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EMIRATES INTERNATIONAL UNIVERSITY FACULTY OF ENGINEERING AND INFORMATION TECHNOLOGY OIL AND GAS ENGINEERING DEPARTMENT

CORRELATION BETWEEN B&Y MODEL AND FUZZY LOGIC MODEL IN ESTIMATING ROP IN AL-TAWILA FIELD BLOCK-14

Senior Project

by

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DECLARATION

We hereby declare that the work in this project is our own except for quotations and summaries which have been duly acknowledge.

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ABSTRACT

Accurate prediction of Rate of Penetration (ROP) is essential for estimating drilling operations and thus reducing the time and cost. This study aims to investigate the correlation between the traditional B&Y model and a machine learning approach, specifically fuzzy logic, in predicting ROP. A comprehensive dataset containing drilling parameters such as weight on bit, rotational speed, bit type, formation lithology, and mud properties is utilized. The performance of both models is evaluated using relevant metrics, and their correlation is analyzed. In this applied research, there were eleven samples taking from three wells and those samples were taking as the inputs in the used software. Two software were used, EXCEL and MATLAB. The EXCEL software was used to build and calculate the B&Y model and also building the graphs and charts for the comparison, while the MATLAB software were used for building the Fuzzy logic model, a model based on the machine ability to learn and create patterns and thus formulas. The results of the classic model have shown compelling results for three samples, while the rest of the samples have shown a very high error percentage thus the overall output is that this model is not efficient with an average error percentage of (13.40927978%) for the time comparison, and (16.647181%) for ROP. The second model which was a machine learning based model named Fuzzy logic model has shown an overall results of low error percentage and high accuracy with an average error percentage of (4.276539253%) for the time comparison, and (4.4732609%) for ROP. This research propose that the Fuzzy logic model has the most promising results with a significance gap for error percentage compared with the classic model, it also minimizes the human error potential. The findings of this study will contribute to a better understanding of the strengths and weaknesses of each model, potentially leading to the development of hybrid models for improved ROP prediction.

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LIST OF SYMBOLS

ROP & $\frac{df}{dt}$	Rate of Penetration
ML	Machine Learning
WOB	Weight on Bit
RPM	Revolution Per Minute
B&Y	Bourgoyne And Young
Q	Flow Rate
SPP	Stand Pipe Pressure
D	Depth
DD	Drilled Depth
TVD	True Vertical Depth
SPSS	Statistical Package for Social Science
GBR	Gradient Boosting Regressor
MW	Mud Weight
ECD & ρc	Equivalent Circulating Density
ρ	Drilling Fluid's Density
db	Diameter of The Bit
dn	Equivalent Bit Nozzle Diameter
gp	Pore Pressure Gradient of The Formation
h	Bit Tooth Dullness
a1	Formation Type Parameter
a2	Normal Compaction Parameter
a3	Under Compaction Parameter

a4	Pressure Differential Parameter
a5	Weight on Bit (WOB) Parameter
a6	RPM Parameter
a7	Tooth Wear Parameter
a8	Hydraulics Parameter
N	Rotary Speed
Q & q	Volumetric Flow Rate
T	Time
FIS	fuzzy inference system
(W/d) t	Threshold Bit Weight At Which The Bit Starts To Drill

CHAPTER 1
INTRODUCTION

1.1 Overview

These days, drilling companies constantly emphasize on the two most prevalent and significant aspects of rig sites: low drilling costs and trouble-free drilling operations. One of the most significant indicators that might provide information on the time and expense of drilling operations is the rate of penetration (ROP). It is challenging to develop a model since drilling variables might have an impact on the ROP. Numerous intricate mathematical models were created in order to pick the right bit, weight, and rotation speed in order to enhance drilling operations and lower drilling costs. The uncontrolled features of the formation, together with the controllable factors of hydraulics, bit weight, and rotary speed, affect the drilling performance. The drilling operations sector uses a variety of techniques from several disciplines to carry out economical, ecologically friendly drilling operations with wells component construction. Simulator technologies are also the most significant fields since they aid in drilling optimization. The advancement of simulation software technology has made it possible to monitor drilling operations, prevent issues, and fix complex problems in a matter of minutes. A precise estimate of the rate of penetration (ROP), a crucial metric in drilling operations, can maximize drilling efficiency and lower drilling costs. There are restrictions on how well the conventional physics-based models for ROP prediction can represent the intricate connections between ROP and drilling parameters. By identifying the non-linear correlations between drilling parameters and ROP, machine learning (ML) techniques have demonstrated encouraging results in the prediction of ROP. The purpose of this research proposal is to investigate whether machine learning techniques can be used to anticipate ROP during drilling operations. The study will be conducted in real-time, with data being received and analyzed through a machine learning model implemented using the "MATLAB" simulation software. The model demonstrates exceptional performance and accuracy in predicting the rate of penetration (ROP). This study delves into the potential of integrating current technologies to minimize the cost and time constraints in drilling operations.

1.2 Problem Statement

A new approach for improved prediction of the drilling rate of penetration (ROP) using fuzzy logic is proposed. ROP is important because when it is calculated with accurate and optimized taking into account factors such as time, drilling cost are more likely to be minimized. There are many factors affecting ROP that need to be taken into account in its accurate prediction. To date several different techniques have been applied to the prediction of ROP. Bourgoyne and Young (1974) is the most established technique used to predict ROP. However, in many cases it does not provide adequate accuracy. A fuzzy logic model, using MATLAB software, is developed and evaluated to predict ROP.

1.3 Research Objectives

The research objectives are to achieve the following in real time basis:

- To build a fuzzy logic model.
- To evaluate & identify the accuracy of fuzzy logic model in predicting ROP in drilling operations.
- To compare the performance of fuzzy logic model with traditional B&Y model for ROP prediction.

1.4 Research Questions

- What are the key factors influencing ROP in oil wells?
- How can machine learning models be applied to predict ROP?
- How does the proposed enhanced oil model differ from traditional models?

1.5 Measurement Units

ROP is usually measured in either feet per minute (ft/min) or meters per hour. The faster the ROP, the faster the drilling goes.

1.6 Factors Affecting ROP

The most important variables affecting penetration rate that have been identified and studied include bit type, formation characteristics, drilling-fluid properties, bit operating conditions (bit weight and rotary speed), bit tooth wear, and bit hydraulics.

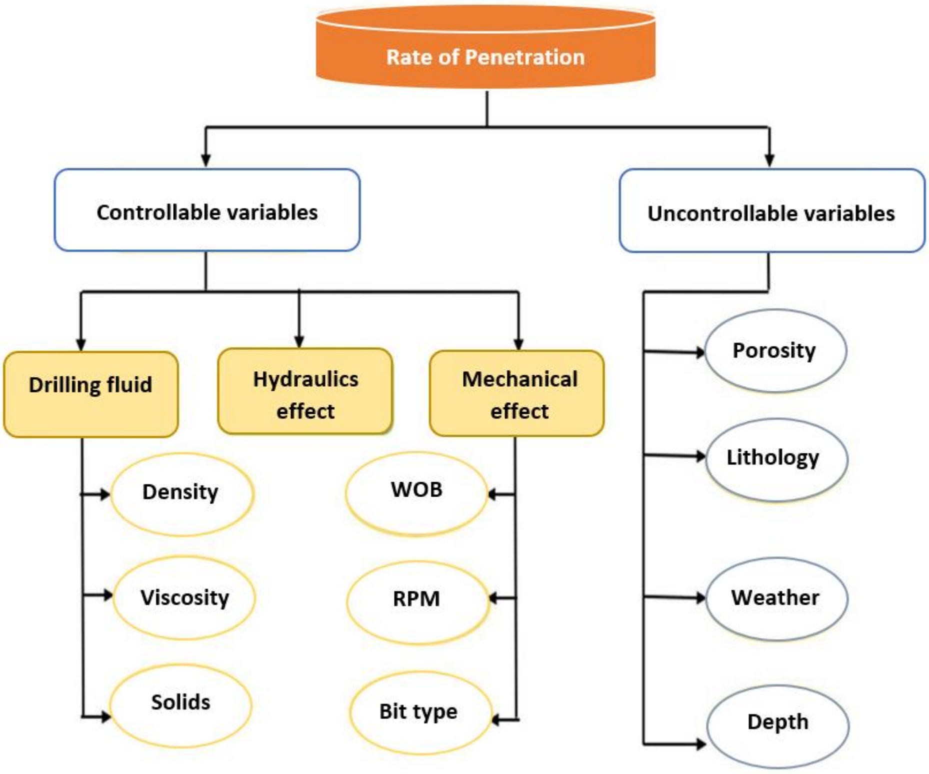

Figure 1.1 Controllable and Uncontrollable Factors Affecting ROP

1.6.1 Bit Type

The bit type selected has a large effect on penetration rate. For roller-cone bits, the initial penetration rate is often highest in a given formation when using bits with long teeth and a large cone-offset angle. However, these bits are practical only in soft formations because of a rapid tooth destruction and decline in penetration rate in hard formations (Chen et al. 2001).

1.6.2 Formation Characteristics

The elastic limit and ultimate strength of the formation are the most important formation properties affecting penetration rate. In addition, hardness, abrasiveness, permeability, and lithology of the rock all influence ROP.

Fast-Drilling Formations (Positive Break): Sandstone formations have advantageous properties that lead to increased ROP. Sandstone allows the bit to penetrate more quickly, resulting in a higher ROP. Slow-Drilling Formations (Reverse Break): Shale formations have slower ROP because to reasons like diagenesis and overburden stress.

1.6.3 Drilling-Fluid Properties

The properties of the drilling fluid reported to affect the penetration rate include density, rheological flow properties, filtration characteristics, solids content and size distribution, viscosity, and chemical composition.

1.6.4 Operating Conditions

Weight on Bit and Rotation Speed.

The effect of bit weight and rotary speed on penetration rate has been studied by numerous authors both in the laboratory and in the field. Typically, a plot of penetration rate vs. bit weight obtained experimentally with all other drilling variables held constant has the characteristic shape shown in Figure a. No significant penetration rate is obtained until the threshold formation stress is exceeded (Point b). Penetration rate increases gradually and linearly with increasing values of bit weight for low-to-moderate values of bit weight (Segment ab). A linear curve is again observed at higher bit weights (Segment bc). Although the ROP vs. the WOB correlations for the discussed segments (ab and bc) are both positive, segment bc has a much steeper slope, representing increased drilling efficiency. Point b is the transition point where the rock-failure mode changes from scraping or grinding to shearing. Beyond Point c, subsequent increases in bit weight cause only slight improvements in penetration rate (Segment cd). In some cases, a decrease in penetration rate is observed at extremely high values of bit weight (Segment de). This type of behavior sometimes is called bit foundering. The poor response of penetration rate at high WOB values is usually attributed to less-efficient hole cleaning because of a higher rate of cuttings generation, or because of a complete penetration of a bit’s cutting elements into the formation being drilled, without room or clearance for fluid bypass.

A typical plot of penetration rate vs. rotary speed obtained with all other drilling variables held constant is shown in Figure b. Penetration rate usually increases linearly with rotary speed at low values of rotary speed. At higher values of rotary speed, the response of penetration rate to increasing rotary speed diminishes. The poor penetration-rate response to increasing rotary speeds is also attributed to inefficient bottomhole cleaning. Maurer (1962) developed a theoretical equation for roller-cone bits, relating penetration rate to bit weight, rotary speed, bit size, and rock strength. The equation was derived from the following observations made in single-insert impact experiments:

1. The crater volume is proportional to the square of the depth of cutter penetration.
2. The depth of cutter penetration is inversely proportional to the rock strength.

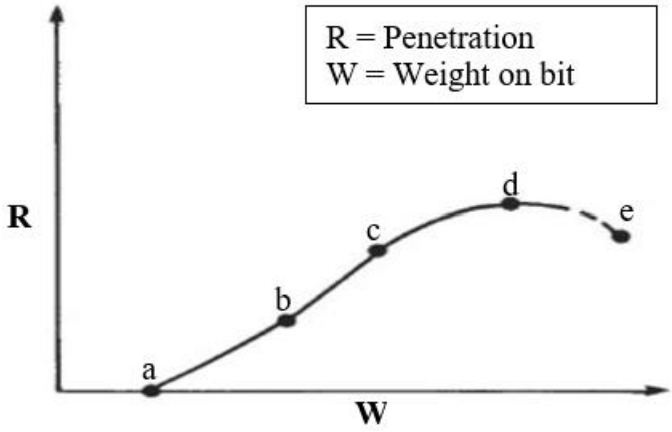

Figure 1.2 (a) Relationship between R&W

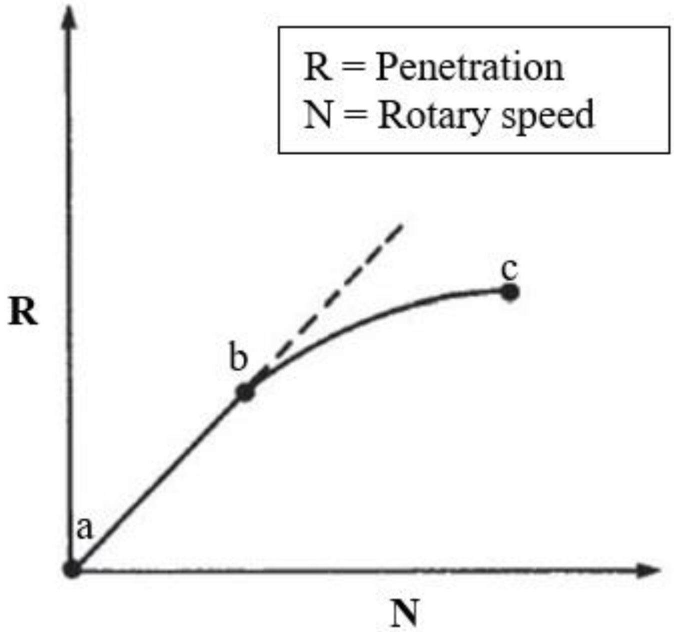

Figure 1.3 (b) Relationship between R&N

1.6.5 Bit Tooth Wear

Most bits tend to drill slower as the bit run progresses because of cutting-element wear. The tooth length of roller-cone bits is reduced continually by abrasion and chipping.

1.6.6 Bit Hydraulics

(Bit hydraulic horsepower, jet-impact force, flow rate, and nozzle velocity).

The level of hydraulics achieved at the bit is thought by many to affect the flounder-point of the bit (i.e., a decrease in rate of penetration although the weight on bit is increased to very high values, which occurs as a result of less-efficient bottomhole cleaning caused by high cuttings generation, or a complete penetration of cutters into the hole bottom.

1.7 Yemen Geology

Petroleum geology in Yemen

Yemen is situated in the southwestern part of the Arabian Peninsula and both contains onshore and offshore sedimentary basins, all of which developed during discrete time intervals in the Paleozoic, Mesozoic, and Cenozoic. Two onshore sedimentary basins, Sab’atayn and Say’un-Masilah, where oil was discovered in 1984 and 1991 respectively, are currently the only petroleum-producing basins in Yemen. Many hydrocarbon fields have been explored and produced in Yemen since the 1990s, mostly in the Masila and Sab'atayn basins which are currently the only petroleum- producing basins in Yemen, while the other basins, including the onshore Paleozoic and offshore Cenozoic basins, and remain little-explored.

