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Optimization of drilling parameters using metaheuristic technique

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To our families, our mothers,
Our fathers, our brothers
And all the friends
Who stood with us
And supported us

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NOMENCLATURE

a_1	formation strength parameter	-
a_2	exponent of the normal compaction trend	-
a_3	under-compaction exponent	-
a_4	pressure differential exponent	-
a_5	bit weight exponent	-
a_6	rotary speed exponent	-
a_7	tooth wear exponent	-
a_8	hydraulic exponent	-
a_c, b_c, and c_c	lithology coefficients	-
B	Bearing model	-
C_b	bit cost	Dollars
C_f	cost per drilled interval	dollars/ft
C_r	daily rig rate	dollars/hour
D	depth of borehole	ft (m)
d_b	bit diameter	In
dD/dt	rate of penetration	ft. /hr.
d_n	equivalent bit nozzle diameter	In
d_p	exponent in dimensionless Pi term	-
f_1	formation strength function	-
f_2	formation normal compaction function	-
f_3	formation compaction function	-
f_4	pressure differential of hole bottom function	-
f_5	bit diameter and weight function	-
f_6	rotary speed function	-
f_7	tooth wear function	-
f_8	hydraulic function	-
F	distance drilled by bit	[L], ft (m)
g_p	pore pressure gradient of the formation	[M/L3], ppg (sg)
h	bit tooth dullness, fractional tooth height worn away	-
H_1, H_2 , H_3	constants for tooth geometry of bit types	-

h_f	final bit tooth dullness	-
i	summation index for ith data point	-
I_m	modified jet impact force	hp(N)
J	summation index for frh drilling parameter	-
J_1	composite drilling parameter representing all but tooth wear	-
J_2	tooth wear composite function used to calculate fractional tooth wear	-
N	rotary speed	rpm
n	data point numbers used in regression analysis	-
$[N]_{opt}$	optimum rotary speed,	rpm
P_e	effective confining pressure	psi
P_g	represents the global previous best from the entire swarm	-
P_i	represents the previous best of the current particle	-
q	volumetric flow rate	$[L^3/T]$, gpm (l/m)
R	rate of penetration	ft. /hr
r	residual error in the drilling ROP equation	-
r_1 and r_2	are random values	-
S	rock strength	-
t	time (usually bit rotating time)	[T], hours
t_b	bit drilling time	[T], hours
t_c	drill pipe connection time	[T], hours
t_t	round trip time	[T], hours
Vi	Velocity of each Particle	-
W	weight on bit	1000 lbf (N)
w/d_b	weight on bit per inch of bit diameter	1000 lbf/in(N/m)
$(W/d_b)_m$	bit weight per diameter where teeth fails instantaneously	1000 lbf/in(N/m)
$\left[\frac{W}{d_b}\right]_{opt}$	optimum bit weight per inch	lb/in
$(w/d_b)_t$	threshold bit weight at which the bit starts to drill	1000 lbf/in

		(N/m)
X	drilling rate of penetration independent parameter	-
x_{2}	normal compaction drilling parameter	-
x_{3}	under-compaction drilling parameter	-
x_{4}	pressure differential drilling parameter	-
x_{5}	bit weight drilling parameter	-
x_{6}	rotary speed drilling parameter	-
x_{7}	tooth wear drilling parameter	-
x_{8}	bit hydraulics drilling parameter	-
x_i	Position of the Particle	-
$\phi 1$, $\phi 2$	Cognitive and Social Components	-
ω	Weighted Inertia Component	-
ρ	density of the fluid	Ppg
μ	drilling fluid viscosity	Cp
Φ	cone offset coefficient	-
σ	rock compressive strength	Psi
ε	rock ductility	-
τ_H	formation abrasiveness constant or life of teeth at standard	Hours
τ_B	bearing constant	Hours

ABBREVIATIONS

DMF	drilling mud flow
ECD	Equivalent Circulating Density
IADC	international Association of Drilling contracter
IS	International System
MR	Multiple Regression
M_PSO	modified version of Particle Swarm Optimiazation
NPT	non productive time
O&G	oil and gas
PSO	Particle Swarm Optimiazation
PDC	Polycrystalline Diamond Compact
PSO	Particle Swarm Optimiazation
RPM	rotation per minute
ROP	rate of penetration
TDS	Top Drive System

General introduction

In today's drilling industry, all considerations are involved to reduce drilling operation expenditure even when the returns on capital in the oil and gas (O&G) sector was 100$ USD/bbl. In several cases, Drilling parameters play a large role in helping drillers achieve a good rate of penetration (ROP), superior drilling performance and long bit life. They are basic recommendations that help the driller to avoid damaging bits and other drilling equipments, Also this means a reduction in non productive time (NPT) and a minimum drilling cost. In consequence a drilling parameters optimization is a key point to make a drilling operation economically satisfied.For these problem, The objective for our study is to focus on the Optimization of the Drilling Parameters, To achieve this goal we will begin our study by a dominant and widely utilized method for drilling rate prediction that called Bourgoyne and Young's Model. It demonstrates a relation between (ROP) and the parameters affecting on it, There are eight (8) variables influencing the drilling rate and they depend on ground formation type and must be determined based on the data gathered in advance. Bourgoyne and Young have suggested the multiple regression (MR) analysis method in order to define these constants.Then our study aims to propose one of the best metaheuristic optimization techniques to improve and compare the quality of solution founded by the multiple regression method . in other words, we used a particle swarm optimization (PSO) algorithm. it's a biologically inspired computational search and optimization method developed in 1995 by Eberhart and Kennedy based on the social behaviors of birds flocking or fish schooling. Compared with other optimization algorithms, the PSO is more objective and easily to perform well, That's why we enhance our study by a some modification in the Particle swam optimization algothim (M_PSO) .

At last, This technique of optimization can be implemented by any programming language and we have chosen MATLAB to solve the optimization model of drilling parameters which is based on the rate of penetration. The simulation results will prove the efficiency of the metaheuristic technique we have used (PSO) specially with the modified one (M_PSO). So more faster drilling rate would result, and the objective of a least possible cost and in the shortest time in compliance with safe operation will achieve in the drilling operation .
In the first chapter we talk about Drilling Parameters:Definition, Classification and Effect On Drilling Performance.

In the next chapter we discussed about Rate Of Penetration Modelling And Optimization Techniques

In the last chapter we make Result Analysis & Discussion

Chapter I

Drilling Parameters

I. 1. Introduction

Oil and gas companies have played a major role in the energy sector, and constantly try to develop technology to maximize their overall revenue. However, as the wells continue to get drilled farther, the drilling wells cost continue to rise. Many researchers have worked for optimizing constant operational parameters. However, these parameters lead to wasted time and money for the operators if they are not well estimated. This is because they constantly change throughout the drilling process. Therefore, it is required to know widely the behavior and the influence of the several parameters, usually known as drilling variables, on the system drilling quality, among these variables we notice: weight on bit (WOB), rotation of the bit (rotation per minute (RPM)) and drilling mud flow (DMF). Especially, determining the optimal rate of penetration (ROP) has been always one of the main concepts of drilling engineering.

In this chapter, we will introduce, classify and define the drilling variables, and we will make a study about bit types and their characteristics, also the different formation we frequently used in.

I. 2. Drilling Principles

The wide variations in drilling conditions encountered under field conditions make it difficult to develop general rules of operation for maximum drilling efficiency. Field experience usually provides the basis for operations in a particular area, but testing often is too costly and experience too late. Consequently, a method for determining optimum drilling techniques and parameters for any particular drilling condition, with a minimum of engineering effort and drilling experience is greatly needed [1]. The drilling parameters, or variables, associated with rotary drilling have been analyzed and divided in two groups as independent and dependent parameters as shown in Figure I.1. The independent variables are those which can be directly controlled by the drilling rig operator and dependent variables are those which represent the response of the drilling system to the drilling operation. There are, of course, many factors other than those discussed here that effect drilling efficiency and footage cost. These include such factors as formation hardness, abrasiveness of formation and well depth. As these items cannot be conveniently controlled, their influence on costs must simply be accepted [2].

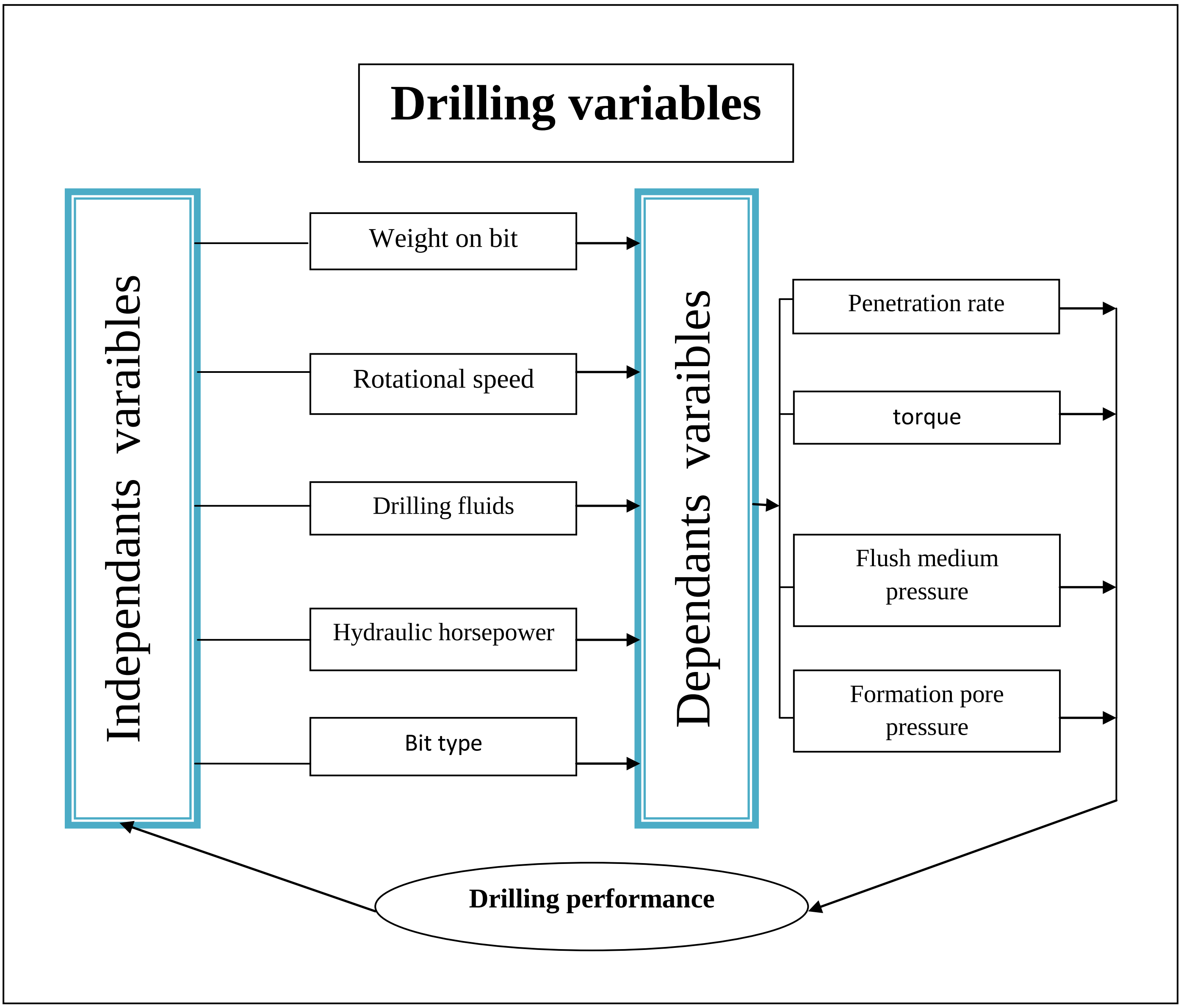

Figure I.1. Drilling variables associated with rotary drilling.

I. 2. 1. Dependent Variables

The dependent variables associated with rotary drilling represent the response of the drilling system to the imposed conditions and are the penetration rate of the bit, the torque and the flush medium pressure and formation pore pressure [2].

I. 2 .1. 1. Penetration Rate

The rate of penetration (ROP), also known as drill rate, is the speed at which a drill bit breaks the rock under it to deepen the borehole. It is normally measured in feet per minute or meters per hour, but sometimes it is expressed in minutes per foot. This parameter is the most important parameter, since all the calculations in this study are based on estimations of ROP in the drilling industry [3].

The factors which effect on rate of penetration are listed under two general classifications such as controllable and environmental. Controllable factors are the factors which can be instantly changed such as weight on bit, bit rotary speed, hydraulics. Environmental factors on the other hand are not controllable such as formation properties and drilling fluids requirements. The reason that drilling fluid is considered to be an environmental factor is due to the fact that a certain amount of density is required in order to obtain certain objectives such as having enough overpressure to avoid flow of formation fluids. Another important factor is the effect of the overall hydraulics to the whole drilling operation which is under the effect of many factors such as lithology, type of the bit, downhole pressure and temperature conditions, drilling parameters and mainly the rheological properties of the drilling fluid. It has been observed that the drilling rate of penetration generally increases with decreased Equivalent Circulating Density (ECD). Another important term controlling the rate of penetration is the cuttings transport. It was concluded that average annular fluid velocity is the dominating parameter on cuttings transport, the more the flow rate is high the less cuttings bed is developed [3].

I. 2 .1. 2. Torque

Torque is a rotational force and it can be described as the ability to overcome resistance to rotation. Its magnitude is measured by multiplying the perpendicular component of the force applied by the distance between the axis of rotation and the point where the force is applied. In drilling applications this distance would of course be the drill pipe radius. It is measured by means of Top Drive System (TDS) systems. Previously the readings for this parameter were relative. This parameter is going to be significantly important for inclined and highly deviated wells, which is also related with the wellbore cleaning issues [2].

