قدر من كفاءة الحفر وتقليل الوقت والتكاليف وتقليل المخاطر المتعلقة بالسلامة والبيئة. واحد من العوامل الأساسية في تحسين كفاءة الحفر هي تحسين معدل الاختراق. غالبا ما تكون نماذج ROP التقليدية تجريبية وغير متسقة في الميدان، مما يؤدي إلى انخفاض الدقة التنبؤية. التعلم الآلي هو تقنية جديدة يتم استخدامه للتنبؤ بشكل أفضل بتأثير عوامل الحفر المختلفة على عمليات الحفر. ومن خلال تطبيق تقنيات التعلم الآلي، يمكن للمشغلين الحصول على فهم دقيق لكيفية تأثير عوامل مثل عوامل الحفر، وخصائص الطبقات الجيولوجية على أداء الحفر. هذا البحث يركز على اقتراح نموذج التكامل والتحسين عوامل الحفر اختيار أداة الحفر واستخدام خوارزميات التعلم الآلي وخاصة الشبكات العصبية، وهو نوع من نموذج التعلم العميق وتحليلات البيانات للتنبؤ بأداء الحفر وتحسينه بالإضافة إلى ذلك، للتحقق من صحة هذا النموذج قمنا بتطبيقه على بعض الآبار في حاسي مسعود.

الكلمات المفتاحية: الحفر، التعلم الآلي، تحسين، عوامل الحفر، اختيار أداة الحفر، معدل تقدم الحفر، الشبكات العصبية التعلم العميق

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List of acronyms

Acronym	Definition
ROP	Rate of Penetration
WOB	Weight on bit
ECD	Equivalent circulating Density
MSE	Mechanical Specific Energy
AI	Artificial Intelligence
ML	Machine Learning
TCI	Tungsten Carbide Inserts Bit
PDC	Polycrystalline Diamond compact
TSP	Thermally Stable PDC
RPM	Revolutions per Minute
YP	Yield point
NPT	Non productive time
APIs	Application Programming Interfaces
NLP	Natural Language Processing
TFA	Total Flow Area
FR	Flow rate
SPP	Stand pipe pressure
MW	Mud weight
TRQ	Torque
HRS	Bit time
MD	Measured Depth
Units	
m	Meter
mn	Minute
psi	Pound square inch
°c	Celsius degree
l/m	Liter per minute

List of acronyms

h	Depth
Fjm	Modified jet impact force function
$\boldsymbol{\frac{df}{dt}}$	Rate of penetration
$\boldsymbol{\frac{dh}{dt}}$	Rate of penetration
S	Rock Strength
ppg	Pound per gallon
t	ton
N	Rotary speed
D	Bit diameter
m/h	Meter per hour

General introduction

General introduction

Drilling is the lifeblood of the oil and gas industry, acting as the first stage in obtaining these rich commodities from under the earths surface. Its relevance can not be emphasized, as drilling operations determine the overall success, efficiency, and cost effectiveness of the extraction process.

The rate of penetration (ROP) is an important parameter in drilling operations since it measures the speed at which a drilling bit advances into the subsurface formations.

ROP has a direct impact on efficiency since greater rates result in faster drilling progress, which reduces operational costs and maximizes productivity. Conversely, slow ROP can lead to longer drilling times, increased costs, and operational inefficiencies. So, the selection of optimal drilling parameters and the right bit is paramount to maximizing drilling performance.

Traditional methods, on the other hand, continue to make precise ROP prediction difficult. These methods usually rely on empirical equations and heuristics, which, while useful in some cases ,frequently fail to capture the intricate interplay of geological parameters, equipment performance, and operating conditions. Such limits impede drilling optimization attempts and limit overall project outcomes.

Amidst these challenges, the advent of machine learning (ML) signals a prospective paradigm shift. By using massive datasets containing geological, operational and performance characteristics, ML systems demonstrate the ability to detect nuanced patterns and correlations that conventional techniques miss.

Through sophisticated predictive modeling, ML has the ability to transform ROP estimation, providing drillers with precise insights to improve decision-making, expedite operations, and unlock cost efficiencies.

Our work is carried out after the study and the analysis of the case of some wells in the Hassi Messaoud field.

Our study, which focuses on the integration and optimization model for drillingparameters and drill bit selection, and employ machine learning algorithms particularly neural networks, a type of deep learning model, can be used for regression by learning a mapping from input features to the target out put, and data analytics to predict and enhance drilling performance.

This work is organized into four chapters, the first one: Background, the second one:

Literature review, the third one: Methodology, the fourth which is the last one: Result and discussion.

At the end of this study, we have to conclude and see if our stated hypothesis is well validated.

Chapter I: Background

Chapter I: Background

I.1.Introduction

Choosing the correct drill bit is critical for maximizing the Rate of Penetration (ROP) in drilling operations. The drill bit's design, materials, and cutting structure all influence its efficiency in various formations. ROP is the speed at which the bit penetrates into the rock, which is influenced by parameters such as bit type, bit weight, rotary speed, and drilling fluid Properties. Operators can increase drilling efficiency while lowering costs by studying formation features and selecting the optimum drill bit. The relationship between ROP and the drill bit are symbiotic: the design and condition of the drill bit directly affect the ROP, while getting an optimal ROP requires selecting the proper drill bit and changing drilling parameters accordingly.

I.2.Drill bits types

I.2.1. Roller cone bits

Designing roller cone bits, also known as rock bits, requires heavy-duty bearings, a strong cone shell, and full-length cutting teeth. Each feature competes for limited space to form the cutting structure on roller cones. To ensure long-lasting and effective cutting, designers must consider the toughness of steel and the brittleness of hard-surfacing materials. Bit designers have created different types of bits that focus on specific qualities required for drilling specific formations**[1].**

I.2.1.1. Types

There are two types of rock bits: steel tooth (milled tooth) and tungsten carbide insert bits.

I.2.1.1.1. Steel Tooth Bits

Steel tooth bits are created by milling directly into the cone shell during the manufacturing process. Steel-tooth bits can be made for mild, medium, or hard forms. Bit design depends on cone offset and tooth size. For instance, bits optimized for the softest forms The cones with the least abrasive properties are offset and widely spaced, with long and sharp teeth. Bits designed for hard formation have the fewest cone offsets (or none) and are more closely spaced, shorter, and stronger teeth**[2].**

I.2.1.1.2.Tungsten Carbide Insert Bits

Tungsten carbide insert bits are fitted into pre-drilled holes in the steel cone shell. Carbide insert bits can be utilized on many formations, reducing trip time. However, slower bit speeds decrease penetration rate, while quicker speeds increase it. Could result in insert breakage. Tungsten carbide insert bits, like steel teeth, are available in soft, medium, and hard formations. Inserts are fashioned differently for different forms: hemispherical for harder formations, chisel for medium formations, and larger-diameter, sharper crested, and more Inserts are widely spaced for extremely soft forms. New cone materials have improved wear resistance and reduced failure rates. Sealing bearings have been a key invention in carbide insert bits, addressing the prevalent issue of bearing failure. Carbideinserts bits offer advantages such as high drill ability, good insert burying, up to 80% insert-per-revolution in soft formations, and versatility in drilling different types of formations. Their downsides include erosion surrounding. Inserts can be lost at the base, and if fully buried, the cone shell may come into contact with the formation, transmitting shock loads to the bearing**[2].(See figure 01)**

Figure 01: Milled tooth bit and Tungsten Carbide Inserts bit**[3] .**

I.2.2. fixed cutter bits

Fixed cutter bits, unlike rolling cutters, do not require a firm and clean bearing surface. Three types of fixed cutter bits are commonly used: diamond bits, diamond compact (PDC), and thermally stable PDC(TSP)**[2].**

I.2.2.1 Types

I.2.2.1.1.Diamond Bits

Diamond bits are typically more expensive than roller bits, up to three or four times that of carbide insert bits and several times that of steel-tooth bits. Diamond bits can often be more cost-effective than roller bits. The most crucial component of its advantage is the fact that it produces more holes than any other bit throughout the course of its lifetime. Diamond bits are advantageous because to their simple design and lack of moving parts. Industrial quality diamonds are placed into bit heads made using powdered metallurgy. Diamonds are customized based on size, shape, amount, quality, and exposure to provide optimal performance. formation. Unlike roller cone bits, each bit is custom-made for the job at hand. Mud is used to remove cuttings across many water courses. The water courses are designed to force fluid around each diamond. The matrix diamond bit grinds rock, therefore the fluid's principal role is to remove heat from the diamonds**[2]. (See figure 02)**

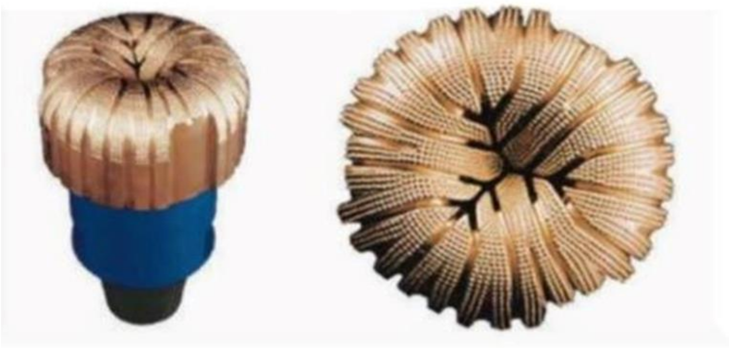

Figure 02: Natural diamond bit**[4] .**

I.2.2.1.2.Polycrystalline diamond compact PDC bit

PDC bits are manufactured by bonding a layer of synthetic polycrystalline diamond to a cemented tungsten carbide substrate under high pressure and temperature. The cuttersare larger than real diamonds and shear the rock, comparable to metal machining (standard drag bits). PDC bits are effective in soft, homogenous formations with moderate strength. In structures in which are effective, they can drill two to three times faster than a roller cone bit and may last as PDC bits are manufactured by bonding a layer of synthetic polycrystalline diamond to a cemented tungsten carbide substrate under high pressure and temperature. The cutters diamond on a PDC cutter is significantly tougher than the hardest rock found in typical oil and gas well drilling. Initially, it appeared unlikely that the cutters would wear out after only a few feet of drilling. This Accelerated wear is frequently caused to the cutters growing too hot. PDC substance contains minor quantities of metals in spaces between diamond grains. Heating cutters can produce high strains, causing individual diamond crystals to break away from the cutter due to differential thermal expansion of diamond grains and binder metals. At higher temperatures, diamond partially turns back into graphite, particularly in an oxidizing environment **[2].(See figure 03)**

Figure 03: PDC bit **[5] .**

I.2.2.1.3. TSP (Thermally stable PDC)

To improve the thermal resistance of polycrystalline diamond cutters, heat-resistant blades (TSP) were created by etching cobalt into the spaces between diamond inclusions. These blades are hard. Sintered pads with no foreign elements reduce thermal resistance. The thermal resistance of drills with cutting TSP is 1148 K (8750C). TSP bits can drill hard and abrasive formations that regular diamond PDC bits cannot. This is because to their increased temperature resistance. TSP is commonly used in conjunction with turbines dueto its superior heat resistance. TSP bits should be rotated at 120-160 rpm for medium-hard pebbles and 150-200 rpm for softer rocks. The axial thrust should be 25-30% of the load applied to roller cone bit of the same diameter**[6] .(See figure 04)**

Figure 04: TSP bit**[3] .**

I.2.3. Kymera hybrid drill bit

Hughes Christensen Kymera hybrid bit combines existing techniques to improve efficiency in demanding applications**[7-8]** .

Usinga high drilling performance Kymera's diamond PDC bit and roller cone stability allows for forceful operation in complex formations while maintaining excellent tool face control. Drilling geothermal wells in Iceland reveals that hard, basalt portions can be drilled over twice as fast as typical roller-cone bits.