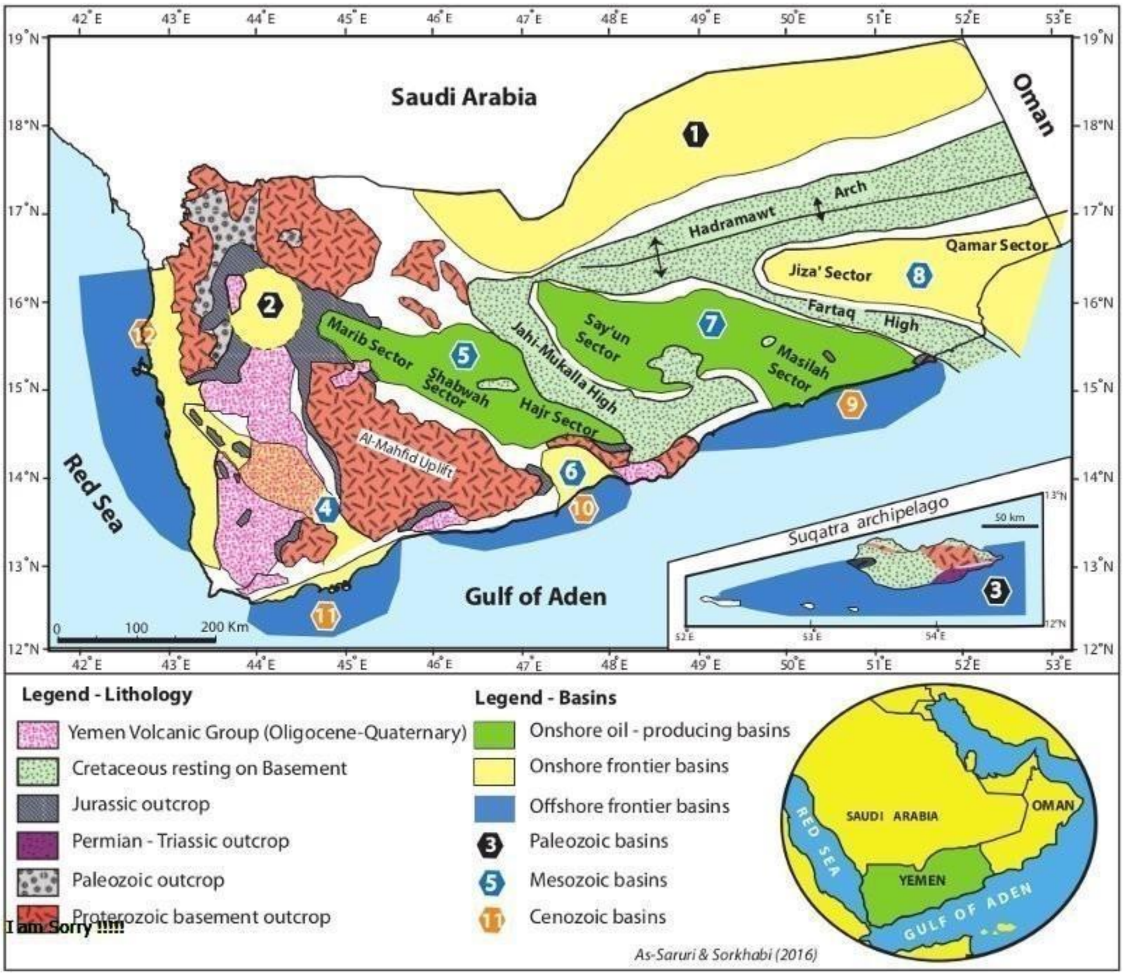

Figure 1.4 Sedimentary Basins in Yemen

Table 1.1 Below is Summarizing the Sedimentary Basins in Yemen

Geological Ear	**Basin**
Paleozoic Basins	- Rub' Al-Khali Basin. - San'a Basin. - Offshore Suqatra (Island) Basin.
Mesozoic Basins	- Siham–Ad-Dali Basin. - Sab'atayn Basin. - Say'un–Masilah Basin. - Balhaf Basin. - Jiza'qamar Basin.
Cenozoic Basins	- The Aden–Abyan Basin. - Hawrah–Ahwar Basin. - Mukalla–Sayhut Basin. - Tihamah Basin.

Say'un-Masilah Basin

The basin is located in eastern part of Yemen. The Upper Jurassic rocks in the Sayun-Masila basin are selected due to its high hydrocarbon potentiality as source rocks. Hydrocarbon produced from the Masila region in the east central republic of Yemen was discovered in 1991, and by November 2002, 656 million bbl of oil had been produced with estimated reserves of at least 1.1 billion bbl of oil.

Geological setting of Masilah basin:

The Upper Jurassic rocks, in the Masilah region, could be differentiated into three rock units from base to top: Shuqra Formation, Madbi Formation and Nayfa Formation. The Shuqra Formation (Oxfordian to Kimmeridgian) is composed of limestone. The Madbi Formation (Late Kimmridjean to Middle Tithonian) is generally, composed of porous lime grainstone to argillaceous lime mudstone and shale. The upper member of Madbi Formation is composed of laminated organic rich shale, mudstone and calcareous sandstone. The Nayfa Formation (Late Tithonian and Berriasian) is composed mainly of silty and dolomitic limestone and lime mudstone with wackestone. The main source rock in the Say'un-Masilah Basin is also bituminous shale and carbonate within the Madbi Formation. The reservoir rocks are found in several stratigraphic levels, but the sandstone of the Qishn clastic member of the Qishn Formation represents the main reservoir in the Masila oilfields. The fractured basement and the vuggy dolomite within the Saar Formation compose the secondary reservoir rocks in the Masila oilfields. The lower Cretaceous limestone and shales of the Qishn Formation were developed in the Masila oilfields and represent good regional seal in all fields of the Masila region. The traps are characterized by structural elements represented by dominant horst and tilted fault blocks, which initial formed during late Jurassic-early Cretaceous and development during Oligocene-Middle Miocene time.

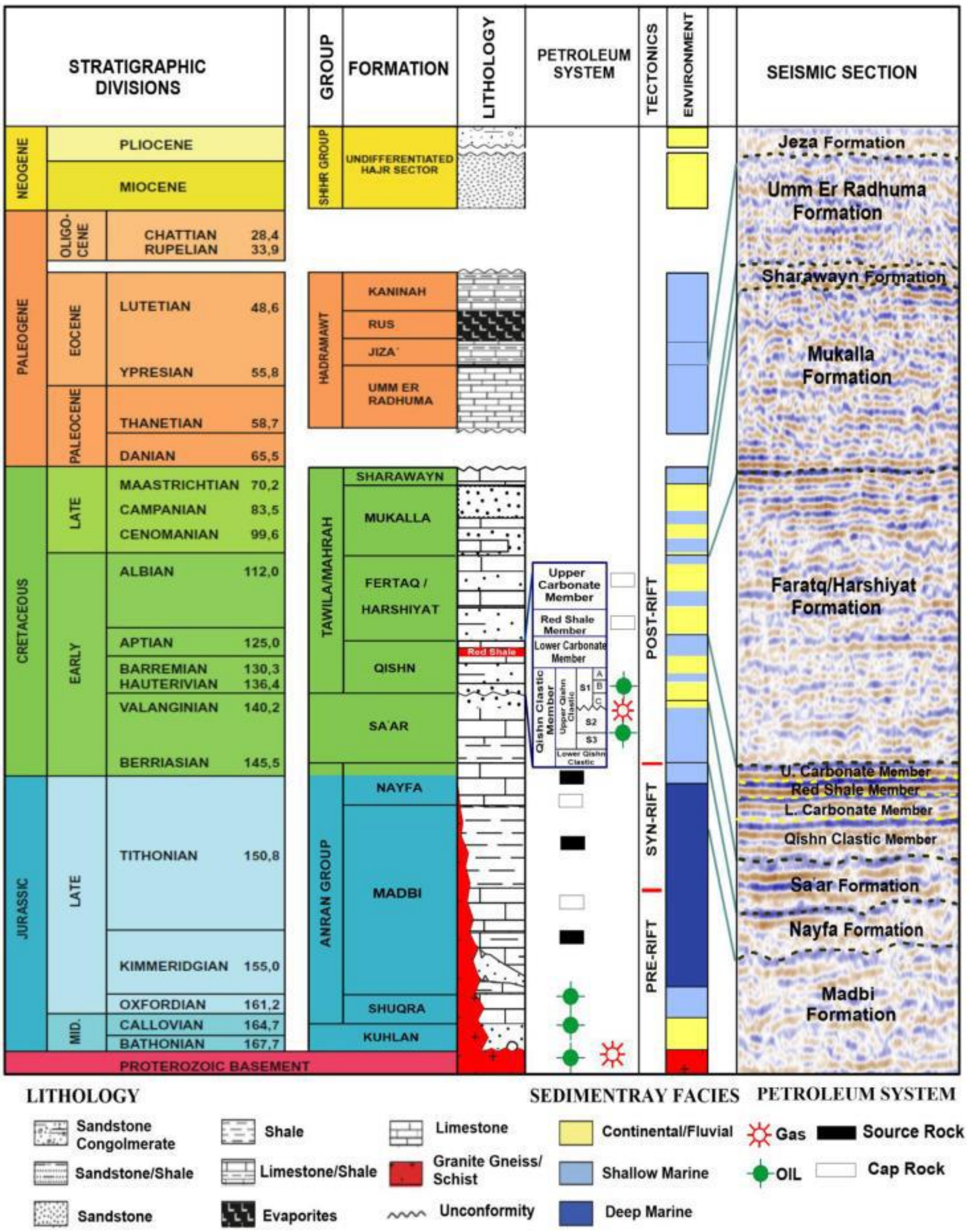

Figure 1.5 Generalized stratigraphic column of the Masilah Basin-Yemen

1.8 Background on The Study Area

Al-Masilah Block-14

Al-Masilah Block-14, located in the Hadhramaut region in the east-central Republic of Yemen, was operated by Canadian Nexen Petroleum Yemen. It is an irregular shaped concession covering 1,257 km2 of area and 44% of Nexen's overall production comes from the Masilah Block-14. Moreover, block-14 is considered to be the second biggest block in Yemen. The main reservoirs in the block are (Qishn Clastic, Saar Carbonate, Basial Sand, Madbi Carbonate, in addition to the basement rock).

Oil was first discovered in late 1990, commerciality declared in late 1991. Oil production began in July 1993. In General, it contains about 19 fields (Camaal, North Camaal, Sunnah, North-East Sunnah, Heijah, Hemiar, South Hemiar, West Hemiar, Tawila, Haru, Nazeia, Bainoon, Qataban & South-East Qataban, North-East Camaal, Ressib & South Rassib, Narr, Dais, Dahban & Gabal-Isbeel, Raydah) with one billion barrels of oil as a reserve and an average production of 58627 BOFD. Furthermore, block-14 contains 56 pools, and the total number of drilled wells until Dec 31, 2010 was 639 wells, of them 274 producers, 122 injectors, 6 disposals, and 2 observations and 90% of the production is produced from the Qishn layer. Additionally, the Block belongs to the Jurassic to lower Cretaceous age. The block is connected with ASShihr export terminal in Hadhramaut and the pipeline length is estimated to be 138 kilometers with a 24 inches diameter. The latest reserves evaluation for Al-Masilah Block 14 as of Dec 31, 2010 yields total 1P (proved) Stock Tank Oil Originally in Place (STOOIP) of 2,251 MMbbl and Estimated Ultimate Recoverable (EUR) oil reserves of 1,092 MMbbl, a 2P (proved + Probable) STOOIP of 2,356 MMbbl and EUR of 1,093 MMbbl and 3P (proved + Probable + Possible) STOOIP of 2,715 MMbbl and EUR of 1,095 MMbbl. At the end of December 2010, the annualized average daily production rate collectively for all block fields was 70,336 BOPD and 1,917,357 BWPD with average water cut 96.5%, and total cumulative oil production from the Block is 1,073,588,574 bbl as of Dec 31, 2010. The location of the Tawila oil field at block-14, Masilah basin is showed in figure 1.6.

Al-Tawila Field:

Tawila field is one of the productive and the largest and most important oilfields in the onshore of Block-14 in the Masila which produces hydrocarbons mainly from clastic deposits. The study area is within the Tawila oilfield, south of the block. Tawila field that was discovered in 1992 then the production started in 1993. The Tawila field has 184 wells 118 of them are producers and 25 are injectors. The field produce 17264.1 barrel of oil per day and 427852.2 barrel of water and has an average pressure of 179 psig. The main production zones are Upper-Qishn, S1A, S2 and S3. Additionally, the cumulative production until 2011 was 355,952 Mbbl from an estimated STOOIP of 640,221 Mbbl most of it is from S2 zone.

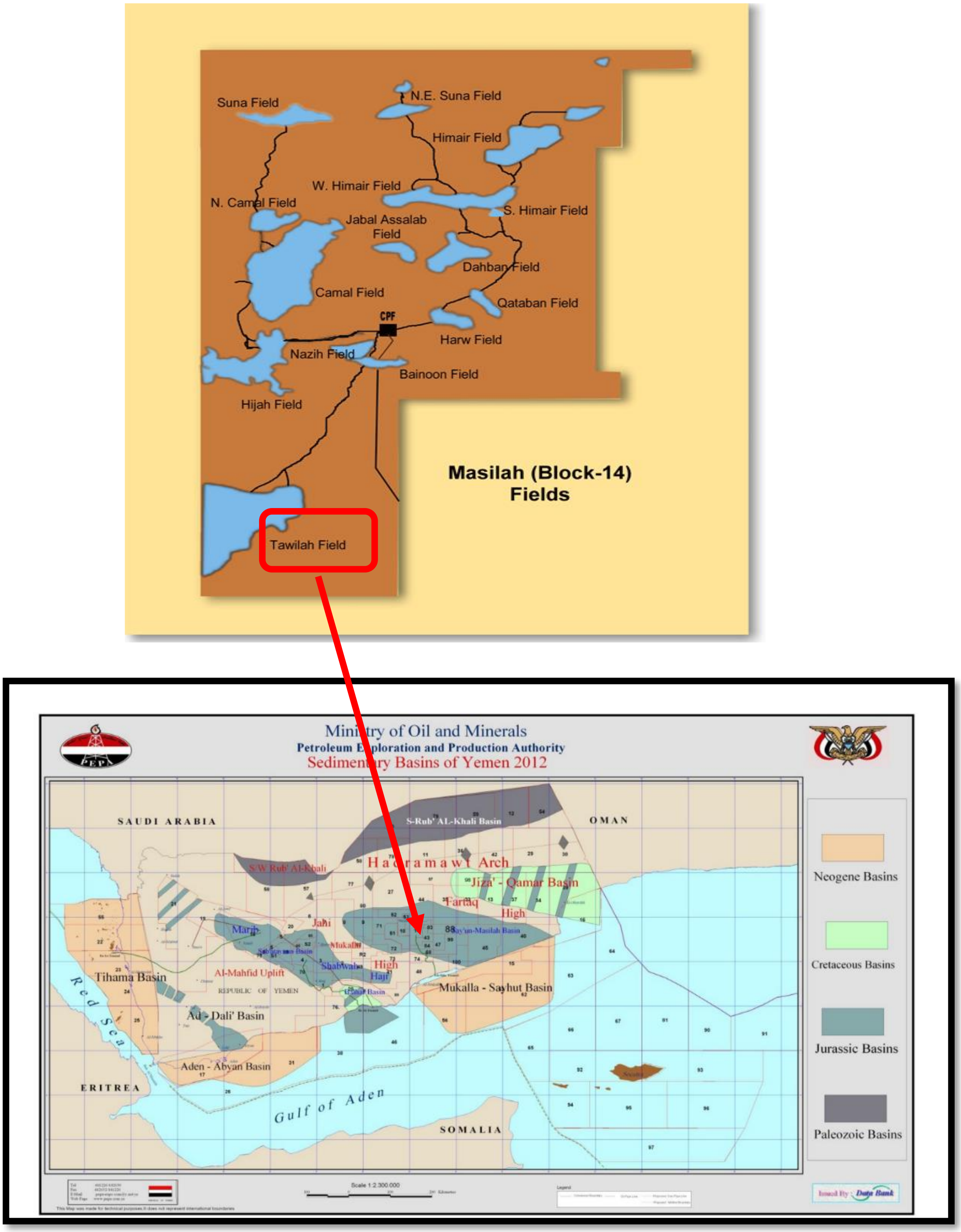

Figure 1.6 Masilah Block-14 Location (PEPA, 2005)