I. 2 .1. 3. Flush Medium Pressure

Drilling fluids in the wellbore can be in either a static or dynamic state. The static system occurs when the fluid stands idle in the well. The dynamic state occurs when the fluid is in motion, resulting from pumping or pipe movement. The static pressure of a column of fluid pressure is known as "hydrostatic pressure" which is an essential feature in maintaining control of well and preventing kicks or blowouts. The hydrostatic pressure of a fluid column is a function of the mud weight or density and the true vertical well depth.

The ROP obtained while a well is drilled generally shows a steady decline as well depth increases. The causes of the reduction in ROP with depth can be divided into two categories [2] :

1) Processes that affects the unbroken rock;

2) Processes that act on the rock once it is broken into chips.

I. 2 .1. 4. Formation Pore Pressure

Formation pore pressure can be major factor affecting drilling operations especially in deep wells. An operator planning a well needs some knowledge of overburden and formation fluid pressure in order to select the necessary hydrostatic or drilling fluid pressure. If this pressure is not properly evaluated, it can cause drilling problems such as lost circulation, blowouts or kicks, stuck pipes, hole instability and excessive costs.

The Formation fluid or pore pressures are usually categorized as normal, subnormal and abnormal or over pressured. When formation pore pressure is approximately equal to hydrostatic pressure of drilling fluid for a given vertical depth, formation pressure is described to be normal. When the formation is opened to the atmosphere during drilling, a column of drilling fluid from the ground surface down to the formation depth (hydrostatic pressure) would balance the formation pressure. If the formation pressure is less than that of the hydrostatic pressure, then it is called subnormal formation pressure. Formations with pressure higher than hydrostatic are encountered at various depth in many areas. These formations are referred to as being abnormally pressured or over pressured. Generally, abnormal pore pressures are associated with fluids trapped within the pore spaces of rocks by low permeability barriers such as salt domes, folds or faults. Numerous authors have demonstrated the severe reduction in ROP with different rotary bits as the borehole pressure increases [2].

I. 2. 2. Independent Variables

The independent variables are the drilling fluids, weight on bit, the bit rotational speed, bit type and the hydraulics horse power.

I. 2. 2. 1. Weight On Bit

It represents the amount of weight applied onto the bit, that is then transferred to the formation which in turn is the energy created together with string speed that advances drillstring.

This amount of downward force exerted on the drill bit provided by thick-walled tubular pieces in the drilling assembly that are known as drill collars.

It is an essential part of drilling optimization to ensure that the well deepens as drilling moves forward. Finding the right amount of WOB per application is crucial to drilling operations. If the WOB is greater than the optimum value, the drill bit has a higher chance of wear or damage and there is even a chance for the drill string to buckle. [2].

I. 2. 2. 2. Revolution Per Minute

The definition of RPM is a measure of frequency of rotations performed by an equipment in one minute. It is a technical term which is associated with any equipment that conducts its operations by performing rotations over a fixed axis. It is an International System (IS) unit of rotations and is abbreviated by many other common terms such as rpm/RPM (or rotations per minute) or rev/minute.

Some of the examples of equipment used in drilling sector that consists of revolutions per minutes include: top drive, drilling mud motor, compressor reciprocating pumps and motors downhole, motor internal combustion engine [2].

I. 2. 2. 3. Drilling Fluids

The bottom hole must be always cleaned, so we have to remove the cuttings from the borehole. This one obtained by using drilling fluids with sufficient flow flushing medium that can be air, water, oil, oil/water emulsion, mud or foam. Drilling rate is proved to be faster and bit life longer with air as compared to water or mud. Drilling was originally performed with air or water as a drilling medium used to cool the bit and flush away the drill cuttings. As these two media were usually, easily available, cheap and satisfactory for the shallow boreholes and hard formations being drilled at that time. Through the years many additional requirements have been placed on the drilling fluid. To satisfy these demands, as boreholes began to be drilled deeper, and especially with the rapid development of oil well drilling in soft and often caving sedimentary formation, the composition has been modified greatly from the air or water that was originally used. A drilling fluid called mud was developed, consisting of water and bentonite clay to overcome problems such as borehole instability, Mud has a number of properties such as its caking ability, its higher density, viscosity and its thixotropic properties, which make it particularly suitable for drilling deep and soft formations that would otherwise prove difficult to drill. However , The selection of the type of drilling fluid is largely determined by the expected hole conditions. The adjustment of drilling fluid properties is intimately related to the well depth, casing program and the drilling equipment [2].

I. 2. 2. 4. Hydraulic Horse Power

Hydraulics has long been recognized as one of the most important considerations in the design of drilling programs. Improved bottom hole cleaning afforded by jet rock bits and high levels of bit hydraulic horsepower permit the use of the most effective combination of weight and rotary speed and minimizes the risk of bit fouling. These benefits became apparent during the early days of jet bit drilling as contractors began to search for ways to maximize the effectiveness of their hydraulic systems. The results are extended bit life and faster penetration rates. An increasing number of commercial bits are becoming available with interchangeable nozzles, providing the flexibility of rig-site hydraulics optimization. With these interchangeable nozzles, the hydraulic power of the drilling fluid that is dissipated across the bit face can be adjusted to match that portion of the rig's hydraulic power that is available for the bit after other system losses have been considered. The degree to which drilling rate was affected by bit hydraulic horsepower depends on the rock/drilling-fluid combination [2].

I. 2. 2. 5. Bit Type

The drill bit is the main tool of the drilling process, positioned at the end of the drill string. Its rotation cuts and the weight on bit indents, resulting in penetration of the formation. Drilling fluid circulates through the bit to decrease bit wear by cooling, and to help the penetration rate by removing cuttings. The aim of every drilling engineer when selecting a drilling bit is to achieve the highest rate of penetration with the least possible bit wear. and because formation properties and bit type are the largest factors that affect penetration rate, the correct bit type is a major importance in achieving high rates of penetration.

There is a great selection of bits available where rotary drilling has two main groups of bits in which we find numerous varieties of bit designs. These are roller-cone bits and fixed-cutter or diamond bits.

I. 2. 2. 5.1 Roller-Cone Bits

Roller-cone bits can be categorized by insert or milled tooth. Insert bits have a cutting structure consisting of a sequence of inserts pressed into the cone. Milled tooth bits have a cutting structure of teeth milled out of the cone. Tooth design and bearing types vary greatly for roller-cone bits, making them applicable for several formation types. Milled tooth bits are usually used in soft formations. Insert bits are appropriate for a wider variety of formations, including hard formations.

Three cones and legs of similar size, connected to a pin, normally make up roller-cone bits. The cones are mounted on each of their bearings, and able to rotate with respect to the bit body. Connection to the drill string is provided by the pin section. Drilling fluid is pumped down the drill string and through the nozzles of the bit. Openings by the legs provide fluid circulation, and give the possibility to achieve high pressure jetting through the nozzles of the bit. A representation of a typical roller-cone bit is provided below in Figure I.2.

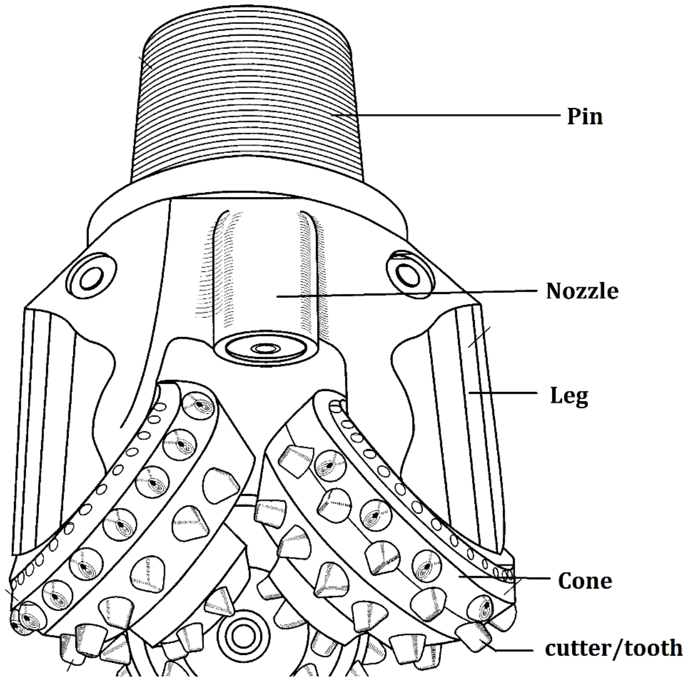

Figure I.2. Roller-cone bit (inserts).[38]

Roller-cone bits are made of steel, which requires sufficient hardenability, yield strength, heat treatment, machinability, and impact resistance. Design of the bit has generally four focus areas: geometry and type of cutting structure, hydraulic requirements, material selection, and mechanical operating requirements. The bit design is chosen based on how it will operate and in what conditions it will operate in. Operating factors influencing the bit design are primarily weight on bit, rotary speed and hydraulics. Operating conditions such as formation, depth, drilling fluid, and hole deviation are also important parts considered when designing a bit. The geometry and type of cutting structure is the significant design area of the bit for providing an efficient penetration. Wear-resistance is also important during the selection of geometry and type of cutting structure. Cutter shape and grade is normally differentiated by its placement on the cone for insert teeth. There is a number of available geometries, sizes and grades for cutters to be optimized depending on the cutters location and conditions [4].

I. 2. 2. 5.2 Diamond Bits

Diamond bits can be regarded as fixed-cutter bits, as the bits have no separately moving parts. Diamond is the hardest readily available material, thus using it as material provides superior hardness. Both rotating as one piece and using diamond material gives a long bit life. The diamond bits are mainly used in soft to moderate formation. In hard formations, the bit has limitations regardless of recent developments [5]. Limitations such as low ROP and high wear is also a result for deep continental gas developments [6]. Two categories of diamond bits are currently on the marked: Polycrystalline Diamond Compact Bits and Natural Diamond Bits. The Polycrystalline Diamond Compact (PDC) Bit is the most common diamond bit, relatively equal in popularity as the roller-cone bit. PDC bits uses inexpensive, fabricated diamonds. Their long bit life and capability of maintaining a high ROP has resulted in wide popularity. Fixed-cutters induce a shearing action more effective than the crushing of the inserts or teeth on the cones of the roller-cone bit [7, 10]. A PDC bit is designed based on four considerations: materials, formation properties, hydraulic conditions, and mechanical parameters. There are four different types of blade profiles for a PDC bit:

1. Flat profile – for hard and non-abrasive formations ;
2. Short parabolic – for hard and medium abrasive formations ;
3. Medium parabolic – for medium/hard and abrasive formation ;
4. Long parabolic – for soft and abrasive formations.

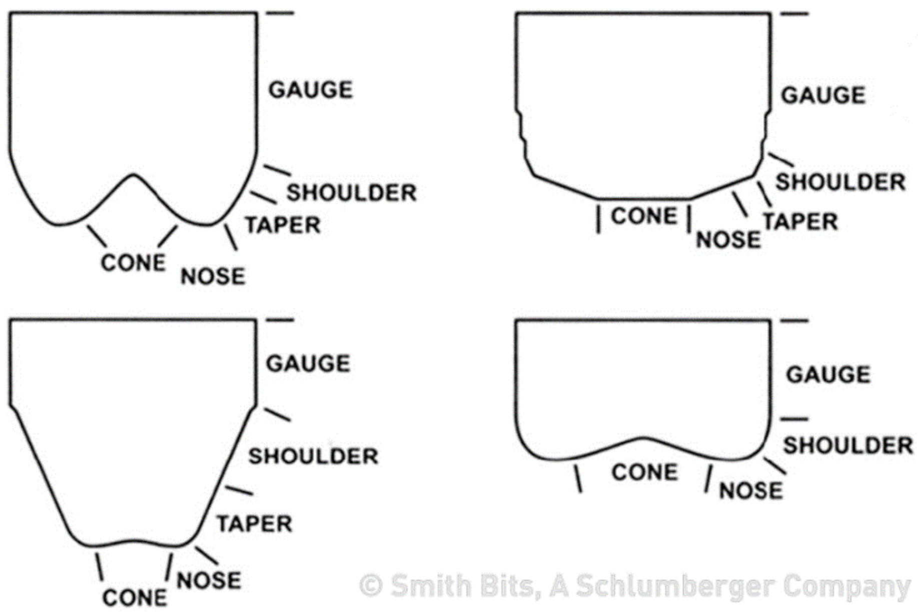

Figure I.3. PDC bit profiles.[39]

Figure I.3.shows various PDC bit profiles, broken into five zones: cone, nose, taper, shoulder, gauge (from center). The profile or shape of the bit is dependent on cutter placements, cutter geometry, cutter density, hydraulics, well geometry, and formation. All elements need to be considered to design a bit capable of high ROP and low bit wear. The shape will have a direct influence on steerability, stability, ROP, durability, fluid circulation, and cutter density [4].

There are many proposed methods for bit selection and often more than one is used before reaching a decision. Bit selection methods include [2] :

1) Cost analysis;
2) Offset well bit record analysis;
3) Offset well log analysis;
4) IADC bit coding;
5) Manufacturer's product guides;
6) Geophysical data analysis;
7) General geological considerations.

I.3. Conclusion

In this chapter, we have mentioned several parameters (variables) of drilling, many references have classified them into two mean categories, dependent and independent. Dependent variables such as ROP, Torque, flush medium pressure, formation pore pressure, and independent variables : RPM, WOB, drilling fluids, hydraulic horse power and bit types. These parameters are keys of successfully drilling operation because of their positive influence on time, cost and security.

In the next chapter we will focus on ROP modeling and the description of the several optimization techniques used in this work.

Chapter II

Rate Of Penetration Modelling And Optimization Techniques

II. 1. Introduction

In this next study we will make a state of the art for different models used in drilling parameters optimization and discus about some models of Warren and specially the model of Bourgoyne & Young in order to obtain optimal value of drilling parameters during drill operation, this could be by one of these important optimization techniques like a Multiple Regression (MR), Particle Swarm Optimization (PSO) and a modified version of Particle Swarm Optimization (M_PSO). So we identify the principle process of each one.