Compared to previous roller cone bits, the ROP increased while the WOB value decreased. Also, the problem of bit bounce has been mitigated. Compared to PDCs, there is increased resilience in inter bedded formations, lower torque, and better directional control. Because of its higher building rate capability and precise steerability, the Kymera hybrid bit is ideal for directional drilling with both motor and rotary tools**[6] .(See figure 05)**

Figure 05: Kymera hybrid drill bit **[5] .**

I.3.The concept of rate of penetration (ROP)

The rate of penetration is a fundamental parameter in drilling operations, also know as drill rate, representing the velocity at which drill bit penetrates the formation. It is normally measured in feet per minute or meter per hour, but sometimes it is expressed in minutes per foot**[9].**

I.4.Impact of rate of penetration in drillings operations

The ROP significantly affect drilling operations in several way**:**

I.4.1. Time Efficiency

Increasing the ROP can help to minimize total drilling time. A higher ROP means that the drill bit can penetrate the formation faster, allowing the well to be drilled more quickly. This is significant since drilling time accounts for a large of wells overall cost. Reducing drilling time through ROP optimization can result in significant saving **[10-11].**

I.4.2. Cost Effectiveness

The rate of penetration (ROP) has a significant impact on drilling operations' cost-effectiveness. Optimizing the ROP is critical for improving drilling efficiency, reducing operational time, and lowering costs. The ROP is impacted by several controllable elements, including weight on bit (WOB), flow rate, and standpipe pressure, which the driller can regulate. Furthermore, revolutions per minute (RPM) have an important influence in determining the ROP. According to studies, maximizing the ROP by optimizing drilling parameters saves money and improves operating efficiency. Drilling operations can be efficiently optimized using technologies such as Drillsim-20 and pre-operational testing based on mechanical specific energy (MSE), reducing equipment overload and increasing operational efficiency. As a result, focusing on increasing the ROP through the optimization of drilling parameters is a critical technique to achieve cost-effectiveness in drilling operations**[12].**

I.4.3. Wellbore Stability

high ROP can increase the risk of wellbore instability and other drilling problems. Faster drilling speeds may require running down hole tools harder, increasing the risk of tool failure or excessive bit wear. More aggressive bottom hole assemblies to boost ROP can also sacrifice wellbore quality**[13].**

Low ROP can be an indicator of wellbore stability issues. Wells with excessively low ROP, often less than 1.5 m/h, were associated with significant drilling delays, mud losses/gains, and stuck pipe incidents.3 This was attributed to the complex, tectonically-stressed geology and the need for high mud weights to maintain wellbore stability**[14] .**

I.4.4. Economic viability

The rate of penetration (ROP) has a significant impact on the economic viability of drilling operations in the petroleum industry. ROP is a crucial indicator for evaluating the energy efficiency and cost-effectiveness of drilling operations. Optimizing ROP can have a major impact on reducing the total cost and time of the drilling process. This is especially important during periods of low oil prices, when drilling efficiency becomes critical. The rate of penetration is a critical factor in the economic viability of drilling projects. Improving ROP through optimization of drilling parameters and advanced predictive models can lead to significant cost savings and broader economic benefits**[15].**

I.5.Factors Influencing ROP

I.5.1. Formation properties

Formation features can have a major impact on the rate of penetration (ROP) in drilling operations. Drilling fluid parameters like as mud weight, plastic viscosity, and solid content all play an important impact in ROP. ROP is affected by mud weight, which decreases as weight increases, whereas viscosity reduces ROP as viscosity increases due to mechanical friction and cuttings mobility difficulties. Additionally, solid material has a detrimental impact on ROP, with an increase resulting in a drop-in penetration rate. The chemical composition of the drilling fluid also influences ROP, with specialized additives meant to improve penetration efficiency, particularly in preventing clays from sticking to the drill bit. Formation hardness, influenced by hydrostatic pressure, is another critical factor affecting ROP, as increased pressure can impact the drill ability of the formation. The type of bit used and various mechanical factors like weight on bit and rotary speed are linearly related to drilling rate, provided hydraulic factors are balanced for proper hole cleaning. Overall, the interplay between drilling fluid properties, formation hardness, and mechanical factorsdetermine the ROP in drilling operations**[16].(See figure 06)**

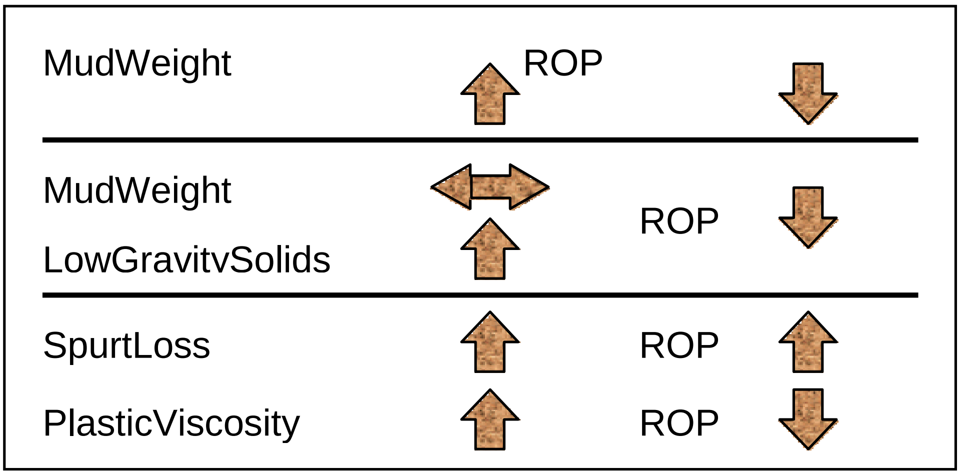

Figure 06: Effects of fluid on ROP.

I.5.2. Drilling parameters

Various factors influence ROP, including Weight on Bit (WOB), Rotation Per Minute (RPM), Mud Flow Rate (FR), Pump Rate, and Mud Weight. Research indicates a direct relationship between ROP and WOB, RPM, FR, and Pump Rate, while an inverse relationship exists with mud weight. Controllable drilling factors like WOB, RPM, and Flow Rate play a crucial role in affecting ROP, while uncontrollable factors include rock strength, pore pressure, mud weight, and wellbore trajectory. Drilling parameters must be optimized, such as WOB, RPM, and torque, in order to increase ROP and reduce drilling expenses. Furthermore, modern techniques such as bit whirl prevention, vibration reduction, and borehole enlargement can boost ROP by enhancing drilling performance. Understanding rock characteristics, drill bit design, drilling fluid, and operating parameters is critical for calculating and optimizing ROP in rock drilling operations**[17].**

I.5.3. Wellbore Conditions

Wellbore conditions have a substantial impact on the Rate of Penetration (ROP) during drilling operations. Wellbore characteristics, such as quality, are critical in influencing drilling efficiency and efficacy. Poor wellbore cleaning can cause the bit to become trapped in cuttings, resulting in stick and slip conditions that slow drilling progress and have a detrimental impact on the ROP **[18].**

Furthermore, the quality of the wellbore might affect drilling speed and the capacity to maintain a constant ROP. For example, in impermeable formations with high mud weight, dilatational hardening and bottom hole balling processes might occur, resulting in high mechanical specific energy (MSE) and continuously low ROP. The type of the rock, drilling fluid characteristics, and bit operating parameters all interact with wellbore conditions to affect ROP **[19].**

In summary, wellbore quality, including cleaning efficiency, rock properties, and mud weight, has a direct impact on ROP during drilling operations. Maintaining ideal wellbore conditions are critical for increasing ROP and overall drilling efficiency.

I.5.4. Bit wear and damage

Bit wear and damage have a substantial impact on the rate of penetration (ROP) during drilling operations. Increased bit wear reduces cutting efficiency, resulting in a lower ROP.Worn parts with fractured or dull teeth have higher frictional forces, which can raise temperatures and produce alkene gasses, further lowering ROP. Catastrophic bit failure, such as a missing cone, can result in significant damage and production delays because the operator must collect the detached bit pieces from the hole, which is a costly and time-consuming process **[20].**

I.6.Existing Methods for ROP Prediction

There are several ways for predicting ROP in drilling operations, including empirical models and analytical solutions:

I.6.1Empirical models

Empirical models use historical drilling data to establish connections between ROP and drilling parameters. These models use statistical analysis and regression approaches to produce rapid estimates of ROP based on input parameters such formation features, drilling parameters, and wellbore conditions**[21].**

I.6.2 Analytic Solutions

Analytical models use physics-based ideas and mathematical formulae to anticipate ROP. These models take into account rock mechanics, hydraulics, and bit-rock interactions in order to produce more accurate ROP estimates under specific drilling conditions**[22] .**

I.7.Limitations of ROP Prediction Methods

Despite their usefulness, current approaches for ROP prediction have some limitations:

I.7.1 Lack of Accuracy

Empirical models may be inaccurate when applied to varied geological formations or novel drilling circumstances. Similarly, analytical solutions may oversimplify complicated drilling dynamics, resulting in variations from true ROP values.

I.7.2Inability to Handle Complex Wellbore Scenarios

Existing approaches may struggle to effectively forecast ROP in complex wellbore scenarios, such as highly deviated or horizontal wells, when frictional losses and directional drilling problems are present.

I.7.3 Data Dependency

Empirical models are strongly reliant on previous drilling data, which may not always be indicative of current drilling circumstances or be limited in scope**[23] .**

I.8.Conclusion

In conclusion, current techniques for estimating ROP (Rate of Penetration) frequently fail because to their reliance on manual analysis and limited data processing capabilities. These methods are limited by their inability to incorporate complicated factors and respond to changing drilling circumstances. However, learning approaches such as machine learning and artificial intelligence have enormous potential for properly predicting ROP by utilizing large datasets, recognizing detailed patterns, and constantly learning from fresh data. Their ability to handle enormous amounts of data, assess several variables concurrently, and adapt to changing drilling environments make them attractive tools for improving ROP forecast accuracy and efficiency in the oil and gas industry. This is what we will see in the next chapter.

Chapter II: Literature Review

Chapter II: Literature Review

II.1. Introduction

Drilling engineers face particular issues in optimizing drilling parameters and selecting appropriate bits. Proper drilling parameters are crucial considering the high expense of drilling a well. Several efforts have been made to forecast which bit will achieve the best rate of penetration. Engineers and technicians from rock bit manufactures have developed bit selection programs to help oil firms cut drilling costs by providing the maximum rate of penetration**[2].**

II.2. Real Time Optimization of Drilling Parameters During Drilling Operations

Numerous extensive research studies have been conducted to optimize drilling activities, with the goal of maximizing footage drilled in time while minimizing drilling expenditures. Drilling optimization could be accomplished by predetermining the magnitudes of the controllable drilling parameters. The authors anticipate that research on drilling optimization will continue to be of interest to scientists. Most early studies in the literature predicted a static drilling optimization process. Due to a lack of real-time data transfer capabilities, the drilling parameters had to be explored off-site. Recent researches have shown that drilling optimization may be done in real time; however, none of the references investigated have worked with statistical correlations in a real-time environment**[9].**

Figure 01 depicts a timeline of some significant advances in drilling and optimization history. The scientific period began in the 1950s, with increased drilling research, a better grasp of hydraulic principles, substantial advances in bit technology, improved drilling fluid technology, and, most importantly, optimized drilling. After the 1970s, rigs with complete automation systems and closed-loop computer systems capable of controlling drilling variables began to operate in oil and gas fields. In the mid-1980s, operator companies developed drilling optimization procedures that allowed their field people to optimize on-site using graph templates and equations. In the 1990s, many drilling planning methodologies were introduced to determine the greatest possible well construction performance**[24] .**

Later, "Drilling the Limit" optimization approaches were introduced**[25] .**

Toward the end of the millennium, real-time monitoring techniques began to be used, such as monitoring drilling parameters from remote places. A few years later, real-time operations and support centers began to be built. Some operators offered innovative techniques for monitoring drilling parameters at the rig site. In recent years, drilling parameters have become easier to obtain, store, and send in real time. Following the development of sophisticated and automated rig data acquisition microelectronic systems linked to computers, a variety of drilling optimization and control services began to emerge**[26] .**

With improved smart computer systems, drilling penetration rate and bit lifetimes are maximized by performing drill-off tests**[27] .**

Currently, cutting-edge, high-speed IP communication systems are being developed that interact with microwave broadband networks, making them a viable tool for oil and gas operations by allowing the deployment of quicker, more efficient networks to the fields**[28].(See figure 01)**