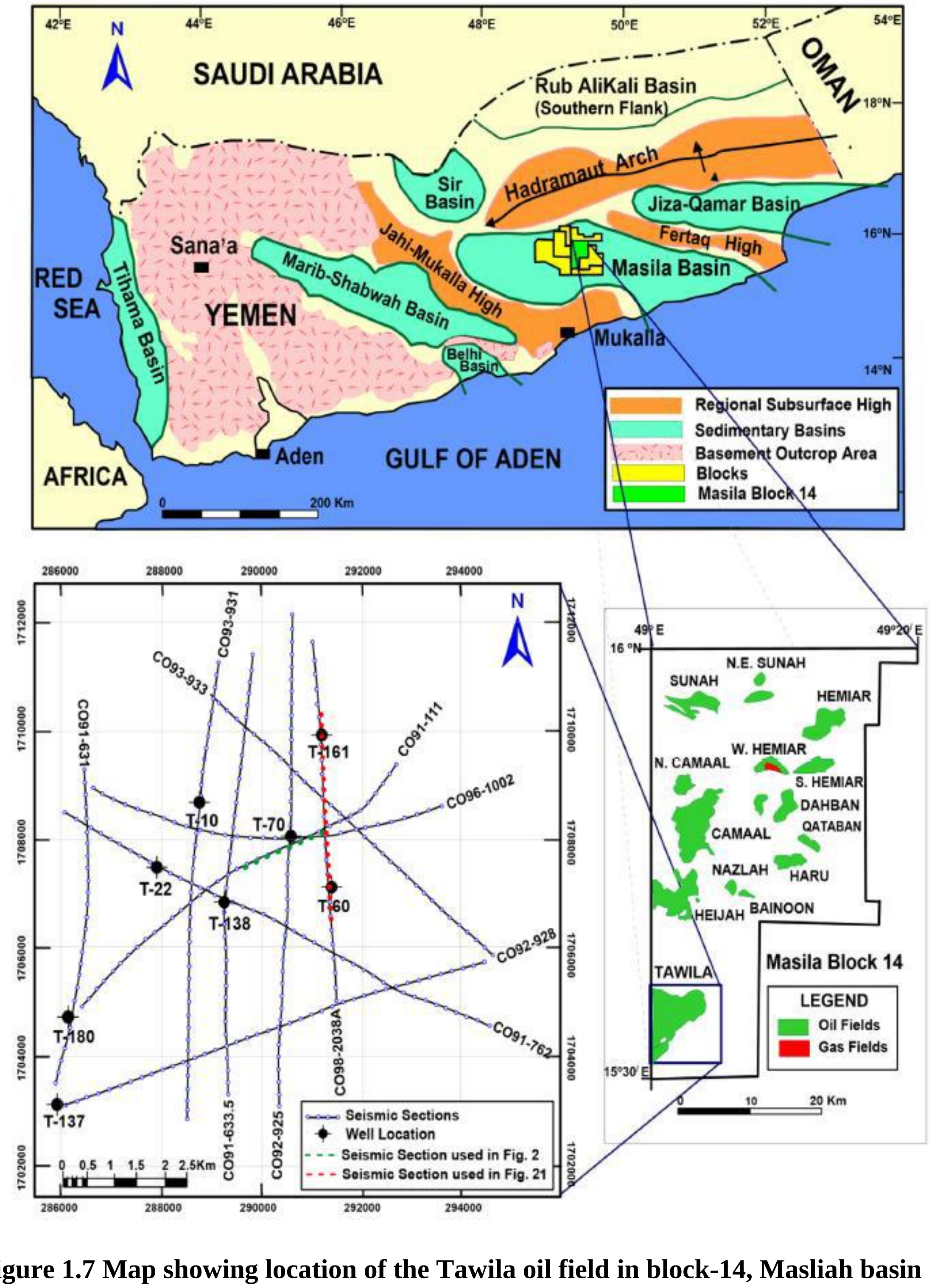

Figure 1.7 Map showing location of the Tawila oil field in block-14, Masliah basin

Formations of AL-Masilah basin

Table 1.2 below is summarizing the formation of AL-Masilah basin

Geological Ear	Formation	Lithological
Cenozoic- Tertiary	Umm Er Radhuma	Limestone Bio-Clastic
Mesozoic- Cretaceous	Sharwayn	Shale
	Mukalla	Sandstone
	Fartaq	Limestone
	Harshiyat	Sandstone
	Qishn Carbonate	Limestone
	Red Shale Marker	Shore
	Up Qishn Clastics S1a	Sandstone
	Up Qishn Clastics S1b	Sandstone
	Up Qishn Clastics S2	Sandstone
	Paleosol	Shale
	Up Qishn Clastics S3	Sandstone
	Lower Qishn Clastics-1	Sandstone
	Lower Qishn Clastics-2	Sandstone
	Upper Saar Clastics A	Dolomite
	Upper Saar Clastics B	Dolomite
	Saar Carbonate	Carbonates

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Intricate drilling is the process of removing numerous types of rocks to reach the desired depth, the most crucial aspects in drilling that affects cost is penetration rate, often known as drilling speed. The length of time required to drill the well has the potential to significantly increase drilling expenses, [1]. Thus, one of the most important goals of drilling engineers is to reduce drilling time, [2-4]. The rate at which penetration occurs (ROP) is the main variable influencing drilling time, [5]. Rate of penetration (ROP) refers to the amount of rock or formation a drill bit can cut in a specific unit of time. Various factors such as mud properties, formation properties, depth, torque, WOB, RPM, Q, and SPP affect ROP. Optimal adjustments of these variables can enhance drilling efficiency and minimize expenses. It is essential to consider all these factors to ensure that drilling operations are successful and profitable, [6-10]. Some of these aspects, such as the formation features (porosity and lithology), are uncontrollable, while others, such as torque, weight on bit (WOB), rotation speed (RPM), and flow rate, are controllable. Most factor that affects the drilling rate is shown in figure 1. There have been numerous attempts to model ROP using mathematical equations and statistical techniques, but they have been unsuccessful due to the great complexity of the ROP model or issues that can arise when results are generated in the lab or using insufficient field data. Intelligent models have gained more and more attention in recent years for its accuracy in calculating various drilling issues. In order to forecast ROP.

2.2 Case Study 1 (Traditional Model)

Rate of Penetration Optimization Using Burgoyne And Young Model (A Case Study of Niger Delta Formation)

Rate of Penetration Models

Burgoyne and young (B&Y) drilling models is the most complete mathematical that has been used for rolling cutter bit. In 1973 B&Y suggested a drilling model considering the effect of several drilling variables on the rate of penetration. In this model the effect of the parameters such as WOB, RPM, Bit tooth wear and other assumed to be independent of one another.[1]

$$ROP= f_1 * f_2 * f_3 * f_4 * f_5 * f_6 * f_7 * f_8 \tag{2.1}$$

$$f1 = e^{\,a1} \tag{2.2}$$

$$f2 = e^{\,a2x2} = e^{a2(8000-D)} \tag{2.3}$$

$$f3 = e^{a3x3} = e^{\,a3\left(D^{0.69}(gp-9)\right)} \tag{2.4}$$

$$f4 = e^{a4x4} = e^{a4}\ D^{0.69}(gp-\rho c) \tag{2.5}$$

$$\mathrm{f5} = e^{a5x5} = e^{a5\mathrm{Ln}\left[\frac{\frac{w}{db}\left(\frac{w}{db}\right)t}{4-\left(\frac{w}{db}\right)t}\right]} \tag{2.6}$$

$$f6 = e^{a6x6} = e^{a6\ln\left(\frac{N}{60}\right)} \tag{2.7}$$

$$f7 = e^{a7x7} = e^{a7(-h)} \tag{2.8}$$

$$f8 = \left(\frac{f_j}{1000}\right)^{a8} \tag{2.9}$$

Materials and Methods

Rate of penetration prediction was done using Burgoyne and Young drilling model. Well data in Niger Delta Basin was collected from Nigeria Petroleum Development Company a subsidiary of Nigeria National Petroleum Company (N.N.P.C). The name of the well was deleted from the given data for confidential purpose, the name of the well was renamed as Well A with a total depth of 9664ft. The Well data consist of drilling parameters such as well depth, rate of penetration, weight on bit, flow rate, rotation per minute, torque, bit diameter, stand pipe pressure, etc. These parameters were analyzed using B&Y models. Well depth from 1000ft to 9000ft at 200ft interval was selected for this analysis. In this model there are some unknown parameters co-efficient which must be determined based on past drilling data obtained from a field in order to determine the unknown parameters, a linear regression technique will be applied which as follows:

$$Y = \alpha_0 + \alpha_1\beta 1 + \alpha_2\beta 2 + \alpha_3\beta + \alpha_4\beta + \alpha_5\beta + \text{----}\ \alpha n\beta n \tag{2.10}$$

Where Y is the dependent variable, α_0 is the intercept term and the regression co-efficient α1, α2, α3, …αn are the analogues of the shape of linear regression. From the above equation Y is the ROP; relevant drilling parameters will make up the regression variable [β1&βn]. α_0 to αn Co-efficient will be determined by using a software called statistical package for social science (SPSS Software). This SPSS software will perform the regression analysis after all the relevant drilling parameters has been uploaded into it and then run. The analysis will then provide an output computed data. The generated output data are now co-efficient of interest. The first value generated will be α_0 while the values after this are the co-efficient i.e. (α1 to αn). The output data from α1 to αn are in Table2.1. These values are to be multiplying with regression variable according to their order which is given as follows:

$$\cdot\ \alpha_1 WOB + \alpha_2 FR + \alpha_3 RPM + \alpha_4 TRQ + \alpha_5 Bd + \alpha_6 SPP \tag{2.11}$$

Results & Discussion

The comparison was made between the actual ROP and predicted ROP. The actual ROP was the ROP contained in the original well Data (Well A Data) while the predicted ROP was the ROP calculated using B&Y models Table 2.2 The comparison was done between the well depths of 1000ft to 9000ft at 200ft depth interval. Percentage error at each depth interval was calculated and finally average percentage error was also calculated. A graph of ROP was plotted against well depth, depth on the horizontal axis in feet (ft.) and ROP on the vertical axis in feet per hour (ft./hr.) on the vertical axis. In figure 2.1, the actual ROP was considered as the reference plot represented with blue line. The predicted ROP are represented with lines in difference colors. B&Y line graph seem to correlate very well in many sections of the well, this model shows a variance between actual ROP and predicted ROP.

Table 2.1 Output computed data from SPSS

Coefficients	α0	α1	α2	α3	α4	α5	α6	α7
Initial B&Y	309.5	0.036	-0.002	0.212	0.017	-4.891	-0.108	--
New B&Y	254.235	0.065	-0.002	0.292	0.017	-5.749	-0.121	8.776

Table 2.2 Predicted ROP using B&Y models

DEPTH ft	ACTUAL ROP ft/hr	B&Y BEFORE		NEW B&Y (TIALS)		DEPTH ft	ACTUAL ROP ft/hr	B&Y BEFORE		NEW B&Y (TIALS)	
		PREDICTED ROP ft/hr	% ERROR	PREDICTED ROP ft/hr	% ERROR			PREDICTED ROP ft/hr	% ERROR	PREDICTED ROP ft/hr	% ERROR
1000	209	160	23	161	23	4800	76	53	30	44	42
1200	329	169	49	170	48	5000	119	96	19	83	30
1400	181	168	7	170	6	5200	169	123	27	129	24
1600	187	161	14	161	14	5400	136	109	20	116	15
1800	145	150	3	149	3	5600	110	109	1	115	5
2000	161	141	12	140	13	5800	100	102	2	107	7
2200	144	142	1	141	2	6000	102	123	20	127	24
2400	120	143	20	142	19	6200	97	120	24	124	28
2600	106	148	39	147	38	6400	86	26	69	29	66
2800	112	148	33	148	32	6600	111	103	7	105	5
3000	109	140	28	138	26	6800	90	99	10	102	13
3200	106	129	22	126	19	7000	110	96	12	98	10
3400	134	157	17	158	18	7200	96	90	6	92	5
3600	125	115	8	111	12	7400	69	87	26	88	27
3800	88	116	31	111	26	7600	111	79	29	79	29
4000	64	113	76	108	69	7800	116	86	26	89	23
4200	100	114	14	111	11	8000	92	121	31	134	46
4400	44	90	108	83	92	8200	118	169	43	169	43
4600	45	82	80	76	67	8400	114	120	5	121	6

Predicted B&Y model was further modeled by including additional drilling parameter (i.e. mud weight) into the initial regression equation and analyzed. The result shows that the average error percentage was minimized from 25.024% to 24.02%. this study shows that the modified B&Y predicted model had less percentage error than the initial one. The error difference between initial & and new predicted ROP using B&Y model can be can be clearly illustrated from the chart in Figure 2.2.

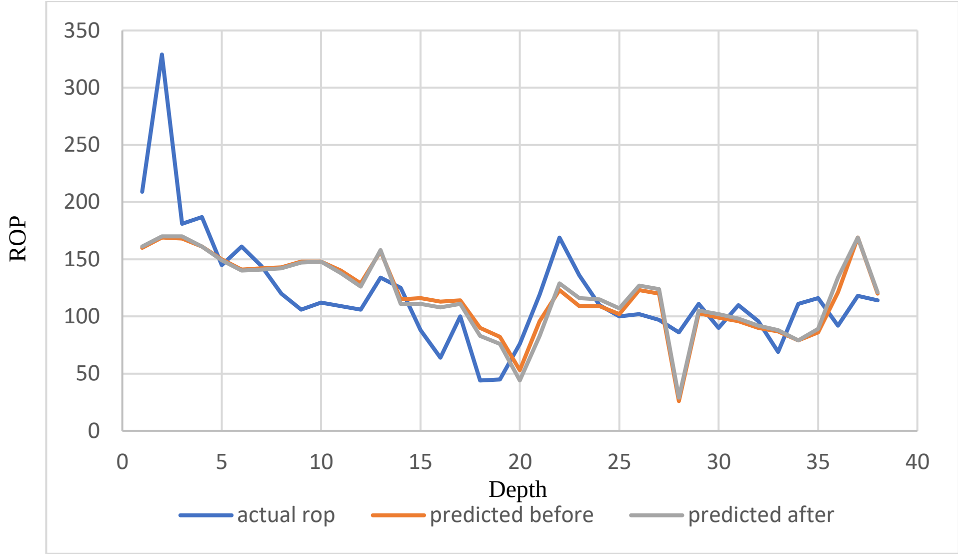

Figure 2.1 Actual, initial B&Y and new B&Y ROP vs. well depth.

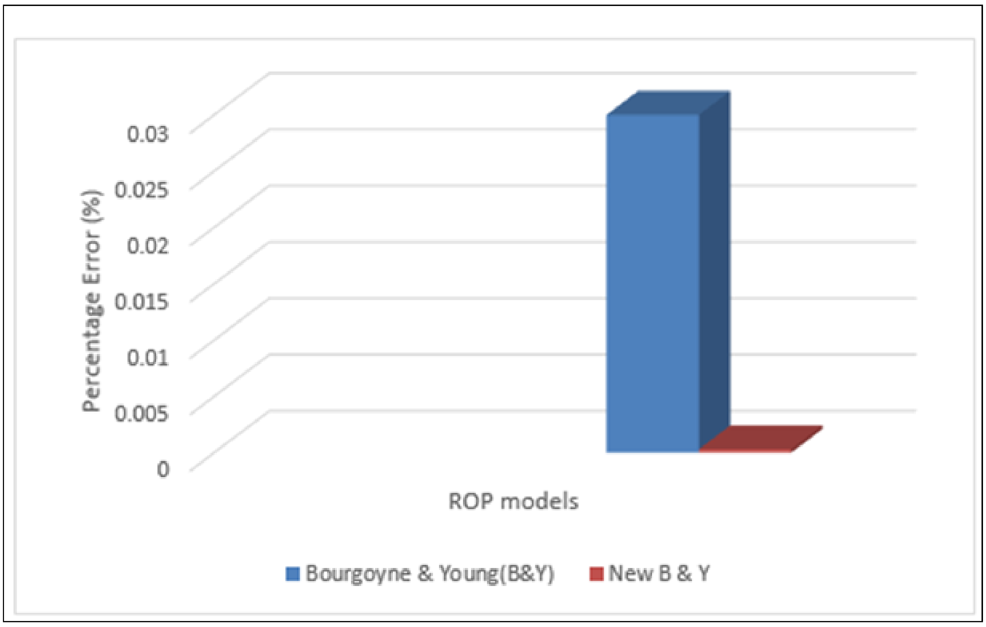

Figure 2.2 Average percentage error vs. Initial B&Y and New B&Y.