II. 2. Drilling Optimization State Of The Art

In the beginning of the 1900. During conception period the rotary drilling principle developed by the introduction of rotary bits, casing installation and cementing techniques, and developments in drilling fluids. after 20 years During the development period, more powerful rigs, better bits, improved cementing and drilling fluid treatment techniques were introduced which took place following Spindletop.

In 1950s the scientific period took place with expansion in drilling research and most important of all optimized drilling, better understanding of the hydraulic principles, significant improvements in bit technology, improved drilling fluid technology. After 1970s rigs with full automation systems, closed-loop computer systems, with ability to control the drilling variables started to operate in oil and gas fields.

One of the first attempts for the drilling optimization purpose was presented in the study of Graham and Muench in 1959 [11]. They derive empirical mathematical expressions for bit life expectancy and for ROP as a function of depth, RPM, and WOB by evaluated the WOB and RPM combinations.

Maurer in 1962 [12] derived ROP equation that based perfect cleaning condition where all of debris is considered to be removed between tooth impact and that equation is for roller-cone type of bits considering the rock cratering mechanisms.

Galle and Woods in 1963 [13] presented procedures for determining the best combination of constant WOB and RPM ; the best constant weight for any given rotary speed and the best constant rotary speed for any given weight. For each of these procedures ,by considering a combination of bit teeth and bearings life, and drilling rate limits economical bit life ,they presented eight cases. They established empirical equations on drilling rate for the effects of weight on bit, rotary speed, and cutting structure dullness, rate of tooth wear and bearing life.

Eckel in 1968 [14] performed microbit studies expressing the drilling rate exponentially as a function of pseudo bottom hole or near bit-nozzle Reynolds number. The relation introduced was reported to be independent of bit weight and speed .and differential borehole pressure, formation.

One of the most important drilling optimization studies performed was in 1974 by Bourgoyne and Young [15]. In order to obtain the optimized drilling parameters They proposed the use of a linear drilling ROP model and performed multiple regression. They have used minimum cost formula, showing that maximum ROP may coincide with minimum cost approach [3].

Warren in 1987 [4] when using roller cone bits that includes the effect of both the initial chip formation and cuttings removal process he defined a new model to explain rate of penetration. And he developed an initial basic model that will be refined by addition of a more varied set of test conditions every time that new data are added

Miska in 1988 [16] presented three governing differential equation: rate of penetration, rate of teeth wear, and rate of bearings wear.

Maidla and Ohara in 1991 [17] they compared a tested drilling model on offshore drilling data with the Bourgoyne and Young's model. Rommetveit and al. in 2004 [18] developed a new innovative drilling automation and monitoring system. The project was named as drilltronics. in order to optimize the drilling process all available surface and subsurface drilling data was utilized, one of the introduced modules was "bit load optimization module" which modulated rotary speed and WOB and observed the how respective changes effected the ROP [19].

II. 3. Rate Of Penetration Modeling

In order to optimize a system we must have a model. It has been found that drilling rate of penetration could be modelled in real time environment as function of independent drilling variables, the ability to the drilling ROP with respect to depth characteristically with certain parameters for specific formation on real time basis could bring new insights to the nature of drilling operation. Therefore, many researchers have developed models that try to capture the physics of the drilling process for all types of bits. Below, we will describe the several models developed by Warren, and then we will focus on the model developed by Bourgoyne and Young. ROP model, bearing wear model and tooth wear model.

II. 3. 1. Warren models

Warren in 1981 [20], developed an ROP model to relate weight on bit (WOB), revolutions per minute of the bit (RPM), bit diameter, rock strength, and bit type to rate of penetration.

$$R = \left(\frac{aS^2 \mathrm{d_b}^3}{N^b W^2} + \frac{c}{N\,\mathrm{d_b}}\right)^{-1} \quad \text{(II.1)}$$

The negative of this model is not taking into account hydraulic effects, and assumed perfect cleaning

So Warren later by taking into account the hydraulics added to this model, a new imperfect cleaning model incorporating a new term into the ROP equation [21]. This term is a function of the diameter of the bit, density of the fluid, drilling fluid viscosity, and modified jet impact force.

$$R = \left(\frac{aS^2 d_b^{\,3}}{N\,W^2} + \frac{b}{N\,d_b} + \frac{c d_b \rho \mu}{I_m}\right)^{-1} \quad \text{(II.2)}$$

Another time this model was again further developed to take into account roller cone offset and formation ductility which added an additional term to the ROP model
[22], consisting of the cone offset coefficient, rock compressive strength, and rock ductility.

$$R = \left(\frac{aS^2 d_b^{\,3}}{N\,W^2} + \frac{b}{N\,d_b} + \frac{c d_b \rho \mu}{I_m} + \frac{\phi \sigma d_b^{\,2}}{NW\varepsilon}\right)^{-1} \quad \text{(II.3)}$$

A few years later, Warren’s model was modified by adding another term for the chip hold down effect [23]. In the end ,the model now takes into account the position that the fluid is with respect to the mud overbalance [24]. This new term is a function of effective confining pressure, and lithology coefficients [25].

$$R = \left(\left(c_c + a_c\left(P_e\text{-}120\right)^{b_c}\right)\left(\frac{aS^2 d_b^{\,3}}{N\,W^2} + \frac{b}{N\,d_b}\right) + \frac{c d_b \rho \mu}{I_m}\right)^{-1} \quad \text{(II.4)}$$

II. 3. 2. Bourgoyne and Young’s Model

The model proposed by Bourgoyne and Young has been adopted for this study in order to derive equations to perform the ROP estimation using the available input data. This model is considered as one of the complete mathematical drilling models in use of the industry for roller-cone type of bits that’s why we have chosen it in our study.

The drilling model selected for predicting the rate of penetration, ROP, by considering the effect of the various drilling parameters is described as: ROP = $(f_1)(f_2)(f_3)\ldots(f_n)$.
Where $\mathbf{f_1}$, $\mathbf{f_2}$, ..., $\mathbf{f_n}$ represents the functional relations between penetration rate and various drilling variables. Each of these functions contains constants which are shown as $\mathbf{a_1}$ through $\mathbf{a_n}$. Determination of these constants is accomplished by using a multiple regression analysis and genetic algorithm of collected drilling data [26].

$\mathbf{f_1}$ function is defined as the formation strength and it should have the same unit as rate of penetration, which is also known as drillability of the formation.$\mathbf{x_1}$ is the dummy variable which is equal to 1 for every observation of rate of penetration. The effect of formation compaction on rate of penetration is represented with two functions. The primary effect is normal compaction, $\mathbf{f_2}$, it is given with an exponentially decreasing response with increasing depth. In other means this function assumes increasing rock strength with depth due to the normal compaction. The secondary effect of normal compaction is represented by $\mathbf{f_3}$. This function considers the effect of under-compaction in abnormally pressured formation. Within over-pressured formations rate of penetration is going to end up with increased magnitudes. There is an exponential increase in penetration with increased pore pressure gradients $\mathbf{f_4}$ represents the function for pressure differential of bottom hole. The less the pressure differential at the hole bottom, the less the penetration rate to be observed. True vertical depth corresponding magnitudes have been used in calculation of the latter three functions. $\mathbf{f_5}$ represents the function for bit diameter and weight applied onto the bit. Rate of penetration general equation is directly linked with the weight applied over the hole diameter. This function is normalized for 4000lb per bit diameter. $(w/d)_t$ is the threshold bit weight, which is known as the force at which rock fracturing begins. $\mathbf{f_6}$ represents the function for rotary speed. Likewise the direct defined relation of bit weight on penetration rate, the rotary speed is also set to have a direct effect [19].

Note : $f_n = EXP(a_n x_n)$

The drilling model selected for predicting the effect of the various drilling parameters, x_j on penetration rate, *dD/dt, is* given by :

$$dD/dt = EXP\left(a_1 + \sum_{J=2}^{8} a_j x_j\right) \quad \text{(II.5)}$$

Where Exp (z) is used to indicate the exponential function e^z.

The modeling of drilling behavior in a given formation type is accomplished by selecting the constants a_l through a_8 in Eq. II.5, since it is linear.

II. 3. 2. 1. Effect of Formation Strength

The constant a_1 primarily represents the effect of formation strength on penetration rate. It is inversely proportional to the natural logarithm of the square of the drillability strength parameter discussed by Maurer [12]. It also includes the effect on penetration rate of drilling parameters that have not yet been mathematically modeled; for example, the effect of drilled solids.

II. 3. 2. 2. Effect of Compaction

The terms a_2x_2 and a_3x_3 model the effect of compaction on penetration rate. x_2 is defined by :

$$x_2 = 10000.0 - D \cdot \quad \text{(II.6)}$$

And thus assumes an exponential decrease in penetration rate with depth in a normally compacted formation. The exponential nature of the normal compaction trend is indicated by the published micro bit and field data of Murray [27], and also by the field data of Combs [28] (see Figure. II. 1).

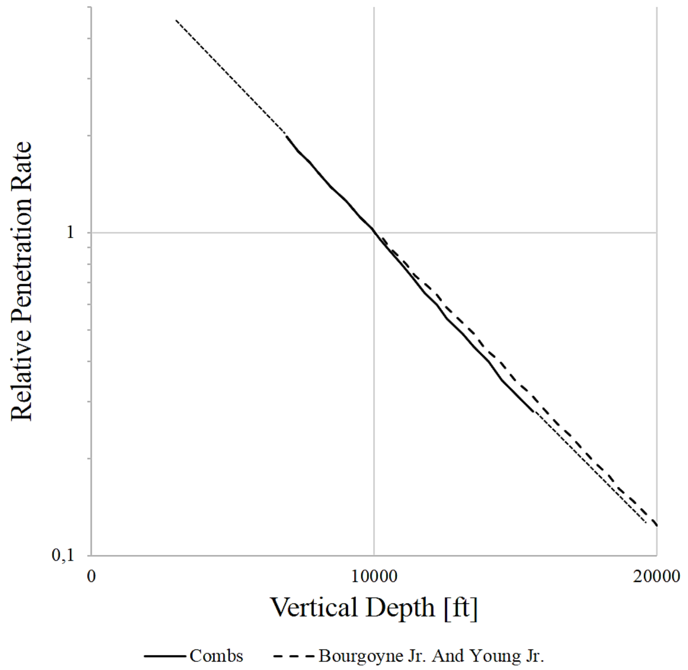

Figure. II. 1. Effect of normal compaction on penetration rate.[15]

Where, x_3 is defined by :

$$X_3=D^{0.69}\left(g_p-9.0\right) \tag{II.7}$$

And thus assumes an exponential increase in penetration rate with pore pressure gradient. The exponential nature of the effect of under compaction on penetration rate is suggested by compaction theory, but has not yet been verified experimentally. Note that the effect of compaction on penetration rate, $e^{a_2x_2+a_3x_3}$, has been normalized to equal 1.0 for a normally compacted formation at 10000ft.

II. 3. 2. 3. Effect of Differential Pressure

The term a_4x_4 models the effect of pressure differential across the hole bottom on penetration rate. x_4 is defined by :

$$x_4=D(g_p-\rho_c) \tag{II.8}$$

And thus assumes an exponential decrease in penetration rate with excess bottom-hole pressure. Field data presented by Vidrine and Benit [29] and by Combs [28], and laboratory data presented by Cunningham and Eenink [30] and by Garnier and van Lingen [31] all indicate an exponential relation between penetration rate and excess bottom-hole pressure up to about1000psi (see Figure. II. 2.). Vidrine and Benit also noted an apparent relation between the effect of differential pressure on penetration rate and bit weight. However, no consistent correlation could be obtained from the available data, so no bit weight term was included in Eq. II.8.

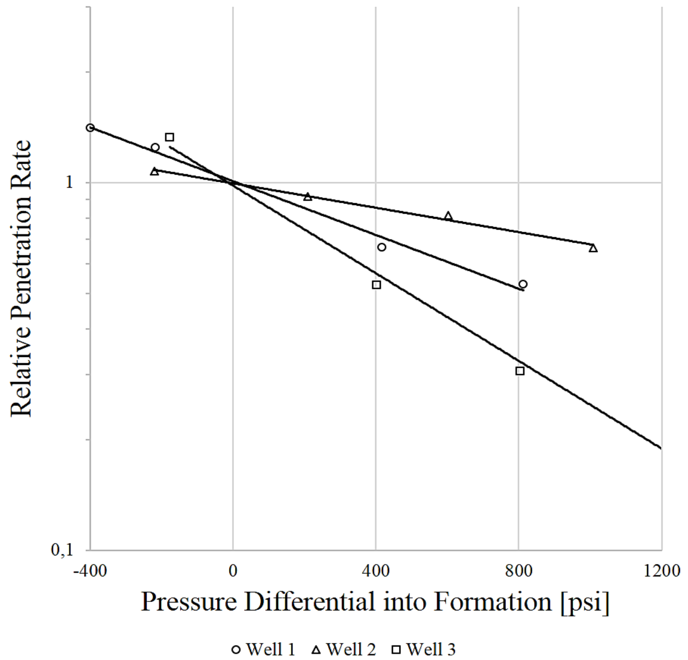

Figure. II. 2. Effect of differential bottom-hole pressure on ROP.[15]

II. 3. 2. 4.Effect Of Bit Diameter And Bit Weight ,W/d

The term a_5x_5 models the effect of bit weight and bit diameter on penetration rate. x_5 is defined by

$$x_5 = \ln \left(\frac{\frac{w}{d} - \left(\frac{w}{d}\right)_t}{4.0 - \left(\frac{w}{d}\right)_t}\right) \quad \text{(II.9)}$$

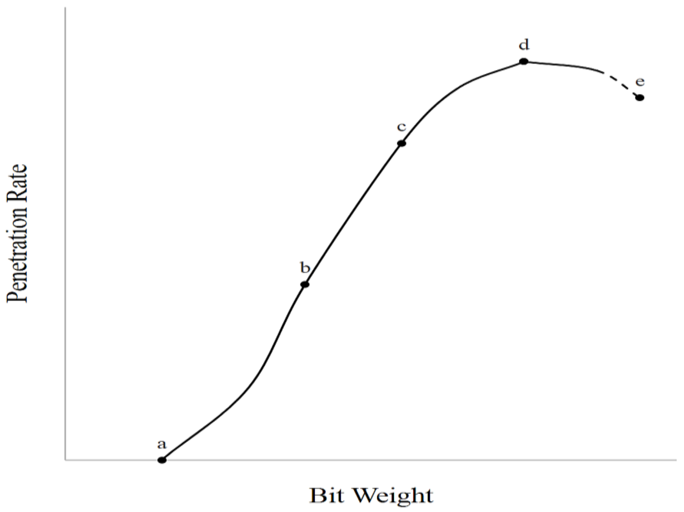

Figure. II. 3. Effect of bit weight on ROP.[40]

and thus assumes that penetration rate is directly proportional to $(W/d)^{a_5}$.Note that the term e^{a5x5} is normalized to equal 1.0 for 4000 lb per inch of bit diameter. The threshold bit weight, $(W/d)_t$, must be estimated with drill-off tests.