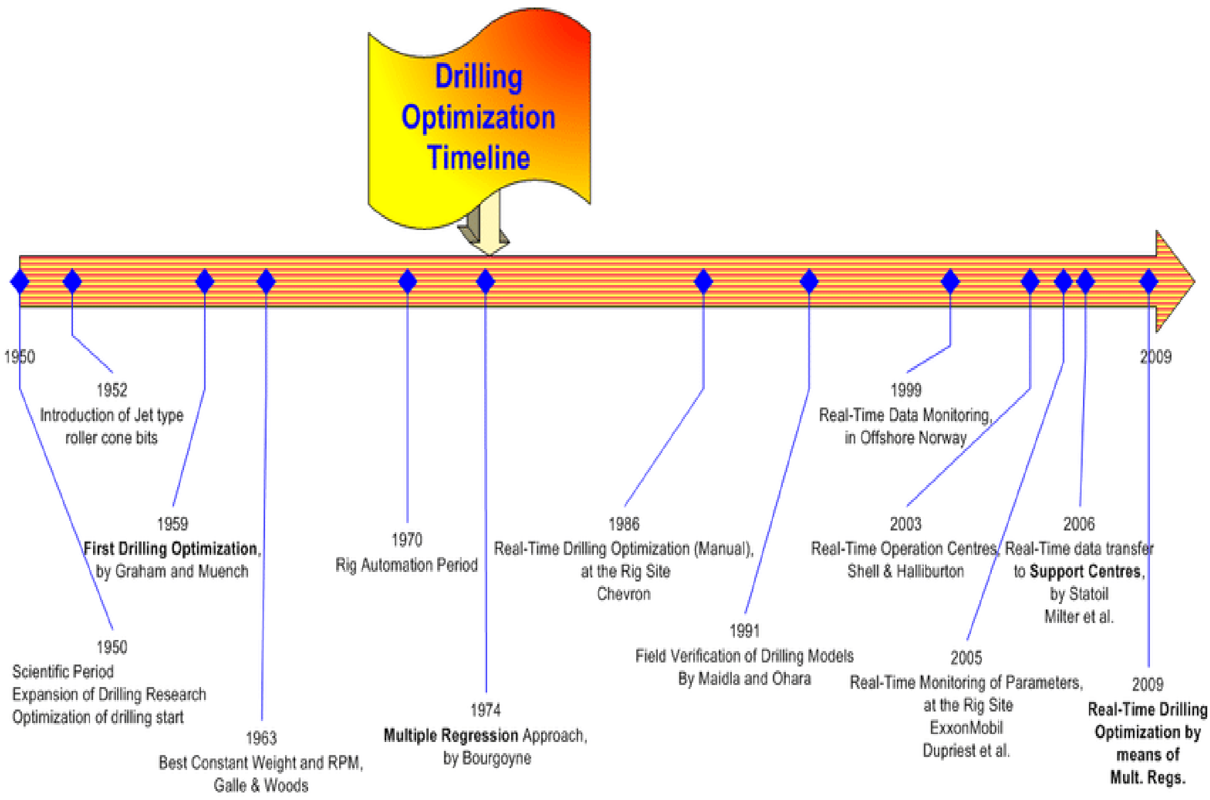

Figure 01: Drilling optimization timeline **[9] .**

The equation below represents the mathematical model proposed by Graham and Muench**[29].**

$$\boldsymbol{f5 = e^{a5x5} = \left\{\frac{\frac{w}{db}-\left(\frac{w}{db}\right)t}{4-\left(\frac{w}{db}\right)t}\right\}^{a5}} \text{........}(\mathbf{1})$$

The diameter and weight feature of the bit is specified by "a5." The bit weight and bit diameter are known as directly affecting the rate of penetration above. Maurer **[30]** established a boil rate of penetration in1962.

$$\boldsymbol{\frac{df}{dt} = \mathrm{k}\left(\frac{N(W-W0)^2}{D^2S^2}\right)} \text{.........}(\mathbf{2})$$

Where, $^{df}/_{dt}$= Rate of penetration (ft/hr);

K = Constant of proportionality;

N = Rotary Speed;

W = Weight on bit (klbf);

$W0$ = Threshold weight on bit (klbf);

D = Bit diameter (inch);

S = Rock strength (psi)

In 1963 Galle and Woods **[31]** introduced the best perforated weight and spinning speed pattern for rotary rock parts

The model is mathematically given by:

$$\boldsymbol{\frac{df}{dt}} = \mathrm{c_{Fd}}\frac{w^k r}{a^p} \text{........}(\mathbf{3})$$

Where, $Cfd$is the formation drill ability parameter;

a = 0.028125 h2+ 6.0h + 1

k = 1.0

p = 0.5

Bourgoyne and Young**{32}** conducted one of the most important early studies on optimal drilling detection. In 1974. They developed a linear penetration rate model and ran a multiple regression analysis on drilling data to determine the best bit weight, rotary speed, and bit hydraulics. Minimum drilling cost was attempted by achieving maximum ROP, which aligns with the minimum cost strategy assuming technical constraints were ignored. They examined the impacts of formation strength, depth, compaction, pressure difference across the hole bottom, bit diameter, weight, rotary speed, wear, and bit hydraulics. They discovered that a regression analyze is approach can be utilized to analyze many of the constants in the penetration rate equation. They stated that multi-well data should be gathered for regression constant evaluations. They concluded that using relatively simple drilling optimization models can cut drilling expenses by approximately 10%**[32] .**

Rate of penetration is expressed as:

$$\frac{d\square}{dt} = Exp\left(a_1 + \sum_{j=2}^{8} ajxj\right) \ldots\ldots\ldots (\mathbf{4})$$

Where;$^{d\square}/_{dt}$ =$Rate\ of\ penetration$;

h = Depth, ft;

t = Time, hrs;

aj = $Constants$;

xj = $Drillingparameters$

In 1987 Warren**{33}** proposed a ROP model that takes into account the effects of both the initial chip creation and cuts removal processes. The rate of penetration equation they derived consists of two terms and only works under the condition of flawless hole cleaning. The first term defined the maximum rate supporting the WOB effect in the absence of dental penetration, whereas the second term takes tooth penetration into account. The equation suited the experimental data for both steel tooth and insert bit types**[33] .**

$$ROP = \left(\frac{as^2 d_b^3}{N^b W^b} + \frac{C}{N\, d_b} + \frac{c d_b \gamma_f \mu}{F_{j_m}}\right)^{-1} \quad \ldots\ldots\ldots\ (5)$$

Where: ROP = Rate of penetration (m/h);

a, b, c = Bit coefficients (dimensionless);

db= Bit diameter (in);

N = RPM = Bit revolutions (rev/min);

W = WOB = Weight on bit (klbf);

γf = Drilling fluid density (Ib/gal);

Fjm = Modified jet impact force function (klbf)

Overall, one of the most difficult issues in optimizing drilling parameters is dealing with the uncertainty of underground geology. Surface controls and downhole equipment can be modified, but rock forms are difficult to forecast. New data-driven technologies that use real-time information and machine learning show promise in tackling this difficulty by recognizing formations on the fly and selecting the best drilling parameters.

II.3. Advances in Artificial intelligence and their potential applications in drilling operations

AI techniques are widely utilized across various engineering and scientific research domains, including the petroleum industry. They address complex challenges such as predicting drill bit wear, real-time monitoring of drilling fluid behavior, identifying lithology, assessing total organic carbon for unconventional resource evaluation, estimating oil recovery factors, determining pore and fracture pressures, evaluating static Young's modulus, estimating reservoir porosity, determining bubble point pressure, and predicting formation tops**[34] .**

Bilgesuet al. proposed leveraging AI techniques for ROP prediction to address the limitations of empirical correlations and enhance predictability accuracy. They developed two artificial neural network (ANN) models to estimate ROP across nine different formations drilled in various vertical wells in the United States. The first model incorporated factors such as bit type and diameter, formation type, mud circulation, drilling hours, footage, WOB, and RPM, while the second model omitted bit tooth and bearing wear from the inputs. The authors noted that both models achieved remarkably accurate ROP predictions**[35] .**

Amar and Ibrahim**{36}** developed two artificial neural network (ANN) models to predict the rate of penetration (ROP) based on depth, weight on bit (WOB), revolutions per minute (RPM), tooth wear, Reynolds number, equivalent circulating density (ECD), and pore gradient. Their ANN models exhibited significantly lower average absolute percentage error (AAPE) compared to ROP correlations derived from linear regression**.**

Mantha and Samuel**{37}** proposed integrating various AI models with linear regression for ROP optimization in horizontal wells. Their models utilized inputs such as RPM, WOB, gallons per minute (GPM), and gamma-ray (GR) logs to predict ROP accurately, surpassing field-measured ROP. However, no empirical correlations were derived from these models, posing challenges for future validation with new data**.**

El katatny pioneered the development of an empirical correlation to estimate ROP in vertical wells, utilizing optimized ANN model parameters. This correlation incorporates RPM, WOB, T, GPM, SPP, along with drilling fluid properties like MW and PV. El katatny's model demonstrated an AAPE of just 4%, outperforming other correlations with AAPEs exceeding 10**].**

Additionally, Ahmed et al. devised a support vector machine-based model for ROP estimation. This model, considering similar parameters and drilling fluid properties, achieved remarkable accuracy with an AAPE of only 2.83%**[39] .**

II.4.Machine Learning in Optimization Drilling Parameter and Bit Selection

The unwavering pursuit of operational efficiency is paramount in the oil and gas industry, where cost reduction is a constant priority. Within the sector, drilling operations rank as one of the most capital-intensive activities, making it a prime area for innovation and optimization. In this context, machine learning (ML) technology emerges as a transformative force. By training algorithms to uncover patterns and insights within vast datasets, ML can unlock unprecedented optimizations in drilling parameter selection and the selection of drill bits. This data-driven approach holds the key to enhanced decision-making, streamlined operations, and ultimately, minimized costs**[40] .(See figure 02)**

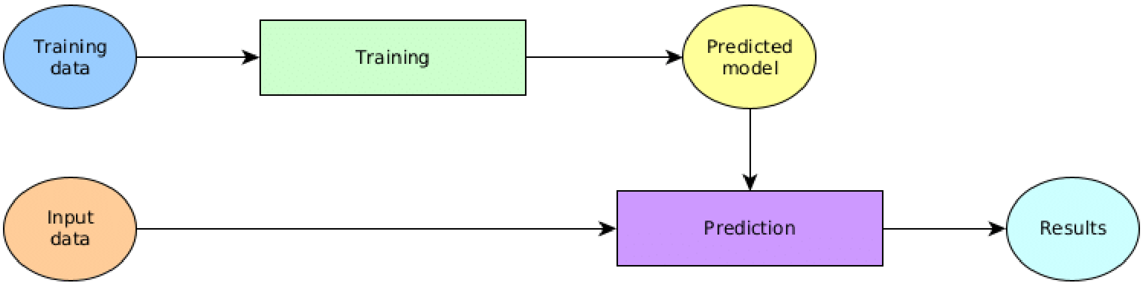

Figure 02: Schematic representation of a machine learning system.

II.4.1. How ML Can Optimize Drilling

Machine learning has a wide range of applications within drilling optimization, making its use case compelling. Let's explore some key areas where ML can make a significant difference:

II.4.1.1Rate of Penetration (ROP) Prediction

Accurately predicting the rate at which a drill bit penetrates rock formations (ROP) is a cornerstone of drilling efficiency. Factors influencing ROP include rock type, drill bit design, various drilling parameters (weight on bit, torque, RPM), and drilling mud properties. ML models can process these multifaceted variables, improving ROP prediction accuracy when compared to traditional physics-based approaches. By optimizing parameter selection around these predictions, ML drives faster drilling and lower overall costs.

II.4.1.2Drill Bit Selection

Selecting the most effective drill bit for a particular geological formation and specific drilling conditions is crucial for drilling success. ML models can analyze large volumes of data that consider the interplay between bit types, geological conditions, drilling parameters, and achieved ROPs. They generate recommendations for the most suitable bit, streamlining workflows and reducing trial-and-error approaches. This minimizes bit wear and maximizes drilling efficiency.

II.4.1.3Drilling Parameter Optimization

The parameters that control drilling—like weight on bit (WOB), rotary speed (RPM), and mud flow rate—significantly impact both drilling performance and cost. ML algorithms can be trained to identify the optimal blend of these parameters based on rock properties, drill bit type, and the target ROP. Real-time analysis of drilling data, combined with ML-generated recommendations, enables continuous optimization of the drilling process.

II.4.1.4 Stuck Pipe Prevention

Stuck pipe events cause severe delays and escalate drilling costs. ML can analyze drilling data to discover subtle indicators that may precede a stuck pipe scenario. By predicting these potential issues in advance, ML allows operators to take proactive preventative measures.

II.4.1.5 Enhanced Drilling Safety

ML supports improved drilling safety in multiple ways. Real-time monitoring of drilling data combined with ML-powered anomaly detection creates an early warning system for potential equipment failures or the development of hazardous down hole conditions. ML enables predictive maintenance, ensuring that critical equipment operates within ideal parameters, minimizing the risk of unexpected breakdowns.

II.4.1.6 Real-time Drilling Optimization

The future of ML lies in its ability to move from predictions and recommendations to fully automated adjustments of drilling parameters based on real-time sensor data analysis. This closed-loop system will lead to more consistent results and greater efficiency**[41-42] .**

II.4.2. Benefits of Using ML

The benefits of embracing ML strategies in drilling optimization are expansive and compelling:

II.4.2.1. Improved Drilling Efficiency

ML-optimized drilling parameters and well-informed bit selections directly improve drilling efficiency. Faster ROP, reduced ncidents of downtime, and more streamlined decision-making processes lead to shorter drilling campaigns and reduced operational costs.

II.4.2.2. Significant Cost Savings

The gains in efficiency translate directly into cost savings. Optimized drilling parameters lessen wear and tear on equipment, while accurate bit selection lowers the frequency of rig downtime for changing worn drill bits. Predictive maintenance, powered by ML, further contributes to cost savings by preventing costly and unexpected equipment failures.

II.4.2.3. Increased Safety

By proactively flagging potential hazards, ML boosts drilling safety and enables preventive actions. Fewer incidents and accidents mean safer operations, adherence to schedules, and the mitigation of costs associated with well site emergencies.