Conclusion

B&Y model has been tested with Niger Delta well data for ROP prediction, the result shows that the model performed very well by producing a little amount of error of about 25.024% and the error was further minimized to 24.02% after inclusion of additional drilling parameter. The model can estimate ROP as function of several drilling parameters such as WOB, RPM, Mud weight, Standpipe Pressure, Torque, flow rate, mud weight etc. with a reasonable accuracy. The result can also provide a guide for next drilling operation near the drilled well within the Niger Delta basin and the predicted values can be used as a reference to obtain optimum drilling performance and therefore reduce cost and time of drilling operation.

2.3 Case Study 2 (Machine Learning)

Predicting Rate of Penetration (ROP) in Oil Wells Using Gradient Boosting

Introduction

Intricate drilling is the process of removing numerous types of rocks to reach the desired depth, the most crucial aspects in drilling that affects cost is penetration rate, often known as drilling speed. The length of time required to drill the well has the potential to significantly increase drilling expenses, [2]. Thus, one of the most important goals of drilling engineers is to reduce drilling time, [3-5]. The rate at which penetration occurs (ROP) is the main variable influencing drilling time, [6].

The accurate prediction of the rate of penetration (ROP) during drilling operations is crucial for optimizing drilling parameters and improving efficiency in oil wells. In this literature review, we explore the application of Gradient Boosting, an ensemble machine learning technique, for ROP prediction.

Data Gathering:

- Data were collected from oil wells drilled in the Rumaila oil field.
- Factors related to drilling operations and drilling fluid characteristics were included.
- Relationships between ROP and other parameters were analyzed (see Figure 4).

Model Development:

- **Gradient Boosting Regressor (GBR)**:

- GBR is a powerful algorithm for regression tasks.
- It combines predictions from multiple decision trees to enhance accuracy.
- Hyperparameters (e.g., number of estimators, learning rate, loss function) are crucial for model performance.

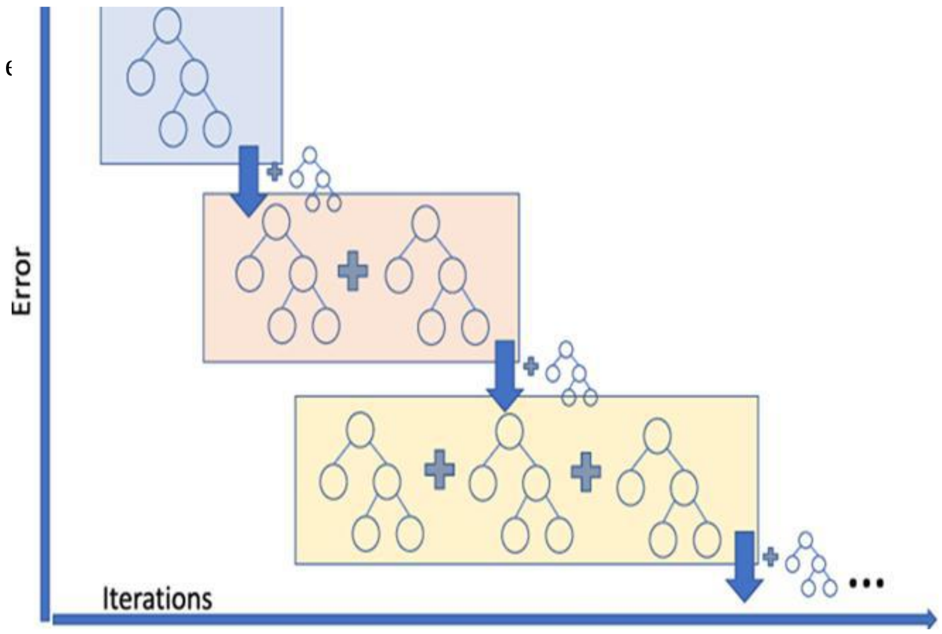

Figure 2.3 A schematic illustration of gradient boosting regression [8]

Results and Discussion

- **Data Preparation and Feature Engineering**:

- The model was trained using 10 scaled predictors (e.g., TVD, WOB, RPM, TORQUE).
- A dataset of 4866 samples was used.

Table 2.3 The import data using in this study.

index	count	mean	min	Max
TVD(m)	4866	1257.96	43.5	2471.2
WOB (ton)	4866	6.637	0.01	20.72
RPM (rpm)	4866	85.11	20.0	135.0
TORQUE (lb*ft)	4866	4911.23	664.0	10077.0
SPP (psi)	4866	1413.143	217.0	2144.0
FLOW pumps(l/mn)	4866	2608.83	1225.0	4039.0
MW (gm/cc)	4866	1.112	1.04	1.21
Pump(spm)	4866	70.52	14.0	98.0
ECD (gm/cc)	4866	1.142	1.01	1.29
BIT SIZE (inch)	4866	12.534	8.5	17.5
ROP(m/hr)	4866	15	1.31	81.55

Table 2.4 The best hyperparameters that used in study

Hyperparameters	The best choice	Description
Loss	Squared error	Optimization function
Learning rate	0.05	learning rate ranges from 0 to 1 and represents the rate of adjustment of weights and the speed of learning.
n estimators	100	The number of trees
criterion	MSE	The function for determining a split's quality.
Min. samples split	4	To split an internal node, the minimal number of samples is necessary.
Min. samples leaf	4	The bare minimum of samples that must be present at a leaf node.
Max. depth	None	The tree's greatest depth.

- **Model Performance**:
  - Data were split into a 70% training set and a 30% test set.
  - Hyperparameters were optimized using GridSearchCV.
  - R2 values: 0.9947 (training) and 0.8611 (testing).
  - Notably accurate predictions in the lower ROP range, particularly in deeper formations.

Figure 2.4 Actual and predicted ROP for training data

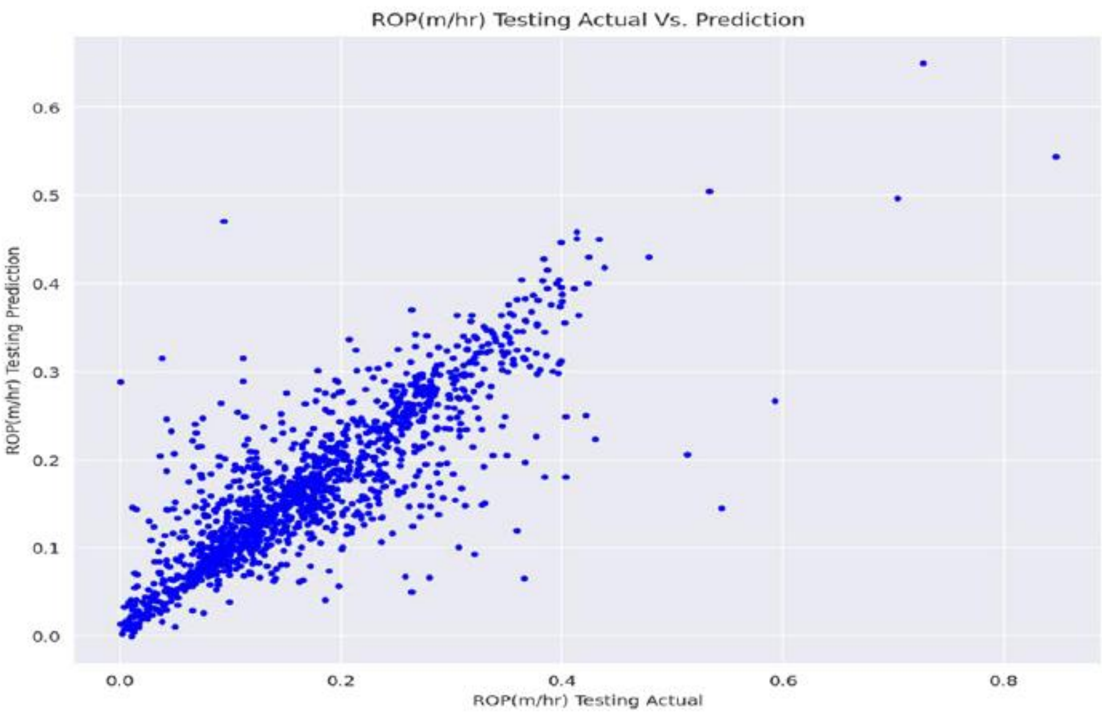

Figure 2.5 Actual and predicted ROP testing data

Figure 2.6 Actual and predicted ROP for the new well

Conclusion

The developed Gradient Boosting model shows significant potential for optimizing drilling operations in the oil and gas industry. Its accurate ROP predictions, especially in deeper formations, can lead to improved efficiency and cost savings.

2.4 Conclusion and Motivation

- Different algorithm and models were created to adjust WOB, RPM and Flow rate in real-time to increase the ROP and drilling efficiency with environmental and economical friendly drilling operations.
- Drilling prediction is performed to decrease the cost and time.
- Drilling efficiency is affected by drill bit problems; therefore, selection of bit is important for optimization.

CHAPTER 3
METHODOLOGY

3.1 Introduction

Real-time analysis for rate of penetration optimization, drilling rate of penetration model is utilized which was defined by Bourgoyne and Young. This study targets to optimize weight on bit, rotation speed and flow rate for a specific formation and by using fuzzy logic analysis in MATLAB. A program is developed to estimate the coefficient of drilling rate of penetration equation and calculate ROP as function of controllable and uncontrollable parameters.

3.2 Data Type and Collection Methods

To conduct this study which is mainly concerning the drilling operations calculating and designing of AL-Tawilah field (block 14), a set of data is required, this data sets include final well report (FWR) which include operations, bits Summary, mud & drilling summary Report. These data which was acquired by CANADIAN NEXEN PETROLEUM in AL-Tawilah field (block 14) well (10, 22, 70 & 138) has been collected by the project group from the Data Bank Development Project (DBDP) which is a part of Petroleum Exploration and Production Authority (PEPA) of Oil and Mineral Ministry.

3.3 Data Required

Given data

- Lithology
- Depth
- WOB
- Rotary speed
- Stand pipe pressure
- Mud weight
- Flow rate
- ROP
- TVD
- Pore pressure gradient

.

3.4 Software Used Description

This study utilizes different software packages, described as the following:

3.4.1 Microsoft Office Package:

Microsoft Office 2021 (Excel, Word and PowerPoint) is used to handle the data, writing graduate project and making presentations for the group discussion and the final graduate project defense.

Figure 3.1 Microsoft Office 2021 (Excel, Word and PowerPoint)

3.4.2 MATLAB

3.4.2.1 Overview

MATLAB is short for "**mat**rix **lab**oratory." It is a high-level programming language and platform that works with matrices and arrays rather than individual numbers. Designed for scientists and engineers, MATLAB is often used in textbooks as an instructional tool for college-level mathematics, science, and engineering. It allows for the most direct and natural expression of matrix and array mathematics.

3.4.2.2 Languages in MATLAB

MATLAB was written in C, C++, and Java. Although the term MATLAB is used to refer to the entire interactive programming environment, it's also a language itself. It built for Engineering Problems MATLAB excels at tasks engineers encounter regularly.

3.4.2.3 Core functionalities

- Solving complex equations.
- Signal and image processing.

- Toolbox Powerhouse.
- Visualization Made Easy.
- Prototyping and Simulation.
- Integration with Other Tools.
- Essential for handling large datasets and complex calculations.

3.4.2.4 Main Windows in MATLAB

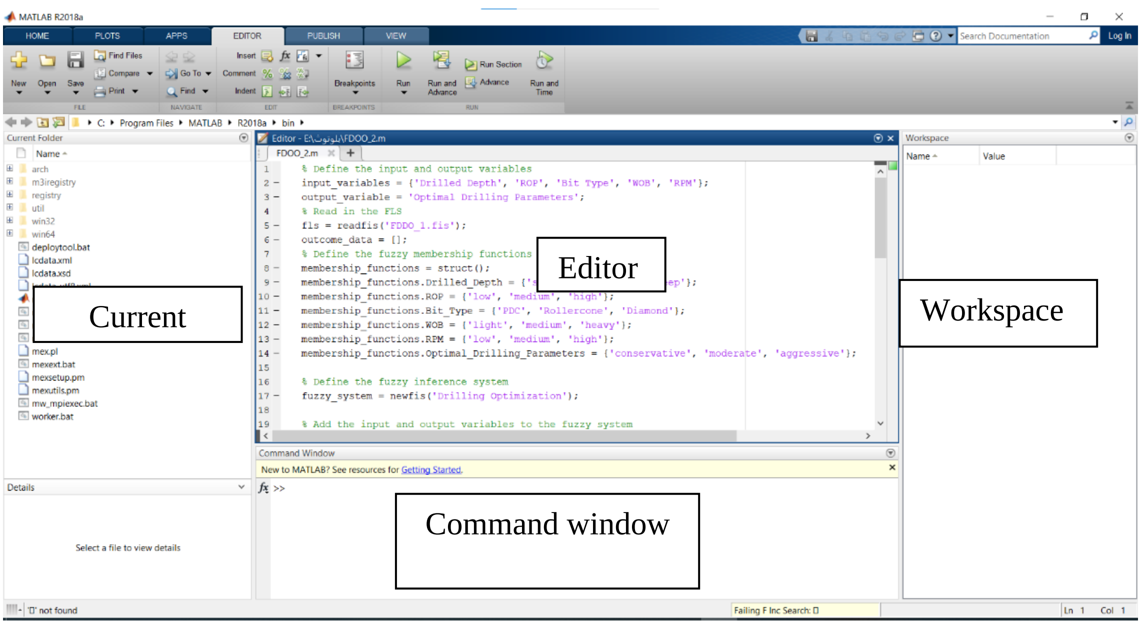

Figure 3.2 Main Windows in MATLAB

- **Command Window**: Used for quickly typing and executing commands without saving them.
- **Editor**: Used for writing larger programs with multiple commands and functions. Programs can be saved in this window.
- **Workspace**: Displays the values of variables created in the Editor.
- **Command History**: Shows a record of commands executed in the current and previous MATLAB sessions.

3.4.2.5 Graphics in MATLAB

- Provides high-level commands for visualizing 2D and 3D data, image processing, animations, and presentations.
- Graphics appearance can be customized using low-level commands.
- Easily create graphical user interfaces (GUIs).

3.4.2.6 Programming and Syntax

- MATLAB uses a straightforward syntax that resembles mathematical notation.
- Variables are created dynamically, and their types are inferred.
- Functions are defined using the `function` keyword, and scripts are created using plain text files with the `.m` extension.

3.4.2.7 Mathematical Operations

- MATLAB excels in matrix operations, linear algebra, and numerical computations.
- You can perform element-wise operations (e.g., `+`, `-`, `*`, `/`) on arrays and matrices.
- Built-in functions cover a wide range of mathematical tasks.

3.4.2.8 Toolboxes and Add-Ons

- MATLAB offers various toolboxes for specialized tasks. Examples include the Signal Processing Toolbox, Image Processing Toolbox, and Statistics and Machine Learning Toolbox.
- You can extend MATLAB's functionality by installing add-ons from the MathWorks File Exchange.

3.4.2.9 Plotting and Visualization

- The **`plot`** function creates 2D line plots, while **`surf`** generates 3D surface plots.
- Customize plots with titles, labels, legends, and color options.
- Use the **`imshow`** function for displaying images.

3.4.2.10 Uses of MATLAB

The MATLAB programming platform is used to design, develop, and analyze systems and products. Originally, it was created for accessing software developed by the LINPACK and EISPACK projects. The MATLAB we know today has numerous use cases thanks to many contributions from users over the years. Examples include:

- Data analysis.
- Large-scale computations.
- Algorithm development.
- Application development.
- Embedded system development.
- Control systems engineering.
- Deployment of Internet of Things (IoT) applications.
- Creation of deep learning models.
- Creation of machine learning models.

3.5 Bourgoyne And Young’s Method

3.5.1 Overview

In the general ROP equation, as an input to the regression cycle the given normalization constants are modified as a function of data property. Due to utilization of modified constants, perfect and accurate predictions of ROP are given by the coefficients. a1 to a8 are the constants in the above equation and it is found out through non-linear regression analysis using the drilling data. For this study, coefficients are determined on real-time basis which are represented by the effects of formation strength, compaction effect, pressure differential, bit weight, rotary speed, tooth wear and hydraulic exponent. Depending on the formation characteristics, threshold weight and bit diameter value might vary and the fractional tooth height is calculated using formation abrasiveness constants of the field.