II. 3. 2. 5. Effect Of Rotary Speed

The term a_6x_6 represents the effect of rotary speed on penetration rate. x_6 is defined by :

$$x_6 = \ln\left(\frac{N}{100}\right) \tag{II.10}$$

and thus assumes that penetration rate is directly proportional to N^{a_6}.Note that the term e a_6x_6 is normalized to equal 1.0 for 100 rpm. Reported values of the rotary speed exponent range from 0.4 for very hard formations to 0.9 for very soft formations.

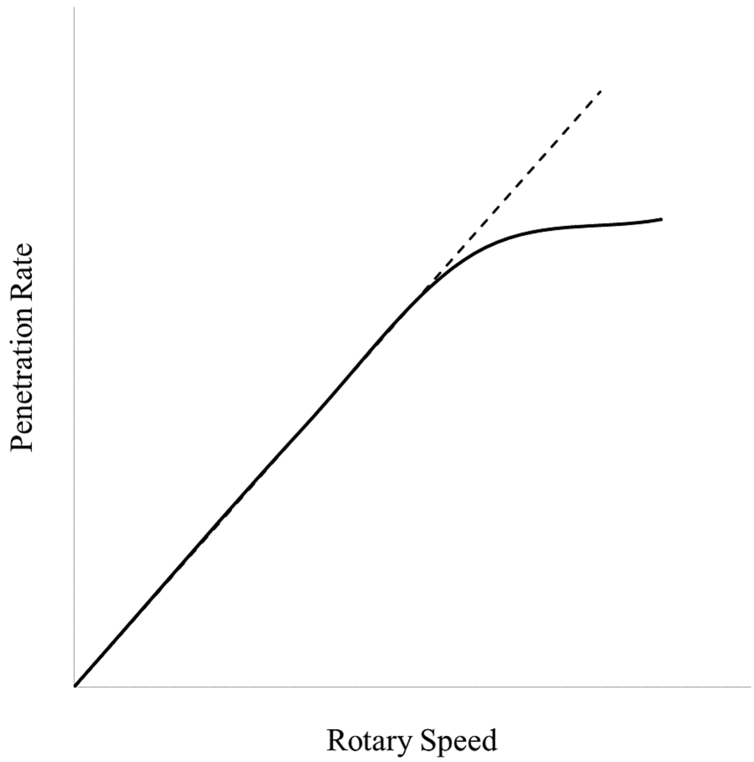

Figure. II. 4. Effect of rotary speed on ROP.[40]

II. 3. 2. 6. Effect of Tooth Wear, h

The term a_7x_7 models the effect of tooth wear on penetration rate. x_7 is defined by :

$$x_7 = -h \tag{II.11}$$

Where h is the fractional tooth height that has been worn away. Previous authors have used more complex expressions to model tooth wear .However those expressions were not ideally suited for the multiple regression analysis procedure used to evaluate the constant a_7 from field data. Figure. II. 5.shows a typical comparison of the previously published relations and

$e^{a_7 x_7}$. The value of a_7 depends primarily on the bit type and, to a lesser extent, the formation type. When carbide insert bits are used, penetration rate does not vary significantly with tooth wear.

Thus the tooth wear exponent, a_7, is assumed to be zero, and the remaining exponents, a_1 through a_6 and a_8, are regressed. Note that $e^{a_7 x_7}$ is 1 when either h or a_7 is zero.

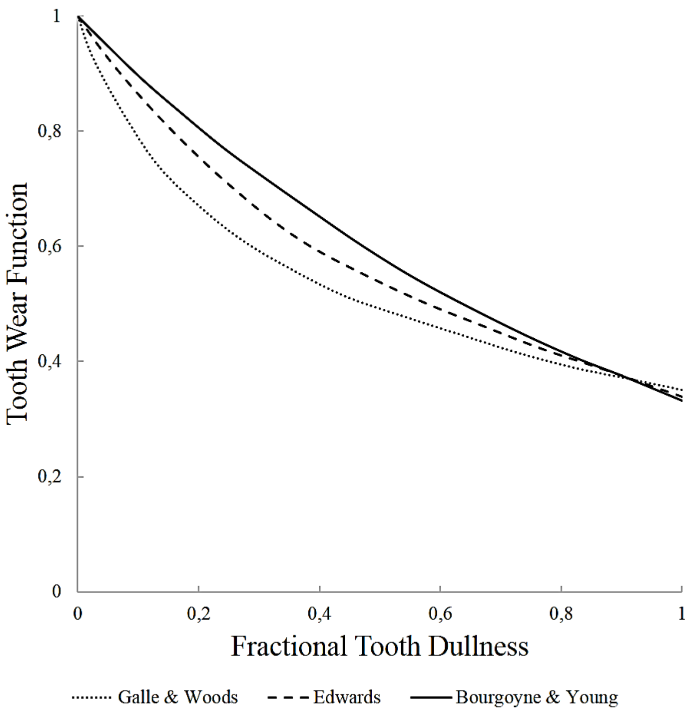

Figure. II. 5. effect of tooth wear on ROP (chipping-type tooth wear).[15]

II. 3. 2. 7. Effect of Bit Hydraulic

The term $a_8 x_8$ models the effect of bit hydraulics on penetration rate. Where, x_8 is defined by :

$$x_8 = \frac{\rho q}{350 \mu d_n} \qquad \text{(II.12)}$$

And is based on micro bit experiments performed by Eckel [14]. Which found that penetration rate was proportional to a Reynolds number group $\left(\frac{\rho q}{\mu d_n}\right)$. Since μ the apparent viscosity at 10000 sec^{-1}, is not routinely measured and recorded it must be estimated using the relation [12].

$$\mu = {\mu_p + \tau_y}/{20} \qquad \text{(II.13)}$$

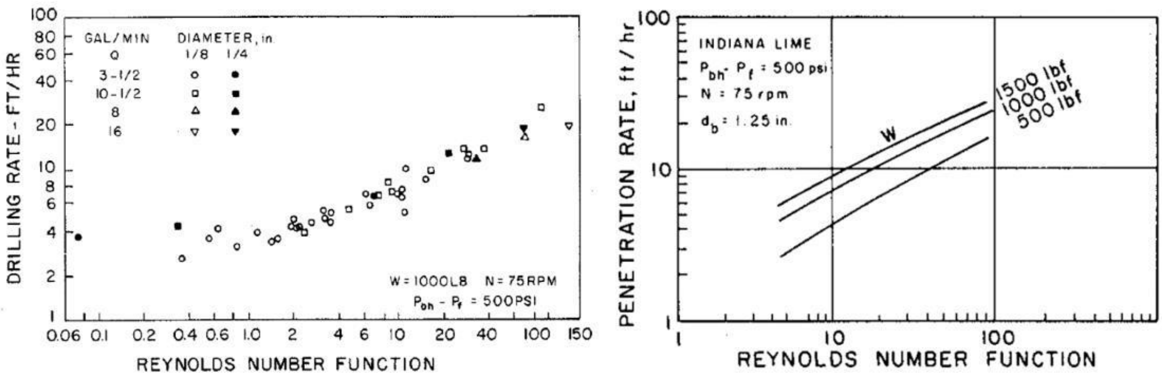

Figure. II. 6. ROP as a function of bit Reynolds number.[40]

II. 4. Tooth Wear Model

Instantaneous tooth wear could be calculated by means of finding the abrasiveness constant for a known bit record in the subject formation. Formation abrasiveness constant is a parameter when reached the bit in use will become inefficient to drill ahead. The instantaneous tooth wear equation is given in terms of the relation in Eq. II.14. It has been defined by the combination of tooth geometry, bit weight and rotary speed.

$$\frac{dh}{dt} = \frac{1}{\tau_H}\left(\frac{N}{60}\right)^{H1}\left[\frac{\left(\frac{W}{d_b}\right)_m - 4}{\left(\frac{W}{d_b}\right)_m - \left(\frac{W}{d_b}\right)}\right]\left(\frac{1+\frac{H_2}{2}}{1+H_2 h}\right) \qquad \text{(II.14)}$$

Where, τ_H is formation abrasiveness constant, hours, hf fractional tooth wear, H_1 and H_2 are tooth geometry constants. The recommended tooth-wear parameter constants for roller cone cutter bits are as given in Table. II. 1. These parameters should be based on general field experience and drilling practices observed in field applications. A particular study could be conducted to update these parameters [12].

Table. II. 1. Recommended tooth-wear parameters for roller cone bits.

Bit Class	H_1	H_2	H_3	$(W/D)_{max}$
1 – 1 to 1 – 2	1.90	7.0	1.00	7.0
1 – 3 to 1 – 4	1.84	6.0	0.80	8.0
2 – 1 to 2 – 2	1.80	5.0	0.60	8.5
2 – 3	1.76	4.0	0.48	9.0
3 – 1	1.70	3.0	0.36	10.0
3 – 2	1.65	2.0	0.26	10.0
3 – 3	1.60	2.0	0.20	10.0
4 – 1	1.50	2.0	0.18	10.0

Note that the tooth wear formula given above is going to be normalized at 60 rpm of bit rotation speed and a constant bit weight of 4,000 lbf/in. The normalization magnitudes are selected accordingly for the specific conditions in the scope of this study.

In order to be able to calculate the formation abrasiveness constant a tooth wear parameter is required to be introduced, which is basically the reciprocal of the some of the given terms in the composite tooth wear Eq. II.10. The tooth wear parameter is symbolized as J_2, Eq.II.15.

$$J_2=\left[\frac{\left(\frac{W}{d_b}\right)_m-\left(\frac{W}{d_b}\right)}{\left(\frac{W}{d_b}\right)_m-4}\right]\left(\frac{60}{N}\right)^{H1}\left(\frac{1}{1+\frac{H_2}{2}}\right) \tag{II.15}$$

If both sides of Eq. II.14. is written in a terms of J_2, the following relation is achieved when integrated with Eq. II.15:

$$\int_0^{t_b} dt = J_2\tau_H\int_0^{h_f}(1+H_2h)dh \tag{II.16}$$

When equation II.16 is integrated, the following relation yields, Eq. II.17.

$$t_b=J_2\,\tau_H\left(h_f+H_2\frac{h_f^2}{2}\right) \tag{II.17}$$

The formation abrasiveness constant could then be written as given in Eq. II.18.

$$\tau_H=\frac{t_b}{J_2\left(h_f+H_2\frac{h_f^2}{2}\right)} \tag{II.18}$$

Once formation abrasiveness constant is known, a t_b, time of bit rotation as a function of predefined constants and tooth wear as a fraction, could be calculated, solving Eq. II.17.

An arbitrary h_f value could first be selected and until a tooth wear fraction is iterated, the selection of h_f should be determined, provided that the bit rotating time that is back calculated equal to the actual bit rotation time that is available in the database [30].

II. 5. Bearing wear model

Bearing wear was estimated by using the following equation :

$$\frac{dB}{dt}=\frac{1}{\tau_B}\left[\frac{N}{100}\right]\left[\frac{W}{4d}\right]^b \tag{II.19}$$

Where the constant b depends upon bearing type and mud type and the bearing constant τ_B is calculated from a dull bit grading.

II. 6. Optimization Techniques

The word optimum, meaning “best”, is synonymous with “most” or “maximum” in one case and with “least” or “minimum” in another. The term, optimize, means to achieve the optimum, and optimization refers to the act of optimizing. Thus, optimization theory encompasses the quantitative study of optimal and methods for finding them. There is no such thing as a "true" optimum drilling program, invariably compromises must be made because of limitations beyond our control that result in something less than optimum.

In general terms, an optimization problem consists in selecting from among a set of feasible alternatives, one which is optimal according to a given criterion. The optimization term in this thesis are considered as the drilling procedure, which the best constant weight and rotary speed together with another controllable drilling parameters yield the penetration rate with the minimum drilling cost.

II. 6. 1. Multiple Regression Method

Eq. II.6 through Eq. II.12 define the general functional relations between penetration rate and the other drilling variables, but the constants a_2 through a_8 must be determined before these equations can be applied. The constants a_2 through a_8 are determined through a multiple regression analysis of detailed drilling data taken over short depth intervals. The idea of using a regression analysis of past drilling data to evaluate constants in a drilling rate equation is not new. For example, it was proposed by Graham and Muench in 1959 [11] in one of the first papers on drilling optimization. This approach was used by Combs in his work on the detection of pore pressure from drilling data. However, much of the past work in this area has been hampered by the difficulty in obtaining large volumes of accurate field data and because the effect of many of the drilling parameters discussed above were ignored. Recent developments in on site well monitoring have made it possible to routinely regress the more complex drilling equation Eq. II.5.