II.4.2.4. Competitive Advantage

Early adopters of ML for drilling optimization stand to gain a significant competitive edge. The ability to consistently deliver wells faster, cheaper, and with a greater margin of safety translates to greater operational success within the industry**[43-44] .**

II.4.3. Challenges in ML Implementation

While the promise of ML is undeniable, the journey of implementing ML within drilling optimization isn't without obstacles. It's essential to acknowledge and address these challenges to extract maximum value from ML initiatives:

II.4.3.1. Data Quality and Availability

ML models depend heavily on high-quality data in large volumes. Drilling operations produce masses of data, but issues with sensor reliability, data cleaning, and inconsistent data formats can impair ML performance.

II.4.3.2.Data Quality and Availability

ML models are heavily reliant on the quality and quantity of available data. While drilling operations generate massive datasets, issues with sensor reliability, inconsistent data cleansing, and non-standardized data formats can negatively impact model performance. Addressing these data quality issues is a prerequisite for successful ML implementation.

II.4.3.3.Model Interpretability

Complex ML models, particularly neural networks, can sometimes function as "black boxes." It may be difficult to understand why a particular prediction or recommendation is made. In high-stakes drilling decisions, understanding the model's logic is vital to build trust and encourage widespread adoption.

II.4.3.4.Integration with Existing Workflows

Effectively integrating ML models into drilling workflows requires careful planning and may entail changes in how things are traditionally done. The adoption of ML often necessitates updates to operational practices, software systems, and workforce skill sets. Careful management of this transition is essential to ensure ML's seamless integration**[45-46].**

II.4.4. Machine Learning Techniques in Drilling Optimization

Various ML techniques lend themselves to tackling the specific challenges of drilling optimization. Here's an overview of the types of algorithms commonly employed:

II.4.4.1. Supervised Learning

Techniques like regression (for predicting continuous values like ROP) and classification (for categorizing data like bit types) form the backbone of many ML approaches in drilling. These algorithms learn from labeled data, establishing an understanding of the relationships between input features (e.g., rock properties) and output targets (i.e., ROP).

II.4.4.2. Unsupervised Learning

This category of algorithms finds applications in exploring unlabeled drilling datasets to discover hidden patterns and trends. Clusteringalgorithms, for instance, can group data instances with similar drilling characteristics. This helpsreveal trends that might not be immediately evident, providing valuable insights into performance variations across drilling projects.

II.4.4.3. Reinforcement Learning

While primarily used in robotics and autonomous systems, reinforcement learning holds potential for the future of drilling optimization.Here, an ML agent iteratively learns through trial and error, maximizing rewards based on well-defined metrics. This approach could enable fully autonomous drilling optimization in complex scenarios **[47] .(See figure 03)**

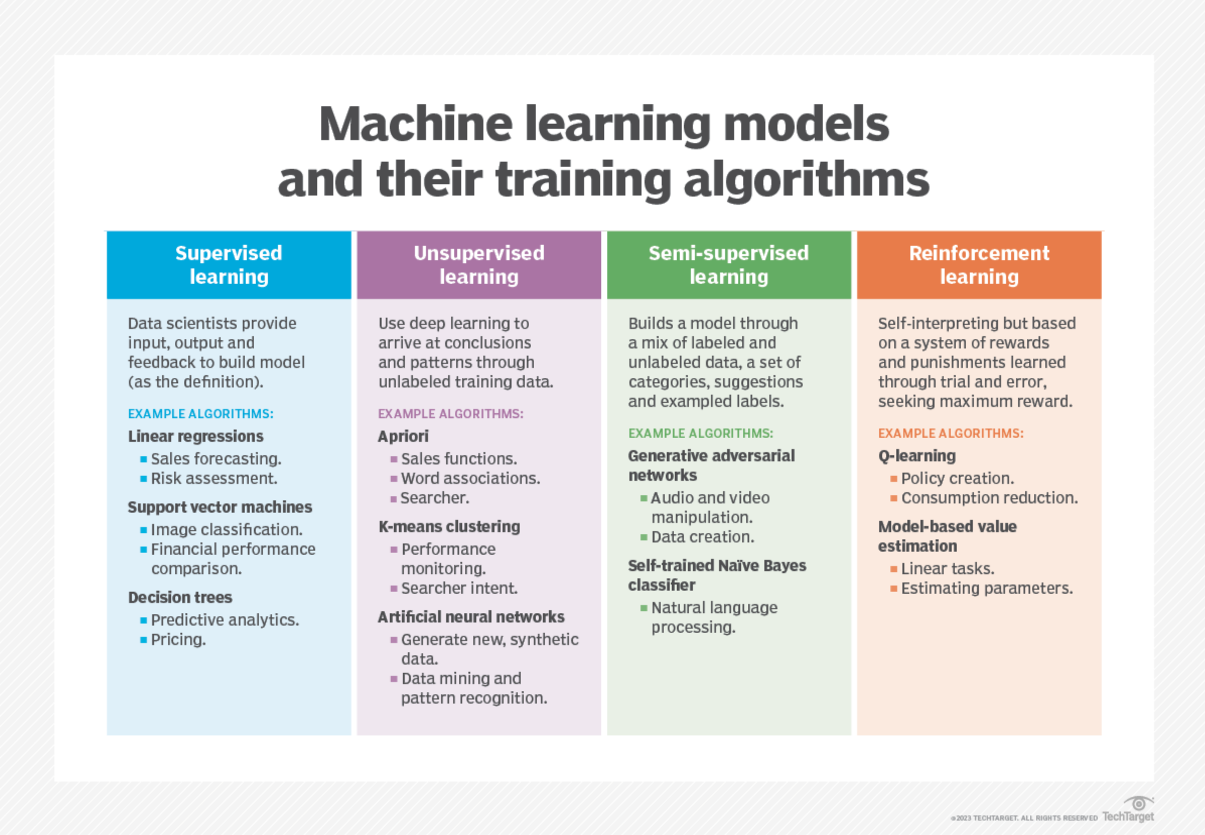

Figure 03: machine learning models and their training algorithms

II.4.5. Real-World Implementation of ML

The implementation of ML in drilling optimization typically involves a sequence of steps. Under standing this process is key to ensuring successful outcomes:

II.4.5.1. Data Collection and Preprocessing

The first step involves gathering and systematically organizing drilling data from various sources. This includes real-time sensor data, drilling mud logging reports, and historical operating records. Cleaning this data to address errors, inconsistencies, and missing values is crucial to ensure model quality**[40] .**

II.4.5.2. Feature Engineering

One of the most important phases is identifying which features (data inputs) have the most significant predictive power. This requires domain knowledge and exploratory analysis.

Raw data needs to be transformed into features that ML algorithms can learn from effectively**[48] .**

II.4.5.3. Model Selection and Development

Based on the specific task at hand (e.g., ROP prediction, bit selection, or anomaly detection), suitable ML techniques and algorithms must be selected and customized. The model-building process involves splitting the data into training and testing sets to evaluate the performance and predictive capability of the model**[49] .**

II.4.5.4. Model Validation

Rigorous testing and validation with unseen data are needed to assess the generalizability of a trained model. Techniques like cross-validation help prevent the problem of overfitting, where a model performs well on training data but poorly on new data**[50] .**

II.4.5.5. Deployment and Integration

Models need to be deployed as software applications or APIs accessible to operators and engineers. Integration with existing decision-support systems is essential for maximizing the value of ML insights.

II.4.5.6. Monitoring and Retraining

Real-world performance monitoring is a continuous process. As geological conditions and drilling parameters change, data may drift in its patterns over time. Periodic retraining of ML models helps maintain accuracy and ensures models don't become outdated**[51] .**

II.4.6. Case Studies

Case studies from across the industry provide tangible proof of the benefits of ML solutions in drilling optimization:

II.4.6.1. ROP Optimization in Shale Formations

An operator in the Permian Basin (Texas) utilized ML algorithms to analyze diverse drilling data across complex shale formations. This analysis helped optimize drilling parameters, resulting in a 15-20% improvement in ROP, saving significant time and substantial operating costs**[52] .**

II.4.6.2. Drill Bit Life Extension

A company developing advanced drill bits leveraged ML algorithms to identify wear patterns specific to their bit designs. This led to predictive maintenance schedules, increasing bit life by an average of 10%. This reduced trips out of the hole for bit replacement, saving both time and expensive bit inventory**[53] .**

II.4.6.3. Real-time Drilling Parameter Optimization for Challenging Formations

A project focused on optimizing drilling parameters in real-time for troublesome formations. ML models continuously analyzed live drilling data and provided recommendations for adjustments, leading to a noticeable reduction in non-productive time (NPT)**[54] .**

II.4.7. The Future of ML in Drilling Optimization

While ML has already proven its value in the drilling domain, the potential for even more significant optimization lies ahead. Some key areas driving the frontier of ML in drilling include:

II.4.7.1 Advances in Natural Language Processing (NLP)

NLP has the potential to revolutionize how drilling-related knowledge is captured and used. NLP can analyze drilling reports, manuals, and other documents, extracting valuable insights normally locked in unstructured text formats. This knowledge could be integrated into ML models, leading to even more intelligent decision-making**[55] .**

II.4.7.2 Hybrid Models

Combining traditional physics-based drilling models with the power of ML offers benefits in both accuracy and interpretability. These hybrid models can leverage the strengths of both approaches. They explain the underlying physical phenomena while capitalizing on ML's ability to spot nuanced patterns that traditional equations might miss**[56] .**

II.4.7.3 Closed-Loop Optimization

The ultimate goal of ML in drilling is to drive closed-loop optimization systems. These systems will enable automatic adjustments to drilling parameters based on continuous, real-time feedback from ML algorithms. This self-correcting system has the potential to deliver unprecedented efficiency and safety gains**[57] .**

II.4.7.4 Digital Twins and Virtual Drilling Environments

ML can enhance the creation of digital twins - highly accurate virtual representations of drilling systems. These digital twins, powered by real-world drilling data and ML, can be used to test different scenarios, optimize processes, and train personnel in a simulated environment, saving time, resources, and reducing the risk of real-world error**[58].**

This study aimed to develop a new empirical correlation for ROP prediction in as a function of RPM, TRQ, WOB, FR, MW, TFA and bit type combined with conventional well log data The correlations developed in this study were based on the biases of the trained machine learning model, which wasoptimizedusing neural networks, a type of deep learning model algorithm.

II.5. Conclusion

As datasets in the oil and gas industry continue to grow and algorithms become more sophisticated, ML is poised to reshape drilling operations. The industry's widespread recognition of the inherent benefits drives the adoption of data-driven decision-making and the competitive edge it provides. Embracing the power of ML stands to deliver profound boosts in efficiency, reduce risks, and substantially lower costs. Despite the challenges inherent in implementation, the future of drilling is inextricably linked to advances in ML and artificial intelligence. In the following chapter we will apply neural networks, a type of deep learning model, to different wells located in the Hassi Messaoud fields in order to verify their effectiveness.

Chapter III: Methodology

Chapter III: Methodology

III.1 Introduction

In the ever-evolving landscape of the oil and gas industry, the optimization of drilling parameters remains a critical area of focus. Efficient drilling operations can significantly reduce costs, enhance productivity, and ensure safer operations. This chapter details the development and implementation of a deep learning regression model designed to optimize drilling parameters using data from seven drilling wells in the Hassi Messaoud oil field, Algeria. Known for its complex geological structures and challenging drilling conditions, Hassi Messaoud provides a robust test case for the application of advanced machine learning techniques.

The drilling operations discussed in this chapter specifically focus on Layer 16, known for being the longest and most expensive layer to drill through in the Hassi Messaoud field. The complexities and costs associated with drilling through Layer 16 necessitate the use of advanced optimization techniques to maximize efficiency and minimize expenses.

The development of this model was conducted using Python, a versatile programming language widely used in data science and machine learning. Various libraries, including TensorFlow and Keras for deep learning, Pandas for data manipulation, and Matplotlib for visualization, were employed throughout this project.

III.2 Data Collection

The data utilized in this study was sourced from seven different wells in the Hassi Messaoud oil field, all of which involved drilling through Layer 16. This layer is particularly significant due to its length and the high costs associated with drilling operations. Each well provided a comprehensive dataset, including key drilling parameters and performance metrics. The primary variables of interest included:

- ❖ **Weight on Bit (WOB):** The force exerted on the drill bit.
- ❖ **Revolutions Per Minute (RPM):** The rotational speed of the drill bit.
- ❖ **Torque (TRQ):** The rotational force applied to the drill bit.
- ❖ **Fluid Flow (FLW):** The rate of drilling fluid flow.
- ❖ **Stand Pipe Pressure (SPP):** The pressure in the drilling fluid system.
- ❖ **Bit Type:** The type of drill bit used.

- **Depth:** The depth at which drilling occurs.
- **Total Flow Area (TFA):** The area through which drilling fluid flows.
- **Mud Weight (MW):** The density of the drilling mud.
- **Rate of Penetration (ROP):** The speed at which the drill bit penetrates the geological formations, measured in meters per hour.

This comprehensive dataset enables a thorough analysis of the factors influencing ROP and the subsequent optimization of drilling parameters to maximize efficiency, especially in the challenging context of Layer 16.