3.5.2 Bourgoyne And Young's Model

The model [1] proposed by Bourgoyne and Young’s is chosen for this study is Regarded to be one of the complete mathematical drilling models. It is used in industry for roller-cone bit type and also specially to derive equations which can accomplish ROP estimation using the available input data. Proposed model coefficient is modified depending on the available data, and during non-linear regression analysis the model is modified based on the controllable parameters.

ROP= $f\,1 * f\,2 * f\,3 * f\,4 * f\,5 * f\,6 * f\,7 * f\,8$

Formation Strength Function

The effect of formation strength coefficient is represented by a1. If the value of this constant is less, then the penetration rate will also be less. Coefficient includes the effect of parameters such as drilled cuttings, drilling fluid, solid content, efficiency of the rig equipment, crew experience and service contractor’s efficiency. Formation strength effects is given by equation 0.0 as described.

$$f1 = e^{a1} \tag{3.1}$$

$f1$: Drill ability of the formation of interest

Formation Compaction Function

Formation compaction has two functions over rate of penetration

- Primary function that is effect of normal compaction defined by $[a2]$. This effect deals with exponential decrease in penetration rate with increasing depth given in the equation below, other way is this function also takes into the consideration of increase in rock strength with depth due to normal compaction.

$$f2 = e^{a2x2} = e^{a2(8000-D)} \tag{3.2}$$

- Additional function of formation compaction over the rate of penetration is the effect of under compaction in abnormally pressured formations defined by $[a3]$. The other way is in over-pressured formations, rate of penetration will show increase behavior that is exponential increase in penetration rate with increasing pore pressure gradient equation below.

$$f3 = e^{a3x3} = e^{a3\left(\mathrm{D}^{0.69}(gp-9)\right)} \tag{3.3}$$

Pressure Differential of Hole Bottom Function

Pressure differential function is defined by coefficient $[a4]$ Penetration rate decreases with decreasing pressure difference, and function will be equal to 1 when pressure differential between the hole and formation is zero as shown in equation below.

$$f4 = e^{a4x4} = e^{a4} \ D^{0.69}(gp-\rho c) \tag{3.4}$$

Bit Diameter and Weight Function

- Weight and bit diameter function is defined by coefficient $[a5]$ It has a direct effect on the penetration rate shown in the equation below; $\left[\frac{\mathrm{w}}{\mathrm{db}}\right] t$ threshold bit weight has a value ranging from 0.6 to 2.0. For this study, magnitude of this term is found out depending on the characteristics of the formation. Threshold force is defined as the force at which fracture begins beneath the tooth.

$$\mathrm{f5} = e^{a5x5} = e^{a5\mathrm{Ln}\left[\frac{(\frac{w}{db})-(\frac{w}{db})t}{4-(\frac{w}{db})t}\right]} \tag{3.5}$$

Rotary Speed Function

Rotary speed function is represented by coefficient $[a6]$. The rotary speed also has a direct effect on penetration rate similar to the weight on bit as given in the equation below.

$$f6 = e^{a6x6} = e^{a6\ln\left(\frac{N}{60}\right)} \tag{3.6}$$

Tooth Wear Function

Tooth wear function is defined by coefficient $[a7]$. Fractional tooth height is an important phenomenon in calculation of tooth wear function, high the tooth wears less the penetration rate as represented in the equation below.

$$f7 = e^{a7x7} = e^{a7(-h)} \quad (3.7)$$

Hydraulic Function

Hydraulic function is represented by coefficient a_8. It represents the effect of bit hydraulics and Reynolds number is most suitable which is given in equation 3.11

$$f8 = \left(\frac{f_j}{1000}\right)^{a8} \quad (3.8)$$

Table 3.1 α1 to α8 constant based on local drilling condition

αl	Formation type parameter
α2	Normal compaction parameter
α3	Under compaction parameter
α4	Pressure differential parameter
α5	Weight on bit (WOB) parameter
α6	RPM parameter
α7	Tooth wear parameter.
α8	Hydraulics parameter

3.6 Fuzzy Logic Model

3.6.1 Overview

Fuzzy logic is a form of artificial intelligence that allows for approximate reasoning rather than precise deductions. It is based on the concept of fuzzy sets, where elements can have degrees of membership rather than being strictly members or non-members. This approach is particularly useful for modeling systems with inherent uncertainty or imprecision.[2]

3.6.2 Application of Fuzzy Logic in Rate of Penetration Prediction

In penetration rate prediction, fuzzy logic can be employed to model the complex relationships between various factors influencing the rate of penetration. These factors might include demographic data, economic indicators, etc. By representing these factors as fuzzy sets and establishing fuzzy rules, a fuzzy logic model can capture the inherent uncertainties and complexities of the market. This approach can lead to more accurate and robust predictions compared to traditional statistical methods.[9][10]

3.6.3 Key Components of a Fuzzy Logic Model

A typical fuzzy logic model consists of:

1. **Identification of linguistic variables:** Key factors affecting penetration rate, such as WOB, RPM, and flow rate, are defined as linguistic variables.
2. **Definition of membership functions:** These functions quantify the degree to which a specific value belongs to a linguistic term.
3. **Rule base creation:** Human expertise and data analysis are used to establish rules linking combinations of linguistic variables to different penetration rate levels.
4. **Fuzzy inference:** The model processes input data (values of linguistic variables) using fuzzy logic operations to generate a fuzzy output representing the predicted penetration rate.
5. **Defuzzification:** The fuzzy output is converted into a crisp value (specific penetration rate) using a defuzzification method.[11][12]

3.6.4 Advantages of Using Fuzzy Logic

- Handles uncertainty: Effectively manages imprecise and subjective information.
- Incorporates human knowledge: Leverages expert insights through rule-based approach.
- Interpretability: Provides a transparent and understandable model structure.
- Flexibility: Can accommodate various input variables and complex relationships.

3.7 Steps of Study

3.7.1 Flow Chart of B&Y Model

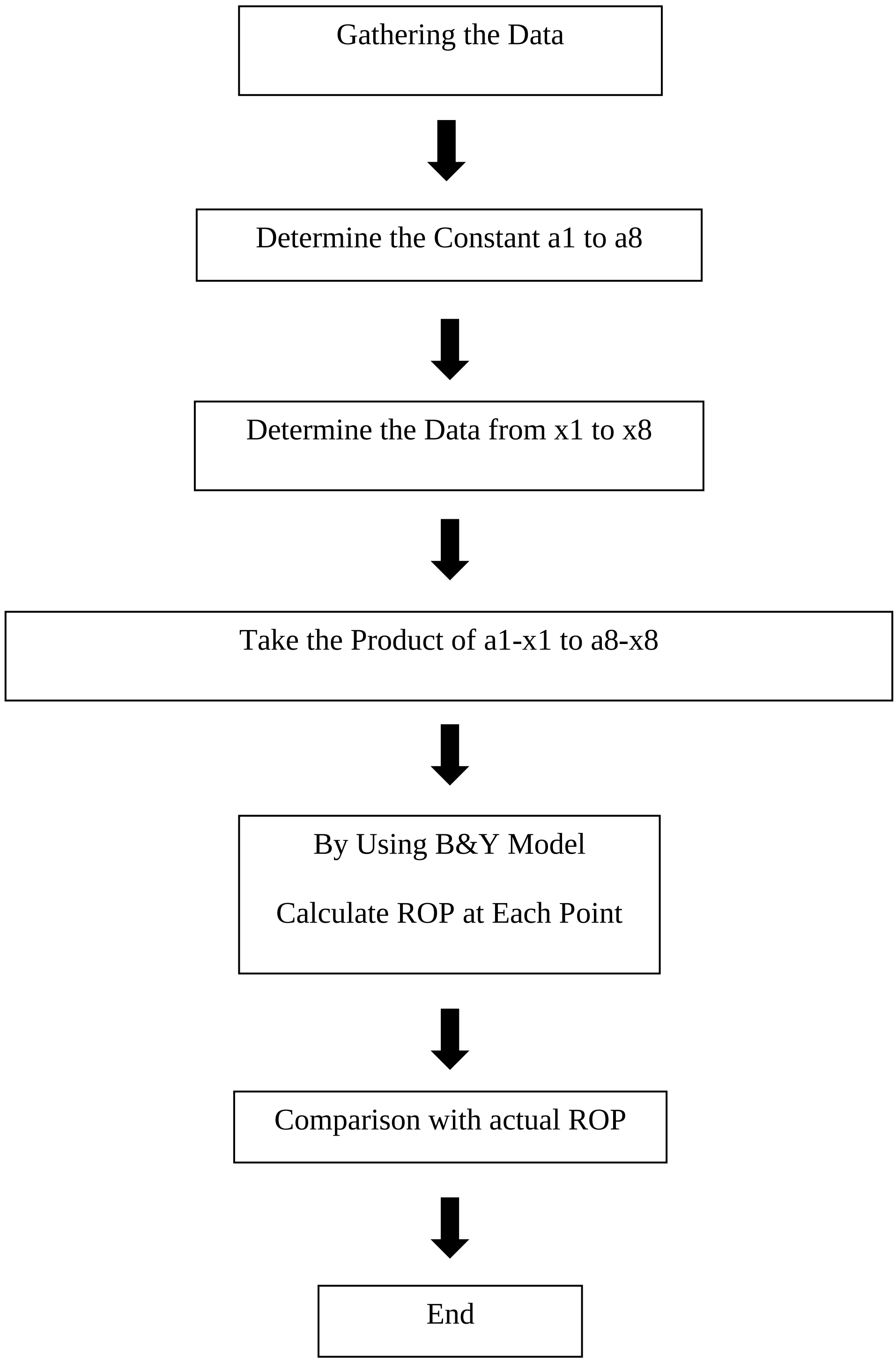

Figure 3.3 Flow Chart for B&Y Model

3.7.2 Flow Chart of Fuzzy Logic Model

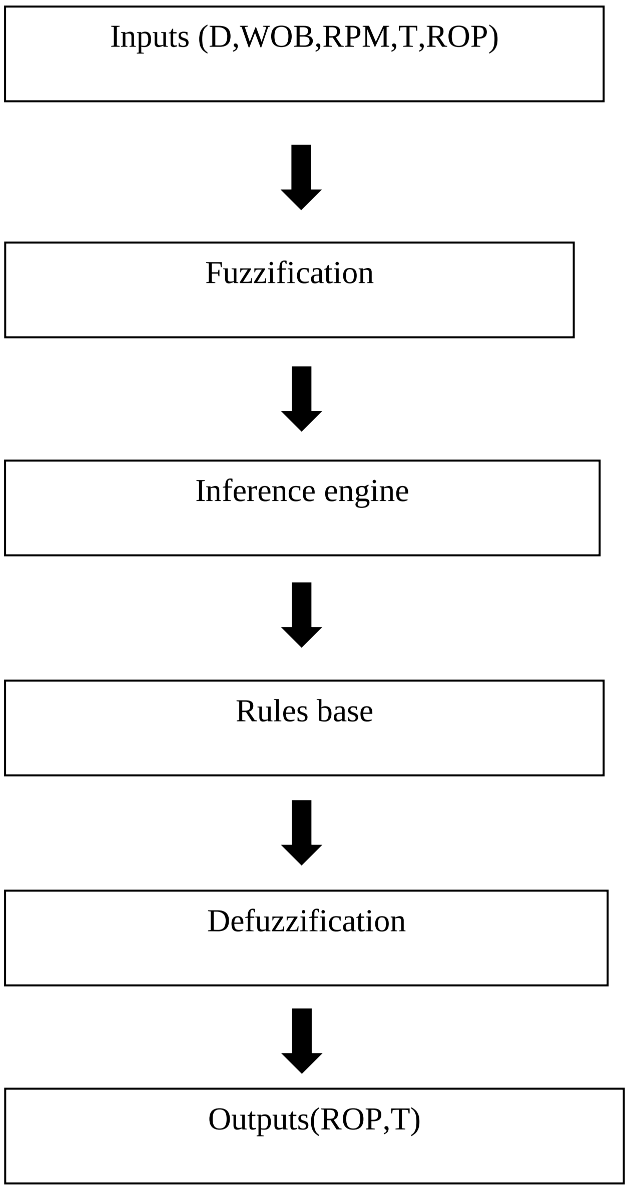

Figure 3.4 Flow Chart of Fuzzy Logic Model

CHAPTER 4

4.1 Introduction

In this chapter we will dive into the core of this research. Walking step by step on how the two proposed models were conducted, computed and applied, which provide us with the essence of the project which is making a clear correlation between the two models, one based on methodical steps.

4.2 Implementation Data

Data was collected from three wells in Al-Tawila field in block[14].

- **Al-Tawila 22**

Table 4.1 Bit Record Well -22-

BIT RECORD WELL -22-										
Formation	**Bit Type**	**Bit Size, in**	**Drilled Depth, ft**	**Bit in at ft**	**Bit out at ft**	**WOB, lbs**	**HPURS ON BITS**	**RPM**	**ROP, ft/hr**	**H tooth dull**
Mukalla	PBC83	18.25	968	0	968	14000-18000	15	100	64.5	0.5
Mukalla, Fartaq, Harshiyat	EHP43H	12.25	3808	968	4776	4000-55000	49.5	111.1057	76.9	0.25
Qishn Carb.	EHP51H	12.25	756	4776	5532	55000-60000	19.5	110	38.8	0.25
Qishn, Saar Carb.	EHP51H	12.25	928	5532	6460	55000-60000	39.5	100	23.5	0.25

Table 4.2 Mud Report Well -22-

MUD REPORT WELL -22-							
Mud Type	**Mud Dens, lb/gal**	**Mud Visc. sec/qt**	**Q gbm**	**PRESSURE psi**	**Pore Grad(ppg)**	**ECD(ppg)**	**Impact force(Ib)**
Poly H2O	8.3	31			9.33893	9.3296	1.86
Gel Chem.	8.6	60-66	752.9	1900	9.33893	9.3296	1.82
Gel Chem.	8.7	68-70	752.9	1975	9.755846	9.7461	2.35
Gel Chem.	8.7	63-65	752.9	2200	10.006	9.996	1.77

- **Al-Tawila 70**

Table 4.3 BIT RECORD WELL -70-

BIT RECORD WELL -70-										
Formation	**Bit Type**	**Bit Size, in**	**Drilled Depth, ft**	**Bit in at ft**	**Bit out at ft**	**WOB, lbs**	**HPURS ON BITS**	**RPM**	**ROP, ft/hr**	**H tooth dull**
Uqishn Clastic S1	CD 104	8.5	30	5840	5870	10000-10000	61	100	30	0.375
UQishn, USaar	EHP51H	12.25	832	5870	6702	55000	31.5	100	26.41	0.25
USaar Clastic, Saar Carb.	EHP51H	12.25	1207	6702	6702	55000	12.5	100	96.56	0.25

Table 4.4 Mud Report -70-

MUD REPORT -70-							
Mud Type	**Mud Dens, lb/gal**	**Mud Visc. sec/qt**	**Q gbm**	**PRESSURE psi**	**Pore Grad(ppg)**	**ECD(ppg)**	**Impact force(Ib)**
Gel Chem.	8.7	50	305	650	10.08938	10.0793	1.85
Gel Chem.	8.8	70	794	650	10.25615	10.2459	2.16
Gel Chem.	9	54	794		10.33953	10.3292	2

- **Al-Tawila 138**

Table 4.5 Bit Record -138-

BIT RECORD -138-										
Formation	**Bit Type**	**Bit Size, in**	**Drilled Depth, ft**	**Bit in at ft**	**Bit out at ft**	**WOB, lbs**	**HPURS ON BITS**	**RPM**	**ROP, ft/hr**	**H tooth dull**
Sharwyn	CUBEX	18.25	1107	0	1107	10000-20000	16.5	100	67.09	0.125
Mukalla, Fartaq, Harshiyat	EHP43H	12.25	3769	1107	4876	35000-50000	77	110	48.95	0.125
Qishn Carb, LQishn	EHP51H	12.25	1360	4876	6236	45000-55000	68	100	20	0.25
Usaar, Saar Carb.	EHP51H	12.25	444	6236	6680	50000-60000	29	100	15.31	0.125