A derivation of the multiple regression-analysis procedure is presented in detail in the section (II. 6. 1. 1).

Theoretically, only eight data points are required to solve for the eight unknowns a_1 through a_8. However, in practice this is true only if Eq. II.5 models the rotary drilling process with 100-percent accuracy. Needless to say, it never happens. When only a few data points are used in the analysis of field data, even negative values are sometimes calculated for one or more of the regression constants. A sensitivity study of the multiple regression-analysis procedure indicated that the number of data points required to give meaningful results depends not only on the accuracy of Eq. II.5 but also on the range of values of the drilling parameters x_2 through x_8. Table. II. 2. summarizes the recommended minimum ranges for each of the drilling parameters and the recommended minimum number of data points to be used in the analysis. When any of the drilling parameters, x_j, have been held essentially constant through the interval analyzed, a value for the corresponding regression constant, a_j , should be estimated from past studies and the regression analysis should be carried out for the remaining regression constants. As the number of drilling parameters included in the analysis are decreased, the minimum number of data points required to calculate the remaining regression constants is also decreased (see Table. II. 2). In many applications, data from more than one well had to be combined in order to calculate all eight regression constants.

Table. II. 2. Recommended minimum data ranges for regression analysis

Parameter	Minimum range	Number of Parameters	Minimum Number of Points
x_2	2.000	8	30
x_3	15.000	7	25
x_4	15.000	6	20
x_5	0.40	5	15
x_6	0.50	4	10
x_7	0.20	3	7
x_8	0.50	2	4

For example, the first of the eight equations defined in the section (II. 6. 1. 1) is given by Taking the logarithm of both sides of (Eq. II.5) yields [15].

$$na_1 + a_2 \Sigma x_2 + a_3 \Sigma x_3 + a_4 \Sigma x_4 + a_5 \Sigma x_5 + a_6 \Sigma x_6 + a_7 \Sigma x_7 + a_8 \Sigma x_8 = \Sigma \ln\frac{dD}{dt} \quad (II.20)$$

II. 6. 1. 1. Multiple Regression Procedure

The equation of the proposed model is :

$$ROP = \frac{dD}{dt} = Exp\left(a_1 + \sum_{j=2}^{8} a_j x_j\right) \quad (II.21)$$

Taking the logarithm of both sides of the above equation yields :

$$ln\frac{dD}{dt} = \left(a_1 + \sum_{j=2}^{8} a_j x_j\right) \quad (II.22)$$

If the residual error of the i^{th} data point, r_i, is defined by :

$$r_i = \left(a_1 + \sum_{j=2}^{8} a_j x_j\right) - ln\frac{dD}{dt} \quad (II.23)$$

In order to minimize the square of the residuals $\sum_{i=1}^{n} r_i^2$, the constants from a_1 to a_8 should be determined properly by taking derivative from the square of the residuals $\sum_{i=1}^{n} r_i^2$.

$$\frac{\partial(\sum_{i=1}^{n} r_i^2)}{\partial a_j} = \sum_{i=1}^{n} 2r_i \frac{\partial r_i}{\partial a_j} = \sum_{i=1}^{n} 2r_i x_j \quad (II.24)$$

For j = 1, 2, 3, ...,8. The constants a_1 through a_8 can be obtained by simultaneously solving the system of equations obtained by expanding $\sum_{i=1}^{n} r_i x_j$ for j = 1, 2, 3,............, 8. The expansion of $\sum_{i=1}^{n} r_i x_j$ yields:

$$a_1 n + a_2 \sum x_2 + a_3 \sum x_3 + \cdots \ldots\ldots\ldots\ldots\ldots\ldots. a_8 \sum x_8 = \sum ln \frac{dD}{dt}$$

$$a_1 \sum x_2 + a_2 \sum x_2^2 + a_3 \sum x_2 x_3 + \cdots \ldots\ldots\ldots\ldots\ldots\ldots\ldots. a_8 \sum x_2 x_8 = \sum x_2 ln \frac{dD}{dt}$$

$$a_1 \sum x_3 + a_2 \sum x_3 x_2 + a_3 \sum x_3^2 + \cdots \ldots\ldots\ldots\ldots\ldots\ldots\ldots. a_8 \sum x_3 x_8 = \sum x_3 ln \frac{dD}{dt}$$

$$\vdots$$

$$a_1 \sum x_8 + a_2 \sum x_8 x_2 + a_3 \sum x_8 x_3 + \cdots \ldots\ldots\ldots\ldots\ldots\ldots\ldots. a_8 \sum x_8^2 = \sum x_8 ln \frac{dD}{dt}$$

After substituting the appropriate functions into Eq. II.6 and Eq. II.12 and by using multiple regression-analysis, in order to calculate the constants a_1 through a_8, the following linear equation system can be obtained by matrix :

$$\begin{bmatrix} n & \sum_{i=1}^{n} x_{i2} & \sum_{i=1}^{n} x_{i3} & \cdots & \sum_{i=1}^{n} x_{i8} \\ \sum_{i=1}^{n} x_{i2} & \sum_{i=1}^{n} x_{i2}^2 & \sum_{i=1}^{n} x_{i2}x_{i3} & \ldots & \sum_{i=1}^{n} x_{i2}x_{i8} \\ \sum_{i=1}^{n} x_{i3} & \sum_{i=1}^{n} x_{i3}x_{i2} & \sum_{i=1}^{n} x_{i3}^2 & \cdots & \sum_{i=1}^{n} x_{i3}x_{i8} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \sum_{i=1}^{n} x_{i8} & \sum_{i=1}^{n} x_{i8}x_{i2} & \sum_{i=1}^{n} x_{i8}x_{i3} & \ldots & \sum_{i=1}^{n} x_{i8}^2 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_8 \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} \mathrm{In}\frac{dD}{dt} \\ \sum_{i=1}^{n} x_{i2}\mathrm{In}\frac{dD}{dt} \\ \sum_{i=1}^{n} x_{i3}\mathrm{In}\frac{dD}{dt} \\ \vdots \\ \sum_{i=1}^{n} x_{i8}\mathrm{In}\frac{dD}{dt} \end{bmatrix}$$

II. 6. 2. Metaheuristic Optimization Technique

For every optimization problem there exists a set of possible solutions which is called the solution space. A solution can be seen as an input for a known model. The model also called objective function that calculates an output for a given input. The output is considered the quality of a solution. A globally optimal solution of an optimization problem is found, if there exists no other solution which evaluates to a better quality. The best quality can be either the highest or the lowest, depending if it is a maximization or a minimization problem. The difficulty of a problem depends, among other factors, on its complexity. Linear optimization problems are problems where the objective function can be described as a linear function. These problems are solvable in polynomial time. There are algorithms such as the Simplex method developed by George Danzig which can solve linear problems efficiently. Non linear or discrete optimization problems are much harder to solve efficiently, except for some special cases. In the general case, no algorithm is known until today which can solve such problems exactly in polynomial time with a deterministic turing machine. To search the solution space of combinatorial problems for an optimal solution, a backtracking algorithm might be used which just enumerates all possible solutions. The best way to tackle large solution spaces of non linear optimization problems is to start with a constructed or randomly created solution and iteratively improve it. To improve the solution, problem independent heuristics also called metaheuristics can be applied. Such metaheuristics are usually based on the quality of solutions, which allows the abstraction of the algorithm from the underlying problem. Of course, the evaluations of a solution as well as manipulating a solution are still problem-specific operations, but the algorithmic steps can be abstracted from the problem.

Metaheuristic optimization techniques typically consist of some stochastic steps and consequently their results underlie a stochastic distribution. It is not guaranteed that a globally optimal solution is found. shows the classification of optimization techniques in a wide context, yet the following sections will describe only metaheuristic methods in more detail, since they are most relevant for this thesis. Metaheuristic algorithms can be categorized into trajectory based and population based metaheuristics [32].

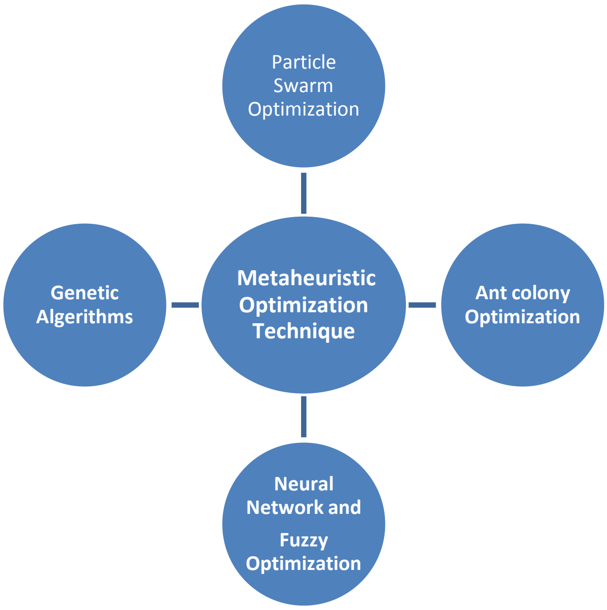

Figure. II. 7. Some of modern or nontraditional optimization techniques.

II. 6. 2. 1. Particle Swarm Optimization

Particle swarm optimization is a powerful and widely used optimization technique that covers a wide range of research areas. PSO is one of the most popular nature inspired metaheuristic optimization algorithm developed by Kennedy and Eberhart in 1995, and it was modelled to mimic how certain groups of animals move in the natural world : such as a school of fish, flock of birds, etc. For this algorithm, a group of animals is referred to as a "swarm" and each animal inside the group is considered a "particle". This algorithm uses a combination of information from the group as a whole and the information from each individual particle to search the space for the optimal solution. For each individual particle, the PSO algorithm uses the current "velocity" of each particle, along with the information from the best values found from both the individual particle and the best global from the swarm, to move the particle around the space.

PSO starts initially by randomly selecting values for all dimensions corresponding to each particle inside a swarm. The swarm is evaluated and the new velocity of each particle and position are updated. The velocity and position equations [33] are shown below, where :

- V_i represents the velocity of a particle;
- P_i represents the previous best of the current particle;
- X_i represents the current position of the particle;
- P_g represents the global previous best from the entire swarm;

Each one of these variables is a vector of d in length, representing the number of dimensions in the problem. The other variables are :

- ϕ_1 and ϕ_2 which are considered acceleration constants, respectively, 1 and 2.
- ω which is a weighted inertia constant [0.4 to 1.4].
- r_1 and r_2, are random values that are taken from the uniform distribution [0, 1].

$$v_i^{k+1} \leftarrow wv_i^k + \phi_1 r_1^k\left(p_i^k - x_i^k\right) + \phi_2 r_2^k\left(p_g^k - x_i^k\right) \quad \text{(II.25)}$$

$$x_i^{k+1} \leftarrow x_i^k + v_i^{k+1} \quad \text{(II.26)}$$

The velocity equation, Eq. II.25, above is comprised of three components, social, cognitive and momentum [34]. The social component, ϕ_2, forces the particles towards the global best solution found; the cognitive component, ϕ_1, forces the particles back towards the previous best solution found by each particle; and the momentum component, ω, forces the particle to continue on the current trajectory. Al three components help the particle swarm optimization technique traverse the exploration/exploitation dilemma that surrounds all optimization problems.

In Our study The PSO algorithm uses the ROP model by having the particles search the solution space and converge on the optimal WOB, RPM, bit selection, and pull depth. The inputs for this algorithm include: rock strength, WOB and RPM operational ranges, and available bit selections [35].

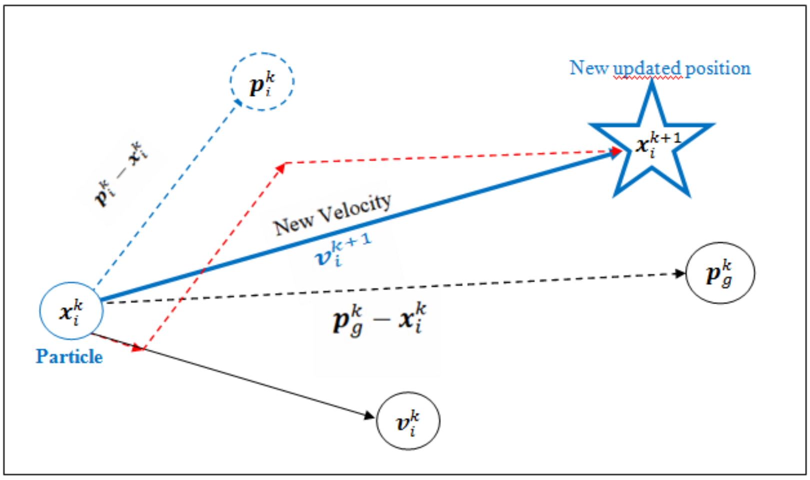

Figure. II. 8. Simple example of how particles move.

II. 6. 2. 2. Modified Particle Swarm Optimization

In standard PSO, because the particle has the ability to know the best position of the group particles have been searched, we need one particle to find the global best position rather than all particles to find it, and other particles should search more domains to make sure the best position is global best position not the local one.

The modification in PSO consists of three categories: extension of field searching space, adjustment the parameters, and hybrid with another techniques. The procedure of modified PSO is as following:

1) Initialize the position and velocity of each particle;

2) Calculate the fitness of each particle;

3) Concern the particle with the biggest fitness value, reinitialize its position; and evaluate the particle with the smallest fitness value whether its new position is acceptable, if the answer is yes, update its position, otherwise, a new position is assigned to the particle randomly in its neighborhood with radius r; then renew the position and velocity of other particles according to Eq II.25.and II.26;

4) For each particle, compare its current fitness value with the fitness of its *pbest*, if the current value is better, then update *pbest* and its fitness value;

5) Determine the best particle of group with the best fitness value, if the current fitness value is better than the fitness value of *gbest*, then update the *gbest* and its fitness value with the position;

6) Check the finalizing criterion, if it has been satisfied, quit the iteration; and return to step 3. [36].