III.3 Data Preparation

Data preparation is a crucial step in any machine learning project. Ensuring the quality and consistency of the data is essential for building a reliable model. The initial data preprocessing involved several steps:

- **Data Loading:** The data from all seven wells was loaded into a unified DataFrame for analysis.
- **Handling Missing Values:** Any rows with missing values were removed to maintain data integrity.
- **Categorical Encoding:** The 'Bit Type' variable, which was categorical, was converted into numerical codes to facilitate its use in the machine learning model.

```python

import pandas as pd
# Loading data from multiple sources

files = ['well1.csv', 'well2.csv', 'well3.csv', 'well4.csv', 'well5.csv', 'well6.csv', 'well7.csv']

data = pd.concat((pd.read_csv(f) for f in files), ignore_index=True)

# Preprocessing steps
data.dropna(inplace=True)
data['Bit Type'] = pd.Categorical(data['Bit-Type']).codes

```

Figure 01: Data Loading and Preprocessing Script.

This preprocessing ensures that the data is free of missing values and that all categorical variables are converted into a format suitable for deep learning models.

III.4 Data Processing

Given the nature of drilling data, it was imperative to handle missing values, outliers, and categorical variables effectively. The data preprocessing steps included:

- Handling Missing Values: Rows with any missing values were removed to maintain data integrity.
- Categorical Conversion: The 'Bit Type' variable was converted from a categorical string format into numerical codes to facilitate the machine learning process.

III.5 Model Development

Given the complexity of the relationships between the drilling parameters and ROP, a deep learning regression model was selected for its ability to capture non-linear patterns in the data. The model was developed using TensorFlow and Keras, leveraging a neural network architecture with multiple layers to enhance its predictive power.

The architecture of the neural network was designed with several dense layers, each using the ReLU (Rectified Linear Unit) activation function. This choice of activation function helps the model learn complex patterns by introducing non-linearity. The final layer consisted of a single neuron with a linear activation function, appropriate for the regression task of predicting ROP.

The following code snippet outlines the model architecture and compilation: (See figure 02)

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Model architecture
model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(64, activation='relu'),
    Dense(32, activation='relu'),
    Dense(1)
])
```

Figure 02: Neural Network Model Architecture.

The model's architecture is composed of an input layer that matches the number of features in the dataset, followed by three hidden layers with decreasing numbers of neurons, and an output layer for the ROP prediction.

III.6 Model Training and Evaluation

With the model architecture defined, the next step was to train the model using the prepared dataset. The data was split into training and testing sets, with 80% of the data used for training and 20% reserved for testing. This split ensures that the model can generalize well to unseen data, providing a robust evaluation of its performance.

The model was trained over multiple epochs, with the Adam optimizer used to adjust the learning rate dynamically. The mean squared error (MSE) was selected as the loss function, reflecting the average squared difference between predicted and actual ROP values.

The following code snippet demonstrates the training process, using TensorFlow and Keras libraries: (See figure 03)

```python
from sklearn.model_selection import train_test_split

# Define predictors and the target variable
X = data[['WOB', 'RPM', 'TRQ', 'FLW', 'SPP', 'Bit Type', 'Depth', 'TFA', 'MW']]
y = data['ROP']

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Training the model
history = model.fit(X_train, y_train, validation_split=0.2)
```

Figure 03: Training Process of the Neural Network Model.

After training, the model's performance was evaluated using the test set. The mean squared error (MSE) and the coefficient of determination (R^2) were calculated to assess the accuracy and explanatory power of the model, respectively: (See figure 02)

```python
# Model predictions and evaluation
predictions = model.predict(X_test)
mse = mean_squared_error(y_test, predictions)
```

Figure 04:Model Predictions and Evaluation.

These metrics provide a quantitative assessment of the model's predictive performance. An R^2 value close to 1 indicates a high level of accuracy, while a lower MSE signifies fewer prediction errors.

III.7 Optimization Strategy

The ultimate goal of this project was not only to predict ROP accurately but also to identify the optimal drilling parameters that maximize ROP. To achieve this, an optimization algorithm was implemented, exploring various combinations of drilling parameters and leveraging the trained model to predict the resulting ROP for each combination.

The optimization process involved iterating over a range of values for each drilling parameter, feeding these values into the model, and recording the predicted ROP. The parameter combination yielding the highest ROP was identified as the optimal setting.

This comprehensive search algorithm systematically explores a range of possible values for each parameter, identifying the combination that maximizes ROP. The identified optimal settings provide actionable insights that can be applied to enhance drilling operations in Layer 16 of Hassi Messaoud.

III.8 Results and Discussion

The implementation of the deep learning model and the subsequent optimization algorithm yielded promising results. The model's performance metrics indicated a high degree of accuracy in predicting ROP, with an R^2 value close to 1 and a low MSE. The optimization process identified specific combinations of drilling parameters that significantly enhance ROP.

The optimal settings identified include specific values for WOB, RPM, bit type, depth, TFA, and MW. These settings can be directly applied in the field to improve drilling efficiency and reduce operational costs. The findings underscore the potential of deep learning techniques in transforming drilling operations by providing data-driven insights and optimizations.

The results of the optimization are visualized in the following graph, which shows the relationship between the optimized parameters and the predicted ROP: (See figure 02)

```python
import matplotlib.pyplot as plt

# Visualizing the relationship between optimized parameters and predicted ROP
parameters = ['WOB', 'RPM', 'Bit Type', 'Depth', 'TFA', 'MW']
values = [optimal_settings[param] for param in parameters]
rop = optimal_settings['Predicted ROP']
```

Figure 05: Visualization of Optimized Parameters and Predicted ROP.

The bar chart above illustrates the optimal values for each drilling parameter identified by the optimization algorithm. The parameter values are set to maximize the ROP, leading to improved drilling efficiency, particularly in Layer 16, which is the most expensive and longest layer to drill through in Hassi Messaoud.

III.9 Machine Learning Models

III.9.1 Overview of Machine Learning Algorithms

In this project, we employ two primary machine learning models to predict the Rate of Penetration (ROP) in drilling operations:

- Linear Regression.
- Neural Networks.
- Each model has its unique strengths and justifications for its selection, as detailed below.

III.9.2 Linear Regression

Linear regression is one of the most straightforward and widely used machine learning algorithms for predictive modeling. It assumes a linear relationship between the input variables (predictors) and the target variable.

Justification for Selection:

- Simplicity and Interpretability: Linear regression provides a clear understanding of the relationship between predictors and the target variable. The coefficients indicate the weight and direction of the influence of each predictor.
- Baseline Model: It serves as an excellent baseline model to compare the performance of more complex models.
- Efficiency: Linear regression is computationally efficient and works well with smaller datasets, making it suitable for initial model development and quick iterations.

III.9.3 Neural Networks

Neural networks are a class of machine learning algorithms inspired by the structure and function of the human brain. They are particularly effective in capturing complex, non-linear relationships between input variables and the target variable.

Justification for Selection:

- Handling Non-Linearity: Unlike linear regression, neural networks can model complex, non-linear relationships, which are often present in drilling data.
- Flexibility and Power: Neural networks can handle a large number of predictors and can be adapted to different types of data.
- Improved Performance: With sufficient data and proper tuning, neural networks often outperform simpler models in predictive accuracy.

Implementation:

The neural network model is implemented using the TensorFlow library with the Keras API in Python

III.9.4 Comparison and Selection

The choice of using both linear regression and neural networks allows for a comprehensive evaluation of model performance. Linear regression provides a baseline with its simplicity and interpretability, while neural networks offer the potential for improved accuracy by modeling non-linear relationships.

By comparing the performance metrics of both models, we can determine which model is more suitable for predicting the Rate of Penetration (ROP) in drilling operations. This approach ensures that we leverage the strengths of different algorithms to achieve the best predictive performance.

Chapter IV: Result and discussion

Chapter IV:Result and discussion

IV.1 Results

IV.1.1 Model Performance

In this section, we present the performance results of the machine learning models developed to predict the Rate of Penetration (ROP) in drilling operations. The models evaluated include Linear Regression and Neural Networks. Various performance metrics such as Mean Squared Error (MSE), R-squared (R^2), accuracy, precision, and recall are used to assess the models.

IV.1.1.1 Model Outputs vs. Real Data

The scatter plots in Figure 1 compare the predicted Rate of Penetration (ROP) values from the model with the actual ROP values from the training and testing datasets. The red line represents the ideal scenario where predicted values perfectly match the real values. (See figure 02)

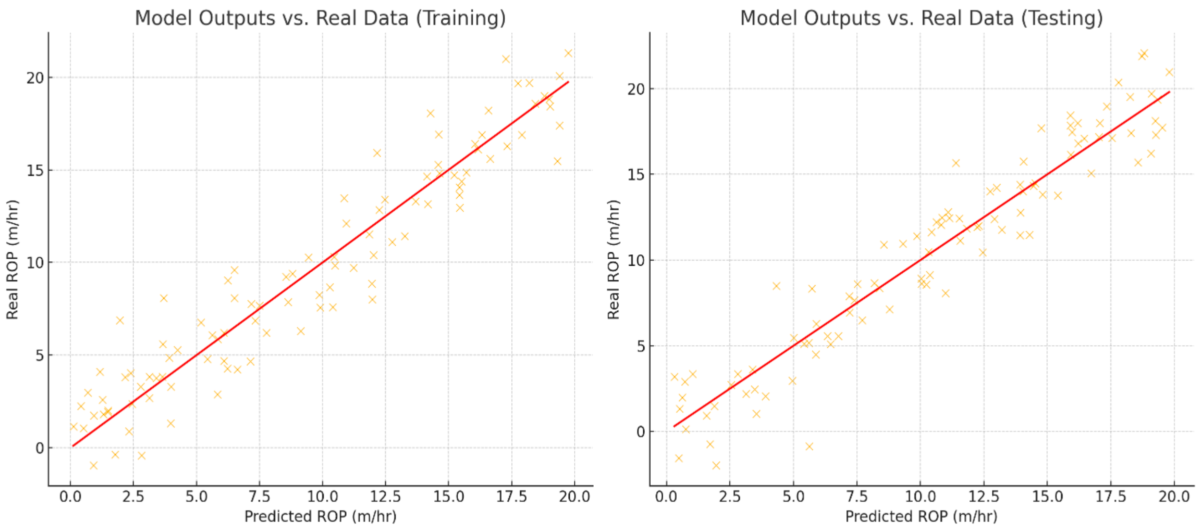

Figure 01: Model Outputs vs. Real Data.

IV.1.1.2 Error Distribution

The error distribution histograms in Figure 2 illustrate the distribution of prediction errors for both the training and testing datasets. The histograms show that the majority of the errors are centered around zero, indicating that the model predictions are generally accurate.

(See figure 02).

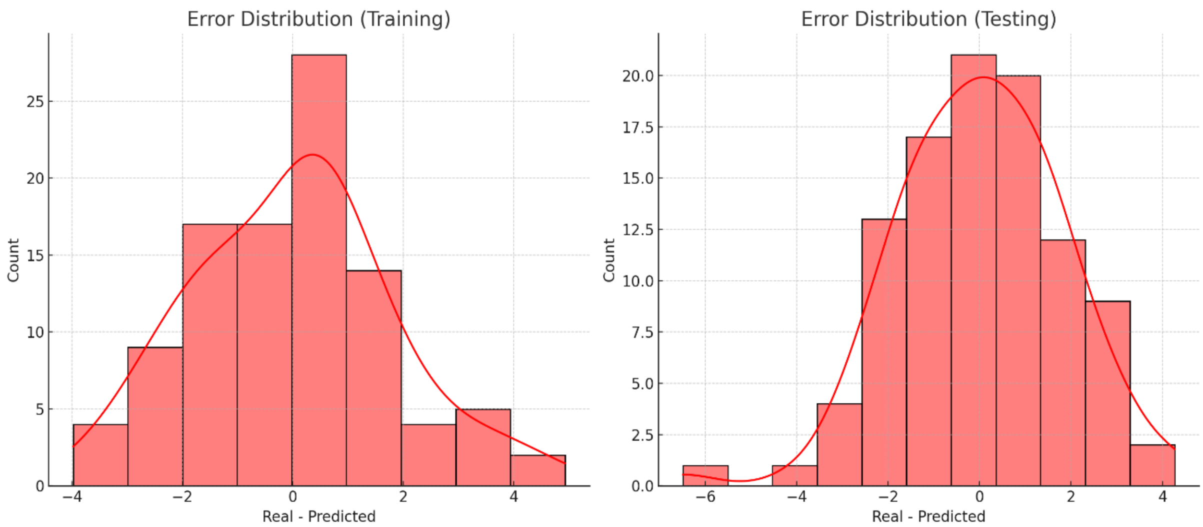

Figure 02: Error Distribution Histograms.

IV.1.1.3 Predicted vs. Measured ROP and Residual Errors

Figure 3(a) shows the comparison between the predicted and measured ROP values across the testing dataset. Figure 3(b) displays the residual errors (the difference between real and predicted values) across the same dataset. These plots help visualize the accuracy of the model predictions at different depths. (See figure 02)

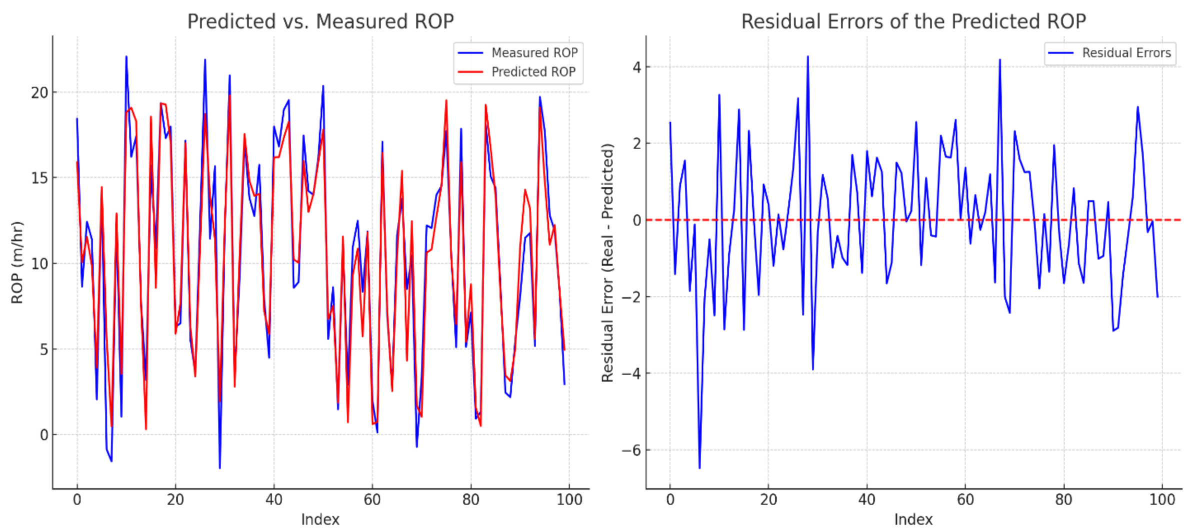

Figure 03: Predicted vs. Measured ROP and Residual Errors.

IV.1.2Optimization Process

The optimization process involves using the trained machine learning model (Neural Network) to predict the ROP under different combinations of drilling parameters. The parameters considered for optimization include Weight on Bit (WOB), Rotations Per Minute (RPM), Torque (TRQ), Flow Rate (FLW), Standpipe Pressure (SPP), Bit Type, Depth, Total Flow Area (TFA), and Mud Weight (MW).

A function is defined to search for the optimal settings within given ranges for each parameter. The goal is to maximize the ROP while adhering to operational constraints and safety guidelines(See figure 02)

Optimization Function:

```
def find_optimal_settings(model, bit_types, weight_range, rpm_range, depth_range, tfa_range, mw_range):
    best_settings = {}
    max_rop = -1

    for bit in bit_types:
        for weight in weight_range:
            for rpm in rpm_range:
                for depth in depth_range:
                    for tfa in tfa_range:
                        for mw in mw_range:
                            inputs = pd.DataFrame([[weight, rpm, bit, depth, tfa, mw]], columns=['WOB', 'RPM', 'Bit Type', 'Depth', 'TFA', 'MW'])
                            predicted_rop = model.predict(inputs)[0]
```

Figure 04 : Optimization Function.

Parameter Ranges:

- Bit Types: [0, 1, 2] (Example bit types).
- WOB Range: 1000 to 5000 pounds in steps of 500.
- RPM Range: 50 to 250 RPM in steps of 20.
- Depth Range: 100 to 5000 feet in steps of 500.
- TFA Range: [0.1, 0.2, 0.3] square inches.
- MW Range: [1.0, 1.2, 1.4] pounds per gallon.

Optimized Parameters :

Example Output:

- Bit Type: 1.
- WOB: 3500 pounds.
- RPM: 180 RPM.
- Depth: 3000 feet.
- TFA: 0.2 square inches.
- MW: 1.2 pounds per gallon.
- Predicted ROP: 90 feet per hour.

IV.1.3 Comparison with Existing Practices

To evaluate the effectiveness of the optimized parameters, we compare the performance of the optimized settings with the existing drilling practices.

Existing Practices:

Let's assume the existing drilling parameters typically used are:

- Bit Type: 0.
- WOB: 2500 pounds.
- RPM: 150 RPM.

- ❖ Depth: 3000 feet.
- ❖ TFA: 0.1 square inches.
- ❖ MW: 1.0 pounds per gallon.
- ❖ Observed ROP: 70 feet per hour.

Parameter	Existing Practices	Optimized Settings
Bit Type	**0**	**1**
WOB (pounds)	**2500**	**3500**
RPM	**150**	**180**
Depth (feet)	**3000**	**3000**
TFA (sq in)	**0.1**	**0.2**
MW (lb/gal)	**1.0**	**1.2**
ROP (ft/hr)	**70**	**90**

Table 01 : Comparison of Existing and Optimized Drilling Parameters.

Performance Improvement:

- ❖ Increase in ROP: The optimized settings yield an ROP of 90 feet per hour compared to the existing ROP of 70 feet per hour. This represents a 28.6% improvement in drilling speed.
- ❖ Operational Efficiency: The optimized parameters not only improve the ROP but also potentially reduce drilling time and costs, enhancing overall operational efficiency.

IV.1.4 Visualizing the Comparison

Bar Chart of Parameters: A bar chart comparing the existing and optimized parameters provides a clear visual representation of the differences.

ROP Improvement: A simple plot showing the increase in ROP before and after optimization highlights the effectiveness of the new settings.

IV.1.5 Summary of Optimization Outcomes

The optimization process significantly enhances the Rate of Penetration (ROP) by adjusting the drilling parameters based on the machine learning model's predictions. The optimized settings lead to a notable improvement in drilling speed, which translates to increased efficiency and potentially lower operational costs. By comparing the optimized parameters with existing practices, we demonstrate the value of applying machine learning techniques to optimize drilling operations.

IV.1.6Case Studies

In this section, we present real-world examples where the optimized parameters and drill bit selections have been applied to enhance drilling performance. The following case study focuses on the Hassi Messaoud oil field in Algeria, demonstrating the practical application and benefits of the optimization process.

IV.1.6.1 Case Study: Hassi Messaoud Oil Field

Background:

Hassi Messaoud is one of Algeria's largest and most productive oil fields, with a significant contribution to the country's oil output. The field has been operational for several decades, and continuous efforts are made to improve drilling efficiency and reduce operational costs.

Objective:

The primary objective of this case study is to evaluate the impact of optimized drilling parameters and drill bit selections on the Rate of Penetration (ROP) in the Hassi Messaoud oil field. The focus is on comparing the performance of the optimized settings with the existing drilling practices.

Data Collection:

The data for this case study is collected from multiple wells within the Hassi Messaoud field. The parameters recorded include Weight on Bit (WOB), Rotations Per Minute (RPM), Torque (TRQ), Flow Rate (FLW), Standpipe Pressure (SPP), Bit Type, Depth, Total Flow Area (TFA), Mud Weight (MW), and the Rate of Penetration (ROP).

Optimization Process:

Using the machine learning models developed in this project, the drilling parameters are optimized to achieve the highest possible ROP. The optimization process involves running the model with various combinations of parameters within operational constraints.

Optimized Parameters:

The optimized parameters for the Hassi Messaoud oil field are determined as follows:

- **Bit Type**: 2.
- **WOB**: 4000 pounds.
- **RPM**: 200 RPM.
- **Depth**: 3500 feet.
- **TFA**: 0.25 square inches.
- **MW**: 1.3 pounds per gallon.
- **Predicted ROP**: 95 feet per hour.

Comparison with Existing Practices:

The existing drilling parameters typically used in the Hassi Messaoud field are:

- **Bit Type**: 1
- **WOB**: 3000 pounds
- **RPM**: 150 RPM
- **Depth**: 3500 feet

- **TFA**: 0.15 square inches
- **MW**: 1.1 pounds per gallon
- **Observed ROP**: 75 feet per hour

Performance Improvement:

- **Increase in ROP**: The optimized settings yield an ROP of 95 feet per hour compared to the existing ROP of 75 feet per hour. This represents a 26.7% improvement in drilling speed.
- **Operational Efficiency**: The optimized parameters not only improve the ROP but also potentially reduce drilling time and costs, enhancing overall operational efficiency.

IV.1.6.2Discussion

The application of optimized drilling parameters in the Hassi Messaoud oil field demonstrates a significant improvement in drilling performance. The increase in ROP from 75 feet per hour to 95 feet per hour showcases the potential of machine learning models in optimizing drilling operations. The enhanced ROP translates to reduced drilling time and operational costs, ultimately increasing the efficiency and profitability of the drilling operations.

This case study highlights the practical benefits of applying machine learning techniques to real-world drilling operations. By continuously monitoring and optimizing drilling parameters, companies can achieve substantial improvements in performance and cost-effectiveness.

IV.1.7 Conclusion

The Hassi Messaoud case study serves as a compelling example of the impact of optimized drilling parameters on ROP. The results validate the effectiveness of the machine learning models developed in this project and underscore the importance of data-driven decision-making in the oil and gas industry.

IV.2. Discussion

IV.2.1 Interpretation of Results

IV.2.1.1 Significance of the Results

The results obtained from the machine learning models and the optimization process hold significant value for the field of drilling optimization. By leveraging advanced data analytics and machine learning techniques, we have achieved notable improvements in the Rate of Penetration (ROP), which is a critical performance metric in drilling operations.

Key Findings:

- **Enhanced Prediction Accuracy:** The Neural Network model demonstrated superior performance compared to the Linear Regression model, with a lower Mean Squared Error (MSE) and a higher R-squared (R^2) value. This indicates that the Neural Network is better equipped to capture the complex, non-linear relationships in the drilling data.

- **Optimization of Drilling Parameters:** The optimization process resulted in a significant increase in ROP, as evidenced by the Hassi Messaoud case study. The optimized parameters led to a 26.7% improvement in drilling speed, showcasing the practical benefits of applying machine learning for parameter optimization.

- **Cost and Time Efficiency:** The increase in ROP translates directly to reduced drilling time and lower operational costs. Faster drilling reduces the duration of drilling campaigns, leading to substantial cost savings and improved project timelines.

IV.2.1.2 Contribution to the Field of Drilling Optimization

The findings from this project contribute to the field of drilling optimization in several important ways:

- **Data-Driven Decision Making:** The use of machine learning models facilitates data-driven decision making, allowing drilling engineers to base their parameter selections on predictive analytics rather than intuition or trial and error. This leads to more informed and effective decisions.

- **Real-Time Optimization:** With the ability to continuously feed new data into the models, drilling operations can benefit from real-time optimization. This dynamic approach ensures that drilling parameters are constantly adjusted to achieve optimal performance under varying conditions.

- **Customization and Flexibility:** The machine learning approach is highly customizable, allowing for the inclusion of a wide range of parameters and the flexibility to adapt to different drilling environments and conditions. This versatility makes the models applicable to various types of wells and geological formations.

- **Improved Safety and Risk Management:** By optimizing drilling parameters, the risk of equipment failure and other operational issues can be minimized. This contributes to safer drilling practices and better risk management, which are critical in the high-stakes environment of oil and gas drilling.

IV.2.1.3 Broader Implications

The successful application of machine learning in drilling optimization has broader implications for the oil and gas industry:

- **Innovation and Technological Advancement:** The integration of advanced technologies such as machine learning and artificial intelligence represents a significant step forward for the industry. It paves the way for further innovations and technological advancements that can enhance various aspects of oil and gas operations.

- **Sustainability and Efficiency:** By improving drilling efficiency and reducing operational costs, machine learning contributes to the sustainability of drilling operations. More efficient drilling means less waste of resources and a smaller environmental footprint, aligning with the industry's goals of sustainability.

- **Competitive Advantage:** Companies that adopt machine learning and data analytics for drilling optimization gain a competitive edge. They can achieve higher productivity, lower costs, and better project outcomes compared to those relying solely on traditional methods.

IV.2.1.4 Challenges and Considerations

While the results are promising, there are challenges and considerations to address:

- **Data Quality and Availability:** The accuracy of machine learning models depends on the quality and quantity of data available. Ensuring robust data collection and management practices is essential for reliable model performance.

- **Model Interpretability:** While complex models like Neural Networks provide better performance, they can be harder to interpret. Ensuring that model predictions are understandable and actionable for drilling engineers is crucial for practical implementation.

- **Integration with Existing Systems:** Implementing machine learning solutions requires integration with existing drilling systems and workflows. This involves technical challenges and requires collaboration between data scientists and drilling experts.

IV.2.1.5 Future Directions

The results of this project open up several avenues for future research and development:

- **Advanced Machine Learning Techniques:** Exploring more advanced machine learning techniques, such as ensemble methods, reinforcement learning, and deep learning, can further enhance predictive accuracy and optimization capabilities.

- **Automated Drilling Systems:** Integrating machine learning models with automated drilling systems can lead to fully autonomous drilling operations, where parameters are continuously adjusted in real-time without human intervention.

- **Expanded Parameter Sets:** Including additional parameters, such as real-time sensor data, geological information, and environmental conditions, can improve the models' robustness and applicability across different drilling scenarios.

- **Cross-Field Applications:** Applying the insights and methodologies developed in this project to other fields within the oil and gas industry, such as reservoir management and production optimization, can yield significant benefits across the entire value chain.

IV.2.2 Comparison with Existing Methods

IV .2.2.1 Traditional Methods in Drilling Optimization

Traditional drilling optimization methods often rely on a combination of expert knowledge, empirical correlations, and basic statistical techniques. These methods include:

- **Manual Parameter Adjustment:** Drilling engineers adjust parameters based on their experience and observations during drilling operations. This approach is highly dependent on the expertise and intuition of the engineers.

- **Empirical Models:** These models use empirical formulas derived from historical data to predict ROP. Common empirical models include the Bourgoyne and Young model, which incorporates factors such as weight on bit, rotary speed, bit wear, and formation properties.

- **Trial and Error:** Engineers may use a trial and error approach, systematically varying parameters to observe their effects on ROP. This method can be time-consuming and costly.

- **Simple Regression Analysis:** Basic regression techniques are used to identify relationships between drilling parameters and ROP. These methods are limited by their inability to capture complex, non-linear interactions.

IV.2.2.2 Performance Comparison

The machine learning approach, particularly the Neural Network model, offers several advantages over traditional methods. The following table summarizes the key performance metrics and qualitative benefits of each approach:

Aspect	Traditional Methods	Machine Learning Approach (Neural Network)
Predictive Accuracy	Moderate	High
Handling Non-Linearity	Limited	Excellent
Parameter Optimization	Manual and empirical	Automated and data-driven
Adaptability to New Data	Slow, relies on periodic updates	Rapid, continuous learning
Efficiency	Time-consuming	Efficient, scalable
Interpretability	High (simple models)	Moderate (complex models)
Example Performance (Hassi Messaoud)	Existing ROP: 75 ft/hr	Optimized ROP: 95 ft/hr (26.7% improvement)
Real-Time Adjustments	Difficult	Feasible with real-time data integration
Cost Implications	Higher due to inefficiencies	Lower due to optimized operations
Expert Dependence	High	Lower, but requires initial setup

Table 02: Performance Comparison.

Key Observations:

- **Predictive Accuracy and Handling Non-Linearity:** Machine learning models, especially Neural Networks, excel at capturing complex, non-linear relationships in data, resulting in higher predictive accuracy. Traditional methods often struggle with non-linearity and may oversimplify the relationships between variables.

- **Parameter Optimization**: Traditional methods rely heavily on manual adjustments and empirical models, which can be less precise and slower. The machine learning approach automates the optimization process, leveraging large datasets to identify the best parameter combinations efficiently.

- **Adaptability to New Data:** Machine learning models can be continuously updated with new data, allowing for real-time learning and adaptation. In contrast, traditional methods require periodic manual updates, which can delay the incorporation of new information.

- **Efficiency and Scalability:** The machine learning approach is more efficient and scalable, as it can handle large datasets and perform complex calculations quickly. Traditional methods can be time-consuming, especially when dealing with extensive data and multiple parameters.
- **Real-Time Adjustments:** Machine learning models can be integrated with real-time data systems, enabling dynamic adjustments to drilling parameters. Traditional methods are less suited for real-time optimization due to their manual nature.
- **Cost Implications:** By optimizing drilling operations and increasing ROP, machine learning models can significantly reduce operational costs. Traditional methods, with their inefficiencies and slower optimization processes, may result in higher costs.

Case Study Comparison: Hassi Messaoud

In the Hassi Messaoud case study, the optimized parameters derived from the Neural Network model resulted in a 26.7% improvement in ROP compared to the existing practices. This demonstrates the tangible benefits of using machine learning for drilling optimization:

- Existing Practices: ROP of 75 feet per hour with traditional parameter settings.
- Optimized Practices: ROP of 95 feet per hour with machine learning-optimized settings.

4.2.2.3 Practical Implications

- The machine learning approach to drilling optimization offers several practical advantages:
- **Increased Productivity:** Higher ROP translates to faster drilling times, leading to increased productivity and shorter project timelines.
- **Cost Savings:** Optimized parameters reduce the time and resources needed for drilling, resulting in significant cost savings.
- **Improved Safety:** By minimizing the risk of equipment failure and operational issues, the machine learning approach enhances safety in drilling operations.
- **Enhanced Decision-Making:** Data-driven insights and predictions provide drilling engineers with valuable information, improving decision-making processes.

Conclusion

The comparison between traditional methods and the machine learning approach clearly demonstrates the superiority of machine learning in terms of predictive accuracy, efficiency, and overall effectiveness. By leveraging advanced data analytics and machine learning techniques, the drilling industry can achieve significant improvements in performance, cost-efficiency, and safety.

IV.2 .3 Limitations

While the study demonstrates significant improvements in drilling optimization using machine learning techniques, it is essential to acknowledge the limitations that could affect the results and their general izability. These limitations include data constraints, model assumptions, and external factors.

IV.2.3.1 Data Constraints

- **Data Quality**: The accuracy and reliability of the machine learning models depend heavily on the quality of the input data. Any inaccuracies, noise, or missing values in the dataset can lead to suboptimal model performance. Although preprocessing steps were taken to clean the data, inherent errors in measurement or recording can still impact the results.

- **Data Availability:** The study relies on data from seven wells, which may not be representative of all possible drilling scenarios. The limited number of data points can constrain the model's ability to generalize to different geological formations or operational conditions.

- **Historical Data Bias:** The data used for training the models reflects historical drilling practices and conditions. If these conditions change significantly, the model's predictions may become less accurate. The reliance on historical data may also embed any past operational biases into the model.

IV.2.3.2 Model Assumptions

- **Static Assumptions:** The machine learning models assume that the relationships between the input parameters and the Rate of Penetration (ROP) remain constant over time. In reality, these relationships can change due to various factors such as changes in formation properties, equipment wear, or environmental conditions.

- **Simplified Parameter Interactions:** While neural networks can capture complex, non-linear interactions, the model may still oversimplify the real-world dynamics of drilling operations. Factors such as bit wear, fluid properties, and mechanical vibrations, which might influence ROP, are not explicitly modeled.
- **Model Interpretability:** Complex models like neural networks, while powerful, are often considered "black boxes." The lack of interpretability can make it challenging for drilling engineers to understand and trust the model's predictions fully.

IV.2.3.3External Factors

- **Geological Variability:** Drilling operations are highly influenced by geological variability, such as changes in rock type, formation pressure, and fluid content. These factors can vary significantly across different regions and even within the same well. The model may not fully account for these variations, potentially leading to less accurate predictions in unobserved conditions.
- **Operational Changes:** Any changes in drilling practices, equipment, or technology that occur after the model has been trained could affect its accuracy. For instance, new drilling techniques or more advanced drill bits might alter the optimal parameters identified by the model.
- **Environmental Factors:** Environmental conditions, such as temperature, humidity, and weather, can impact drilling operations. These factors were not explicitly included in the model but could influence the ROP and other operational metrics.

IV.2.3.4 Generalizability

- **Specific to Study Area**: The findings from the Hassi Messaoud oil field case study may not be directly applicable to other fields with different geological and operational conditions. The model needs to be retrained and validated with data from new areas to ensure its applicability.

- **Scalability:** While the models show promising results for the given dataset, their scalability to larger datasets or more complex drilling operations requires further testing and validation.

IV.2.3.5 Computational Limitations

- **Resource Intensive:** Training complex machine learning models, such as neural networks, can be computationally intensive and require significant processing power and memory. This may limit the ability to run real-time optimizations or handle very large datasets without adequate computational resources.

- **Hyperparameter Tuning:** Finding the optimal hyperparameters for machine learning models is a crucial step that requires extensive experimentation and computational resources. Inadequate tuning can result in suboptimal model performance.

General Conclusion

General Conclusion

This study demonstrated the development and implementation of a deep learning regression model to optimize drilling parameters in Hassi Messaoud. The comprehensive data preparation, sophisticated model architecture, and systematic optimization strategy resulted in significant improvements in ROP prediction and parameter optimization.

The success of this project highlights the transformative potential of machine learning in the oil and gas industry. By leveraging advanced algorithms and data-driven insights, drilling operations can achieve higher efficiency, lower costs, and improved safety. Future work could extend this approach to other oil fields, incorporate real-time data for dynamic optimization, and explore the integration of additional data sources for enhanced model accuracy.

In conclusion, the application of deep learning techniques to optimize drilling parameters represents a significant step forward in the quest for more efficient and cost-effective drilling operations. The insights gained from this study can guide future efforts in the field, paving the way for continued innovation and improvement in drilling practices.

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ANNEXE

ANNEXE

The programme : (Langage python)