Table 4.6 Mud Report Well-138-

MUD REPORT WELL-138-							
Mud Type	**Mud Dens, lb/gal**	**Mud Visc. sec/qt**	**Q gbm**	**PRESSURE psi**	**Pore Grad(ppg)**	**ECD (ppg)**	**Impact force (Ib)**
Spud mud	8.4	50	10	360	10.75645	10.7457	1.96
Mud, Gel Poly.	9.3	48-56	794	2000	11.17336	11.1622	2.22
Gel Poly.	9.3	52-56	836	2350	11.17336	11.1622	2.24
Gel Poly.	9.4	53-66	836	2500	11.25675	11.2455	1.88

4.3 Implementation Summary

4.3.1 Burgoyne and Young's model

Burgoyne and Young's model may be the most important among the models named earlier, as it is based on statistical analysis of previous drilling parameters [6]. The model proposed by Burgoyne and Young has thus been adopted for this project in order to derive equations to perform ROP estimation using the available input data. This model was selected as the most complete mathematical drilling model in use in the industry for roller-cone type bits. Burgoyne and Young proposed the following equation to model the drilling process when using roller cone bits:

$$\frac{df}{dt} = e^{\left[a_1 + \sum_j^8 = 2ajxj\right]} \qquad (4.1)$$

Where

$\frac{df}{dt}$ - rate of penetration
$a_1 - a_8$ - constant
$x_1 - x_8$- drilling parameters or functions

The model can therefore be expressed as

$$\text{ROP}= f\,1 *f\,2 *f\,3 *f\,4 *f\,5 *f\,6* f\,7 *f\,8 \qquad (4.2)$$

The first term ($f1$) expresses the effect of rock drillability

$$f1 = e^{\,a1} \qquad (4.3)$$

a_1 − Formation type parameter

The second term ($f2$) models the compaction effect and is given by

$$f2 = e^{a2x2} = e^{a2(8000-D)} \tag{4.4}$$

$$x_2 = (10000 - D) \tag{4.5}$$

a_2 − Normal compaction parameter

The third term models ($f3$) under-compaction due to differential pressure as

$$f3 = e^{a3x3} = e^{a3\left(\mathrm{D}^{0.69}(gp-9)\right)} \tag{4.6}$$

a_3 − Under compaction parameter

$$x_3 = \left(\mathrm{D}^{0.69}(gp - 9)\right) \tag{4.7}$$

where gp is the pore pressure gradient in pounds per gallon equivalent.

The fourth term ($f4$) is the effect of differential pressure

$$f4 = e^{a4x4} = e^{a4D(gp-\rho c)} \tag{4.8}$$

a_4 − Pressure differential parameter

$$x_4 = \mathrm{D}(gp - \rho c) \tag{4.9}$$

where (ρc) is the mud weight in pound per gallon.

The fifth term ($f5$) models the effect on ROP caused by changing the WOB

$$f5 = \left[\frac{\left(\frac{w}{db}\right) - \left(\frac{w}{db}\right)t}{4 - \left(\frac{w}{db}\right)t}\right]^{a_5} \tag{4.10}$$

a_5 − Weight on bit (WOB) parameter

$$x_5 = \ln\left[\frac{\left(\frac{w}{db}\right) - \left(\frac{w}{db}\right)t}{4 - \left(\frac{w}{db}\right)t}\right]^{a_5} \tag{4.11}$$

The sixth term ($f6$) models the effect of rotary speed (RPM) on the ROP and is given by

$$f6 = e^{a6x6} = \left(\frac{N}{60}\right)^{a6} \tag{4.12}$$

a_6 − RPM parameter

$$x_6 = \ln\left(\frac{N}{60}\right) \tag{4.13}$$

The seventh term ($f7$) models the effect of bit wear on the ROP; this depends on bit type and formation
type and is given by

$$f7 = e^{a7x7} = e^{a7(-h)} \tag{4.14}$$

a_7 − Tooth wear parameter.

$$x_7 = -h \tag{4.15}$$

The last term ($f8$) is the effect of bit hydraulics on the ROP, given as

$$f8 = \left(\frac{f_j}{1000}\right)^{a8} \tag{4.16}$$

a_8 – Hydraulics parameter

$$x_8 = \left(\frac{f_j}{1000}\right) \tag{4.17}$$

$$f_j = \left[\frac{\rho q}{350 \mu d n}\right] \tag{4.18}$$

where (f_j) is the hydraulic jet impact force beneath the bit

and
D - True vertical depth (ft)
db - Bit diameter (in)
f_j - Jet impact force (lbf)
gp - Pore pressure gradient (lbm/gal)
h - Fractional bit tooth wear
ρc - Equivalent mud density (lbm/gal)
N - Rotary speed (rpm)
w - Weight on bit (1000 lbf)
$\left(\frac{w}{db}\right) t$ -Threshold bit weight per inch

Table 4.7 Data from Al-Tawila (22-70-138) Wells

Drilled depth ft	ROP (ft/hr)	RPM	Pore Grad(ppg)	ECD (ppg)	W/d (Ib/in)	H	f_j (Ib)	TIME hr
968	64.5	100	9.33893	9.3296	526.9014	0.5	1.86	15.00775
3808	76.9	111.1057	9.33893	9.3296	526.9014	0.25	1.82	49.51886
756	38.8	110	9.755846	9.7461	526.9014	0.25	2.35	19.48454
928	23.5	100	10.006	9.996	438.989	0.25	1.77	39.48936
30	30	100	10.08938	10.0793	979.0203	0.375	1.85	1
832	26.41	100	10.25615	10.2459	979.0203	0.25	2.16	31.50322
1207	96.56	100	10.33953	10.3292	979.0203	0.25	2	12.5
1107	67.09	100	10.75645	10.7457	979.0203	0.125	1.96	16.50022
3769	48.95	110	11.17336	11.1622	1678.729	0.125	2.22	76.99694
1360	20	100	11.17336	11.1622	1067.85	0.25	2.24	68
444	15.31	100	11.25675	11.2455	1067.85	0.125	1.88	29.00065

The parameters $x_1$through x_8 were calculated using Equations above for each data entry shown in table 4.1 and uniform formation imposed. To calculate the best values of the regression constants a_1 through a_8 using the data shown in the table 4.1, eight equations with the eight unknowns, a_1 through a_8 , were obtained from $x_1$through x_8. Using the values of $x_1 - x_8$ shown in table 4.2 for the relevant data points in table 4.1 in the general equation for rate of penetration.

Table 4.8 Values of Parameters x1-x8

X1	X2	X3	X4	X5	X6	X7	X8
1	8064.8	62.79873	18.05542	4.880719	0.510826	-0.5	-6.28718
1	6529.76	93.96326	32.37734	4.880719	0.616137	-0.25	-6.30892
1	5877.04	236.0085	40.18237	4.880719	0.606136	-0.25	-6.05334
1	5486.72	334.3472	45.1328	4.69818	0.510826	-0.25	-6.33678
1	3039.84	488.1875	70.15841	5.500258	0.510826	-0.375	-6.29257
1	2023.04	618.4567	81.76384	5.500258	0.510826	-0.25	-6.13765
1	1458.88	691.3495	88.22977	5.500258	0.510826	-0.25	-6.21461
1	1124.32	930.8826	95.41356	5.500258	0.510826	-0.125	-6.23481
1	858.64	1175.518	102.0176	6.039498	0.606136	-0.125	-6.11025
1	71.44	1244.466	110.8027	5.587108	0.510826	-0.25	-6.10128
1	-807.6	1370.114	121.5855	5.587108	0.510826	-0.125	-6.27648

Table 4.9 Values of Constants a1-a8

a1	29.6151
a2	-0.00284
a3	0.006345
a4	-0.32809
a5	1.239237
a6	-4.80025
a7	5.463498
a8	-0.06485

The eight equations were solved for the eight unknowns and the constants, *a1* through *a8*, thus obtained. A rate of penetration model was then constructed for the field. The prediction of rate of penetration using the constructed model and the actual rate of penetration taken from the actual drilling report are shown in figure 4.1 and the values of Actual and Predicted ROP are shown in table 4.5.

Table 4.10 Product of a-x

a1X1	a2X2	a3X3	a4X4	a5X5	a6X6	a7X7	a8X8	Sum
29.6151	-22.904032	0.398458	-5.9238	6.048368	-2.45209	-2.73175	0.407724	2.457976
29.6151	-18.5445184	0.596197	-10.6227	6.048368	-2.95761	-1.36587	0.409133	3.17811
29.6151	-16.6907936	1.497474	-13.1834	6.048368	-2.9096	-1.36587	0.392559	3.403796
29.6151	-15.5822848	2.121433	-14.8076	5.822158	-2.45209	-1.36587	0.41094	3.761761
29.6151	-8.6331456	3.09755	-23.0183	6.816123	-2.45209	-2.04881	0.408073	3.784524
29.6151	-5.7454336	3.924108	-26.8259	6.816123	-2.45209	-1.36587	0.398026	4.364061
29.6151	-4.1432192	4.386613	-28.9473	6.816123	-2.45209	-1.36587	0.403017	4.312364
29.6151	-3.1930688	5.90645	-31.3042	6.816123	-2.45209	-0.68294	0.404327	5.109669
29.6151	-2.4385376	7.458659	-33.4709	7.484369	-2.9096	-0.68294	0.39625	5.452353
29.6151	-0.2028896	7.89614	-36.3533	6.923751	-2.45209	-1.36587	0.395668	4.456536
29.6151	2.293584	8.693372	-39.891	6.923751	-2.45209	-0.68294	0.40703	4.906823

After taking the sum, we will calculate the ROP by taking the Exponential (e) of each value of the sum.

Table 4.11 ROP Final Results of (B&Y) Model

ROP act (ft/hr)	**ROP pre** (ft/hr)	**Error %**
64.5	82.92797	28.57051
76.9	62.49417	18.73316
38.8	36.65521	5.527805
23.5	22.06606	6.101882
30	30.9237	3.079
26.41	37.46083	41.84336
96.56	96.58804	0.029041
67.09	67.6007	0.761219
48.95	53.72011	9.744871
20	30.88509	54.42546
15.31	17.49974	14.30268

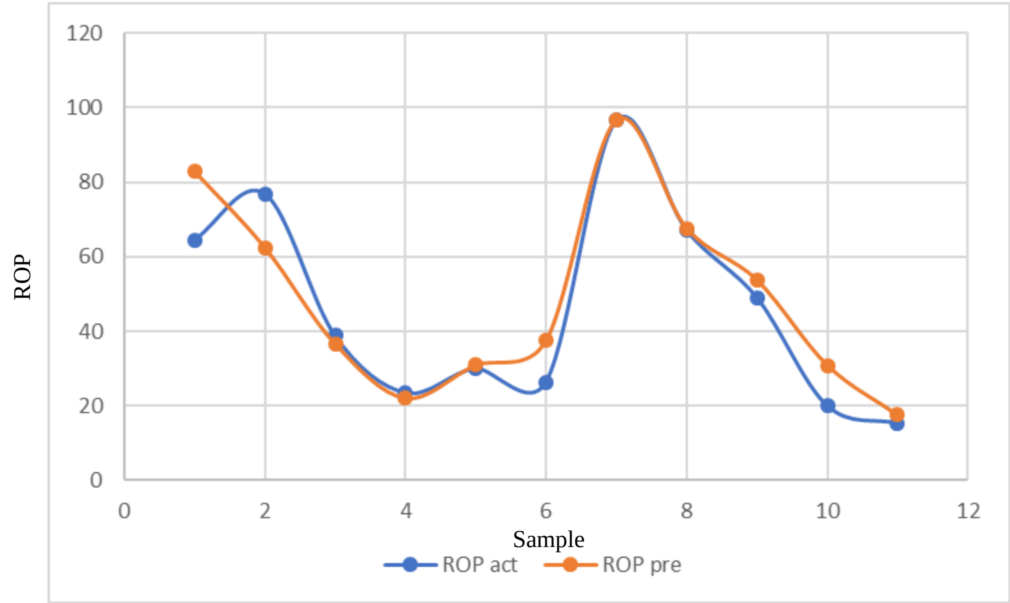

Figure 4.1 ROP Final Results of (B&Y) Model

Figure 4.1 represents the rate of penetration of the actual occurrence and the predicted ones against the depth. To compare the performance of both actual and predicted it is important to have error band.

Table 4.12 Time Final Results of (B&Y) Model

Sample	**T actual** (hr)	**T predicted** (hr)	**Errors %**
1	15.00775	11.67278061	22.2216481
2	49.51886	60.93368389	23.05146745
3	19.48454	20.62462608	5.851234242
4	39.48936	42.05553687	6.49840077
5	1	0.970129706	2.987029366
6	31.50322	22.20986561	29.49969682
7	12.5	12.49637119	0.029030509
8	16.50022	16.37557008	0.755444016
9	76.99694	70.15994569	8.879566267
10	68	44.05342	35.21556
11	29.00065	25.3718	12.513

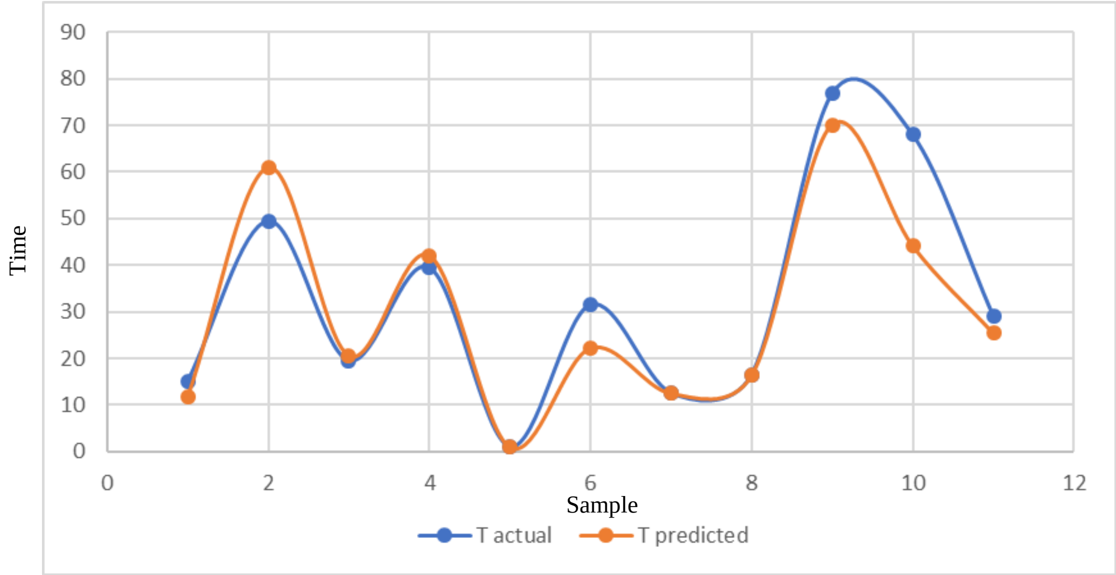

Figure 4.2 Time Final Results of (B&Y) Model

Figure 4.2 represents the time of the actual occurrence and the predicted ones against the depth. To compare the performance of both actual and predicted it is important to have error band.

4.3.1.1 Results

1. The Bourgoyne and Young Model produces a reliable ROP and time models. On datasets 5, 7 and 8. It predicted accurate ROP as compared with the actual ROP and time obtained from the field.
2. While the rest of the datasets had shown uncertainty compared to the three datasets mentioned above.
3. The model had shown an average error percentage of (13.40927978%) for the time comparison, and (16.647181%) for ROP.

4.3.2 Fuzzy Logic Model

Fuzzy logic can be exploited to predict ROP. In order to build a fuzzy-logic model to predict drilling ROP, this study has used the field data published for the Al-Tawila field. This data consists of three variables: weight on bit, rotation speed, and depth of the wellbore. Drilling ROP related to these variables (1 to 3) has been used to calibrate the model. These variables are the same as those used in the Bourgoyne and Young (1974) model.

In constructing a fuzzy model, using an appropriate membership function (MF) is critical and essential, because MFs express the fuzziness of the model. There are many suggestions on how to build the appropriate MF for a particular model (Ross, 1995). One of the advantages of MFs is that they can be produced based on subjective judgment and intuition especially in cases where there is a lack of hard data.