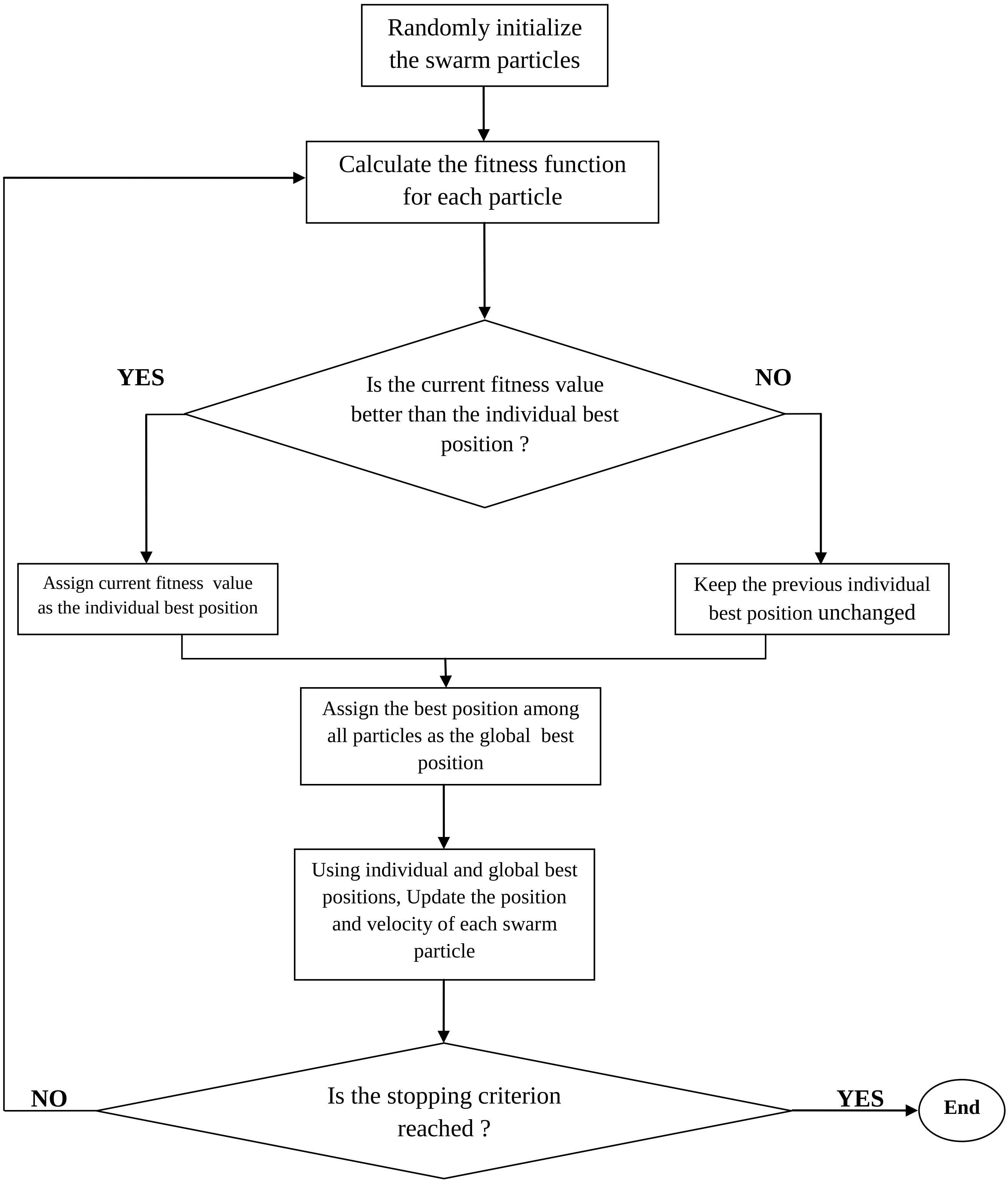

Figure. II. 9. Flowchart of the standard PSO algorithm.

II. 7. Drilling cost

Drilling cost per foot equation is as defined in Eq II.18. It has been defined to be a function of daily rig rate, bit cost, and timing required in the course of the bit runs. This equation is known to be the mostly applied drilling cost formula in the literature.

$$C_f = \frac{C_b + C_r(t_t + t_c + t_b)}{\Delta F} \quad \text{(II.27)}$$

Where, C_f is the cost per drilled interval, C_r is the daily rig rate, C_b is the bit cost, t_t round trip time, t_c connection time, hr, and t_b bit drilling time. ΔF is the footage drilled with the bit in the use, ft. Bit drilling time, t_b, (with respective to tooth wear), Eq II.16.and drilling interval, ΔF, (with respect to general drilling functions and tooth wear), the equation:

$$dF = \left(j_1 e^{(-a_7 h)}\right) j_2 \tau_H (1 + H_2 h) dh$$

When inserted into equation : $f_2 = e^{a_2 x_2}$, after modifying the same, the cost per foot equation could be redefined.

$$C_f = \frac{C_r}{\left(J_1 e^{(-a.h)}\right) J_2 \tau_H (1 + H_2 h) dh} \left(\frac{C_b}{C_r} + t_t + t_c + J_2 \tau_H \int_0^{h_f} (1 + H_2 h) dh\right) \quad \text{(II.28)}$$

Calculus states that any differentiable equation when differentiated to the first order it would have been maximized. This statement could be written as below in order to optimize the drilling cost with respect to WOB.

$$f'(C_f) = \frac{\partial (C_f)}{\partial \left(\frac{W}{d_b}\right)} = 0 \quad \text{(II.29)}$$

The second derivative of the Eq II.29.would define whether the response of the function is a relative minimum or a maximum [37], such as :

$f''(C_f) > 0$, then $f(C_f)$ is a relative minimum

$f''(C_f) < 0$, then $f(C_f)$ is a relative maximum

When Eq II.28 is re-arranged, one gets the following :

$$C_f = \frac{Cr}{e^{(-a.h)}(1 + H_2 h) dh} \left(\frac{\frac{C_b}{C_r} + t_t + t_c}{J_1 J_2 \tau H} + \frac{\int_0^{h_f} (1 + H_2 h) dh}{J_1} \right) \quad \text{(II.30)}$$

The detailed drilling cost equation could be written in a form including the equivalent forms of composite drilling, J_1, and tooth wear, J_2 parameters respectively from the equations:

$$j_2 = e^{a_1} e^{a_2 x_2} e^{a_3 x_3} e^{a_4 x_4} e^{a_5 \ln \left(\frac{\frac{W}{d_b} - \left(\frac{W}{d}\right) t}{4.0 - \left(\frac{W}{d_b}\right) t} \right)} e^{a_6 x_6} e^{a_8 x_8} \quad \text{(II.31)}$$

and Eq II.15 :

$$C_f = \frac{Cr}{e^{(-a.h)}(1 + H_2 h) dh} \left(\frac{\frac{C_b}{C_r} + t_t + t_c}{XY} + \frac{\int_0^{h_f} (1 + H_2 h) dh}{Z} \right) \quad \text{(II.32)}$$

Where ;

$$X = \left(e^{a_1} e^{a_2 X_2} e^{a_3 X_3} e^{a_4 X_4} e^{a_5 ln\left(\frac{A}{4-\left(\frac{W}{db}\right)t}\right)} e^{a_6 X_6} e^{a_8 X_8} \right) \quad (II.33)$$

$$A = \frac{W}{d_b} - \left(\frac{W}{d_b}\right)_t \quad (II.34)$$

$$Y = B \left(\frac{60}{N}\right)^{H1} \left(\frac{1}{1+\frac{H_2}{2}}\right) \tau_H \quad (II.35)$$

$$B = \left[\frac{\left(\frac{W}{d_b}\right)_m - \left(\frac{W}{d_b}\right)}{\left(\frac{W}{d_b}\right)_m - 4}\right] \quad (II.36)$$

$$Z = \left(e^{a_1} e^{a_2 X_2} e^{a_3 X_3} e^{a_4 X_4} e^{a_5 ln\left(\frac{\frac{W}{d_b} - \left(\frac{W}{d_b}\right)_t}{4-\left(\frac{W}{d_b}\right)_t}\right)} e^{a_6 X_6} e^{a_8 X_8} \right) \quad (II.37)$$

Differentiating Eq II. 32. to the first order and equalizing to zero with respect to WOB independent parameter would result in drilling cost optimization for WOB parameter

$$f'(C_f) = \frac{\partial(C_f)}{\partial\left(\frac{W}{d_b}\right)} = \frac{C_r}{e^{(-a.h)} U dh} \left[-\frac{N}{\xi}\frac{1}{\psi}\frac{1}{[B]}\frac{a_5}{(A)} + \frac{N}{\xi}\frac{1}{\psi}\frac{1}{\left(\left(\frac{W}{d_b}\right)_m - \left(\frac{W}{d_b}\right)\right)^2}\left(4 - \left(\frac{W}{d_b}\right)_t\right) - \frac{\int_0^{h_f} U dh}{\theta}\frac{1}{\psi}\frac{a_5}{(A)} \right] \quad (II.38)$$

Where;

$$U = (1 + H_2 h) \quad (II.39)$$

$$N = \left[\frac{C_b}{C_r} + t_t + t_c\right] \quad (II.40)$$

$$\xi = (e^{a_1} e^{a_2 X_2} e^{a_3 X_3} e^{a_4 X_4} e^{a_6 X_6} e^{a_8 X_8}) \left(\left(\frac{60}{N}\right)^{H1}\right) \left(\left(\frac{1}{1+\frac{H2}{2}}\right) \tau_H\right) \quad (II.41)$$

$$\psi = e^{a_5 \mathrm{Ln}\left(\frac{\frac{W}{d_b} - \left(\frac{W}{d_b}\right)_t}{4-\left(\frac{W}{d_b}\right)}\right)} \quad (II.42)$$

$$\theta = e^{a_1} e^{a_2 X_2} e^{a_3 X_3} e^{a_4 X_4} e^{a_6 X_6} e^{a_8 X_8} \quad (II.43)$$

Rearranging Eq II.38 with a simplified evaluation :

$$\frac{\partial(C_f)}{\partial\left(\frac{W}{d_b}\right)} = \left[-\frac{N}{\left(\left(\frac{60}{N}\right)^{H1}\right)\left(\left(\frac{1}{1+\frac{H_2}{2}}\right)\tau_H\right)} \frac{1}{[J_2]} \frac{a_5}{\left(\left(\frac{W}{d_b}\right) - \left(\frac{W}{d_b}\right)_t\right)} + \frac{N}{\left(\left(\frac{60}{N}\right)^{H1}\right)\left(\left(\frac{1}{1+\frac{H_2}{2}}\right)\tau_H\right)} \frac{1}{\left(\left(\frac{W}{d_b}\right)_m - \left(\frac{W}{d_b}\right)\right)^2}\left(4 - \left(\frac{W}{d_b}\right)_t\right) - \int_0^{h_f} U dh \frac{a_5}{\left(\left(\frac{W}{d_b}\right) - \left(\frac{W}{d_b}\right)_t\right)} \right] = 0 \quad (II.44)$$

Using the distribute law of mathematics, equation above can be re-written,

$$\frac{\partial(C_f)}{\partial\left(\frac{W}{d_b}\right)} = \left[\frac{\left[\frac{C_b}{C_r} + t_t + t_c\right]}{\left(\left(\frac{60}{N}\right)^{H1}\right)\left(\left(\frac{1}{1+\frac{H_2}{2}}\right)\tau_H\right)} \left[a_5 - \frac{\left(\left(\frac{W}{d_b}\right) - \left(\frac{W}{d_b}\right)_t\right)\left(4 - \left(\frac{W}{d_b}\right)_t\right)}{\left(\left(\frac{W}{d_b}\right)_m - \left(\frac{W}{d_b}\right)\right)^2} \right] + a_5 J_2 \tau_H \int_0^{h_f} (1 + H_2 h) dh = 0 \right] \quad (II.45)$$

Simplifying equation above results in having the relation below,

$$\left[\frac{C_{\mathrm{b}}}{C_{\mathrm{r}}}+t_{\mathrm{t}}+t_{\mathrm{c}}\right]\left[a_5\text{-}\frac{\left(\left(\frac{W}{d_{\mathrm{b}}}\right)-\left(\frac{W}{d_{\mathrm{b}}}\right)_{\mathrm{t}}\right)}{\left(\left(\frac{W}{d_{\mathrm{b}}}\right)_{\mathrm{m}}-\left(\frac{W}{d_{\mathrm{b}}}\right)\right)}\right]+\ a_5\mathrm{J}_2\tau_{\mathrm{H}}\int_0^{h_{\mathrm{f}}}(1+H_2h)dh=0 \qquad \text{(II.46)}$$

Eq II.30 should also be differentiated as a function of rotary speed, N.

$$f'(C_{\mathrm{f}})=\frac{\partial(C_{\mathrm{f}})}{\partial(N)}=0 \qquad \text{(II.47)}$$

The solution of the respective derivative for Eq II.47. is as give,

$$\left[\frac{C_{\mathrm{b}}}{C_{\mathrm{r}}}+t_{\mathrm{t}}+t_{\mathrm{c}}\right]\left(1-\frac{H_1}{a_6}\right)+\ \mathrm{J}_2\tau_{\mathrm{H}}\int_0^{h_{\mathrm{f}}}(1+H_2h)dh=0 \qquad \text{(II.48)}$$

The optimum equation for the weight for each diameter of bit size is as given below, Eq II.49 .

$$\left[\frac{W}{d_{\mathrm{b}}}\right]_{\mathrm{opt}}=\frac{a_5H_1\left(\frac{W}{d_{\mathrm{b}}}\right)_{\mathrm{max}}-a_6\left(\frac{W}{d_{\mathrm{b}}}\right)_{\mathrm{t}}}{a_5\mathrm{H}_1+a_6} \qquad \text{(II.49)}$$

In a similar manner the optimum bit speed can be expressed in the following form Eq. II.50 after being obtained using the Eq II.21.

$$[N]_{\mathrm{opt}}=60\left[\frac{\tau_{\mathrm{H}}}{t_{\mathrm{b}}}\frac{\left(\frac{W}{d_{\mathrm{b}}}\right)_{\mathrm{max}}-\left(\frac{W}{d_{\mathrm{b}}}\right)_{\mathrm{opt}}}{\left(\frac{W}{d_{\mathrm{b}}}\right)_{\mathrm{max}}-4}\right] \qquad \text{(II.50)}$$

II. 8. Conclusion

In this chapter we talked about ROP modelling and their different estimation during the years, so we defined the importance of them, and we have detailed in the model of Bourgoyne and Young which we is the selected one in our study. Some several techniques of optimization (MR, PSO and MPSO) are explained with their different procedure and characteristics have been proposed to optimize the different drilling parameters.