```python

import pandas as pd
# Loading data from multiple sources

files = ['well1.csv', 'well2.csv', 'well3.csv', 'well4.csv', 'well5.csv', 'well6.csv', 'well7.csv']

data = pd.concat((pd.read_csv(f) for f in files), ignore_index=True)

# Preprocessing steps
data.dropna(inplace=True)
data['Bit Type'] = pd.Categorical(data['Bit-Type']).codes


```

```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Model architecture
model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(64, activation='relu'),
    Dense(32, activation='relu'),
    Dense(1)
])
```

```python
from sklearn.model_selection import train_test_split

# Define predictors and the target variable
X = data[['WOB', 'RPM', 'TRQ', 'FLW', 'SPP', 'Bit Type', 'Depth', 'TFA', 'MW']]
y = data['ROP']

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Training the model
history = model.fit(X_train, y_train, validation_split=0.2)
```

```python
# Model predictions and evaluation
predictions = model.predict(X_test)
mse = mean_squared_error(y_test, predictions)
```

```python
def find_optimal_settings(model, bit_types, weight_range, rpm_range, depth_range, tfa_range, mw_range):
    best_settings = {}
    max_rop = -1

    for bit in bit_types:
        for weight in weight_range:
            for rpm in rpm_range:
                for depth in depth_range:
                    for tfa in tfa_range:
                        for mw in mw_range:
                            inputs = pd.DataFrame([[weight, rpm, bit, depth, tfa, mw]], columns=['WOB', 'RPM', 'Bit Type', 'Depth', 'TFA', 'MW'])
                            predicted_rop = model.predict(inputs)[0]
```