Input variables are Depth, ROP, Bit Type, WOB, and Rotary Speed.

Output variable are ROP and Time.

Table 4.13 Descriptive Statistics of Data

Input			
No.	**Variables**	**Classes**	**Range**
1	Depth 1*1000 FT	shallow medium deep	1 - 10
2	ROP	Low medium high	1 - 100
3	WOB 1*1000 Ton	light medium heavy	20 - 100
4	Speed 100 r/m	slow medium fast	1 - 100
Out put			
1	ROP	Low Medium High	1 - 100
2	Time Hrs	Short Medium High	20 - 120

The fuzzy-model input and output variables are setup in the fuzzy inference system (FIS) editor in MATLAB software. Both input and output variables are fuzzified by a membership function graphically designed (i.e., with a triangular form) using the MATLAB toolbox. Both input and output variables can be fuzzy propositions (e.g., Mamdani & Assilian, 1975) model.

Table 4.14 Building the Rules Using OR Tool

Rule No.	Inputs				Outputs	
	Depth	**ROP**	**WOB**	**RPM**	**ROP**	**Time**
1	shallow	low	Light	Slow	Low	Short
2	shallow	medium	Medium	Medium	Low	Short
3	shallow	high	Heavy	High	Low	Short
4	medium	low	Light	Slow	Low	Short
5	medium	medium	Medium	Medium	Medium	Medium
6	medium	high	Heavy	High	Medium	Medium
7	deep	low	Light	Slow	Low	Medium
8	deep	medium	Medium	Medium	Medium	Medium
9	deep	high	Heavy	High	High	High

Build Rules

The fuzzy-logic rules must be constructed for the model based on knowledge available for the system being modeled and number of data points available for the model. For the proposed fuzzy-logic drilling ROP model, 27 rules were configured to cover the possible (plausible) cases Table below.

Table 4.15 Fuzzy-Logic Rules

No.	Inputs			Outputs	
	Drill Depth	**WOB**	**RPM**	**ROP**	**TIME**
1	Deep	Light	Slow	Low	Long
2	Deep	Light	Medium	Low	Long
3	Deep	Light	Fast	Low	Long
4	Deep	Medium	Slow	Medium	Medium
5	Deep	Medium	Medium	Medium	Medium
6	Deep	Medium	Fast	Medium	Medium
7	Deep	Heavy	Slow	High	Medium
8	Deep	Heavy	Medium	High	Medium
9	Deep	Heavy	Fast	High	Medium
10	Medium	Light	Slow	Low	Long
11	Medium	Light	Medium	Low	Long
12	Medium	Light	Fast	Low	Long
13	Medium	Medium	Slow	Medium	Medium
14	Medium	Medium	Medium	Medium	Medium
15	Medium	Medium	Fast	Medium	Medium
16	Medium	Heavy	Slow	High	Medium
17	Medium	Heavy	Medium	High	Short
18	Medium	Heavy	Fast	High	Short
19	Shallow	Light	Slow	Low	Medium
20	Shallow	Light	Medium	Medium	Medium
21	Shallow	Light	Fast	High	Short
22	Shallow	Medium	Slow	Low	Short
23	Shallow	Medium	Medium	Medium	Short
24	Shallow	Medium	Fast	High	Short
25	Shallow	Heavy	Slow	High	Short
26	Shallow	Heavy	Medium	High	Short
27	Shallow	Heavy	Fast	High	Short

Table above shows fuzzy-logic rules describing the proposed drilling ROP model. L, M, H represent low, medium, low medium, low high and high, respectively.

Defuzzification

Centroid defuzzification is the most commonly used method. For the proposed fuzzy-logic drilling ROP model the centroid method is applied. This method was developed by Takagi & Sugeno (1985).

Table 4.16 ROP Final Results (Fuzzy) Model

ROP act (ft/hr)	**ROP pre** (ft/hr)	**Error %**
64.5	67.29896	4.339475
76.9	80.02767	4.067187
38.8	40.53484	4.471228
23.5	24.63257	4.81943
30	31.46375	4.879153
26.41	27.25241	3.189721
96.56	101.525	5.141868
67.09	70.45179	5.010871
48.95	50.96094	4.10815
20	20.65333	3.266635
15.31	16.21515	5.912152

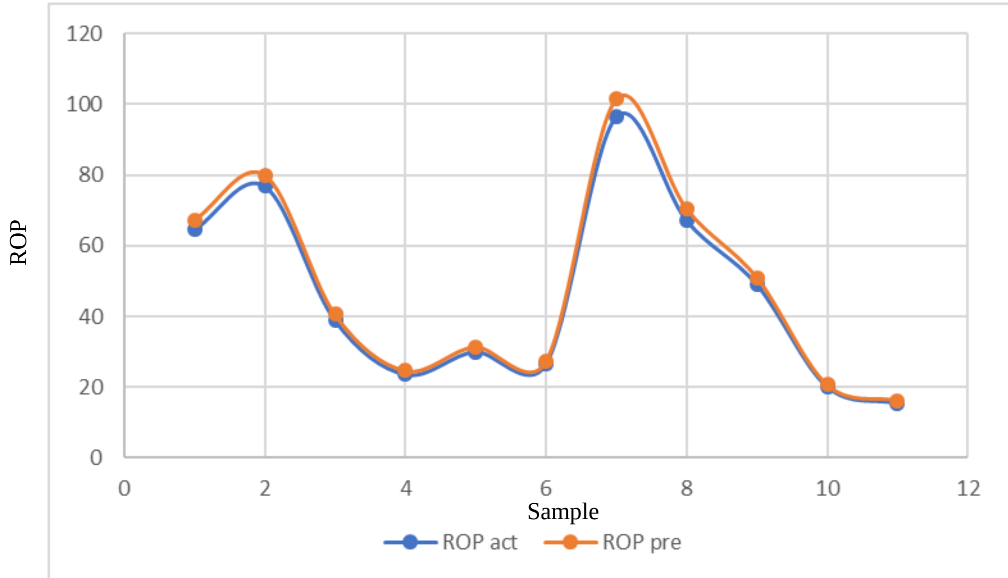

Figure 4.3 ROP Final Results (Fuzzy) Model

Table 4.17 Time Final Results (Fuzzy) Model

Sample	**T act** (hr)	**T pre** (hr)	**Errors %**
1	15.00775	14.38358	4.158982057
2	49.51886	47.58354	3.908244167
3	19.48454	18.65062	4.279893053
4	39.48936	37.6737	4.597851491
5	1	0.953478	4.652179095
6	31.50322	30.52941	3.091144145
7	12.5	11.8887	4.890421079
8	16.50022	15.71287	4.771738862
9	76.99694	73.9586	3.94604724
10	68	65.84895	3.163315553
11	29.00065	27.3818	5.582115044

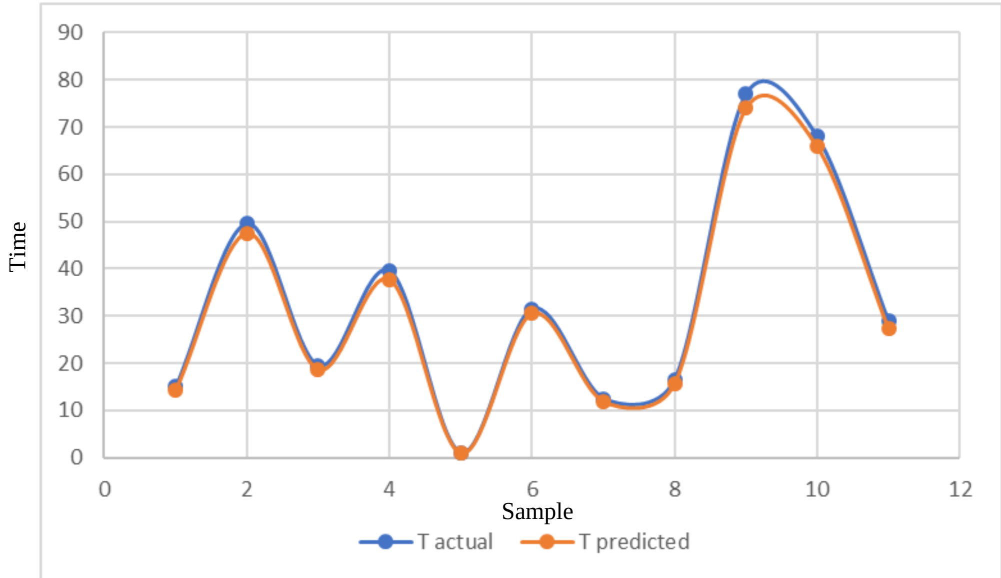

Figure 4.4 Time Final Results (Fuzzy) Model

With the membership functions (MF) established and OR rules applied the fuzzy logic model is ready to put to the test, i.e., comparing the model results (i.e. ROP predictions and Time) with real wellbore measurements of ROP and time from the field (Table 3). A graphical comparison of the measured and predicted ROP values is shown in Figure 6.

Results

1. The Fuzzy logic Model produces a reliable Rate of Penetration and Time models. On most of the datasets. It predicted accurate (ROP-Time) as compared with the actual (ROP-Time) obtained from the field.
2. While the rest of the datasets had shown a real close result compared to the majority of the datasets mentioned above.
3. The model had shown an average error percentage of (4.276539253%) for the time comparison, and (4.4732609%) for ROP.
4. The results of this research provide guidance for further drilling operations close to the observed well in Al-Tawila Field, as these optimal values can be used as reference to obtain optimum drilling performance and reduce drilling cost.

4.4 Comparison

4.4.1 Time Datasets

Table 4.18 Comparison of Time Results

Sample	**T** (hr) **actual**	**T** (hr) **(B&Y)**	**T** (hr) **(FUZZY**
1	15.00775	11.67278061	14.38358037
2	49.51886	60.93368389	47.58354204
3	19.48454	20.62462608	18.65062253
4	39.48936	42.05553687	37.67369787
5	1	0.970129706	0.953478209
6	31.50322	22.20986561	30.52941006
7	12.5	12.49637119	11.88869737
8	16.50022	16.37557008	15.71287259
9	76.99694	70.15994569	73.95860437
10	68	44.05342	65.84894542
11	29.00065	25.3718	27.38180035

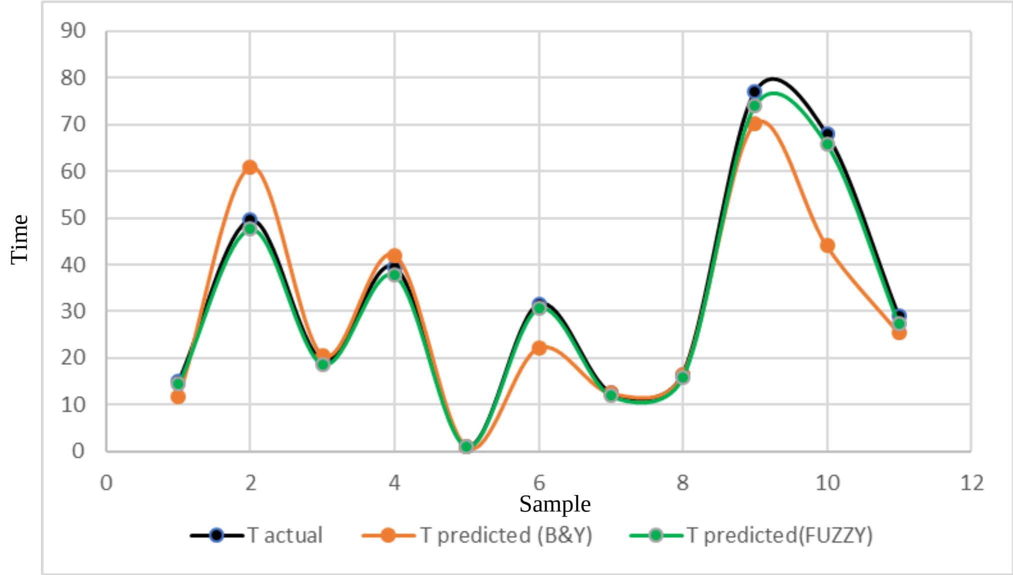

Figure 4.5 Comparison of Time Results

4.4.2 ROP Datasets

Table 4.19 Comparison of ROP Results

Sample	**ROP** (ft/hr) **act**	**ROP** (ft/hr) **(B&Y)**	**ROP** (ft/hr) **(FUZZY)**
1	64.5	82.92797	67.29896
2	76.9	62.49417	80.02767
3	38.8	36.65521	40.53484
4	23.5	22.06606	24.63257
5	30	30.9237	31.46375
6	26.41	37.46083	27.25241
7	96.56	96.58804	101.525
8	67.09	67.6007	70.45179
9	48.95	53.72011	50.96094
10	20	30.88509	20.65333
11	15.31	17.49974	16.21515

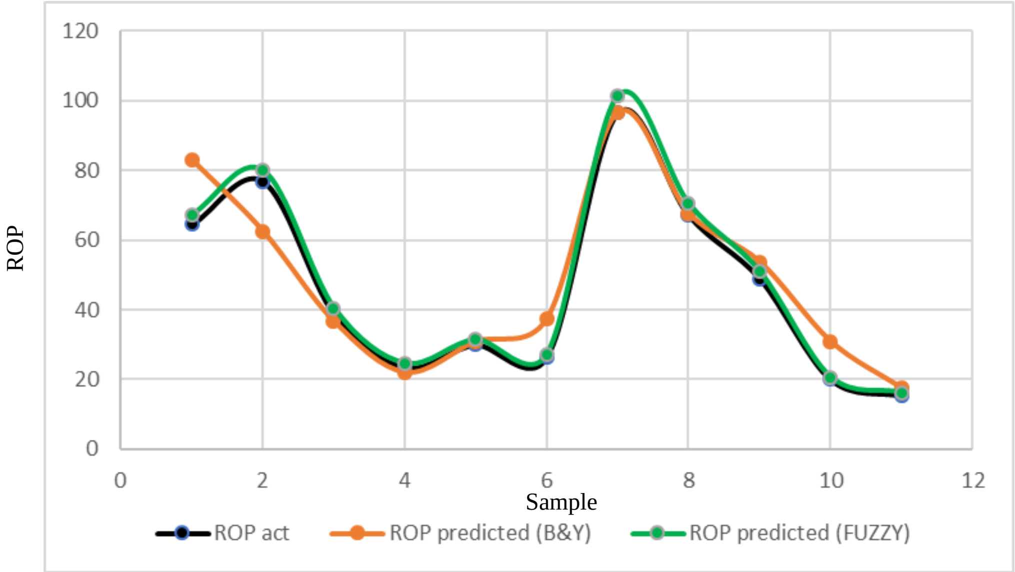

Figure 4.6 Comparison of ROP Results

CHAPTER 5
CONCLUSION AND FUTURE WORK

5.1 Conclusion

In this study the aim was to establish a correlation model between the traditional methods and the modern methods for calculating the ROP and determine which method and model is giving the best results in correlation with the actual data taking from the wells of this study in Al-Tawila field in block (14).

We first took the data available and put them as inputs in the Excel software, we then inserted the equation of the traditional Bourgyone and Young's model in Excel and tabled the results in order to create charts to correlate the calculated results and the actual results, and the findings were that the error percentage was relatively high in the majority of the samples.

Afterwards, we created the modern Fuzzy logic model using MATLAB software, we took the data as inputs and wrote the probability rules and programming codes to have the desired outputs, then we took the results and organized, tabled and charted them and made the same previous correlation and found that the error percentage was much more reasonable and valid compared to the actual data.

As a final conclusion, based on our analysis the fuzzy logic model demonstrated superior accuracy in predicting ROP. While the B&Y model provided reasonable estimates in a few datasets showing a real modest prediction and not as effective and efficient results as the fuzzy logic model.

5.2 Recommendations

- Obtaining all necessary and required data for more accurate modeling.
- Having a better background on machine learning.
- Integrating machine learning approaches in more areas in the drilling operations.
- Building a hybrid model could be useful in compensating the weaknesses in each model alone, and so that the results would be more accurate and real.