In the next chapter we will calculate the model constant and the optimal drilling parameters with the aforementioned optimization techniques by using MATLAB programming language.

Chapter III

Results Analysis & Discussion

III. 1. Introduction

In this final chapter we will describe our results after using the concept of the following methods : Multiple Regression, Particle Swarm Optimization and Modified Particle Swarm Optimization in order to obtain the best optimal solution for the objective function (ROP value). In the metaheuristic techniques we will make a test for three different swarm populations with a fixed number of iterations (300). Then we will compare the techniques results by using different approximation errors (relative error, absolute error and the Root Mean Square Error).

III. 2. Experimental Data

The field data are taken from an offshore Louisiana well that are shown in Table. III. 1 [15].

Table. III. 1. Field data taken in shale, offshore Louisiana area.

Data entry	Depth (ft)	Bit Number	Driling rate (ft/hr)	Bit weight (1000lb/in	Rotary speed (rpm)	Tooth Wear	Reynols number Function	ECD (lb/gal)	Pore Gradient (lp/gal)
1	9515	7	23	2.58	113	0.77	0.964	9.5	9.0
2	9830	8	22	1.15	126	0.38	0.964	9.5	9.0
3	10130	9	14	0.81	129	0.74	0.827	9.6	9.0
4	10250	11	10	0.95	87	0.15	0.976	9.7	9.0
5	10390	12	16	1.02	78	0.24	0.984	9.7	9.0
6	10500		19	1.69	81	0.61	0.984	9.7	9.1
7	10575		13	1.56	81	0.73	0.984	9.7	9.2
8	10840	13	16.6	1.63	67	0.38	0.932	9.8	9.3
9	10960		15.9	1.83	65	0.57	0.878	9.8	9.4
10	11060		15.7	2.03	69	0.72	0.878	9.8	9.5
11	11475	15	14	1.69	77	0.20	0.887	10.3	9.5
12	11775	18	13.5	2.31	58	0.12	0.852	11.8	10.1
13	11940	21	6.2	2.26	67	0.2	0.976	15.3	12.4
14	12070	22	9.6	2.07	84	0.06	0.993	15.7	13.0
15	12315		15.5	3.11	69	0.40	1.185	16.3	14.4
16	12900	23	31.4	2.82	85	0.42	1.150	16.7	15.9
17	12975	24	42.7	3.48	77	0.17	1.221	16.7	16.1
18	13055		38.6	3.29	75	0.29	1.161	16.8	16.2
19	13250		43.4	2.82	76	0.43	1.161	16.8	16.2
20	13795	25	12.5	1.60	81	0.56	0.272	16.8	16.2

21	14010	26	21.1	1.04	75	0.46	0.201	16.8	16.2
22	14455	28	19	1.76	64	0.16	0.748	16.9	16.2
23	14695		18.7	2.00	76	0.27	0.819	17.1	16.2
24	14905	29	20.2	2.35	75	0.33	0.419	17.2	16.4
25	15350	30	27.1	2.12	85	0.31	1.290	17.0	16.5
26	15740		14.8	2.35	78	0.81	0.802	17.3	16.5
27	16155	32	12.6	2.47	80	0.12	0.670	17.9	16.5
28	16325		14.9	3.76	81	0.50	0.532	17.5	16.6
29	17060	34	13.8	3.76	65	0.91	0.748	17.6	16.6
30	20265	40	9	3.41	60	0.01	0.512	17.7	16.6

Note that the primary drilling variables required for the MR, PSO and MPSO are depth, penetration rate, bit weight per inch of bit diameter, rotary speed, fractional tooth wear, Reynolds number parameter, mud density, and pore pressure gradient. To calculate the best values of the model constants a_1 through a_8 using the data shown, the parameters x_2 through x_8 must be calculated using Eq. II.6 through Eq. II.12 for each data entry.

III. 3. Result Analysis And Discussion

III. 3. 1. Multiple Regression

By using the equation of the proposed model of Bourgoyne and Young's and the procedures of MR that have been indicate in the previous chapter . the solutions are shown in the table below.

Table III. 2. Results obtained from Multiple Regression method.

A1	A2	A3	A4	A5	A6	A7	A8
3.90557	$1.96e^{-4}$	$2.0035e^{-4}$	$4.2839e^{-5}$	0.40740	0.45315	0.48380	0.06024

III. 3. 2. Particle Swarm Optimization

Based on the general working principal of PSO and its standard settings where the personal acceleration constant : $\boldsymbol{\phi_1 = \phi_2 = 2}$ and the weighted inertia constant $\boldsymbol{\Omega = 0.9}$, the test results are shown in the table and figure bellow for three different swarm population (n).

Table III. 3. Different PSO test results on three different population size (n).

PSO	A1	A2	A3	A4	A5	A6	A7	A8	It. n	OF
n=30	3.51587	$1.4083e^{-4}$	$1.7067e^{-4}$	$4.3373e^{-5}$	0.31975	0.38019	0.43195	0.28276	35	0.06468
n=50	3.17740	$1.3824e^{-4}$	$1.8056e^{-4}$	$4.2326e^{-5}$	0.23963	0.17381	0.33643	0.42340	30	0.06324
n=100	3.24331	$1.3582e^{-4}$	$1.7483e^{-4}$	$4.2081e^{-5}$	0.25953	0.22309	0.34038	0.39374	24	0.06250

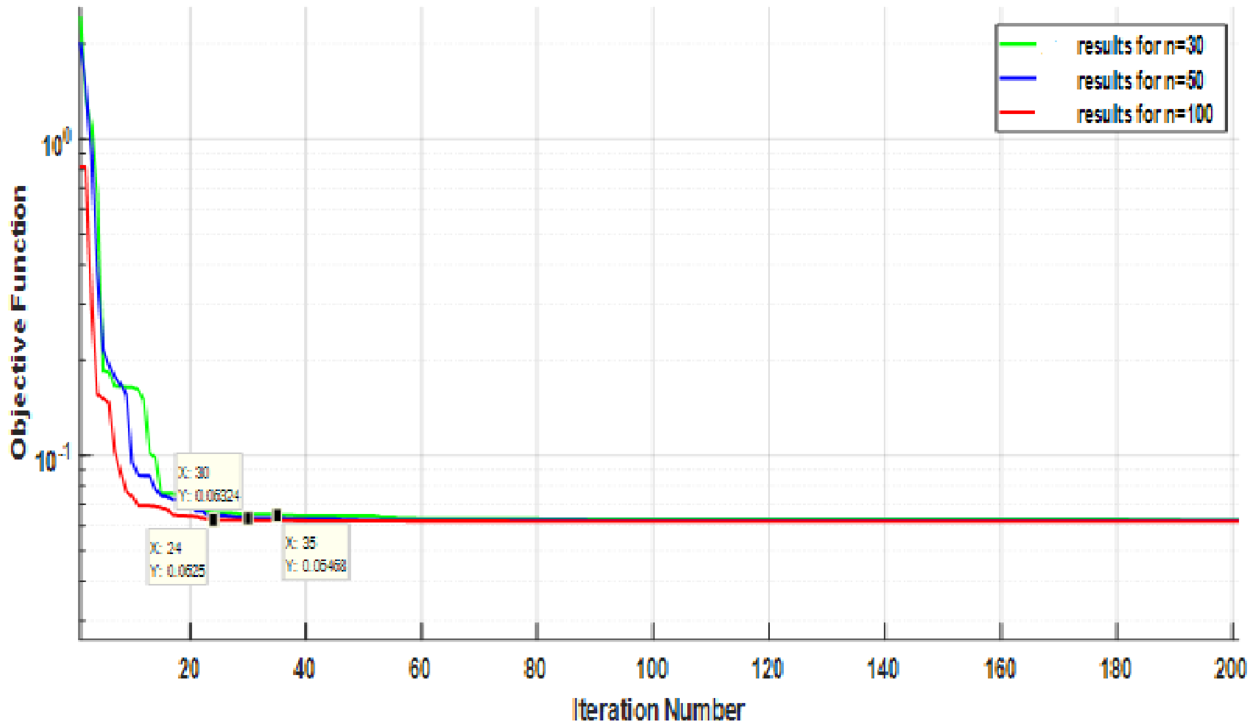

Figure III.1 : Comparison of the three PSO results convergence.

Where, It.n is the iteration number abbreviation and OF is for the objective function. From the figure III.1 and the table III.1 above, and after several tests we observed that the best value of the objective function in PSO is obtained in the third test with n=100 . As well it's the fastest test because the best result of the objective function (OF = 0.06250) is obtained after just 24 iterations.

III. 3. 3. Modified Particle Swarm Optimization

A Several PSO standard settings are modified on the test of the objective function during the course of our study and we evaluated their performances each time. the main modification of MPSO that we used where in the constants personal acceleration coefficient ($\boldsymbol{\phi_1}$ and $\boldsymbol{\phi_2}$) into this equation :

$$\lambda = \frac{2\alpha}{|2-b-\sqrt{b^2-4b}\ |} \qquad \text{(III.1)}$$

With $\alpha = 1$, $b_1 = 1.5$, $b_2 = 2$ and $b = b_1 + b_2$. Therefore $\boldsymbol{\phi_1} = \lambda . b_1$ and $\boldsymbol{\phi_2} = \lambda . b_2$. also we modified in the weighted inertia constant from $\boldsymbol{\Omega} = 0.9$ in PSO into $\boldsymbol{\Omega} = 0.4$ in MPSO . The performance of the resulting algorithm in three population size is shown in the next table and figure.

Table III. 4. Test results using Modified Particle Swarm Optimization.

MPSO	A1	A2	A3	A4	A5	A6	A7	A8	It. n	OF
n=30	3.27143	1.3715 e^{-4}	1.7455 e^{-4}	4.2565 e^{-5}	0.27357	0.22273	0.34158	0.39087	54	0.06259
n=50	3.34587	1.3787e^{-4}	1.7241e^{-4}	4.2744e^{-5}	0.28732	0.26191	0.36737	0.35411	45	0.06177
n=100	3.34602	1.3788e^{-4}	1.7241e^{-4}	4.2745e^{-5}	0.28735	0.26195	0.36742	0.35404	61	0.06176

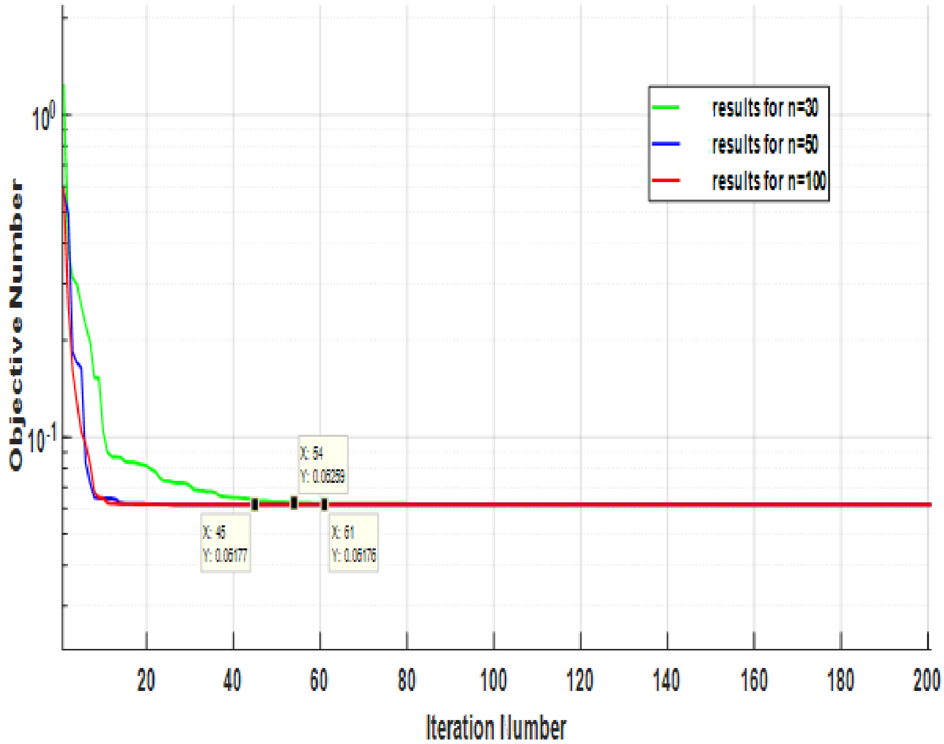

Figure III.2 : Comparison of the three M_PSO results convergence

From this results, we found that Modified PSO achieves better values of the objective function the more we increased the population size from n=30 through n=100. So we identify that this parameter (n) always affect on the convergence rate and the optimal solution in this optimization technique too, in addition to that we noted that the simulation time in MATLAB increased (the simulation time took about 23.5 seconds when we used MPSO with n = 100).

III. 4. Comparison Between The Several Optimization Techniques

III. 4. 1. Comparison Between PSO and MPSO

In the next tables and figure we will pick and compare the best previous results for PSO and MPSO with each other.