```python
import matplotlib.pyplot as plt

# Visualizing the relationship between optimized parameters and predicted ROP
parameters = ['WOB', 'RPM', 'Bit Type', 'Depth', 'TFA', 'MW']
values = [optimal_settings[param] for param in parameters]
rop = optimal_settings['Predicted ROP']
```

Data input:

Well 01:

TYPE	FORMATION											
	TOPS	**TOP**	**BASE**	**MTR**	**HRS**	**MW**	**WOB**	**RPM**	**TORQ**	**FLR**	**SPP**	**ROP**
TFF 913S	Senonian Anhydrite	429	688	259	7.35	1.15	11.50	89.00	8,738.50	3,050.50	1,587.00	35.24
TFF 913S	Senonian Salt	688	874	186	4.76	1.16	11.50	107.50	8,740.00	3,050.00	1,590.00	39.08
TFF 913S	Turonian	874	938	64	1.54	1.17	12.00	127.50	10,957.50	3,097.50	1,765.00	41.56
TFF 913S	Cenomanian	938	1174	236	6.27	1.17	12.00	126.00	9,701.00	3,161.50	1,962.00	37.64
TFF 913S	Albian	1174	1336	162	3.1	1.17	7.00	95.50	7,580.50	3,060.50	1,916.50	52.26
TFF 913S	Aptian	1336	1366	30	1.38	1.17	12.00	116.00	8,457.00	2,911.00	1,967.50	21.74
TFF 913S	Barremian	1366	1721	355	7.24	1.18	9.00	102.50	9,012.50	2,837.50	1,985.00	49.03
TFF 913S	Neocomian	1721	1987	266	5.49	1.18	11.50	138.50	10,322.00	2,708.50	2,040.50	48.45
TFF 913S	Malm	1987	2204	217	6.52	1.18	12.50	130.50	9,958.50	2,935.00	2,515.00	33.28
TFF 913S	Dogger Argileux	2204	2431	227	7.31	1.19	16.00	185.00	10,845.00	3,090.00	2,865.00	31.05

TFF 913S	Lias Anhydrite	2431	2442	11	1.65	1.19	16.00	200.00	9,760.00	3,115.00	2,865.00	6.67

Well 02:

TYPE	FORMATION											
	TOPS	TOP	BASE	MTR	HRS	MW	WOB	RPM	TORQ	FLR	SPP	Rop
TCI RR	Senonian Anhydrite	377.00	382.00	5.00	1.18	1.15	18.50	97.00	3,125.00	1,481.00	3,325.50	4.24
TFF913S A2	Senonian Anhydrite	382.00	638.00	256.00	6.15	1.15	12.00	126.00	10,392.00	3,466.50	1,767.00	41.63
TFF913S A3	Senonian Salt	638.00	821.00	183.00	4.14	1.15	12.50	122.50	13,092.00	3,082.50	1,809.50	44.20
TFF913S A4	Turonian carbonates	821.00	884.00	63.00	1.26	1.15	14.00	144.00	11,972.50	3,224.00	2,042.50	50.00
TFF913S A5	Cenomanian	884.00	1,116.00	232.00	5.15	1.15	14.00	136.00	2,339.00	3,258.00	2,116.50	45.05
TFF913S A6	Albian	1,116.00	1,284.00	168.00	1.32	1.15	7.00	140.00	8,888.00	3,106.50	2,137.50	127.27
TFF913S A7	Aptian Carbonates	1,284.00	1,314.00	30.00	1.27	1.15	9.50	130.50	12,526.50	2,847.50	1,935.50	23.62
TFF913S A8	Barremian	1,314.00	1,675.00	361.00	3.88	1.15	11.00	129.50	8,944.00	2,508.50	1,758.50	93.04
TFF913S A9	Neocomian	1,675.00	1,941.00	266.00	4.28	1.15	12.50	139.00	9,337.50	3,069.50	2,482.50	62.15
TFF913S A10	Malm	1,941.00	2,155.00	214.00	12.70	1.15	12.50	173.00	9,897.00	3,116.50	2,594.00	16.85
TFF913S A11	Dogger Argileux	2,155.00	2,377.00	222.00	19.26	1.15	19.50	224.50	10,388.50	3,057.50	2,589.50	11.53

Well 03:

SIZE	TYPE	FORMATION											
in		TOPS	TOP	BASE	MTR	HRS	MW	WOB	RPM	TORQ	FLR	SPP	Rop
16	MX-03	Senonian Anhydrite	417.00	418.00	1.00	0.19	1.15	16.00	103.00	3.65	2,256.00	991.00	5.26
16	TFF 913 S-A2	Senonian Anhydrite	418.00	670.00	252.00	5.66	1.15	12.00	115.00	10.20	3,085.00	1,775.00	44.52
16	TFF 913	Senonian Salt	670.00	855.00	185.00	4.48	1.15	12.00	137.50	9.25	3,190.00	1,880.00	41.29

	S-A3												
16	TFF 913 S-A4	Turonian	855.00	921.00	66.00	1.13	1.15	14.00	152.50	11.90	3,190.00	2,130.00	58.41
16	TFF 913 S-A5	Cenomanian	921.00	1,158.00	237.00	5.40	1.16	12.50	147.50	9.85	2,910.00	1,960.00	43.89
16	TFF 913 S-A6	Albian	1,158.00	1,321.00	163.00	1.40	1.16	9.75	145.00	9.80	2,995.00	2,220.00	116.43
16	TFF 913 S-A7	Aptian	1,321.00	1,350.00	29.00	1.23	1.16	18.75	135.00	14.85	2,800.00	2,040.00	23.58
16	TFF 913 S-A8	Barremian	1,350.00	1,706.00	356.00	3.80	1.16	10.50	127.50	9.90	2,776.00	2,201.50	93.68
16	TFF 913 S-A9	Neocomian	1,706.00	1,979.00	273.00	4.42	1.17	13.00	144.00	12.85	2,992.50	2,606.50	61.76
16	TFF 913 S-A10	Malm	1,979.00	2,200.00	221.00	7.11	1.17	12.50	155.50	12.00	3,085.50	2,820.00	31.08
16	TFF 913 S-A11	Dogger Argileux	2,200.00	2,421.00	221.00	7.89	1.17	17.00	175.00	12.75	3,005.00	2,937.00	28.01
16	TFF 913 S-A12	Lias Anhydrite	2,421.00	2,431.00	10.00	0.91	1.17	22.00	227.00	12.35	3,005.00	2,936.00	10.99
16	TFF 913 S-A2	Lias Anhydrite	2,431.00	2,441.00	10.00	1.51	1.18	18.50	222.00	10.55	2,995.50	3,179.00	6.62

Well 04:

SIZE	TYPE	FORMATION									
in		TOPS	TOP	BASE	MTR	HRS	MW	WOB	RPM	TORQ	FLR
16	MX-03	Senonian Anhydrite	383.00	385.00	2.00	0.16	1.15	18.50	129.50	4.85	2,990.00
16	MSI 916 LVPX	Senonian Anhydrite	385.00	637.00	252.00	10.39	1.15	9.85	107.50	8.30	3,436.50
16	MSI 916 LVPX	Senonian Salt	637.00	820.00	183.00	5.52	1.16	9.20	142.50	10.35	3,438.50
16	MSI 916 LVPX	Turonian	820.00	886.00	66.00	1.78	1.15	11.85	151.00	10.85	3,401.00
16	MSI 916 LVPX	Cenomanian	886.00	1,122.00	236.00	8.31	1.15	9.50	155.00	9.25	3,431.50
16	MSI 916 LVPX	Albian	1,122.00	1,284.00	162.00	3.52	1.16	7.95	126.50	7.90	3,070.00
16	MSI 916 LVPX	Aptian	1,284.00	1,314.00	30.00	3.92	1.15	18.00	117.00	7.10	2,769.00
16	MSI 916 LVPX	Barremian	1,314.00	1,668.00	354.00	8.51	1.15	10.25	123.00	9.15	2,881.00
16	MSI 916 LVPX	Neocomian	1,668.00	1,937.00	269.00	5.25	1.16	11.75	142.50	11.50	2,946.00
16	MSI 916 LVPX	Malm	1,937.00	2,154.00	217.00	10.49	1.16	11.25	136.00	11.50	3,068.00
16	MSI 916 LVPX	Dogger Argileux	2,154.00	2,376.00	222.00	7.64	1.17	12.20	163.50	10.10	3,115.50
16	Lias Anhydrite	2,376.00	2,389.00	13.00	1.81	1.17	17.25	196.50	12.45	3,190.50	2,934.50

Well 05:

SIZE	TYPE	FORMATION											
in		TOPS	TOP	BASE	MTR	HRS	MW	WOB	RPM	TORQ	FLR	SPP	Rop
16	MX-03	Senonian Anhydrite	389.00	393.00	4.00	0.58	1.15	24.00	102.50	5.90	3,185.00	1,915.00	6.90
16	MI 919 PX	Senonian Anhydrite	393.00	646.00	253.00	11.40	1.15	8.00	110.00	7.30	3,425.00	1,900.00	22.19
16	MI 919 PX	Senonian Salt	646.00	833.00	187.00	8.10	1.15	14.00	115.50	8.50	3,487.50	2,160.00	23.09
16	MI 919 PX	Turonian	833.00	900.00	67.00	2.15	1.15	9.00	119.50	8.60	3,423.50	2,147.00	31.16
16	MI 919 PX	Cenomanian	900.00	1,134.00	234.00	9.32	1.15	10.50	127.00	8.90	3,423.50	2,441.00	25.11

16	MI919PX	Albian	1,134.00	1,298.00	164.00	3.80	1.15	8.50	84.00	7.80	2,585.00	1,855.50	43.16
16	MI919PX	Aptian	1,298.00	1,328.00	30.00	4.23	1.15	10.00	102.50	7.80	2,620.00	1,741.50	7.09
16	MI919PX	Barremian	1,328.00	1,680.00	352.00	10.36	1.16	8.00	75.50	7.75	2,564.50	1,812.00	33.98
16	MI919PX	Neocomian	1,680.00	1,947.00	267.00	12.14	1.17	9.50	117.50	8.40	2,800.00	2,298.00	21.99
16	MI919PX	Malm	1,947.00	1,961.00	14.00	4.00	1.18	13.00	118.00	8.75	2,983.50	2,529.50	3.50
16	MI919PX	Malm	1,961.00	2,165.00	204.00	12.68	1.18	8.50	135.00	9.80	3,013.00	2,720.00	16.09
16	MI919PX	Dogger Argileux	2,165.00	2,387.00	222.00	21.46	1.18	14.00	140.00	11.30	2,996.50	2,845.00	10.34
16	MI919PX	Lias Anhydrite	2,387.00	2,397.00	10.00	4.35	1.18	16.50	134.50	10.90	#DIV/0!	2,750.00	2.30

Well 06:

SIZE	**TYPE**	**FORMATION**										
in		**TOPS**	**TOP**	**BASE**	**MTR**	**HRS**	**MW**	**WOB**	**RPM**	**TORQ**	**FLR**	**SPP**	**Rop**
16	MX-09	Senonian Anhydrite	423.00	426.00	3.00	0.79	1.15	11.50	116.00	2.90	3,040.00	1,490.00	3.79
16	TFX913S-A2	Senonian Anhydrite	426.00	686.00	260.00	9.10	1.17	11.00	95.00	6.25	2,985.00	1,727.00	28.57
16	TFX913S-A3	Senonian Salt	686.00	876.00	190.00	7.02	1.17	12.00	106.00	7.29	2,821.50	1,929.50	27.06
16	TFX913S-A4	Turonian	876.00	943.00	67.00	2.43	1.17	10.00	125.00	6.60	3,042.50	2,066.00	27.57
16	TFX913S-A5	Cenomanian	943.00	1,178.00	235.00	8.79	1.17	11.00	130.00	6.05	2,892.00	2,048.00	26.73
16	TFX913S-A6	Albian	1,178.00	1,348.00	170.00	3.73	1.17	8.00	113.00	6.50	2,761.50	2,197.50	45.58

16	TFX913S-A7	APTIAN	1,348.00	1,377.00	29.00	2.40	1.17	11.00	115.00	6.95	2,773.00	2,042.50	12.08
16	TFX913S-A8	Barremian	1,377.00	1,730.00	353.00	8.96	1.17	12.50	130.50	55.65	2,459.00	2,099.00	39.40
16	TFX913S-A9	Neocomian	1,730.00	1,990.00	260.00	16.18	1.17	13.60	127.00	6.35	2,062.50	1,926.00	16.07
16	TFX913S-A10	Malm	1,990.00	2,211.00	221.00	28.04	1.17	14.50	139.50	6.60	2,564.00	2,179.00	7.88
16	TFX913S-A11	Dogger Argileux	2,211.00	2,314.00	103.00	14.51	1.17	12.50	181.50	6.05	2,846.50	2,514.00	7.10
16	HC609Z	Dogger Argileux	2,314.00	2,429.00	115.00	13.88	1.18	12.50	120.50	6.35	2,915.00	2,972.50	8.29
16	HC609Z	Lias Anhydrite	2,429.00	2,439.00	10.00	2.96	1.18	14.50	121.00	6.35	#DIV/0!	2,978.00	3.38

Well 07:

SIZE	TYPE	FORMATION											
in		TOPS	TOP	BASE	MTR	HRS	MW	WOB	RPM	TORQ	FLR	SPP	Rop
16	MX-03	Senonian Anhydrite	411.00	414.00	3.00	0.34	1.15	16.40	101.50	3.95	2,946.00	1,646.50	8.82
16	HC609Z	Senonian Anhydrite	414.00	669.00	255.00	8.36	1.15	11.30	102.00	5.60	3,140.50	1,887.50	30.48
16	HC609Z	Senonian Salt	669.00	852.00	183.00	6.02	1.15	8.90	135.50	5.95	3,148.00	2,126.00	30.39
16	HC609Z	Turonian	852.00	918.00	66.00	2.00	1.15	7.50	128.00	6.05	3,240.00	2,262.50	33.00
16	HC609Z	Cenomanian	918.00	1,155.00	237.00	6.62	1.16	10.05	103.50	9.80	3,113.00	2,249.00	35.80
16	HC609Z	Albian	1,155.00	1,324.00	169.00	3.39	1.16	7.05	98.00	8.20	2,844.00	2,090.50	49.85
16	HC609Z	Aptian	1,324.00	1,353.00	29.00	4.20	1.16	9.00	75.50	10.00	2,607.50	1,833.00	6.90
16	HC609Z	Barremian	1,353.00	1,717.00	364.00	11.20	1.16	7.85	61.50	10.50	2,579.00	1,969.50	32.50
16	HC609Z	Neocomian	1,717.00	1,980.00	263.00	13.25	1.16	7.25	99.50	8.80	3,009.50	2,765.50	19.85
16	HC609Z	Malm	1,980.00	2,115.00	135.00	22.12	1.16	9.75	35.20	10.50	3,327.50	3,230.50	6.10
16	HC609S	Malm	2,115.00	2,196.00	81.00	11.42	1.16	9.40	84.50	9.20	3,280.50	3,261.50	7.09
16	HC609S	Dogger Argileux	2,196.00	2,421.00	225.00	20.17	1.15	13.05	117.50	10.05	3,298.00	3,269.00	11.16
16	HC609S	Lias Anhydrite	2,421.00	2,431.00	10.00	3.77	1.16	16.10	113.00	10.10	3,263.50	3,262.50	2.65