5.3 Limitations

- Lack of the required data for some parameters.
- Small number of the samples for each parameter required.
- Working on a machine learning model without having a good reference was a challenging step that consumed a lot of our time.

5.4 Future Work

- Building a comparison reference regarding different machine learning approaches to determine which provide the most accurate results.
- Establishing an optimization model for ROP.

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APPENDIX A:
IMPLEMENTATION DETAILS

```
clc
close all;
clear all;
fis = readfis('ROP.fis');

%%
% This command returns a |mamfis| object that contains
the properties of
% the fuzzy system. For a Sugeno system, this command
returns a |sugfis|
% object.

%%
% You can access the FIS properties using dot
notation. For example,
% view the inputs of the fuzzy system.
fis.Inputs

%%
% To set the properties of your fuzzy system, use dot
notation. For
% example, set the name of the FIS.
fis.Name = "Rate of Penteration";

%% FIS Object
% You represent fuzzy inference systems using
% <docid:fuzzy#mw_83080bc8-a7f2-45e3-b89a-
13bf08fd6f62> and
% <docid:fuzzy#mw_7219a982-c98d-4a71-bd2d-
c1d1d8ccfbde> objects. These
% objects contain all the fuzzy inference system
information, including the
% variable names, membership function definitions, and
fuzzy inference
% methods. Each FIS is itself a hierarchy of objects.
The following objects
% are used within a fuzzy system:
%
% * <docid:fuzzy#mw_40b5c1de-8f3d-4e35-a06f-
f9e44f943c35> objects represent
% both input and output variables.
```

```
% * <docid:fuzzy#mw_35c9a8ef-d038-4570-b473-
08f1cf2fd5c5> objects represent
% membership functions within each input and output
variable.
% * <docid:fuzzy#mw_18bf97aa-b218-4dce-85d6-
ba0d1a9ada52> objects represent
% fuzzy rules that map inputs to outputs.
%
% View all the information for a FIS by directly
listing its properties.
fis

%%
% You can view the properties of the objects within a
FIS object using dot
% notation. For example, view the |fisvar| object for
first input
% variable.
fis.Inputs(1)

%%
% Also, view the membership functions for this
variable.
fis.Inputs(1).MembershipFunctions

%% System Display Functions
% To get a high-level view of your fuzzy system from
the command line, use
% the |plotfis|, |plotmf|, and |gensurf| functions.
|plotfis| displays the
% whole system as a block diagram, as shown in the
*Fuzzy Logic Designer*.
figure (1)
plotfis(fis)
title('Fuzzy System' , 'Fontsize', 10')
%%
% The |plotmf| function plots all the membership
functions associated with
% a given variable. For example, view the membership
functions for the
% first input variable.
figure (2)
subplot(1,3,1)
plotmf(fis,'input',1)
title('Memebership function of 1st input' ,
'Fontsize', 10')
```

```
subplot(1,3,2)
plotmf(fis,'input',2)
title('Memebership function of 2ed input' ,
'Fontsize', 10')
subplot(1,3,3)
plotmf(fis,'input',3)
title('Memebership function of 3ed input' ,
'Fontsize', 10')
%%
% Similarly, to view the membership functions for the
first output, type:
figure (3)
plotmf(fis,'output',1)
title('Memebership function of output' , 'Fontsize',
10')

%%
% |plotmf| does not support viewing the output
membership functions for
% Sugeno systems.

%%
% To view the rules of the fuzzy system, type:
fis.Rules

%%
% The |gensurf| function plots the output of the FIS
for any one or two
% input variables.
figure (4)
gensurf(fis)
%% Build Fuzzy Inference System
% As an alternative to using the *Fuzzy Logic
Designer* app, you can
% construct a FIS entirely from the command line.

%%
% First, create a Mamdani FIS, specifying its name.
fis = mamfis('Name',"ROP");

%%
% Add the first input variable for the service quality
using
% <docid:fuzzy#mw_c87db63b-66a1-416a-95ff-
d47c43e0acde>.
```

```
% fis = addInput(fis,[1000 10000],'Name',"Drill
Depth");

% Add the first input variable and its mmebership
functions
fis = addInput(fis,[1000 10000],'Name',"Drill Depth");
fis = addMF(fis,"Drill Depth","trimf",[0 2500
5000],'Name',"shallo");
fis = addMF(fis,"Drill Depth","trimf",[2500 5000
7500],'Name',"medium");
fis = addMF(fis,"Drill Depth","trimf",[5000 7500
10000],'Name',"deep");
% Add the third input variable and its mmebership
functions
fis = addInput(fis,[0 100],'Name',"wob");
fis = addMF(fis,"wob","trimf",[ 0 25 50],
'Name',"light");
fis = addMF(fis,"wob","trimf",[ 25 50 75],
'Name',"medium");
fis = addMF(fis,"wob","trimf",[ 50 75 100],
'Name',"heavy");
% Add the third input variable and its mmebership
functions
fis = addInput(fis,[0 100],'Name',"rpm");
fis = addMF(fis,"rpm","trimf",[ 0 25 50],
'Name',"slow");
fis = addMF(fis,"rpm","trimf",[ 25 50 75],
'Name',"medium");
fis = addMF(fis,"rpm","trimf",[ 50 75 100],
'Name',"fast");
% Add the first output and its mmebership functions
fis.Outputs(1).Name = "ROP";
fis.Outputs(1).Range = [0 100];
fis = addMF(fis,"ROP","trimf",[ 0 25 50],
'Name',"conservative");
fis = addMF(fis,"ROP","trimf",[ 25 50 75],
'Name',"moderate");
fis = addMF(fis,"ROP","trimf",[ 50 75 100],
'Name',"aggressive")
%%
% Specify the following three rules for the FIS as a
numeric array:
%
% # If (service is poor) or (food is rancid), then
(tip is cheap).
% # If (service is good), then (tip is average).
```

```
% # If (service is excellent) or (food is delicious),
then (tip is
% generous).
%
% Each row of the array contains one rule in the
following format.
%
% * Column 1 - Index of membership function for first
input
% * Column 2 - Index of membership function for second
input
% * Column 3 - Index of membership function for output
% * Column 4 - Rule weight (from |0| to |1|)
% * Column 5 - Fuzzy operator (|1| for AND, |2| for
OR)
%
% For the membership function indices, indicate a NOT
condition using a
% negative value. For more information on fuzzy rule
specification, see
% <docid:fuzzy#FP40034>.
ruleList = [  3 1 1  1  1 2;
3 1 2 1 1 2;
3 1 3 1 1 2;
3 2 1 2 1 2;
3 2 2 2 1 2;
3 2 3 2 1 2;
3 3 1 3 1 2;
3 3 2 3 1 2;
3 3 3 3 1 2;
2 1 1 1 1 2;
2 1 2 1 1 2;
2 1 3 1 1 2;
2 2 1 2 1 2;
2 2 2 2 1 2;
2 2 3 2 1 2;
2 3 1 3 1 2;
2 3 2 3 1 2;
2 3 3 3 1 2;
1 1 1 1 1 2;
1 1 2 2 1 2;
1 1 3 3 1 2;
1 2 1 1 1 2;
1 2 2 2 1 2;
1 2 3 3 1 2;
1 3 1 3 1 2;
```

```
1 3 2 3 1 2;
1 3 3 3 1 2];
%%
% Add the rules to the FIS.
fis = addRule(fis,ruleList);

%%
% Alternatively, you can create the fuzzy inference
system using a
% combination of dot notation and |fisvar|, |fismf|,
and |fisrule| objects.
% This method is not a good practice for most
applications. However, you
% can use this approach when your application requires
greater flexibility
% in constructing and modifying your FIS.

%%
% Create the fuzzy inference system.
fis = mamfis('Name','ORP');

%%
% Add and configure the first input variable. In this
case, create a
% default |fisvar| object and specify its properties
using dot notation.
fis.Inputs(1) = fisvar;
fis.Inputs(1).Name = "Drill Depth";
fis.Inputs(1).Range = [1000 10000];

%%
% Define the membership functions for the first input
variable. For each
% MF, create a |fismf| object, and set the properties
using dot notation.
ffis.Inputs(1).MembershipFunctions(1) = fismf;
fis.Inputs(1).MembershipFunctions(1).Name = "shallo";
fis.Inputs(1).MembershipFunctions(1).Type = "trimf";
fis.Inputs(1).MembershipFunctions(1).Parameters = [0
2500 5000];
fis.Inputs(1).MembershipFunctions(2) = fismf;
fis.Inputs(1).MembershipFunctions(2).Name = "medium";
fis.Inputs(1).MembershipFunctions(2).Type = "trimf";
fis.Inputs(1).MembershipFunctions(2).Parameters =
[2500 5000 7500];
fis.Inputs(1).MembershipFunctions(3) = fismf;
```

```
fis.Inputs(1).MembershipFunctions(3).Name = "deep";
fis.Inputs(1).MembershipFunctions(3).Type = "trimf";
fis.Inputs(1).MembershipFunctions(3).Parameters =
[5000 7500 10000];

% % Specify the membership functions for the second
input.
 fis.Inputs(2) = fisvar([1 100],'Name',"wob");
fis.Inputs(2).MembershipFunctions(1) = fismf;
fis.Inputs(2).MembershipFunctions(1).Name = "light";
fis.Inputs(2).MembershipFunctions(1).Type = "trimf";
fis.Inputs(2).MembershipFunctions(1).Parameters = [0
25 50];
fis.Inputs(2).MembershipFunctions(2) = fismf;
fis.Inputs(2).MembershipFunctions(2).Name = "medium";
fis.Inputs(2).MembershipFunctions(2).Type = "trimf";
fis.Inputs(2).MembershipFunctions(2).Parameters = [25
50 75];
fis.Inputs(2).MembershipFunctions(3) = fismf;
fis.Inputs(2).MembershipFunctions(3).Name = "heavy";
fis.Inputs(2).MembershipFunctions(3).Type = "trimf";
fis.Inputs(2).MembershipFunctions(3).Parameters = [50
75 100];

% % Specify the membership functions for the third
input.
fis.Inputs(3) = fisvar([1 100],'Name',"rmp");
fis.Inputs(3).MembershipFunctions(1) = fismf;
fis.Inputs(3).MembershipFunctions(1).Name = "slow";
fis.Inputs(3).MembershipFunctions(1).Type = "trimf";
fis.Inputs(3).MembershipFunctions(1).Parameters = [0
25 50];
fis.Inputs(3).MembershipFunctions(2) = fismf;
fis.Inputs(3).MembershipFunctions(2).Name = "medium";
fis.Inputs(3).MembershipFunctions(2).Type = "trimf";
fis.Inputs(3).MembershipFunctions(2).Parameters = [25
50 75];
fis.Inputs(3).MembershipFunctions(3) = fismf;
fis.Inputs(3).MembershipFunctions(3).Name = "fast";
fis.Inputs(3).MembershipFunctions(3).Type = "trimf";
fis.Inputs(3).MembershipFunctions(3).Parameters = [50
75 100];
% Similarly, add and configure the output variable and
its membership
% functions.
fis.Outputs(1) = fisvar([1 100],'Name',"ROP");
```

```
%%
% In this case, specify the output membership
functions using a vector of
% |fismf| objects.
mf1 = fismf("trimf",[0 25 50],'Name',"low");
mf2 = fismf("trimf",[25 50 75],'Name',"medium");
mf3 = fismf("trimf",[50 75 100],'Name',"high");
fis.Outputs(1).MembershipFunctions = [mf1 mf2 mf3];

%%
% Create the rules for the fuzzy system. For each rule
create a |fisrule|
% object. Then, specify the rules using a vector of
these objects. When
% creating a |fisrule| object using numeric values,
you must specify the
% number of inputs variables.
fis = readfis('ROP.fis');
fis.Rules = [ ];
rule1 = fisrule([3 1 1 1  1 2],2);
rule2 = fisrule([3 1 2 1 1 2],2);
rule3 = fisrule([3 1 3 1 1 2],2);
% % rule4 = fisrule([3 2 1 2 1 2],2);
% % rule5 = fisrule([3 2 2 2 1 2],2);
% % rule6 = fisrule([3 2 3 2 1 2],2);
% % rule7 = fisrule([3 3 1 3 1 2],2);
% % rule8 = fisrule([3 1 2 1 1 2],2);
% % rule9 = fisrule([3 1 3 1 1 2],2);
% % rule10 = fisrule([3 1 1  1  1 2],2);
% % rule11 = fisrule([3 1 2 1 1 2],2);
% % rule12 = fisrule([3 1 3 1 1 2],2);
% % rule13 = fisrule([3 1 1  1  1 2],2);
% % rule14 = fisrule([3 1 2 1 1 2],2);
% % rule15 = fisrule([3 1 3 1 1 2],2);
% % rule16 = fisrule([3 1 1  1  1 2],2);
% % rule17 = fisrule([3 1 2 1 1 2],2);
% % rule18 = fisrule([3 1 3 1 1 2],2);
% % rule19 = fisrule([3 1 1  1  1 2],2);
% % rule20 = fisrule([3 1 2 1 1 2],2);
% % rule21 = fisrule([3 1 3 1 1 2],2);
% % rule22 = fisrule([3 1 1  1  1 2],2);
% % rule23 = fisrule([3 1 2 1 1 2],2);
% % rule24 = fisrule([3 1 3 1 1 2],2);
% % rule25 = fisrule([3 1 1  1  1 2],2);
% % rule26 = fisrule([3 1 2 1 1 2],2);
```

```
% % rule27 = fisrule([1 3 3 3 1 2],2);
rules = [rule1 rule2 rule3];

%%rules = [rule1 rule2 rule3 rule4 rule5 rule6 rule7
rule8 rule9 rule10 rule11 rule12 rule13 rule14 rule15
rule16 rule17 rule18 rule19 rule20 rule21 rule22
rule23 rule24 rule25 rule26 rule27 ];

%%
% Before adding your rules to your fuzzy system, you
must update them using
% the data in the FIS object. Update the rules using
the |update| function,
% and add them the fuzzy system.
% rules = update(rules,fis);
% fis.Rules = rules;??????


%%
% When constructing your fuzzy system, you can also
specify custom
% membership functions and inference functions. For
more information, see
% <docid:fuzzy#brkiiwg-1>.

%% Evaluate Fuzzy Inference System
% To evaluate the output of a fuzzy system for a given
input combination,
% use the <docid:fuzzy#FP312> command. For example,
evaluate |fis| using
% input variable values of |1| and |2|.
% evalfis(fis,inputs)????????

%%
% You can also evaluate multiple input combinations
using an array where
% each row represents one input combination.
ruleList = [  3 1 1  1  1 2;
3 1 2 1 1 2;
3 1 3 1 1 2;
3 2 1 2 1 2;
3 2 2 2 1 2;
3 2 3 2 1 2;
3 3 1 3 1 2;
3 3 2 3 1 2;
3 3 3 3 1 2;
```

```
2 1 1 1 1 2;
2 1 2 1 1 2;
2 1 3 1 1 2;
2 2 1 2 1 2;
2 2 2 2 1 2;
2 2 3 2 1 2;
2 3 1 3 1 2;
2 3 2 3 1 2;
2 3 3 3 1 2;
1 1 1 1 1 2;
1 1 2 2 1 2;
1 1 3 3 1 2;
1 2 1 1 1 2;
1 2 2 2 1 2;
1 2 3 3 1 2;
1 3 1 3 1 2;
1 3 2 3 1 2;
1 3 3 3 1 2];
% evalfis(fis,inputs)??????
[xOut] = plotmf(fis,'input',1);
[yOut] = plotmf(fis,'output',1);
% [xOut,yOut] = plotmf(fis,'input',1);
 figure(5)
plot(xOut(:,1),yOut(:,1))
xlabel('Drill Depth')
ylabel('ROP')
m = 181;
n = 3;
for i = 1 : m
    for j = 1 : n
        xOut1 = sum(xOut, 2);
        yOut1 = sum(yOut, 2);
    end
end
figure(6)
plot(xOut1(:,1),yOut1(:,1))
xlabel('Drill Depth')
ylabel('ROP')
%  plotmf(fis,'output',1,101)
 K =3;
 W = 20;
%  wob_val = 20;
 d = 100;
 s = 0.5;
rop = (K*W/(d*s))*0.01;
```