Table III. 5. Comparison between the best results of PSO with MPSO.

For n=100	A1	A2	A3	A4	A5	A6	A7	A8	It. n	OF
PSO	3.24331	$1.3582e^{-4}$	$1.7483e^{-4}$	$4.2081e^{-5}$	0.25953	0.22309	0.34038	0.39374	24	0.06250
MPSO	3.34602	$1.3788e^{-4}$	$1.7241e^{-4}$	$4.2745e^{-5}$	0.28735	0.26195	0.36742	0.35404	61	0.06176

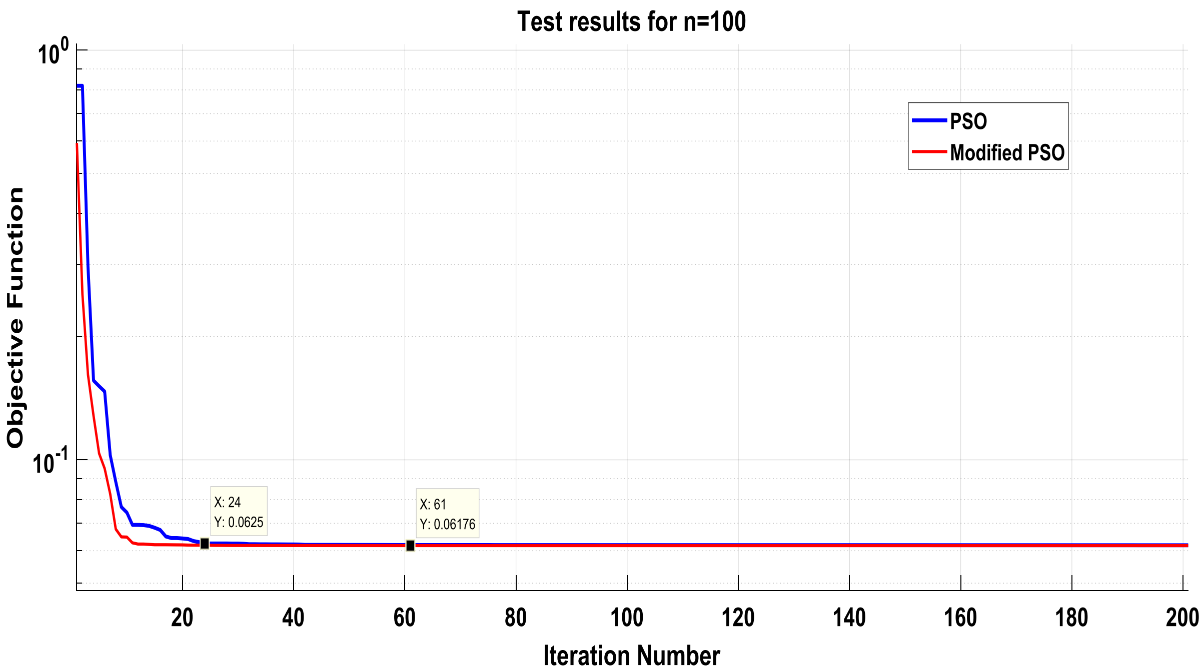

Figure III.3 : Comparison of PSO and MPSO results convergence for n = 100.

The table III.3 and figure III.3 above have been compared with all the previous results, And after we checked The objective function results many times, the value OF=0.06176 of the Modified PSO proved and confirmed its best performance specially for n=100. Therefore this best value needs more iterations number (61). And for more accuracy and precision of the comparison we will use two Relative Error (ε) tests for both of this optimization techniques, where :

$$\varepsilon = \left|\frac{X_r - X_c}{X_r}\right| \cdot 100 \qquad \text{(III.2)}$$

While, X_r is the reference value, X_c is the other calculated value, ε is a relative error.

Table III. 6. References values we have been used for the relative error tests.

References values	A1	A2	A3	A4	A5	A6	A7	A8
PSO	3.24331	$1.3582e^{-4}$	$1.7483e^{-4}$	$4.2081e^{-5}$	0.25953	0.22309	0.34038	0.39374
MPSO	3.34602	$1.3788e^{-4}$	$1.7241e^{-4}$	$4.2745e^{-5}$	0.28735	0.26195	0.36742	0.35404

Table III.7. Relative error test results for PSO and MPSO.

Relative error tests		ε_{a1}	ε_{a2}	ε_{a3}	ε_{a4}	ε_{a5}	ε_{a6}	ε_{a7}	ε_{a8}
PSO	Test1	5.69 %	0.0898 %	3.63 %	3.34 %	20.45%	36.65 %	15.23 %	16.86 %
	Test2	6.91 %	3.97 %	6.18 %	4.45 %	20.56 %	59.20 %	24.68 %	22.25 %
MPSO	Test1	0.0016 %	0.0016 %	0.0028 %	2.16e-04 %	0.0039 %	0.0091%	0.0019 %	0.0083 %
	Test2	0.0011 %	0.0031 %	0.0039 %	9.72e-04 %	0.0036 %	0.0070%	0.0013 %	0.0065 %

From table III.5, it's easy to find out that the percentage error of MPSO is so far smaller than the one of PSO in all tests , and that's an indication of how good the constants A_1 through A_8 are when we used MPSO. Otherwise , this means that the particles of the MPSO have searched for more optimal solution than the PSO. That's why the MPSO convergence is better and takes more iterations number.

III. 4. 2. Final Comparison Of The Optimization Techniques

In this section , we compared the test results of PSO with MPSO and MR based on the Root Mean Square Error (RMSE) and the Absolute Error, as presented in Table III.8.

Table III. 8. comparison of the several optimization technique results.

Technique of optimization		RMSE Ln(ROP)	RMSE ROP	Absolute Error
PSO	n=30	0.16735	3.11840	0.04425
	n=50	0.16655	3.08693	0.04492
	n=100	0.16631	3.11550	0.04416
MPSO	n=30	0.16625	3.06860	0.04411
	n=50	0.16619	3.09460	0.04384
	n=100	0.16619	3.09457	0.04384
MR		0.21	3.5213	0.1471

From the table III.8 it can be seen that both of the proposed optimization technique MPSO and PSO give us best optimal solution than the Multiple Regression, they can achieve excellent convergence on this optimization problems. In addition to that the simulation results have shown that the MPSO is a better algorithm to solve complex optimization problems and the best result is improved on a high number of population (n=100). Which indicates the better searching performance and the more excellent convergence ability.

III.5 Optimum Bit Weight And Rotary Speed

Table III. 9. Required data according to Bourgoyne study.

Trip time, hours	6.0
Bit class	1-3
Bit weight, 1,000 lb/in.	4.1
Rotary speed, rpm	60
Tooth wear	T-6
$(W/d)_t$, 1,000 lb/in.	0.5

And From the best results of M_PSO that obtained in the previous study ,we took a_1=3.34602, a_2= $1.3788e^{-4}$, a_3 = $1.7241e^{-4}$, a_4 = $4.2745e^{-5}$, a_5 = 0.28735, a_6 = 0.26195, a_7 = 0.36742, a_8 = 0.35404.

Solution :

1. Calculation of formation abrasiveness constant by using Eq. II.10

$$\tau_H = H_3\left(\frac{N}{60}\right)^{H1}\left[\frac{\left(\frac{W}{d_b}\right)_m - 4}{\left(\frac{W}{d_b}\right)_m - \left(\frac{W}{d_b}\right)}\right]\left(\frac{1+\frac{H_2}{2}}{h+(H_2h^2)/2}\right)t_b \qquad \text{(III.3)}$$

From Table. II. 1, H_1 = 1.84, H_2 = 6, H_3 = 0.8, $(Wld)_m$ = 8.0.

$$\tau_H = 0.8(1)^{1.84}\left[\frac{8-4}{8-4}\right]\left(\frac{1+\frac{6}{2}}{0.75+(6(0.75)^2)/2}\right)12 = 15.75$$

2. Calculation the optimum bit weight by using Eq II.29 :

$$\left[\frac{W}{d_b}\right]_{opt} = \frac{0.28735(1.84)8-0.26195(0.5)}{0.28735(1.84)+0.26195} = 5.18 \text{ lb/in}$$

3. Calculation of the expected bit life by using Eq.II 13:

$$t_b = \left(\frac{400}{500}+6+1\right)(3.07-1) = 16.1\text{h}$$

4. Calculation the optimum rotary speed by using Eq. II.30

$$[N]_{opt} = 60\left[\frac{15.7}{16.1}\frac{(8-5.18)}{(8-4)}\right] = 41.25 \text{ rpm}$$

III. 6. Conclusion

This chapter focuses on the optimization of the drilling parameters results and the capability of the modified particle swarm optimization to find the best optimal solutions when its parameters are optimized specifically for this problem. We have shown in more than 20 tests that the more we increase the population size the more we obtain better values of the objective function in both PSO and MPSO, but it takes more time of convergence.

We have shown that the MPSO has a better performance in terms of stability and speed of convergence to find the global optimum.

General conclusion

One of the most important perspectives from both technical and economic sides for the petroleum industry during the drilling operations is the decreased ROP. So the deeper we understand the processes, properties, and driving mechanisms of the ROP, also the different classification of the drilling parameters and their effects the more we will capable of increase The ROP. For this reason we have used a viable approach to understand and calculate the above-mentioned details, It’s the Bourgoyne and Young ROP model.

In this study and after we have determined and calculated the constant values A_1 through A_8 of the proposed model by the multiple regression method, another metaheuristic technique of optimization called particle swarm optimization (PSO) we have utilized to reach more optimal values of the objective function and more reliable constants. The results we have achieved were better than the multiple regression method, but we have faced a problem that the PSO doesn’t always converge to the best values and optimal solution. That’s why we proposed a Modified particle swarm optimization (M_PSO), The modification were generally in the constants personal acceleration coefficient of the PSO.

Finally, through the results we have achieved in several tests and the different comparison of the MR,PSO, and M_PSO using some of the approximation errors, we validate that the best convergence, optimization performance and the optimal values are all obtained by the M_PSO. This leads results lead us to calculate and Optimum bit weight and rotary speed for the drilling operation.

In the future work, we will plan to implement our results on a real time drilling operation in order to increase the ROP and the well productivity also to reduce the drilling cost. In addition this study leads the readers to search and look for a better modification of the PSO approach.

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SUMMARY

More than ever in the drilling industry, all considerations are involved to reduce drilling operation expenditure. That’s why The objective for our study is to focus on the Optimization of the Drilling Parameters, To achieve this goal we began our study by a dominant and widely utilized method for drilling rate prediction that called Bourgoyne and Young’s Model. And their suggested analysis method the multiple regression (MR) to define these constants.

Then our study aims to propose one of the best metaheuristic optimization techniques (PSO) and the modified one (M_PSO) to improve and compare the quality of solution founded by the multiple regression method. Through the final the results we have achieved in several tests and the different comparison of the MR,PSO, and M_PSO using some of the approximation errors, we validate that the best convergence, optimization performance and the optimal values are all obtained by the M_PSO. These results lead us to calculate and Optimum bit weight and rotary speed for the drilling operation

Keywords:Drilling expenditure Optimization drilling rate multiple regression metaheuristic errors

أكثر من أي وقت مضى في مجال التنقيب عن البترول, كل التفكير و الدراسات باتت للحد من نفقات عمليات الحفر. لذلك كان الهدف في دراستنا هو التركيز على تحسين خصائص الحفر الى الامثل,لتحقيق هذا الهدف بدأنا بالطريقة السائدة والتي تستخدم على نطاق واسع لتنبؤ بمعدل الحفر(ROP) للباحثين بوركوين و يونغ .باستعمال طريقة التحليل المتعدد (MR) الذي اعتمداه. ثم تهدف دراستنا إلى اقتراح واحدة من أفضل الخوارزميات المصممة لإيجاد حلول عاليه الجوده المسماة باستمثال عناصر السرب (PSO) والنسخة المعدلة و المهجنة منها (M_PSO) وهذا لتحسين ومقارنة جودة الحل الناتج عن طريقة التحليل المتعدد (MR). ومن خلال النتائج النهائية التي حققناها في العديد من الاختبارات والمقارنة المختلفة بين MR و PSO و M_PSO باستخدام بعض الاخطاء المطلقة و النسبية و غيرها. أكدنا أن أفضل تقارب وأداء والقيم المثلى يتم الحصول عليها جميعًا من M_PSO. هذه النتائج تقودنا إلى حساب الوزن على اداة الحفر الأمثل والسرعة الدورانية المناسبة لعملية الحفر.

الكلمات المفتاحية: التنقيب نفقات تحسين معدل الحفر التحليل المتعدد الخوارزميات الاخطاء المطلقة

Plus que jamais dans l'industrie du forage, toutes les considérations sont impliquées pour réduire les dépenses d'opération de forage. C'est pourquoi l'objectif de notre étude est de concentrer sur l'optimisation des paramètres de forage, nous avons commencé notre étude par une méthode dominante et largement utilisée pour la prédiction du taux de forage, c’est le model de Bourgoyne and Young's. Tell que leurs méthode d'analyse suggérée est la régression multiple (MR) pour définir ces constantes.

Ensuite, notre étude vise à proposer l'un des meilleures techniques d'optimisation métaheuristique appelée l’optimisation par essaims particulaires (PSO) et sa version modifiée (M_PSO) pour améliorer et comparer la qualité des solutions fondées par la méthode de régression multiple. Grâce aux résultats finaux obtenus dans les plusieurs tests et la comparaison entre le MR, PSO et M_PSO et après l’utilisation des erreurs d'approximation, Nous avons confirmé et valider que la meilleure convergence, performance et les valeurs optimales sont toutes obtenues à partir de M_PSO. Ces résultats nous conduisent à calculer le poids optimal sur l'outil de forage et aussi la meilleure vitesse de rotation adaptée au fora

Les mots clé : forage dépenses optimisation taux de forage régression multiple métaheuristique erreurs